ESSAYS ON LABOUR ECONOMICS: UNDERSTANDING STRUCTURAL CHANGES

By

AITOR IRASTORZA-FADRIQUE

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To the memory of my grandparents and Fidel

Author's declaration

I, Aitor Irastorza-Fadrique, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

I declare that the work in this thesis was carried out in accordance with the requirements of the University's Regulations and that it has not been submitted for any other academic award.

Chapter 1 of this thesis is sole-authored. Chapter 2 is joint work with Peter Levell (IFS) and Matthias Parey (University of Surrey). Chapter 3 is joint work with Michael J. Böhm (TU Dortmund) and Ben Etheridge (University of Essex). All errors remain mine.

Signed by: Aitor Irastorza-Fadrique
Date: 4th of September, 2023

Abstract

This thesis contains three self-contained chapters, seeking to provide valuable insights into recent changes shaping modern labour markets.

Chapter 1 studies the impact of industrial robots – one of the leading automation technologies over recent decades – on local labour markets in Great Britain during 1998-2018. The analysis shows that robots have reshaped the demand for labour and caused reallocation across sectors but have not reduced total employment. Robot exposure resulted in a decline in job opportunities within manufacturing industries like transport equipment, counterbalanced by a more than compensatory surge in labour demand within the service industry.

Chapter 2, co-authored with Peter Levell and Matthias Parey, studies the labour market responses of individuals and their households to increased Chinese import competition in the 2000s. Drawing on large-scale data from linked decadal censuses in England and Wales, the chapter explores various margins of adjustment, including self-employment, retirement, family stability, and partners' labour supply. The analysis underscores the importance of investigating household responses and the self-employment margin to fully understand the effects of trade shocks.

Chapter 3, co-authored with Michael J. Böhm and Ben Etheridge, studies the responsiveness of labour supply to the changing demand for jobs during 1985-2010. The chapter proposes a measure of occupation-specific labour supply elasticities, capturing the impact on employment of changes in the wage structure across occupations. These include wage changes in the occupation itself and wage changes in other occupations. It shows that an important catalyst of recent shifts in employment is the flexibility of labour supply to react to them. The analysis also underscores the importance of accounting for wage changes in other occupations to fully understand the evolution of the employment structure.

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Throughout my academic journey, I have been lucky to have a circle of friends and colleagues who have served as a constant source of mutual inspiration, challenge, and happiness. To each and every one of them, too numerous to name individually, I will always be thankful.

Lastly, a sincere tribute to my family. To my parents, for their constant presence. To my sister, for making me a more resilient person. To my aunts, cousins, and extended family, whose unconditional and emotional support has been invaluable. With their permission, I dedicate this thesis to the memory of Fidel, Justi, and Jesus, who lost their lives during the time of its creation.

Data and Funding Statement

This thesis makes use of a number of data sources. Chapter 1 uses robotics data from the International Federation of Robotics (IFR). The Department of Economics at the University of Essex provided funding to purchase the data. Neither the owner nor the distributor of any of these data bears any responsibility in relation to the interpretation or analysis presented in Chapter 1.

Chapter 2 uses Office for National Statistics Longitudinal Study (ONS LS) data. The permission of the Office for National Statistics (ONS) to use the LS is gratefully acknowledged, as is the help provided by the staff of the Centre for Longitudinal Study Information & User Support (CeLSIUS). CeLSIUS is funded by the ESRC under project ES/V003488/1. The authors of Chapter 2 alone are responsible for the interpretation of the data. The chapter contains statistical data from ONS which is Crown Copyright. The use of the ONS statistical data does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. Chapter 2 uses research datasets which may not exactly reproduce National Statistics aggregates. The analysis was carried out in the Secure Research Service (SRS), part of the Office for National Statistics. This chapter is part of a project that was supported by the Economic and Social Research Council (ESRC) through the ESRC-funded Centre for Microeconomic Analysis of Public Policy at the Institute for Fiscal Studies (grant reference ES/M010147/1) and through the grant 'Productivity, Wages and the Labour Market' (grant reference ES/W010453/1).

Chapter 3 uses the weakly anonymous Sample of Integrated Labour Market Biographies SIAB data (version 7519). Remote data access was provided by the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). The help provided by the staff of the University of College London (UCL) and the Institute for Social and Economic Research (ISER) at the University of Essex Safe Room is gratefully acknowledged.

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Seminar and Conference Presentations

As of September 2023, the chapters of this thesis have been presented in several places, which are listed below. I would like to thank conference and seminar participants for their valuable comments and suggestions.[1]

Chapter 1 was presented at: University of Essex, University of the Basque Country (UPV/EHU), University of Bristol, University of Stirling, University of Bologna, Goethe University Frankfurt, the Irish Postgraduate and Early Career Economics Workshop (online), and the PhD-EVS (online).

Chapter 2 was presented at: University of Warwick, University of Essex, University of Sussex*, University of Glasgow, European University Institute*, the Institute for Fiscal Studies, TU Dortmund, US International Trade Commission*, Collegio Carlo Alberto, Universitat Pompeu Fabra, University of Cagliari*, University of Surrey, and the 5th IZA Workshop on Gender and Family Economics (online).

Chapter 3 was presented at: Charles University in Prague, University of Essex, the IAB Nuremberg*, Uppsala University*, the ZEW Mannheim*, Helsinki*, TU Darmstadt*, University of Duisburg-Essen*, RWI-Essen*, Mercator School of Management*, and the 6th User Conference of the FDZ-IAB (online).

[1]The symbol * means presented by a co-author.

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CHAPTER 0

INTRODUCTION

The labour market has undergone significant structural changes in recent decades. Technological change and globalisation are two major drivers transforming today's world. New technologies reshape production processes by complementing workers and enabling the automation of specific tasks. Globalisation results in greater integration of factors of production among countries. Together, they have brought about profound changes in the nature and geography of employment, contributing to economic growth but posing severe challenges for certain areas and workers. We must learn where these changes are taking place, and how they affect different people if we are to know where support should be targeted, and what form it should take.

This thesis consists of three self-contained chapters that touch on important topics in understanding recent structural changes in the labour market: studying the effects of industrial robots on local labour markets, investigating the adjustment mechanisms and family responses to increased import competition, and exploring the responsiveness of workers' labour supplies to the changing demand for jobs. Together, they offer a comprehensive exploration of the underlying factors contributing to recent changes in the labour market, providing valuable insights into the experiences of local areas and workers as they navigate these shifts.

In this introductory chapter, we begin by establishing a guide to help in understanding the context and focus of recent empirical research on the effects of technological progress, international trade, and occupational change on labour markets. In doing so, we aim to set the stage for the subsequent chapters, outlining the key contributions that each of them brings to the overall discourse. The final section of this introductory chapter offers the roadmap of the thesis.

0.1 Technological Change

The impact of technology on the labour market has been subject to continuous interest among economists for a long time (see Mokyr et al. (2015) for a summary). David Ricardo was an early voice of worry, writing 'the substitution of machinery for human labour is often very injurious to the interests of the class of labourers' (Ricardo, 1821, Ch. 31). A century later, John Maynard Keynes introduced the concept of *technological unemployment*, referring to the effective substitution of capital for labour (Keynes, 1930). Wassily Leontief (1952) was also drawn into the debate, claiming 'automatisation, while solving some problems, will everywhere create new and possibly more difficult ones'.

More recent technological anxieties stem from increased computing power, digitalisation, and advances in machine learning and robotics (Brynjolfsson & McAfee, 2014). Alarmist rhetoric animates today's debate about technology and employment. Jeremy Rifkin's The End of Work (1995) predicts a future where automation and 'the information age' increase productivity but those displaced by machines will not have the means to fully participate in society. In The Rise of the Robots (2015), Martin Ford believes that, unlike in previous centuries, the emerging technologies will this time fail to generate new forms of employment. The debate has also been fed by studies forecasting drastic job losses in occupations susceptible to automation (Frey & Osborne, 2017).

The European Commission gauged public perception of automation technologies in the 2017 Special Eurobarometer. While more than six in ten respondents (of 28,000 EU citizens) have a positive view of robots and artificial intelligence (AI), an even higher proportion – 72% – agree with the statement that they steal people's jobs (European Commission, 2017). Whilst public and expert opinions frequently differ on economic issues, a 2017 Chicago Booth poll confirms that leading academic economists, although to a lesser extent, also share this worry. 38% of leading US economists and 28% of leading European economists believe that the rising use of robots and AI is likely to increase long-term unemployment rates.[1] Politicians have also demonstrated a willingness to take action on these issues. A 'robot tax' was considered – though rejected – by the European Parliament in 2018.

Chapter 1 of this thesis considers the plausibility of these prophecies of massive job loss by empirically studying the equilibrium impact of industrial robots on local labour markets in Great Britain. We focus on industrial robots, one of the leading automation technologies over recent decades, which are machines that operate independently and perform a range of manual tasks, such as welding, painting, material handling, and packaging (IFR, 2019). The analysis closely aligns with the empirical methodology used by Acemoglu & Restrepo (2020), who revealed negative impacts on labour demand in the United States. In contrast, our study reveals no such adverse effects of predicted robot exposure on overall employment in Great Britain.[2] Predicted robot exposure results in a decline in job opportunities within the manufacturing sector (in particular, within heavy manufacturing industries such as the transport equipment industry), counterbalanced by a more than compensatory surge in labour demand within the service industry.

0.2 Globalisation and International Trade

Besides technological change, the post-1990 globalisation era – characterised by a rapid expansion of international trade and an extraordinary rise in the role of low-income countries in world trade – has led to significant changes in the labour market of many developed economies. While countries like Germany have seen large increases in both their imports and exports during this period (Dauth et al., 2014), other countries such as the UK and the US have mainly been confronted

[1] See here the results for the leading US economists and the European economists.

[2] This finding is consistent with Dauth et al. (2021) for Germany, and Dottori (2020) for Italy, who also study the complex relation between robots and employment using a similar empirical approach. We provide a detailed review of the literature at the beginning of each chapter.

with a significant increase in import competition. One major contributing factor is the swift incursion of Chinese products into the world economy. China's share in worldwide goods exports grew from a mere 0.9% in 1980 to a high of 13.6% in 2015 (Dorn & Levell, 2021). Its significant role in altering the global landscape during the globalisation period of the 1990s and 2000s, especially after joining the World Trade Organisation (WTO) in December 2001, explains why many recent studies examining the effects of trade shocks on individuals, firms, and local areas focus on the 'China shock' (Autor et al., 2016).

Several robust findings arise from these studies. First, local areas with higher exposure to Chinese import competition (owing to the regional concentration of tradable industries) experienced larger reductions in manufacturing employment (Autor et al., 2013, Balsvik et al., 2015). Second, firms that operate in industries with larger growth of Chinese imports suffered falling employment and a greater likelihood of firm exit (Utar, 2014, Bloom et al., 2016). Consistent with the earlier, evidence at the individual level finds significant negative persistent effects on earnings and employment trajectories of affected workers. Greater exposure to import competition, however, causes only greater subsequent worker mobility across firms and industries, but not greater worker mobility across local areas (Autor et al., 2014, De Lyon & Pessoa, 2021).

These findings raise the question of whether other forms of self-insurance are available to the workers affected by adverse trade shocks and their families, either through responses by the partner, or adjustments in labour force participation choices. Chapter 2, co-authored with Peter Levell and Matthias Parey, contributes to this particular literature by documenting workers' responses to increased Chinese import competition along the self-employment and retirement margins, and by studying responses of partners in the same household as exposed workers. Furthermore, our study provides insights into the impact of trade shocks on family formation and dissolution. Overall, we show there is substantial heterogeneity in labour market and life decisions in response to increased Chinese import competition. Men and women do not respond to trade shocks in the same way, nor do they respond in the same way to shocks affecting their partners.

0.3 Occupational Change

Labour demand changes induced by, among others, technological change (Ch. 1) and globalisation (Ch. 2), are shown to be the main drivers of recent shifts in the structure of employment across occupations – notably in the form of "job polarisation", with employment growth in lovely and lousy occupations (to paraphrase Goos & Manning (2007)) and employment declines in middling occupations.[3] A large literature has connected these changes in the job structure to changes in wages across occupations and rising wage inequality (see, e.g. Dustmann et al. (2009), Cortes (2016), Cavaglia & Etheridge (2020), Böhm et al. (2022)).

The impact of a shift in labour demand on employment and wages, however, will depend on the elasticity of labour supply. Despite its prominence in policy discussions, there is still a need for comprehensive research on how labour supply responds to changes in job demand. This refers to the ability of the workforce to react to the changing job landscape. As advocated by Autor (2019), it highlights the importance of investing in education and training programs that equip and raise the supply of workers with the skills needed for in-demand occupations. More generally, understanding and addressing the responsiveness of labour supply are key components of promoting equitable economic opportunities and supporting the workforce in adapting to the changing job market.

Chapter 3, co-authored with Michael J. Böhm and Ben Etheridge, explores the role of the heterogeneity of occupational labour supply in explaining the variation of employment and wage growth between 1985 and 2010. We propose a measure of occupation-specific labour supply elasticities, capturing the impact on employment of changes in the wage structure across occupations. These include wage changes in the occupation itself (own-price elasticities) and wage changes in other occupations (cross-price elasticities). We show that an important catalyst of recent shifts in employment is the flexibility of labour supply to react to them. Our analysis also highlights the importance of accounting for wage changes in other occupations to fully understand the evolution of the employment structure.

[3] See, e.g. Autor et al. (2003), Grossman & Rossi-Hansberg (2008), Autor et al. (2013), Keller & Utar (2023). Recent work has also studied the role of the supply of skills (Glitz & Wissmann, 2021).

Organisation of the Thesis

All three subsequent chapters are self-contained and can be read independently. Chapter 1 studies the impact of industrial robots on total employment in Great Britain. Chapter 2 examines the adjustment mechanisms and household responses to rising Chinese import competition. Chapter 3 explores the role of occupation-specific labour supply in explaining changes in employment and wages over recent decades. Appendices for Chapters 1 to 3, containing supplementary tables and figures, further details on the theory and data, as well as further robustness checks, can be found at the end of this thesis.

CHAPTER 1

Industrial Robots and Worker Reallocation in Great Britain

Robots can now perform a considerable range of economically valuable tasks, such as soldering and packaging, with very little or no human intervention. Theoretically, the overall effect of robots on employment is not clear as it involves forces moving in opposite directions.[1] While in some cases robots displace labour from automatable tasks (*displacement effect*), they can also boost productivity, reduce prices, increase the demand for complementary non-automatable tasks, and create new tasks (*reallocation effects*). Understanding their aggregate impact is thus an open empirical question. In this chapter, we empirically investigate the impact of industrial robots on employment in Great Britain.

Evidence from the United States, Germany, and Italy reveals contrasting results thus far. On the one hand, Acemoglu & Restrepo (2020) show the displacement effect prevails in the US, estimating large and significant negative effects on both employment and wages. Their estimates imply that one robot in a commuting zone reduces employment by about six workers. In contrast, Dauth et al. (2021) find no effect on total employment in Germany. Within manufacturing, robot

[1] Whenever this chapter refers to 'robots' or 'robotics' it means industrial robots as defined by the International Federation of Robotics (IFR). See Section 1.1 for details and the definition.

exposure leads to fewer jobs but new labour demand in the service sector leads to an offsetting force. For Italy, Dottori (2020) also finds no evidence of a systematic and statistically significant impact of higher robot exposure on overall employment growth, nor on the change in the employment-to-population ratio.

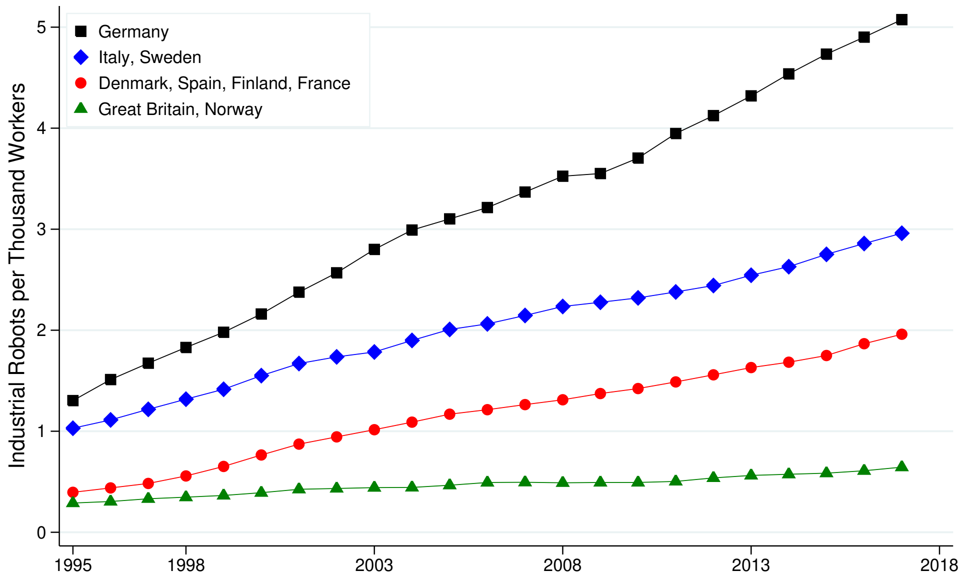
These three countries are at the forefront of robot adoption. Germany emerges as Europe's frontrunner in robotics. Italy has been ranked second after Germany since the 1990s for operational stock of robots (IFR, 2019). Robots in the US are neither negligible nor new. Against this background, Great Britain (GB), another large developed economy, offers an interesting and insightful case study of the impact of industrial robots at the bottom of the adoption distribution. GB lags well behind these countries in adopting industrial robots, as shown in Figure 1.1a, which shows the evolution of robot adoption (defined by the number of industrial robots per thousand workers) for different groups of European countries since 1995.[2] While most of the existing empirical evidence focuses on heavy robot adopter countries, there is limited evidence of the impact of robots on employment in countries that adopt robots at a significantly lower rate.

Drawing on the substantial variation in Britain's labour market, at both the industry and geographical levels, this chapter studies the impact of industrial robots on total employment in Great Britain over the period 1998-2018. The empirical approach follows the paper by Acemoglu & Restrepo (2020), wherein the effects are estimated by regressing changes in employment on a measure of local robot exposure. This measure combines baseline district-level industry-employment shares with industry-level variations in the adoption of industrial robots. Differences in local robot exposure result from the historical concentration of various areas in specific industries, which subsequently exhibited differing rates of robot adoption. We instrument the growth in robots in each industry using data on robot adoption in other European countries that are not heavy robot adopters. We also include a comprehensive set of baseline local controls on relevant labour market variables to control for confounding changes in trade patterns, other technological changes, sectoral trends, or demographic factors.

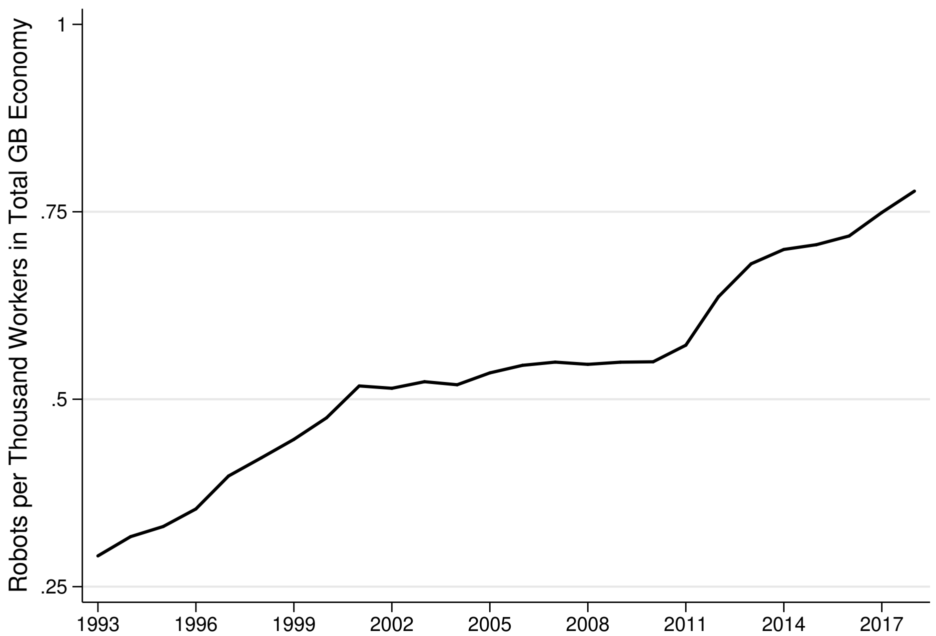
[2] For ease of exposition, Figure 1.1a displays averages across groups of countries with similar robot adoption rates. Figure 1.1b, which we discuss later, shows robot adoption in GB separately.

Figure 1.1: Industrial Robots per Thousand Workers in Europe and GB

(a) Industrial Robots per Thousand Workers in Europe (1995-2017)



(b) Industrial Robots per Thousand Workers in GB (1993-2018)



Source: Own calculations based on IFR, EU KLEMS, and EUROSTAT data

In a concurrent paper, Kariel (2021) looks at the impact of robots in England and Wales. Their analysis uses UK Census data, which means their analysis ends in 2011. Instead, we use district-level employment data from the Business Register and Employment Survey (BRES), which offers representative data by detailed industry and geography, and extend the time window to 2018. As shown in Figure 1.1b, robot adoption in GB accelerated after 2011, suggesting the Great Recession induced firms to restructure their production towards greater use of robots.[3] We also incorporate insights from recent literature that formalises the basis for identification and inference in shift-share settings (Adao et al., 2019, Borusyak et al., 2022). We draw on this recent literature to discuss the basis for econometric identification, present results using alternative methods for constructing standard errors, and provide an analysis of pre-trends in the data.

We estimate a small but positive employment effect of industrial robots in GB over the period 1998-2018. One additional industrial robot per thousand workers is associated with a relative increase in a district's employment-to-working-age population ratio of 0.075 percentage points. This estimate includes both direct and indirect effects across districts and translates into one robot increasing employment by approximately 1.1 workers. To put this number into perspective, consider that a total of 17,500 industrial robots have been installed in GB over the period 1998-2018. A quick back-of-the-envelope calculation implies an increase of 19,250 jobs.

We show this finding masks the presence of considerable displacement and reallocation effects. On the one hand, we provide evidence the displacement effect of robots takes place mostly in heavy manufacturing industries and especially in the transport equipment industry. On the other hand, we find a significant and positive effect of robots on the employment share for services. The displacement effect is more than offset by the latter reallocation effect, explaining the overall small but positive effect. Robots in GB are thus contributing to within-district across-industry worker reallocation, from heavy manufacturing industries to the service sector, but without detriment to the overall employment. The analysis is robust to a battery of sensitivity checks, including the exclusion of the districts with the highest robot exposure, or the exact construction of the exposure measure.

[3]This is consistent with the US study by Hershbein & Kahn (2018).

This chapter is related to and builds on growing literature studying the complex relation between robots and employment. Appendix Table A.1 provides a synoptic analysis of key papers.[4] Besides the aforesaid Acemoglu & Restrepo (2020), Dottori (2020), Dauth et al. (2021), and Kariel (2021), this work relates to other studies using industry-level robot data provided by the IFR. In a cross-country analysis, Graetz & Michaels (2018) find no effect of robots on total employment, with some evidence of reduced employment of low-skill workers relative to middle- and high-skill workers. Instead, they show that industrial robots are associated with increases in labour productivity and wages. Chiacchio et al. (2018), using regional data from six European countries, find negative employment effects of robots on employment, particularly affecting young and medium-educated workers.[5]

As robot data by the IFR is provided at the industry and national level, a recent series of papers use firm-level data to estimate the employment effects of robots at a more granular level. Koch et al. (2021) use Spanish firm-level data to show that ex-ante larger, more productive and export-oriented firms are more likely to adopt robots. They estimate robots raise firm-level employment by around 10 percent. Aghion et al. (2023) use French data to show firms using more automation technologies (including robots) increase their total sales, total employment, as well as employment of medium- and low-skill workers. Acemoglu et al. (2020) also show firms adopting robots expand their employment in France. However, those gains are offset by employment losses at the industry level as employment decreases at other firms that are not adopting robots and are losing market share.[6]

More broadly, the work in this chapter relates to the empirical literature on the effects of automation technologies on employment and wages. Following the seminal work by Autor et al. (2003), an important amount of papers show computer technology (ICT) has contributed to job polarisation (i.e. the simultaneous growth

[4] Beyond employment, recent papers consider outcomes such as job quality (Antón et al., 2023), political preferences (Frey et al., 2018, Gallego et al., 2022, Anelli et al., 2021), physical/mental health of workers (Patel et al., 2018, Abeliansky & Beulmann, 2019, Gihleb et al., 2022), family behaviour (Anelli et al., 2021), gender pay gap (Aksoy et al., 2021), and labour force participation (Fossen & Sorgner, 2019, Grigoli et al., 2020, Korchowiec, 2020, Schmidpeter & Winter-Ebmer, 2021). While acknowledging the importance of these other dimensions, they require another exercise in data collection and are therefore left for future research.

[5] See also Faber (2020), Borjas & Freeman (2019), de Vries et al. (2020), Adachi et al. (2022).

[6] See also Dixon et al. (2020), Humlum (2021), Bessen et al. (2019), Bonfiglioli et al. (2020).

of high- and low-wage jobs, at the expense of middle-wage jobs) and wage inequality (Goos & Manning, 2007, Michaels et al., 2014, Cavaglia & Etheridge, 2020).[7] There are fewer studies of the effects of artificial intelligence (AI) specifically, though this body of work is expected to grow fast in the coming years (Babina et al., 2023, Acemoglu et al., 2022, Alekseeva et al., 2021).

The chapter proceeds as follows. Section 1.1 describes the data and presents descriptive statistics. Section 1.2 discusses the empirical and identification strategy. The main results are presented in Section 1.3, before the final section, Section 1.4, concludes. Appendix A includes supporting tables and figures, a summary of the theoretical model, additional discussion on data, and further robustness checks.

1.1 Data and Descriptive Statistics

1.1.1 Industrial Robots Data

The International Federation of Robotics (IFR) provides data on the number of industrial robots delivered and operational stock by industry, country and year since 1993, based on yearly surveys of robot suppliers and capturing around 90% of the robots' world market. An industrial robot is defined as *an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications*. Its main application areas include handling operations, welding and soldering, dispensing, processing, and assembling (IFR, 2019).

When estimating the operational stock, the IFR assumes an industrial robot fully depreciates after 12 years of service usage. Following Graetz & Michaels (2018), we reconstruct the stock of industrial robots based on annual installations and a yearly depreciation rate of 5 and 10%. Figure A.1 in the Appendix shows the evolution of the stock of industrial robots in GB, in absolute value, for each of the three cases. They show very similar patterns. GB is characterised by a relatively constant positive robot adoption rate during the 1990s. This upward trend becomes almost flat in the 2000s. After the Great Recession, however, there is again a clear

[7] See also Autor et al. (2006, 2008), Spitz-Oener (2006), Goos et al. (2009, 2014), Dustmann et al. (2009), Acemoglu & Autor (2011), Autor & Dorn (2013), Autor (2015), Cortes (2016).

upward trend, suggesting the last financial crisis induced firms to restructure their production towards greater use of robots. For the remainder of the chapter, our measure for the stock of robots is based on the 5% depreciation rate. The results are robust to using any of the other robot stock measures.

Robot data is broken down at the industry level, with eleven industrial sectors for manufacturing and six for non-manufacturing. Table 1.1 shows how robot adoption varies over time and across industries in GB. The industry with the highest robot adoption is the transport equipment industry (which includes the automotive industry), where almost 47.5 robots are employed per thousand workers. In 1998, there were only 15 robots per thousand workers. Other industries that become more robot-intensive include the electrical equipment industry and the industry of rubber and plastics products. In contrast, robot adoption is close to zero in most non-manufacturing industries, as is the case for agriculture and fishing, utilities, and the service sector.

Despite being one of the main data sources for recent papers on robotisation (Graetz & Michaels, 2018, Dauth et al., 2021, Acemoglu & Restrepo, 2020), the IFR data has some weaknesses. First, data on robot prices and quality are only provided until 2005, making it impossible to know how the quality of robots has improved after that. A further limitation is the lack of geographical information on the within-country distribution of industrial robots. Finally, not all robots are classified into one of the IFR industries. Around 6% of total robots are classified as *unspecified*, and not considered in our analysis.

1.1.2 District-Level Employment Data

Our primary data sources for measuring employment by industry and geography consist of three datasets covering different time periods. The Business Register and Employment Survey (BRES) is available from 2009 onwards and collects annual employment data from businesses across the whole of the GB economy. We complement this data with its two predecessor datasets: the Annual Business Inquiry (ABI) covers the years 1998-2008, while the Annual Employment Survey (AES) spans 1991-1997. The three employment surveys are available on the National Online Manpower Information Service (NOMIS), a service provided by the Office

Table 1.1: Industrial Robots per Thousand Workers by Industry in GB (1998-2018)

	1998	2003	2008	2013	2018	Employment (1995, thousands)
Panel A. MANUFACTURING INDUSTRIES						
Food products, beverages and Tobacco	0.38	0.81	1.51	2.49	3.12	507.78
Textiles, wearing apparel, leather and related products	0.05	0.08	0.15	0.14	0.13	390.09
Wood and Paper products; publishing and printing	1.95	2.02	1.95	1.94	1.66	388.98
Chemical products, pharmaceuticals, cosmetics	8.96	10.62	11.28	12.07	11.19	245.34
Rubber and plastics products; other non-metallic mineral products	0.16	0.24	2.47	4.97	7.06	407.01
Basic metals and fabricated metal products, except machinery and equipment	1.44	2.09	2.45	3.37	3.81	554.22
Computer, electronic and optical products	0.53	1.57	2.33	2.38	2.38	238.84
Electrical equipment	3.65	4.49	5.27	5.49	6.85	154.47
Machinery and equipment	1.21	1.26	1.37	1.86	2.72	304.73
Transport equipment	14.93	26.91	32.43	45.84	47.42	357.78
Other manufacturing; repair and installation of machinery and equipment	0.52	0.68	0.93	1.01	3.11	436.24
Panel B. NON-MANUFACTURING INDUSTRIES						
Agriculture, hunting and forestry; fishing	0.02	0.03	0.03	0.03	0.03	476.77
Mining and quarrying	0.11	0.48	0.49	0.34	0.76	59.29
Electricity, gas and water supply	0.01	0.05	0.07	0.06	0.04	252.21
Construction	0.01	0.04	0.05	0.05	0.04	1849.43
Education, Research and Development	0.04	0.07	0.06	0.09	0.11	1813.29
Services	0.00	0.00	0.00	0.01	0.19	17377.88

Notes: Table shows how robot adoption varies over time and across industries in Great Britain. The number of industrial robots comes from the IFR and the number of workers in each industry from the EU KLEMS.

for National Statistics (ONS).[8] They are all comprehensive employment surveys of the number of jobs held by employees broken down by detailed geography (up to Local Authority Districts) and industry. With a coverage sample of approximately 80,000 businesses, they intend to cover all GB businesses registered for Value Added Tax (VAT) and/or Pay As You Earn (PAYE).[9]

We focus on workplace-based employee estimates. An employee is referred to as anyone aged 16 years or over who is paid directly from the payroll, in return for carrying out a full-time or part-time job or being on a training scheme. It excludes voluntary workers, self-employed, and working owners who are not paid via PAYE. As for the geographical unit of analysis, we use Local Authority Districts (LAD). Overall, we have industry-employment data for 380 LADs, which are 326 in England, 22 in Wales, and 32 in Scotland.

1.1.3 Other Data Sources

We use the open access data from NOMIS for population estimates. Industry-level data starting in 1995 on ICT capital, employment, hours worked, value-added, and wage bill come from the EU KLEMS database (Stehrer et al., 2019). Finally, we use trade data from the United Nations Comtrade. This is an international database of six-digit product-level information on all bilateral imports and exports between any given pair of countries. We aggregate from the HS96 six-digit product level to the 17 IFR industries. To this end, product concordances from the UN Statistics Division and the World Integrated Trade Solution (WITS) are used. We leave further details about data for Appendix A.2.

[8]Safeguarded Access estimates are used (rather than open access) to obtain more accurate results. We rescale data to be comparable across surveys. See Appendix A.2 for further details.

[9]Very small businesses that are not registered for VAT or PAYE, which make up a small part of the economy, are not included. Northern Ireland data is collected independently by the Department for Finance and Personnel Northern Ireland (DFPNI).

1.2 Empirical and Identification Strategy

1.2.1 Empirical Strategy

The empirical strategy follows from the model in Acemoglu & Restrepo (2020), where robots compete against workers in the production of different tasks. A summary of the model, with and without trade between local areas, is provided in Appendix A.3. It shows that the relation between robots and employment can be examined by estimating a long-difference equation of the form

$$\Delta Y_i = \alpha + \beta \cdot \text{Exposure to Robots}_i + \epsilon_i \tag{1.1}$$

where the subscript i refers to a district (i.e. a local labour market). The dependent variable ΔY_i is either employment growth or the difference in the employment to total (or working age) population ratio. The coefficient of interest is β, which estimates the effect on the employment outcome of the change in exposure to robots. Following Acemoglu & Restrepo (2020), we consider a measure of local robot exposure that weights the adoption of robots in each industry (adjusted for the overall expansion of each industry's output) by the initial industry share out of total local employment:

$$\text{Exposure to Robots}^{GB}_{i,(t_0,t_1)} = \sum_{j \in J} \ell^{1995}_{ij} \cdot \left[\frac{R^{GB}_{j,t_1} - R^{GB}_{j,t_0}}{L^{GB}_{j,1995}} - g^{GB}_{j,(t_0,t_1)} \frac{R^{GB}_{j,t_0}}{L^{GB}_{j,1995}} \right] \tag{1.2}$$

where $R_{j,t}$ is the number of industrial robots in industry j at time t, $g_{j,(t_0,t_1)}$ is the growth rate of output of industry j between t_0 and t_1, $L_{j,1995}$ represents the baseline employment level in industry j, and ℓ^{1995}_{ij} represents the employment share of industry j in district i for the baseline year 1995.[10] The exposure to robots is thus a Bartik-type or shift-share measure that combines local industry-employment shares and industry-level variation in the usage of robots, which we refer to as the adjusted robot penetration rate (RPR). Variation in robot exposure across districts results from the fact that different areas were initially specialised in industries which have later experienced different robot adoption rates.

[10] In our main regression specifications, we take $t_0 = 1998$ and $t_1 = 2018$. Jaeger et al. (2018) raise a concern that Bartik or shift-share specifications using short time horizons may be misleading if the effect of the treatment takes time to arise.

This regression setup, however, raises several concerns about endogeneity. Industries could adopt robots in response to other changes they are undergoing, which could directly impact their labour demand (omitted variable bias). Furthermore, any shock to labour demand in a district affects the decisions of local businesses to adopt robots (reverse causality). Identification could also be problematic if there is evidence of pre-trends. Industries particularly exposed to robots could be on a different employment trajectory relative to other industries even before the adoption of robots started. Finally, industries adopting robots could differ from other industries in non-random ways – one should therefore check for balance.

1.2.2 Identification Strategy

The possibility of identifying a causal impact is challenged by potential contemporaneous shocks that confound the genuine effect of industrial robots. Increased import competition from China (see Chapter 2 of this thesis) and computerisation are shown to have had a significant impact on the British labour market over recent decades (Goos & Manning, 2007, De Lyon & Pessoa, 2021). Moreover, sectoral and demographic dynamics might also change the labour supply conditions that correlate with both robot adoption and employment. We thus control for the exposure of rising import competition, the exposure of ICT capital diffusion, and a set of baseline industry and demographic characteristics in our regression analysis.[11] Finally, to control for inherent structural differences across broader labour markets, we include 11 regional dummies.

To address the reverse causality concern, we adopt an instrumental variable strategy, which is close in spirit to the approach by Autor et al. (2013). Exposure to robots in GB is instrumented using data on robot adoption in other European countries. The idea behind the instrument is that these other European countries are also exposed to the rise of robots but cope with potentially different supply

[11]These include the share of manufacturing employment, the share of light manufacturing employment, the share of employment in services, the female share of manufacturing employment, the log total population, the female share of population, the share of population aged 16-24, the share of the population over 65 years old, the share of educated population with degree and with higher degree, and the shares of white people, Indians, Pakistanis, Bangladeshis, and black people in 1995. Recall that both the exposure of import competition from China and ICT capital diffusion are constructed analogously to eq. (1.2).

and demand shocks. More specifically, we construct the instrument analogously to eq. (1.2) but use the average robot adoption in other European countries, and lagged local employment counts from 1991:[12]

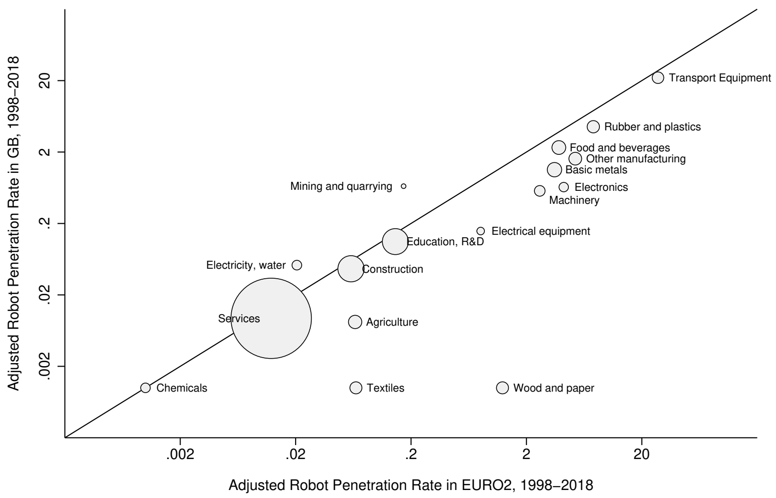
$$\text{Exposure to Robots}^{IV}_{i,(t_0,t_1)} = \sum_{j\in J} \ell^{1991}_{ij} \cdot \frac{1}{N} \sum_{c\in \text{EURO}} \left[\frac{R^c_{j,t_1} - R^c_{j,t_0}}{L^c_{j,1995}} - g^c_{j,(t_0,t_1)} \frac{R^c_{j,t_0}}{L^c_{j,1995}} \right] \tag{1.3}$$

where c is for country, EURO is the set of European countries for which robot data is available, and N is the number of countries considered in the construction of the measure. For our baseline measure, we use France and Norway, which we refer to as EURO2. We motivate this choice as follows. We first focus on such countries where robotics data is available as comprehensively as for GB and have similar income levels (see Figure 1.1a). Countries adopting robots much more heavily than GB are then excluded, as their adoption trends might be less relevant for capturing GB patterns. The trend of our selected EURO2, we suggest, does a good job when capturing the robot adoption trend in Britain over the last two decades and a half. Using the average robot adoption as in Acemoglu & Restrepo (2020), which comprises Denmark, Finland, France, Italy, and Sweden, is less useful as it is so far ahead of what is happening in GB. We show this in Figure A.2 of the Appendix.

Three major conditions determine the quality of the instruments. First, they should have explanatory power to avoid a weak instrument problem. Second, for the exclusion restriction to hold, there should not be independent effects on GB districts following the adoption of robots in France and Norway. Third, the unobservable supply and demand shocks in these two countries should not be correlated with those of GB. We provide evidence of the strong explanatory power (first-stage) of the instrument in Figure 1.2 and Figure 1.3. The second and third points are not possible to test for directly, but we argue correlations in unobservable demand and supply shocks between GB and EURO2, and possible independent effects of shocks in France and Norway on GB local labour markets, are relatively modest. As a way of supporting the previous, Figure A.3 of the Appendix displays the evolution of the manufacturing employment share for GB, France, and Norway. GB shows a different downward trend relative to the trend observed in France and

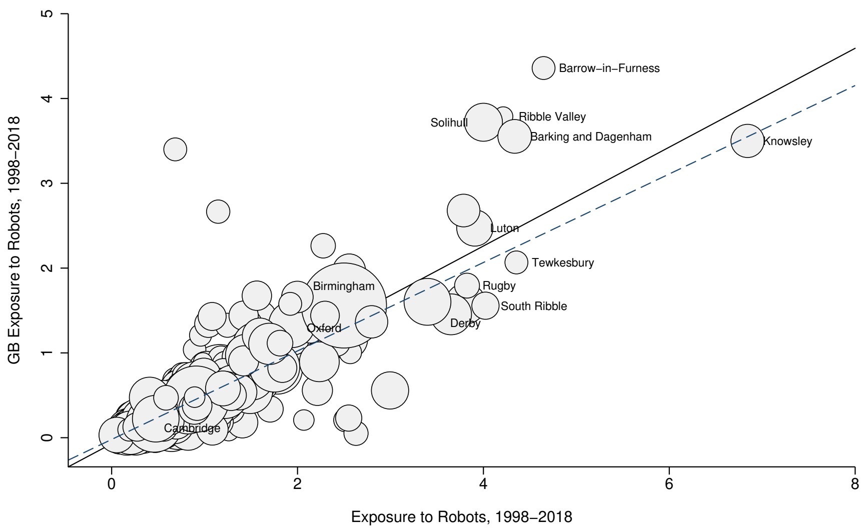
[12]The use of 1991 in the instrument is aimed at further limiting the endogeneity concerns described above, if employment reacted in anticipation of future robot exposure.

Figure 1.2: Industry-Level First Stage.
Adjusted Robot Penetration Rate in GB and EURO2



Notes: Figure presents the relationship between the adjusted Robot Penetration Rate in GB and EURO2 by industry. See text for further details about how these measures are constructed. The solid line corresponds to the 45-degree line. The circle size indicates the baseline GB employment in each industry.

Figure 1.3: District-Level First Stage. Exposure to Robots in GB and EURO2



Notes: Figure presents the relationship between the GB Exposure to Robots and Exposure to Robots. See text for details about these measures (eq. (1.2) and eq. (1.3)). The solid line corresponds to a regression with district population in 1995 as weights. The dashed blue line is for a regression that in addition excludes the districts with the highest exposure to robots. Marker size indicates the baseline population in each district.

Norway, especially in the years before the Great Recession. Still, we conduct several robustness checks where we explore several alternatives for the construction of the instrument using different combinations of European (not heavy robot adopter) countries. We discuss them in Section 1.3.

1.2.2.1 Bartik-Type Identification

Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022) emphasise that Bartik-type identification schemes must rely on some assumptions about the shocks, the initial exposure shares, or both. While a best-case scenario is for both the exogenous shares and shocks assumptions to hold, in most of the cases, this coincidence seems unlikely. We view the assumption of exogenous exposure shares, as discussed by Goldsmith-Pinkham et al. (2020), to be *ex-ante* implausible in our setting. The assumption requires the baseline local employment share of each industry to be uncorrelated with all unobserved labour supply shocks. The latter is unlikely to hold in our setting. By contrast, we hypothesise that the exogeneity of the robot shocks – the continued rise of robots – is an *ex-ante* plausible research design in our setting. Borusyak et al. (2022) show that shift-share IV coefficients are numerically equivalent to a weighted shock-level (i.e. industry-level) regression. The shocks could serve as valid instruments even when the industry-employment shares are endogenous. The identifying assumption is that industry-level shocks are as-good-as-randomly assigned, as if arising from a natural experiment, conditional on covariates.

We thus implement falsification tests to formally assess the plausibility of the previous assumption. The details are shown in Appendix A.4. First, we show there are no significant pre-trends correlated with the robot penetration rate for employment and hours worked. We consider periods prior to the onset of rapid advances in robotics technology, going back to the 1970s. The results are robust to the exclusion of the transport industry. Second, we test for balance on a set of potential confounders, as discussed above. The four controls we consider are the growth rate of imports from China, the intensity of ICT capital, industry value added in 1995, and the gross output of the industry in 1995. If the robot shocks are as-good-as-randomly assigned to industries, we expect them to not be correlated with these controls. This is the case when all industries are considered. Furthermore, we report the results of our district-level balance tests. The controls cover baseline demographic characteristics of a district, including age, gender, education, and ethnic distribution. Broadly, these variables reflect the composition of a district's workforce. We again find no statistically significant relationships between these variables and our instrument, except for the female employment fraction. Districts exposed to higher robot penetration tend to have a lower female share in employment, suggesting females are under-represented in manufacturing industries.[13] Overall, the results of these falsification tests allow us to see the robot shocks as close to randomly assigned across industries.

Finally, as Adao et al. (2019) emphasise when using Bartik-type estimators, traditional inference methods might suffer from an over-rejection problem. Residuals could be correlated across districts, even when geographically apart from each other, if they have a similar industrial composition. We show our main results are robust to account for such correlation in Appendix A.1.

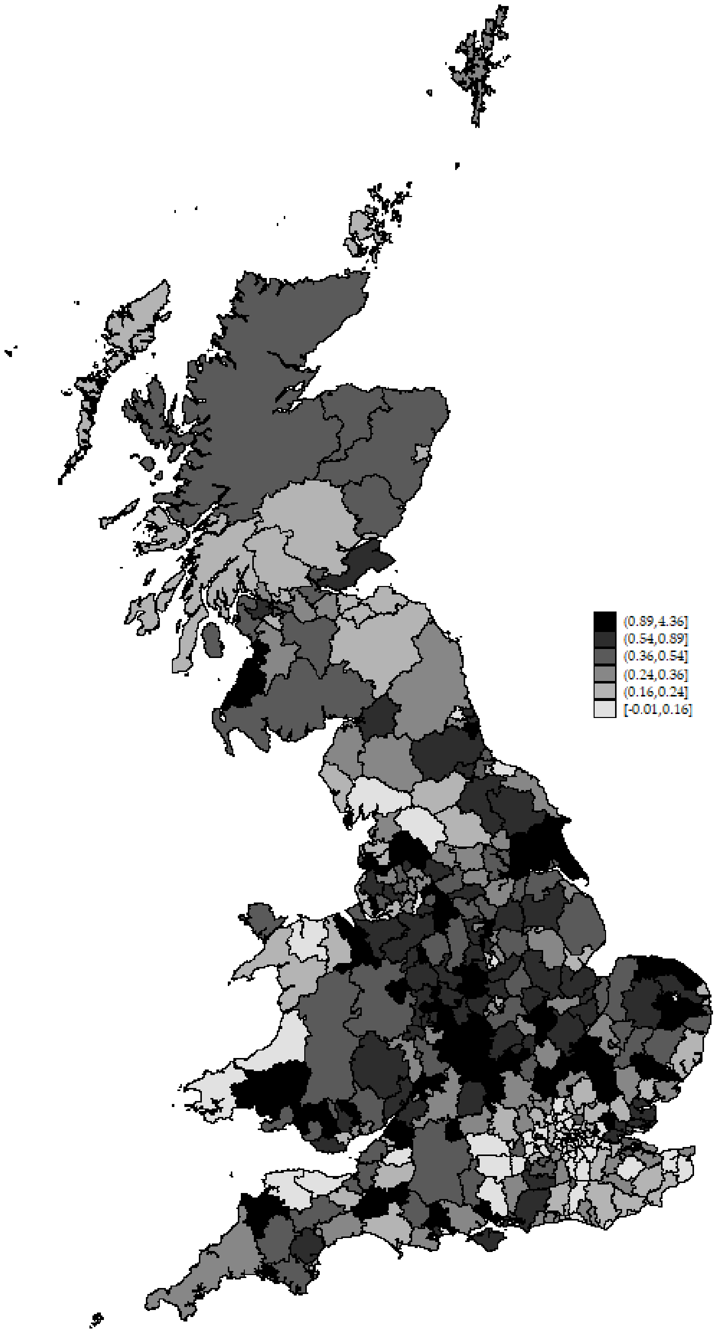
1.3 Results

1.3.1 The Geography of Industrial Robots

We start by discussing some local-level descriptive statistics. Figure 1.4 presents the geographic distribution of robot exposure (as defined in eq. (1.2)) in Great Britain. Local robot exposure is predicted to be low in the South East of England or the North West of Wales, reflecting the relatively smaller importance of manufacturing industries in those regions. On the other hand, the North West of England and the region of West Midlands appear to be the most robot-exposed regions. As for the districts, Barrow-in-Furness, Ribble Valley, Solihull, and Barking and Dagenham emerge as the highest-ranking ones (see also Figure 1.3). The former two are factory towns of BAE Systems, a multinational defence, security, and aerospace company. Solihull, and Barking and Dagenham, are the home of Land Rover's and Ford's main production plants, respectively.

[13] As already discussed, we control for the initial female share of manufacturing employment as well as the female share out of the total population in a district.

Figure 1.4: Geographical Distribution of Robot Exposure in Great Britain (1998-2018).



Source: Own elaboration based on IFR, EU KLEMS, and the AES.

As discussed in the previous section, industries adopting robots are not the same industries investing more intensively in ICT capital, nor are they the industries most affected by Chinese import competition (see columns (1)-(2) in Table A.6). We show in Appendix A.1 the previous is translated locally. Figure A.4 illustrates the correlation between exposure to robots and exposure to ICT capital is low and insignificant (0.0238), reflecting that robots are pervasive in manufacturing while ICT has been stronger in non-manufacturing industries. Areas investing more intensively in computer technology include Oxford, Cambridge, Lancaster, and Colchester. It is not by chance that they are university cities which, rather than industrial robots, rely on human capital, (other types of) innovation, and knowledge hubs. Similarly, Figure A.5 shows no systematic relation between exposure to robots and exposure to Chinese imports (the correlation is 0.0677 and not statistically significant). That is, districts experiencing a higher Chinese import penetration do not show a pattern towards adopting industrial robots more heavily. These include areas such as East Northamptonshire, Ashfield, Rossendale, and the Scottish Borders, where the textile industry has been historically important.

1.3.2 Employment Effects of Industrial Robots

We now turn to the main regression findings. Table 1.2 presents results for long-difference specifications where we regress changes in several outcomes between 1998 and 2018 on local robot exposure. We use the exposure to robots as defined in eq. (1.2) (instrumented by eq. (1.3)) to compute two-stage least squares (2SLS) estimates of β in eq. (1.1). The table focuses on three outcome variables: the employment-to-working-age population ratio (panel A), the employment-to-total population ratio (panel B), and total employment (panel C). The regressions in columns (1)-(5) are weighted by baseline district population, while the regressions in column (6) are unweighted. Standard errors that are robust against heteroskedasticity and clustered at the county level are given in parentheses (alternative inference is discussed later in this section). We report first-stage coefficients, all significant at 1% significance level, as well as the first-stage F-statistics, well above the conventional threshold of ten in all columns, at the bottom of the table.[14]

[14]The first-stage F statistic we report is the Kleibergen-Paap rk Wald F statistic.

We also report the p-values from under-identification tests. The null hypothesis of under-identification (meaning the instrument is irrelevant) is rejected in all columns.

We consider the employment-to-working-age population ratio as an outcome in panel A. Column (1) presents a parsimonious specification that includes only region dummies and baseline demographics as covariates. We obtain a positive coefficient of 0.026 which is only marginally significant. In column (2), we control for baseline industry characteristics. Their inclusion increases our estimate of the impact of exposure to robots on the employment-to-working-age population ratio to 0.048 and makes it precisely estimated. In columns (3) and (4), we control for other changes that have affected labour market outcomes during our period of analysis: exposure to computer technology and Chinese imports between 1998 and 2018, respectively. The point estimate remains positive and significant, and it is larger now: 0.075 (standard error = 0.028). This estimate implies that an increase of one industrial robot per thousand workers in exposure to robots is associated with a relative increase in the employment-to-working age population ratio of 0.075 percentage points. Column (5) estimates the specification in column (4) after excluding the top 1% of districts with the highest exposure. This has a minor effect on our coefficient of interest. Finally, column (6) shows that the point estimate is also similar in the unweighted specification. We discuss the magnitude later below.

Panel B considers a slightly different labour outcome: the employment-to-total population ratio. By doing so, we aim to capture the fact that some districts may have similar working-age populations but a higher total population, as the fraction of people older than 65 years old is larger. People in the latter group, we suggest, would not be directly affected by industrial robots as they are out of the labour market, but they could indirectly contribute to the aggregate impact as they are part of the local economy (for example, as consumers). Our preferred estimate in column (4), when we control for all our covariates, implies that an increase of one robot per thousand workers in exposure to robots is associated with a relative increase in the employment-to-total population ratio of 0.047 (standard error = 0.019). Excluding the top 1% of districts with the highest exposure or considering the unweighted specification has a minor effect on the coefficient of interest.

Table 1.2: Effects of Industrial Robots on Employment

	IV ESTIMATES, LONG-DIFFERENCE SPECIFICATIONS, 1998-2018					
	Weighted by Population					Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment-to-Working-Age Population (change in pp)						
GB Exposure to Robots	0.0259*	0.0478***	0.0753***	0.0755***	0.0826***	0.0914**
	(0.0142)	(0.0182)	(0.0280)	(0.0283)	(0.0309)	(0.0361)
R-squared	0.30	0.32	0.32	0.32	0.31	0.22
Panel B. Employment to Total Population (change in pp)						
GB Exposure to Robots	0.0153*	0.0296**	0.0469**	0.0470**	0.0517**	0.0591**
	(0.0092)	(0.0119)	(0.0187)	(0.0190)	(0.0207)	(0.0241)
R-squared	0.24	0.26	0.26	0.27	0.26	0.16
Panel C. Log Change in Total Employment						
GB Exposure to Robots	0.0318	0.0679**	0.1075**	0.1078**	0.1200**	0.1376**
	(0.0251)	(0.0301)	(0.0464)	(0.0474)	(0.0517)	(0.0595)
R-squared	0.26	0.28	0.28	0.29	0.29	0.21
First-Stage Coefficient	0.56***	0.48***	0.36***	0.36***	0.32***	0.32***
Underidentification, p-value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
First-Stage F-statistic	179.30	68.39	45.20	44.72	46.91	34.23
Observations	380	380	380	380	380	380
Region dummies	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Industry characteristics		✓	✓	✓	✓	✓
ICT exposure			✓	✓	✓	✓
Exposure of China imports				✓	✓	✓
Exclude top 1% districts					✓	

Notes: Table presents 2SLS estimates of the effects of exposure to robots on several district-level outcome variables for the period 1998-2018. Panel A presents estimates for changes in the employment-to-working-age population ratio. Panel B presents estimates for changes in the employment-to-total population ratio. Panel C for changes in log total employment. The regressions in columns (1)-(5) are weighted by baseline population, while the regressions in column (6) are unweighted. The covariates are reported at the bottom of the table. We also report the first-stage coefficients, first-stage F-statistics, and the p-values of the under-identification tests. Standard errors that are robust against heteroskedasticity and clustered at the county level are given in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

We look at a third alternative measure of employment in panel C, namely the log change in total employment, to further bolster our finding of an overall small but positive employment effect of robots. We also find a positive and significant employment effect in our preferred specification with all covariates. In particular, the point estimate of 0.11 (standard error = 0.05) in column (4) means that one more industrial robot per thousand workers in our exposure to robots measure is associated with a 0.11 percentage point increase in total employment. This estimate is robust to excluding high-exposure districts (column (5)) or considering the unweighted specification of the model (column (6)). Overall, the results obtained in panels A, B, and C show a consistent total employment effect of industrial robots that is small, but positive and statistically significant.

Interpretation of the Results. The estimates in Table 1.2 offer valuable insights into the impact of one additional robot per thousand workers on employment. The results from column (4) in panels A and B reveal that the adoption of one more robot per thousand workers in a district increases its employment-to-working-age population by 0.075 percentage points or its employment-to-total population by 0.047 pp, respectively. The question arises about what this means for job creation. We note that the increase of one more robot per thousand workers between 1998 and 2018 is equivalent to an increase of 0.68 robots per thousand working-age people (obtained by dividing the average number of workers by the average working-age population) or an increase of 0.43 robots per thousand people (obtained by dividing the average number of workers by the average total population). Our estimates then imply one robot increases employment by about 1.1 workers ($\approx 0.000754 \times (1000/0.68)$ or $\approx 0.000470 \times (1000/0.43)$). Equivalently, the increase of 17,500 industrial robots during the period 1998-2018 (as shown in Figure A.1) is predicted to have increased employment by about 19,250 jobs.[15]

Robustness Checks. Table 1.2 reports standard errors that are clustered at the county level and robust against heteroskedasticity. As discussed in the previous section, Adao et al. (2019) argue that residuals could be correlated across dis-

[15]By way of comparison, Acemoglu & Restrepo (2020) report one robot reducing employment by six workers in the US, or equivalently, a total reduction in employment of 756,000 jobs for their period of analysis, 1993-2007.

tricts, even geographically apart, if they have a similar industrial composition. Table A.3 in the Appendix reports the standard errors computed following Borusyak et al. (2022) to account for such correlation. Our main findings are unchanged. Appendix A.1 presents a range of additional robustness checks. First, we report estimates for an exposure measure based on the raw penetration of robots without the adjustment term. Second, we explore several alternatives for the construction of the instrument using different combinations of European countries. We also consider an exposure measure based on the stock of robots provided by the IFR rather than our constructed stock based on a yearly depreciation rate of 5%. In all cases, the IV estimates are both qualitatively and quantitatively similar. Results are presented in Table A.4 and Table A.5.

Manufacturing vs Non-Manufacturing. Table 1.3 investigates the impact of robots on local employment inside (columns (2)-(4)) and outside manufacturing (columns (5)-(7)). For ease of interpretation, column (1) reports the estimates from column (4) in Table 1.2. By construction, the estimates in columns (4) and (7) add up to the estimate in column (1). Panel A presents the results for changes in the employment-to-working age population, while panel B considers changes in the employment-to-total population. The estimates in columns (2)-(4) (for manufacturing employment) turn out statistically insignificant. The absence of a negative impact warrants further exploration to fully characterise the displacement effect within the manufacturing sector, a task we undertake in the next section. In contrast, the estimates in columns (5)-(7) (for non-manufacturing employment) are all positive and statistically significant. Focusing on panel A and the estimate in column (7), which includes all the covariates, an increase of one industrial robot per thousand workers is associated with a relative increase in the non-manufacturing employment-to-working-age population ratio of 0.067 percentage points. This means one robot increases non-manufacturing employment by about 1 worker. These results point to a crucial insight: any potential (negative) displacement effects of robots seem to be outshined by the emergence of new labour demand, primarily within non-manufacturing industries. We now direct our focus towards gaining a more complete understanding of this.

Table 1.3: Composition Effects: Manufacturing vs Non-Manufacturing Employment

	TOTAL	MANUFACTURING			NON-MANUFACTURING		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. EMP/WA pop (change in pp)							
GB Exposure to Robots	0.0755***	0.0099	0.0082	0.0083	0.0379**	0.0671***	0.0672***
	(0.0283)	(0.0061)	(0.0091)	(0.0091)	(0.0143)	(0.0235)	(0.0236)
R-squared	0.32	0.54	0.54	0.55	0.28	0.29	0.29
Effect of 1 robot	[1.10]			[0.12]			[0.98]
Panel B. EMP/TOT pop (change in pp)							
GB Exposure to Robots	0.0470**	0.0063*	0.0054	0.0054	0.0233**	0.0416***	0.0416**
	(0.0190)	(0.0038)	(0.0056)	(0.0057)	(0.0097)	(0.0161)	(0.0163)
R-squared	0.27	0.55	0.55	0.56	0.25	0.25	0.26
First-Stage F-statistic	44.72	68.39	45.20	44.72	68.39	45.20	44.72
Observations	380	380	380	380	380	380	380
Region, demographics, industry	✓	✓	✓	✓	✓	✓	✓
ICT exposure	✓		✓	✓		✓	✓
Exposure of Chinese imports	✓			✓			✓

Notes: Table presents 2SLS estimates of the effects of exposure to robots on two district-level outcome variables for the period 1998-2018 separately for manufacturing and non-manufacturing industries. Panel A presents estimates for changes in the employment-to-working-age population ratio. Panel B presents estimates for changes in the employment-to-total population ratio. Column (1) repeats the main estimates from column (4) in Table 1.2. Columns (2)-(4) focus on the manufacturing industries. Columns (5)-(7) focus on the non-manufacturing industries. All regressions are weighted by baseline district population. The covariates included in each model are reported at the bottom of the table. We also report the first-stage F-statistics. Standard errors that are robust against heteroskedasticity and clustered at the county level are given in parentheses. Results are robust to the alternative inference by Adao et al. (2019) and Borusyak et al. (2022), reported in Appendix A.1. * p<0.1, ** p<0.05, *** p<0.01.

1.3.3 Displacement vs Reallocation Effects

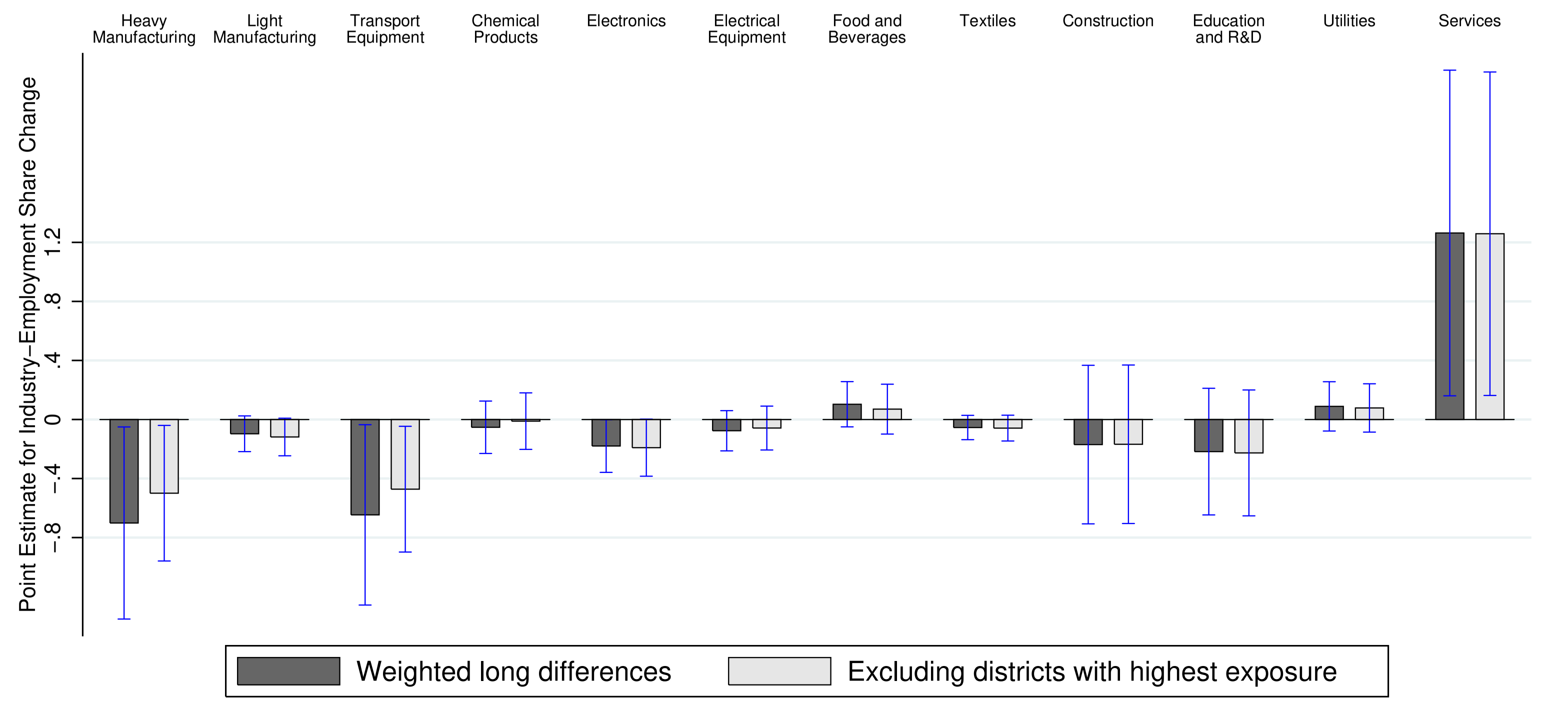
In this section, by investigating how exposure to robots has affected employment in different industries separately, we aim to uncover where the (negative) displacement effects and the (positive) reallocation effects are taking place.

Figure 1.5 presents estimates of the effects of exposure to robots on the change in employment share in different industries. We provide point estimates and 95% confidence intervals for two long-difference specifications. First, we consider our preferred specification with the full set of covariates and weighted by baseline population (as in column (4) of Table 1.2), represented by the dark grey bar in the figure. We then check the results are not sensitive to the removal of the districts most-exposed to robots (the light grey bar).

The figure shows that the displacement effect of robots concentrates especially in heavy manufacturing industries, which include the transport equipment industry, the chemical industry, the industry of rubber and plastics products, and the electrical equipment industry. A more disaggregated analysis reveals that the displacement effect takes place mostly in the transport equipment industry. The point estimate is negative and significant for the specifications considered. An increase of one industrial robot per thousand workers in exposure to robots is associated with a relative decline in the employment share of the transport equipment industry of 0.64 percentage points. Excluding districts with the highest exposure reduces the magnitude of the estimate to almost 0.4 (consistent with the relatively higher importance of this industry in those areas) but remains statistically significant. Although the evidence is statistically weaker, we also find a negative displacement effect taking place in the electronics industry. There are no statistically significant displacement effects on the remaining manufacturing industries.

On the flip side, there is evidence that the reallocation effects are taking place mostly in the service sector. In particular, the point estimate implies one more robot per thousand workers increases the employment share of services by 1.2 percentage points. In this case, excluding the most exposed districts has no effect on the magnitude of the estimate. There is no evidence of positive reallocation effects in other non-manufacturing industries such as construction or education.

Figure 1.5: The Effects of Industrial Robots on Industries.



Notes: Figure presents estimates of exposure to robots on the (percentage point) change in the industry-employment share. The capped (blue) lines provide 95% confidence intervals. The first set of estimates (dark grey bar) are from long-difference specifications with covariates as in column (4) of Table 1.2. The second set of estimates (light grey bar) are from long-difference specifications where we remove the top 1% of districts with the highest exposure to robots as in column (5) of Table 1.2. Note that not all industries are reported for the sake of illustration. Those not reported are shown to have insignificant point estimates (available upon request).

1.3.4 Discussion of the Results

The findings of this chapter suggest that the aggregate employment effects of industrial robots have ultimately consisted in reshaping the demand for new labour forces and their reallocation but without detriment to the overall employment. This is consistent with the analysis in a concurrent paper by Kariel (2021), who documents that robots have directly replaced workers in automotive and metal manufacturing while increasing employment in services.[16]

Nonetheless, it is worth noting that our quantitative conclusions diverge from those of Kariel (2021). Their study indicates that the introduction of one robot leads to a noteworthy increase in employment by around 10 workers, implying a rise in employment of over 60,000 for their period of analysis 1993-2011 (as the total number of robots increased by 6,150 over this period). In contrast, our findings point towards a more conservative estimate that one robot increases employment by around 1.1 workers, resulting in a more modest rise of less than 20,000 jobs over the period 1998-2018 (with a total of 17,500 robots added during those two decades). These disparities in our respective estimates could be attributed to differences in the instrumental approach and the time frame under consideration.[17] Specifically, their instrumental approach encompasses a second instrument involving the flow of new robots and other automation ideas across industries, in contrast to our focus solely on the current stock of adopted robots. In addition, our more conservative estimates may indicate that as robots become more pervasive across industries in Britain (as shown in Figure 1.1b, robot adoption in GB accelerated after 2011), the forces driving labour reallocation might weaken at the time the labour market could face challenges in effectively redistributing displaced workers.[18]

[16] For a different automation technology – the automation of telephone operation in the early 20th century – Feigenbaum & Gross (2020) find the decline in demand for telephone operators was counteracted by growth in middle-skill jobs (e.g. secretarial work) and lower-skill service jobs.

[17] Related to the last point, a recent paper by Chung & Lee (2023) shows the impact of industrial robots on jobs has changed over time in the US. In contrast to Acemoglu & Restrepo (2020), they find positive effects of robots and reallocation effects to other industries using more recent data.

[18] Consistent with this idea, Acemoglu & Restrepo (2019) discuss the possibility of 'excessive automation', meaning faster automation than socially desirable. This leads to plenty of labour displacement, but not much productivity gains, which hinders reallocation forces.

Next Steps. The essence of this chapter lies in empirically examining the net effects of industrial robots on total employment, using local areas – districts in Great Britain – as the main unit of observation. We thus view this chapter as a first step in understanding the labour market implications of robots. We have yet to pinpoint the exact mechanisms or fully characterise adjustments at the individual level. In what follows, we offer an overview of potential mechanisms and provide pointers for follow-up research directions using more granular data on individuals.

The observed increase in employment in the services sector is a noteworthy phenomenon that demands further exploration. As industrial robots replace certain tasks in manufacturing, workers may seek employment either inside or outside manufacturing. The extent of the impacts depends on the level of skill transferability and the demand for specific skills in other sectors. As such, workers moving from manufacturing to services could experience negative wage impacts if, for example, demand for low-paid service jobs prevails over higher-paying alternatives.

Another potential mechanism is related to the productivity gains achieved in manufacturing through the introduction of robots (Acemoglu & Restrepo, 2019, Graetz & Michaels, 2018). As manufacturing becomes more efficient and cost-effective, businesses may experience increased profitability. This, in turn, could lead to higher demand for services in other areas, such as marketing, distribution, logistics, and customer support. The rising demand for services may result in an overall increase in labour demand and potentially lead to an increase in wages for workers employed in the services sector.

The district-level analysis conducted in this chapter calls now for a complementary analysis using data on individuals. This will allow us to directly study the effects of robots on earnings (or wages), industry and occupational mobility, as well as to perform heterogeneity analysis by gender, age, and education (or skill level). Understanding the potential disparate effects of industrial robots on different demographic groups can shed light on issues of equity and inequality in the labour market. Certain groups may be more vulnerable to job displacement or experience greater challenges in transitioning to new roles. Identifying these disparities can inform policymakers about the need for targeted interventions to ensure a more inclusive and fair labour market.

Finally, the analysis of this chapter focuses on industrial robots, which are primarily adopted in manufacturing industries but to a lesser extent in non-manufacturing sectors. Whether the new advances in artificial intelligence (AI) or machine learning (ML) will affect differently to local labour markets (and consequently, individuals) is an important question to address in the coming years.

1.4 Summary and Conclusion

With industrial robots rapidly growing over recent decades, the concern about their employment consequences has become central for a wide audience, both inside and outside academia. This chapter takes Great Britain as a case study to investigate the impact of industrial robots on employment.

The analysis presented closely aligns with the empirical methodology used by Acemoglu & Restrepo (2020). Combining district-level employment data with industry-level robot adoption data over the period 1998-2018, our study reveals a small but positive employment effect of robots in GB. Our estimates translate into one robot increasing employment by about 1.1 workers. This overall effect, however, masks the presence of displacement and reallocation effects. Predicted robot exposure results in a decline in job opportunities within the manufacturing sector (in particular, within heavy manufacturing industries such as the transport equipment industry), counterbalanced by a more than compensatory surge in labour demand within the service industry.

This chapter thus concludes that industrial robots in GB are contributing to worker reallocation from heavy manufacturing industries to the service sector but without detriment to total employment. Nevertheless, we caution that the rise of robots is not a blessing for all: different types of workers in particular industries might lose out, as we show that industrial robots have displaced workers in certain industries. We see a more explicit analysis of this, as discussed in the previous section, as an important avenue for future research.

CHAPTER 2

HOUSEHOLD RESPONSES TO TRADE SHOCKS[1]

A large literature has documented the labour market outcomes of workers exposed to trade shocks in different countries.[2] This literature has mainly focused on the direct implications for employment, earnings and sectoral reallocation of affected workers, typically finding persistent negative effects from increasing import competition. This raises the question of whether other forms of self-insurance (other than sectoral reallocation) are available to the workers affected by adverse trade shocks and their families. Does self-employment provide a buffer for workers who lose their jobs? Do partners provide insurance by increasing labour supply? Do affected workers adjust the timing of their retirement?

In this chapter, we investigate these adjustment mechanisms in response to increased import competition in the 2000s. Drawing on large-scale panel data which links individuals across decadal censuses in England and Wales, we study the effects of the rapid growth in Chinese manufacturing imports on individuals and their households. The data allows us to observe changes in labour market status, including whether the worker is employed or self-employed (distinguishing between

[1]Joint work with Peter Levell (IFS) and Matthias Parey (University of Surrey).

[2]See, among others, Autor et al. (2013, 2014) for the US; Dauth et al. (2014, 2021) for Germany; Balsvik et al. (2015) for Norway; Utar (2018) for Denmark; Citino & Linarello (2021) for Italy; and De Lyon & Pessoa (2021) for the UK. See Dorn & Levell (2021) for a recent summary.

solo self-employed or self-employed with employees), and, for those inactive in the labour market, the reason for inactivity. A further strength of the data is that it includes information on the labour market activity of co-residents, allowing us to study the degree to which households offer insurance against trade shocks.

Our empirical analysis compares own and partner outcomes for workers with similar characteristics, but who were initially employed in industries with different levels of exposure to import competition. We measure how workers' and their partners' outcomes changed from 2001 to 2011, following China's entry into the World Trade Organisation (WTO) in 2001. We instrument for the growth in import competition in each industry using the growth in Chinese exports to other developed economies, following Autor et al. (2013, 2014). Our main outcome variables are employment, self-employment and retirement; measures of family stability; and partner labour supply. We allow for heterogeneity in effects by gender and age, which we find to be quantitatively important.

We first document the direct effect of trade exposure on individuals' labour market outcomes. Workers initially employed in industries exposed to import competition are more likely to exit manufacturing, with the majority of them reallocating to non-manufacturing sectors. This confirms the findings of previous studies, which we discuss in detail below. Men and women, however, do not respond to trade shocks in the same way. For women, while we observe a decline in their manufacturing employment, we find no significant effects on their overall labour force participation or rates of self-employment in response to trade shocks. For men, in addition to a movement into non-manufacturing sectors and increased unemployment, we find a significant increase in self-employment, which mitigates their employment losses. Most of the increase in self-employment is accounted for by an increase in solo self-employment (i.e. own account workers without employees); this is especially true at older ages. We find a smaller, but still statistically significant, effect of import exposure on the proportion of men who become self-employed with employees. The effect on labour force participation differs by age: while young men initially employed in exposed industries are less likely to be active in the labour market 10 years later, old males in exposed industries are more likely to remain active due to reduced flows into retirement.

These findings suggest that male workers use self-employment and delayed retirement to offset the adverse effects of the shock. Both of these adjustment mechanisms to trade shocks have been relatively underexplored so far. While providing an alternative source of employment to displaced workers, self-employment, and in particular solo self-employment, is likely to be associated with economic insecurity for many former manufacturing employees (Boeri et al., 2020, Giupponi & Xu, 2020). The role of self-employment for displaced workers is perhaps analogous to the role played by the informal sector in developing countries, which has been found to similarly act as an employment 'buffer' against the effects of trade shocks (Dix-Carneiro et al., 2021). Our finding that trade-exposed male workers retire later could be partially driven by the increase in male self-employment, as self-employed workers tend to retire later than the employed (Crawford et al., 2021). Delayed retirement is also another way workers can compensate for any income losses that result from exposure to import competition. The fact we find no significant effects on retirement or rates of self-employment for women suggests that either the availability or use of these insurance mechanisms appears to differ by gender.

We next turn to the impact of trade shocks on family formation and dissolution. We find that for women below 45, exposure to import competition significantly reduces the likelihood of divorce or of living with a new partner. This could be because trade shocks, by reducing their future expected earnings, leave married women more financially reliant on their current partners. In contrast, we find no evidence that married men exposed to import competition are either more or less likely to get divorced. This latter finding contrasts with Autor et al. (2019), who find substantial effects of import competition in male-dominated industries on divorce and marriage rates in more exposed local labour markets in the US, and an accompanying increase in premature male mortality. It is however consistent with findings for other European countries (Keller & Utar, 2022, Giuntella et al., 2022). Our results suggest that family breakdown and other negative social impacts that studies of the US have identified following reductions in manufacturing employment (Che et al., 2018, Pierce & Schott, 2020) are not inevitable, and may depend on other country-specific aspects, such as labour market institutions.

Our final set of results looks at the responses of partners of those affected by import competition. Here, we find no evidence that women are more likely to enter or stay in the labour force in response to shocks affecting their male partners (irrespective of whether young children are present in the household). Our finding of limited added worker effects among female partners is consistent with some other studies (Goux et al. (2014), Halla et al. (2020)). By contrast, we find that, in households where women are exposed to import competition, their male partners are more likely to stay in the labour force. This effect is larger for older men, who see greater reductions in inactivity in response to shocks affecting their female partners. The literature on added worker effects has typically focused on female responses to shocks affecting the household (e.g. Lundberg (1985)), but our results show that male responses can be relevant too. We note that men respond to shocks affecting their partners in the same way that they respond to shocks affecting themselves - through reduced flows into inactivity at older ages and through greater self-employment.

We subject all of our results to several robustness checks. Our main results already control for detailed socio-demographic characteristics of workers. We assess the sensitivity of our results to various alternative samples and specifications, and to controls for the impact of workers' exposure to increased export demand from China or to exposure to increased import competition from Eastern Europe during this period. Our findings are consistent across these alternative specifications. We also verify that our results do not reflect industry-specific trends that predate the rise of import competition from China using data from the 1980s and 90s.

Our work contributes to various broad strands of the literature. The first is the literature on the labour market effects of trade shocks. Prior work has focused on the consequences of rising Chinese import competition at the local labour market (Autor et al., 2013, Dauth et al., 2014, Balsvik et al., 2015, Foliano & Riley, 2017), firm (Utar, 2014, Bloom et al., 2016, Autor et al., 2020), and individual level (Autor et al., 2014, Utar, 2018, Dauth et al., 2021, Citino & Linarello, 2021, De Lyon & Pessoa, 2021).[3] We contribute to this particular literature by additionally docu-

[3] A broader literature examines the effects of trade shocks based on other episodes, including the large import tariff reductions in emerging economies such as India and Brazil (see, among others, Topalova (2010), Dix-Carneiro & Kovak (2017, 2019), Gaddis & Pieters (2017)).

menting workers' responses along the self-employment and retirement margins, and by studying responses of partners in the same household as exposed workers.[4] This chapter is also related to recent empirical studies on the impact of trade shocks on marriage and fertility. The literature on household-level outcomes of import competition is much smaller than that studying employment and earnings, probably because the administrative datasets used to study the impacts of these shocks on individual workers often do not include information on other members of their household. Autor et al. (2019), as discussed above, study how Chinese import competition affects marriage, divorce and single parenthood rates across local labour markets in the US. Keller & Utar (2022) study the impacts of exposure to Chinese import competition on divorce rates and fertility in Denmark. Our finding on a reduction in divorce rates among women under 45 exposed to import competition is consistent with the 'retreat to family' phenomenon proposed in Keller & Utar (2022), although we do not find evidence of the same effects on childbirth they document in their paper. Giuntella et al. (2022) also find a negative and marginally significant effect of import competition on women's divorce rates in Germany.[5]

We also contribute to the more general empirical literature on added worker effects, which studies spousal labour supply responses to labour demand shocks affecting their partners. Earlier work has found mixed results and tended to focus on employment responses for women (Layard et al., 1980, Heckman & Macurdy, 1980, 1982, Lundberg, 1985, Maloney, 1987, 1991, Spletzer, 1997, Cullen & Gruber, 2000, Halla et al., 2020). In a cross-country comparison, Bredtmann et al. (2018) show that the existence and the magnitude of added worker effects vary over the different welfare regimes within Europe. In contrast to these reduced-form estimates, studies estimating life cycle models tend to find that family labour supply is an important insurance mechanism to income shocks, allowing households to smooth consumption (Stephens, 2002, Attanasio et al., 2005, Blundell et al., 2016).

[4]Previous studies of the impacts of trade shocks have restricted their samples to those of working age only, and so have not explored the role of the retirement margin. For example, Autor et al. (2014) study a sample who are aged 22-64 over the whole period of analysis while Dauth et al. (2021) restrict their sample to individuals aged 22-54.

[5]Huber & Winkler (2019) study correlations in exposure to trade shocks within couples. While their paper focuses on how differences within couples affect the impact of trade shocks on across-household inequality, they also find that own earnings decrease if partners are positively exposed to export shocks.

We contribute to this literature by studying family labour supply responses in the context of a trade shock, which represents a large-scale structural change.

A further contribution is to the understanding of how economic shocks affect transitions into self-employment. Hacamo & Kleiner (2022) show that college graduates who graduate in a recession are more likely to enter self-employment as 'forced entrepreneurs'. Babina (2020) shows firms' financial distress induces employees to move into self-employment. The analysis in this chapter documents that trade shocks might induce similar movements into self-employment.

More generally, by providing evidence for the UK, this chapter contributes to the understanding of patterns in the effects of trade shocks across countries. The UK is an interesting case for investigating the economic adjustment processes to trade shocks, given that it experienced the largest percentage decline in manufacturing employment among OECD countries between 1999 and 2007, at the same time as a large increase in its trade deficit with China (Dorn & Levell, 2021). Previous work has emphasised differences in labour market institutions and flexibility (Balsvik et al., 2015, Keller & Utar, 2022), and differences in trade patterns (Dauth et al., 2021, Giuntella et al., 2022) as potential explanations for the varying impact of Chinese import competition across countries.

The chapter proceeds as follows. Section 2.1 describes the ONS Longitudinal Study and other data sources we draw on. Section 2.2 sets out our empirical research design. We present the main results in Section 2.3. Section 2.4 concludes. Appendix B presents supplementary results and robustness checks.

2.1 Data and Sample Description

2.1.1 The ONS Longitudinal Study Data

The main dataset we draw on is the Office for National Statistics (ONS) Longitudinal Study (LS) (Office for National Statistics, 2019). The LS contains linked census and life events data for a roughly 1% sample of the population of England and Wales (people born on one of four selected dates in a calendar year). It includes census records for over 500,000 people usually resident in England and Wales from the 1971, 1981, 1991, 2001, and 2011 censuses.[6] The LS data includes core socio-demographic variables including the age, sex, marital status and locations of sampled individuals, as well as data on workers' employment, occupation, industry, hours worked and type of employment (whether they are employees, self-employed with employees, or solo self-employed).[7] Although the census asks for detailed information about the nature of individuals' work, it does not include information about earnings. Life events data are linked for LS members, including births to sample mothers, deaths, and cancer registrations.

The LS has a number of advantages for our purposes. First, it is a panel, allowing us to track individuals across different censuses held every 10 years. Most of our analysis concerns the impact of import competition on outcomes between the years 2001 and 2011. We use data from 1981 and 1991 for placebo and robustness exercises. Second, the LS includes not only individuals who are employed but also those who are self-employed or out of the labour force. Those out of the labour force also report the reason they are not working (e.g. because they are studying, retired, sick, at home, etc). Administrative data sources often do not include this information.[8] Third, it includes the survey responses of co-residents of study members. This allows us to study family labour supply responses to shocks affecting an LS member, as well as to examine the correlation between exposure to trade shocks across spouses. Fourth, in contrast to most household surveys, participation in the census is a legal requirement and the ONS goes to considerable lengths to maximise its coverage (Office for National Statistics, 2015a). Both the 2001 and 2011 censuses have an estimated response rate of 94%. The LS also has low rates of attrition relative to other longitudinal datasets. 88% of LS members in the 2001 census was matched to records in the 2011 census, after excluding those who were known to have died or emigrated (Lynch et al., 2015).

[6] A 'usual resident' of the UK is anyone who, on census day, was in the UK and had stayed or intended to stay in the UK for a period of 12 months or more, or had a permanent UK address and was outside the UK and intended to be outside the UK for less than 12 months.

[7] Hours worked are reported in bands in the 2011 wave, allowing us to observe part-time and full-time status but not precise hours worked.

[8] For instance, the UK Annual Survey of Hours and Earnings (ASHE) used in De Lyon & Pessoa (2021) covers employees and thus cannot distinguish movements into self-employment from job loss, and unemployment from non-participation. The administrative data used to study trade shocks in Germany (Dauth et al., 2021) does not cover the self-employed.

2.1.2 Other Data Sources

To construct measures of industries' exposure to import competition, we draw on trade flows from the United Nations Commodity Trade Statistics Database (UN Comtrade). This contains detailed statistics on trade in individual commodities. To obtain imports and exports by industry, we map the commodity codes from various years into the Classification of Product by Activity (CPA) codes, which are identical in their first four digits to 1992 UK Standard Industry Classification (SIC92) codes.[9] We deflate values so that they are expressed in 2010 pounds.[10]

As we describe in more detail below, we measure each industry's import exposure as imports relative to total domestic sales. To calculate this, we need information on the turnover (i.e. the total amount of sales) of different UK industries, which we compute using the Business Structure Database (BSD) (Office for National Statistics, 2021). The BSD is administrative data covering plant-level information on employment, turnover, geography, and main industry for almost all business organisations in the UK from 1997 until the present (only very small businesses are not included in the register).[11] We calculate industry turnover by summing turnover across individual plants in the BSD.

2.1.3 Sample Description

We track workers from 2001, the year China acceded to the World Trade Organisation (WTO), and measure how outcomes change between 2001 and 2011. We focus on employees who were born between 1942 and 1983 and who were therefore aged between 18 and 59 in 2001. As a result, by 2011, some individuals in our sample are above the state pension age (which in 2011 was 65 for men and 60 for women).

[9]Mappings from Harmonised System (HS) products codes to CPA industry codes are taken from the Eurostat Reference and Management of Nomenclatures (RAMON) Index of Correspondence Tables, accessible here: `https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL`.

[10]The data shows a rapid and sustained increase in reported UK imports from China between 1999 and 2000. This most likely reflects a change in the treatment of imports from Hong Kong which originated in China that year (Baranga, 2018). We include imports from Hong Kong in our measures of Chinese imports for the UK, but not in our measures of Chinese imports to other countries (which we use as an instrument for UK imports), as they are not affected by this issue.

[11]The BSD is derived from the Inter-Departmental Business Register (IDBR), a live register of plant data collected by HM Revenue and Customs via VAT and Pay As You Earn (PAYE) records.

This allows us to study the extent to which individuals adjust the length of their working lives in response to a shock.

Prior work has shown the effects and responses to economic shocks differ by gender and age (Keller & Utar, 2022, Salvanes et al., 2022); we thus split our sample into subgroups on these dimensions. Our sample includes 83,627 male employees (with almost 24% working in manufacturing in 2001) and 85,170 female employees (9% of whom worked in manufacturing in 2001). Splitting the sample by age, we denote those aged 18-44 in 2001 as 'young', and those aged 45-59 as 'old'.

Table 2.1 shows descriptives for our sample at baseline in 2001. Columns (1) and (4) (for men and women, respectively) include employees in all industries, columns (2) and (5) only include those employed in manufacturing industries, and columns (3) and (6) only include those employed in the top 20 industries most exposed to Chinese import competition (all in manufacturing, see Table B.1 for the list). As our regressions control for one-digit industry fixed effects, the empirical analysis effectively compares changes in outcomes for workers in more and less exposed manufacturing industries. Table 2.1 shows workers in the most exposed manufacturing industries are broadly similar to other manufacturing workers in terms of baseline characteristics, although there are some differences, as we now discuss.

Panel A presents some basic demographic characteristics on age and whether born abroad. The average age of workers is similar across all workers, manufacturing workers, and those in the most highly exposed industries (38-39 years old). Workers in highly exposed industries were slightly more likely to be foreign-born than other manufacturing workers. This is more true for women than for men: 12% of women in highly exposed industries are foreign-born, compared to 9% of women in manufacturing as a whole, while the figures for men were 10% and 7% respectively. To account for these differences, we control for both age and foreign-born status in our empirical analysis.

Panel B shows information on individuals' marital status and family situation. Men working in manufacturing industries are four percentage points more likely to have a partner and to be married than those working in non-manufacturing industries, highlighting the importance of studying partner responses and family dynamics in this context. However, both men and women in the most exposed manufacturing industries are similar in terms of their partnering, and in terms of whether they have children, with respect to other manufacturing workers.

Panel C shows that general patterns of employment differ across men and women. 41% of female employees work part-time, while the fraction of male employees working part-time is just 6% (21% and 2% if employed in manufacturing). Consequently, men work on average longer hours than women (42 vs 32 hours per week). Men and women are also employed in different occupations, which we group into low-skill, blue-collar, and white-collar occupations.[12] Overall, 24% of men work in low-skill occupations, 46% work in white-collar occupations, and 30% work in blue-collar occupations. By contrast, 61% of women work in low-skill occupations, 34% in white-collar occupations, and only 5% in blue-collar occupations. A much larger proportion of workers of both sexes are employed in blue-collar occupations in highly-exposed industries (columns (3) and (6)) and the fractions of workers in these occupations are more similar for men and women: 50% of men employed in trade-exposed industries are employed in blue-collar industries compared to 46% of women. However, men in highly trade-exposed industries are much more likely to work in white-collar roles (36% of men compared to 20% of women), while women in these industries are much more likely to work in low-skill occupations. The proportions of men in different occupations in highly-exposed industries are almost identical to the proportions for manufacturing as a whole. Women in highly-exposed occupations are however more likely to be in blue-collar occupations than women in other manufacturing industries. 46% of women in highly exposed industries are in blue-collar occupations, compared to 31% of women in manufacturing as a whole. We control for baseline occupation in our main empirical specification to account for these differences. We also show that our results are not sensitive to the inclusion of occupation controls in our robustness checks.

[12] We define blue-collar workers as those employed in “skilled trades occupations” and “process, plant and machine operatives”. Low-skill workers are those employed in “administrative and secretarial occupations”, “caring, leisure, and other service occupations”, “sales and customer service occupations” and “elementary occupations”. Finally, white-collar workers are defined as those working in “managers, directors, and senior officials”, “professional occupations”, and “associate professional and technical occupations”. This follows from the UK Standard Occupational Classification SOC2000.

Table 2.1: Summary Statistics: Worker Characteristics in 2001.

	MEN			WOMEN		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Industries	Manuf. Industries	High Exposed Industries	All Industries	Manuf. Industries	High Exposed Industries
Observations	83,627	19,970	4,578	85,170	7,889	2,521
(with partners)	(57,415)	(14,651)	(3,258)	(58,084)	(5,510)	(1,797)
	Panel A. Demographic Characteristics					
Age	38.44	39.53	38.91	38.61	38.60	39.34
Foreign-born	0.083	0.069	0.095	0.081	0.093	0.120
	Panel B. Marriage and Family Characteristics					
Single	0.346	0.297	0.312	0.299	0.311	0.286
Married	0.581	0.625	0.610	0.583	0.574	0.604
Widowed	0.004	0.005	–	0.014	0.013	0.015
Divorced	0.068	0.073	0.075	0.104	0.102	0.095
Has Partner	0.687	0.729	0.713	0.683	0.699	0.714
Has Children	0.426	0.439	0.433	0.432	0.358	0.374
Has Young Children	0.157	0.157	0.171	0.126	0.116	0.110
	Panel C. Labour Market Characteristics					
Part-time	0.062	0.019	0.029	0.409	0.212	0.200
Hours worked	42.19	42.37	41.95	31.56	35.59	35.84
Low-skill	0.243	0.144	0.144	0.605	0.404	0.340
Blue-collar	0.302	0.499	0.500	0.054	0.316	0.464
White-collar	0.455	0.356	0.355	0.341	0.279	0.196
	Panel D. Partner Characteristics					
Partner age	39.70	40.18	39.46	43.21	42.88	43.54
Partner hours worked	21.51	20.77	20.61	38.88	38.77	38.11
Partner manufacturing	0.103	0.177	0.195	0.232	0.425	0.444
Partner active	0.786	0.790	0.770	0.929	0.929	0.925
Partner employed	0.730	0.741	0.716	0.764	0.784	0.780
Partner self-employed	0.039	0.032	0.033	0.147	0.127	0.126
Partner unemployed	0.017	0.017	0.020	0.018	0.018	0.019
Partner inactive home	0.151	0.146	0.167	0.007	–	–

Notes: Table shows mean values for employees in the 2001 Longitudinal Study. Columns (1) and (4) (for the sample of men and women, respectively) include employees in all industries, columns (2) and (5) include only those employed in manufacturing industries, and columns (3) and (6) only include those employed in the top 20 three-digit SIC92 industries most exposed to Chinese import competition (see Table B.1). Cells marked "–" are cases where average values have been suppressed because they were calculated with fewer than 10 individuals. Source is ONS Longitudinal Study.

For LS members with partners, Panel D summarises partner characteristics.[13] The average man's partner is aged 40 and works 22 hours per week. 21% of men's partners are not active participants in the labour market. Of these, about 71% report being inactive because they are "looking after the home". Only 10% of men's partners are employed in manufacturing (rising to 18% for the partners of men who are themselves employed in manufacturing). By contrast, the average partner of women is aged 43 and works 38 hours per week. Only 7% of them are inactive and 23% work in manufacturing (43% for partners of women who themselves work in manufacturing). Those in the most exposed industries are similar in terms of their partner's baseline characteristics to other manufacturing workers.

2.2 Empirical Approach

Our analysis exploits the rapid increase in Chinese exports surrounding China's entry into the WTO in 2001. This increase has been attributed to a number of factors including a reduction in trade uncertainty (Handley & Limao, 2017), a reduction in the tariffs China itself charged on its imported inputs (Pierce & Schott, 2016, Amiti et al., 2020), the end of international import quotas under the multi-fibre agreement (Keller & Utar, 2022), as well as continued rapid Chinese productivity growth during this period.

Appendix Figure B.1 shows the increase in Chinese imports to the UK from 1993 to 2016. As shown, most of this increase occurred in the 2000s. Real imports from China increased from approximately £20 billion in 2001 to around £50 billion in 2011. This led to China doubling its share of UK imports from 5% to over 10%. The extent of that import competition varied substantially across industries. Appendix Table B.1 shows the 20 industries most affected by import competition between 2001-2011. Imports were concentrated in low-tech manufacturing (e.g. the manufacture of games and toys; luggage and handbags; footwear; leather), consistent with China's strong comparative advantage in labour-intensive activities during this period (Amiti & Freund, 2010). In parallel, Figure B.2 shows the decline in manufacturing employment for the same period, separately for more

[13] This includes married and cohabiting couples where both partners are observed.

and less trade-exposed manufacturing industries. The decline starts in the early 2000s (mirroring the figure on imports), and it is more pronounced for the top 20 manufacturing industries most affected.[14]

The empirical strategy presented in this chapter uses this cross-industry variation, following Autor et al. (2013, 2014). For a worker i initially employed in industry j,[15] exposure to import competition IE_j^{UK} is defined as the growth in imports from China during 2001-2011 relative to that industry's total domestic sales (i.e. industry turnover (sales) plus UK imports minus UK exports):

$$IE^{UK}_{j,2011-2001} = \frac{\Delta Imports^{China\rightarrow UK}_{j,2011-2001}}{Turnover_{j,2001} + Imports_{j,2001} - Exports_{j,2001}} \tag{2.1}$$

We compare own and partner outcomes for workers with similar characteristics but initially employed in industries with different levels of exposure to import competition. The baseline specification controls for age and gender, as well as fixed effects for initial occupation, local labour market and broad industry sector:

$$\Delta Y_{ij,t_1-t_0} = \alpha + \beta IE^{UK}_{j,t_1-t_0} + \delta X_{ij,t_0} + \gamma^{occ} + \gamma^{ind} + \gamma^{ttwa} + \epsilon_{ij,t_1-t_0} \tag{2.2}$$

where i is for individual, j is for industry, and $t_1 = 2011$ and $t_0 = 2001$. $\Delta Y_{ij,t_1-t_0}$ is the change in outcome Y between 2001-2011 for individual i who was employed in industry j in 2001. The coefficient β captures the effect of increased import competition. The vector X_{ij,t_0} contains baseline controls for workers' gender, five-year age groups and their interaction with gender, and foreign-born status. We include two-digit occupation (γ^{occ}) and one-digit industry fixed effects (γ^{ind}) to account for industry and occupation-specific trends (e.g. those related to the automation of routine tasks). We also include local labour market fixed effects (γ^{ttwa}), which are defined as 2001 Travel to Work Areas (TTWAs); geographical units analogous to Commuting Zones (CZ) in the US.[16] In the household-level analysis, we additionally include partners' age, (one-digit) occupation and (one-digit) industry fixed

[14]Figure B.2 also shows that most of the decline occurred before 2007 and the impact of the Great Recession did not differ for more vs less trade-exposed manufacturing industries.

[15]Workers' initial industry is the three-digit UK Standard Industrial Classification SIC92 code of their employer in 2001 (a total of 179 industries).

[16]There are 186 TTWAs in England and Wales. These are generated such that at least 75% of the area's resident workforce work in the area and at least 75% of the people who work in the area also live in the area. Individuals are assigned to TTWAs using a time-consistent definition of TTWAs across censuses from Montresor (2019).

effects. We cluster standard errors at the level of three-digit industries, allowing for correlation in error terms among workers who were initially employed in the same narrow industry. We scale eq. (2.1) by the interquartile range of exposure across all manufacturing workers, such that the reported coefficients can be interpreted as the effect of moving a worker from the 25th to the 75th percentile in the exposure distribution among manufacturing workers. For individuals initially employed in manufacturing, the average increase in import exposure from China between 2001-2011 was 3.96 percentage points, and the interquartile range was 5.87 pp (summary statistics are provided in Appendix Table B.4).[17]

The growth in import exposure could in part reflect domestic demand or productivity shocks, which we could confound with the role of growing import competition. To address this, we follow the standard approach in the literature and employ an instrumental variable (IV) strategy aimed at isolating the role of factors driving Chinese export growth that is specific to China. Import exposure in eq. (2.1) is thus instrumented with

$$\widetilde{IE}_{j,2011-2001} = \frac{\Delta Imports^{China \to Other}_{j,2011-2001}}{Turnover_{j,1997} + Imports_{j,1997} - Exports_{j,1997}} \tag{2.3}$$

where the numerator is the change in imports from China from 2001 to 2011 to other non-UK high-income countries.[18] Equation (2.3) uses turnover, import, and export levels from 1997, the earliest year in which we observe industry turnover, to avoid the potential endogeneity of using 2001 imports and sales that may have already been influenced by Chinese import growth.[19] The identifying assumption underlying the use of this instrument is that common patterns in Chinese trade across developed countries do not reflect correlated demand or technology shocks across high-income countries. While this cannot be ruled out completely, Autor et al.

[17] In Appendix B.1, we also investigate the degree to which partners are differently affected by increased Chinese import competition. The exposure of partners in the same household tends to be low, at just 0.22 across all workers (Table B.5). This means that in most cases when an LS member is exposed to a large trade shock, their partner is employed in an unexposed industry.

[18] These countries are Australia, Canada, Denmark, France, Germany, Italy, Japan, Spain, Switzerland, and the United States. As we show in Appendix B.2, our results are robust to using different sets of countries to construct the instrument.

[19] In Appendix B.1, we regress the value in eq. (2.1) on the value in eq. (2.3), which is equivalent to the first-stage regression. The results in Table B.2 and Table B.3 show that import growth for different industries in these other countries is highly predictive of UK import growth from China.

(2014) obtain very similar results when measuring the change in import exposure using residuals from a gravity model of trade flows, suggesting that correlated import demand shocks across high-income countries play little role.[20]

We run several checks to confirm that our results do indeed reflect the effects of increased import competition rather than other factors. To verify our results do not reflect industry-specific trends that predate the rise of import competition from China, we repeat our main regression specifications for the decades 1981-1991 and 1991-2001, using workers' *future* (2001-2011) exposure to growing Chinese import competition in Appendix B.2. We find no evidence that workers employed in 1981 in industries that would later be exposed to Chinese import competition saw greater exits from manufacturing or a higher unemployment rate in 1991. The effects of future import competition on unemployment and manufacturing employment are slightly greater when we measure them for the 1991-2001 period but they remain small and statistically insignificant at 5%. This is not unexpected as the rapid growth in Chinese imports to the UK began towards the end of this later period.

We also check whether the growth in immigration to the UK in the 2000s, particularly from Eastern Europe, could confound our results by examining the extent to which trade-exposed industries saw greater growth in the share of foreign-born workers. This appears not to be the case. We find that the correlation between import exposure and the growth in the share of foreign workers is essentially zero, which is true for all industries (-0.018) as well as for only manufacturing industries (-0.040). We discuss further robustness checks in the next section.

2.3 Results

2.3.1 Individual Labour Responses to Import Competition

In this section, we report results on how rising exposure to Chinese import competition affects the labour market status of individual workers. Table 2.2 shows

[20]The gravity approach neutralises demand conditions in importing countries by using the change in China's exports relative to its exports within destination markets, helping isolate supply and trade cost-driven changes in China's export performance. See Autor et al. (2013, 2014) for more.

regression results for different labour market outcomes: employment in manufacturing, unemployment, employment in any industry, self-employment and being active in the labour force (columns (1)-(5), respectively).[21] By construction, the coefficients in columns (2)-(4) sum to those in column (5). The regressions are estimated by two-stage least squares (2SLS), using the variable described in eq. (2.3) as an instrument for the change in import exposure given in eq. (2.1). All regressions include the full set of controls discussed in Section 2.2. We also report the mean of the dependent variable for each outcome to benchmark the magnitudes of the effects relative to general trends.

Panel A shows the results for all workers in our sample. We return to the differences by gender and age groups below. Exposure to Chinese import competition significantly decreases the probability of being employed in manufacturing and increases the probability of unemployment. Increasing import exposure from the 25th percentile to the 75th percentile among manufacturing workers reduces the probability that a worker is employed in manufacturing in 2011 by 7.5 percentage points and increases the probability they are unemployed by 0.5 ppt (for comparison regarding the scale of this effect, the unemployment rate in 2011 was 7.4%, Office for National Statistics (2013)). While the effect on manufacturing employment is considerable, we do not detect a statistically significant effect on the probability of being in employment (column (3)). This implies that workers initially employed in industries exposed to import competition are more likely to exit manufacturing, with the majority reallocating to non-manufacturing sectors. Appendix B shows that workers initially employed in import-competing industries mostly found new employment in different, typically worse-paid, occupations. Table B.6 presents results on how import competition affected the change in workers' employment in low-skill, blue-collar, and white-collar occupations (as described in footnote 12 of this chapter). Trade-exposed workers are more likely to shift out of blue-collar occupations and move into lower-paid, low-skill occupations. These results are consistent with findings that workers exposed to the China shock experienced lower earnings growth, conditional on employment, as shown in the US (Autor et al., 2014), Denmark (Utar, 2018) and the UK (De Lyon & Pessoa, 2021).

[21]To save space, we do not report employment in non-manufacturing as an additional outcome in the tables. Implicitly, as we discuss later, this could be inferred from columns (1) and (3).

Panels B and C of Table 2.2 show how the effects of import competition differ by gender. Men and women in exposed industries respond quite differently. The negative impact of import exposure on manufacturing employment is greater for men than women; with a one unit change in import exposure associated with a 7.4 ppt decline in male employment in manufacturing, compared to a 5.8 percentage

Table 2.2: Import Exposure and Labour Market Responses by Gender

	(1) Δ manuf	(2) Δ unempl	(3) Δ empl	(4) Δ self-empl	(5) Δ active
	Panel A. All				
Import Exposure	-7.483^{***}	0.480^{**}	-0.736	0.296	0.039
	(2.243)	(0.235)	(0.604)	(0.282)	(0.399)
Mean Dep. Var.	-7.60	2.65	-28.35	7.50	-18.19
First-Stage F-stat	[32.12]	[32.12]	[32.12]	[32.12]	[32.12]
Observations	168,797	168,797	168,797	168,797	168,797
	Panel B. Men				
Import Exposure	-7.410^{***}	0.802^{***}	-1.116^{*}	0.897^{**}	0.583^{*}
	(2.187)	(0.274)	(0.675)	(0.371)	(0.348)
Mean Dep. Var.	-10.14	3.24	-27.87	10.23	-14.39
First-Stage F-stat	[29.23]	[29.23]	[29.23]	[29.23]	[29.23]
Observations	83,627	83,627	83,627	83,627	83,627
	Panel C. Women				
Import Exposure	-5.801^{**}	0.057	-0.117	-0.620	-0.681
	(2.314)	(0.309)	(0.721)	(0.388)	(0.542)
Mean Dep. Var.	-5.12	2.07	-28.82	4.81	-21.92
First-Stage F-stat	[35.25]	[35.25]	[35.25]	[35.25]	[35.25]
Observations	85,170	85,170	85,170	85,170	85,170

Notes: Table shows the effect of import exposure on individual labour market outcomes. Dependent variables in columns (1)-(5) are: being employed in manufacturing, being unemployed, employed in any industry, self-employed and active in the labour market (unemployed or in-work). The regressions in all columns are estimated using two-stage least squares (2SLS), with the variable described in eq. (2.3) as an instrument for the change in import exposure given in eq. (2.1). Controls are the worker's gender, five-year age groups interacted with gender, and a dummy for whether the worker was foreign-born. We also include a two-digit occupation, one-digit industry, and local labour market (defined as 2001 Travel to Work Areas) fixed effects. See Section 2.2 for more details. Standard errors are clustered at the (SIC92) three-digit industry level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

point decline in female manufacturing employment. For men, there is also a significant increase in unemployment, alongside an increase in economic activity (column (5)), while for women the point estimates in columns (2) and (5), although not statistically significant, suggest that import exposure leads to economic inactivity rather than unemployment.

As discussed in Section 2.2, an advantage of our data is that we can follow transitions into self-employment, which cannot be observed in other administrative datasets that follow employees only. As the mean dependent variables in Table 2.2 show, there was a general increase in self-employment over this period, particularly among men. The share of our sample who were self-employed increased by 10.2 percentage points among men and 4.8 ppt among women.[22] Self-employment may have acted as an 'employment buffer' for male workers, allowing displaced workers to remain at work following the shock. While a one-unit increase in import exposure decreases the likelihood that men are employees in 2011 by 1.1 ppt, it increases the likelihood they are self-employed by 0.9 ppt (columns (3)-(4)). Our results indicate that for male workers, these transitions were an important means of insurance against job loss caused by import competition. By contrast, we do not find evidence of such a buffer effect for women, who are no more likely to move into self-employment if exposed to the trade shock.

Self-employment includes both solo self-employment (i.e. own account workers without employees) and self-employment with employees (those who run businesses and hire workers). This distinction and the transitions across these self-employment outcomes matter for the interpretation of the effects. In Appendix Table B.7, we decompose self-employment into solo self-employment and self-employment with employees. Most (around two-thirds) of the self-employment effect for men is accounted for by an increase in solo self-employment. There is a smaller, but still statistically significant, effect of import exposure on the proportion of men who become self-employed with employees.

In Table 2.3, we report results split by age ('young' workers aged 18-44 in 2001 and 'old' workers aged 45-59) and gender. The impact of import exposure

[22]Our results suggest that rising import competition contributed to this trend for men, although the size of this contribution is likely to have been small, as only a minority of workers were employed in trade-exposed industries.

on manufacturing employment is substantially stronger for young workers than for old, among both men and women: A one-unit change in the import exposure measure decreases the probability a worker is employed in manufacturing by almost 9 ppt for young men (6.3 ppt for young women) relative to 5 ppt for old men (4.8 ppt for old women).

Table 2.3: Import Exposure and Labour Market Responses by Gender and Age

	(1) Δ manuf	(2) Δ unempl	(3) Δ empl	(4) Δ self-empl	(5) Δ active
	Panel A. Young Men				
Import Exposure	-8.946^{***}	0.870^{**}	-2.041^{***}	0.766^{**}	-0.405^{**}
	(2.520)	(0.357)	(0.686)	(0.401)	(0.206)
Mean Dep. Var.	-7.64	3.45	-19.04	11.63	-3.96
First-Stage F-stat	[26.20]	[26.20]	[26.20]	[26.20]	[26.20]
Observations	56,472	56,472	56,472	56,472	56,472
	Panel B. Old Men				
Import Exposure	-5.018^{**}	0.717^{**}	0.564	1.018^{*}	2.298^{**}
	(2.087)	(0.313)	(0.972)	(0.593)	(0.895)
Mean Dep. Var.	-15.34	2.82	-46.23	7.32	-36.09
First-Stage F-stat	[35.32]	[35.32]	[35.32]	[35.32]	[35.32]
Observations	27,155	27,155	27,155	27,155	27,155
	Panel C. Young Women				
Import Exposure	-6.268^{***}	0.317	-0.312	-0.685	-0.679
	(2.276)	(0.441)	(0.596)	(0.459)	(0.421)
Mean Dep. Var.	-4.68	2.47	-18.21	5.68	-10.05
First-Stage F-stat	[31.42]	[31.42]	[31.42]	[31.42]	[31.42]
Observations	56,800	56,800	56,800	56,800	56,800
	Panel D. Old Women				
Import Exposure	-4.843^{*}	-0.425^{**}	0.430	-0.526	-0.521
	(2.726)	(0.199)	(1.254)	(0.443)	(1.070)
Mean Dep. Var.	-5.99	1.28	-50.05	3.07	-45.69
First-Stage F-stat	[40.95]	[40.95]	[40.95]	[40.95]	[40.95]
Observations	28,370	28,370	28,370	28,370	28,370

Notes: Table shows the effect of import exposure on individual labour market outcomes. See notes of Table 2.2 for a list of the controls and details on the IV. Standard errors clustered at the (SIC92) three-digit industry level are reported in parentheses. The mean dependent variable and first-stage F statistics are reported below the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table 2.3 also reveals substantial differences in the labour market responses of young and old men. While young male workers exposed to import competition are much less likely to be in work (increases in self-employment are not sufficient to compensate for decreases in employment), the opposite is true for old male workers, who are *more* likely to be in work and economically active if initially employed in an exposed industry. To understand what lies behind this effect, we decompose the effects of import exposure on economic inactivity according to different possible reasons: retirement, studying, looking after the home, sickness, and 'other' reasons. The results are reported in Appendix Table B.8. The key reason for higher rates of economic activity is the reduced probability of retirement. A one-unit increase in import exposure decreases the likelihood of retirement in 2011 by 3.5 percentage points. This could be partially driven by the increase in self-employment shown in Panel B of Table 2.3, as older self-employed workers are more likely to remain in paid work at any given age than permanent employees (Crawford et al., 2021, Banks, 2016).[23]. Another possible reason for delayed retirement is to compensate for reduced earnings following displacement, or a wealth effect on lifetime labour supply. The use of delayed retirement to compensate for lower retirement savings due to job loss has been explored in life-cycle models including Stock & Wise (1990), Scheiber (1992) and Merkurieva (2019), but this phenomenon is relatively underexplored in the context of responses to trade competition. For women, we do not find a significant effect on self-employment or retirement.

Appendix B.2 reports a range of robustness checks for these results. Table B.16 and Table B.17 summarise them. First, we show that our results are robust to using different country combinations when constructing our instruments for import exposure in eq. (2.3). Second, we include a richer set of industry- and occupation-specific controls. Industry-specific controls we add are the intensity of R&D stock over capital, ICT stock intensity over capital, computer stock intensity over capital, and the intensity of net capital stock over industry output (measured in the year 1997 and at the two-digit SIC92 industry level). Occupation-specific controls we include are the Routine Task Intensity (RTI, Autor et al. (2003)) and the offshorability

[23]Most (72%) of the effect on older men's self-employment is accounted for by an increase in solo self-employment (Table B.7). Younger men in exposed industries see a larger increase in self-employment with employees than older men.

index.[24] These additional controls do not change our main results. We also show that our results do not change if we exclude occupation fixed effects. Third, we assess the sensitivity of our results to another major contemporary trade shock, namely the accession to the European Union of a number of Eastern European countries in 2004.[25] Accounting for import competition with Eastern Europe does not alter our main findings, consistent with these countries specialising in quite different exports to China (Foliano & Riley, 2017). Finally, we examine whether our results are affected if we control for workers' exposure to rising export demand from China. Controlling for UK exports to China also leaves our main results unchanged.[26]

2.3.2 Effects of Import Competition on Family Outcomes

We now turn to consider the impacts of import competition on partnering and divorce. Changes in family formation and family stability may be an important mechanism through which labour market shocks can affect broader social outcomes, including for subsequent generations. Recent work documents how trade shocks affect family outcomes, and the findings appear to differ by country. Focusing on individuals aged 18-39, Autor et al. (2019) show how US areas more exposed to Chinese import competition saw significantly lower marriage rates, lower fertility, and increased single-parenthood and child poverty. They link the declines in marriage rates to higher crime and greater mortality among men in affected areas. However, the effects differ according to whether shocks predominantly affected male or female workers in the local labour market. In labour markets where relatively more men were affected, marriage rates and fertility declined. In labour markets where relatively more women were affected, marriage rates and fertility

[24] These measures are initially constructed at the four-digit US-SOC2010 occupational classification level from the US O*NET database. Official crosswalks are then used to map these measures into the corresponding four-digit UK-SOC2000 occupation categories.

[25] Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia.

[26] Autor et al. (2013) also find that incorporating changes in US exports to China had no effect on their estimates. In contrast, Dauth et al. (2014) find that, in Germany, exports to the 'East' (China and Eastern Europe) helped to offset the negative employment effects. All of this is consistent with the fact the US and the UK saw large growth in their imports from China but only limited growth in their exports to China, while Germany saw large increases in both its imports from and exports to China, and so a smaller deterioration in its bilateral trade balance (Dorn & Levell (2021)).

increased. In line with this latter result, Keller & Utar (2022) find that female workers in Denmark who were exposed to Chinese competition in the apparel sector were more likely to have children, drop out of the labour force and get married than other comparable workers. The effects were greater for women in their late 30s, with fewer remaining fertile years. They argue their results are consistent with a reduction in the opportunity costs of raising a family for women. Unlike Autor et al. (2019), however, they did not find effects on marriage and fertility for men affected by the shock. In Germany, Giuntella et al. (2022) find that exposure to import competition from China and Eastern Europe in the 2000s led to lower fertility, while greater exposure to export opportunities to this region increased it. They also find a negative and marginally significant effect on divorce for women.

Table 2.4 shows how import competition affected family status, split again by age and gender. Column (1) focuses on marriage. Different from Autor et al. (2019) but similar to Keller & Utar (2022), we do not find evidence for the effects on the marriage rates of young men who were initially unmarried, or on the divorce rates of young men who were initially married. Among old men, singles in exposed industries are by contrast significantly less likely to get married.

Turning to divorce, the results in column (2) imply that import competition leads to a reduction in the likelihood that trade-affected (married) women under 45 get divorced, which is consistent with Keller & Utar (2022) and Giuntella et al. (2022).[27] In particular, a one-unit increase in exposure to import competition decreases the likelihood of divorce by 2 percentage points. This response is greater in the presence of children in the household (not shown in Table 2.4), where the estimated coefficient increases to 2.64 (standard error 0.77). Similarly, we find that exposure to import competition means that married women under 45 are less likely to find and cohabit with a new partner (column (5)).

Columns (3) and (4) of Table 2.4 show the effects of import competition on whether those initially in a couple (column (3)), and those who were initially uncoupled (column (4)), have a partner in the subsequent wave (irrespective of whether they are married or not). The effects are small and not statistically

[27] Note that in England and Wales overall in 2001, the median age of women at divorce is 37.7 years. The corresponding figure for males is 40.0 years (Office for National Statistics, 2015b).

significant across all subgroups. This implies that, while the likelihood that young women (who are exposed to import competition) in married couples divorce their partners is lower than for other workers, the effect of import exposure on whether young women have a married or unmarried partner is not as great.

Table 2.4: The Effects of Import Exposure on Divorce and Partnering

	(1) Δ married (if unmarried)	(2) Δ divorced (if married)	(3) Δ has part. (if couple)	(4) Δ has part. (if not couple)	(5) Δ new partner (if couple)
	Panel A. Young Men				
Import Exposure	0.428	0.216	0.211	−0.351	0.651
	(1.122)	(0.693)	(0.436)	(0.859)	(0.553)
First-Stage F-stat	[21.22]	[30.42]	[28.66]	[21.16]	[27.88]
Observations	29,854	26,648	34,636	21,866	30,699
	Panel B. Old Men				
Import Exposure	−3.218***	0.754	−1.304	−2.639	−0.856
	(1.237)	(0.768)	(0.878)	(2.192)	(0.618)
First-Stage F-stat	[47.76]	[33.06]	[36.84]	[28.64]	[36.62]
Observations	5,233	21,930	22,844	4,319	21,184
	Panel C. Young Women				
Import Exposure	−0.083	−2.041***	0.553	1.358	−1.201***
	(1.211)	(0.655)	(0.573)	(1.229)	(0.458)
First-Stage F-stat	[30.24]	[33.31]	[30.17]	[34.34]	[31.24]
Observations	28,716	28,126	36,004	20,838	30,698
	Panel D. Old Women				
Import Exposure	1.906	−0.097	0.824	0.905	0.013
	(1.475)	(0.461)	(0.680)	(1.429)	(0.320)
First-Stage F-stat	[38.69]	[41.65]	[40.05]	[44.05]	[40.46]
Observations	6,878	21,498	22,227	6,149	19,647

Notes: Table shows the effect of import exposure on individuals' family status. Column (1) shows the effects on marriage for a sample of initially unmarried people. Column (2) shows the effects on divorce for a sample of initially married individuals. Columns (3)-(4) show the effects on partnering for coupled and uncoupled individuals, respectively. Column (5) shows the effects on new partnering, that is, finding and cohabiting with a new person. Recall that we denote those aged 18-44 in 2001 as 'young' and those aged 45-59 as 'old'. We use age and other characteristics of the partner to assess whether partners of LS members observed in two different waves are likely to be the same individual or not. In this process, we lose a few observations, which is the reason why the number of observations between columns (3) and (5) differs. See notes of Table 2.2 for a list of the controls and details on the IV. Standard errors clustered at the three-digit industry level are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Source is ONS Longitudinal Study.

Unlike Keller & Utar (2022), we do not find significant effects of import exposure on fertility, measured as the count of children aged under 10 in the 2011 wave (not reported in Table 2.4, the coefficient is 0.014 with standard error of 0.971), nor do we find significantly greater reductions in labour force participation among young women (column (5) in Table 2.3). This suggests the lower divorce rate among young women we observe is not driven by a fall in the opportunity costs of starting a family. A possible explanation for lower divorce rates among young women is that, by reducing their future expected earnings, exposure to import competition may leave women more financially reliant on their current partners.

2.3.3 Family Labour Supply Responses to Import Competition

We next look at the responses of *partners* of those affected by import competition. We restrict attention to the sample of 'stable' couples, defined as households with LS members who have a partner in both waves, and whose partners' characteristics – the year of birth and gender – do not change. For ease of exposition, we focus on heterosexual couples – including non-heterosexual couples (approximately 1% of our sample) in the analysis does not change our results.

The own and partner labour supply responses in response to import competition are shown for men in Table 2.5 and for women in Table 2.6. In these regressions, we include controls for partner characteristics (partner's age, one-digit occupation and one-digit industry fixed effects), in addition to the previous controls used in Section 2.3.1. The own-response effect sizes in these tables differ from those in Table 2.2 and Table 2.3 mainly because those in stable couples respond to the shock differently to singles. Appendix Table B.9 shows these effects alongside those for singles. Men in couples who are exposed to import competition are just as likely to leave manufacturing as single men but are more likely to remain in work, less likely to be unemployed, and more likely to shift towards self-employment. Women in couples also behave differently to single women following the trade shock; the point estimates, although statistically insignificant, suggest that those in stable couples are more likely to leave the labour force and become inactive than single women (who are instead more likely to move into unemployment).

Table 2.5: Import Exposure and Family Labour Supply Responses (MEN)

	OWN RESPONSE					PARTNER RESPONSE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ manuf	Δ unempl	Δ empl	Δ self-empl	Δ active	Δ partner in work	Δ partner active
Panel A. Men							
Import Exposure	-7.715^{***}	0.580^{**}	-0.697	1.298^{***}	1.182^{***}	-0.764	-0.581
	(2.153)	(0.236)	(0.657)	(0.395)	(0.402)	(0.616)	(0.433)
Mean Dep. Var.	-11.20	2.18	-28.69	10.20	-16.31	-7.01	-6.91
First-Stage F-stat	[30.98]	[30.98]	[30.98]	[30.98]	[30.98]	[30.98]	[30.98]
Observations	51,302	51,302	51,302	51,302	51,302	51,302	51,302
Panel B. Young Men							
Import Exposure	-9.406^{***}	0.628^{**}	-2.336^{***}	1.622^{***}	-0.085	-0.907	-0.457
	(2.503)	(0.312)	(0.677)	(0.502)	(0.225)	(0.553)	(0.565)
Mean Dep. Var.	-8.26	2.12	-17.25	12.08	-3.05	4.55	4.85
First-Stage F-stat	[27.53]	[27.53]	[27.53]	[27.53]	[27.53]	[27.53]	[27.53]
Observations	30,277	30,277	30,277	30,277	30,277	30,277	30,277
Panel C. Old Men							
Import Exposure	-5.917^{***}	0.444	1.603	0.722	2.770^{***}	-0.807	-1.018
	(2.215)	(0.304)	(1.322)	(0.746)	(0.945)	(1.336)	(1.239)
Mean Dep. Var.	-15.43	2.26	-45.17	7.50	-35.41	-23.67	-23.83
First-Stage F-stat	[36.55]	[36.55]	[36.55]	[36.55]	[36.55]	[36.55]	[36.55]
Observations	21,025	21,025	21,025	21,025	21,025	21,025	21,025

Notes: Table shows the effects of import exposure on men's own labour supply and the labour supply of their female partners. Samples are for those in stable couples (those who remain in the same relationship over the period 2001-2011). In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, one-digit occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table 2.6: Import Exposure and Family Labour Supply Responses (WOMEN)

	OWN RESPONSE					PARTNER RESPONSE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ manuf	Δ unempl	Δ empl	Δ self-empl	Δ active	Δ partner in work	Δ partner active
Panel A. Women							
Import Exposure	-6.424^{***}	-0.251	-0.212	-0.646^{*}	-1.108	1.249^{***}	1.064^{***}
	(2.436)	(0.237)	(0.906)	(0.359)	(0.740)	(0.403)	(0.399)
Mean Dep. Var.	-5.21	1.46	-30.34	4.86	-24.02	-14.89	-14.42
First-Stage F-stat	[35.49]	[35.49]	[35.49]	[35.49]	[35.49]	[35.49]	[35.49]
Observations	49,767	49,767	49,767	49,767	49,767	49,767	49,767
Panel B. Young Women							
Import Exposure	-6.820^{***}	0.091	-0.353	-0.711	-0.973	1.092^{**}	0.703^{**}
	(2.364)	(0.335)	(0.810)	(0.455)	(0.606)	(0.506)	(0.329)
Mean Dep. Var.	-4.83	1.74	-17.53	6.02	-9.78	-3.26	-2.57
First-Stage F-stat	[30.91]	[30.91]	[30.91]	[30.91]	[30.91]	[30.91]	[30.91]
Observations	30,289	30,289	30,289	30,289	30,289	30,289	30,289
Panel C. Old Women							
Import Exposure	-5.720^{**}	-0.779^{***}	0.103	-0.598	-1.273	1.627^{*}	1.802^{**}
	(2.914)	(0.227)	(1.824)	(0.513)	(1.711)	(0.848)	(0.811)
Mean Dep. Var.	-5.79	1.03	-50.25	3.05	-46.17	-32.98	-32.85
First-Stage F-stat	[40.86]	[40.86]	[40.86]	[40.86]	[40.86]	[40.86]	[40.86]
Observations	19,478	19,478	19,478	19,478	19,478	19,478	19,478

Notes: Table shows the effects of import exposure on women's own labour supply and the labour supply of their male partners. Samples are for those in stable couples (those who remain in the same relationship over the period 2001-2011). In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, one-digit occupation and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

The final two columns of Table 2.5 and Table 2.6 test for the presence or absence of added worker effects. In these tables, we focus on the extensive margin of responses (we discuss changes in part-time status below). Table 2.5 shows that women in a relationship with men do not increase their labour market activity to compensate for any earnings losses their partner may have experienced as a result of rising import competition. Effects on the likelihood that female partners move into work are negative, small, and not significantly different from zero. This is true for both young and old women, despite the fact that their male partners are more likely to be unemployed in 2011 if in an exposed industry in 2001. In Appendix B, we also investigate heterogeneity in responses across subsamples, including whether children are present in the household or not, and whether partners were initially active in the labour market, employed full-time or employed part-time. The results do not change when we restrict the sample to those with children or young children, remaining negative and statistically insignificant (Table B.12).

A potential explanation for the absence of an added worker effect among women is that women's labour market responses are restricted by social norms that men should be the 'breadwinners' in the couple, particularly if increasing labour supply would make the woman the couple's main earner (Bertrand et al., 2015). Another possible explanation is that the UK unemployment benefit system, based on means-tested benefits over this period, creates disincentives for women to enter the labour market if their male partners lose their jobs (Bredtmann et al., 2018).

The results are different when it comes to the responses of men in households where women are exposed to rising import competition (Table 2.6). The male partners of women in trade-exposed industries increase their labour supply: each one-unit increase in import exposure raises the probability their partner is in work by 1.2 ppt. The effects are stronger for older women, for whom each one-unit increase in import exposure results in a 1.6 ppt increase in their partner's employment. The responses of men to import competition affecting their partners shown in Table 2.6, mirror those we found for older men directly affected by import competition shown in Table 2.3, showing an increase in labour market activity at older ages (when there is, of course, more scope to increase activity). Thus, increased activity at older ages by men appears to be a means of compensating for lost household earnings, whether they arise through shocks affecting men directly or through shocks affecting their partners.

Appendix Table B.10 and Table B.11 split the changes in the probabilities partners are in work into self-employment and employment, by gender. The increase in labour supply by the male partners is almost entirely driven by an increase in self-employment. Partners of older women exposed to trade shocks are also less likely to transition into part-time employment: each one-unit increase in women's import exposure increases the probability their partners remain in full-time work by 2.4 ppt. In other words, older men respond to shocks affecting their partners by increasing labour supply on both intensive and extensive margins.

The results on male partners' labour supply (Table B.13) show that male responses to shocks affecting their partners are greatest for families where the youngest child was aged 5-10. A natural question is whether the increase in male partners' activity is an increase in activity from men who were initially inactive, or a reduction in flows into inactivity from those who were initially active. We first note that about 93% of male partners are active in 2001 (see Table 2.1). We find that the effects of import exposure on male partner's labour supply are similar when we condition on households where male partners were initially active in the labour market or in (full-time) work in 2001 (see Table B.13, Panels B.1, B.2, and B.4, respectively). This implies that much of the increase in labour force participation of men in households in which women are exposed to import competition is driven by the fact these men are less likely to move into inactivity by 2011. Male partners who were initially working full-time are also less likely to transition to part-time work when their partners are exposed to Chinese import competition.

A further question is whether our results are driven by the fact that partners are exposed to correlated shocks (e.g. partners work in the same industry). As discussed in Section 2.2, the cross-partner correlation in import exposure is low, suggesting this is unlikely to be driving our results. To further check this, we restrict our sample to cases where the partners of LS members are not employed in trade-exposed industries. The results are shown in Table B.18-B.19 for women and Table B.20-B.21 for men. The results are similar to those in our main sample, implying cross-partner correlations in import exposure are not driving our findings.

To summarise, our results suggest that household labour supply is a potentially important channel of insurance, especially in households where women are exposed to trade shocks: male partners of these women increase labour force participation through greater self-employment and reduced inactivity at older ages.

2.4 Summary and Conclusion

In this chapter, we use linked census data to investigate the responses of households in England and Wales to increased Chinese import competition in the 2000s. In addition to studying the impact of this shock on individuals' employment in manufacturing and participation in the workforce, we study broader margins of adjustment at both the individual and the household level, including the shock's impact on self-employment, retirement, family formation and family stability, and family labour supply. Our analysis allows for heterogeneity by gender and age.

We have three key findings. First, we show that the decline in manufacturing that resulted from the trade shock not only led to an increase in unemployment but also to an increase in self-employment among males, which acted as a buffer for affected workers. Most of this increase was accounted for by a greater likelihood of solo self-employment rather than self-employment with employees. This emphasises the importance for researchers of observing self-employment outcomes to understand worker adjustment mechanisms, especially in settings (such as the UK) where self-employment accounts for a substantial share of the workforce. We also observe that older males in exposed industries delay their retirement; this could either reflect more flexible retirement patterns associated with self-employment, or workers extending their working lives in response to earnings losses.

Second, we find that, in the UK, import competition significantly reduces the likelihood of divorce or of living with a new partner for women aged below 45. By reducing their future expected earnings, exposure to import competition may leave women more financially reliant on their current partners. In contrast, we find no evidence of an impact on the divorce rates of married men exposed to import competition. This is different from the US experience: Autor et al. (2019) find substantial increases in divorce and marriage rates in local labour markets where men were more exposed to the China trade shock. It is however consistent with findings from other European countries such as Germany and Denmark (Giuntella et al., 2022, Keller & Utar, 2022). Our results suggest that family breakdown and other negative social impacts following reductions in manufacturing employment (e.g. Che et al. (2018) on crime, Pierce & Schott (2020) on 'deaths of despair') need not be inevitable. One possibility is that the scale and nature of these broader social impacts depend on whether affected individuals transition into inactivity (as appears to be the case for men in the US) or move into other forms of employment. Future research is needed to understand the importance of this particular channel.

Third, while we find no evidence that women respond to shocks affecting their male partners, we do find an added worker effect for men, who are significantly more likely to be working ten years later if their female partner was initially employed in a trade-exposed industry. The stronger responsiveness of males here mirrors our finding on gender differences regarding their own response to trade shock exposure. The effect is larger for older men, who see greater reductions in inactivity in response to shocks affecting their partners.

Overall, this chapter shows there is substantial heterogeneity in labour market and life decisions in response to increased import competition. Men and women do not respond to trade shocks in the same way, nor do they respond in the same way to shocks affecting their partners. Future research should investigate to what extent these differences are driven by differences in opportunities or differences in constraints, such as social norms. More broadly, heterogeneity in responses to labour market shocks is important for understanding how they will affect gender inequality. Understanding how different workers and their families adapt to trade shocks, and how responses differ across them, is also important for understanding the welfare implications of such shocks and for designing appropriate policy responses. The findings on the partner responses suggest that the family plays an important part in providing insurance to workers; individuals without strong intra-household insurance are likely to be more in need of public insurance.

CHAPTER 3

Heterogeneous Price Elasticities of Labour Supply and Occupational Change[1]

The structure of employment and wages across occupations has changed considerably in most developed countries over recent decades. Autor et al. (2003) and Goos & Manning (2007), among the first, show that shifts in occupational employment are linked to the effect that technological change has on the labour market. Later research has connected these changes in the job structure to changes in wage inequality and wages in occupations (Dustmann et al., 2009, Acemoglu & Autor, 2011, Cortes, 2016, Cavaglia & Etheridge, 2020, Böhm et al., 2022).

Today it is well-established that shifts in the demand for occupations over time have led to large changes in employment and wages, with many economic and societal consequences. A smaller body of research has also explored the role of shifts across occupations in the supply of labour (e.g. Glitz & Wissmann, 2021). One aspect that has received a lot of discussion in the policy sphere, but with still limited systematic treatment in research, is the responsiveness of labour supply to the changing demand for jobs. This refers to the ability of the workforce to adapt to the changing job market.

[1]Joint work with Michael J. Böhm (TU Dortmund) and Ben Etheridge (University of Essex).

In this chapter, we study the role of the heterogeneity of occupational labour supply in explaining the variation of employment and wage growth between 1985 and 2010. We set up a random utility model of workers' preferences for occupations related to, among others, Cortes & Gallipoli (2018) and Card et al. (2018). In this model, occupational choice depends on wages and the costs of switching between occupations. The strength of the model is that price elasticities of occupational labour supply – the elasticity of occupation j's employment with respect to any occupation k's price – can be computed from empirical transition rates between occupations and baseline employment shares. Given that transition probabilities and size vary across occupations, the model provides an intuitive reason for why price elasticities of labour supply vary by occupation.[2]

As comes naturally out of the model, we distinguish between cross-price elasticities, which capture the impact on employment of changes in the price or wage in a *different* occupation, and own-price elasticities, which capture the impact of price changes in the occupation itself. We show how these price elasticities can be interpreted in terms of moments of the job flows. For example, we show that a key term in the cross-price elasticity of occupation j with respect to price changes in k is the covariance of job flows into these occupations from *all* other occupations. This covariance term can be interpreted straightforwardly: Two occupations that attract the same type of workers are more substitutable than occupations that attract workers from completely different sources.

We then proceed to use the model to theoretically assess the outcome of an economy-wide set of wage changes. We decompose the predicted employment changes into those coming from own-price and total cross-price effects. The own-price effect is determined both by the own-price elasticity and the size of the wage (or price) change. Similarly, the total cross-price effect depends on the interaction of cross-price elasticities and outside wage changes. The resulting outcome depends subtly on whether close substitute occupations saw wage improvements or declines.

We implement these insights using administrative panel data from Germany, the Sample of Integrated Employment Biographies (SIAB), which are uniquely suited for the purpose. The SIAB data follows workers over their entire labour

[2] In this chapter, we use wages and prices interchangeably.

market careers and provides a consistent set of 120 occupations for the years 1975-2010. We use workers' transition flows and occupations' employment sizes during the baseline period of 1975-1984 to estimate the price elasticities.[3] These display substantial heterogeneity: Own-price elasticities vary by a factor of ten between the most elastic (e.g. nursery teachers, occupations attending on guests) and the most inelastic (e.g. physicians and pharmacists, bank and building society specialists). Similarly, cross-price elasticities vary considerably across occupation pairs. Most cross-price elasticities are small, but there exist a number of pairs, often related through broader groups (such as nursery teachers and social work teachers, or carpenters and concrete workers), that lead to high elasticities of employment with respect to each others' price changes.

We validate these price elasticity estimates by comparing them to external measures. Own-price elasticities are correlated with occupational certification and regulation requirements, as well as skill requirements captured by the share of university graduates, or the analytical task intensity of the occupation. However, there is still a large variation in occupations' own-price elasticities conditional on any observables. Cross-price elasticities are correlated with task distance between occupations, measured as in Cortes & Gallipoli (2018), although again, these distances cannot explain the majority of actual worker-flow-based cross-price elasticities, let alone their skewness and high-impact values.

We then analyse changes observed in the economy during 1985-2010 by exploiting our decomposition and first focusing on own-price effects alone. We start by visualising employment growth against wage growth separately for occupations that are estimated to be more versus less own-price elastic. We show that more elastic occupations display significantly higher employment growth per unit of wage growth than do less elastic occupations. When we formalise this by regressing employment change onto wage change alongside its interaction with the own-price elasticity, the interaction term is statistically significant and economically strong.[4] This is our first result that heterogeneity in labour supply responsiveness matters.

[3] We use transitions over five years, i.e. between 1975-1980, 1976-1981, and so on. The SIAB stands out in its ability to precisely measure workers' transitions even at longer frequencies.

[4] The linear correlation of occupations' employment and wage growth has been analysed by, e.g. Mishel et al. (2013), Hsieh et al. (2019), Böhm et al. (2022).

While the own-price effects are illustrative and suggestive, our model implies that employment growth is also impacted by patterns of wage growth in other occupations. We show that both own-price and total cross-price effects are significant and in the predicted direction. Consistent with the theory, coefficient sizes turn out to be very similar across each of these sources. Our estimates also imply that occupation pairs with higher similarity tended to experience more correlated wage growths. In terms of explanatory power, the model including cross-price effects explains substantially more than the model with own-price elasticities alone: The R-squared of the model increases from 0.31 to almost 0.4. Overall, these findings indicate that accounting for wage changes in *other* occupations – and hence for occupations' substitutability – is crucial for explaining the evolution of the employment structure of the economy.

One concern for this analysis pertains to the extent to which occupational wage growth is exogenous. The chapter's appendix (Appendix C) studies in detail the demand side of a model that yields changes in wage rates as an equilibrium outcome from labour supply and shifts in the relative productivities of occupations over time. Empirically, we resort to initial task contents (i.e. routine, manual, and analytical intensities in the early 1980s) in order to isolate shifts in the demand for occupations during our period of analysis, 1985-2010. We obtain similar results with this approach, alleviating endogeneity concerns regarding our main results.

The chapter offers a series of extensions and robustness checks. First, we extend the model to account for non-employment transitions. While we cannot observe prices or wages for non-employment states directly in our data, we can compute price elasticities with respect to these states using observed transitions (to and from non-employment states) as before, and use them in our regression framework to estimate shadow price changes.[5] The estimated role of own- and cross-price effects turn out similar to our main results. Second, the main results are robust to estimating the model in shorter intervals (i.e. five-year sub-periods for 1985-2010). Finally, our findings are also similar whether we measure changes in occupational

[5]These elasticities can be separately measured (and controlled for) from flows and sizes as long as the respective non-employment states are in the data (e.g. young workers' labour market entry, old workers' retirement, unemployment).

prices as the wage growth of period-to-period staying workers or estimate them via time-varying occupation fixed effects following Cortes (2016).

This chapter contributes to the analysis of occupational change. A large body of research has studied whether and what kinds of demand shocks have worked on the occupation and task structures (e.g. Spitz-Oener, 2006, Autor & Dorn, 2013, Goos et al., 2014), and what effects this has had on employment and wages (e.g. Autor et al., 2008, Dustmann et al., 2009, Acemoglu & Autor, 2011, Cortes, 2016, Cavaglia & Etheridge, 2020, Böhm et al., 2022). We advance this literature by highlighting that a fundamental catalyst of these changes is the flexibility of labour supply to react to them. Occupation-specific price elasticities implied from our model can be readily inferred in longitudinal data and they have substantial power to explain changes in employment and wages over time.

A key advantage of the framework we adopt, in contrast to methods that rely directly on observed wages, is that the identification of occupation-specific price elasticities of labour supply is primarily based on worker flow data. Gathmann & Schönberg (2010) and Cortes & Gallipoli (2018) estimate the components (pecuniary and non-pecuniary including task distance) of occupational switching costs in this type of model, while Hsieh et al. (2019) study the effects of discrimination and Card et al. (2018) market power and wage setting. Our contribution to this model is to derive price elasticities in closed form, provide direct economic interpretations, and study their implications for occupational changes over time.

More generally, the results of this work inform a broader debate about how the labour market will generate the jobs of the future. Autor (2019) discusses training and re-training options to endow workers with the skills that are needed. More recently, Autor et al. (2022) show how new occupations and job types emerge from labour-augmenting and automating innovations. We complement this research agenda by studying the ability of labour supply to shift employment among the existing set of occupations at a given period in time.

The chapter proceeds as follows. Section 3.1 presents the model. Section 3.2 describes the data and presents descriptive statistics. The main estimation results are discussed in Section 3.3. Section 3.4 extends the model and provides robustness checks. Section 3.5 concludes. Appendix C includes further details on the theory and data, supplementary tables and figures, and further robustness checks.

3.1 The Model

We adopt a random utility model of worker preferences that characterises occupation-specific labour supply functions. This builds on Cortes & Gallipoli (2018) and Hsieh et al. (2019), who adapt the environment in Eaton & Kortum (2002) to occupational choices, and Card et al. (2018) who study the selection of workers into firms. We start by focusing on a static partial equilibrium model with perfect information, providing a tractable framework for labour mobility decisions under frictions. We then close the model by specifying labour demand and characterising equilibrium.

3.1.1 Environment

There is a continuum of workers $\omega \in \Omega$ and a finite set of N occupations. The number of employers in each occupation is large, such that labour demand is competitive and there is no strategic wage setting. Every worker is initially and predeterminedly assigned to an occupation i. Workers subsequently choose occupations to maximise their utility, which can be interpreted as a total lifetime payoff and is occupation-combination as well as individual-specific. It includes wages as pecuniary benefits, a specific cost of switching between occupations i and j, and an idiosyncratic preference for working in occupation j.

The indirect utility of worker ω with initial occupation i choosing occupation j is given by:

$$u_{ij}(\omega) = \theta p_j + a_{ij} + \varepsilon_j(\omega) \tag{3.1}$$

where θp_j is the general pecuniary payoff to occupation j. The component p_j can be interpreted as the log occupational price or wage rate offered to all workers per unit of their skill (we will later simplify our language and refer to this as 'price') and θ as their pecuniary preference or 'wage elasticity' parameter.

The occupation-combination-specific term a_{ij} summarises potential pecuniary and non-pecuniary costs of selecting occupation j for individuals initially assigned to occupation i. These can include lower payoffs as switchers may need to learn new tasks in j or institutional barriers. Gathmann & Schönberg (2010) and Cortes & Gallipoli (2018) analyse these costs explicitly – we further discuss this in Section 3.2 – while we let them flexibly affect the labour supply functions that we are after.

The final summand $\varepsilon_j(\omega)$ is an idiosyncratic preference shock for working in occupation j, which may, for example, include non-pecuniary match components with occupation-specific amenities or types of coworkers. We assume $\varepsilon_j(\omega)$ is independently drawn from a type I extreme value (i.e. Gumbel) distribution.[6] Draws, including for the current occupation, occur at the beginning of the period. Based on realised shocks, switching costs, and log occupational prices, workers decide whether to stay in their occupation or switch to a different one.

3.1.2 Occupational Choice and Price Elasticities

By standard arguments (McFadden, 1973), the assumptions on eq. (3.1) imply that workers' occupational choice probabilities are of the form:

$$\pi_{ij}(\mathbf{p}) = \frac{\exp(\theta p_j + a_{ij})}{\sum_{k=1}^{N} \exp(\theta p_k + a_{ik})}, \tag{3.2}$$

where $\mathbf{p}$ is the vector of N log occupational prices. We follow the convention that, by the law of large numbers, π_{ij} is the fraction of workers switching from occupation i to j. Choice probabilities are occupation-combination-specific and they may involve staying in the current occupation ($i = j$). Intuitively, eq. (3.2) says the more attractive occupation j is relative to all other occupations, and the lower the cost of switching to it from i, the higher will be the fraction of workers who will move to that occupation. Since they are aggregated over idiosyncratic shocks, the probabilities are not individual-specific and we can omit the index ω from now on.

Let τ_i denote the share of the working population originating in occupation i, such that $\sum_i \tau_i = 1$. One can think of $\{\tau_i\}$ as the stationary distribution of employment in a baseline period. Further, let $E_j(\mathbf{p})$ be the fraction ending up working in

[6] Gumbel location μ and scale δ are general because equation (3.1) can always be recast as $u_{ij}(\omega) = \frac{\theta}{\delta} p_j + \frac{a_{ij}}{\delta} + \frac{\varepsilon_j(\omega) - \mu}{\delta}$, yielding the same choice probabilities (see Card et al., 2018). In that sense, θ can be thought of as scaling the importance of wages relative to idiosyncratic shocks.

occupation j as a function of log occupational prices. This implies that

$$\begin{aligned} E_j(\mathbf{p}) &= \sum_i \tau_i \pi_{ij}(\mathbf{p}) \\ &= \tau_j \text{ if } \mathbf{p} = \mathbf{p}^* \end{aligned} \tag{3.3}$$

with $\mathbf{p}^*$ the vector of baseline log occupational prices. From now, we simplify our language by using 'prices' to mean log occupational prices as described in eq. (3.1).

Effect of Individual Price Changes

Our interest centres on (own- and cross-occupation) price elasticities, that is, the elasticity of occupation j's employment with respect to any occupation k's price (including $k = j$). Writing $e_j \equiv \ln E_j(\mathbf{p})$, and differentiating eq. (3.3), we obtain:

Remark 1 (Elasticities and Job Flows)**.** *The short-term partial derivative of occupation j's log employment share with respect to k's log price is equal to:*

$$\frac{\partial e_j(\mathbf{p})}{\partial p_k} = \theta d_{jk} \tag{3.4}$$

with

$$d_{jk} = \begin{cases} \frac{\sum_i \tau_i(\pi_{ij}(1-\pi_{ij}))}{\tau_j} & \text{if } j = k \\ -\frac{\sum_i \tau_i(\pi_{ij}\pi_{ik})}{\tau_j} & \text{otherwise} \end{cases} \tag{3.5}$$

Appendix C.1 contains the derivation.

Equation (3.4) shows how these price elasticities can be computed using transition probabilities (as we discuss in the next section, the transition probabilities have direct analogues in the data as job flows), baseline employment shares, and an unobserved pecuniary parameter θ. We return to the estimation of θ in Section 3.3. We now focus our attention on eq. (3.5).

Element d_{jk} in eq. (3.5) can be thought of as a constituent of an $N \times N$ matrix of price elasticities, which we also refer to as 'elasticity matrix' or 'matrix D' throughout the chapter. With a slight abuse of notation, we thus refer to elements d_{jj} and d_{jk} as own- and cross-price elasticities, respectively.[7] To gauge the empirical content of this result further, we derive alternative formulations of these elasticities

[7]Strictly speaking, these elements should be multiplied by θ as shown in eq. (3.4).

more explicitly in terms of moments of job flows. This provides further intuition on what determines the elasticities as well as metrics to compare to other related measures used in the literature.

To do this, we define some additional terms. First, and as standard, let $\mathbb{E}_{\tau_i} x \equiv \sum \tau_i x_i$ be the average of vector elements x_i weighted by the stationary employment distribution $\{\tau_i\}$. Then define $\tilde{\pi}_{iq} \equiv \frac{\pi_{iq}}{\tau_q}$, such that $\tilde{\pi}_{iq}$ gives normalised job flows, with $\mathbb{E}_{\tau_i} \tilde{\pi}_{iq} = 1$. Normalising the transition probabilities in this way yields moments that are invariant to occupation size. In this spirit, and in parallel, let $Cov_{\tau_i}(x, y) \equiv \sum \tau_i \left(x_i - \mathbb{E}_{\tau_i} x\right)\left(y_i - \mathbb{E}_{\tau_i} y\right)$. This leads us to the following result:

Remark 2 (Individual Cross-Price Elasticities)**.** *For all $j \neq k$, the off-diagonal elements of matrix D can be expressed as:*

$$-d_{jk} = \underbrace{\tau_k}_{\substack{occupational\\ importance}} \times \underbrace{Cov_{\tau_i}\left(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k}\right)}_{\substack{occupational\\ similarity}} + \underbrace{\tau_k}_{\substack{price\\ index}} \tag{3.6}$$

where we examine the negative of d_{jk}, rather than d_{jk} itself, so that we can interpret higher elasticities by larger positive numbers. Appendix C.1 contains the derivation.

Equation (3.6) above consists of two additive components. First is a substitutability component $\tau_k Cov_{\tau_i}\left(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k}\right)$. It consists of an 'occupational-similarity' term that is symmetric between j and k, is invariant to the fineness of the occupational classification, and captures the pure similarity of occupation in-flows: If $Cov_{\tau_i}\left(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k}\right) > 0$, then occupations j and k are 'competing' for workers and the cross-price elasticity (i.e. the responsiveness of employment in occupation j to changes in the price of occupation k) will be higher. This occupational similarity term is then weighted by an 'occupational-importance' term τ_k that depends on the size of the occupation of the price change: Price increases in a smaller competing occupation will have smaller percentage ripple effects than price increases in a larger occupation. Second is an occupation-specific intercept which captures occupation k's contribution to a price index and which, in terms of variability across occupations, turns out to be quantitatively relatively unimportant.

Likewise, we can reformulate the on-diagonal elements of the elasticity matrix D, which capture the own-price elasticities. This leads us to the following result:

Remark 3 (Individual Own-Price Elasticities)**.** *For all $j = k$, the on-diagonal elements of D, can be expressed as:*

$$d_{jj} = \underbrace{\sum_{k \neq j} \tau_k Cov_{\tau_i}\left(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k}\right)}_{\substack{\text{aggregate} \\ \text{substitutability}}} + \underbrace{1}_{\text{direct}} - \underbrace{\tau_j}_{\substack{\text{price} \\ \text{index}}} = \underbrace{-\tau_j Var_{\tau_i}\left(\tilde{\pi}_{\cdot,j}\right)}_{\substack{\text{job-flow} \\ \text{dispersion}}} + \underbrace{1}_{\text{direct}} - \underbrace{\tau_j}_{\substack{\text{price} \\ \text{index}}} \tag{3.7}$$

where $Var_{\tau_i}(x) \equiv \sum \tau_i \left(x_i - \mathbb{E}_{\tau_i} x\right)^2$. Appendix C.1 contains the derivation.

Equation (3.7) captures the effect of an isolated change in occupation j's own price and has a similar structure to eq. (3.6), though in this case it can be constructively formulated in two ways, each of which provides informative interpretations. The first formulation includes an 'aggregate substitutability' term, that sums substitutability components from all other occupations. This term captures the fact that a unit increase in the price of occupation j is equivalent to an equal and opposite price decline in all other occupations. It is in this sense that the own-price elasticity captures aggregate substitutability with other occupations.

In the second formulation, on the right-hand side of expression (3.7), the term $\tau_j Var_{\tau_i}\left(\tilde{\pi}_{\cdot,j}\right)$ can be interpreted as a 'job-flow dispersion' term, reflecting how dispersed or concentrated are the inflows to occupation j: Occupations hiring from a diversity of sources (in this case, a *small* $Var_{\tau_i}\left(\tilde{\pi}_{\cdot,j}\right)$) are more elastic. Following this line of thought, it is useful to consider that inflows are typically concentrated if the diagonal element of the transition matrix is close to 1 (meaning everyone remains in the current occupation) and the off-diagonal elements are close to 0. In this case, $Var_{\tau_i}\left(\tilde{\pi}_{\cdot,j}\right)$ is large, the job-flow dispersion component is more negative, and d_{jj} is lower, indicating a lower own-price elasticity. Finally, in both formulations are 'direct' and price-index effects. As in the discussion following Remark 2, these terms contribute to the *level* of the elasticity, but little to the observed variability.

Remarks 2 and 3 show that we can express the price elasticities in terms of simple moments of the distribution of job flows. Before moving on, it is worth commenting that in eq. (3.6) we conceptually separate $Cov_{\tau_i}\left(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k}\right)$ from τ_k in the final summand, while in eq. (3.7) we interpret $\tau_j Var_{\tau_i}\left(\tilde{\pi}_{\cdot,j}\right)$ jointly. We formulate the expressions in this way because it is $Cov_{\tau_i}\left(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k}\right)$ and $\tau_j Var_{\tau_i}\left(\tilde{\pi}_{\cdot,j}\right)$

(rather than $Var_{\tau_i}(\tilde{\pi}_{\cdot,j})$) which are invariant to the fineness of the occupational classification. We discuss this point further in Appendix C.1 using both empirical evidence and theoretical justification.

Effect of Multiple Price Changes

We now generalise the formulation given in eq. (3.4). The response of the vector of employment shares to a change in the vector of prices can be approximated by:

$$\Delta \mathbf{e} \approx \frac{\nabla \mathbf{e}}{\nabla \mathbf{p}} \Delta \mathbf{p} = \theta D \Delta \mathbf{p} \tag{3.8}$$

with $\Delta \mathbf{e}$ representing the change of the $N \times 1$ vector of log employment shares, $\{e_j\}$, and $\frac{\nabla \mathbf{e}}{\nabla \mathbf{p}}$ the $N \times N$ matrix of partial derivatives $\frac{\partial e_j(\mathbf{p})}{\partial p_k}$ $\forall\, j,k$. Given some demand-side shock and ensuing shock to prices, which we discuss below, the change to employment shares can be approximated by eq. (3.8). This approximation is exact for marginal changes in prices.

Equation (3.8) shows how the model traces out a supply curve vector, $\mathbf{e}(\mathbf{p})$, of log employment shares. With a view to our empirical application, we rewrite the inner product of elasticity matrix D with the vector of price changes as follows:

$$\begin{aligned} \Delta e_j &\approx \theta \mathbf{d_j} \Delta \mathbf{p} \\ &= \theta \Big(\underbrace{d_{jj} \Delta p_j}_{\substack{\text{own-price} \\ \text{effect}}} + \underbrace{\sum_{k \neq j} d_{jk} \Delta p_k}_{\substack{\text{total cross-} \\ \text{-price effect}}} \Big) \end{aligned} \tag{3.9}$$

where $\mathbf{d_j}$ is the jth row of matrix D, and, in the bottom line, we separate the effects of on-diagonal elements in D from those of all off-diagonal elements. To summarise the intuition, the own-price effect in eq. (3.9) represents the part of occupations' employment changes that are due to their own price changing. The total cross-price effect captures the effect of heterogeneity in price changes across all other occupations: Intuitively, large price changes in occupations that are very substitutable with j (i.e. $d_{jk} \ll 0$) will have potentially important effects on j's employment share. We provide additional formal details in Appendix C.1.

3.1.3 Labour Demand and Equilibrium

Having primarily addressed the supply side thus far, we proceed to close the model by specifying an explicit theory of occupational labour demand. We provide a short discussion here (and later in Section 3.3.3) leaving details to Appendix C.1.

We consider an economy-wide constant elasticity of substitution (CES) production function

$$Y = A\left(\sum_j \beta_j E_j^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad \text{s.t.} \ \sum \beta_j = 1 \tag{3.10}$$

where β_j are the factor intensities of different occupation inputs and $\sigma > 0$ is the elasticity of substitution across occupations. As we show in Appendix C.1, this full supply and demand model allows characterisation of the equilibrium prices $\{p_j\}$ and quantities $\{E_j\}$ as a function of productivity shifts ($\Delta\mathbf{b}$), supply shocks ($\Delta\mathbf{s}$), elasticities d_{jk}, and model parameters θ and σ. The thought experiment we imagine is that the economy is hit by a sudden change in the technology of final goods production $\{\beta_j\}$, which shifts demands for the different intermediate inputs either to the right (an increase) or to the left (a decrease).[8] This leads to a new set of equilibrium prices $\{p_j\}$ and quantities of $\{E_j\}$ labour inputs in all occupations. In the absence of supply shocks (eq. (3.9)), these price changes are sufficient statistics for the implied changes in demand – we consider this case in Section 3.3.2. In the presence of supply shocks ($\Delta\mathbf{e} \approx \theta\mathbf{d_j}\Delta\mathbf{p} + \Delta\mathbf{s}$), the equilibrium model (discussed in Appendix C.1.2) provides an identification framework which can be implemented with appropriate instruments – we consider this case in Section 3.3.3.

[8]Our focus is not on a particular demand-side shock, i.e. production function (3.10) and parameters β_j should be viewed as an example production technology. More generally, forces of occupational demand may include, among others, routine-biased technological change (e.g. Autor et al., 2003), international trade and offshoring (Autor et al., 2013, Goos et al., 2014), transformation of the industry structure (Bárány & Siegel, 2018), changes in consumption patterns (Autor & Dorn, 2013, Mazzolari & Ragusa, 2013), or social skills content (Deming, 2017). See also Chapters 1 and 2.

3.2 Data and the Elasticity Matrix

3.2.1 Data Sources

Our objective is to estimate eq. (3.9). To take the model to the data, we use the Sample of Integrated Labour Market Biographies (SIAB, Frodermann et al., 2021), a 2% sample of administrative social security records in Germany since 1975. The SIAB data contains complete employment histories and wage information for more than one million employees. This data is representative of all individuals covered by the social security system, roughly 80% of the German workforce. It excludes self-employed, civil servants, and individuals performing military service.[9]

The SIAB data is uniquely suited for the purpose. First, the panel dimension allows us to measure worker flows over long frequencies. Second, the administrative nature ensures that we observe the exact date of a job change and the wage associated with each job. Third, occupation codes are consistently coded from 1975 to 2010 ($N = 120$ occupations). Employers are required to report the kind of job their employees perform. Miscoding of occupations is thus less likely than in the case of survey-based data collection. Finally, the wage information is highly reliable. The SIAB is based on process data used to calculate retirement pensions and unemployment insurance benefits, so misreporting is subject to severe penalties.

We restrict the main sample of analysis to men aged 25–59 who are working full-time (excluding apprentices and foreigners) in West Germany.[10] We further drop spells of workers with missing information on occupation and wage, and wages below the limit for which social security contributions have to be paid.[11] Following Böhm et al. (2022), we transform the spell structure of the SIAB data into a yearly panel by using the longest spell in a given year. Our final sample

[9] The German SIAB data has previously been used to study job polarisation (Goos et al., 2014), earning shocks (Sanchez & Wellschmied, 2020), wage mobility (Riphahn & Schnitzlein, 2016) or the effects of international trade (Dauth et al., 2014).

[10] Excluding East Germans allows the sample to be defined consistently during the whole period 1975–2010. Potentially confounding trends that may have affected the price elasticities of women and foreigners – such as rapidly rising education and full-time labour force participation as well as declining workplace discrimination (e.g. Hsieh et al., 2019) – are also removed.

[11] In preparing the data, we impute censored wages above the upper earnings threshold for social security contributions (Dustmann et al., 2009, Card et al., 2013) and correct for the wage break in 1983-1984 (Fitzenberger, 1999, Dustmann et al., 2009). See Appendix C.2 for all the details.

consists of approximately 600,000 unique individuals and 9 million individual × year observations for the whole period 1975-2010.

Importantly, the SIAB data allows us to compute worker flows (sufficient statistics for the elasticities d_{jk}), changes in occupational employment ($\Delta\mathbf{e}$), as well as changes in occupational prices ($\Delta\mathbf{p}$). As for the latter, we follow the literature on this, which emphasises that raw wages need to be selection-corrected (Cavaglia & Etheridge, 2020, Böhm et al., 2022), and use occupation stayers' (i.e. workers who do not switch occupations from one year to the next) wage changes as the main estimate of changes in occupational prices. We show the robustness of our results using an alternative price estimation procedure following Cortes (2016) that corrects for worker-occupation-spell fixed effects in Section 3.4. The SIAB data also allows us to construct other occupational characteristics (e.g. workers' mean age by occupation, the share of workers with university degrees by occupation) that we use below to relate to our price elasticity measures.

To obtain task information in occupations, we use the Qualifications and Career Surveys (QCS, Hall et al., 2012).[12] The QCS, conducted by the Federal Institute for Vocational Education and Training (BiBB), consists of cross-sectional surveys with 20,000–35,000 individuals in each wave. Respondents report on the tasks performed in their occupations, and we categorise them into analytical, routine, and manual tasks, assigning values based on response frequency. By averaging responses from pooled QCS data in 1979 and 1985/1986, we compute task intensities among those three categories by occupation, which we also use to construct a measure of task distance between occupations following Cortes & Gallipoli (2018). We study how they relate to our elasticity measures below. In Section 3.3.3, we use them to instrument demand changes across occupations between 1985–2010.

Finally, to obtain measures of occupation's certification requirements and degree of regulation, we use the indicators for standardised certificates and regulation developed by Vicari (2014). These indicators are based on BERUFENET, the online career information portal provided by the German Federal Employment Agency – a rich job title database similar to the US O*NET.

[12]The QCS have been used to study task intensities in previous studies (see, e.g. Spitz-Oener, 2006, Antonczyk et al., 2009, Gathmann & Schönberg, 2010)

Table 3.1 presents summary statistics for the 120 occupations. We highlight the main points as follows. First, variation in employment growth in the cross-section of occupation is substantial, with the fastest occupations shrinking at 1.8 log points annually (averaged over the period 1985-2010), or growing at 2.4, respectively (see also Figure 3.2 below). Second, the annualised wage growth of occupational stayers (i.e. our main estimate of changes in occupational prices), is positive on average at 0.58 log points per annum, again with considerable variation around this average (-0.96 and +2.17 log points for the occupations with the lowest and highest wage growth, respectively). The same is true for our alternative measure of occupational prices.[13] When it comes to other occupational characteristics, Table 3.1 shows there exists substantial variation in terms of occupational certification and regulation, or the share of workers with university degrees (which, on average across occupations, is below 14%). Finally, we see how task usage (analytical, routine, manual) varies across the 120 occupations contained in our data. Consistent with earlier work (Gathmann & Schönberg, 2010), the table shows that there is a great deal of variation. For example, the median occupation is more than twice routine-intensive relative to the occupation in the lowest decile. As a result, task distance between occupation pairs (see Appendix C.2 for details about how this measure is constructed) ranges from essentially zero (i.e. occupations use identical task sets) to essentially one (i.e. occupations use completely different task sets). We leave further details on the data, variable construction and descriptive statistics for Appendix C.2.

3.2.2 The Elasticity Matrix

A strength of the elasticity matrix implied by the theory (eq. (3.5)) is that it can be computed directly from baseline worker flows. We construct transition rates across all occupation pairs for individuals who are observed at the endpoints of five-year periods within 1975–1984.[14] The flow of switchers from origin occupation

[13] Table C.3 using five-year sub-periods shows there is also substantial variation of employment and wage growth over time which is, e.g. slower in the economically sluggish early 2000s.

[14] The baseline period (1975-1984) sample consists of 252,309 unique individuals and 1,794,286 individual × year observations. Using two-yearly or ten-yearly period lengths for the flows does not make a material difference to our findings. The resulting analysis period 1985–2010 is similar to Card et al. (2013) and Böhm et al. (2022).

Table 3.1: Summary Statistics for the 120 occupations.

	Mean	Weighted Mean	Std.Dev.	p10	p50	p90	Observ.
Annualised Employment and Occupational Price Changes (1985-2010)							
Log Employment ($\Delta\mathbf{e}$)	0.107	−0.123	1.921	−1.843	−0.065	2.369	120
Stayers' Wage Growth ($\Delta\mathbf{p}$)	0.586	0.516	1.354	−0.959	0.408	2.168	120
Prices á la Cortes (2016) ($\Delta\mathbf{p}$)	1.102	1.065	0.953	−0.009	0.949	2.308	120
Other Occupational Characteristics							
Initial employment Size in 1985	0.833	1.763	0.883	0.213	0.543	1.639	120
Employment Size in 2010	0.833	1.789	1.030	0.193	0.501	1.738	120
Occupational Certification	0.712	0.751	0.258	0.290	0.810	0.970	120
Occupational Regulation	0.103	0.079	0.228	0	0	0.380	120
Share of University Degree	0.135	0.117	0.232	0.006	0.018	0.463	120
Mean Workers' Age	40.55	40.92	1.68	38.59	40.46	42.35	120
Task Intensity and Distance							
Analytical	0.069	0.064	0.075	0.010	0.039	0.181	120
Manual	0.095	0.089	0.071	0.016	0.075	0.186	120
Routine	0.151	0.153	0.079	0.062	0.131	0.271	120
Task Distance	0.499	0.497	0.296	0.061	0.541	0.870	14280

Notes: Table presents summary statistics for annualised employment and occupational price changes during 1985-2010, occupational characteristics (e.g. the share of workers with university degrees by occupation), and task content information (i.e. analytical, manual, routine, and task distance á la Cortes & Gallipoli (2018)). The weighted mean is weighted by each occupation's employment size in 1985.

i to destination occupation j (which includes staying in occupation i) is defined as the number of individuals who are employed in occupation i in year t and employed in occupation j in year $t+5$. Dividing each element by total flows from origin occupation i we obtain the transition probability matrix Π, which is of size 120×120, and element π_{ij} represents the empirical probability that a worker employed in origin occupation i switches to j in five years' time. The transition probability matrix also implies a steady state vector τ of size 120×1, with element τ_i representing occupation i's size as a share of total employment. With that, we compute the elasticity matrix D following eq. (3.5).[15]

Table 3.2 reports occupations at different quantiles of the elasticity distribution. In Panel A, we consider the own-price elasticities d_{jj}. Elasticities with respect to changes in the own price range from 0.07 among physicians and pharmacists to 0.80 among personnel in medical, social, and gastronomy service occupations. This is consistent with findings below where occupations with higher regulation and certification requirements, like physicians and pharmacists, are substantially less own-elastic. A full list of the 120 occupations ranked by their respective own-price elasticities, together with their employment size can be found in Table C.4.

Panel B shows cross-price elasticities (d_{jk}) between occupation pairs. The highest effects of price changes on employment are naturally among related occupations: from 'home wardens, social work teachers' on 'nursery teachers, child nurses'; from 'non-medical practitioners, masseurs, physiotherapists' on 'medical receptionists'; and from 'office specialists' on 'stenographers, shorthand typists, data typists'. While quantitatively these top pairs are within the range of the own-price elasticities, cross-price elasticities fall off quickly from the top and become an order of magnitude smaller than any own-price elasticities already at the 90th percentile. This skewness of cross-price elasticities will be underscored below.

[15] Appendix Table C.2 presents summary statistics for both matrices, the transition probability matrix Π and the elasticity matrix D. We also construct these matrices for different five-year periods (1975-1980,..., 2000-2005, 2005-2010) and study the relation of the respective own-price and cross-price elasticities across periods. Autocorrelation turns out high, in the range of 0.7-0.85, even for the long time distances between the early and late periods. This is consistent with the high autocorrelation of occupational task distance reported in Gathmann & Schönberg (2010) and with the analysis in Section 3.4 when estimating our model pooled in five-year sub-periods.

Table 3.2: Summary Statistics. Own- and Cross-Price Elasticities

Panel A	Own-price elasticity (d_{jj})	Occupation
Minimum	0.074	Physicians, pharmacists
10th percentile	0.294	Health or property insurance specialist
25th percentile	0.358	Members of parliament, association leaders, officials
50th percentile	0.430	Stucco workers, plasterers, rough casters, proofers
75th percentile	0.517	Sheet metal pressers, drawers, stampers, metal moulders
90th percentile	0.604	Salespersons
Third highest	0.740	Other attending on guests
Second highest	0.797	Medical receptionists
Maximum	0.798	Nursery teachers, child nurses
Panel B	Cross-price elasticity ($-d_{jk}$)	Occupation of price change (k) → Occupation of employment change (j)
50th percentile	0.001	Paviours, road makers → Sheet metal workers
90th percentile	0.009	Miners, shaped brick/concrete block makers → Engine fitters
Fifth highest	0.144	Bricklayers, concrete workers → Carpenters, scaffolders
Fourth highest	0.182	Restaurant, inn, bar keepers, hotel and catering personnel → Other attending on guests
Third highest	0.185	Office specialists → Stenographers, shorthand typists, data typists
Second highest	0.253	Non-medical practitioners, masseurs, physiotherapists → Medical receptionists
Maximum	0.464	Home wardens, social work teachers → Nursery teachers, child nurses

Notes: Table shows summary statistics of own- and cross-price elasticities in panels A and B, respectively.

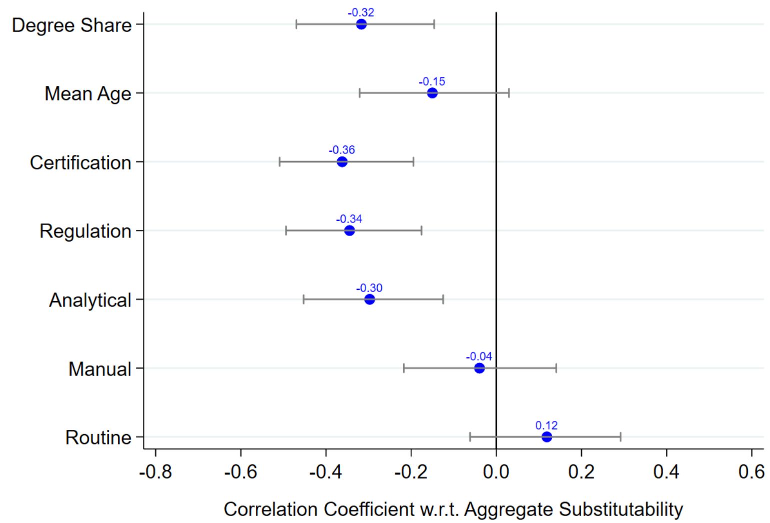
Figure 3.1 focuses on the key components of the price elasticities analysed in Remarks 2 and 3. In Figure 3.1a, we show how aggregate substitutability ($\sum_{k \neq j} \tau_k Cov_{\tau_i}(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k})$) correlates with education, age, task content, and occupational requirements. Employment in occupations with higher degree share, more demanding analytical tasks, and higher regulation or certification requirements are significantly less own-price elastic. As discussed above, this substitutability is the key component of eq. (3.7), dominating the price index component.[16]

Finally, Figure 3.1b plots the occupational similarity component in eq. (3.6), namely $Cov_{\tau_i}(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k})$, against occupational task distance. Because it abstracts from the role of occupational importance, 'occupational similarity' is the fitting comparison to task distance which is also symmetric and size-independent (alternatively, the parallel Appendix Figure C.3 shows the plot for cross-elasticities against occupational task distance). The figure illustrates a negative (and significant) relationship between measured task distance and occupational similarity, and by extension cross-elasticities. In other words, the figure shows that the higher the distance in the task content between two occupations, the lower the cross-price elasticity (i.e. lower 'substitutability' of these occupations). However, we note that task distance is based only on the set of tasks reported in survey responses and it explains at most a subset of occupational similarity, which in contrast contains all information implied by realised worker flows. This last point is underscored by the fact that task distance is essentially an ordinal variable whereas the skewness of occupational similarity / cross-elasticities has a natural quantitative interpretation. Accordingly, Spearman's rank coefficient provides a substantially better fit in Figure 3.1b than standard linear correlation.

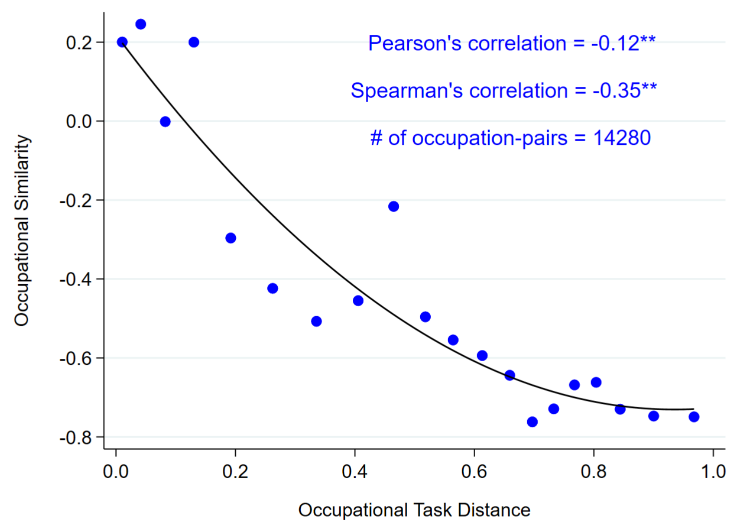
[16] The variation in $\sum_{k \neq j} \tau_k Cov_{\tau_i}(\tilde{\pi}_{\cdot,j}, \tilde{\pi}_{\cdot,k})$ is substantially larger than in τ_j. As a result, the relationship of the own-price elasticity with the external characteristics is almost parallel to those of the substitutability component (see Appendix Figure C.3)

Figure 3.1: Elasticity Components: Comparison with External Metrics

(a) Aggregate Substitutability and Occupational Characteristics



(b) Ocupational Similarity and Task Distance



Notes: Figure shows the relationship of the elasticity components with respect to external metrics. Panel (a) reports how the aggregate substitutability component of the own-price elasticity, namely $\sum_{k\neq j}\tau_k Cov_{\tau_i}(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k})$, relates to skill requirements captured by the share of university graduates and workers' average age, occupational certification and regulations (taken from Vicari (2014)), and occupational task content (analytical, manual, and routine). Panel (b) shows the relationship (with a quadratic fit) between the occupational similarity component of the cross-price elasticity, namely $Cov_{\tau_i}(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k})$, and occupational task distance measured as in Cortes & Gallipoli (2018). Appendix Figure C.3 does the same plots for d_{jj} and $-d_{jk}$ instead.

3.3 Estimation Results

In this section, we present the main estimation results. We start by considering a version of the model without cross-price effects. We then estimate the full model to show the role heterogeneous labour supply elasticities play in how occupational change unfolds. We show this both in linear projections and when isolating occupational demand shocks via instrumental variables based on initial task content.

3.3.1 Heterogeneity of Own-Price Elasticities

Figure 3.2a plots occupations' changes in (log) employment – annualised over the period 1985-2010 – against our measure of changes in occupational prices, based on stayers' wage growth. These wage growth rates clearly line up with their employment growth, consistent with earlier work (Cavaglia & Etheridge, 2020, Böhm et al., 2022). However, there is a significant amount of variation in the movements of employment and wages across occupations. For example, the explicitly labelled occupation 'physicians and pharmacists' has high occupational wage growth (over five log points per year) but rather small employment growth, while 'assistants' exhibit high employment but only modest wage growth.

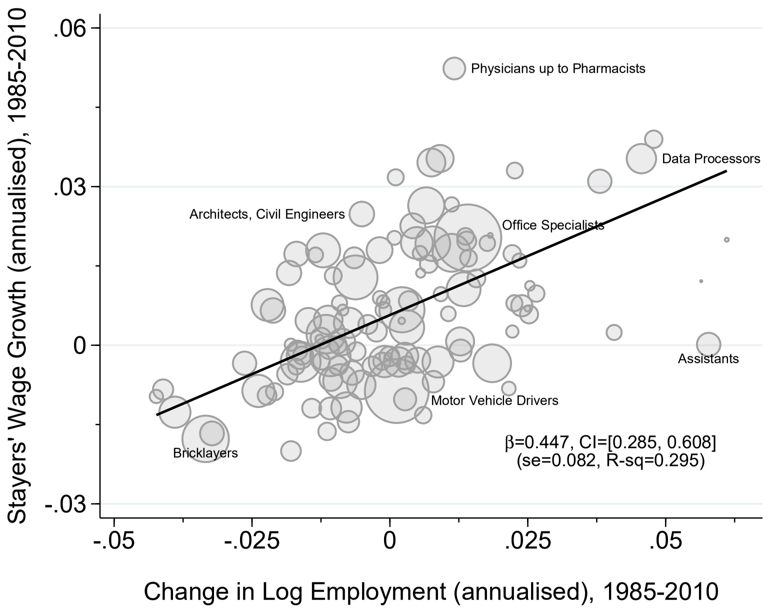
This chapter's hypothesis is that a substantial part of such heterogeneity is due to differences in labour supply curves across occupations. To investigate this empirically, we start by considering own price changes in isolation (i.e. ignoring cross-price effects) and approximate eq. (3.9) as follows:

$$\Delta e_j(\mathbf{p}) \quad \approx \quad \underbrace{\theta d_{jj} \Delta p_j}_{\substack{\text{own-price} \\ \text{effect}}} \tag{3.11}$$

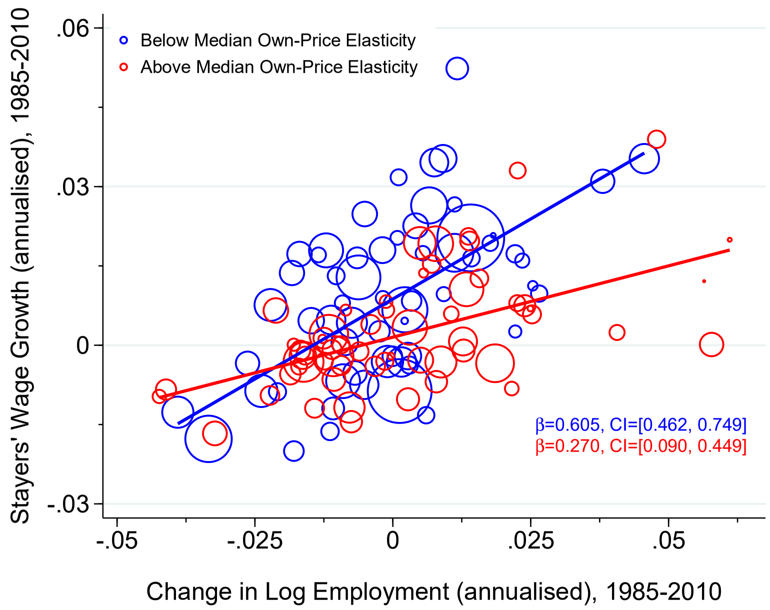
That is, we hypothesise that the effect of occupations' own price changes on their employment should be governed by the heterogeneity in elasticities d_{jj}. In the accompanying Figure 3.2b, we split occupations at the median of d_{jj} and draw two separate regression lines. The blue circles, including 'physicians and pharmacists', are the occupations predicted to be relatively inelastic in terms of employment response with respect to changes in their own price, while the red circles, including 'assistants', are predicted to be relatively elastic.

Figure 3.2: Stayers' Wage Growth and Employment Changes (1985-2010)

(a) All 120 Occupations



(b) By Own-Price Elasticity Median Split



Notes: Figure shows scatter plots of occupations' change in the log of employment (x-axis) and stayers' wage growth (y-axis) between 1985–2010. Panel (a) shows the overall regression line for the 120 occupations. Panel (b) shows colour codes and linear regression lines by occupations below (blue, inelastic) and above (red, elastic) the median predicted elasticity of labour supply with respect to own price (d_{jj}). β refers to the slope coefficient, *CI* stands for the 95% confidence interval, *se* refers to standard error, and *R-sq* stands for the R squared of the regression.

Indeed, we find that the relationship between occupational employment and price changes is substantially flatter among the red than among the blue circles. That is, the employment response associated with a given price change is substantially stronger among the above-median d_{jj} (high predicted elasticity) than among the below-median d_{jj} (low elasticity) occupations. The differences on the regression slopes are not only strongly significant (p-value < 0.01), but also economically meaningful. As shown in the plot labels, a 1% increase in wages increases employment by 0.6% for the group with high predicted elasticities but increases employment by under 0.3% for the low-elasticity group. Appendix Figure C.4 alternatively splits occupations into d_{jj} quartiles. The resulting four regression lines are visibly ranked by predicted labour supply elasticity, with the lowest d_{jj} quartile exhibiting the steepest relation of employment vs prices, the highest d_{jj} quartile exhibiting the flattest relationship, and the middle quartiles ranked in between.

3.3.2 Full Model Implementation. Estimating θ

The analysis in the previous section shows that even a simplified version of our model helps explain whether occupational changes are characterised by relatively larger shifts in employment or wages. The full model presented in Section 3.2 is however equally characterised by price effects that work across *all* occupations.

We take our model to data fully by developing eq. (3.9) as follows:

$$\begin{aligned}\Delta e_j &\approx \theta\left(d_{jj}\Delta p_j + \textstyle\sum_{k\neq j} d_{jk}\Delta p_k\right)\\ &= \underbrace{\theta \overline{d}_{diag}\Delta p_j}_{\substack{\text{fixed relationship of}\\ \text{price with employment}}} + \underbrace{\theta(d_{jj}-\overline{d}_{diag})\Delta p_j}_{\substack{\text{heterogeneity of}\\ \text{own-price effect}}} + \underbrace{\theta\sum_{k\neq j} d_{jk}\Delta p_k}_{\substack{\text{total cross-}\\ \text{-price effect}}}\end{aligned} \tag{3.12}$$

The top line of eq. (3.12) repeats that displayed in Section 3.2, and includes both own- and cross-price effects. Following up on the discussion in the preceding section, it is instructive to further split the own-price effect into a fixed relationship that one would obtain when regressing employment onto price changes (Figure 3.2a) and the additional effect of the pure heterogeneity in elasticities d_{jj} (Figure 3.2b). This is done in the last line of eq. (3.12), where $\overline{d}_{diag}$ is the mean of matrix D's main diagonal elements, and the heterogeneity is captured by $d_{jj} - \overline{d}_{diag}$.

We rewrite eq. (3.12) in a vector regression format as follows:

$$\Delta \mathbf{e} = \alpha + \theta_1 \overline{D}_{diag} \Delta \mathbf{p} + \theta_2 (D_{diag} - \overline{D}_{diag}) \Delta \mathbf{p} + \theta_3 (D - D_{diag}) \Delta \mathbf{p} + \boldsymbol{\varepsilon}, \tag{3.13}$$

with $\Delta\mathbf{e}$ and $\Delta\mathbf{p}$ representing the $N \times 1$ vectors of stacked log employment and price changes, $\overline{D}_{diag}$ and D_{diag} the $N \times N$ diagonal matrices with elements $\overline{d}_{diag}$ and d_{jj}, and $\boldsymbol{\varepsilon}$ the $N \times 1$ vector of approximation error. Intercept α accounts for overall changes in log employment. We have further replaced here the pecuniary preference parameter with some generic θ_1, θ_2, and θ_3 to indicate that the common θ represents a model restriction that can be tested in data, as we do below.

Table 3.3 reports the estimates from specifications (3.12) and (3.13).[17] The first column shows the regression of Δe_j onto $\overline{d}_{diag} \Delta p_j$ only. As seen in Figure 3.2a as well as in prior work (e.g. Böhm et al., 2022), this fixed relationship of employment with price changes results in a clearly positive and significant slope parameter with R-squared of 0.29. Then column (2), which allows for heterogeneity in own-price elasticities d_{jj}, yields an additional positive and significant effect, consistent with the strong implications of Figure 3.2b. The point estimate on $\overline{d}_{diag} \Delta p_j$ is also statistically larger (Wald test p-value < 0.05) than in column (1) and the R-squared rises by 2 percentage points.

Column (3) of Table 3.3 then adds the cross effects of price changes in *other* occupations. Consistent with theory, the coefficient on this is also positive and significant. To see why this should be so, notice that, since $d_{jk} < 0$ for $k \neq j$, a positive regression coefficient implies that rising prices in other occupations k leads to a decline of employment in occupation j (see also column (2) of Table C.4). As discussed above, a stronger implication of the theory is that coefficients θ_1–θ_3 should all capture the same pecuniary preference parameter. Although econometrically they are allowed to differ, estimated coefficients turn out almost identical across regressors. Accordingly, we examine the equality of coefficients more formally in columns (4) and (5). Consistent with $\theta_1 = \theta_2 = \theta_3$ being fulfilled, the estimates do not change very much when we run the restricted models (3.11) and (3.12).

[17] Alternatively, Appendix Table C.4 considers the case in which own-price effects are not split into a fixed relationship and the additional effect of the heterogeneity in elasticities d_{jj}, corresponding to eq. (3.11). The main findings remain the same.

Table 3.3: Full Model: Three-Type Decomposition (OLS)

Three-Type Decomposition	Dependent Variable: $\Delta \mathbf{e}$				
	Unrestricted Model			Restricted Model	
	(1)	(2)	(3)	(4)	(5)
fixed relationship: $\overline{d}_{diag}\Delta p_j$	1.59***	1.79***	4.09***		
	(0.30)	(0.31)	(0.89)	1.81***	
heter. own effect: $(d_{jj}-\overline{d}_{diag})\Delta p_j$		1.25***	4.07***	(0.32)	4.15***
		(0.36)	(1.00)		(0.70)
total cross effect: $\sum_{j\neq k} d_{jk}\Delta p_k$			4.02***		
			(1.33)		
R-squared	0.295	0.314	0.394	0.310	0.394
Number of occupations	120	120	120	120	120

Notes: Regressor in column (4) is $d_{jj}\Delta \ln p_j$. In column (5), the regressor is $\sum_j d_{jk}\Delta \ln p_k$, i.e. corresponding to the full model. Standard errors in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by occupation j's initial employment size. Period 1985–2010.

An equally noteworthy feature of columns (3) and (5) is that the estimated coefficients are all substantially larger than those in the other columns (Wald test p-value < 0.05). The mechanical reason for this feature is that the own-price and total cross-price effects are negatively correlated. The underlying economics is that similar, and therefore more substitutable, occupations experienced correlated price changes over time. To consider this in formal terms, note that when $-d_{jk}$ is large, j and k tend to also experience similar price changes. This leads to $\mathrm{cov}(\Delta p_j, d_{jk}\Delta p_k) < 0$. Then we have that the covariance of the own effect with the total cross-price effect is given by:

$$\begin{aligned}\mathrm{cov}(d_{jj}\Delta p_j, \sum_{k\neq j} d_{jk}\Delta p_k) &= d_{jj}\sum_{k\neq j}\mathrm{cov}(\Delta p_j, d_{jk}\Delta p_k)\\ &< 0\end{aligned}$$

A further noteworthy feature of columns (3) and (5) is that the R-squared rises by another substantial 8 percentage points when including the total cross-price effect. This feature, together with the change in the coefficients, shows that including these cross-price effects is crucial for a fuller understanding of how changes in the wage and employment structure of the economy unfold.

It is instructive to compare our implied labour supply elasticities to existing work. The literature on employer wage effects finds that the labour supply elasticity to the firm is around 2–7 (e.g. see Lamadon et al., 2022, and papers cited therein). Given that switching occupations is likely more costly than switching firms, it seems plausible that our implied own-price elasticities (now accounting for θ as discussed in footnote 7 in Section 3.2) fall into the lower end of this range (average $\theta d_{jj} = 1.8$ as $\overline{d}_{diag} = 0.43$). The novelty of our approach lies in the heterogeneity around the average for own-price (from $0.07 \cdot 4.15 = 0.3$ to $0.80 \cdot 4.15 = 3.3$) as well as cross-price elasticities (from essentially 0 to 1.9). This stems from the flows and substitutabilities between occupations that we model explicitly.[18] Our pecuniary preference parameter can also be compared to Cortes & Gallipoli (2018), who estimate θ using US wage data and obtain estimates in the range of 2 and 8.87.[19]

3.3.3 Instrumental Variables Estimation

One worry in the analysis so far pertains to the extent to which a substantial share of the movements in employment and prices may be due to shifts in workers' supply to occupations. In this section, we provide a high-level summary of the full equilibrium model of demand and supply considered in Appendix C.1.2 to guide the empirics of extracting arguably pure shocks to occupational demand.

The full demand and supply model presented in Appendix C.1.2 allows characterisation of the equilibrium as

$$e_j(\mathbf{b}, \mathbf{s}) = e_j^s(\langle p(\mathbf{b}, \mathbf{s})\rangle, \mathbf{s}) = e_j^d(\langle p(\mathbf{b}, \mathbf{s})\rangle, \mathbf{b}) \tag{3.14}$$

where $\mathbf{b}$ is the vector of relative productivities (i.e. demand shifters $\left(\ln \frac{\beta_j}{1-\beta_j}\right)$), $\mathbf{s}$ is the vector of supply shifters, j is for occupation as before, and both supply (s) and demand (d) curves depend on the full system of prices. We define matrices for gradients of equilibrium quantities $\{E_j\}$ and prices $\{p_j\}$ as follows:

[18] Berger et al. (2022) and Jarosch et al. (2019) derive heterogeneity in labour supplies to firms due to granularity / size differences, a feature contained in but not dominating our mechanism.

[19] Cortes & Gallipoli (2018) set $\theta = 1$ in what corresponds to eq. (3.1) but estimate it via the dispersion of $\varepsilon_j(\omega)$, which is equivalent (see also footnote 6 of this chapter).

Notation	Typical element
Ξ	$\frac{de_i}{d\left(\ln \frac{\beta_j}{1-\beta_j}\right)}$
Γ	$\frac{de_i}{ds_j}$
V	$\frac{dp_i}{d\left(\ln \frac{\beta_j}{1-\beta_j}\right)}$
S	$\frac{dp_i}{ds_j}$

Then we have that changes in prices and employment are given by:

$$\Delta \mathbf{p} = V\Delta \mathbf{b} + S\Delta \mathbf{s} \tag{3.15}$$

and

$$\begin{aligned}\Delta \mathbf{e} &= \Xi\Delta \mathbf{b} + \Gamma\Delta \mathbf{s} \\ &= \theta DV\Delta \mathbf{b} - \sigma(I-W)S\Delta \mathbf{s}\end{aligned} \tag{3.16}$$

with $V = \left(\frac{\theta}{\sigma}D + I\right)^{-1}(I-W)$ where W stacks occupation sizes τ_j. These expressions describe changes to employment and prices in terms of demand and supply shocks, price elasticities, and model parameters θ and σ.

Combining eq. (3.15) and eq. (3.16), we obtain our basic regression equation $\Delta \mathbf{e} \approx \theta \mathbf{d_j}\Delta \mathbf{p} + \Delta \mathbf{s}$. In the absence of supply shocks (i.e. $\Delta \mathbf{s} = 0$), OLS is sufficient. The logic of requiring the IV is that $\mathbf{d}\Delta p$ might be correlated with supply shocks.

Instrumentation. Suppose we have a variable, which we denote r_j, which is correlated with demand shifters $\ln \frac{\beta_j}{1-\beta_j}$ but not with supply shifters Δs_i. In matrix notation, we have that:

$$\Delta \mathbf{b} = \kappa 1_N + \lambda \mathbf{r} + \bar{\eta}$$

where κ and λ are scalars, 1_N is a vector of ones and $\bar{\eta}$ is a vector of shocks.

Then, from eq. (3.15):

$$
\begin{aligned}
\Delta\mathbf{p} &= V\Delta\mathbf{b} + S\Delta\mathbf{s} \\
\implies \Delta\mathbf{p} &= \lambda V\mathbf{r} + \bar{\epsilon} + S\Delta\mathbf{s} \\
\implies D\Delta\mathbf{p} &= \lambda DV\mathbf{r} + D\bar{\epsilon} + DS\Delta\mathbf{s} \\
&= \lambda D\left(\frac{\theta}{\sigma}D + I\right)^{-1}(I - W)\mathbf{r} + D\bar{\epsilon} + DS\Delta\mathbf{s} \\
&= \lambda D\left(\frac{\theta}{\sigma}D + I\right)^{-1}\tilde{\mathbf{r}} + D\bar{\epsilon} + DS\Delta\mathbf{s}
\end{aligned}
$$

where the second line follows from the first because, if v_{ij} is the i,jth element of V, then $\sum_j v_{ij} = 0$ (see Appendix C.1.2 for more details on this). Vector $\tilde{\mathbf{r}}$ is the employment-share-weighted-demeaned version of $\mathbf{r}$ and finally, $\bar{\epsilon} \equiv V\bar{\eta}$.

In terms of regressing Δe_j on the vector of price changes, this implies that, if $G = D\left(\frac{\theta}{\sigma}D + I\right)^{-1}$ and $\mathbf{g}_j$ is the jth row of this matrix, then an appropriate instrument for $\mathbf{d}_j\Delta\mathbf{p}$ is $\mathbf{g}_j\tilde{\mathbf{r}}$, or equivalently $\mathbf{g}_j(I - W)\mathbf{r}$. For cases in which we focus only on the own-price effects (i.e. assuming the off-diagonal elements of the elasticity matrix D equal zero), we have that the vector $\tilde{\mathbf{r}}$ will be pre-multiplied by $G_{diag} = D_{diag}\left(\frac{\theta}{\sigma}D + I\right)^{-1}$. We assume $\frac{\theta}{\sigma} = 1$ throughout the chapter as a benchmark. In Appendix Table C.5, we show the robustness of our results to different values of $\frac{\theta}{\sigma}$. We now turn to the vector $\mathbf{r}$.

We proxy for relative productivity shocks based on initial task content. As discussed in Section 3.2, we employ survey information that asks workers which tasks they carry out in their jobs to construct measures of analytical, routine, and manual task intensity across occupations in the late 1970s and early 1980s. Following the literature on routine-biased technical change (RBTC, Autor et al., 2003), several important papers have shown that occupations intensive in analytical tasks grew quite strongly, whereas employment in routine-intensive occupations declined in the late 1980s and the 1990s (Autor et al., 2008, Acemoglu & Autor, 2011). For Germany, Böhm et al. (2022) shows that the overall demand shift was negative for manual-intensive occupations, with employment, average wages, as well as skill prices declining after 1985.[20] We thus approximate occupation j's (negative) demand shocks during 1985-2010 as

$$\mathbf{r}_j = (routine_j + manual_j) - analytical_j$$

The idea is that occupations initially scoring high on routine and manual relative to analytical tasks will decline during the sample period, in terms of wages and employment, compared to occupations that score low on our measure $\mathbf{r}_j$.

Table 3.4 reports the estimation results from the full model, comparing the IV to the OLS from above. We focus directly on the restricted model (Table 3.3 already indicated that the estimates for θ are very similar across regressors). Remarkably, the IV estimates turn out not too different from the OLS, both in terms of size and significance, confirming the conclusions from the previous section and alleviating endogeneity concerns regarding our main results.

Table 3.4: Full Model (OLS-IV)

Three-Type Decomposition (Restricted Model)		Dependent Variable: $\Delta\mathbf{e}$					
		(1)		(2)		(3)	
		OLS	IV	OLS	IV	OLS	IV
fixed relationship:	$\overline{d}_{diag}\Delta p_j$	1.59***	1.21***				
		(0.30)	(0.36)				
own effect:	$d_{jj}\Delta p_j$			1.81***	1.32***		
				(0.32)	(0.38)		
own & cross effect:	$\sum_{k=1}^{N} d_{jk}\Delta p_k$					4.15***	4.95***
						(0.70)	(1.47)
Number of Occupations		120	120	120	120	120	120
R-squared		0.295	-	0.310	-	0.394	-
F-stat 1st Stage		-	101	-	96	-	11

Notes: OLS and instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted model. In columns (1)-(2), the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. In column (3), the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. Standard errors are in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by j's initial employment size. Period 1985–2010.

[20] Böhm et al. (2022) caution the QCS questionnaires have some difficulty distinguishing between routine and manual job tasks. See also Rohrbach-Schmidt & Tiemann (2013) for details about classifying tasks in the German context. It is likely that our manual measure is capturing what other papers (e.g. Spitz-Oener (2006)) have referred to as 'routine manual'.

3.4 Extensions and Robustness

This section summarises findings from extensions and robustness checks of the main results. The model is extended to non-employment transitions in Section 3.4.1. We then discuss estimates in five-year sub-periods and finally, in Section 3.4.3, with an alternative method of estimating occupational prices.

3.4.1 Accounting for Non-Employment Transitions

A driver of heterogeneity in occupational growth that we have omitted so far is the extensive margin of employment. This may be particularly important if young workers' entry and old workers' exit from the labour market affects specific occupations' growth (in the case of US routine occupations this was prominently shown by Autor & Dorn, 2009). The secular decline of German unemployment from the mid-2000s may also be relevant in this respect.

In line with eq. (3.1), we interpret indirect utility in M different non-employment states $m \in \{N+1,\dots,N+M\}$ as containing pecuniary payoffs, transition costs, and idiosyncratic components. While pecuniary payoffs p_m are unobserved, the empirical framework can be extended in order to model-consistently control for switches to and from different non-employment states.[21]

We start by computing a new elasticity matrix that includes all transitions to and from non-employment states. Then consider eq. (3.12) with $N+M$ occupations, with M referring to non-employment sectors:

$$\Delta e_j \approx \theta \sum_{k=1}^{N+M} d_{jk}\Delta p_k = \theta \sum_{k=1}^{N} d_{jk}\Delta p_k + \sum_{m=N+1}^{N+M} (\theta \Delta p_m) d_{jm} \tag{3.17}$$

The first summation on the right-hand side represents our standard (own- and cross-occupation) effects, while in the second summation, we explicitly group factors $\theta\Delta p_m$ together. This is to indicate that d_{jm} are control variables for the occupation j's predicted elasticity with respect to non-employment state m. The $\theta\Delta p_m$ coefficient on the respective control represents the combination of pecuniary preferences

[21] As discussed in the previous section, regressions so far included a constant that captures employment growth from sources other than direct occupational transitions (e.g. due to general growth of the working-age population). Now we allow for such contributions to vary by occupation.

and changes in non-employment 'prices'. This product cannot be disentangled, as Δp_m is unobserved, but other than that the model is again identified.

Appendix C.4.1 shows the results from these estimations with $M = 3$ different non-employment sectors: unemployment, out of the labour force (during the career and including part-time as well as employment with benefit receipt), and entry or exit due to newly joining the labour force at age 25–32 or retiring at age 52–59.[22] The R-squared is consistently higher in all specifications as more of the heterogeneity in employment growth can be explained when allowing for occupations' different elasticities with respect to non-employment states. However, the estimated role of own- and cross-price effects turn out similar to before (see Table C.6 and Table C.7). Results also do not substantively change when further separating part-time work and work with benefit receipt from out of labour force, or when merging the three states into one single non-employment sector (results not reported but available upon request).

3.4.2 Analysis in Five-Year Sub-Periods

In the main analysis, we study changes in occupational prices and employment over the period 1985–2010. We now split this longer interval into five-year sub-periods (1985–1990, 1990–1995, 1995–2000, 2000–2005, and 2005–2010), to explore robustness and potential temporal heterogeneity.

The pooled panel sample containing 600 observations (120 occupations x 5 sub-periods) is used to estimate an extended version of eq. (3.12):

$$\Delta e_{jt} = \alpha + \theta d_{jj} \Delta p_{jt} + \theta \sum_{k \neq j} d_{jk} \Delta p_{kt} + \delta_t (+\gamma_j) + \varepsilon_{jt} \tag{3.18}$$

where t refers to a five-year period, and the matrix of elasticities D can be obtained using the baseline period 1975–1984 as previously or using the lagged matrix from the preceding five-year period (e.g. for the period 1995–2000, the matrix of

[22]A limitation of the records from unemployment insurance is that we cannot observe the exact reasons for individuals entering or leaving the dataset (e.g. health shock, discouraged worker, emigration, self-employment, military service or becoming a civil servant). Outside the age range for labour market entry or retirement, these are all treated as out of the labour force for our purposes.

elasticity is computed using employment transitions over the period 1990–1995).[23] The period fixed effects (δ_t) capture unobserved time-specific shocks or trends that affect all occupations uniformly within each sub-period. A more demanding specification additionally includes occupation fixed effects (γ_j), removing average occupational growth over 1985–2010 and identifying only from accelerations / decelerations in the respective sub-period.

The results are shown in Appendix C.4.2. Graphically, Figure C.5 plots prices against employment growth for the pooled sample of 600 occupation-sub-periods (panel a) as well as separately for each sub-period (panel b), analogous to the main text Figure 3.2b. The previous finding is strengthened in the sense that each regression slope for above-median own-price elastic occupations is flatter than any slope for below-median own-price inelastic occupations. Linear OLS (Table C.8) and IV estimation (Table C.9) on the pooled data essentially reproduce the results obtained in Section 3.3. Even in estimations with occupation fixed effects (γ_j), which only use deviations of price changes from their 1985–2010 averages interacted with the price elasticities, results are broadly similar to before.[24] Overall, estimation in a series of shorter intervals shows that the role of occupational price elasticities persists, with some evidence that even acceleration / deceleration of price growth in different sub-periods is translated into employment growth according to these elasticities. These results are also robust to using alternative estimates of occupational prices, which we now turn to discuss.

3.4.3 Alternative Price Estimation

The results so far use the annual wage growth of workers who do not switch occupations (i.e. occupation stayers) as the main estimate of an occupation's changing log price or wage rate per efficiency unit of skill. This accounts flexibly for the selection into occupations based on observable and unobservable individual characteristics. Now we use an alternative price estimation that also controls for the occupation-specific effect of time-varying observable characteristics on wages.

[23] Consistent with the high autocorrelation of matrix D over time, results are similar whether we use the baseline or the lagged elasticity matrix.

[24] We can only do the OLS for this as the instrument does not vary by period.

In this approach, originally proposed by Cortes (2016), observed log wages for individual ω in period t are estimated by

$$\ln w_t(\omega) = \sum_j Z_{jt}(\omega)\varphi_{jt} + \sum_j Z_{jt}(\omega)X_t(\omega)\zeta_j + \sum_j Z_{jt}\kappa_j(\omega) + \mu_t(\omega) \tag{3.19}$$

where $Z_{jt}(\omega)$ is an occupation selection indicator that equals one if individual ω chooses occupation j at time t, φ_{jt} are occupation-time fixed effects, and $\kappa_j(\omega)$ are occupation-spell fixed effects for each individual. The model allows for time-varying observable skills (e.g. due to general human capital evolving over the life cycle) by including in the control variables X_t a set of dummies for five-year age bins interacted with occupation dummies.[25] Finally, $\mu_t(\omega)$ reflects classical measurement error, which is orthogonal to $Z_{jt}(\omega)$. It may be interpreted as a temporary idiosyncratic shock that affects the wages of individual ω in period t regardless of their occupational choice. The estimated occupation-year fixed effects (φ_{jt}) are the parameters of interest, which allow studying changes over time (in our case, 1985-2010) in occupation's log prices (Δp_j).

The results using prices á la Cortes (2016) are presented in Appendix C.4.3. The main figures of this chapter are replicated using these alternative prices in Figure C.6. The main regression results (Table C.10-C.11-C.12-C.13), including those when accounting for non-employment transitions, turn out very similar. Our findings hence remain consistent and robust to this alternative price estimation.

3.5 Summary and Conclusion

Shifts in the demand for occupations have led to large changes in employment and wages (Goos & Manning, 2007, Cavaglia & Etheridge, 2020). One important aspect that remains unexplored is the responsiveness of labour supply (i.e. the ability of the workforce to react) to the changing demand for jobs. In this chapter, we study the role of the heterogeneity of occupational labour supply in explaining the variation of employment and wage growth between 1985 and 2010.

[25] The bins are for ages 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, and 55–59.

We propose a measure of occupation-specific labour supply elasticities, capturing the impact on employment of changes in the wage structure across occupations. These include wage changes in the occupation itself (own-price elasticities) and wage changes in other occupations (cross-price elasticities). We show how these price elasticities can be interpreted in terms of moments of the job flows and study how they relate to several occupational characteristics such as occupational certification or task content. We implement our framework in administrative panel data from Germany with long-running occupation information. The findings of this chapter show that heterogeneity in labour supply responsiveness matters, and that accounting for wage changes in other occupations is crucial for explaining the evolution of the employment structure of the economy.

We close the chapter by discussing several avenues this research opens up for further exploration. First, our framework allows us to conduct "what-if" scenarios to better understand the potential impact of specific changes. For example, a pertinent counterfactual might involve considering a scenario where occupations with lower elasticities were brought up to the median (own-price) elasticity. This could provide insights into potential policy interventions to enhance labour market flexibility and responsiveness. Second, while the research's primary focus spans from 1985-2010, there exists an opportunity to extend the analysis to more recent years, specifically from 2012 onwards, with a new classification of occupations.[26] Finally, exploring the ripple effects of labour supply elasticity on individuals' careers presents another future avenue. This entails understanding how shifts in demand and supply dynamics influence occupational mobility, career trajectories, and wage growth prospects for different segments of the workforce.

[26] The introduction of the new occupation code KldB 2010 in 2011 led to several serious problems (e.g. an increase in missing values for variables relevant in our framework) for the year 2011.

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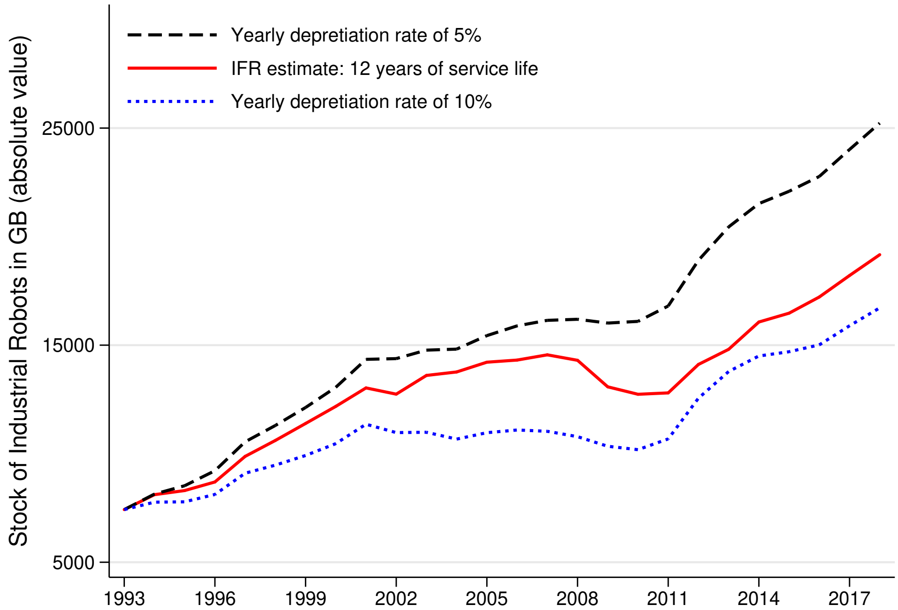
APPENDIX

A

Appendix to Chapter 1

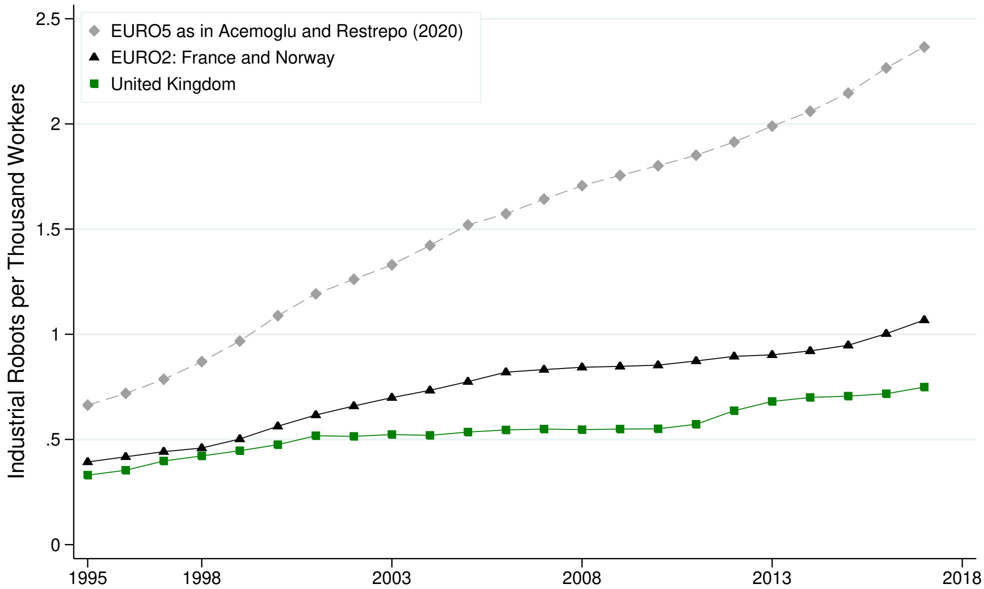
A.1 Supplementary Figures & Tables

Figure A.1: Industrial Robots in GB (1993-2018), in Absolute Value



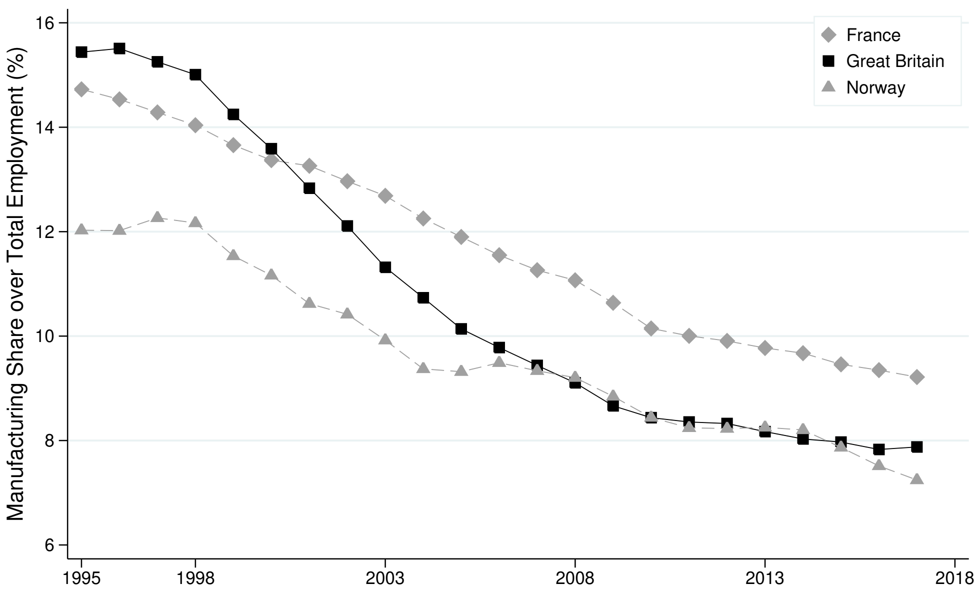
Source: Own calculations based on IFR data

Figure A.2: Capturing the GB Robot Penetration Trend: EURO2 vs EURO5



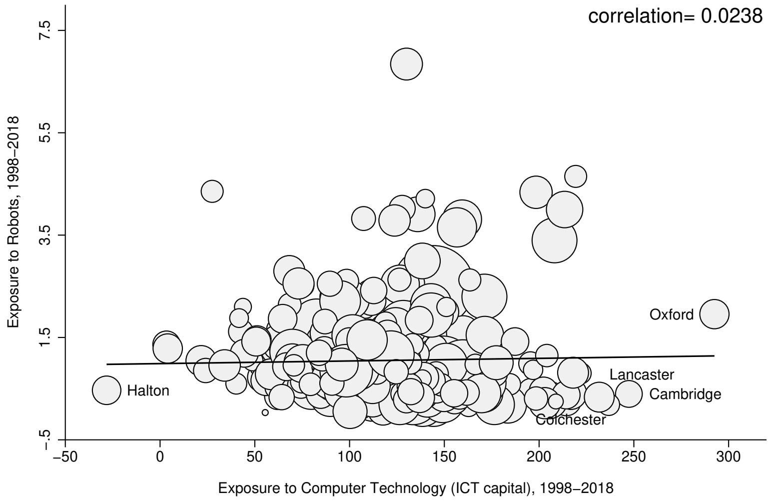
Notes: EURO5 refers to the average of the following countries: Denmark, Finland, France, Italy, and Sweden. Source: Own calculations based on IFR, EU KLEMS, and EUROSTAT data.

Figure A.3: Share of Manufacturing Employment: GB vs EURO2



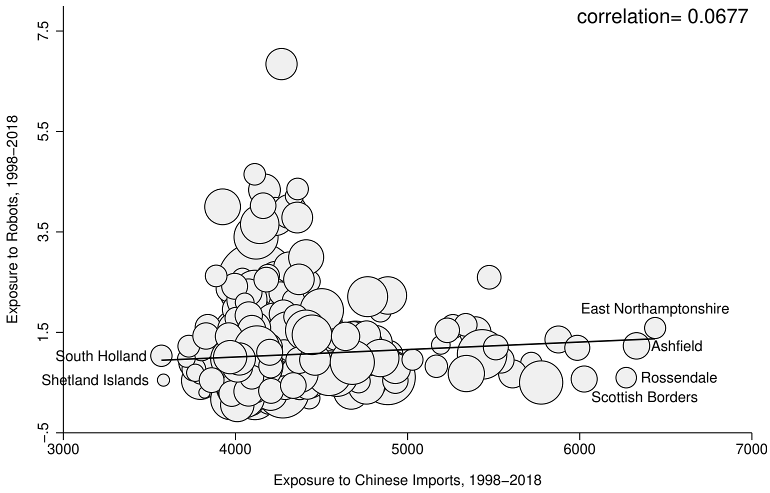
Source: Own calculations based on EU KLEMS, and EUROSTAT data.

Figure A.4: Exposure to Robots and Exposure to Computer Technology



Notes: Plot of the exposure to robots and the exposure to computer technology (ICT capital). Data comes from the IFR and the EU KLEMS. The solid line corresponds to a linear fit with the baseline district population as weights. Marker size indicates the baseline 1995 population in the district.

Figure A.5: Exposure to Robots and Exposure to Chinese Imports



Notes: Plot of the exposure to robots and the exposure to Chinese imports. Data comes from the IFR and the UN Comtrade. The solid line corresponds to a linear fit with the baseline district population as weights. Marker size indicates the baseline 1995 population in the district.

Table A.1: Summary Overview of Most Relevant Papers.

Authors	Country(s)	Period	Observations	Model	Main Datasets used	Main Results
Graetz & Michaels (2018)	17 countries (US, 14 EU, South Korea, Australia)	1993-2007	238 country-industry observations	OLS and IV	- IFR data, EU KLEMS	- Robot densification increased annual growth of labour productivity by about 0.36 percentage points. - Robot densification is associated with increases in both TFP and wages, and reductions in output prices. - Robots reduce the share of hours worked by low-skilled workers.
Acemoglu & Restrepo (2020)	US	1990-2007	722 US commuting zones (local labour markets)	OLS and IV	- IFR data, EU KLEMS - US industry-data: i) County Businness Patterns (CBP), ii) NBER-CES dataset, iii) Bureau of Economic Analysis (BEA), and iv) Bureau of labour Statistics (BLS). - 1970, 1990, 2000 Census data - American Community Survey (ACS)	- Large and robust negative effects of robots on employment and wages (mainly in manufacturing). - The negative employment effects are mostly in routine manual occupations, and in particular in blue collar. - Negative impacts for both men and women. - Robots have very different effects from ICT.
Dauth et al. (2021)	Germany	1994-2014	402 local labour markets	OLS and IV	- IFR data, EU KLEMS, UN Comtrade - German administrative labour data - Establishment History Panel (EHP)	- Robot exposure reduces the labour share and increases productivity. No employment effect at all: displacement effects in manufacturing are offset by new jobs in services. - Two adjustment mechanisms: i) reduced creation of new jobs for younger workers, and ii) skill upgrading. - Earnings inequality: workers who are retained by their plants experienced positive earnings effects. Workers forced to switch plants, industries, or leave manufacturing see significant earnings losses.
Chiacchio et al. (2018)	Finland, France, Germany, Italy, Spain, Sweden	1995-2007	116 regions, 18 demographic groups, 2088 observations	OLS	- IFR data, EU KLEMS, UN Comtrade - European Community Household Panel - European Union Statistics on Income and Living Conditions (EU-SILC)	- One additional robot per thousand workers reduces employment rate by 0.16-0.20 percentage points. - Displacement effect is particularly evident for middle education workers and young cohorts. - Men are more affected than women. - No robust results on the impact of robots on wages.
Faber (2020)	Mexico	1990-2015	1,806 commuting zones	OLS and IV	- IFR data, UN Comtrade - Mexican Census data: 1990, 2000, 2015	- Robots in the US have an important negative impact on employment in Mexico. The effect is mirrored in lower exports to the US and fewer exports-producing factories (*Maquiladoras*). - Foreign robots reduced engagement in Mexico by about 2 million workers between 2000 and 2015.
Koch et al. (2021)	Spain	1990-2016	approx. 4,600 firms in 20 industries	OLS and Probit	- Encuesta Sobre Estrategias Empresariales (ESEE)	- Positive and significant output effects of robot adoption. Robots raise firm-level employment by around 10%. - Larger and more productive firms are more likely to become first time robot adopters. More skill-intensive firms are less likely. - An increase in robot density has a significant negative impact on employment in firms that do not adopt robots.
Aghion et al. (2023)	France	1994-2015	19,448 plants within 16,227 firms in 245 manufacturing industries	OLS and IV	- French administrative data, the DADS and INSEE databases.	- Firms that use more automation technologies increase their total sales, total employment, as well as employment of medium-skill and low-skill workers. - The productivity gains from higher automation benefit both consumers through lower prices and firm owners via increased profits.

Table A.2: Industry Mapping from the IFR and EU KLEMS Data.

	IFR code	EU KLEMS code	Description
Agriculture, hunting and forestry; fishing	A-B	A	Crop and animal production, hunting and related service activities, forestry and logging, fishing and aquaculture.
Mining and quarrying	C	B	Mining and coal and lignite, extraction of crude petroleum and natural gas, mining of metal ores, mining support service.
Food products, beverages and Tobacco	10-12	10-12	Food products and beverages; Tobacco products.
Textiles, wearing apparel, leather and related products	13-15	13-15	Textiles; Wearing apparel; dressing and dyeing of fur; luggage, handbags, saddlery, harness and footwear.
Wood and Paper products; publishing and printing	16; 17-18	16-18	Manufacture of wood, products of wood, manufacture of pulp, paper and converted paper production, printing of products.
Chemical products, pharmaceuticals, cosmetics	19; 20-21; 229	20; 21	Manufacture of basic pharmaceutical products and preparations; manufacture of medicinal chemical and botanical products.
Rubber and plastics products; other non-metallic mineral products	22; 23	22-23	Rubber and plastic products without automotive parts; manufacture of intermediate and final products from mined or quarried non-metallic minerals.
Basic metals and fabricated metal products, except machinery and equipment	24; 25	24-25	Basic metals (e.g. iron, steel, aluminium, copper), metal products (e.g. metal furniture, tanks, metal doors, nails).
Computer, electronic and optical products	260; 261; 262; 263; 265	26	Electronic components/devices; semiconductors, LCD, LED; computers and peripheral equipment; info communication equipment domestic and professional; medical, precision and optical instruments.
Electrical equipment	271; 275; 279	27	Electrical machinery and apparatus n.e.c.; household/domestic appliances.
Machinery and equipment	28	28	e.g. machinery for food processing and packaging, machine tools, industrial equipment, construction machinery, agricultural and forestry machinery.
Transport equipment	29; 30	29-30	Manufacture of cars, trucks, buses and their engines; manufacture of bodies for motor vehicles; manufacture of trailers; other transport equipment.
Other manufacturing; repair and installation of machinery and equipment	91	31-33	All other manufacturing branches.
Electricity, gas and water supply	E	D; E	Electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management activities.
Construction	F	F	General construction and specialised construction activities for buildings and civil engineering works.
Education, Research and Development	P	P	Education; research and development activities.
Services	90	S	All other non-manufacturing branches.

Table A.3: Effects of Industrial Robots on Employment: Alternative Inference following Borusyak et al. (2022)

	IV ESTIMATES, LONG-DIFFERENCE SPECIFICATIONS, 1998-2018					
	Weighted by Population					Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Employment-to-Working-Age Population (change in pp)						
GB Exposure to Robots	0.0259***	0.0478***	0.0753***	0.0755***	0.0826***	0.0914***
	(0.0070)	(0.0037)	(0.0068)	(0.0054)	(0.0053)	(0.0079)
R-squared	0.38	0.52	0.62	0.71	0.68	0.58
Panel B. Employment to Total Population (change in pp)						
GB Exposure to Robots	0.0153***	0.0296***	0.0469***	0.0470***	0.0517***	0.0591***
	(0.0043)	(0.0027)	(0.0053)	(0.0042)	(0.0041)	(0.0054)
R-squared	0.33	0.43	0.51	0.61	0.59	0.54
Panel C. Log Change in Total Employment						
GB Exposure to Robots	0.0318***	0.0679***	0.1075***	0.1078***	0.1200***	0.1376***
	(0.0099)	(0.0088)	(0.0168)	(0.0130)	(0.0131)	(0.0182)
R-squared	0.23	0.37	0.35	0.52	0.51	0.44
Number of Industries	17	17	17	17	17	17
Number of Districts	380	380	380	380	380	380
Region dummies	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Industry characteristics		✓	✓	✓	✓	✓
ICT exposure			✓	✓	✓	✓
Exposure of China imports				✓	✓	✓
Exclude top 1% districts					✓	

Notes: Table presents 2SLS estimates of the effects of exposure to robots on several district-level outcome variables for the period 1998-2018. Panel A presents long-difference estimates for changes in the employment-to-working-age population ratio. Panel B presents changes in the employment-to-total population ratio. Panel C for changes in log total employment. The regressions in columns (1)-(5) are weighted by baseline population, while the regressions in column (6) are unweighted. Robuts standard errors following Borusyak et al. (2022) in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table A.4: District-level Results: Further Robustness Checks (I)

	IV ESTIMATES, LONG-DIFFERENCE SPECIFICATIONS, 1998-2018						
	Baseline Estimates	Unadjusted EURO2	Adjusted EURO3	Adjusted EURO4	Only Finland	Only France	IFR robot stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Employment to Working Age Population (change in pp)							
GB Exposure to Robots	0.0755***	0.0755***	0.0783**	0.0792**	0.0841**	0.0745***	0.0739**
	(0.0283)	(0.0282)	(0.0308)	(0.0323)	(0.0370)	(0.0272)	(0.0304)
R-squared	0.32	0.32	0.32	0.32	0.32	0.32	0.33
Panel B. Employment to Total Population (change in pp)							
GB Exposure to Robots	0.0470**	0.0471**	0.0496**	0.0511**	0.0551**	0.0462**	0.0464**
	(0.0190)	(0.0190)	(0.0207)	(0.0217)	(0.0248)	(0.0183)	(0.0199)
R-squared	0.27	0.27	0.26	0.26	0.25	0.27	0.27
Panel C. Log Change in Total Employment							
GB Exposure to Robots	0.1078**	0.1078**	0.1144**	0.1193**	0.1290**	0.1065**	0.1137**
	(0.0474)	(0.0473)	(0.0511)	(0.0532)	(0.0605)	(0.0453)	(0.0525)
R-squared	0.29	0.29	0.29	0.28	0.28	0.29	0.29
Region dummies	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓
Industry characteristics	✓	✓	✓	✓	✓	✓	✓
ICT exposure, China Exposure	✓	✓	✓	✓	✓	✓	✓

Notes: Table presents 2SLS estimates of the effects of exposure to robots on several district-level outcome variables for the period 1998-2018, as in Table 1.2. Each column presents different specifications as robustness checks. Column (1) reports the baseline estimates as in column (4) in Table 1.2. Column (2) presents results for the penetration of robots without the adjustment term. Column (3) considers the EURO3 adjusted RPR. EURO3 refers to the average of Finland, France, and Norway. Column (4) uses the EURO4 adjusted RPR. EURO4 refers to the average of Denmark, Finland, France, and Norway. Column (5) uses Finland as the instrument country. Column (6) uses France instead. Finally, column (7) considers the stock of robots as provided by the IFR. All models control for a full set of covariates. The regressions are weighted by baseline district population. Standard errors that are robust against heteroskedasticity and clustered at the county-level are given in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A.5: District-level Results by Sectors: Further Robustness Checks (II)

	IV ESTIMATES, LONG-DIFFERENCE SPECIFICATIONS, 1998-2018						
	Baseline Estimates	Unadjusted EURO2	Adjusted EURO3	Adjusted EURO4	Only Finland	Only France	IFR robot stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. MANUFACTURING, Employment to Working Age Population (change in pp)							
GB Exposure to Robots	0.0083	0.0083	0.0079	0.0080	0.0068	0.0084	0.0049
	(0.0091)	(0.0091)	(0.0099)	(0.0104)	(0.0120)	(0.0089)	(0.0118)
R-squared	0.55	0.55	0.55	0.55	0.55	0.55	0.55
Panel B. NON-MANUFACTURING, Employment to Working Age Population (change in pp)							
GB Exposure to Robots	0.0672***	0.0672***	0.0704***	0.0712***	0.0773**	0.0661***	0.0690***
	(0.0236)	(0.0236)	(0.0256)	(0.0268)	(0.0304)	(0.0225)	(0.0262)
R-squared	0.29	0.29	0.29	0.29	0.29	0.30	0.29
Panel C. MANUFACTURING, Employment to Total Population (change in pp)							
GB Exposure to Robots	0.0054	0.0054	0.0052	0.0054	0.0048	0.0055	0.0032
	(0.0057)	(0.0056)	(0.0062)	(0.0064)	(0.0074)	(0.0055)	(0.0074)
R-squared	0.56	0.56	0.56	0.56	0.57	0.56	0.57
Panel D. NON-MANUFACTURING, Employment to Total Population (change in pp)							
GB Exposure to Robots	0.0416**	0.0416**	0.0444**	0.0457**	0.0503**	0.0407***	0.0432**
	(0.0163)	(0.0163)	(0.0177)	(0.0186)	(0.0211)	(0.0156)	(0.0174)
R-squared	0.26	0.26	0.25	0.25	0.24	0.26	0.25
Region dummies	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓
Industry characteristics	✓	✓	✓	✓	✓	✓	✓
ICT exposure, China Exposure	✓	✓	✓	✓	✓	✓	✓

Notes: Table presents 2SLS estimates of the effects of exposure to robots on two district-level outcome variables for the period 1998-2018 separately for manufacturing and non-manufacturing industries, as in Table 1.3. Each column presents different specifications as robustness checks. Column (1) reports the baseline estimates as in columns (4) and (7) in Table 1.3. Column (2) presents results for the penetration of robots without the adjustment term. Column (3) considers the EURO3 adjusted RPR. EURO3 refers to the average of Finland, France, and Norway. Column (4) uses the EURO4 adjusted RPR. EURO4 refers to the average of Denmark, Finland, France, and Norway. Column (5) uses Finland as the instrument country. Column (6) uses France instead. Finally, column (7) considers the stock of robots as provided by the IFR. All models control for a full set of covariates. The regressions are weighted by baseline district population. Standard errors that are robust against heteroskedasticity and clustered at the county level are given in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

A.2 Data Appendix

A.2.1 Industry Mapping

The industry classification available in the Business Register and Employment Survey (BRES) corresponds to SIC 2007, whereas SIC 1992 is used in both predecessors, the Annual Business Inquiry (ABI) and the Annual Employment Survey (AES). To consistently map SIC 1992 industries into the 17 main industries considered in the analysis of Chapter 1 (corresponding to SIC 2007 classification or ISIC Revision 4 codes, see Table A.2), we proceed as follows. First, note that SIC 2003 is essentially identical to SIC 1992 at the three-digit aggregation level and above. We then use an official spreadsheet with proportions mapping each SIC 2003 industry category to one or more SIC 2007 industry categories at each of the three-digit level (with proportions describing the likelihood of each such correspondence). These spreadsheets are based on mappings created using the Inter-Departmental Business Register (IDBR), the continually-updated universe of UK VAT- or PAYE-registered businesses maintained by the ONS. The mapped industries at the three-digit level are then aggregated into the 17 industries.[1]

A.2.2 Comparable Data across GB Employment Surveys

From 2016 onwards, the coverage of the ONS Standard Business Survey Population was extended to include a population solely Pay-As-You-Earn (PAYE) based businesses. This improvement in coverage is estimated to have increased the business survey population by around 100,000 businesses. This increase has led to an increase in the estimate of the number of employees. For 2015, data is provided for both samples (the old one and the new one, with the mentioned improvement). We perform a comparison between both datasets by industry and region to assess the extent to which employee estimates are affected. Later, this information is used to rescale surveys accordingly. See ONS (2017) for further details.

[1]There are a few industries we are not able to map due to data unavailability for the crosswalk. These include: "010: DEFRA/Scottish Executive Agricultural Data", "102: Mining and agglomeration of hard coal", "120: Mining of uranium and thorium ores", "950: Private household with employed persons", and "990: Extra-territorial organisations".

A.2.3 Trade Data Mapping

Trade information is used from the United Nations Commodity Trade Statistics Database (UN Comtrade). This is an international database of six-digit product-level information on all bilateral imports and exports between any given pair of countries. It provides product-level trade values (in $US) using a six-digit Harmonised System (HS) commodity description. For the purposes of Chapter 1, HS-1996 (also known as HS1) is used. In order to link trade information to the SIC 2007 industry codes, product concordances from the United Nations Statistics Division and the World Integrated Trade Solution (WITS) are used.

A.3 Theory Appendix: Robots and Employment

The empirical approach adopted in Chapter 1 is based on the theoretical task-based model in Acemoglu & Restrepo (2020), which builds on some of their earlier work (Acemoglu & Restrepo, 2018, 2019). Below, we provide a brief summary of the model where robots compete against workers in the production of different tasks. Robots can perform some tasks, while other tasks can only be completed by human labour. The demand for labour thus depends on the set of tasks robots can perform. To develop intuition, we start by considering the model without trade between local labour markets. A summary of the model with trade is considered later.

A.3.1 Without Trade between Local Labour Markets

An economy is made up of local labour markets (hereon, LLM)[2] where most adjustments to shocks take place (Moretti, 2011). Each LLM i has constant elasticity of substitution (CES) preferences over an aggregate of the output of several industries (denoted by j), given by the following expression

$$Y_i = \left(\sum_{j \in J} v_j^{1/\sigma} Y_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{A.3.1}$$

where $\sigma > 0$ denotes the elasticity of substitution across goods produced by different industries and v_j's are share parameters that designate the importance of industry

[2] We employ the term *local labour market* here for a more general theoretical formalisation. Recall that this chapter uses Local Authority Districts (LAD) as a proxy of GB local labour markets.

j in the consumption aggregate, with $\sum_{j\in J} v_j = 1$. In the autarky equilibrium, each LLM consumes all its own production of each industry-good, X_{ij}, such that $X_{ij} = Y_{ij}$ for all $i \in I$ and $j \in J$. Let the consumption aggregate in each LLM be the numeraire (with price normalised to one) and P^X_{ij} be the price of the output of industry j in LLM i.

An industry produces output by combining tasks $s \in [0,1]$ in fixed proportions such that

$$X_{ij} = A_{ij} \min_{s\in[0,1]} \{x_{ij}(s)\} \tag{A.3.2}$$

where A_{ij} is the productivity of LLM i in industry j and $x_{ij}(s)$ is the quantity of task s utilised in order to produce X_{ij}. It follows that differences in productivity (A_{ij}) and the relative importance of the industry in the consumption aggregate (v_j) result in differing shares of industry employment across LLMs. Next, assume the productivity of robots for every task is normalised to one and the (relative) productivity of labour is equal to $\lambda > 0$. In each industry, tasks $s \in [0, M]$ are assumed to be technologically automatable. Then, the production function for task s follows

$$x_{ij}(s) = \begin{cases} \lambda L_{ij}(s) & \text{if } s > M_j \\ \lambda L_{ij}(s) + R_{ij}(s) & \text{if } s \le M_j \end{cases} \tag{A.3.3}$$

where $L_{ij}(s)$ and $R_{ij}(s)$ denote labour and robots used in the production of tasks s in LLM i and industry j, respectively. Recall that the model is task-based; there is a cutoff point M below which tasks are technologically automatable and hence can be performed by workers (labour) or robots. Because tasks above the threshold M have not yet been technologically automatable, they must be completed by labour. The model assumes this cutoff point is common across all LLMs.[3]

Further, supply of labour L_i and robots R_i in each LLM are defined such that

$$W_i = \omega_i Y_i L_i^{\epsilon} \tag{A.3.4}$$

$$Q_i = q_i \left(\frac{R_i}{Y_i}\right)^{\eta} \tag{A.3.5}$$

[3]Note that whereas ICT is modelled complementing labour (increasing λ), robotisation takes the form of an increase in the number of tasks where robots can replace labour (dM_j) (Faber, 2020).

with $\epsilon > 0$ and $\eta > 0$, Q_i the price of robots, W_i the wage rate, and ω_i and q_i the local supply curve shifters in LLM i. It follows that $1/\epsilon$ is the Frisch elasticity of labour supply, while $1/\eta$ is the elasticity of the supply of robots. These supply equations, together with market clearing conditions for labour and robots, are considered when firms maximise their profits. Finally, a simpliflying assumption is made that it is profitable for firms to use robots in all tasks that are technologically automatable. Let $\pi_i = 1 - \frac{Q_i \lambda}{W_i}$ be the cost-saving gains from using robots instead of labour in a task. The profitability assumption implies that $\pi_i > 0$ in all LLMs. This assumption is necessary so that improvements in robotic automation, increases in M_j, are binding and affect labour.

Under the previous framework, the following equation provides a partial equilibrium characterisation of how the demand for labour changes following robotics automation[4]

$$d\ln L_i = \underbrace{-\sum_{j\in J} \ell_{ij} \frac{dM_j}{1-M_j}}_{\substack{\textbf{displacement}\\ \textbf{effect}}} \underbrace{-\sigma \sum_{j\in J} \ell_{ij} d\ln P_{ij}^X}_{\substack{\textbf{price-productivity}\\ \textbf{effect}}} \underbrace{+\, d\ln Y_i}_{\substack{\textbf{scale-productivity}\\ \textbf{effect}}} \tag{A.3.6}$$

where ℓ_{ij} denotes industry j's share of total employment in LLM i, P_{ij}^X denotes the price for industry-product X_j in LLM i, and Y_i denotes LLM i's total output. The displacement effect means that holding prices and output constant, robots displace workers as they are more efficient in the production process. This displacement effect thus always reduces the labour share in the industry undergoing robotisation. The second effect is the price-productivity effect. Higher robot use results in lower cost of production, allowing the industry to expand and increase its demand for labour (the higher is σ, the higher this expansion). Finally, the scale-productivity effect captures the fact that reduction in costs leads to increase total output, which subsequently raises the demand for labour in all industries. It follows that whether the negative displacement effect or the positive countervailing forces are larger, robots might lead to decrease or increase the labour demand.

Note that the first term in eq. (A.3.6) is in terms of M_j, which is unobservable, not in terms of the number of industrial robots. For (empirical) convenience, assume

[4] See Acemoglu & Restrepo (2020) for derivations and proofs.

$M_j \approx 0$, that is, the number of tasks that can be automated is close to 0. The latter is a reasonable approximation to the GB economy back to 1990. Then, it follows that $\frac{dM_j}{1-M_j} \approx \frac{1}{\lambda}\frac{dR_j}{L_j}$, where $\frac{1}{\lambda}$ is the productivity of robots relative to humans.[5] Also, eq. (A.3.6) provides a partial equilibrium characterisation of the labour response to automation as a function of the share of automatable tasks, product price, and total output. A general equilibrium in this economy is defined such that in all LLMs, firms maximise their profits, households maximise their utility, labour and robot supplies are given by eq. (A.3.4) and eq. (A.3.5), and the markets for final goods, labour and robots clear. The problem yields the following general equilibrium expression for the employment response to robots

$$d\ln L_i = \left(\frac{1+\eta}{1+\epsilon}\pi_i - \frac{1+\eta}{1+\epsilon}\right)\frac{1}{\lambda}\cdot\sum_{j\in J}\ell_{ij}\left(\frac{dR_j}{L_j}\right) + \varepsilon_i \tag{A.3.7}$$

where π_i, η, ϵ, and λ are as defined above, and ε_i is the idiosyncratic error term. It establishes that the response of employment to robotics automation is shaped by the term $\sum_{j\in J}\ell_{ij}(\frac{dR_j}{L_j})$, which is the basis of the robot exposure measure used in Chapter 1. The latter is a Bartik-type or shift-share measure that combines local (district) industry-employment shares and industry-level variation in the usage of robots. Variation in exposure to robots across districts results from the fact that different areas were initially specialised in different industries which have later experienced different robot penetration rates. Note that the corresponding coefficient depends on several elasticities and parameters of the model, which shows the impact of robotisation on employment is *a priori* theoretically ambiguous.[6]

A.3.2 With Trade between Local Labour Markets

We now extend the model to a more realistic setting by considering trade between local labour markets. The model relaxes the autarky assumption by allowing each good to be consumed not only locally, but also in all other LLMs. It is assumed there are no trade costs such that the price of the product of industry j from LLM i, denoted by P^X_{ij}, is the same across space. Market clearing then implies that

[5] This follows from the cost minimisation problem (see eq. (A.3.2) and eq. (A.3.3)). Taking the resulting equations, integrating over LLMs, and log differentiating come to this approximation.

[6] See also Caselli & Manning (2019).

the production of each LLM's industry good equals aggregate demand for this good over all LLMs. Preferences in a LLM are defined by the same aggregate over consumption goods as in the autarky model (eq. (A.3.1)), but now with inputs sourced from all LLMs so that for all i and j

$$Y_{ij} = \left(\sum_{s \in C} \kappa_{sj}^{1/\psi} X_{sij}^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}} \tag{A.3.8}$$

where ψ is the elasticity of substitution between varieties sourced from different LLMs, and the share parameters (κ_{sj}) capture the desirability of varieties from different sources. The assumption that varieties of the same good from different LLMs are more substitutable than different products in the consumption aggregator means that $\psi > \sigma$. It follows from the assumptions of common technological opportunities and no trade costs across space that all LLMs have the same prices of the consumption aggregates of different industries, denoted by P_j^Y. Under the previous framework, the change in the labour demand in the trading equilibrium satisfies the following equation:

$$d\ln L_i = -\sum_{j \in J} \ell_{ij} \frac{dM_j}{1-M_j} - \psi \sum_{j \in J} \ell_{ij} d\ln P_{ij}^X + (\psi - \sigma) \sum_{j \in J} \ell_{ij} d\ln P_j^Y + d\ln Y \tag{A.3.9}$$

The displacement effect with trade is identical to the partial equilibrium case under autarky. Nonetheless, eq. (A.3.9) and eq. (A.3.6) differ in several ways. Now there are three terms making up the productivity effect. First, the price-productivity effect, which is greater than under autarky due to higher substitutability of the same good from different LLMs ($\psi > \sigma$). Intuitively, the price-productivity effect reflects higher robot usage results in lower cost of production, allowing the industry to expand and increase its demand for labour. Whereas in autarky an industry is only able to expand relative to other industries in its LLM, in the trade setting an industry can raise its market share, resulting in an even larger increase in labour demand. The latter effect is somewhat dampened because the greater use of robots in industry j reduces the cost of production in all LLMs. This lower cost of production in all LLMs results in a reduction in labour demand. Finally, the scale-productivity effect is still present, with the difference that now it works through an expansion of total output in the whole economy rather than just in the LLM. Acemoglu & Restrepo (2020) then show that these effects are not functions of exposure to robots in the own LLM, and thus the same reduced-form relationship as in the autarky model (eq. (A.3.7)) is obtained.

A.4 Identification with Bartik Instruments

This section presents the details on the identification strategy under the shift-share IV framework. We start by summarising recent papers on Bartik instruments' identification. We then discuss the plausibility of exogenous shocks in our setting.

Section 1.2.1 of Chapter 1 describes our empirical strategy. The Bartik instrument in our setting is formed by interacting local industry-employment shares and national industry-level variation in robot use. Named after Bartik (1991), the approach has since been used across many fields in economics, including labour, public development, international trade, and finance. More recently, various papers have raised concerns with shift-share or Bartik approaches like the one used in Chapter 1, which we now proceed to discuss.

Goldsmith-Pinkham et al. (2020) discuss the Bartik instruments's identification as coming from the shares. They show that the two-stage least squares (2SLS) estimator with the Bartik instrument is numerically equivalent to a generalised method of moments (GMM) estimator with local industry employment shares as instruments and a weight matrix constructed from the shock. In contrast, the discussion of the consistency of the estimator in Borusyak et al. (2022) follows from the shock point of view. Based on the inner-product structure of the Bartik measure, they show that shift-share IV coefficients are numerically equivalent to a weighted shock-level (industry-level) regression. The shocks could serve as valid instruments even when the industry-employment shares are endogenous. The identifying assumption is that industry-level shocks are as good-as-randomly assigned, as if arising from a natural experiment, conditional on covariates.[7]

Which of these quasi-experimental designs fits best with our application? We view the assumption of exogenous exposure shares, as discussed by Goldsmith-Pinkham et al. (2020), to be *ex-ante* implausible in our setting. The assumption

[7]Borusyak et al. (2022) provide a Stata package *ssaggregate* which creates shock-level aggregates based on their equivalence result, available at `https://github.com/borusyak/shift-share`.

requires the initial local employment share of each industry to be uncorrelated with all unobserved labour supply shocks. The latter is unlikely to hold in our setting. By contrast, we hypothesise the exogeneity of the robot shocks, the continued rise of industrial robots, is an *ex-ante* plausible research design in our setting. Shocks are tailored to a specific question (the penetration of industrial robots) while the shares are 'generic', in that they could conceivably measure an observation's exposure to multiple shocks, both observed and unobserved. Consider the same example as in Borusyak et al. (2022): both Autor et al. (2013) and Acemoglu & Restrepo (2020) build shift-share instruments with similar lagged employment shares but different shocks – the former uses the rising trade with China while the latter uses the adoption of industrial robots. According to the share view of Goldsmith-Pinkham et al. (2020), these papers use essentially the same instruments (lagged employment shares) for different endogenous variables (growth of import competition and growth of robot usage) and are therefore mutually inconsistent.

We next implement falsification tests to formally assess the plausibility of the previous assumption – the exogeneity of the robot shocks.

Both Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022) highlight that shift-share IV identification could be problematic if there is evidence of pre-trends. In our setting, we should be worried that industries particularly exposed to the robot shock, for some reason, were on a different employment trajectory relative to other industries even before the shock (e.g. the rise of industrial robots) occurred. We verify that in Table A.8 and Figure A.6. No significant pre-trends correlated with the adjusted robot penetration rate for log employment (the extensive margin) and log hours worked (the intensive margin) are found. We consider periods prior to the onset of rapid advances in robotics technology, going back to the 1970s. Note that column (4) in Table A.8 shows results are robust to the exclusion of the transport equipment industry.

Recall that the identifying assumption in the framework of Borusyak et al. (2022) is that industry-level shocks are as-good-as-randomly assigned, conditional on covariates. We study the latter in our setting by testing the balance of the industry-level robot shock with respect to industry-level and district-level covariates. Table A.6 reports the results of our industry-level balance tests. The four controls we consider are the penetration rate of Chinese imports, the intensity in ICT capital, the value added of the industry in 1995, and the gross output of the industry in 1995. If the robot shocks are as-good-as-randomly assigned to industries, we expect them to not be correlated with these controls. Table A.6 shows that there is no statistically significant correlation when all industries are considered (columns (1)-(2)). We find that the adjusted $\overline{RPR}_j$ is positively correlated with intensity in ICT capital when only considering manufacturing industries. ICT capital has been stronger in non-manufacturing industries such as education, and research and development. We therefore see this significant correlation within manufacturing industries as unlikely to invalidate the research design. Table A.7 reports the results of our district-level balance tests. Each row presents coefficients, standard errors, and R-squared from separate regressions using covariates' industry-level averages as dependent variables, and exposure shares as weights.[8] Overall, the estimates indicate no significant relationships between the robot shocks and the baseline covariates. There is one exception. The female employment share in the baseline appears to be negatively correlated with the robot penetration rate. Districts with higher robot penetration tend to have a lower female share in employment, suggesting females are under-represented in manufacturing industries.

Overall, the results of these falsification tests – the pre-trends test and the balance tests – allow us to see the robot shocks as close to randomly assigned across industries.

[8]Before calculating the industry averages, we residualise by the initial manufacturing employment share. One of the sources of variation which aims to exploit our empirical strategy is the heterogeneous industry composition of the districts. This is why we control for the initial manufacturing employment share in all our regressions.

Table A.6: Industry-level Balance

	Adjusted Robot Penetration Rate, $\overline{RPR}_j$			
	Across All Industries		Only Manufacturing	
	(1)	(2)	(3)	(4)
Balance Variable	correlation	p-value	correlation	p-value
Chinese Import Competition	−0.0549	(0.8342)	−0.3017	(0.3672)
Intensity in ICT Capital	−0.2527	(0.3279)	0.6693**	(0.0243)
Value Added, 1995	−0.0528	(0.8405)	0.0577	(0.8661)
Gross Output, 1995	0.1142	(0.6627)	0.3140	(0.3471)

Notes: Table presents the correlation between the adjusted robot penetration rate, $\overline{RPR}_j$, and several industry covariates, weighted by average industry exposure shares. We present the overall correlation across 17 industries, and the correlation within manufacturing (across 11 industries). ** p<0.05

Table A.7: District-level Balance

	Adjusted Robot Penetration Rate, $\overline{RPR}_j$		
DEPENDENT VARIABLE:	(1)	(2)	(3)
BASELINE COVARIATE (year 1995)	coeff	std.error	R-squared
Share of people aged 16-24	0.0053	(0.0044)	0.0263
Share of population above 65 years old	−0.0024	(0.0017)	0.0116
Female employment share	−0.0310***	(0.0071)	0.2911
Female population share	−0.0011	(0.0010)	0.0366
Population share higher degree	0.0022	(0.0032)	0.0053
Population share degree	0.0037	(0.0073)	0.0023
Population share diploma	−0.0059	(0.0102)	0.0032
Share of White population	−0.0013	(0.0122)	0.0001
Share of Indian population	−0.0048	(0.0052)	0.0158
Share of Pakistani population	0.0040	(0.0027)	0.0276
Share of Bangladeshi population	0.0006	(0.0010)	0.0062
Share of Black population	−0.0014	(0.0034)	0.0016
Share of Chinese population	−0.0009	(0.0017)	0.0039

Notes: Table presents shock-level balance check á la Borusyak et al. (2022). Each row in the table corresponds to a separate regression. Coefficients are obtained from regressing industry-specific weighted averages of base year district-level characteristics on the robot shock. Robust standard errors are shown in parentheses. Regressions are weighted by the exposure weights. Coefficients are multiplied by 100 for readability. *** p<0.01.

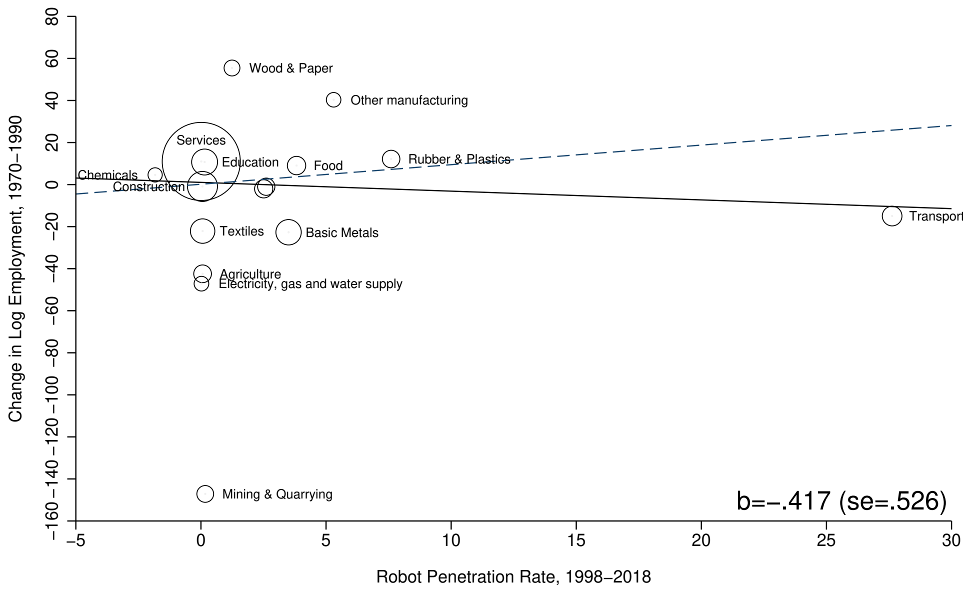
Table A.8: Industry Pre-trends

	All Industries			Exclude Transport Industry
	(1)	(2)	(3)	(4)
Panel A. Change in Log Employment, 1970-1980 (extensive margin)				
Robot Penetration Rate, $\overline{RPR}_j$	1.2675	0.4171	0.3955	0.6062
	(0.8988)	(0.3121)	(0.4358)	(2.1838)
R-squared	0.5656	0.6372	0.6374	0.6329
Panel B. Change in Log Hours Worked, 1970-1980 (intensive margin)				
Robot Penetration Rate, $\overline{RPR}_j$	0.8626	0.2295	0.2519	0.8906
	(0.7496)	(0.3900)	(0.5272)	(2.3324)
R-squared	0.4694	0.5182	0.5184	0.5105
Panel C. Change in Log Employment, 1970-1985 (extensive margin)				
Robot Penetration Rate, $\overline{RPR}_j$	0.1951	−0.2884	−0.2884	2.0303
	(0.6728)	(0.4358)	(0.4358)	(2.6228)
R-squared	0.6505	0.6688	0.6688	0.6520
Panel D. Change in Log Hours Worked, 1970-1985 (intensive margin)				
Robot Penetration Rate, $\overline{RPR}_j$	−0.0379	−0.3872	−0.3071	2.2906
	(0.5877)	(0.4901)	(0.6277)	(2.7089)
R-squared	0.5378	0.5495	0.5519	0.5286
Panel E. Change in Log Employment, 1970-1990 (extensive margin)				
Robot Penetration Rate, $\overline{RPR}_j$	−0.0195	−0.4516	−0.4161	3.1545
	(0.6988)	(0.3642)	(0.5261)	(2.6944)
R-squared	0.5603	0.5742	0.5747	0.5544
Panel F. Change in Log Hours Worked, 1970-1990 (intensive margin)				
Robot Penetration Rate, $\overline{RPR}_j$	−0.2228	−0.5554	−0.4540	3.3756
	(0.6190)	(0.3951)	(0.5754)	(2.7370)
R-squared	0.4999	0.5101	0.5138	0.4888
Manufacturing dummy	✓	✓	✓	✓
Light manufacturing dummy		✓	✓	✓
Chinese imports			✓	✓

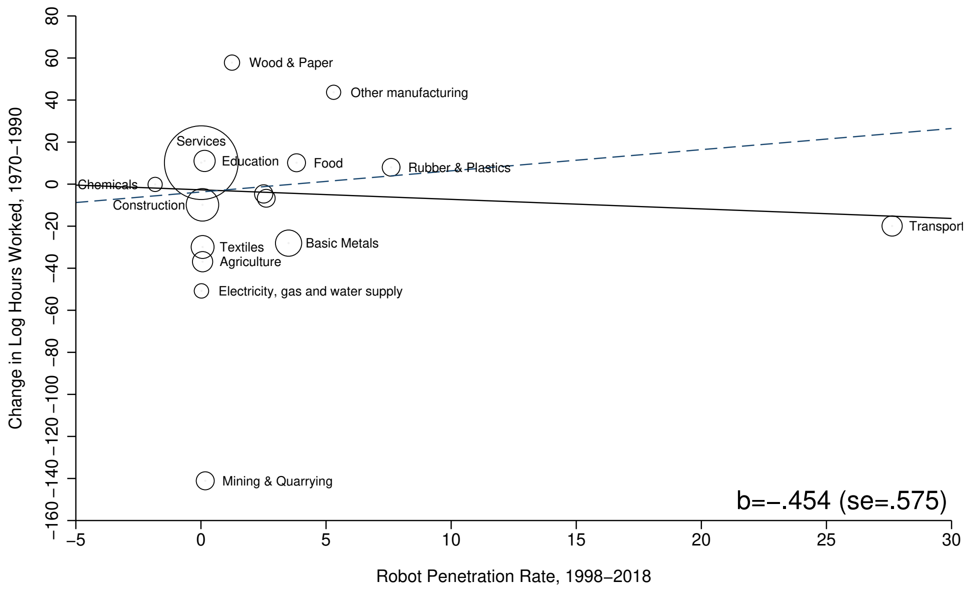
Notes: Table presents estimates of the effects of the adjusted robot penetration rate on past employment. Panel A, C and E present estimates for changes in log employment (extensive margin) for the periods 1970-1980, 1970-1985, and 1970-1990, respectively. Panel B, D, and F present estimates for changes in log hours worked (intensive margin) for the periods 1970-1980, 1970-1985, and 1970-1990, respectively. The covariates included in each model are reported at the bottom of the table. Column (1) includes the manufacturing dummy. Column (2) adds the light manufacturing dummy. Finally, columns (3) and (4) add the exposure of China imports. Robust standard errors are shown in parentheses. We find no significant effect on employment for pre-trends.

Figure A.6: Industry Pre-trends (1970-1990)

(a) Change in Log Employment (extensive margin), 1970-1990



(b) Change in Log Hours Worked (intensive margin), 1970-1990



Notes: Figure presents residual plots of the relationship between the adjusted robot penetration rate for 1998-2018 ($\overline{RPR}_j$) and the 1970-1990 change in log employment (top figure), and log hours worked (bottom figure). The solid lines correspond to regression models analogous to those in column (3) of Panel E and F of Table A.8. The coefficients of these models and their standard errors are reported at the bottom of each plot. The dashed line is for a regression which in addition excludes the transport equipment industry. Marker size indicates the baseline employment in the industry.

APPENDIX

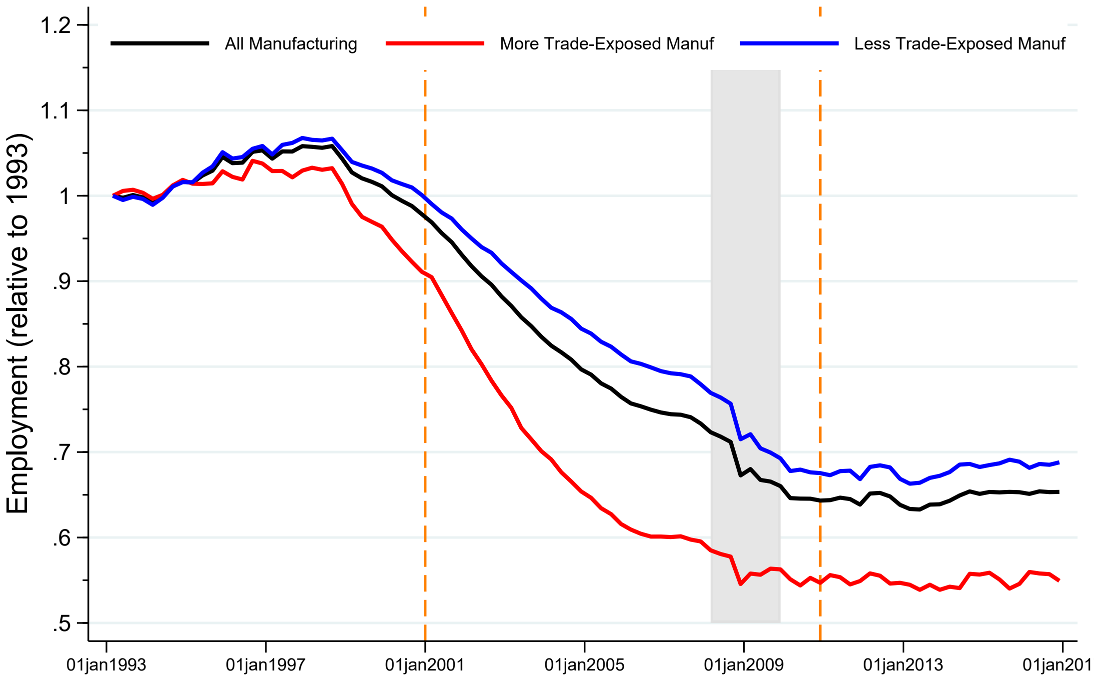
B

APPENDIX TO CHAPTER 2

B.1 Supplementary Figures & Tables

Figure B.1: Import Competition between the UK and China (1993-2016)

Figure B.2: Manufacturing Employment: More vs Less Trade-Exposed (Relative to Year 1993)



Source: ONS -- UK Total Employee Jobs by Industry, Quarterly Data
More Trade-Exposed Manuf: Textiles, Wearing Apparel, Leather, Footwear, Office Machinery, Electrical Machinery, Radio & TV equipment, Other Transport Equipment, Furniture, Games and Toys

Table B.1: Top 20 Industries Most Exposed to Import Competition.

Industry (UK SIC92 classification)	**Employment Share, %** (all manufacturing industries)
Games and Toys	0.30
Luggage, Handbags	0.11
Footwear	0.38
Leather	-
Transport Equipment not elsewhere classified	-
Sports Goods	0.15
Wearing Apparel; Dressing and Dyeing of Fur	2.45
Domestic Appliances not elsewhere classified	0.82
Office Machinery and Computers	1.57
Manufacturing not otherwise specified	1.90
Radio, Television and Communication Equipment	2.81
Furniture	3.74
Miscellaneous Manufacturing not elsewhere classified	1.41
Textiles	3.46
Cutting, Shaping and Finishing of Stone	0.11
Musical Instruments	0.10
Rubber Products	0.94
Refractory Ceramic Products	0.78
Electrical Machinery not elsewhere classified	4.18
Glass and Glass Products	0.91

Notes: Table shows the 20 (three-digit SIC92) industries most affected by import competition between 2001-2011. See Section 2.2 for details about how import exposure is constructed. Source is ONS Longitudinal Study.

Table B.2: First-Stage Regressions (All Employees)

	(1) No Controls	(2) Individual Controls	(3) Partner Controls
Import Exposure IV	1.041***	1.034***	1.035***
	(0.161)	(0.182)	(0.179)
R^2	0.744	0.769	0.772
Sample Size	168,797	168,797	115,523
Controls	No	Yes	Yes
Ind, Occ, TTWA FE	No	Yes	Yes
Partner FE	No	No	Yes

Notes: Table shows the first-stage results, where we regress exposure to import competition (see eq. (2.1)) on the instrument (see eq. (2.3)) for all employees. See notes of Table 2.2 and Table 2.5 for a list of the controls. Section 2.2 provides more details. Standard errors clustered at the industry level. ***$p < 0.01$. Source is ONS Longitudinal Study.

Table B.3: First-Stage Regressions (By Age and Gender)

	Panel A. Men			**Panel B. Women**		
Import Exposure IV	0.982***	0.973***	0.974***	1.141***	1.127***	1.132***
	(0.153)	(0.180)	(0.173)	(0.176)	(0.190)	(0.193)
R^2	0.717	0.740	0.743	0.787	0.817	0.818
Sample Size	83,627	83,627	57,431	85,170	85,170	58,092
	Panel C. Young Men			**Panel D. Young Women**		
Import Exposure IV	0.989***	0.983***	0.985***	1.117***	1.111***	1.121***
	(0.159)	(0.192)	(0.184)	(0.181)	(0.198)	(0.204)
R^2	0.722	0.742	0.747	0.779	0.809	0.808
Sample Size	56,472	56,472	34,605	56,800	56,800	35,951
	Panel E. Old Men			**Panel F. Old Women**		
Import Exposure IV	0.966***	0.952***	0.954***	1.188***	1.157***	1.148***
	(0.143)	(0.160)	(0.157)	(0.168)	(0.181)	(0.181)
R^2	0.708	0.739	0.742	0.802	0.834	0.834
Sample Size	27,155	27,155	22,826	28,370	28,370	22,141
Controls	No	Yes	Yes	No	Yes	Yes
Ind, Occ, TTWA FE	No	Yes	Yes	No	Yes	Yes
Partner FE	No	No	Yes	No	No	Yes

Notes: Table shows the first-stage results, where we regress exposure to import competition (see eq. (2.1)) on the instrument (see eq. (2.3)). See Section 2.2 for more details. Standard errors clustered at the three-digit industry level reported in parentheses. ***$p < 0.01$. Source is ONS Longitudinal Study.

Table B.4: Descriptive Overview. Import Exposure by Gender

	(1) All Workers	(2) Manufacturing Workers	(3) High Exposed Workers
	Panel A. All		
Import Exposure	0.65	3.96	12.10
P90, P10 interval	[0.91, 0.00]	[12.77, 0.09]	[20.25, 6.13]
P75, P25 interval	[0.00, 0.00]	[6.12, 0.25]	[14.34, 6.31]
Observations	168,797	27,859	7,099
	Panel B. Men		
Import Exposure	0.85	3.58	11.58
P90, P10 interval	[1.97, 0.00]	[10.74, 0.07]	[17.23,6.13]
P75, P25 interval	[0.00, 0.00]	[5.57, 0.25]	[14.34, 6.31]
Observations	83,627	19,790	4,578
	Panel C. Women		
Import Exposure	0.49	4.93	13.04
P90, P10 interval	[0.13, 0.00]	[14.34, 0.21]	[20.26, 6.14]
P75, P25 interval	[0.00, 0.00]	[6.31, 0.38]	[17.22, 9.00]
Observations	85,170	7,889	2,521

Notes: See Section 2.2 for details about how import exposure is constructed. Sources are ONS Longitudinal Study and UN Comtrade Database.

Table B.5: Import Exposure within Households

	Correlation with Partner's Exposure	
	All Industries	Manufacturing
All	0.220	0.216
	151,228	19,836
Men	0.165	0.181
	67,190	13,849
Women	0.274	0.243
	84,038	5,987
Young Men	0.142	0.175
	38,290	8,145
Young Women	0.265	0.263
	53,348	3,892
Old Men	0.197	0.189
	28,900	5,704
Old Women	0.288	0.209
	30,690	2,095

Notes: Sample size reported below the correlation coefficient.
Source is ONS Longitudinal Study.

Table B.6: Import Exposure and Labour Reallocation

	(1) Δ low-skill	(2) Δ blue-collar	(3) Δ white-collar
	Panel A. All		
Import Exposure	1.465^{***}	-2.056^{***}	0.590
	(0.444)	(0.633)	(0.789)
First-stage F-stat	[31.00]	[31.00]	[31.00]
Observations	133,605	133,605	133,605
	Panel B. Men		
Import Exposure	1.172^{**}	-2.708^{***}	1.536^{*}
	(0.468)	(0.811)	(0.851)
First-stage F-stat	[28.21]	[28.21]	[28.21]
Observations	68,875	68,875	68,875
	Panel C. Women		
Import Exposure	1.151^{*}	0.594	-1.745^{**}
	(0.611)	(0.531)	(0.816)
First-Stage F-stat	[33.78]	[33.78]	[33.78]
Observations	64,730	64,730	64,730

Notes: Table shows the effects of import exposure on flows into different occupational groups conditional on remaining in employment. Blue collar workers are those employed in “skilled trades occupations” and “process, plant, and machine operatives”. Low-skill workers are those employed in “administrative and secretarial occupations”, “caring, leisure, and other service occupations”, “sales and customer service occupations” and “elementary occupations”. Finally, white-collar workers are defined as those working in “managers, directors, and senior officials”, “professional occupations”, and “associate professional and technical occupations”. This follows from the UK Standard Occupational Classification SOC2000. The findings for men are consistent with a recent paper by Keller & Utar (2023). Standard errors clustered at the three-digit industry level are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.7: Import Exposure and Types of Self-Employment (by Age and Gender)

	(1) SE	(2) Solo SE	(3) SE with employees	(1) SE	(2) Solo SE	(3) SE with employees
	Panel A. Men			**Panel B. Women**		
Import Exposure	0.897**	0.577**	0.320*	−0.620	−0.679*	0.059
	(0.371)	(0.257)	(0.173)	(0.388)	(0.370)	(0.109)
First-stage F-stat	[29.23]	[29.23]	[29.23]	[35.25]	[35.25]	[35.25]
Sample Size	83,627	83,627	83,627	85,170	85,170	85,170
	Panel C. Young Men			**Panel D. Young Women**		
Import Exposure	0.766***	0.428	0.338*	−0.685	−0.783*	0.098
	(0.401)	(0.301)	(0.182)	(0.459)	(0.418)	(0.176)
First-stage F-stat	[26.20]	[26.20]	[26.20]	[31.42]	[31.42]	[31.42]
Sample Size	56,472	56,472	56,472	56,800	56,800	56,800
	Panel E. Old Men			**Panel F. Old Women**		
Import Exposure	1.018*	0.721*	0.296	−0.526	−0.508	−0.017
	(0.593)	(0.435)	(0.319)	(0.443)	(0.393)	(0.119)
First-stage F-stat	[35.32]	[35.32]	[35.32]	[40.95]	[40.95]	[40.95]
Sample Size	27,155	27,155	27,155	28,370	28,370	28,370

Notes: Table shows the effects of import exposure on whether or not individuals go into self-employment (SE), solo self-employment (solo SE) and self-employment with employees. See notes of Table 2.2 for a list of the controls and details on the IV. Panels (a) and (b) consider men and women, respectively. Panels (c)-(f) show results by different age and gender subsamples. Standard errors clustered at the three-digit industry level reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.8: Import Exposure and Economic (In)activity

	(1) Δ inactivity	(2) Δ retired	(3) Δ studying	(4) Δ at home	(5) Δ sickness	(6) Δ other
			Panel A. Young Men			
Import Exposure	0.405**	−0.036	−0.069	0.257**	0.111	0.143
	(0.206)	(0.121)	(0.073)	(0.112)	(0.167)	(0.102)
First-Stage F-stat	[26.20]	[26.20]	[26.20]	[26.20]	[26.20]	[26.20]
Observations	56,472	56,472	56,472	56,472	56,472	56,472
			Panel B. Old Men			
Import Exposure	−2.298**	−3.472***	−0.057	0.590**	0.079	0.562**
	(0.895)	(0.856)	(0.041)	(0.234)	(0.356)	(0.226)
First-Stage F-stat	[35.32]	[35.32]	[35.32]	[35.32]	[35.32]	[35.32]
Observations	27,155	27,155	27,155	27,155	27,155	27,155
			Panel C. Young Women			
Import Exposure	0.679	−0.059	0.085	0.319	−0.002	0.336
	(0.421)	(0.079)	(0.109)	(0.401)	(0.205)	(0.221)
First-Stage F-stat	[31.42]	[31.42]	[31.42]	[31.42]	[31.42]	[31.42]
Observations	56,800	56,800	56,800	56,800	56,800	56,800
			Panel D. Old Women			
Import Exposure	0.521	0.330	−0.127	0.447*	−0.052	−0.075
	(1.070)	(0.831)	(0.086)	(0.242)	(0.277)	(0.208)
First-Stage F-stat	[40.95]	[40.95]	[40.95]	[40.95]	[40.95]	[40.95]
Observations	28,370	28,370	28,370	28,370	28,370	28,370

Notes: Table reports the effect of import exposure on whether or not individuals are inactive in the labour force (column (1)). This is then decomposed into columns (2)-(6) based on the reason they are not participating: because they are retired (column (2)), studying (column (3)), looking after the home (column (4)), sick (column (5)), or for other reasons (column (6)). See notes of Table 2.2 for a list of the controls and details on the IV. Standard errors clustered at the three-digit industry level reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.9: Import Exposure and Labour Market Responses by Family Type

	(1) Δ manuf	(2) Δ unempl	(3) Δ empl	(4) Δ self-empl	(5) Δ active
	Panel A. Men in Stable Couples				
Import Exposure	-7.715^{***}	0.580^{***}	-0.697	1.298^{***}	1.182^{***}
	(2.153)	(0.236)	(0.657)	(0.395)	(0.402)
Mean Dep. Var.	-11.20	2.18	-28.69	10.20	-16.31
First-Stage F-stat	[30.98]	[30.98]	[30.98]	[30.98]	[30.98]
Observations	51,302	51,302	51,302	51,302	51,302
	Panel B. Single Men (in 2001 and 2011)				
Import Exposure	-7.837^{***}	1.439^{**}	-1.842^{*}	0.769	0.336
	(2.263)	(0.702)	(1.072)	(0.995)	(0.995)
Mean Dep. Var.	-8.03	5.60	-24.84	10.35	-8.89
First-Stage F-stat	[27.62]	[27.62]	[27.62]	[27.62]	[27.62]
Observations	17,578	17,578	17,578	17,578	17,578
	Panel C. Women in Stable Couples				
Import Exposure	-6.424^{***}	-0.251	-0.212	-0.646^{*}	-1.108
	(2.436)	(0.237)	(0.906)	(0.359)	(0.740)
Mean Dep. Var.	-5.21	1.46	-30.34	4.86	-24.02
First-Stage F-stat	[35.49]	[35.49]	[35.49]	[35.49]	[35.49]
Observations	49,767	49,767	49,767	49,767	49,767
	Panel D. Single Women (in 2001 and 2011)				
Import Exposure	-5.842^{**}	1.376^{*}	-0.164	0.063	1.275
	(2.199)	(0.785)	(1.064)	(0.655)	(0.878)
Mean Dep. Var.	-5.23	3.53	-20.68	4.71	-12.44
First-Stage F-stat	[29.92]	[29.92]	[29.92]	[29.92]	[29.92]
Observations	14,639	14,639	14,639	14,639	14,639

Notes: Table shows the effect of import exposure on individual labour market outcomes for men and women in stable couples (Panels A and C) and male and female singles (panels B and D). Stable couples refer to those who remain in the same relationship over the period 2001-2011. Single refers to those who never married and were without a partner in both 2001 and 2011. In addition to the controls described in the notes of Table 2.2, the regressions for those in stable couples control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.10: Import Exposure and Women's Labour Supply Responses by Age

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time
	Panel A. Partners of Men				
Import Exposure	−0.581	−0.764	−0.616	−0.149	−1.384
	(0.433)	(0.616)	(0.731)	(0.288)	(0.851)
Mean Dep. Var.	-6.91	-7.01	-9.20	2.19	3.51
First-Stage F-stat	[30.98]	[30.98]	[30.98]	[30.98]	[34.34]
Observations	51,302	51,302	51,302	51,302	30,773
	Panel B. Partners of Young Men				
Import Exposure	−0.457	−0.907	−0.613	−0.294	−0.683
	(0.565)	(0.553)	(0.608)	(0.479)	(0.951)
Mean Dep. Var.	4.85	4.55	1.17	3.38	2.82
First-Stage F-stat	[27.53]	[27.53]	[27.53]	[27.53]	[30.17]
Observations	30,277	30,277	30,277	30,277	20,556
	Panel C. Partners of Old Men				
Import Exposure	−1.018	−0.807	−0.777	−0.031	-3.012^{**}
	(1.239)	(1.336)	(1.172)	(0.561)	(1.555)
Mean Dep. Var.	-23.83	-23.67	-24.13	0.47	4.88
First-Stage F-stat	[36.55]	[36.55]	[36.55]	[36.55]	[47.29]
Observations	21,025	21,025	21,025	21,025	10,217

Notes: Table shows the effects of import exposure on the labour supply of men's female partners. Panels A (partners of all men), B (partners of young men), and C (partners of old men) report results for different sub-samples. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. Source is ONS Longitudinal Study.

Table B.11: Import Exposure and Men's Labour Supply Responses by Age

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time
	Panel A. Partners of Women				
Import Exposure	1.064***	1.249***	0.115	1.134***	1.227**
	(0.399)	(0.403)	(0.576)	(0.436)	(0.508)
Mean Dep. Var.	-14.42	-14.89	-16.86	1.96	6.99
First-Stage F-stat	[35.49]	[35.49]	[35.49]	[35.49]	[34.27]
Observations	49,767	49,767	49,767	49,767	37,018
	Panel B. Partners of Young Women				
Import Exposure	0.703**	1.092**	−0.173	1.265**	0.690
	(0.329)	(0.506)	(1.095)	(0.572)	(0.448)
Mean Dep. Var.	-2.57	-3.26	-8.33	5.07	3.72
First-Stage F-stat	[30.91]	[30.91]	[30.91]	[30.91]	[31.73]
Observations	30,289	30,289	30,289	30,289	26,997
	Panel C. Partners of Old Women				
Import Exposure	1.803**	1.627*	0.790	0.837	2.437**
	(0.811)	(0.848)	(1.090)	(0.785)	(1.178)
Mean Dep. Var.	-32.86	-32.98	-30.11	-2.86	15.84
First-Stage F-stat	[40.86]	[40.86]	[40.86]	[40.86]	[38.68]
Observations	19,478	19,478	19,478	19,478	10,021

Notes: Table shows the effects of import exposure on the labour supply of women's male partners. Panels A (partners of all women), B (partners of young women), and C (partners of old women) report results for different sub-samples. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.12: Import Exposure and Women's Labour Supply Responses.
By Presence of Children and Labour Market Status in 2001.

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time	(6) Sample Size [F-S F-stat]
Panel A. Presence of Children in 2001						
(A.1) those with at least one child	−0.148	−0.596	−0.118	−0.478	−2.154	28,012
	(0.514)	(0.562)	(0.641)	(0.361)	(1.365)	[33.57]
(A.1.1) youngest child aged 0-4	−0.484	−0.712	−0.180	−0.532	−2.932*	11,178
	(0.779)	(0.701)	(0.859)	(0.533)	(1.721)	[31.19]
(A.1.2) youngest child aged 5-10	−0.164	−0.336	1.437	−1.773*	−1.485	7,142
	(1.613)	(1.529)	(1.724)	(0.930)	(1.841)	[34.25]
(A.2) those without children	−1.097	−0.931	−1.076	0.145	0.123	23,290
	(0.922)	(1.056)	(1.151)	(0.446)	(1.763)	[27.89]
Panel B. Partners' (Women) Labour Status in 2001						
(B.1) women active in 2001	−0.463	−0.925	−0.530	−0.396	−1.384	40,429
	(0.739)	(0.713)	(0.844)	(0.359)	(0.851)	[33.33]
(B.2) women in work in 2001	−0.474	−0.787	−0.462	−0.325	−1.384	39,607
	(0.761)	(0.738)	(0.880)	(0.366)	(0.851)	[32.26]
(B.3) women part-time in 2001	−0.809	−0.978	0.279	−1.257**	−0.926	18,517
	(0.949)	(0.872)	(1.090)	(0.633)	(1.345)	[35.39]
(B.4) women full-time in 2001	−0.324	−0.735	−1.039	0.304	−0.821	21,090
	(0.801)	(0.842)	(1.302)	(0.702)	(1.142)	[29.24]

Notes: Table shows the effects of import exposure on the labour supply of men's female partners. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Source is ONS Longitudinal Study.

Table B.13: Import Exposure and Men's Labour Supply Responses.
By Presence of Children and Labour Market Status in 2001.

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time	(6) Sample Size [F-S F-stat]
Panel A. Presence of Children in 2001						
(A.1) those with at least one child	1.314***	1.300*	−0.105	1.405	1.404*	23,699
	(0.462)	(0.725)	(1.626)	(1.057)	(0.839)	[40.73]
(A.1.1) youngest child aged 0-4	0.841*	1.285*	1.417	−0.132	0.574	7,450
	(0.441)	(0.753)	(2.126)	(1.742)	(1.176)	[43.12]
(A.1.2) youngest child aged 5-10	1.661**	2.296**	−1.549	3.846**	1.871	6,371
	(0.781)	(0.996)	(1.658)	(1.768)	(1.190)	[34.07]
(A.2) those without a dependent child	0.831	1.209**	0.359	0.850	1.016*	26,070
	(0.516)	(0.477)	(0.953)	(0.902)	(0.544)	[29.94]
Panel B. Partners' (Men) Labour Status in 2001						
(B.1) men active in 2001	1.021***	1.358***	−0.023	1.381***	1.227**	46,543
	(0.391)	(0.394)	(0.613)	(0.489)	(0.508)	[34.30]
(B.2) men in work in 2001	0.913**	1.257***	−0.068	1.325**	1.227**	45,723
	(0.406)	(0.372)	(0.637)	(0.541)	(0.508)	[34.22]
(B.3) men part-time in 2001	−0.024	1.889	−6.353	8.242	5.865	2,117
	(1.973)	(2.101)	(5.276)	(5.160)	(3.721)	[35.87]
(B.4) men full-time in 2001	0.919**	1.201***	0.191	1.011	1.016**	43,606
	(0.422)	(0.357)	(0.706)	(0.615)	(0.457)	[33.54]

Notes: Table shows the effects of import exposure on the labour supply of women's male partners. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01. Source is ONS Longitudinal Study.

B.2 Placebo & Robustness Checks

Figure B.3: Placebo Exercise. Manufacturing Employment.

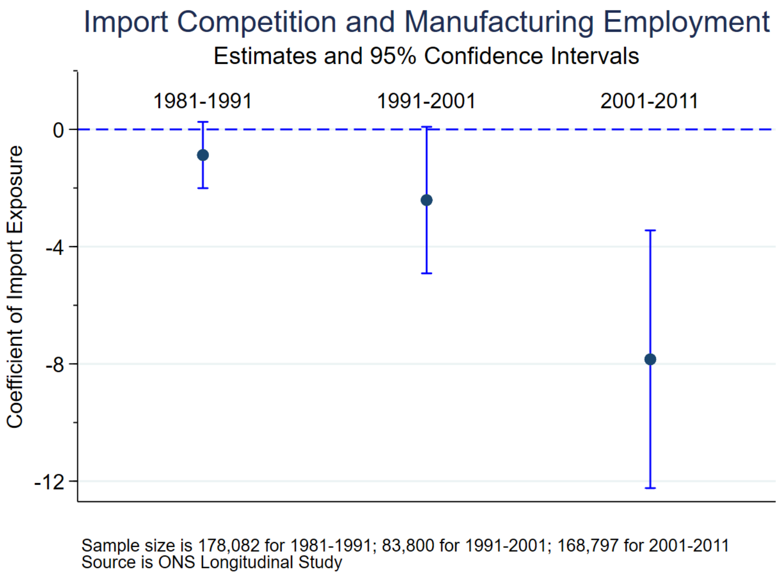


Figure B.4: Placebo Exercise. Unemployment.

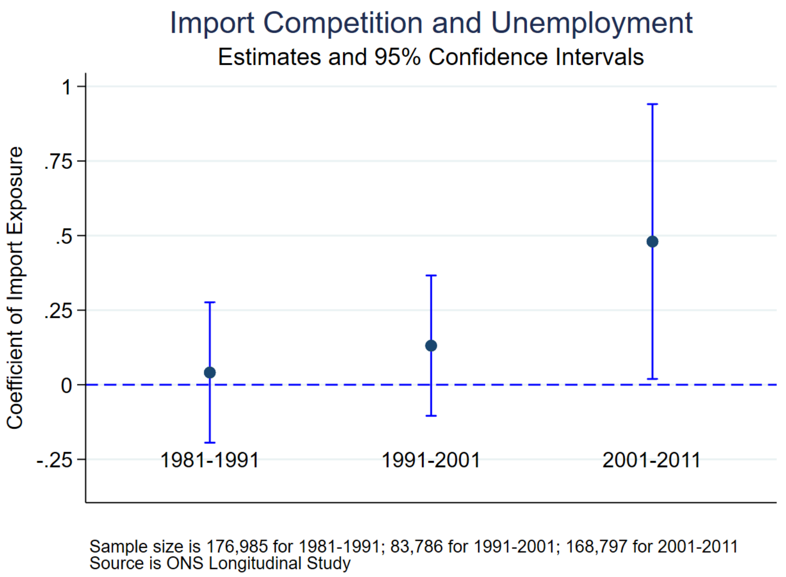


Table B.14: Placebo Exercise. 1981-1991.

	(1) Δ manuf	(2) Δ unempl	(3) Δ in work	(4) Δ active
	Panel A. All			
Import Exposure	−0.875	0.041	0.115	0.106
	(0.577)	(0.120)	(0.215)	(0.179)
First-Stage F-stat	[17.53]	[17.51]	[17.51]	[17.49]
Observations	178,082	176,985	176,985	178,066
	Panel B. Men			
Import Exposure	−0.526	−0.033	0.402	0.330*
	(0.659)	(0.155)	(0.245)	(0.192)
First-Stage F-stat	[24.12]	[23.92]	[23.92]	[24.00]
Observations	104,523	103,822	103,822	104,512
	Panel C. Women			
Import Exposure	0.176	0.153	0.216	0.294
	(0.449)	(0.126)	(0.292)	(0.297)
First-Stage F-stat	[12.68]	[12.76]	[12.76]	[12.68]
Observations	73,559	73,163	73,163	73,554

Notes: Table reports results of regressing changes in labour market outcomes between 1981-1991 in industries' future changes in import exposure (2001-2011). 'Being in work' cannot be decomposed between being in work as an employee and being self-employed in 1981. See notes of Table 2.2 for a list of the controls and details on the IV. Standard errors clustered at the three-digit industry level reported in parentheses. *p < 0.1. Source is ONS Longitudinal Study.

Table B.15: Placebo Exercise. 1991-2001.

	(1) Δ manuf	(2) Δ unempl	(3) Δ in work	(4) Δ empl	(5) Δ self-empl	(6) Δ active
			Panel A. All			
Import Exposure	-2.412^{*}	0.131	-0.391	-0.452	0.060	-0.261
	(1.275)	(0.120)	(0.298)	(0.406)	(0.225)	(0.289)
First-Stage F-stat	[76.98]	[76.98]	[76.98]	[76.98]	[76.98]	[76.98]
Observations	83,786	83,786	83,786	83,786	83,786	83,786
			Panel B. Men			
Import Exposure	-2.957^{*}	0.027	-0.035	-0.616	0.580	-0.008
	(1.730)	(0.203)	(0.354)	(0.594)	(0.505)	(0.371)
First-Stage F-stat	[83.54]	[83.54]	[83.54]	[83.54]	[83.54]	[83.54]
Observations	50,484	50,484	50,484	50,484	50,484	50,484
			Panel C. Women			
Import Exposure	-0.187	0.258	-0.598	-0.062	-0.536	-0.341
	(0.417)	(0.230)	(0.367)	(0.682)	(0.386)	(0.347)
First-Stage F-stat	[59.35]	[59.35]	[59.35]	[59.35]	[59.35]	[59.35]
Observations	33,302	33,302	33,302	33,302	33,302	33,302

Notes: Table reports results of regressing changes in labour market outcomes between 1991-2001 in industries' future changes in import exposure (2001-2011). See notes of Table 2.2 for a list of the controls and details on the IV. Standard errors clustered at the three-digit industry level reported in parentheses. $^{*}p < 0.1$. Source is ONS Longitudinal Study.

Table B.16: Summary of Main Robustness Checks. MEN.

	Panel A. Manufacturing Employment.			Panel B. Unemployment.		
	Men	Young Men	Old Men	Men	Young Men	Old Men
A. Excluding EU countries	−7.587***	−9.264***	−5.024**	0.830***	0.913**	0.721**
	(2.223)	(2.605)	(2.032)	(0.288)	(0.383)	(0.313)
B. Adding industry controls	−7.495***	−9.132***	−4.919**	0.816***	0.884**	0.714**
	(2.149)	(2.525)	(1.968)	(0.281)	(0.366)	(0.324)
C. Adding occupation controls	−7.424***	−8.952***	−5.056**	0.811***	0.885**	0.717**
	(2.186)	(2.517)	(2.086)	(0.273)	(0.356)	(0.315)
D. No occupation fixed effects	−7.591***	−9.134***	−5.138**	0.757***	0.892**	0.681**
	(2.295)	(2.632)	(2.184)	(0.262)	(0.337)	(0.316)
E. Trade with Eastern Europe	−6.433**	−8.272***	−3.524	0.738**	0.804*	0.627
	(2.575)	(2.804)	(2.607)	(0.350)	(0.456)	(0.383)
F. Export Exposure	−7.269***	−8.645***	−5.065**	0.769***	0.789**	0.748**
	(2.271)	(2.591)	(2.147)	(0.261)	(0.347)	(0.339)
	Panel C. Employment.			**Panel D. Self-Employment.**		
	Men	Young Men	Old Men	Men	Young Men	Old Men
A. Excluding EU countries	−1.179*	−2.138***	0.630	0.881**	0.744*	0.976
	(0.697)	(0.670)	(1.064)	(0.376)	(0.392)	(0.642)
B. Adding industry controls	−1.004	−1.842***	0.612	0.678*	0.526	0.826
	(0.676)	(0.663)	(1.024)	(0.379)	(0.385)	(0.583)
C. Adding occupation controls	−1.121*	−2.064***	0.607	0.881**	0.763*	0.964*
	(0.668)	(0.685)	(0.957)	(0.273)	(0.404)	(0.583)
D. No occupation fixed effects	−1.019	−1.820**	0.407	0.902**	0.698*	1.205*
	(0.717)	(0.779)	(1.005)	(0.416)	(0.414)	(0.666)
E. Trade with Eastern Europe	−1.312	−2.206**	0.237	1.389***	1.127**	1.809***
	(0.851)	(0.923)	(1.056)	(0.452)	(0.491)	(0.699)
F. Export Exposure	−1.059	−1.845***	0.444	0.800**	0.645	0.959
	(0.688)	(0.702)	(0.999)	(0.384)	(0.436)	(0.588)

Notes: Table summarises the robustness checks for our main results for men. Sample size is 83,627 for men; 56,472 for young men; and 27,155 for old men. See notes of Table 2.2 for a list of the controls and details on the IV. A excludes European Union countries when constructing eq. (2.3). B considers industry-specific controls, which are the intensity of R&D stock over capital, ICT stock intensity over capital, computer stock intensity over capital, and the intensity of net capital stock over industry output (measured in the year 1997 and at the two-digit SIC92 industry level). C considers occupation-specific controls, which are the Routine Task Intensity (RTI, Autor et al. (2003)) and the offshorability index (measured in the year 2001 and at the four-digit SOC2000 occupation categories). D does not include occupation fixed effects. E accounts for import competition with Eastern Europe. F accounts for export exposure. Standard errors clustered at the three-digit industry level are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.17: Summary of Main Robustness Checks. WOMEN.

	Panel A. Manufacturing Employment.			Panel B. Unemployment.		
	Women	Young Women	Old Women	Women	Young Women	Old Women
A. Excluding EU countries	−5.830**	−6.483***	−4.519*	0.110	0.365	−0.376*
	(2.315)	(2.340)	(2.670)	(0.332)	(0.463)	(0.223)
B. Adding industry controls	−5.823***	−6.319***	−4.768*	0.056	0.331	−0.475**
	(2.246)	(2.215)	(2.640)	(0.309)	(0.439)	(0.203)
C. Adding occupation controls	−5.823**	−6.283***	−4.879*	0.048	0.315	−0.453**
	(2.314)	(2.275)	(2.728)	(0.312)	(0.441)	(0.200)
D. No occupation fixed effects	−5.865**	−6.262***	−5.013*	0.106	0.384	−0.398**
	(2.545)	(2.395)	(2.917)	(0.301)	(0.437)	(0.197)
E. Trade with Eastern Europe	−5.943**	−6.591***	−4.760	0.034	0.318	−0.457**
	(2.427)	(2.328)	(2.905)	(0.263)	(0.382)	(0.181)
F. Export Exposure	−5.748**	−6.098**	−4.980*	0.071	0.333	−0.415**
	(2.405)	(2.391)	(2.780)	(0.309)	(0.442)	(0.204)

	Panel C. Employment.			Panel D. Self-Employment.		
	Women	Young Women	Old Women	Women	Young Women	Old Women
A. Excluding EU countries	−0.073	−0.460	0.834	−0.615	0.642	−0.583
	(0.751)	(0.654)	(1.304)	(0.379)	(0.461)	(0.458)
B. Adding industry controls	0.011	−0.099	0.370	−0.724*	−0.813*	−0.583
	(0.717)	(0.583)	(1.262)	(0.386)	(0.460)	(0.441)
C. Adding occupation controls	−0.097	−0.301	0.470	−0.627	−0.687	−0.542
	(0.716)	(0.596)	(1.232)	(0.390)	(0.461)	(0.439)
D. No occupation fixed effects	−0.165	−0.296	0.132	−0.809*	−0.886*	−0.657
	(0.747)	(0.628)	(1.277)	(0.435)	(0.502)	(0.488)
E. Trade with Eastern Europe	−0.358	−0.425	0.051	−0.395	−0.451	−0.330
	(0.713)	(0.604)	(1.134)	(0.339)	(0.404)	(0.377)
F. Export Exposure	−0.114	−0.171	0.247	−0.696*	−0.827*	−0.513
	(0.729)	(0.604)	(1.219)	(0.400)	(0.457)	(0.444)

Notes: Table summarises the robustness checks for our main results for women. See notes of Table 2.2 for a list of the controls and details on the IV. Sample size is 85,170 for women; 56,800 for young women; and 28,370 for old women. See notes in Table B.16 for details of different specifications. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.18: Robustness Sample. Partner Not Exposed to Import Competition. Import Exposure and Women's Labour Supply Responses (I)

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time
	Panel A. Men				
Import Exposure	−0.009	−0.213	0.266	−0.478	−1.335
	(0.775)	(0.689)	(0.838)	(0.412)	(0.817)
First-Stage F-stat	[31.99]	[31.99]	[31.99]	[31.99]	[33.53]
Observations	36,515	36,515	36,515	36,515	28,398
	Panel B. Young Men				
Import Exposure	−0.240	−0.692	−0.137	−0.555	−1.049
	(0.472)	(0.516)	(0.687)	(0.648)	(1.123)
First-Stage F-stat	[28.37]	[28.37]	[28.37]	[28.37]	[29.07]
Observations	21,459	21,459	21,459	21,459	18,942
	Panel C. Old Men				
Import Exposure	0.135	0.353	0.805	−0.218	−2.018
	(1.691)	(1.620)	(1.439)	(0.330)	(1.523)
First-Stage F-stat	[38.69]	[38.69]	[38.69]	[38.69]	[47.65]
Observations	15,056	15,056	15,056	15,056	9,456

Notes: Table shows the effects of import exposure on the labour supply of men's female partners. Sample is those with partners that are working but in industries not exposed to import competition. Standard errors clustered at the three-digit industry level reported in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.19: Robustness Sample. Partner Not Exposed to Import Competition. Import Exposure and Women's Labour Supply Responses (II)

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time	(6) Sample Size [F-S F-stat]
Panel A. Presence of Children in 2001						
(A.1) those with at least one dependent child	−0.132	−0.382	0.657	−1.039	−2.025	18,985
	(0.598)	(0.665)	(0.733)	(0.583)	(1.382)	[35.65]
(A.1.1) dependent child aged 0-4	−0.511	−1.324	0.368	−1.692*	−3.063	6,270
	(0.795)	(0.845)	(1.095)	(0.922)	(2.045)	[42.60]
(A.1.2) dependent child aged 5-10	0.482	0.970	3.272**	−2.302	−0.530	5,205
	(1.454)	(1.571)	(1.436)	(1.445)	(1.973)	[31.66]
(A.2) those without a dependent child	0.185	−0.019	−0.136	0.116	0.196	17,530
	(1.395)	(1.264)	(1.477)	(0.522)	(1.765)	[28.65]
Panel B. Partners' Labour Status in 2001						
(B.1) partner in work in 2001	−0.009	−0.213	0.266	−0.478	−1.335	36,515
	(0.775)	(0.689)	(0.838)	(0.412)	(0.817)	[31.99]
(B.2) partner part-time in 2001	−0.813	−0.926	0.556	−1.482**	−0.875	17,657
	(0.953)	(0.883)	(1.102)	(0.673)	(1.616)	[33.83]
(B.3) partner full-time in 2001	0.639	0.366	−0.048	0.413	−1.001	18,858
	(0.904)	(0.821)	(1.430)	(0.876)	(1.111)	[29.29]

Notes: Table shows the effects of import exposure on the labour supply of men's female partners. Sample is those with partners that are working but in industries not exposed to import competition. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

Table B.20: Robustness Sample. Partner Not Exposed to Import Competition. Import Exposure and Men's Labour Supply Responses (I)

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time
	Panel A. Women				
Import Exposure	0.943***	1.269***	0.468	0.802	1.340***
	(0.456)	(0.495)	(0.733)	(0.614)	(0.399)
First-Stage F-stat	[31.38]	[31.38]	[31.38]	[31.38]	[31.50]
Observations	37,221	37,221	37,221	37,221	30,159
	Panel B. Young Women				
Import Exposure	0.398	0.863	−0.191	1.054	1.000*
	(0.488)	(0.549)	(1.258)	(0.995)	(0.546)
First-Stage F-stat	[25.97]	[25.97]	[25.97]	[25.97]	[27.53]
Observations	23,554	23,554	23,554	23,554	22,018
	Panel C. Old Women				
Import Exposure	2.441*	2.476*	2.162*	0.314	2.216**
	(1.343)	(1.387)	(1.306)	(0.814)	(0.970)
First-Stage F-stat	[39.75]	[39.75]	[39.75]	[39.75]	[39.33]
Observations	13,667	13,667	13,667	13,667	8,141

Notes: Table shows the effects of import exposure on the labour supply of women's male partners. Sample is those with partners that are working but in industries not exposed to import competition. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Source is ONS Longitudinal Study.

Table B.21: Robustness Sample. Partner Not Exposed to Import Competition. Import Exposure and Men's Labour Supply Responses (II)

	(1) Δ partner active	(2) Δ partner in work	(3) Δ partner employed	(4) Δ partner self-empl	(5) Δ partner full-time	(6) Sample Size [F-S F-stat]
Panel A. Presence of Children in 2001						
(A.1) those with at least one dependent child	1.577***	0.893	0.009	0.884	1.610*	18,194
	(0.461)	(0.929)	(1.993)	(1.433)	(0.961)	[42.12]
(A.1.1) dependent child aged 0-4	1.312**	1.621**	2.523	−0.902	1.496	5,807
	(0.528)	(0.704)	(2.329)	(2.103)	(1.553)	[41.40]
(A.1.2) dependent child aged 5-10	2.631***	2.603*	−1.373	3.975	0.687	4,868
	(0.982)	(1.362)	(2.841)	(2.722)	(2.648)	[37.97]
(A.2) those without a dependent child	0.492	1.594**	1.010	0.584	1.149	19,027
	(0.734)	(0.694)	(1.136)	(1.058)	(0.702)	[24.29]
Panel B. Partners' Labour Status in 2001						
(B.1) partner in work in 2001	0.943**	1.269**	0.468	0.802	1.340**	37,221
	(0.456)	(0.495)	(0.733)	(0.614)	(0.399)	[31.38]
(B.2) partner part-time in 2001	−1.437	1.677	0.113	1.565	13.84**	1,882
	(2.630)	(3.012)	(6.436)	(5.768)	(6.943)	[39.71]
(B.3) partner full-time in 2001	0.930**	1.165**	0.446	0.719	1.119***	35,339
	(0.456)	(0.462)	(0.713)	(0.680)	(0.410)	[31.17]

Notes: Table shows the effects of import exposure on the labour supply of women's male partners. Sample is those with partners that are working but in industries not exposed to import competition. In addition to the controls described in the notes of Table 2.2, all regressions control for partner characteristics: partners' age, occupation, and one-digit industry fixed effects. Standard errors clustered at the three-digit industry level reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source is ONS Longitudinal Study.

APPENDIX

C

Appendix to Chapter 3

C.1 Theory Appendix

This section further develops the model introduced in Chapter 3, integrating additional aspects for a more comprehensive analysis. We begin by presenting formal derivations of the main remarks and a deeper exploration of their underlying intuition. We then enhance the model by considering occupational labour demand and characterising the equilibrium.

C.1.1 Derivation of Formal Results: The Elasticity Matrix

We start by formally deriving Remarks 1-3.

C.1.1.1 Remark 1 (Elasticities and Job Flows)

We define the inverse 'choice index' as $\lambda_i(\mathbf{p}) = \frac{1}{\sum_{k=1}^{N}\exp(\theta_i p_k + a_{ik})}$, where $\mathbf{p}$ represents the vector of log occupational prices (for simplicity, 'prices'). The fraction of individuals working in occupation j as a function of prices, denoted by $E_j(\mathbf{p})$ and presented in eq. (3.3), can then be expressed as follows:

$$E_j(\mathbf{p}) = \sum_i \tau_i \lambda_i(\mathbf{p}) \exp\left(\theta_i p_j + a_{ij}\right)$$

Recall that our interest centers on (own- and cross-occupation) price elasticities: the response of employment in occupation j to occupation k's price change. We formally write this as follows:

$$\frac{\partial E_j(\mathbf{p})}{\partial p_k} = \sum_i \tau_i \left(\lambda_i(\mathbf{p}) \frac{\partial \exp\left(\theta_i p_j + a_{ij}\right)}{\partial p_k} + \frac{\partial \lambda_i(\mathbf{p})}{\partial p_k} \exp\left(\theta_i p_j + a_{ij}\right) \right)$$

Differentiating the second element in the brackets, $\frac{\partial \lambda_i(\mathbf{p})}{\partial p_k}$, gives:

$$\begin{aligned}
\frac{\partial \lambda_i(\mathbf{p})}{\partial p_k} &= -\frac{\theta_i \exp(\theta_i p_k + a_{ik})}{(\sum_s \exp(\theta_i p_s + a_{is}))^2} \\
&= -\theta_i \frac{1}{\sum_s \exp(\theta_i p_s + a_{is})} \frac{\exp(\theta_i p_k + a_{ik})}{\sum_s \exp(\theta_i p_s + a_{is})} \\
&= -\theta_i \lambda_i(\mathbf{p}) \pi_{ik}(\mathbf{p})
\end{aligned}$$

By combining the results obtained thus far, and using the accounting identity presented in eq. (3.3), we derive the following expression:

$$\frac{\partial E_j(\mathbf{p})}{\partial p_k} = \begin{cases} \sum_i \tau_i \theta_i \left(\pi_{ij}(\mathbf{p})\left(1 - \pi_{ij}(\mathbf{p})\right)\right) & \text{if } j = k \\ -\sum_i \tau_i \theta_i \left(\pi_{ij}(\mathbf{p}) \pi_{ik}(\mathbf{p})\right) & \text{otherwise} \end{cases}$$

Finally, assuming $\theta_i = \theta$ and writing $e_j \equiv \ln E_j(\mathbf{p})$, we obtain:

$$\begin{aligned}
\frac{\partial e_j(\mathbf{p})}{\partial p_k} &= \frac{1}{E_j(\mathbf{p})} \frac{\partial E_j(\mathbf{p})}{\partial p_k} \\
&= \begin{cases} \frac{\sum_i \tau_i \theta(\pi_{ij}(\mathbf{p})(1-\pi_{ij}(\mathbf{p})))}{\sum_i \tau_i \pi_{ij}(\mathbf{p})} & \text{if } j = k \\ \frac{-\sum_i \tau_i \theta(\pi_{ij}(\mathbf{p}) \pi_{ik}(\mathbf{p}))}{\sum_i \tau_i \pi_{ij}(\mathbf{p})} & \text{otherwise} \end{cases}
\end{aligned}$$

This is eq. (3.4) in Section 3.1. It shows the short-term partial derivative of occupation j's log employment share with respect to k's log price can be computed using transition probabilities, and a pecuniary parameter θ. We next discuss alternative formulations of the price elasticities in terms of moments of job flows.

C.1.1.2 Remark 2 (Individual Cross-Price Elasticities)

We have described the off-diagonal elements of the elasticity matrix D as:

$$d_{jk} = -\frac{1}{\tau_j}\sum_i \tau_i \pi_{ij}\pi_{ik}$$

where π_{ij}, π_{ik} are elements of the transition matrix and τ_i is the ith element of the associated stationary vector. To interpret this further, consider the weighted covariance between columns of the normalised transition matrix:

$$\begin{aligned}
Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right) &\equiv \sum_i \tau_i\left(\tilde{\pi}_{ij} - \mathbb{E}_{\tau_i}\tilde{\pi}_{.,j}\right)\left(\tilde{\pi}_{ik} - \mathbb{E}_{\tau_i}\tilde{\pi}_{.,k}\right) \\
&= \sum_i \tau_i\left(\tilde{\pi}_{ij} - 1\right)(\tilde{\pi}_{ik} - 1)
\end{aligned}$$

where

$$\tilde{\pi}_{iq} \equiv \frac{\pi_{iq}}{\tau_q}$$

and the second line follows from the first because $\sum_i \tau_i \tilde{\pi}_{iq} = \frac{1}{\tau_q}\sum_i \tau_i \pi_{iq} = \frac{\tau_q}{\tau_q} = 1$. Expanding this further:

$$\begin{aligned}
Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right) &= \sum_i \tau_i\left(\tilde{\pi}_{ij} - 1\right)(\tilde{\pi}_{ik} - 1) \\
&= \sum_i \tau_i\tilde{\pi}_{ij}\tilde{\pi}_{ik} - \sum_i \tau_i\tilde{\pi}_{ij} - \sum_i \tau_i\tilde{\pi}_{ik} + \sum_i \tau_i \\
&= \frac{1}{\tau_j\tau_k}\sum_i \tau_i\pi_{ij}\pi_{ik} - 1 - 1 + 1 \\
&= -\frac{1}{\tau_k}d_{jk} - 1
\end{aligned}$$

Rearranging gives eq. (3.6).

C.1.1.3 Remark 3 (Individual Own-Price Elasticities)

Turning to the on-diagonal elements of the elasticity matrix D. These are:

$$d_{jj} = \frac{1}{\tau_j}\sum_i \tau_i\pi_{ij}\left(1 - \pi_{ij}\right)$$

Similarly to the above, we can express this in terms of the variance of normalised transition probabilities:

$$
\begin{aligned}
d_{jj} &= \frac{1}{\tau_j}\sum_i \tau_i \pi_{ij} - \frac{1}{\tau_j}\sum_i \tau_i \pi_{ij}^2 \\
&= 1 - \frac{1}{\tau_j}\left(Var_{\tau_i}\left(\pi_{.,j}\right) + \left(\mathbb{E}_{\tau_i}\pi_{.j}\right)^2\right) \\
&= 1 - \frac{1}{\tau_j}\left(Var_{\tau_i}\left(\pi_{.,j}\right) + \tau_j^2\right) \\
&= 1 - \tau_j\left(1 + \frac{1}{\tau_j^2} Var_{\tau_i}\left(\pi_{.,j}\right)\right) \\
&= 1 - \tau_j\left(1 + \frac{1}{\tau_j} Var_{\tau_i}\left(\breve{\pi}_{.,j}\right)\right) \qquad \text{(C.1)}
\end{aligned}
$$

Rearranging gives expression (3.7).

C.1.1.4 Further Discussion on Remarks 1-3

We turn now to justifying our choices of normalisations. We first consider that $Cov_{\tau_i}\left(\tilde{\pi}_{.,j}, \tilde{\pi}_{.,k}\right) \equiv \sum_i \tau_i \left(\tilde{\pi}_{ij} - \mathbb{E}_{\tau_i}\tilde{\pi}_{.,j}\right)\left(\tilde{\pi}_{ik} - \mathbb{E}_{\tau_i}\tilde{\pi}_{.,k}\right)$. Because $\mathbb{E}_{\tau_i}\tilde{\pi}_{.,j} = \mathbb{E}_{\tau_i}\tilde{\pi}_{.,k} = 1$, we argue this term is invariant to occupation size. To show this empirically, we compute this term for occupational classifications at various levels of coarseness (i.e. 4 main occupation groups, 10 occupation groups, 120 occupations), see Table C.1 below.

We now consider the variance terms. We can also write d_{jj} as follows

$$
\begin{aligned}
d_{jj} &= -\sum_{k \neq j} d_{jk} \\
&= \sum_{k \neq j} \tau_k \left(1 + Cov_{\tau_i}\left(\tilde{\pi}_{.,j}, \tilde{\pi}_{.,k}\right)\right) \\
&= \sum_{k \neq j} \tau_k + \sum_{k \neq j} \tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j}, \tilde{\pi}_{.,k}\right) \\
&= 1 - \tau_j + \sum_{k \neq j} \tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j}, \tilde{\pi}_{.,k}\right) \qquad \text{(C.2)}
\end{aligned}
$$

Equating eq. (C.1)) and eq. (C.2)), we see that

$$
\begin{aligned}
Var_{\tau_i}\left(\tilde{\pi}_{.,j}\right) &= -\frac{1}{\tau_j}\sum_{k \neq j} \tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j}, \tilde{\pi}_{.,k}\right) \\
\implies Var_{\tau_i}\left(\breve{\pi}_{.,j}\right) &= -\sum_{k \neq j} \tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j}, \tilde{\pi}_{.,k}\right)
\end{aligned}
$$

These expressions show two things. First of all, because $Var_{\tau_i}\left(\tilde{\pi}_{.,j}\right)$ is necessarily greater than zero, then $Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right)$ is below zero on average.[1] Second, if $Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right)$ is of order $\mathcal{O}(1)$, then $\frac{1}{\tau_j}\sum_{k\neq j}\tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right)$ is of order $\mathcal{O}(N)$. In contrast, $Var_{\tau_i}\left(\tilde{\pi}_{.,j}\right) = -\sum_{k\neq j}\tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right)$ is a weighted average of the covariance terms, and so is of order $\mathcal{O}(1)$. To show this empirically, we compute this term for occupational classifications at various levels of coarseness. In particular, Table C.1 reports the median for the covariance, and two measures of the variance. It shows this for three levels of occupational aggregation: 4 main occupation groups as described below in the data appendix section, 10 occupation groups corresponding to one-digit occupation categories, and the 120 occupations considered in the analysis (see Table C.4 for the full list).

Table C.1: Median Values of Model Components Across Occupation Pairs

# Occs	$Cov(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k})$	$Var(\tilde{\pi}_{.,j})$	$\tau_j Var(\tilde{\pi}_{.,j})$
4	-0.76	2.20	0.54
10	-0.75	5.48	0.58
120	-0.78	126.91	0.57

Vector of Price Changes

We make this intuition more rigorous by expressing the price elasticities in terms of distributions of worker flows. At the same time, we complete the interpretation of eq. (3.6)) and eq. (3.7)) in Remark 2.

Remark 4 (Vector of Price Changes). *Matrix D can be expressed as follows*

$$D = I - W - W \otimes C$$

where I is the identity matrix, W is the matrix of stationary employment shares with j,k-th element τ_k, $\otimes$ is the element-by-element product, and C is the symmetric matrix with j,k-th element $c_{jk} = Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right)$, which captures the 'occupational-similarity' between occupations j and k.

[1]This also shows that $\sum_k \tau_k Cov_{\tau_i}\left(\tilde{\pi}_{.,j},\tilde{\pi}_{.,k}\right) = 0$.

Accordingly, following a vector of price changes $\Delta\mathbf{p}$*, then the change in the employment share in occupation* j *is given by*

$$
\begin{aligned}
\Delta e_j &\approx \theta \mathbf{d_j} \Delta \mathbf{p} \\
&= \theta \left(\underbrace{\Delta p_j - \Delta \mathbb{E}_{\tau_i} p}_{\substack{\textit{real price} \\ \textit{change}}} + \underbrace{Cov_{\tau_i}\left(c_{.,j}, \Delta p_j - \Delta p_{.}\right)}_{\substack{\textit{occupational} \\ \textit{substitutability}}} \right) && \text{(C.3)} \\
&= \theta \left(\underbrace{\left(1 - \tau_j - \tau_j c_{jj}\right) \Delta p_j}_{\substack{\textit{own-price} \\ \textit{effect}}} + \underbrace{\sum_{k \neq j} \left(-\tau_k - \tau_k c_{jk}\right) \Delta p_{k.}}_{\substack{\textit{total cross-} \\ \textit{-price effect}}} \right) && \text{(C.4)}
\end{aligned}
$$

where $\mathbb{E}_{\tau_i} p$ *is the (weighted) average of prices across occupations and we drop a time subscript for ease of notation. Similarly* $Cov_{\tau_i}\left(c_{.,j}, \Delta p_j - \Delta p_{.}\right)$ *captures the (weighted) covariance between the* j*-th column of* C*,* $c_{.,j}$*, and the vector of relative price changes* $\Delta p_j - \Delta p_{.}$ *across occupations.*

Remark 4 complements the interpretation contained in Remark 2 above. In the formulation in eq. (C.3), the effect of a vector of price changes on a given occupation consists of two components. First is the direct effect of real price changes in that occupation itself, net of the change in the economy-wide price index. This term aggregates the 'direct' and 'price index' terms contained in eq. (3.6) and eq. (3.7). Second is the total effect of occupational substitutabilities: Employment growth is larger if price growth is higher relative to more similar occupations. In fact, empirically, price changes are positively correlated across similar occupations, and so this last component tends to attenuate the direct effect of price changes. To see this, consider, for example, price growth in occupations high in analytical tasks. Price growth in these sectors has been highest relative to routine occupations, which saw the largest declines, but are also dissimilar in terms of occupational flows. Therefore, for these analytical occupations, this last term is likely negative, offsetting the positive effect from the first two terms.

Equation (C.4) then builds on this formulation by relating it back to eq. (3.9), which forms the basis of our empirical application. Equation (C.4) therefore expresses the effect of a vector of price changes in terms of two components which we can easily take to data, and which can be interpreted in terms of the joint distribution of these price changes with steady-state job flows.

The expression $D = I - W - W \otimes C$ follows directly from Remark 2. The diagonal element c_{jj} of C is $Var_{\tau_i}\left(\tilde{\pi}_{.,j}\right) = \frac{1}{\tau_j} Var_{\tau_i}\left(\breve{\pi}_{.,j}\right)$. We therefore have that

$$\begin{aligned}
\Delta e_j &= \theta d_{j,.} \Delta \mathbf{p} \\
&= \theta \sum_k \left(i_{jk} - \tau_k - \tau_k c_{jk}\right) \Delta p_k \\
&= \theta \left(\sum_k i_{jk} \Delta p_k - \sum_k \tau_k \Delta p_k - \sum_k \tau_k c_{jk} \Delta p_k \right) \\
&= \theta \left(\Delta p_j - \Delta \mathbb{E}_{\tau_i} p - \sum_k \tau_k c_{jk} \left(\Delta p_k - \Delta p_j\right) \right) \\
&= \theta \left(\Delta p_j - \Delta \mathbb{E}_{\tau_i} p + Cov_{\tau_i}\left(c_{.,j}, \Delta p_j - \Delta p_.\right)\right)
\end{aligned}$$

as given in the text. The fourth line follows from the third because $\sum_k \tau_j c_{jk} = 0 \implies \sum_k \tau_j c_{jk} \Delta p_j = 0$. The final line follows from the fourth because similarly $\mathbb{E}_{\tau_i} c_{.,j} = 0$ and column vector $c_{.,j} = c_{j,.}$ because C is symmetric.

C.1.2 Labour Demand, Equilibrium, and Estimation Strategy

This section extends the model by incorporating occupational labour demand. In what follows, we present the main features of the demand and supply sides, characterise equilibrium, and discuss its practical implementation.

C.1.2.1 Labour Demand

We consider an economy-wide constant elasticity of substitution (CES) production technology

$$Y = A \left(\sum_i \beta_i E_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad \text{s.t.} \ \sum \beta_i = 1$$

where i is for occupation, E for employment, β_i are the factor intensities of different occupation inputs and $\sigma > 0$ is the elasticity of substitution across occupations.

The first order conditions yield, for all i,

$$\beta_i E_i^{\frac{-1}{\sigma}} A \left(\sum_i \beta_i E_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}-1} = \mathfrak{p}_i$$

To begin, consider demands relative to occupation N:

$$\begin{aligned} \tilde{E}_i \quad \equiv \ln \tfrac{E_i}{E_N} \quad &= \ln \left(\frac{\beta_i}{\beta_N} \frac{\mathfrak{p}_N}{\mathfrak{p}_i} \right)^{\sigma} \\ &= \ln \left(\beta_{-i} \frac{\beta_i}{1-\beta_i} \frac{1}{\tilde{\mathfrak{p}}_i} \right)^{\sigma} \end{aligned}$$

where $\tilde{\mathfrak{p}}_i \equiv \frac{\mathfrak{p}_i}{\mathfrak{p}_N}$ and $\beta_{-i} \equiv \frac{1-\beta_i}{\beta_N} = \frac{\sum_{j \neq i} \beta_j}{\beta_N}$. In what follows, we will consider incremental changes to $\ln \frac{\beta_j}{1-\beta_j}$ with proportionate off-setting changes to β_k for $k \neq j$.

It is worth noting that $\frac{d \ln \frac{\beta_i}{\beta_N}}{d \ln \frac{\beta_i}{1-\beta_i}} = \frac{d \ln \beta_{-i} \frac{\beta_i}{1-\beta_i}}{d \ln \frac{\beta_i}{1-\beta_i}} = 1$. On the other hand, $\frac{d \ln \frac{\beta_i}{\beta_N}}{d \ln \frac{\beta_j}{1-\beta_j}} = 0$ because proportional changes to β_i and β_N are equal and offsetting.

In more compact notation, we can therefore write

$$\tilde{E}_i^d \left(\tilde{p}_i (\mathbf{b}, \mathbf{s}), \tilde{\beta}_i \right) = \ln \left(\tilde{\beta}_i \frac{1}{\tilde{\mathfrak{p}}_i} \right)^{\sigma} \tag{C.5}$$

where $\mathbf{b}$ is the $(N-1)$ vector of relative productivities, $\mathbf{s}$ is a vector of supply shifters that do not directly affect demand, and $\tilde{\beta}_i = \frac{\beta_i}{\beta_N}$. Note that relative demand for employment in occupation i depends on the relative price in that occupation *only*.

In fact, we are interested in log employment shares $e_i = \ln \frac{E_i}{\sum_j E_j} = \ln \frac{E_i}{\bar{E}}$. In this case, demands depend on productivities and prices of other occupations. We will be interested in perturbations around the steady state, so in keeping with the rest of Chapter 3, we will denote steady-state share of occupation i by τ_i. This gives a demand curve $e_i^d \left(\langle \tilde{p} (\mathbf{b}, \mathbf{s}) \rangle, \mathbf{b} \right)$, which is a function of all prices and demand shifters.

To calculate derivatives, first note that, around the steady state:

$$\frac{\partial e_j^d}{\partial p_i} |_{p_{k \neq i}} = - \frac{\tau_i}{1-\tau_i} \frac{\partial e_i^d}{\partial p_i} |_{p_{k \neq i}}$$

i.e. given a change to p_i, and holding fixed all other prices (made explicit by the notation $|_{p_{k\neq i}}$), then adding up ensures this identity, because all other sectors are equally proportionately offset.[2] Therefore, we have that:

$$\begin{aligned}
\frac{\partial e_i^d}{\partial p_i} &= \frac{\partial \ln \frac{E_i}{E_N}}{\partial p_i} + \frac{\partial \ln \frac{E_N}{\bar{E}}}{\partial p_i} \\
&= \frac{\partial \ln \frac{E_i}{E_N}}{\partial p_i} + \frac{\partial e_N^d}{\partial p_i} \\
&= -\sigma - \frac{\tau_i}{1-\tau_i}\frac{\partial e_i^d}{\partial p_i} \\
\implies \frac{\partial e_i^d}{\partial p_i} &= -(1-\tau_i)\sigma
\end{aligned}$$

This also implies that for $j \neq i$:

$$\begin{aligned}
\frac{\partial e_i^d}{\partial p_j} &= -\frac{\tau_j}{1-\tau_j}\frac{\partial e_j^d}{\partial p_j} \\
&= \tau_j \sigma
\end{aligned}$$

A similar logic implies that $\frac{\partial e_i^d}{\partial \ln \frac{\beta_j}{1-\beta_j}}$ follows a similar structure.

We therefore have a demand function $e_i^d(\langle p(\mathbf{b},\mathbf{s})\rangle, \mathbf{b})$ with partial derivatives for prices given by elements of the matrix $\sigma(W-I)$, with rank $N-1$, where I is the identity matrix, and W is the matrix of employment shares, as defined in Appendix C.1.1.4. The matrix of derivatives with respect to demand shifters is given by $\sigma(I-W)$, equally of rank $N-1$.

C.1.2.2 Labour Supply

As extensively discussed in Section 3.1, we have that $\frac{\partial e_j^s}{\partial p_k} = \theta d_{jk}$. The matrix of supply derivatives is therefore given by θD, similarly of rank $N-1$.

[2]Note that adding up requires $\sum_k \frac{\partial e_k^d}{\partial p_i} E_k = 0$, which implies $\frac{\partial e_i^d}{\partial p_i} E_i + \sum_{k\neq i} \frac{\partial e_k^d}{\partial p_i} E_k = 0$. Noting that a property of CES demands given by eq. (C.5) are that $\frac{\partial e_k^d}{\partial p_i} = \frac{\partial e_l^d}{\partial p_i} \equiv \frac{\partial e_{-i}^d}{\partial p_i}$ for $k,l \neq i$, then we have that $\frac{\partial e_i^d}{\partial p_i} E_i + \frac{\partial e_{-i}^d}{\partial p_i} \sum_{k\neq i} E_k = 0 \implies \frac{\partial e_i^d}{\partial p_i} e_i + \frac{\partial e_{-i}^d}{\partial p_i} \sum_{k\neq i} e_k = 0$. Rearranging and using τ_i give the result.

C.1.2.3 Equilibrium Characterisation

Similarly to before, we can write

$$e_i(\mathbf{b},\mathbf{s}) = e_i^s(\langle p(\mathbf{b},\mathbf{s})\rangle,\mathbf{s}) = e_i^d(\langle p(\mathbf{b},\mathbf{s})\rangle,\mathbf{b}) \tag{C.6}$$

where both supply and demand curves depend on the full system of prices.

In what follows, for ease of exposition, we define the following matrices for gradients of equilibrium quantities $\{E_j\}$ and prices $\{p_j\}$.

Notation	Typical element
Ξ	$\frac{de_i}{d\left(\ln\frac{\beta_j}{1-\beta_j}\right)}$
Γ	$\frac{de_i}{ds_j}$
V	$\frac{dp_i}{d\left(\ln\frac{\beta_j}{1-\beta_j}\right)}$
S	$\frac{dp_i}{ds_j}$

Solving for Price Gradients using $e_i^s() = e_i^d()$

Differentiating $e_i^s() = e_i^d()$ from eq. (C.6) with respect to $\ln\frac{\beta_j}{1-\beta_j}$ we obtain:

$$\sum_k \frac{\partial e_i^s}{\partial p_k}\frac{\partial p_k}{\partial\left(\ln\frac{\beta_j}{1-\beta_j}\right)} = \sum_k \frac{\partial e_i^d}{\partial p_k}\frac{\partial p_k}{\partial\left(\ln\frac{\beta_j}{1-\beta_j}\right)} + \frac{\partial e_i^d}{\partial \ln\frac{\beta_j}{1-\beta_j}} \tag{C.7}$$

Expressing this in matrix notation gives

$$\begin{aligned} \theta DV &= \sigma(W-I)V + \sigma(I-W) \\ \implies (\theta D + \sigma(I-W))V &= \sigma(I-W) \end{aligned} \tag{C.8}$$

where V is a matrix with i,jth element $\frac{\partial p_i}{\partial\left(\ln\frac{\beta_j}{1-\beta_j}\right)}$ that we wish to solve.

At this point, we notice that $(\theta D + \sigma(I-W))$ has rank $N-1$. However, we can also notice that $(I-W)$ is the de-meaning operator, such that for vector x, then $(I-W)x = x - \sum_i \tau_i x_i$. Therefore, we can solve eq. (C.8)) as long as we make the appropriate normalisation. Specifically, we define price gradients such that $\sum_i \tau_i \frac{\partial p_i}{\partial\left(\ln\frac{\beta_j}{1-\beta_j}\right)} = 0$, i.e. the weighted price gradient is 0.

Recall that this normalisation is without loss of generality because the model is invariant to additive shifts in prices. In this case, we can solve for V as

$$V = \left(\frac{\theta}{\sigma} D + I\right)^{-1} (I - W)$$

which in fact guarantees the normalisation by construction.

Next, we consider gradients with respect to supply shifters. Differentiating with respect to s_j we obtain:

$$\begin{aligned} \sum_k \frac{\partial e_i^s}{\partial p_k} \frac{\partial p_k}{\partial s_j} + \frac{\partial e_i^s}{\partial s_j} &= \sum_k \frac{\partial e_i^d}{\partial p_k} \frac{\partial p_k}{\partial s_j} \\ \implies \theta D S + I &= \sigma (W - I) S \\ \implies (\theta D + \sigma (I - W)) S &= -I \end{aligned}$$

Note that one could solve for S explicitly using a similar normalisation to that above, but this is not needed for the analysis.

Solving for Quantity Gradients using $e_i() = e_i^d()$ and $e_i() = e_i^s()$

Differentiating the identity $e_i(\mathbf{b}, \mathbf{s}) = e_i^d(\langle p(\mathbf{b}, \mathbf{s}) \rangle, \mathbf{b})$ w.r.t. s_j we get

$$\begin{aligned} \frac{\partial e_i}{\partial s_j} &= \sum_k \frac{\partial e_i^d}{\partial p_k} \frac{\partial p_k}{\partial s_j} \\ \implies \Gamma &= -\sigma (I - W) S \end{aligned}$$

and then differentiating the identity $e_i(\mathbf{b}, \mathbf{s}) = e_i^s(\langle p(\mathbf{b}, \mathbf{s}) \rangle, \mathbf{b})$ w.r.t. $\ln \frac{\beta_j}{1-\beta_j}$ we get

$$\frac{de_i}{d\left(\ln \frac{\beta_j}{1-\beta_j}\right)} = \sum_k \frac{\partial e_i^s}{\partial p_k} \frac{\partial p_k}{\partial \left(\ln \frac{\beta_j}{1-\beta_j}\right)}$$

which provides the matrix equation

$$\Xi = \theta D V$$

C.1.2.4 Observed Changes

Let $\Delta\mathbf{e}$ be the vector of observed changes in labour shares, with ith element, Δe_i. Similarly let $\Delta\mathbf{b}$ be the vector of productivity (or demand) shifts, $\Delta\mathbf{s}$ the vector of supply shifts, and $\Delta\mathbf{p}$ be the change in prices. Then we have that

$$\Delta\mathbf{p} = V\Delta\mathbf{b} + S\Delta\mathbf{s} \tag{C.9}$$

and

$$\begin{aligned}\Delta\mathbf{e} &= \Xi\Delta\mathbf{b} + \Gamma\Delta\mathbf{s} \\ &= \theta DV\Delta\mathbf{b} - \sigma(I-W)S\Delta\mathbf{s} \end{aligned} \tag{C.10}$$

These expressions describe changes to labour shares and prices in terms of demand and supply shocks, price elasticities, and model parameters θ and σ.

C.1.2.5 Estimation Strategy

Expressions (C.9) and (C.10) also inform the regression framework. From eq. (C.9), note that $\theta D\Delta\mathbf{p} = \theta DV\Delta\mathbf{b} + \theta DS\Delta\mathbf{s}$. Using this to substitute $\Delta\mathbf{b}$ out of eq. (C.10)) yields:

$$\begin{aligned}\implies \Delta\mathbf{e} &= \theta D\Delta\mathbf{p} - \theta DS\Delta\mathbf{s} - \sigma(I-W)S\Delta\mathbf{s} \\ &= \theta D\Delta\mathbf{p} - (\theta D + \sigma(I-W))S\Delta\mathbf{s} \\ &= \theta D\Delta\mathbf{p} - (-I)\Delta\mathbf{s} \\ &= \theta D\Delta\mathbf{p} + \Delta\mathbf{s} \end{aligned} \tag{C.11}$$

This is our basic regression equation (eq. (3.9) in the absence of supply shocks). The logic of requiring the IV is that, given that $\Delta\mathbf{s}$ is not observed, then an OLS regression of Δe on $\mathbf{d}\Delta p$ will not work, because $\mathbf{d}\Delta p$ is correlated with these shocks.

Suppose we have a variable, which we denote r_i, which is correlated with $\Delta b_i \equiv \ln\frac{\beta_j}{1-\beta_j}$ but not with Δs_i. In matrix notation:

$$\Delta\mathbf{b} = \kappa 1_N + \lambda\mathbf{r} + \bar{\eta}$$

where κ and λ are scalars, 1_N is a vector of ones and $\bar{\eta}$ is a vector of shocks.

Then, from eq. (C.9):

$$
\begin{aligned}
\Delta\mathbf{p} &= V\Delta\mathbf{b} + S\Delta\mathbf{s} \\
\implies \Delta\mathbf{p} &= \lambda V\mathbf{r} + \bar{\epsilon} + S\Delta\mathbf{s} \\
\implies D\Delta\mathbf{p} &= \lambda DV\mathbf{r} + D\bar{\epsilon} + DS\Delta\mathbf{s} \\
&= \lambda D\left(\frac{\theta}{\sigma}D + I\right)^{-1}(I-W)\mathbf{r} + D\bar{\epsilon} + DS\Delta\mathbf{s} \\
&= \lambda D\left(\frac{\theta}{\sigma}D + I\right)^{-1}\tilde{\mathbf{r}} + D\bar{\epsilon} + DS\Delta\mathbf{s}
\end{aligned}
$$

where the second line follows from the first because, if v_{ij} is the i,jth element of V, then $\sum_j v_{ij} = 0$. Vector $\tilde{\mathbf{r}}$ is the employment-share-weighted-demeaned version of $\mathbf{r}$ and finally, $\bar{\epsilon} \equiv V\bar{\eta}$.

In terms of regressing Δe_i on the vector of price changes, this implies that, if $G = D\left(\frac{\theta}{\sigma}D + I\right)^{-1}$ and $\mathbf{g}_i$ is the ith row of this matrix, then an appropriate instrument for $\mathbf{d}_i\Delta\mathbf{p}$ is $\mathbf{g}_i\tilde{\mathbf{r}}$, or equivalently $\mathbf{g}_i(I-W)\mathbf{r}$.

For cases in which we ignore the cross-price effects and focus only on the own-price effects (i.e. assuming the off-diagonal elements of the elasticity matrix equal zero), we have that the vector $\tilde{\mathbf{r}}$ will be pre-multiplied by $G_{diag} = D_{diag}\left(\frac{\theta}{\sigma}D + I\right)^{-1}$.

As we discuss in Section 3.3.3, we assume $\frac{\theta}{\sigma} = 1$ throughout the chapter. In Table C.5, we show the robustness of our results to different values of $\frac{\theta}{\sigma}$.

C.2 Data Appendix

This section provides more details on the main data sources and supplementary descriptive statistics. We first delve into the SIAB data and outline the procedures for sample selection and wage imputation. We then bolster the insights offered in Section 3.2 by presenting additional descriptive statistics on the main variables.

C.2.1 The SIAB Data

We use the Sample of Integrated Labour Market Biographies (*Stichprobe der Integrierten Arbeitsmarktbiographien* – SIAB) for our analyses.[3] The SIAB is a 2% sample of the population of the Integrated Employment Biographies (IEB) provided by the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung* – IAB). It includes employees covered by social security, marginal part-time workers (after 1999), unemployment benefit recipients, individuals who are officially registered as job-seeking, and individuals who are participating in programs of active labour market policies. It is possible to track the employment status of a person exact to the day. The source of data regarding employment is the Employee History (*Beschäftigtenhistorik* - BeH) of the IAB. The BeH covers all white- and blue-collar workers as well as apprentices as long as they are not exempt from social security contributions. It excludes civil servants, self-employed people, regular students, and individuals performing military service.

The SIAB data contains an individual's full employment history, including a consistent-over-time occupational classifier (up to 2010), the corresponding nominal daily wage, and socio-demographic variables such as age, gender, or level of education. Data is available in a spell structure, making it possible to observe the same person at several employers within a year. In a few cases, these spells overlap when workers have multiple employment contracts at a time. We transform the spell structure into a yearly panel by identifying the longest spell within a given year and deleting all the remaining spells (this follows from Böhm et al. (2022)).

C.2.1.1 Sample Selection and Variable Description

To work with a homogeneous sample throughout, the main sample is restricted to West German full-time male workers aged 25–59. Since the level and structure of wages differ substantially between East and West Germany, we drop from our sample all workers who were ever employed in East Germany. Our focus on full-time jobs is driven by the absence of data on hours worked. Excluding younger workers, we ensure the vast majority of our sample will have concluded their formal

[3] Access to the data is subject to signing a contract with the Research Data Center of the German Federal Employment Agency. See Frodermann et al. (2021) for more details.

education by the time they enter the sample. Besides, we stop relatively early (at 59) because early retirement programs were common in Germany, particularly in the late 1970s and the 1980s.

We further exclude workers with wages below the limit for which social security contributions have to be paid, mainly workers in marginal jobs (also known as mini-jobs). These jobs were not subject to social security taxation prior to 1999. After the first reform in 1999, the tax-free wage threshold was fixed during the period 1999 to 2003 at 325 euro per month. In 2003, the range of exempted earnings was expanded up to 400 euro, which was effective until 2012. The minimum threshold for mini-jobbers increased in 2013 from 400 to 450 euro per month. Approximately 10% of observations are affected by this restriction. We drop wage spells of workers whose last spell is in apprenticeship training as the first wage after apprenticeship is often a mixture between new wage and apprenticeship wage (this only affects 0.48% of the sample). We also drop all spells of workers who are always foreign workers (less than 5% of observations).[4] Finally, workers without information on their occupation or wages are dropped from the analysis.

Occupations. We use the 120 three-digit occupations from the SIAB's Scientific Use File as our main units of analysis. These occupations are consistently coded (from the detailed KldB 1988 classification system), available during the long time period of 1975–2010, and listed in Table C.4. After 2010, a new classification system is used (the KldB 2010 classification system), which results in a relatively sharp break of the occupation codes. In Table C.1, we also consider occupations at the one-digit level and aggregate them into four broad groups following the literature (Acemoglu & Autor, 2011, Böhm et al., 2022). These are (1) managers, professionals, and technicians (Mgr-Prof-Tech), (2) sales and office workers (Sales-Office), (3) production workers, operators, and craftsmen (Prod-Oper-Crafts), and (4) workers in services and care occupations (Serv-Care).

Wages. The available wage variable is the employee's gross daily nominal wage in euro. It is calculated from the fixed-period wages reported by the employer and the duration of the original notification period in calendar days. Despite being accurately measured as the employer can be punished for incorrect reporting,

[4]Workers who are German at some point but foreign at another are not dropped.

two major drawbacks are of special relevance to our analysis. First, due to a cap on social security contributions, wages are right-censored. As is common in administrative data sources, earnings above the upper earnings limit for statutory pension insurance are only reported up to this limit. The upper earnings limit for statutory pension insurance differs from year to year as well as between East and West Germany, where the decisive factor is the location of the establishment. Second, the income components being subject to social security tax were extended in 1984. Prior to that, one-time payments such as bonuses were not included in the daily wage benefit measure. We discuss how we deal with these two issues below. We deflate wages by the Consumer Price Index (CPI) reported in the Federal Statistical Office of Germany, with 2010 as the base year.

C.2.1.2 Imputation of Right-Censored Wages

The SIAB data is based on process data used to calculate retirement pensions and unemployment insurance benefits, implying the wage information is top-coded and only relevant up to the social security contribution ceiling. While this feature only affects approximately 8.5% of observations on average across years in our main sample (25–59 years old, full-time, excluding marginal workers), the proportion of censored observations differs across subgroups. By gender, top-coded wages amount to roughly 11% for men and 3.3% for women. Differences are also substantial by education groups. Whereas only 1.1% of the spells of individuals who enter the labour market without post-secondary education are affected by top-coding, the share of right-censored wages increases to 5.2%, 9.4%, and 30.8% for those who completed vocational education and training, an *Abitur*, and a university degree, respectively. The share of top-coded wages also increases over the life cycle. While censoring only affects less than 2% of observations for those aged 25-29, the fraction of top-coded wages rises to more than 11% for those older than 40.

To impute top-coded wages, we follow Dustmann et al. (2009) and Card et al. (2013).[5] We first define age-education cells based on seven age groups (with 5-year intervals; 25–29; 30–34; 35–39; 40–44; 45–49; 50–54; 55–59) and four education

[5] To ensure that all censored wages are covered in the imputation process, we mark all observations with wages four euro below the assessment ceiling as in Dauth & Eppelsheimer (2020).

groups (as described above). Within each of these cells (and thereby allowing a different variance for each education and age group), we estimate Tobit wage equations separately by year, gender, and East-West Germany. We predict the upper tail of the wage distribution including controls for age (quadratic), tenure (quadratic), a part-time dummy, as well as interactions between age (quadratic) and the different education groups. To control for worker fixed effects, we construct the mean of an individual's log wage in other years, the fraction of censored wages in other years, and a dummy variable if the person was only observed once in her life.[6] We use the predicted values $X'\hat{\beta}$ from the Tobit regressions together with the estimated standard deviation $\hat{\sigma}$ to impute the censored log wages y^c as follows:

$$y^c = X'\hat{\beta} + \hat{\sigma}\Phi^{-1}[k + u(1-k)]$$

where Φ is the standard normal density function, u is a random draw from a uniform distribution ranging between zero and one, $k = \Phi[(c - X'\hat{\beta})/\hat{\sigma}]$ and c is the censoring point, which differs by year and East-West Germany. See Gartner (2005) for further details.[7] In a very few cases ($< 0.001\%$), imputed wages are exceedingly high. As a minor adjustment, we limit imputed wages to ten times the 99th percentile of the latent wage distribution.

C.2.1.3 The Structural Wage Break in 1983/1984

The income components being subject to the social security tax were extended in Germany in 1984 (for details, see Bender et al. (1996) and Steiner & Wagner (1998)). Before 1984, one-time payments, such as bonuses, were not included in the daily wage benefit measure. Starting in 1984, these parts of the wage were included. We follow Fitzenberger (1999) and Dustmann et al. (2009) and deal with this structural break by correcting wages prior to 1984 upwards. The correction is based on the idea that higher quantiles appear to be more affected by the structural break than

[6]For those observed once, mean wage and mean censoring indicator are set to sample means.

[7]Dustmann et al. (2009) consider different imputation methods, such as restricting the variance to be the same across all education and age groups, or assuming the upper tail of the wage distribution follows a Pareto distribution. They conclude that the imputation method that assumes that the error term is normally distributed with a different variance by age and education works better than the other imputation methods. This method is also chosen in more recent papers such as Böhm et al. (2022) and Cortes et al. (2023).

lower quantiles, as higher percentiles are likely to receive higher bonuses. To this end, we estimate locally weighted regressions, separately for men and women, of the wage ratio between 1982 and 1983 (i.e. before the break), and between 1983 and 1984 (i.e. after the break) on the wage percentiles in 1983 and 1984, respectively. The correction factor is then computed as the difference between the predicted, smoothed values from the two wage ratio regressions. In a way similar to that of Dustmann et al. (2009), to account for differential overall wage growth between the periods from 1982 to 1983 and from 1983 to 1984, we subtract from the correction factor the smoothed value of the wage ratio in 1983, averaged between the second and fortieth quantiles. Finally, wages prior to 1984 are corrected by multiplying them by 1 plus the correction factor. After this, some wages are corrected above the censoring limit. Dustmann et al. (2009) reset these wages back to the censoring limit and impute them in the same way they imputed wages that were above the limit anyway. Instead of doing that, here we follow Böhm et al. (2022) and do not reset wages back to the censoring limit if they were corrected above the limit but leave them at their break corrected values.

C.2.2 Data on Tasks and Occupational Characteristics

We use the Qualifications and Career Surveys (QCS, Hall et al., 2012), conducted by the Federal Institute for Vocational Education and Training (BiBB), to obtain information on tasks performed in occupations. The QCS, which have been previously used, e.g. by Spitz-Oener (2006), Antonczyk et al. (2009) and Gathmann & Schönberg (2010), are representative cross-sectional surveys with 20,000–35,000 individuals in each wave who respond about the tasks required in their occupations. These include, for example, how often they repair objects, how often they perform fraction calculus, or how often they have to persuade co-workers. We classify questions as representing either analytical, routine, or manual tasks and assign a value of 0, 1/3, or 1, depending on whether the answer is ‘never’, ‘sometimes’, or ‘frequently’. We pool the QCS waves in 1979 and 1985/1986 to compute task intensities across occupations by averaging over all the responses. We use this information to study how task intensity relates to our price elasticity measures, and instrument demand changes across occupations over the period 1985–2010.

To measure the distance between occupations in the task space (reflecting the degree of dissimilarity in the mix of tasks), we follow Cortes & Gallipoli (2018) and use the angular separation (correlation) of the observable vectors x_j and x_k:[8]

$$\text{AngSep}_{jk} = \frac{\sum_{a=1}^{A} \left(x_{aj} \cdot x_{ak}\right)}{\left[\sum_{a=1}^{A} \left(x_{aj}\right)^2 \cdot \sum_{a=1}^{A} \left(x_{ak}\right)^2\right]^{\frac{1}{2}}} \tag{C.12}$$

where x_{aj} is the intensity of task dimension a in occupation j and A is the total number of dimensions being considered (analytical, routine, and manual). We transform this to a distance measure $dist_{jk}$ that is increasing in dissimilarity:

$$dist_{jk} = \frac{1}{2}(1 - AngSep_{jk})$$

The measure varies between zero and one; it will be closer to zero the more two occupations overlap in their skill requirements. The mean task distance between occupations in our data is 0.5, with a standard deviation of 0.29. The most distant possible move is between an 'economic and social scientist' and a carpenter. Examples of pairs of occupations with low distance measures are between a sheet metal worker and a tile setter, or between a glass processor and a plastic processor.

To obtain measures of occupation's certification requirements and degree of regulation, we use the indicators for standardised certificates and regulation developed by Vicari (2014). These indicators are based on BERUFENET, the online career information portal provided by the German Federal Employment Agency – a rich job title database similar to the US O*NET. The degree of standardised certification of an occupation indicates whether access to exercising a professional activity is linked to a standardised training certificate. The degree of regulation indicates whether legal and administrative regulations exist which bind the access to and practice of the occupation as well as bearing the title to the proof of a specific qualification. These indicators are constructed as a metric value between 0 and 1, with the indicator increasing in the degree of certification and regulation.

[8] The angular separation is the cosine angle between the occupations' vectors in the task space.

C.2.3 Descriptive Statistics

This section presents further tables and descriptive statistics to complement the analysis in Section 3.2. We start by presenting summary statistics for the transition probability matrix Π and the elasticity matrix D in Table C.2. Similarly, Table C.3 displays summary statistics for annualised employment and occupational price changes separately by each five-year sub-period from 1985 to 2010.

We study how own-price elasticities d_{jj} relate to several occupational characteristics in Figure C.1 (i.e. share of workers with university degree, workers' mean age, occupational certification, occupational regulation) and Figure C.2 (i.e. analytical, routine, and manual task intensities). We summarise these figures in panel (a) of Figure C.3. Panel (b) of Figure C.3, on the other hand, plots cross-price elasticities against occupational task distance. Finally, Table C.4 offers the full list of the 120 occupations ranked by their respective own-price elasticities, together with their employment size in 1985 and 2010.

Table C.2: Summary Statistics. Elasticity Matrix D and Transition Probability Matrix Π

	Elasticity Matrix D		**Transition Probability Matrix Π**	
	Own-Price Elasticity (d_{jj})	Cross-Price Elasticity ($-d_{jk} \times 100$)	Diagonals Elements (Π_{jj})	Off-Diagonal Elements ($\Pi_{jk} \times 100$)
Mean	0.434	0.364	0.746	0.214
Std. Dev.	0.128	0.939	0.090	0.660
Skewness	0.177	14.672	−0.722	17.449
Kurtosis	3.634	493.494	4.393	585.670
p10	0.294	0.007	0.627	0.000
p50	0.430	0.111	0.754	0.046
p90	0.604	0.867	0.839	0.516
p99	0.796	4.021	0.931	2.585
Number of Observations	120	14,280	120	14,280

Notes: Table provides summary statistics for the elasticity matrix D and the transition probability matrix Π, separately for on-diagonal and off-diagonal elements. For readability, summary statistics for off-diagonal elements are multiplied by 100.

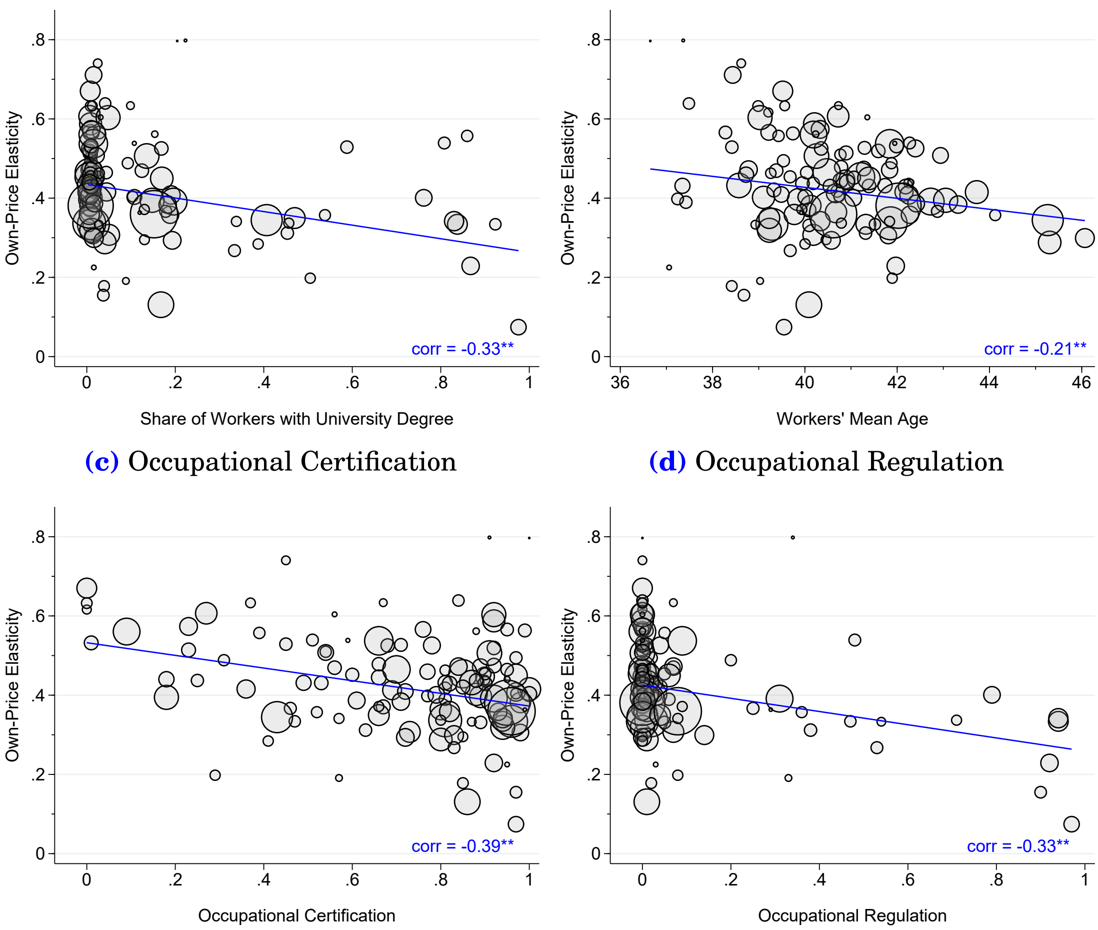
Table C.3: Summary Statistics. Annualised Employment and Occupational Price Changes by Sub-Periods

	Mean	Weighted Mean	Std.Dev.	p10	p50	p90	Autocorr. L1
Panel A. 1985-1990							
Log Employment Change	2.59	2.28	2.57	−0.15	2.32	5.72	-
Stayers' Wage Growth	2.10	2.08	1.44	0.40	1.85	4.07	-
Prices á la Cortes (2016)	2.38	2.38	1.19	0.99	2.23	4.08	-
Panel B. 1990-1995							
Log Employment Change	0.05	0.13	2.51	−3.13	−0.25	3.62	0.56
Stayers' Wage Growth	0.17	0.11	1.36	−1.33	−0.04	1.97	0.84
Prices á la Cortes (2016)	0.58	0.50	1.09	−0.71	0.33	2.11	0.75
Panel C. 1995-2000							
Log Employment Change	−0.19	−0.24	2.67	−2.87	−0.46	2.71	0.46
Stayers' Wage Growth	0.48	0.52	1.79	−1.57	0.25	2.56	0.83
Prices á la Cortes (2016)	0.75	0.82	1.51	−0.97	0.56	2.50	0.75
Panel D. 2000-2005							
Log Employment Change	−1.64	−1.43	2.27	−4.49	−1.46	1.35	0.71
Stayers' Wage Growth	−0.24	−0.17	1.32	−1.90	−0.24	1.51	0.84
Prices á la Cortes (2016)	0.09	0.12	1.07	−1.15	0.01	1.54	0.82
Panel E. 2005-2010							
Log Employment Change	−0.27	−0.04	2.18	−3.07	−0.31	2.07	0.59
Stayers' Wage Growth	0.42	0.61	1.38	−1.14	0.12	2.17	0.77
Prices á la Cortes (2016)	0.57	0.76	1.25	−0.88	0.22	2.25	0.82

Notes: Table presents summary statistics for annualised employment and occupational price changes separately for different sub-periods. These are: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. The final column, 'autocorr. L1' refers to the correlation with respect to the preceding 5-year period (e.g. the correlation between the employment change in the period 1990-1995 with respect to the employment change in the preceding period 1985-1990).

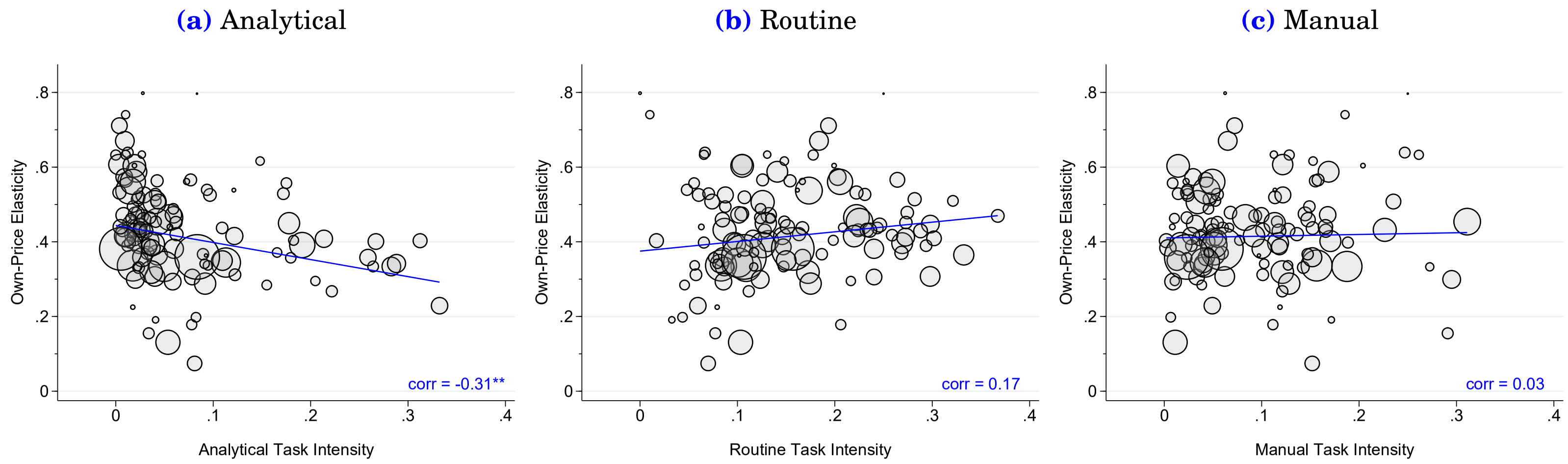
Figure C.1: Correlation between Own-Price Elasticities and Occupational Characteristics

(a) Share of Workers with University Degree
(b) Workers' Mean Age
(c) Occupational Certification
(d) Occupational Regulation



Notes: Figure shows the correlation between own-price elasticities (d_{jj} elements) and other measures of occupational characteristics. Panel (a) considers the share of workers with university degrees in each occupation. Panel (b) considers the average age among workers. Panels (c) and (d) consider occupational certification and regulation, respectively (Vicari, 2014). Each circle represents one of the 120 occupations, with the size of the circle indicating the occupation's share of employment in 1985. ** means statistically significant at the 5% level.

Figure C.2: Correlation between Own-Price Elasticities and Occupational Task Content

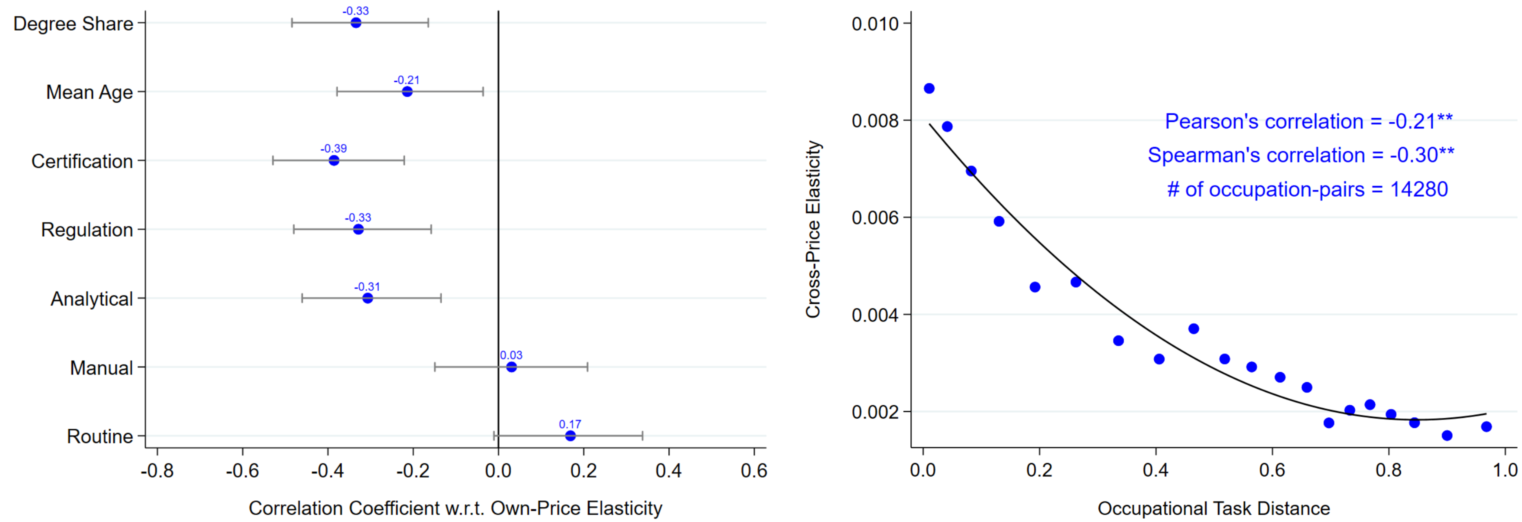


Notes: Figure shows the correlation between own-price elasticities (d_{jj} elements) and occupational task dimensions. Panels (a)-(c) consider analytical, routine, and manual, respectively. Each circle represents one of the 120 occupations, with the size of the circle indicating the occupation's share of employment in 1985. See Section 3.2 for further details. ** means statistically significant at the 5% level.

Figure C.3: Own-Price and Cross-Price Elasticity: Comparison with External Metrics

(a) Own-Price Elasticity and Occupational Characteristics

(b) Cross-Price Elasticity and Task Distance



Notes: Figure shows the relationship of the own- and cross-price elasticities with respect to external metrics. Panel (a) reports how the own-price elasticity, namely d_{jj}, relate to skill requirements captured by the share of university graduates and workers' average age, occupational certification and regulations (taken from Vicari (2014)), and occupational task content (analytical, interactive, manual, and routine). Panel (b) shows the relationship (with a quadratic fit) between the cross-price elasticity, namely $-d_{jk}$, and occupational task distance measured as in Cortes & Gallipoli (2018).

Table C.4: All 120 Occupations Ranked by Own-Price Elasticities d_{jj}, and their Employment Size

	Own-Price Elasticity		% Share of Employment	
Occupations (based on German KlDB 1988 Classification)	d_{jj}	d_{jj}^{NE}	1985	2010
Physicians up to Pharmacists	0.07	0.27	0.65	0.81
Bank specialists up to building society specialists	0.13	0.18	1.79	1.98
Nurses, midwives	0.16	0.24	0.37	0.67
Dental technicians up to doll makers, model makers, taxidermists	0.18	0.31	0.32	0.24
Non-medical practitioners up to masseurs, physiotherapists	0.19	0.27	0.13	0.22
Journalists up to librarians, archivists, museum specialists	0.20	0.28	0.28	0.35
Hairdressers up to other body care occupations	0.23	0.37	0.06	0.06
Architects, civil engineers	0.23	0.30	0.83	0.69
Soldiers, border guards, police officers up to judicial enforcers	0.27	0.36	0.38	0.51
Musicians up to scenery/sign painters	0.28	0.39	0.29	0.31
Foremen, master mechanics	0.29	0.37	1.39	0.75
Health insurance specialists up to life, property insurance specialists	0.29	0.37	0.85	0.89
Chemical laboratory assistants up to photo laboratory assistants	0.30	0.33	0.26	0.25
Doormen, caretakers up to domestic and non-domestic servants	0.30	0.40	0.97	0.97
Type setters, compositors up to printers (flat, gravure)	0.31	0.35	0.75	0.36
Gardeners, garden workers up to forest workers, forest cultivators	0.31	0.40	1.18	1.15
Social workers, care workers up to religious care helpers	0.31	0.39	0.42	0.68
Joiners (Carpentry)	0.32	0.39	1.57	1.17
Tile setters up to screed, terrazzo layers	0.33	0.43	0.42	0.30
Nursing assistants	0.33	0.42	0.20	0.33
Mechanical, motor engineers	0.33	0.38	1.07	1.21
Electrical fitters, mechanics	0.33	0.38	2.78	2.76
Chemists, chemical engineers up to physicists, physics engineers, mathematicians	0.33	0.39	0.35	0.34
Bricklayers up to concrete workers	0.34	0.43	2.95	1.20
Home wardens, social work teachers	0.34	0.41	0.28	0.46
Music teachers, n.e.c up to other teachers	0.34	0.41	0.27	0.32
Electrical engineers	0.34	0.37	1.00	1.18
Entrepreneurs, managing directors, divisional managers	0.34	0.43	2.63	2.11
Data processing specialists	0.35	0.38	1.18	3.46
Members of Parliament, Ministers, elected officials up to association leaders	0.36	0.46	0.33	0.48
Measurement technicians up to remaining manufacturing technicians	0.36	0.41	0.81	0.48
Painters, lacquerers (construction)	0.36	0.43	1.11	0.91
Office specialists	0.36	0.43	6.10	8.15
Dietary, pharmaceutical assistants up to medical laboratory assistants	0.36	0.38	0.03	0.05
Chemical plant operatives	0.36	0.43	1.25	0.97
Navigating ships officers up to air transport occupations	0.37	0.45	0.39	0.28
Paper, cellulose makers up to other paper products makers	0.37	0.44	0.53	0.50
Artistic and audio, video occupations up to performers, professional sportsmen, auxiliary artistic occupations	0.37	0.44	0.27	0.25

Table C.4—continued

Occupations (based on German KlDB 1988 Classification)	Own-Price Elasticity d_{jj}	d_{jj}^{NE}	% Share of Employment 1985	2010
Motor vehicle drivers	0.38	0.44	5.57	5.39
Toolmakers up to precious metal smiths	0.38	0.43	1.13	0.80
Cost accountants, valuers up to accountants	0.38	0.45	0.82	0.51
Railway engine drivers up to street attendants	0.39	0.47	0.77	0.61
Bakery goods makers up to confectioners (pastry)	0.39	0.46	0.41	0.41
Other technicians	0.39	0.45	1.96	2.43
Commercial agents, travellers up to mobile traders	0.39	0.45	1.58	1.10
Miners up to shaped brick/concrete block makers	0.40	0.47	1.33	0.47
Roofers	0.40	0.49	0.37	0.40
Survey engineers up to other engineers	0.40	0.46	0.75	1.82
Plumbers	0.40	0.46	1.35	1.23
Technical draughtspersons	0.40	0.45	0.60	0.48
Biological specialists up to physical and mathematical specialists	0.40	0.45	0.30	0.20
Mechanical engineering technicians	0.41	0.45	0.91	0.82
Butchers up to fish processing operatives	0.41	0.48	0.65	0.47
Turners	0.41	0.46	0.97	0.73
Generator machinists up to construction machine attendants	0.42	0.48	1.42	0.73
Goods examiners, sorters, n.e.c	0.42	0.49	0.90	0.58
Ceramics workers up to glass processors, glass fishers	0.42	0.49	0.40	0.22
Agricultural machinery repairers up to precision mechanics	0.42	0.46	0.53	0.54
Machine attendants, machinists' helpers up to machine setters	0.43	0.50	0.58	0.51
Stucco workers, plasterers, rough casters up to insulators, proofers	0.43	0.50	0.53	0.32
Metal grinders up to other metal-cutting occupations	0.43	0.49	0.50	0.35
Cooks up to ready-to-serve meals, fruit, vegetable preservers, preparers	0.43	0.54	0.62	1.05
Spinners, fibre preparers up to skin processing operatives	0.43	0.50	0.56	0.19
Motor vehicle repairers	0.43	0.48	1.63	1.65
Goods painters, lacquerers up to ceramics/glass painters	0.44	0.49	0.50	0.37
Chemical laboratory workers up to vulcanisers	0.44	0.51	0.41	0.30
Cutters up to textile finishers	0.44	0.52	0.24	0.08
Cashiers	0.44	0.51	0.10	0.07
Street cleaners, refuse disposers up to machinery, container cleaners	0.44	0.51	0.63	0.72
Drillers up to borers	0.44	0.50	0.59	0.41
Iron, metal producers, melters up to semi-finished product fettlers and other mould casting occupations	0.45	0.52	0.96	0.60
Electrical engineering technicians up to building technicians	0.45	0.48	1.39	1.47
Wine coopers up to sugar, sweets, ice-cream makers	0.45	0.52	0.46	0.37
Room equippers up to other wood and sports equipment makers	0.45	0.51	0.39	0.27
Plant fitters, maintenance fitters up to steel structure fitters, metal shipbuilders	0.45	0.51	2.18	1.36
Carpenters up to scaffolders	0.46	0.53	0.63	0.49
Post masters up to telephonists	0.46	0.57	0.30	0.36

Table C.4—continued

Occupations (based on German KlDB 1988 Classification)	Own-Price Elasticity d_{jj}	Own-Price Elasticity d_{jj}^{NE}	% Share of Employment 1985	% Share of Employment 2010
Forwarding business dealers	0.46	0.51	0.42	0.47
Engine fitters	0.47	0.50	2.04	1.43
Farmers up to animal keepers and related occupations	0.47	0.55	0.49	0.42
Welders, oxy-acetylene cutters	0.47	0.52	0.72	0.51
Telecommunications mechanics, craftsmen up to radio, sound equipment mechanics	0.47	0.52	0.82	0.45
Steel smiths up to pipe, tubing fitters	0.47	0.53	0.58	0.34
Wood preparers up to basket and wicker products makers	0.48	0.56	0.48	0.26
Office auxiliary workers	0.49	0.57	0.34	0.31
Sheet metal workers	0.49	0.55	0.40	0.36
Wholesale and retail trade buyers, buyers	0.51	0.55	1.65	1.88
Factory guards, detectives up to watchmen, custodians	0.51	0.59	0.67	0.67
Special printers, screeners up to printer's assistants	0.51	0.56	0.35	0.21
Sheet metal pressers, drawers, stampers up to other metal moulders	0.51	0.56	0.53	0.32
Paviours up to road makers	0.52	0.59	0.49	0.32
Tourism specialists up to cash collectors, cashiers, ticket sellers, inspectors	0.53	0.59	0.49	0.65
Tracklayers up to other civil engineering workers	0.53	0.61	0.78	0.32
Metal polishers up to metal bonders and other metal connectors	0.53	0.58	0.44	0.28
Management consultants, organisors up to chartered accountants, tax advisers	0.53	0.58	0.41	1.29
Transportation equipment drivers	0.53	0.58	0.52	0.45
Warehouse managers, warehousemen	0.54	0.61	2.21	1.58
Housekeeping managers up to employees by household cheque procedure	0.54	0.63	0.05	0.08
University teachers, lecturers at higher technical schools up to technical, vocational, factory instructors	0.54	0.60	0.38	0.50
Economic and social scientists, statisticians up to scientists	0.56	0.62	0.35	0.57
Stowers, furniture packers up to stores/transport workers	0.56	0.64	1.95	2.91
Stenographers, shorthand-typists, typists up to data typists	0.56	0.61	0.11	0.12
Other mechanics up to watch-, clockmakers	0.56	0.59	0.45	0.79
Electrical appliance fitters	0.57	0.59	0.43	0.60
Plastics processors	0.57	0.62	0.67	0.86
Packagers, goods receivers, despatchers	0.57	0.64	0.86	0.92
Locksmiths, not specified up to sheet metal, plastics fitters	0.59	0.63	1.32	1.54
Salespersons	0.60	0.65	1.57	2.06
Laundry workers, pressers up to textile cleaners, dyers, and dry cleaners	0.60	0.66	0.06	0.06
Building labourer, general up to other building labourers, building assistants	0.61	0.70	1.26	0.97
Electrical appliance, electrical parts assemblers	0.62	0.66	0.22	0.20
Other assemblers	0.63	0.68	0.31	0.81
Household cleaners up to glass, building cleaners	0.63	0.73	0.26	0.41
Publishing house dealers, booksellers up to service-station attendants	0.63	0.67	0.17	0.13

Table C.4—continued

Occupations (based on German KlDB 1988 Classification)	Own-Price Elasticity d_{jj}	Own-Price Elasticity d_{jj}^{NE}	% Share of Employment 1985	% Share of Employment 2010
Restaurant, inn, bar keepers, hotel proprietors, catering trade dealers up to waiters, stewards	0.64	0.71	0.35	0.58
Metal workers (no further specification)	0.67	0.71	1.07	1.38
Assistants (no further specification)	0.71	0.75	0.75	3.00
Other attending on guests	0.74	0.80	0.21	0.12
Medical receptionists	0.80	0.83	0.01	0.02
Nursery teachers, child nurses	0.80	0.79	0.02	0.09

Notes: Table provides the full list of the 120 occupations used in the analysis, ranked by the diagonal elements of the elasticity matrix D (column (1)). The corresponding d_{jj} elements accounting for non-employment are displayed in column (2). Columns (3)-(4) report the occupation's percentage share of employment in 1985 (the initial year of our period of analysis) and 2010 (the final year of our period of analysis), respectively.

C.3 Further Empirical Results: Figures & Tables

This section provides further tables and figures to complement the main estimation results presented in Section 3.3.

Table C.4: Full Model: Two-Type Decomposition (OLS)

Two-Type Decomposition		Dependent Variable: $\Delta\mathbf{e}$ (1)	(2)	(3)	(4)
own effect:	$d_{jj}\Delta p_j$	1.81***		4.10***	
		(0.32)		(0.88)	4.15***
total cross effect:	$\sum_{j\neq k} d_{jk}\Delta p_k$		−2.14***	4.03***	(0.70)
			(0.59)	(1.29)	
R-squared		0.310	0.163	0.394	0.394
Number of occupations		120	120	120	120

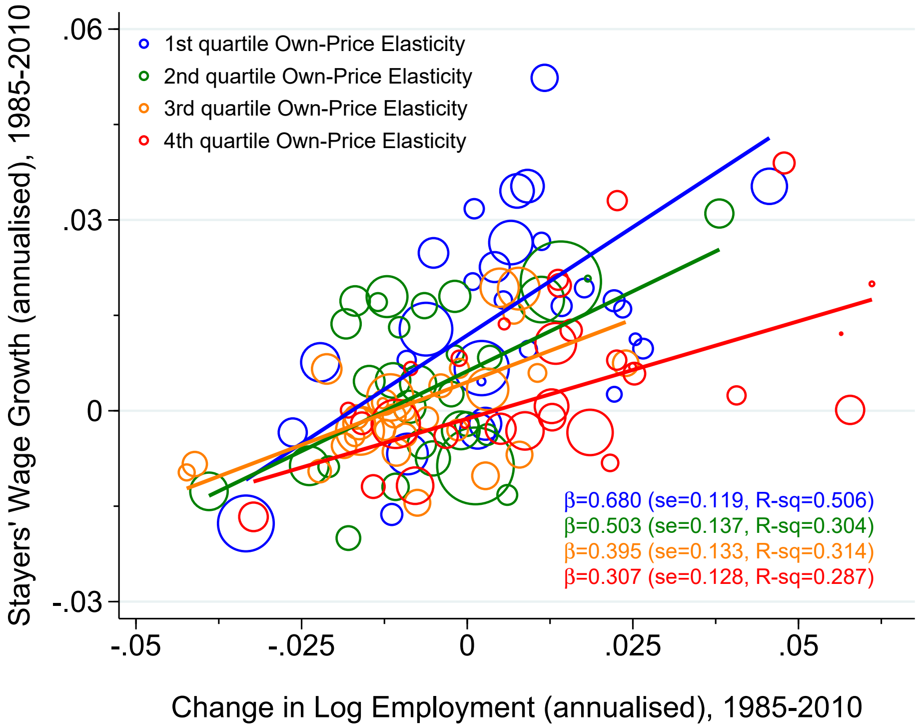
Notes: Regressor in column (4) is $\sum_j d_{jk}\Delta \ln p_k$, i.e. corresponding to the full model. Standard errors in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by j's initial employment size. Period 1985–2010.

Table C.5: Structural IV: Different Values of $\frac{\theta}{\sigma}$

Restricted Model		Dependent Variable: $\Delta\mathbf{e}$					
		$\frac{\theta}{\sigma}=0.25$	$\frac{\theta}{\sigma}=0.5$	$\frac{\theta}{\sigma}=1.5$	$\frac{\theta}{\sigma}=2$	$\frac{\theta}{\sigma}=3$	$\frac{\theta}{\sigma}=4$
Fixed relationship:	$\overline{d}_{diag}\Delta p_j$	1.23^{***}	1.22^{***}	1.20^{***}	1.20^{***}	1.20^{***}	1.19^{***}
		(0.37)	(0.36)	(0.35)	(0.35)	(0.35)	(0.35)
F-stat 1st Stage		78	86	113	124	141	153
Own effect:	$d_{jj}\Delta p_j$	1.34^{***}	1.33^{***}	1.32^{***}	1.31^{***}	1.30^{***}	1.30^{***}
		(0.39)	(0.39)	(0.38)	(0.38)	(0.37)	(0.37)
F-stat 1st Stage		75	82	107	116	131	143
Own & cross effect:	$\sum_{k=1}^{N} d_{jk}\Delta p_k$	5.12^{***}	5.05^{***}	4.87^{***}	4.81^{***}	4.72^{***}	4.66^{***}
		(1.65)	(1.58)	(1.39)	(1.33)	(1.25)	(1.19)
F-stat 1st Stage		8	9	12	13	15	16

Notes: Results on instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted model (3.12) for different values of $\frac{\theta}{\sigma}$. For the fixed relationship as well as the own effect, the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. For the full model, the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. See Section 3.3.3 for details about the IV approach. Standard errors are in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by j's initial employment size. Period 1985–2010.

Figure C.4: Stayers' Wage Growth and Employment by d_{jj} Quartiles



Notes: Figure shows the scatter of occupations' change in the log of employment (x-axis) and stayers' wage growth (y-axis) during 1985–2010. The graph shows colour codes and linear regression lines by occupations in the lowest (blue), second (green), third (orange), and highest (red) quartile of the predicted elasticity of labour supply with respect to own price d_{jj}. β refers to the slope coefficient, *se* refers to standard error, and *R-sq* stands for the R squared of the regression.

C.4 Extensions and Robustness: Supplementary Material

In this section, we present the details of the extensions and robustness checks of the main findings. We first extend the model to incorporate non-employment transitions. Second, we study changes in occupational prices and employment by sub-periods. Lastly, we introduce an alternative method for estimating changes in occupational prices.

C.4.1 Accounting for Non-Employment Transitions

A driver of heterogeneity in occupational growth that we omit in the main analysis is the extensive margin of employment. This may be particularly important if young workers' entry and old workers' exit from the labour market affect specific occupations' growth. The secular decline of German unemployment from the mid-2000s may also be relevant in this respect.

In line with eq. (3.1), we interpret indirect utility in M different non-employment states $m \in \{N+1,\dots,N+M\}$ as containing pecuniary payoffs, transition costs, and idiosyncratic components. While pecuniary payoffs p_m are unobserved, the empirical framework can be extended in order to model-consistently control switches to and from different non-employment states.

We start by computing a new elasticity matrix that includes all transitions to and from non-employment states. Then consider eq. (3.12) with $N+M$ occupations, with M referring to non-employment sectors:

$$\Delta e_j \approx \theta \sum_{k=1}^{N+M} d_{jk}\Delta p_k = \theta \sum_{k=1}^{N} d_{jk}\Delta p_k + \sum_{m=N+1}^{N+M} (\theta\Delta p_m) d_{jm} \tag{C.13}$$

The first summation on the right-hand side represents our standard (own- and cross-occupation) effects, while in the second summation, we explicitly group factors $\theta\Delta p_m$ together. This is to indicate that d_{jm} are control variables for the occupation j's predicted elasticity with respect to non-employment state m. The $\theta\Delta p_m$ coefficient on the respective control represents the combination of pecuniary preferences and changes in non-employment 'prices'. This product cannot be disentangled, as Δp_m is unobserved, but other than that the model is again identified.

In what follows, we show the results from these estimations with $M = 3$ different non-employment sectors: unemployment, out of the labour force (during the career and including part-time as well as employment with benefit receipt), and entry or exit due to newly joining the labour force at age 25–32 or retiring at age 52–59. A limitation of the records from unemployment insurance is that we cannot observe the exact reasons for individuals entering or leaving the dataset (e.g. health shock, discouraged worker, emigration, self-employment, military service or becoming a civil servant). Outside the age range for labour market entry or retirement, these are all treated as out of the labour force for our purposes. As shown in Table C.6 (for both the restricted and the unrestricted models) and Table C.7, the R-squared is consistently higher in all specifications as more of the heterogeneity in employment growth can be explained when allowing for occupations' different elasticities with respect to non-employment states. Importantly, the estimated role of own- and cross-price effects turn out similar to the main results (both OLS and IV estimates). In unreported results, we verify the main results do not change when further separating part-time work and work with benefit receipt from 'out of the labour force', or when merging the three states into one single non-employment sector.

Table C.6: Accounting for Non-Employment Transitions (I)

Three-Type Decomposition		Dependent Variable: $\Delta\mathbf{e}$				
		Unrestricted Model			Restricted Model	
		(1)	(2)	(3)	(4)	(5)
fixed relationship:	$\overline{d}_{diag}\Delta p_j$	2.41^{***}	2.55^{***}	3.70^{***}		
		(0.41)	(0.40)	(0.74)	2.49^{***}	
heter. own effect:	$(d_{jj}-\overline{d}_{diag})\Delta p_j$		1.41^{**}	3.27^{***}	(0.39)	4.06^{***}
			(0.63)	(0.99)		(0.68)
total cross effect:	$\sum_{j\neq k} d_{jk}\Delta p_k$			2.83^{**}		
				(1.19)		
elast wrt unemp:	d_{jN+1}	-0.59^{***}	-0.58^{***}	-0.54^{***}	-0.52^{***}	-0.47^{***}
		(0.17)	(0.16)	(0.14)	(0.14)	(0.13)
elast wrt olf:	d_{jN+2}	0.25	0.18	0.24	0.07	0.22
		(0.20)	(0.17)	(0.19)	(0.12)	(0.20)
elast wrt entry/exit:	d_{jN+3}	0.04	0.04	0.03	0.05	0.04
		(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
R-squared		0.421	0.438	0.470	0.426	0.463
Number of occupations		120	120	120	120	120

Notes: Regressor in column (4) is $d_{jj}\Delta\ln p_j$. In column (5), the regressor is $\sum_j d_{jk}\Delta\ln p_k$, i.e. corresponding to the full model. We consider $M=3$ different non-employment sectors: unemployment 'unemp', out of the labour force 'olf' (during the career and including part-time as well as employment with benefit receipt), and entry or exit due to newly joining the labour force at age 25–32 or retiring at age 52–59. Standard errors in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. Observations weighted by occupation j's initial employment size. Period 1985–2010.

Table C.7: Accounting for Non-Employment Transitions (II)

Three-Type Decomposition (Restricted Model)		Dependent Variable: $\Delta\mathbf{e}$					
		(1)		(2)		(3)	
		OLS	IV	OLS	IV	OLS	IV
fixed relationship:	$\overline{d}_{diag}\Delta p_j$	2.41^{***}	1.70^{***}				
		(0.41)	(0.49)				
own effect:	$d_{jj}\Delta p_j$			2.49^{***}	1.75^{***}		
				(0.39)	(0.49)		
own & cross effect:	$\sum_{k=1}^{N} d_{jk}\Delta p_k$					4.06^{***}	4.48^{***}
						(0.68)	(1.24)
elast wrt unemp:	d_{jN+1}	-0.59^{***}	-0.37^{*}	-0.52^{***}	-0.32^{*}	-0.47^{***}	-0.54^{**}
		(0.17)	(0.19)	(0.14)	(0.17)	(0.13)	(0.23)
elast wrt olf:	d_{jN+2}	0.25	0.03	0.07	-0.11	0.22	0.29
		(0.20)	(0.27)	(0.12)	(0.18)	(0.20)	(0.29)
elast wrt entry/exit:	d_{jN+3}	0.04	0.07	0.05	0.08	0.04	0.03
		(0.19)	(0.19)	(0.19)	(0.20)	(0.19)	(0.18)
Observations		120	120	120	120	120	120
R-squared		0.421	-	0.426	-	0.463	-
F-stat 1st Stage		-	102	-	53	-	36

Notes: OLS and instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted model (C.13) controlling for non-employment transitions in matrix D of dimension $N+M$. We consider $M=3$ different non-employment sectors: unemployment 'unemp', out of the labour force 'olf' (during the career and including part-time as well as employment with benefit receipt), and entry or exit due to newly joining the labour force at age 25–32 or retiring at age 52–59. For the IV, in columns (1)-(2), the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. In column (3), the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. See Section 3.3.3 for details about the IV approach. Standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. Observations weighted by j's initial employment size. Period 1985–2010.

C.4.2 Analysis in Five-Year Sub-Periods

In the main analysis, we study changes in occupational prices and employment over the period 1985–2010. In this section, we split this longer interval into five-year sub-periods (1985–1990, 1990–1995, 1995–2000, 2000–2005, and 2005–2010), to explore robustness and potential temporal heterogeneity.

The pooled panel sample containing 600 observations (120 occupations x 5 sub-periods) is used to estimate an extended version of eq. (3.12):

$$\Delta e_{jt} = \alpha + \theta d_{jj} \Delta p_{jt} + \theta \sum_{k \neq j} d_{jk} \Delta p_{kt} + \delta_t (+\gamma_j) + \varepsilon_{jt} \tag{C.14}$$

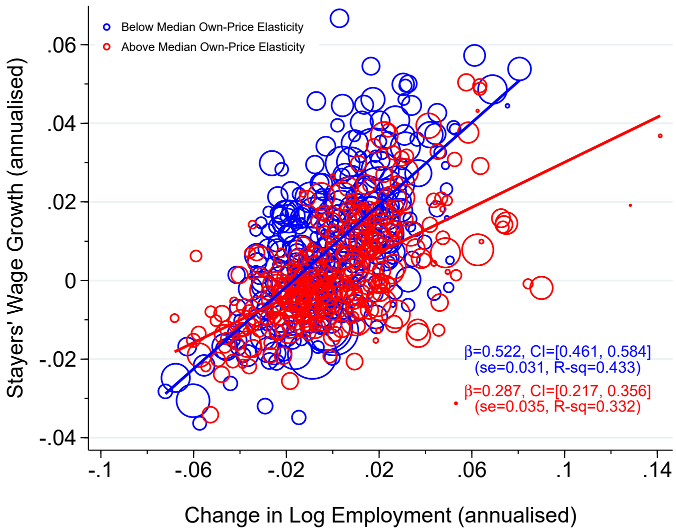
where t refers to a five-year period, and the matrix of elasticities D can be obtained using the baseline period 1975–1984 as previously or using the lagged matrix from the preceding five-year period (e.g. for the period 1995–2000, the matrix of elasticity is computed using employment transitions over the period 1990–1995).[9] The period fixed effects (δ_t) capture unobserved time-specific shocks or trends that affect all occupations uniformly within each sub-period. A more demanding specification additionally includes occupation fixed effects (γ_j), removing average occupational growth over 1985–2010 and identifying only from accelerations / decelerations in the respective sub-period.

Figure C.5 plots prices against employment growth for the pooled sample of 600 occupation-sub-periods (panel a) as well as separately for each sub-period (panel b), analogous to the main text Figure 3.2b. The previous finding is strengthened in the sense that each regression slope for above-median own-price elastic occupations is flatter than any slope for below-median own-price inelastic occupations. From Table C.8 and Table C.9, we see that linear OLS and IV estimation on the pooled data essentially reproduce the results obtained in Section 3.3. Even in estimations with occupation fixed effects (γ_j), which only use deviations of price changes from their 1985–2010 averages interacted with the price elasticities, results are broadly similar to before. Note that we can only do the OLS for this as our instrument does not vary by period. In sum, estimation in a series of shorter intervals shows that the role of occupational price elasticities persists, with some evidence that even acceleration / deceleration of price growth in different sub-periods is translated into employment growth according to these elasticities.

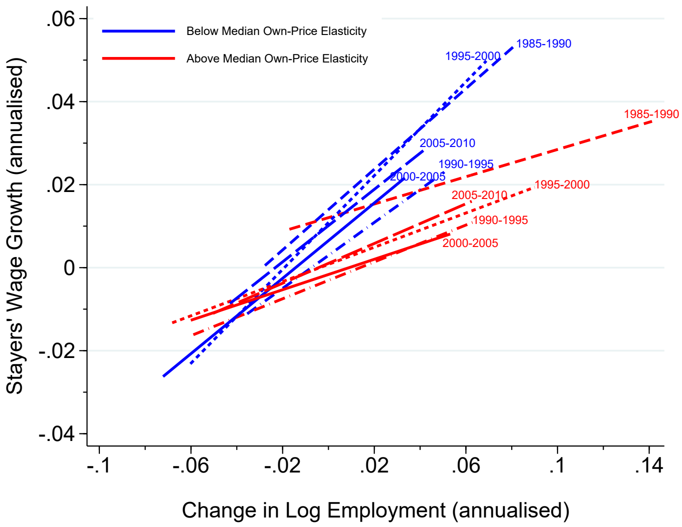
[9] Consistent with the high autocorrelation of matrix D over time discussed in footnote 15 of Chapter 3, results are similar whether we use the baseline or the lagged matrix.

Figure C.5: Stayers' Wage Growth and Employment Changes (by Own-Price Elasticity Median Split)

(a) Pooled Sub-Periods. 600 Occupations x Sub-Periods



(b) By Sub-Periods.



Notes: Figure shows scatter plots of occupations' change in the log of employment (x-axis) and stayers' wage growth (y-axis) for the pooled sample of 600 occupation-sub-periods (panel (a)) as well as separately for each sub-period (panel (b)). Sub-periods are: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. The graphs depict colour codes and linear regression lines by occupations below (blue, inelastic) and above (red, elastic) the median predicted elasticity of labour supply with respect to own price (d_{jj}). β refers to the slope coefficient, CI stands for the 95% confidence interval, se refers to standard error, and R-sq stands for the R squared of the regression.

Table C.8: Full Model Pooled Sub-Periods (OLS)

Three-Type Decomposition	Dependent Variable: $\Delta\mathbf{e}$				
	Unrestricted Model			Restricted Model	
	(1)	(2)	(3)	(4)	(5)
fixed relationship: $\overline{d}_{diag}\Delta p_j$	1.69***	1.93***	3.90***		
	(0.29)	(0.29)	(0.67)	2.41***	
heter. own effect: $(d_{jj} - \overline{d}_{diag})\Delta p_j$		1.57***	4.04***	(0.34)	4.43***
		(0.30)	(0.83)		(0.70)
total cross effect: $\sum_{j \neq k} d_{jk}\Delta p_k$			3.69***		
			(1.09)		
R-squared	0.419	0.438	0.492	0.456	0.486
Period fe	yes	yes	yes	yes	yes
Cluster Std. Errors	yes	yes	yes	yes	yes
Number of occupations	600	600	600	600	600

Notes: Results on pooled panel sample containing 600 observations (120 occupations x 5 sub-periods). Sub-periods are: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. The regressor in column (4) is $d_{jj}\Delta \ln p_j$. In column (5), the regressor is $\sum_j d_{jk}\Delta \ln p_k$, i.e. corresponding to the full model. Standard errors clustered at the occupation level in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by occupation j's initial employment size (e.g. for the period 1985-1990, this is 1985; for the 2000-2005 period, this is 2000, and so on).

Table C.9: Full Model Pooled Sub-Periods (OLS-IV)

Three-Type Decomposition (Restricted Model)		Dependent Variable: $\Delta\mathbf{e}$								
		(1)			(2)			(3)		
		OLS period fe	OLS period & occ fe	IV period fe	OLS period fe	OLS period & occ fe	IV period fe	OLS period fe	OLS period & occ fe	IV period fe
fixed relationship:	$\overline{d}_{diag}\Delta p_j$	1.69^{***}	2.89^{***}	1.09^{***}						
		(0.29)	(0.40)	(0.41)						
own effect:	$d_{jj}\Delta p_j$				1.93^{***}	2.81^{***}	1.18^{***}			
					(0.29)	(0.40)	(0.44)			
own & cross effect:	$\sum_{k=1}^{N} d_{jk}\Delta p_k$							4.01^{***}	3.18^{***}	4.17^{***}
								(0.56)	(0.51)	(1.32)
Observations		600	600	600	600	600	600	600	600	600
R-squared		0.419	0.796	-	0.437	0.799	-	0.491	0.791	-
F-stat 1st Stage		-	-	124	-	-	111	-	-	13

Notes: OLS and instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted pooled model (C.14). The pooled panel sample contains 600 observations (120 occupations x 5 sub-periods). Sub-periods are: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. For the IV, in columns (1)-(2), the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. In column (3), the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. See Section 3.3.3 for details about the IV approach. Standard errors clustered at the occupation level in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by occupation j's initial employment size (e.g. for the period 1985-1990, this is 1985; for the 2000-2005 period, this is 2000, and so on).

C.4.3 Alternative Price Estimation

The main results in Section 3.3 use the annual wage growth of occupation stayers as the main estimate of an occupation's changing log price or wage rate per efficiency unit of skill. This accounts flexibly for the selection into occupations based on observable and unobservable individual characteristics. In this section, we use an alternative price estimation that also controls for the occupation-specific effect of time-varying observable characteristics on wages.

In this approach, originally proposed by Cortes (2016), observed log wages for individual ω in period t are estimated by

$$\ln w_t(\omega) = \sum_j Z_{jt}(\omega)\varphi_{jt} + \sum_j Z_{jt}(\omega)X_t(\omega)\zeta_j + \sum_j Z_{jt}\kappa_j(\omega) + \mu_t(\omega) \tag{C.15}$$

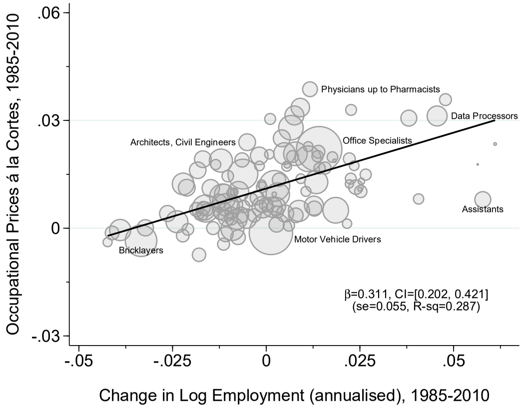
where $Z_{jt}(\omega)$ is an occupation selection indicator that equals one if individual ω chooses occupation j at time t, φ_{jt} are occupation-time fixed effects, and $\kappa_j(\omega)$ are occupation-spell fixed effects for each individual. The model allows for time-varying observable skills (e.g. due to general human capital evolving over the life cycle) by including in the control variables X_t a set of dummies for five-year age bins interacted with occupation dummies.[10] Finally, $\mu_t(\omega)$ reflects classical measurement error, which is orthogonal to $Z_{jt}(\omega)$. It may be interpreted as a temporary idiosyncratic shock that affects the wages of individual ω in period t regardless of their occupational choice. The estimated occupation-year fixed effects (φ_{jt}) are the parameters of interest, which allow studying changes over time in occupation's log prices (Δp_j).

The results using prices á la Cortes (2016) turn out similar to our main results. The main figures of Chapter 3 are replicated using these alternative prices in Figure C.6. The main regression results (Table C.10-C.11-C.12-C.13), including those when accounting for non-employment transitions, turn out very similar. Our findings hence remain consistent and robust to this alternative price estimation.

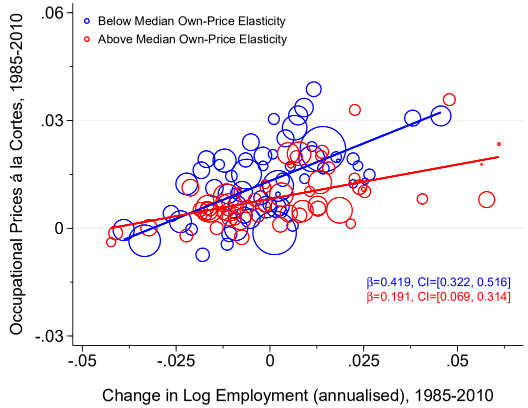
[10]The bins are for ages 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, and 55–59.

Figure C.6: Occupational Prices á la Cortes (2016) and Employment. Main Figures.

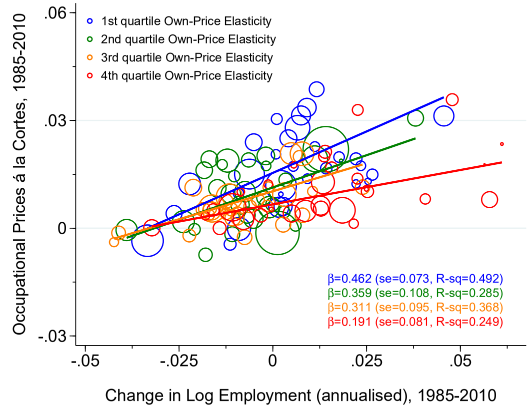
(a) Overall Relationship



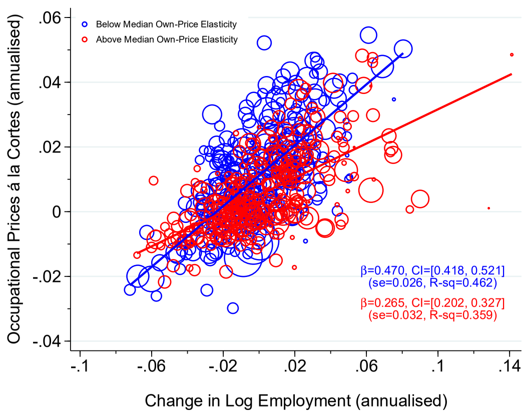
(b) By d_{jj} Median Split



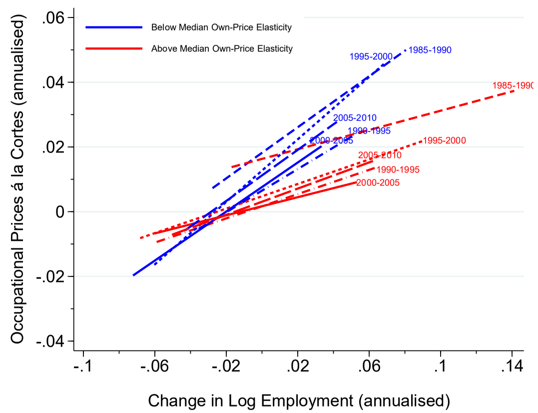
(c) By d_{jj} Quartiles



(d) Pooled Sub-Periods. By d_{jj} median split



(e) Sub-Periods. By d_{jj} median split



Notes: Panels (a)-(c) show the scatter of occupations' change in the log of employment (x-axis) and occupational prices á la Cortes (2016) (y-axis) during 1985–2010. Panel (a) shows the overall regression line. Panel (b) shows colour codes and linear regression lines by occupations below (blue, inelastic) and above (red, elastic) the median predicted elasticity of labour supply with respect to own price d_{jj}. Panel (c) shows colour codes and linear regression lines by occupations in the lowest (blue), second (green), third (orange), and highest (red) quartile of the predicted elasticity of labour supply with respect to own price d_{jj}. Panel (d) shows the split by d_{jj} median of the pooled occupations x sub-periods sample. Panel (e) shows separately for each sub-period.

Table C.10: Prices á la Cortes (2016) and Employment: Full Model (OLS)

Three-Type Decomposition	Dependent Variable: $\Delta\mathbf{e}$				
	Unrestricted Model			Restricted Model	
	(1)	(2)	(3)	(4)	(5)
fixed relationship: $\overline{d}_{diag}\Delta p_j$	2.23^{***}	2.70^{***}	4.46^{***}		
	(0.45)	(0.49)	(1.30)	2.70^{***}	
heter. own effect: $(d_{jj}-\overline{d}_{diag})\Delta p_j$		2.25^{***}	4.65^{***}	(0.49)	5.18^{***}
		(0.67)	(1.73)		(1.15)
total cross effect: $\sum_{j\neq k} d_{jk}\Delta p_k$			3.23^{*}		
			(1.81)		
R-squared	0.287	0.340	0.371	0.337	0.350
Number of occupations	120	120	120	120	120

Notes: Results using prices á la Cortes (2016). The regressor in column (4) is $d_{jj}\Delta\ln p_j$. In column (5), the regressor is $\sum_j d_{jk}\Delta\ln p_k$, i.e. corresponding to the full model. Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Observations weighted by j's initial employment size. Period 1985–2010.

Table C.11: Prices á la Cortes (2016) and Employment: Full Model (OLS-IV)

Three-Type Decomposition (Restricted Model)	Dependent Variable: $\Delta\mathbf{e}$					
	(1)		(2)		(3)	
	OLS	IV	OLS	IV	OLS	IV
fixed relationship: $\overline{d}_{diag}\Delta p_j$	2.23^{***}	1.71^{***}				
	(0.45)	(0.50)				
own effect: $d_{jj}\Delta p_j$			2.70^{***}	2.05^{***}		
			(0.49)	(0.57)		
own & cross effect: $\sum_{k=1}^{N} d_{jk}\Delta p_k$					5.18^{***}	6.48^{***}
					(1.15)	(2.12)
Number of Occupations	120	120	120	120	120	120
R-squared	0.287	-	0.337	-	0.350	-
F-stat 1st Stage	-	91	-	69	-	10

Notes: OLS and instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted model using prices á la Cortes (2016). In columns (1)-(2), the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. In column (3), the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. Standard errors are in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by j's initial employment size. Period 1985–2010.

Table C.12: Prices á la Cortes (2016). Accounting for Non-Employment (OLS-IV)

Three-Type Decomposition (Restricted Model)		Dependent Variable: $\Delta\mathbf{e}$					
		(1)		(2)		(3)	
		OLS	IV	OLS	IV	OLS	IV
fixed relationship:	$\overline{d}_{diag}\Delta p_j$	3.05***	2.25***				
		(0.63)	(0.68)				
own effect:	$d_{jj}\Delta p_j$			3.00***	2.29***		
				(0.57)	(0.68)		
own & cross effect:	$\sum_{k=1}^{N} d_{jk}\Delta p_k$					4.76***	5.45***
						(1.10)	(1.78)
elast wrt unemp:	d_{jN+1}	−0.49***	−0.32	−0.30**	−0.19	−0.29**	−0.36
		(0.18)	(0.20)	(0.13)	(0.16)	(0.14)	(0.24)
elast wrt olf:	d_{jN+2}	0.08	−0.08	−0.09	−0.19	0.06	0.14
		(0.19)	(0.25)	(0.12)	(0.17)	(0.20)	(0.28)
elast wrt entry/exit:	d_{jN+3}	0.06	0.09	0.13	0.13	0.12	0.12
		(0.20)	(0.20)	(0.21)	(0.21)	(0.20)	(0.20)
Observations		120	120	120	120	120	120
R-squared		0.386	-	0.401	-	0.402	-
F-stat 1st Stage		-	79	-	28	-	23

Notes: Results using prices á la Cortes (2016). OLS and instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted model (C.13) controlling for non-employment transitions in matrix D of dimension $N+M$. We consider $M=3$ different non-employment sectors: unemployment 'unemp', out of the labour force 'olf' (during the career and including part-time as well as employment with benefit receipt), and entry or exit due to newly joining the labour force at age 25–32 or retiring at age 52–59. For the IV, in columns (1)-(2), the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. In column (3), the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. See Section 3.3.3 for details about the IV approach. Standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.. Observations weighted by j's initial employment size. Period 1985–2010.

Table C.13: Prices á la Cortes (2016). Full Model Pooled Sub-Periods (OLS-IV)

Three-Type Decomposition (Restricted Model)		Dependent Variable: $\Delta\mathbf{e}$								
		(1)			(2)			(3)		
		OLS period fe	OLS period & occ fe	IV period fe	OLS period fe	OLS period & occ fe	IV period fe	OLS period fe	OLS period & occ fe	IV period fe
fixed relationship:	$\overline{d}_{diag}\Delta p_j$	2.06^{***}	2.85^{***}	1.33^{***}						
		(0.35)	(0.42)	(0.50)						
own effect:	$d_{jj}\Delta p_j$				2.41^{***}	2.78^{***}	1.51^{***}			
					(0.34)	(0.42)	(0.54)			
own & cross effect:	$\sum_{k=1}^{N} d_{jk}\Delta p_k$							4.43^{***}	3.24^{***}	4.92^{***}
								(0.70)	(0.55)	(1.56)
Observations		600	600	600	600	600	600	600	600	600
R-squared		0.426	0.789	-	0.456	0.792	-	0.486	0.785	-
F-stat 1st Stage		-	-	110	-	-	85	-	-	11

Notes: Results using prices á la Cortes (2016). OLS and instrumental variable two-stage least squares (IV-2SLS) estimation results of the restricted pooled model (C.14). The pooled panel sample contains 600 observations (120 occupations x 5 sub-periods). Sub-periods are: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. For the IV, in columns (1)-(2), the instrument is $D_{diag}\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. In column (3), the instrument is $D\left(\frac{\theta}{\sigma}D+I\right)^{-1}(I-W)\mathbf{r}$. See Section 3.3.3 for details about the IV approach. Standard errors clustered at the occupation level in parentheses; all coefficients shown are significant at the 1% level. Observations weighted by occupation j's initial employment size (e.g. for the period 1985-1990, this is 1985; for the 2000-2005 period, this is 2000, and so on).