**London School of Economics and Political Science**

*Essays in Trade and Labour Markets*

João Paulo Cordeiro de Noronha Pessoa

Thesis submitted to the Department of Economics of the London School of Economics for the degree of Doctor of Philosophy, London, May 2015.

## Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

The copyright of this thesis rests with the author. Quotation from it is permitted, provided that full acknowledgement is made. This thesis may not be reproduced without my prior written consent.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 39,071 words.

## Statement of Conjoint Work

I confirm that Chapter 2 was jointly co-authored with Francisco JM Costa and Jason Garred and I contributed a minimum of one-third of this work. I confirm that Chapters 3 and 4 were jointly co-authored with John Van Reenen and I contributed a minimum of one-half of this work.

## Statement of Use of Third Party for Editorial Help

I can confirm that Chapter 1 of my thesis was partially copy-edited for conventions of language, spelling and grammar by American Journal Experts.

# Abstract

My thesis studies aspects related to international trade, labour markets and productivity. The first chapter analyses how countries adjust to the rise of China considering that labour markets are imperfect. I provide a theoretical framework to structurally quantify the impact of trade shocks and I find that China's integration generates overall gains worldwide. However, in low-tech manufacturing industries in the UK and in the US, which face severe import competition from China, workers' real wages fall and unemployment rises.

The second chapter studies the recent boom in commodities-for-manufactures trade between China and other developing countries. Brazilian census data show that local labour markets more affected by Chinese import competition experienced slower growth in manufacturing wages and in-migration rates between 2000 and 2010. However, locations benefiting from rising Chinese demand experienced higher wage growth and positive effects on job quality.

The third chapter suggests a possible explanation for poor productivity after the "Great Recession" in the UK: Low growth in the effective capital-labour ratio. This is likely to have occurred because there has been a fall in real wages and increases in the cost of capital due to the financial crisis. After accounting for (simulated) changes in the capital-labour ratio, the evolution of total factor productivity appears much more similar to earlier severe recessions and possibly related to underutilised resources.

The last chapter shows that there is almost no "net decoupling" (the difference in growth of GDP per hour and average compensation, both deflated by the GDP deflator) over the past 40 years in the UK, although there is evidence of "gross decoupling" (the difference in growth of GDP per hour deflated by the GDP deflator and median wages deflated by a measure of consumer price inflation) in the US and, to a lesser extent, in the UK.

# Acknowledgments

Foremost, I am eternally indebted to my supervisor John Van Reenen for all his immense support throughout the PhD. His motivation, encouragement and knowledge were greater than any supervisee would have hoped for.

I am also very grateful to my advisors Emanuel Ornelas and Gianmarco Ottaviano for their valuable help and guidance during all these years.

I would like to express my sincere gratitude to Mounir and Caroline Guen. Without their financial support through the LSE Guen Partnership Scholarship this work would have never been accomplished.

I thank my friends Andy Feng, Daniel Silva, Daniela Scur, Dimitri Szerman, Frank Pisch, Francisco Costa, Jason Garred, Katalin Szemeredi, Markus Riegler, Oriol Carreras, Pedro Franco, Pedro Souza and all my colleagues at the productivity and innovation group at CEP for the fruitful discussions and companionship during the last six years.

Last but not least, I would like to thank my family: My sisters, Maria Clara and Maria Beatriz, my mother, Cencita, and my grandfather, João Gabriel (*in memoriam*). I cannot thank them enough for their endless affection, encouragement and emotional support not only during the PhD but throughout my entire life.

# Contents

# List of Tables

# List of Figures

# Chapter 1

# International Competition and Labor Market Adjustment

## 1.1 Introduction

It has been recognized that trade openness is likely to be welfare improving in the long-run, by decreasing prices and allowing countries to expand their production to new markets. These gains, however, generally neglect important labour market aspects that take place during the adjustment process, such as displacement of workers in sectors harmed by import competition and the fact that workers do not move immediately to growing exporting sectors.

In the last decades China has emerged as powerful player in international trade. In 2013, it surpassed the United States of America (US) to become the world's largest goods trader in value terms. In this paper I study how countries adjust to the rise of China in a world with imperfect labour markets.

The main contribution of this paper is to provide a tractable framework to structurally quantify the impact of trade shocks in a world with both search frictions and labour mobility frictions between sectors. I calculate changes in real income per capita arising from the emergence of China using numerical methods, both in the new equilibrium and along the transition period. My calculations take into account not only the benefits but also account for potential costs linked to labour market adjustments. I find that China's integration generate gains worldwide also in the short-run. However, there are winners and losers in the labour market.

My dynamic trade model incorporates search and matching frictions from Pissarides (2000) into a multi-country-sector Costinot et al. (2012) framework.[1] In this set-up goods

[1] This is a multi-sector version of Eaton and Kortum (2002) where labour is the solely factor of production.

can be purchased at home, but consumers will pay the least-cost around the world accounting for trade costs. Hence, individuals benefit from more trade integration by accessing imported goods at lower costs. On the other hand, a rise in import competition in a sector will decrease nominal wages and increase job destruction in this sector. Wages will not be equal across sectors within countries because of labour mobility frictions, which are added to the model assuming that workers have exogenous preferences over sectors. To analyze how all these effects interact following a trade shock I use numerical simulations.

The "China shock" used in my numerical exercise consists of a decrease in Chinese trade barriers and an increase in Chinese productivity that emulates the growth rate of China's share of world exports following China's entry to the WTO. I find that northern economies gain from this shock. For example, annual real consumption in the US and in the United Kingdom (UK) increase by 1.3% and 2.3%, respectively, in the new steady state compared to the initial one.

The effects of the shock on wages and unemployment are heterogeneous across sectors within countries. In low-tech manufacturing industries in the UK and in the US, which face severe import competition from China, workers' real wages fall and unemployment rises. The fall in the real average wage in this sector is approximately 1.7% in the US and 0.9% in the UK during the adjustment period five years after the shock. However, at the same point in time workers in the service sector experience a rise in the real average wage and no significant change in the unemployment rate: The real average wage in services increases by approximately 2% in the US and 2.6% in the UK.

The numerical exercise also demonstrates the dynamic effects associated with the rise of China. Immediately after the shock, nominal wages rise in exporting sectors and fall in industries facing fierce import competition from China. As workers move from sectors hit badly by China in search of better paid jobs in other industries, wages in exporting sectors start to fall due to a rise in labour supply. This implies that wages are lower in the final steady state than during the transition in these industries. In some import competing sectors, however, the effects go in the opposite direction: Wages fall immediately after the shock and recover over time.[2]

In order to perform counterfactual analysis I estimate a sub-set of the parameters of the model using country-sector level data. I estimate a gravity equation delivered by the model using data on bilateral trade flows to obtain the trade elasticity parameter. I also use equations from my theoretical framework to estimate the parameters related to job

[2]More precisely, in the low-tech manufacturing sector, wages fall during the first five years after the shock in the US and during the first six years in the UK before starting to recover. Note also that wages in import competing sectors hit badly by China will still be lower in the new steady state than in the initial one.

destruction and labour mobility frictions between sectors. The remaining parameters are either calibrated or taken from the literature.

Even though countries experience overall real income gains in my counterfactual exercise, workers in import competing sectors lose from a fall in real wages and an increase in unemployment not only during the transition but also in the new steady state. Another prediction from my model is that low-paid (low-productivity) jobs are the ones destroyed in sectors that experience a negative shock. I validate the qualitative predictions discussed above by drawing on detailed employer-employee panel data from one developed mid-size economy, the UK. Quantitative trade exercises usually focus on the US. I also look at the US in my counterfactuals, but as a very large and rich country, I find it useful to validate the micro implications of my model on a smaller and more open economy, the UK.

By analyzing the period between 2000 (the year before China entered into the WTO) and 2007 (the year before the "Great Recession") I provide support for the three main predictions discussed, i.e., that more Chinese import competition in an industry: i) decrease worker's earnings; ii) increase worker's number of years spent out of employment; iii) has a stronger impact on low-paid workers.[3]

I find that workers initially employed in industries that suffered from high levels of import exposure to Chinese products between 2000 and 2007 earned less and spent more time out of employment when compared to individuals that were in industries less affected by imports from China. I find a negative and significant effects in terms of both weekly and hourly earnings, and that workers that received lower wages between 1997 and 2000 (a proxy for skills) experienced higher subsequent employment losses between 2000 and 2007.

Many other papers study the effects of trade openness on labour markets by quantifying theoretical models. However, to my knowledge this is the first paper that explicitly quantifies the effects of a trade shock, the emergence of China, analyzing all the following aspects: general equilibrium effects across countries, the dynamic adjustment path to a new equilibrium (in a set-up where jobs can be endogenously destroyed) and labour mobility frictions between sectors.[4]

An example of a paper that quantifies the effects of a trade shock on labour markets

[3] My empirical strategy builds on Autor et al. (2013b).

[4] di Giovanni et al. (2014) evaluate the welfare impact of China's integration considering a multi-sector, multi-country framework and also find that welfare increase in developed economies. Levchenko and Zhang (2013) study not only the aggregate but also the distributional impacts of the trade integration of China and other developing economies considering factor immobility, finding that reallocation of factors across sectors contributes relatively little for aggregate gains, but has large distributional impacts. Both papers, however, consider a static framework with full-employment. Bloom et al. (2014) use a dynamic "trapped factors" model (with perfect labour markets) to analyze the impact of China's integration on the growth rate of OECD countries, finding that it increases the profit from innovation, and hence, the long-run growth rate.

is Artuç et al. (2010), where the authors consider a dynamic model with labour mobility frictions across sectors. They estimate the variance of US workers' industry switching costs using gross flows across industries and simulate a trade liberalisation shock. This and other papers in this literature, however, consider a small open economy set-up, disregarding general equilibrium effects across countries.[5]

Another strand of the literature quantifies models in which labour markets are imperfect taking into account general equilibrium effects across countries, but usually ignore multi-sector economies (and consequently that workers do not move freely between sectors) and are silent about transitional dynamics, due to the static nature of their framework. The most similar paper to mine in this area is Heid and Larch (2012), that considers search generated unemployment in an Arkolakis et al. (2012) environment and calculate international trade welfare effects in the absence of full employment.[6]

The validation of the predictions of my model also contributes to the literature that uses worker level information to identify effects of international trade on labour market outcomes, including out of employment dynamics. Examples are Autor et al. (2013b), which considers the China shock to identify impacts on labour markets in the US, and Pfaffermayr et al. (2007), which uses Austrian data to estimate how trade and outsourcing affect transition probabilities between sectors and/or out of employment states.[7]

The paper is organised as follows. In Section 2 I present my model and discuss its most important implications. In section 3 I structurally estimate a sub-set of the parameters of the model, explain how to numerically compute my counterfactual exercise and present its results. In Section 4 I validate the key micro implications of the model using employer-employee panel data from the UK. I offer concluding comments in Section 5.

[5]Another interesting study is Dix-Carneiro (2014), which estimates a dynamic model using Brazilian micro-data to study the adjustment path after a Brazilian trade liberalisation episode in the nineties. Utar (2011) calibrates a model using Brazilian data to answer a similar question, while Helpman et al. (2012a) use linked employer-employee data to analyze also the trade effects in this same country, but with a greater focus on wage inequality. Cosar et al. (2013) and Utar (2006) use Colombian firm level data to estimate a dynamic model of labour adjustment and study how the economy fairs following an import competition shock.

[6]Felbermayr et al. (2013) construct a static one sector Armington model with frictions on the goods and labour markets and use a panel data of developed countries to verify the predictions of the model. Felbermayr et al. (2014) builds a dynamic two country one sector model a la Melitz (2003) to study inequality response to trade shocks in Germany, but consider only a static framework in their calibration exercise using matched employer-employee data from Germany.

[7]More broadly, the paper adds to a growing literature on the effects of trade shocks on labour markets, such as Revenga (1992), Bernard et al. (2006), Topalova (2007), Filho and Muendler (2007), McLaren and Hakobyan (2010), Bloom et al. (2015), Dauth et al. (2012), Kovak (2013), Autor et al. (2013a) and Costa et al. (2014).

## 1.2 Model

My dynamic trade model incorporates frictional unemployment with endogenous job destruction (Pissarides, 2000) into a multi-country/multi-sector Costinot et al. (2012) framework. I also add labour mobility frictions between sectors using some features from Artuç et al. (2010).

The model takes into account that labour markets are imperfect. The economy is composed of many countries and sectors. Workers without a job can choose the sector in which to search for employment according to their personal exogenous preferences. Within a sector, firms and workers have to engage in a costly and uncoordinated process to meet each other. Each sector produces many types of varieties, and consumers will shop around and pay the best available price for each type of variety (considering trade costs).

The model is tractable and allows the ability to quantify changes in real income per capita (my welfare proxy) following a trade shock (the emergence of China) considering not only the positive aspects associated with cheaper consumption goods but also the potential negative aspects associated with labour market adjustments. My dynamic framework will also enable me to study how different groups of workers are affected at different points in time. I start the section by providing the main components of the model. I then demonstrate how to compute the equilibrium and discuss some of the implications of the model.

### 1.2.1 Set up

In terms of notation, $a^t_{k,i}$ represents variable 'a' in sector $k$ in country $i$ at time $t$. Some variables represent a bilateral relationship between two countries. In this case, the variable $a^t_{k,oi}$ is related to exporter $o$ and importer $i$ in sector $k$. Finally, in other cases it will be necessary to highlight that a variable depends on a worker, on a variety or on a different productivity level. In such cases, $a^t_{k,i}(l)$ means that the variable is related to the worker $l$, $a^t_{k,i}(j)$ is a variable associated with the variety $j$ and $a^t_{k,i}(x)$ is linked to idiosyncratic productivity $x$. For the sake of simplicity, I omit the variety index $j$ whenever possible.

#### Consumers

There are $N$ countries. Each country has an exogenous labour force $L_i$ and is formed by $K$ sectors containing an (endogenous) mass of workers $L^t_{i,k}$ and an infinite mass of potential entrant firms. I assume that heterogeneous family members in each country pool their income, which is composed of unemployment benefits, labour income, firm profits and government lump-sum transfers/taxes, and maximize an inner C.E.S, outer Cobb-Douglas utility function subject to their income:[8]

$$Max \sum_t \sum_k \frac{\mu_{i,k}}{\epsilon} \frac{\ln \int_0^1 (C_{k,i}^t(j))^{\epsilon} dj}{(1+r)^t}.$$

Where $k$ indexes sectors, $\epsilon = (\sigma - 1)/\sigma$, $\sigma$ is the constant elasticity of substitution (between varieties) and $C_{k,i}^t(j)$ represents consumption of variety $j$. $\mu_{i,k}$ is country $i$'s share of expenditure on goods from sector $k$, and $\sum_k \mu_{i,k} = 1$. Note that consumers do not save in this economy. The dynamic effects in the model arise from labour market features, as shown below.

### Labour Markets

Each sector has a continuum of varieties $j \in [0, 1]$. I treat a variety as an ex-ante different labour market. I omit the variety index $j$ from this point forward, but the reader should keep in mind that the following expressions are country-sector-variety specific.

Firms and workers have to take part in a costly matching process to meet each other in a given market. This process is governed by a matching function $m(u_{k,i}^t, v_{k,i}^t)$. It denotes the number of successful matches that occur at a point in time when the unemployment rate is $u_{k,i}^t$ and the number of vacancies posted is $v_{k,i}^t$ (expressed as a fraction of the labour force). As in Pissarides (2000), I assume that the matching function is increasing in both arguments, concave and homogeneous of degree 1. Homogeneity implies that labour market outcomes are invariant to the size of the labour force in the market. For convenience, I work with $\theta_{k,i}^t = v_{k,i}^t / u_{k,i}^t$, a measure of labour market tightness.

So the probability that any vacancy is matched with an unemployed worker is given by

$$\frac{m(u_{k,i}^t, v_{k,i}^t)}{v_{k,i}^t} = q(\theta_{k,i}^t),$$

and the probability that an unemployed worker is matched with an open vacancy is

$$\frac{m(u_{k,i}^t, v_{k,i}^t)}{u_{k,i}^t} = \theta_{k,i}^t q(\theta_{k,i}^t).$$

Workers are free to move between markets to look for a job but not between sectors as will become clearer later. Unemployed workers receive a constant unemployment benefit $b_i$. New entrant firms are also free to choose a market in which to post a vacancy and are

[8] Under the assumption of a "big household" with heterogeneous individuals (employed/unemployed in different sectors), and that households own some share of firms, household consumption equals its income $Consumption_i^t = Income_i^t = Wages_i^t + Profits_i^t + UnempBenefits_i^t + Tgov_i^t$
The government uses lump-sum taxes/transfers $Tgov_i^t$ to pay unemployment benefits and finance vacancy costs, as will see later. When the economy is aggregated, I must have that total expenditure in a country (consumption) will be equal to total revenue obtained with its sales around the world.

constrained to post a single vacancy. While the vacancy is open they have to pay a per period cost equals to $\kappa$ times the productivity of the firm.

Jobs have productivity $z_{k,i}x$. $x$ is a firm specific component, which changes over time according to idiosyncratic shocks that arrive to jobs with probability $\rho$, changing the productivity to a new value $x'$, independent of $x$ and drawn from a distribution $G(x)$ with support $[0, 1]$. $z_{k,i}$ is a component common to all firms within a variety, constant over time and taken as given by the firm (I postpone its description until the end of this subsection). Conditional on producing variety $j$, each firm can choose its technology level and profit maximisation trivially implies firms initially operate at the frontier, i.e., all vacancies are opened with productivity $z$ (at maximum $x$).

After firms and workers meet, production starts in the subsequent period. Firms are price takers and their revenue will be equal to $p^t_{k,i}z_{k,i}x$. During production periods, firms pay a wage $w^t_{k,i}(x)$ to employees.

When jobs face any type of shock (including the idiosyncratic one), firms have the option of destroying it or continuing production. Let $J^t_{k,i}(x)$ be the value of a filled vacancy for a firm. Then, production ceases when $J^t_{k,i}(x) < 0$ and continues otherwise. So, job destruction takes place when $x$ falls below a reservation level $R^t_{k,i}$, where $J^t_{k,i}(R^t_{k,i}) = 0$. Defining the expected value of an open vacancy as $V^t_{k,i}$, I can write value functions that govern firms' behavior:

$$V^t_{k,i} = -\kappa p^t_{k,i}z_{k,i} + \frac{1}{1+r}[q(\theta^t_{k,i})J^{t+1}_{k,i}(1) + (1 - q(\theta^t_{k,i}))V^{t+1}_{k,i}]. \tag{1.1}$$

$$J^t_{k,i}(x) = p^t_{k,i}z_{k,i}x - w^t_{k,i}(x) + \frac{1}{1+r}[\rho \int_{R^{t+1}_{k,i}}^{1} J^{t+1}_{k,i}(s)dG(s) + (1 - \rho)J^{t+1}_{k,i}(x)]. \tag{1.2}$$

The value of an open vacancy is equal to the per-period vacancy cost plus the future value of the vacancy. The latter term is equal to the probability that the vacancy is filled, $q(\theta^t_{k,i})$, times the value of a filled vacancy next period, $J^{t+1}_{k,i}(1)$, plus the probability that the vacancy is not filled multiplied by the value of an open vacancy in the future, all discounted by $1 + r$.

I am implicitly assuming that firms are not credit constrained, even though some papers, e.g. (Manova, 2008), argue that financial frictions matter in international trade. So, governments will lend money to firms (financed by lump-sum taxes on consumers) as long as the value of posting a vacancy is greater or equal to zero. The value of a filled job is given by the per period revenue minus the wage cost plus the expected discounted value of the job in the future. The last term is equal to the probability that idiosyncratic shocks arrive multiplied by the expected value of the job next period, $\rho \int_{R_{k,i}^{t+1}}^{1} J_{k,i}^{t+1}(s)dG(s)$, plus the value that the job would have in the absence of a shock times the probability of such event, $(1-\rho)J_{k,i}^{t+1}(x)$.

$U_{k,i}^{t}$ and $W_{k,i}^{t}(x)$ are, respectively, the unemployment and the employment value for a worker. The value functions governing workers choices are:

$$U_{k,i}^{t} = b_i + \frac{1}{1+r}[\theta_{k,i}^{t} q(\theta_{k,i}^{t}) W_{k,i}^{t+1}(1) + (1-\theta_{k,i}^{t} q(\theta_{k,i}^{t}))U_{k,i}^{t+1}]. \tag{1.3}$$

$$W_{k,i}^{t}(x) = w_{k,i}^{t}(x) + \frac{1}{1+r}[\rho(\int_{R_{k,i}^{t+1}}^{1} W_{k,i}^{t+1}(s)dG(s) + G(R_{k,i}^{t+1})U_{k,i}^{t+1}) + (1-\rho)W_{k,i}^{t+1}(x)]. \tag{1.4}$$

The unemployment value is equal to the per period unemployment benefit plus the discounted expected value of the job next period, given that workers get employed with probability $\theta_{k,i}^{t} q(\theta_{k,i}^{t})$.

The value of a job for a worker is given by the per-period wage plus a continuation value, which is composed by two terms. First, the worker could get the value that the job would have in the absence of a shock, $W_{k,i}^{t+1}(x)$, a value that is realised with probability $1-\rho$. If a shock arrives, with probability $\rho G(R_{k,i}^{t+1})$ the shock will be sufficiently bad to drive the worker into unemployment and he/she obtains only $U_{k,i}^{t+1}$ next period. If after the shock productivity remains above the destruction threshold, then the worker gets on average $\rho \int_{R_{k,i}^{t+1}}^{1} W_{k,i}^{t+1}(s)dG(s)$.

Wages are determined by means of a Nash bargaining process, where employees have exogenous bargaining power $0 < \beta_{k,i} < 1$. Hence, the surplus that accrues to workers must be equal to a fraction $\beta_{k,i}$ of the total surplus,

$$W_{k,i}^{t}(x) - U_{k,i}^{t} = \beta_{k,i}(J_{k,i}^{t}(x) + W_{k,i}^{t}(x) - U_{k,i}^{t} - V_{k,i}^{t}). \tag{1.5}$$

**Firm Entry and Worker Mobility within a Sector**

Remember that workers and firms are free to look for jobs and to open vacancies across varieties. Hence, at every point in time the unemployment value must be equal for all varieties that are produced in equilibrium. Because markets are competitive, firms cannot obtain rents from opening vacancies. This implies that the value of a vacancy will be equal to zero in any market inside a country. These two conditions can be summarised as follows,

$$U_{k,i}^t(j) = U_{k,i}^t(j') \tag{1.6}$$

$$V_{k,i}^t(j) = V_{k,i}^t(j') = 0, \tag{1.7}$$

where here I explicitly indicate that the unemployment value and the value of an open vacancy are ex-ante market specific.

The fact that unemployment values are equalised across different varieties (condition 1.6) implies that $p_{k,i}^t z_{k,i}$ must be equal across markets that produce in equilibrium. Suppose that there are two varieties $j$ and $j'$ with distinct values of $p_{k,i}^t z_{k,i}$ and without loss of generality, assume that job market tightness is greater in market $j$, meaning that it is easier for a worker to find a job there. In this case, $p_{k,i}^t z_{k,i}$ must be greater in market $j'$, such that the lower probability of finding a job in this market is compensated by higher wages. However, if this is the case, firms will only be willing to open vacancies in market $j$, where they have a higher probability of finding a worker and can pay lower wages. Hence, the only possible equilibrium is a symmetric one where $\theta_{k,i}^t$ and $p_{k,i}^t z_{k,i}$ are equalised across varieties inside a sector in a country. Hence, all varieties also have the same labour market outcomes $R_{k,i}^t$ and $u_{k,i}^t$, as well as the same wage distribution. As will be discussed below, the only variety dependent variable is the price (a sketch of proof is presented in Appendix 1.A).

**Worker Mobility between Sectors**

Before looking for a job in a particular sector, an unemployed worker must choose a sector, and in contrast to the variety case, they do not move freely between sectors. I assume that each worker has a (unobserved by the econometrician) preference $\nu_k(l)$ for each sector, invariant over time. I further assume that workers know all the information necessary before taking their decision. Hence, the value of being unemployed in a particular sector for a worker $l$, $\hat{U}_{k,i}^t(l)$, is given by

$$\hat{U}_{k,i}^t(l) = U_{k,i}^t + \nu_k(l).$$

A high $\nu_k(l)$ relative to $\nu_{k'}(l)$ means that the worker has some advantage of looking for jobs in sector $k$ relative to sector $k'$, for example, because he/she prefers to work in industry $k$ as it is located in an area where he/she owns a property or his/her family members are settled. I do not provide a more detailed micro foundation for $\nu_k(l)$ to keep the model as simple as possible.

So the probability that a worker will end up looking for job in sector $k$ while unemployed is given by

$$Pr(\hat{U}^t_{k,i}(l) \geq \hat{U}^t_{k',i}(l)) = Pr(\nu_k(l) \geq \nu(l)_{k'} + U^t_{k',i} - U^t_{k,i}). \tag{1.8}$$

For simplicity, I assume that $\nu_k(l)$ are i.i.d. across individuals and industries, following a type I extreme value (or Gumbel) distribution with parameters $(-\gamma\zeta, \zeta)$.[9] The parameter $\zeta$, which governs the variance of the shock, reflects how important non-pecuniary motives are to a worker's decision to switch sectors. When $\zeta$ is very large, pecuniary reasons play almost no role and workers will respond less to wage (or probability of finding a job) differences across sectors. In the polar case of $\zeta$ going to infinity, workers are fixed in a particular industry. When $\zeta$ is small the opposite is true and workers tend to move relatively more across sectors following unexpected changes in sectoral unemployment values.

This assumption implies a tractable way of adding labour mobility frictions to the model. In my counterfactual exercise, I will be able to analyze how different levels of mobility frictions influence the impacts on several outcomes following a trade shock. It also incorporates an interesting effect on the model: It allows sectors with high wages and high job-finding rates to coexist in equilibrium with sectors with low wages and low job-finding rates. If there were no frictions (workers were completely free to move) sectors with higher wages would necessarily have lower job-finding rates (as long as the value of posting vacancies were equal to zero in both sectors).

Note also from equation 1.5 that I am assuming that the bargaining game in one sector is not *directly* affected by the unemployment value in the other sectors. In my model, an employed individual (or an individual who has just found a job) behaves as if he/she is "locked-up" in the sector, i.e., his/her outside option at the bargaining stage in sector $k$ is independent of the preference shocks $\nu_{k'}(l)$ in all other sectors. If I further assume that workers also benefit from this preference shock while they are employed, implying that a worker in sector $k$ gets a total of $W^t_{k,i}(x) + \nu_k(l)$, then wages will not depend directly on the $\nu$'s. This assumption is similar to the one used in Mitra and Ranjan (2010).

### Job Creation and Job Destruction

Before workers decide on a sector to look for an open vacancy, job creation and job destruction take place in this economy:

[9] The Gumbel cumulative distribution with parameters $(-\gamma\zeta, \zeta)$ is given by $S(z) = e^{-e^{-(z-\gamma\zeta)/\zeta}}$ and I have that $E(z) = -\gamma\zeta + \gamma\zeta = 0$ and $Var(z) = \pi^2\zeta^2/6$, where $\pi \approx 3.1415$ and $\gamma \approx 0.5772$.

$$u_{k,i}^{t+1} = u_{k,i}^{t} - m(u_{k,i}^{t}, v_{k,i}^{t}) + \rho G(R_{k,i}^{t})(1 - u_{k,i}^{t}). \tag{1.9}$$

The unemployment rate in period $t+1$ is equal to the rate at period $t$ reduced by the number of new matches and inflated by the number of individuals who become unemployed (all terms expressed as a fraction of the labour force). One implicit assumption is that the labour force remains constant during this process, i.e., all movement of workers has already taken place. Notice also that this process takes place at the variety level, but the fact that the varieties are symmetric will permit me to easily aggregate it up to the sector level.

**International Trade**

All goods are tradable. Each variety $j$ from sector $k$ can be purchased at home at price $p_{k,i}^{t}(j)$ (which is equivalent to the term $p_{k,i}^{t}$ used in my description of the labour market, the only difference being that I now make explicit that it is a country-market specific variable), but local consumers can take advantage of the option provided by a foreign country and pay a better price. In short, consumers will pay for variety $j$ the $min\{d_{k,oi}\, p_{k,o}^{t}(j); o = 1, ..., N\}$, where $d_{k,oi}$ is an iceberg transportation cost between exporter $o$ and importer $i$, meaning that delivering a unit of the good requires producing $d_{k,oi} > 1$ units. I assume that $d_{k,ii} = 1$ and that is always more expensive to triangulate products around the world than exporting goods bilaterally $(d_{k,oi}d_{k,ii'} > d_{k,oi'})$.

In any country $i$, the productivity component $z_{k,i}$ is drawn from a Frechet distribution $F_{k,i}(z) = e^{-(A_{k,i})^{\lambda} z^{-\lambda}}$, i.i.d for each variety in a sector. The parameter $A_{k,i} > 0$ is related to the location of the distribution: A bigger $A_{k,i}$ implies that a higher efficiency draw is more likely for any variety. It reflects home country's absolute advantage in the sector. $\lambda > 1$ pins down the amount of variation within the distribution and is related to comparative advantage: a lower $\lambda$ implies more variability, i.e., comparative advantage will exert a stronger force in international trade.

As in Eaton and Kortum (2002), the fact that consumers shop for the best price around the world implies that each country $i$ will spend a share $\pi_{k,oi}^{t}$ of its income on goods from country $o$ in sector $k$. It is not trivial to calculate this share, however. In the next subsection I will show that some equilibrium properties will deliver relatively simple expressions for it. For now, I just assume that it is possible to find an expression for these expenditure shares. In any case markets must clear

$$Y_{k,o}^{t} = \sum_{i'} \pi_{k,oi'}^{t} Y_{i'}^{t}, \tag{1.10}$$

where $Y^t_{i'} = \sum_k Y^t_{k,i'}$ is aggregate income in country $i'$. Following Krause and Lubik (2007) and Trigari (2006), I assume that the government pays for unemployment benefits and vacancy costs through lump sum taxes/transfers. This implies that aggregate income in a sector is given by the total revenue obtained from sales around the world.

### 1.2.2 Steady State

I analyze the steady state of the economy, henceforth omitting the superscript "t". My first key equation is the Beveridge Curve, the point where transition from and to employment are equal. I find it by using Equation 1.9 and my definition of $\theta = v/u$. I then obtain

$$u_{k,i} = \frac{\rho G(R_{k,i})(1-u_{k,i})}{\theta q(\theta_{k,i})}. \tag{1.11}$$

From the free entry condition 1.7 above combined with equation 1.1, I can find the value of the highest productivity job,

$$J_{k,i}(1) = \frac{(1+r)\kappa p_{k,i} z_{k,i}}{q(\theta_{k,i})}. \tag{1.12}$$

Equation 1.12 is the zero profit condition, which equates job rents to the expected cost of finding a worker. By manipulating expression 1.2 and using equation 1.12, I obtain the following expression:

$$\frac{\kappa}{q(\theta_{k,i})} = \frac{(1-\beta_{k,i})(1-R_{k,i})}{r+\rho}. \tag{1.13}$$

This is the job creation condition. It equates the expected gain from a job to its expected hiring cost. Note that this expression is independent of $z_{k,i}$ and $p_{k,i}$ because both revenue and costs for the firm are affected by these variables linearly.

I can find a relatively simple expression for wages by combining equations 1.3 and 1.4, the sharing rule 1.5 and the job creation condition 1.13. It is given by

$$w_{k,i}(x) = (1-\beta_{k,i})b_i + \beta_{k,i} p_{k,i} z_{k,i}(x + \kappa\theta_{k,i}). \tag{1.14}$$

Wages are increasing in prices and in the productivity parameters. And the job destruction condition can then be derived by manipulating expression 1.2,

$$\frac{b_i}{p_{k,i} z_{k,i}} + \frac{\beta_{k,i}\kappa\theta_{k,i}}{1-\beta_{k,i}} = R_{k,i} + \frac{\rho}{r+\rho}\int_{R_{k,i}}^{1} (s - R_{k,i})dG(s). \tag{1.15}$$

Symmetric varieties will permit me to find relatively simple expressions for the trade shares of each country around the world. Since the term $p_{k,i} z_{k,i}$ is constant across varieties and $z_{k,i}$ is a random variable, it must be that the price of each variety is also a random variable inversely proportional to $z_{k,i}$. There are some ways to see this. One of them is to use my wage equation 1.14 to find the highest wage in the sector, $w_{k,i}(1)$, and subtract from it the lowest wage, $w_{k,i}(R_{k,i})$. This will imply that:

$$p_{k,i}(j) = \frac{1}{z_{k,i}(j)} \frac{w_{k,i}(1) - w_{k,i}(R)}{\beta_{k,i}(1 - R_{k,i})} = \frac{\tilde{w}_{k,i}}{z_{k,i}(j)}. \quad (1.16)$$

$\tilde{w}_{k,i}$ is simply a way of writing the slope of the wage profile in the sector. For everything else constant, a steeper wage profile implies that the wage bill in the country is higher, and prices will also be higher.

I am now in the position to calculate trade shares around the world. Given iceberg trade costs, prices of goods shipped between an exporter $o$ and an importer $i$ are a draw from the random variable $P_{k,oi} = \frac{d_{k,oi}\,\tilde{w}_{k,o}}{Z_{k,o}}$. The probability that country $o$ offers the cheapest price in country $i$ is

$$H_{k,oi}(p) = Pr(P_{k,oi} \leq p) = 1 - F_{k,o}(d_{k,oi}\,\tilde{w}_{k,o}/p) = 1 - e^{-(pA_{k,o}/d_{k,oi}\,\tilde{w}_{k,o})^{\lambda}}, \quad (1.17)$$

and since consumers will pay the minimum price around the world, I have that the distribution of prices actually paid by country $i$ is

$$H_{k,i}(p) = 1 - \prod_{o'=1}^{N} (1 - H_{k,o'i}(p)) = 1 - e^{-\Phi_{k,i} p^{\lambda}}, \quad (1.18)$$

where $\Phi_{k,i} = \sum_{o'} (A_{k,o'}/d_{k,o'i}\,\tilde{w}_{k,o'})^{\lambda}$, is the parameter that guides how labour market variables, technologies and trade costs around the world govern prices. Each country takes advantage of international technologies, discounted by trade costs and the wage profile of each country.

Hence, I can calculate any moment of the price distribution, including the exact price index for tradable goods in steady state,

$$P_{k,i} = \gamma(\Phi_{k,i})^{(-1/\lambda)}, \quad (1.19)$$

where $\gamma = [\Gamma(\frac{\lambda+1-\sigma}{\lambda})]^{1/(1-\sigma)}$ and $\Gamma$ is the Gamma function.

As in Eaton and Kortum (2002), I calculate the probability that a country $o$ provides a good at the lowest price in country $i$ in a given sector:

$$\pi_{k,oi} = \frac{(A_{k,o}/d_{k,oi}\,\tilde{w}_{k,o})^{\lambda}}{\Phi_{k,i}}. \quad (1.20)$$

Eaton and Kortum also show that the price per variety, conditional on the variety being supplied to the country, does not depend on the origin, i.e., the price of a good that $i$ actually buys from any exporter $o$ also has the distribution $H_{k,i}(p)$. This implies that average expenditure does not vary by country of origin. Exporters with cheaper wages or with lower trade costs take advantage by exporting a wider range of goods. Because there is a continuum of goods, it must be that the expenditure share of country $i$ on varieties coming from $o$ is given by the probability that $o$ supplies a variety to $i$,

$$\frac{X_{k,oi}}{X_{k,i}} = \pi_{k,oi}, \tag{1.21}$$

where $X_{k,oi}$ is country $i$'s expenditure on goods from $o$, and $X_{k,i} = \sum_{o'} X_{k,o'i}$ is its total expenditure in a given sector.

To close the model I have to find an expression for income in country $i$. Income in the sector is given by its total revenue[10]

$$Y_{k,o} = \tilde{w}_{k,o} L_{k,o}(1 - u_{k,o})(G(R_{k,o}) + \int_{R_{k,o}}^{1} sdG(s)). \tag{1.22}$$

The market clearing condition in steady state implies that

$$Y_{k,o} = \sum_{i'} X_{k,oi'} = \sum_{i'} \pi_{k,oi'} \mu_{k,i'} Y_{i'}. \tag{1.23}$$

Finally, the Gumbel distribution allows me to calculate a simple expression for the number of individuals attached to each sector by using expression 1.8. I must have that the share of workers in each sector equals the probability that a worker is looking for a job in that sector whenever he/she is unemployed. And it can be shown that this probability will be equal to:[11]

$$\frac{L_{o,k}}{\sum_{k'} L_{o,k}} = \frac{e^{U_{k,i}/\zeta}}{\sum_{k'} e^{U_{k',i}/\zeta}}, \tag{1.24}$$

where $U_{k,i} = \frac{1+r}{r}(b_i + \frac{\beta_{k,i}}{(1-\beta_{k,i})}\kappa p_{k,i} z_{k,i} \theta)$.

[10]To calculate production I follow Ranjan (2012). First, note that output changes over time equals (i) the output from new jobs created at maximum productivity $\theta_{k,i} q(\theta_{k,i}) u_{k,i}$, plus (ii) the output of the existing jobs that are hit by a shock and survive $\rho \int_{R_{k,i}}^{1} sdG(s)$, minus (iii) the loss in production due to destroyed jobs $\rho Q_{k,i}$, where $Q_{k,i}$ equals production per worker in the sector. Setting the total change to zero, I find $Q_{k,i} = (1 - u_{k,i})(G(R_{k,i}) + \int_{R_{k,i}}^{1} sdG(s))$. I then subtract vacancy costs, multiply it by the total workers and the value $\tilde{w}_{k,i}$ in each variety market and integrate over the mass of varieties being produced to find revenue. The only non-constant term among varieties is the number of workers, that must sum up to $L_{k,i}$. I also use the fact that in Pissarides' model rescaling the labour force does not affect equilibrium outcomes.

[11]See Artuç et al. (2010), online Appendix, for a similar proof.

To find my steady state equilibrium, note that from the labour market equations (1.11, 1.13 and 1.15) I can find the values of $R_{i,k}$, $\theta_{i,k}$ and $u_{i,k}$ as a function of $\tilde{w}_{i,k}$ for every country and sector. I can then use the trade share equation, also expressed as a function of $\tilde{w}_{i,k}$, together with my market clearing condition above to find the relative values of the slope of the wage profile that balance trade around the world. Finally, the labour force size in each of the sectors can be determined through the equation that determines the share of unemployed individuals in each sector. Naturally, all these effects take place simultaneously, and hence, I have to solve the system of non-linear equations described above to find my endogenous variables.

In short, I use the Beveridge curve (1.11), the job creation (1.13) and job destruction (1.15) conditions, the market clearing equation (1.23) together with the trade share expressions (1.20) and the unemployment share condition (1.24), to find my endogenous variables $R_{i,k}$, $\theta_{i,k}$, $u_{i,k}$, $\tilde{w}_{i,k}$, $L_{i,k}$ for al $i$'s and $k$'s. There are a total of $N$x$K$ equations of the type of Equation 1.23, but only $N$x$K - 1$ independent ones. I have to assume that the sum of all countries' income is equal to a constant.

### 1.2.3 Implications of the Model

Consider a rise in productivity ($A_{k,oi}$) in a foreign country $o$ or a fall in trade costs ($d_{k,oi}$) from the same foreign country to home country $i$, holding productivity in the home country fixed. Consumers in the home country will benefit as they have access to cheaper goods coming from abroad. However, this can also have negative effects in the labour market. If the demand for goods produced locally fall, prices of local goods will fall, implying that jobs will have to be destroyed in the home country[12] and nominal wages will decrease. Note that the jobs destroyed in any country-sector following a bad shock are the ones with low idiosyncratic productivity $x$. These are the low-paid (low-productivity) jobs in the sector that become non-profitable after a fall in prices.

The effect on real wages is ambiguous, however. For example, if the rise in productivity takes place in a sector $k$ in which the home country has a high level of production and most part of it is exported (meaning that the consumption share $\mu_{k,i}$ is low in the home country), real wages will tend to fall at home in sector $k$, as the benefits from cheaper prices are small (if $\mu_{k,i}$ is zero there is no benefit at all) and nominal wages decrease in this sector as the foreign country increases its market share around the world. On the other hand, if home country $i$ has a low production level in sector $k$ but has a high consumption

[12] Note that the assumption that the unemployment benefit $b$ is constant plays an important role in my model. It will imply that wages will *not* absorb all the impact from shifts in productivity/prices in the new equilibrium and, consequently, such shocks will have an effect on the unemployment rate even in the long-run.

share in this sector (high $\mu_{k,i}$), then real wages will most likely rise as the fall in prices will tend to be the dominant effect in the home country.

Workers have preferences over sectors in my model. This means that after a trade/productivity shock some (but not all) unemployed workers will be willing to move from sectors that experience losses and to start looking for jobs in other sectors. Which sectors lose or gain in each country will depend on the new configuration of comparative and absolute advantages around the world following the trade/productivity shock.

The model also delivers interesting dynamic implications that are deeper investigated in my numerical exercise performed in the next section. After analyzing the results obtained with my counterfactuals, I test some of the observed partial-equilibrium implications of the model in Section 1.4 by drawing on detailed worker-level micro-data from one open developed economy, the UK.

## 1.3 Quantification of the Model

My model provides a rich set of mechanisms that are difficult to study analytically. In this section, I perform a counterfactual numerical exercise to analyze how advanced economies responded to the emergence of China in a world with imperfect labour markets. This will allow me to analyze both the transition path to a new equilibrium and the heterogeneous effects across sectors within countries. My calculations take into account not only that labour markets are imperfect and that workers do not move freely across sectors, but also that exporting sectors can gain from more trade with China and that consumers have access to cheaper imported goods.

In the first part of this section, I estimate three parameters that will be used in my counterfactual. In the second part, I demonstrate how to obtain the remaining parameters (either by calibration from data or from previous papers) and the methodology used to construct my numerical exercise. In the last part, I present the results and conduct a few robustness tests considering different parameter values.

### 1.3.1 Structural Estimation

I start by estimating a sub-set of the parameters for the UK ($\zeta$ and $\rho$). Then, I proceed to estimate the trade elasticity ($\lambda$) using bilateral trade flows. The labour share ($\beta$), the expenditure share ($\mu$) and the productivity parameter that drives absolute advantage ($A$) will be taken directly from the data. All the other parameters will either be calibrated or taken from previous papers.

#### Labour Market Parameters

I estimate the probability of an idiosyncratic shock arriving to a job ($\rho$) and the parameter that governs labour mobility frictions across sectors ($\zeta$).

These labour market parameters are estimated only for the UK and used for all other countries in my counterfactuals. Naturally, it would be more accurate to estimate the parameters for all the countries considered in the next sub-section, and I recognize that this approximation may be unsuitable especially for economies that are very distinct, but data restrictions do not allow me to follow this route and I believe that applying UK parameters to other countries can still provide important qualitative insights for adjustment dynamics. Estimating these parameters for other countries is an important topic for future work but is beyond the scope of this paper.

The data used to estimate labour market variables are from different sources and the regressions used to obtain $\rho$ and $\zeta$ are at the industry level (ISIC3 2-digit), at yearly frequency from 2002 to 2007. Total employment, job creation, and job destruction by industry are from the Business Structure Database (BSD). Unemployment by sector is obtained from the Labour Force Survey (LFS) micro-data. I assume that unemployed individuals are attached to the last industry they worked for, and this information is available in the LFS.[13] Wage data are from the Annual Survey of Hours and Earnings (ASHE) and vacancy data are from the NOMIS, provided by the UK Office for National Statistics.

I calculate $\beta_k$'s as the share of labour costs in value added in each sector in the UK. They are obtained from firm-level micro-data, the Annual Respondent Database (ARD), which I aggregate up to the 2-digit ISIC3 level. I set the interest rate $r = 0.031$ —a value in the range used by (Artuç et al., 2010) that corresponds to a time discount factor of approximately 0.97.

I estimate $\rho$ by using the fact that the total number of jobs destroyed in a sector at any point in time is $\rho G(R_k^t)(1 - u_k^t)L_k^t$. My empirical job destruction measure is calculated using the BSD. It is the sum of all jobs lost in an industry either because firms decreased size or ceased to produce in a particular year. I then run the following industry-level regression,

$$ln(JobDestruction_k^t) = ln(\rho) + ln((1 - u_k^t)L_k^t) + ln(G(R_k^t)) + \varepsilon_k^t, \tag{1.25}$$

and since I do not observe $G()$, I control for a polynomial function (of $4^{th}$ degree) of $R_k^t$ (the idiosyncratic productivity threshold below which jobs are destroyed) in the sector.[14] The first column of Table 1.1 shows my OLS result. The second column restricts the coefficient of $ln((1 - u_k^t)L_k^t)$ to be equal to one, while column 3 additionally includes instruments suggested by the model: the lagged right-hand side variables. Observe that the value of $\rho$ decreases in the 2SLS estimates. The value I use in my counterfactuals (column 3) corresponds to approximately $\rho = 0.0129$.

$\zeta$ can be found using the shares of workers employed in each sector. My model predicts that the number of workers increase in a sector whenever wages increase and/or it is easier to find a job. So, I use an equation that relates increases in the number of employed individuals to changes in wages and job-finding rates in a sector. To obtain this equation,

[13] Not all unemployed in the LFS respond to the question related to the last industry of work, so I assume that the industry share of unemployed individuals is equal to the industry share of unemployed that actually responded to this question, something that is likely to add measurement error to my estimates.

[14] I obtain $R_k^t$ using ARD. First, I calculate average labour productivity by firm. To adjust for outliers I windsorize the labour productivity measure per industry, both at the top $99^{th}$ percentile and at the bottom $1^{st}$ percentile. Second, I divide each firm-level labour productivity by the maximum value in the industry, such that the distribution of productivity in each sector is between zero and one as suggested by the model. Third, I obtain $R_k^t$ as the minimum of the normalised labour productivity measure in each sector.

Table 1.1: Estimates of $\rho$

| | (1) OLS | (2) OLS | (3) 2SLS |
|---|---|---|---|
| | **Total Job Destruction** | | |
| $ln(\rho)$ | -2.697** | -2.901** | -4.342* |
| | (1.228) | (1.163) | (2.421) |
| Restricted Coefficients | - | Yes | Yes |
| Obs | 282 | 282 | 282 |

NOTES: $ln(\rho)$ is the constant term in equation 1.25, which has total job destruction as a dependent variable and a $4^{th}$ degree polynomial function of $R_k^t$ and the logarithm of the total number of employed individuals ($ln((1-u_k^t)L_k^t)$) as controls. Yearly data (from 2002 to 2007) at the industry-level (ISIC3 2-digit) obtained from ARD, BSD, NOMIS and LFS. Column (3) uses the lagged control variables as instrument. Clustered standard errors at the industry-level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I make the strong assumption that the economy is in a different steady state in every year of my sample.

From the steady state versions of equations 1.3 and 1.4, I can write the following expression:[15]

$$\Delta ln(L_k) = \frac{1}{\zeta}\Delta\frac{JFR_k w_k(1)}{1+r} + \psi_k + \psi_t + \hat{\varepsilon}_k^t, \tag{1.26}$$

where $JFR_k^t$ (equivalent to $\theta_k^t q(\theta_k^t)$ in my model) is the probability of a worker finding a job in the sector. This is obtained directly as total job creation (from BSD) divided by the total number of unemployed (calculated using LFS and BSD). $w_k^t(1)$ represents the maximum wage in the sector. To account for possible outliers in the data, I use the $95^{th}$ percentile of the wages in the industry from ASHE instead of the maximum value. The estimates consider normalised wage values such that the average in the sample is equal to 1. My results are shown in the table below:

Column 1 shows my OLS estimates, while the second column presents the 2SLS estimates using the lagged value $JFR_k w_k(1)$ as an instrument. My estimates of $\zeta$ are higher than the ones in Artuç et al. (2010), corresponding to $\zeta = 36.57$ on column 2, the value that will be used in my counterfactuals. Indeed, in my model this coefficient should be higher as it captures all the labour movement frictions between sectors, while in their

[15]First, from 1.3 and 1.4 I can write $U_k^{tss1} - U_k^{tss0} = \frac{JFR_k^{tss1} w_k^{tss1}(1)}{1+r} - \frac{JFR_k^{tss0} w_k^{tss0}(1)}{1+r} + \Theta(k,t)$, where $JFR_k^t$ is the job finding rate (equivalent to $\theta_k^t q(\theta_k^t)$ in my model) and $w_k^t(1)$ is the maximum wage in the sector. $t = tss0$ and $t = tss1$ represent the final and initial steady state, respectively. $\Theta(k,t)$ is a sector-time-level function that depends on present and future variables in the sector, which I approximate using two distinct fixed effects, one for time and the other for sectors. Obviously this is not a very rich approximation, but permits me to take a very simple equation to the data, which is obtained by taking logs and first differences of 1.24 and using the value of $U_k^{tss1} - U_k^{tss0}$ written above.

Table 1.2: Estimates of $\zeta$

| | (1) OLS | (2) 2SLS |
|---|---|---|
| | **Change in the Labor Force** | |
| $1/\zeta$ | 0.032*** | 0.027 |
| | (0.008) | (0.029) |
| $95^{th} Percentile$ | Yes | Yes |
| Obs | 285 | 285 |

NOTES: $\zeta$ is the coefficient of $\Delta\frac{JFR_k w_k(1)}{1+r}$ in equation 1.26, which uses the change in the number of workers in a industry over time as a dependent variable and fixed effects for time and industry as controls. $\Delta\frac{JFR_k w_k(1)}{1+r}$ is the difference over time between the product of the job finding rate and maximum wages (calculated as the $95^{th}$ percentile) in the sector. Yearly data (from 2002 to 2007) at the industry-level (ISIC3 2-digit) obtained from ASHE, BSD, NOMIS and LFS. Column (2) has the lag of $\frac{JFR_k w_k(1)}{1+r}$ as instrument. Estimates consider normalised wage values such that the average in the sample is equal to 1. Clustered standard errors at the industry-level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

paper part of the rigidity is also captured by high fixed moving costs.[16] So, using their estimates in my model would imply that workers are much more mobile than they actually are, possibly leading my real income per capita calculations to overestimate gains (or underestimate losses).

### Matching Function, Idiosyncratic Productivity and Vacancy Costs

I assume the following constant returns to scale matching function:

$$m(v_k^t, u_k^t) = m(u_k^t)^{1-\delta}(v_k^t)^{\delta}.$$

I use the estimates from Borowczyk-Martins et al. (2013, Table 1), $\delta = 0.412$. To find $m$, I start with an estimate of 0.231 (from the same paper) and adjust the parameter such that the probabilities of finding workers and vacancies are always between 0 and 1. The value that will be used is $m = 0.19$.

In all my counterfactuals I assume that idiosyncratic productivity shocks are uniformly distributed between zero and one (Ranjan, 2012). This assumption was not used in my previous estimates. To verify the robustness of my counterfactuals to this and other assumptions I perform additional counterfactual exercises with alternative parameter values.

The parameter $\kappa$, the cost of posting vacancies, is also obtained from another paper. I consider the same value used in Shimer (2005): 0.213.

[16] Another reason is that in my model this is the elasticity of employed and unemployed workers in the UK, while in their model they consider only employed individuals in the US. Hence, workers in their model take into account only wages when moving across sectors, while here workers also look at the probability of finding a job. Secondly, they consider average wages, while I consider the maximum wage ($95^{th}$ percentile) as suggested by my model.

**Trade Parameters**

The trade elasticity $\lambda$ is estimated using a gravity equation. First, I obtain bilateral trade flows from the World Input Output Database (WIOD).[17] Information on labour market characteristics by sector and country comes from the EU KLEMS dataset.[18] As in Costinot et al. (2012), I measure the variation in productivity across countries and industries using differences in producer price indexes. Producer price data is taken from the GGDC Productivity Level Database, which is calculated from raw price data observations at the plant level for several thousand products (often with hundreds of products per industry, which can be associated with varieties in my model, as in Costinot, Donaldson, and Komunjer, 2012).[19] These prices are aggregated into a producer price index at the industry level using output data. I use the inverse of this measure as my $A_k^t$ to identify the trade elasticity.

All my gravity estimations are based on the year 2005, and 1997 lags are used as instruments for my productivity parameter $A_k^t$ (GGDC data is available only for these two years). To compare my estimates to Costinot et al. (2012), I restrict my sample to the same 21 developed countries they consider plus China, and I exclude the so called non-tradable sectors (services). I add China as an importer in all regressions and whenever possible as an exporter since GGDC (1997) and KLEMS data are not available for this country.

By taking logs of expression 1.20, I obtain the following gravity equation: $ln(X_{oi}^k) = \lambda ln(A_o^k) + ln(X_i^k/\Phi_{k,i}) - \lambda ln(\tilde{w}_o^k) + \lambda ln(d_{k,oi})$.

Following Head and Mayer (2013), I replace $ln(X_i^k/\Phi_{k,i})$ with an importer-product fixed effect. I do not observe $\tilde{w}_o^k$.[20] In order to control for the last two terms of the gravity equation and still be able to identify $\lambda$ as the coefficient of $A_k^t$, I replace their values by a sector fixed effect, an exporter fixed effect, an importer-exporter fixed effect and a $4^{th}$ degree polynomial function of labour compensation, total employment, hourly wage and labour share for each exporter-sector pair.[21] So, I run the following regression at the sector-exporter-importer-level

$$ln(X_{oi}^k) = \lambda ln(A_o^k) + \bar{f}_{k,o} + \chi_{ik} + \chi_k + \chi_o + \chi_{oi} + \bar{\varepsilon}_k, \tag{1.27}$$

where the $\chi$ are the respective fixed effects and $\bar{f}_{k,o}$ is the $4^{th}$ degree polynomial of

[17] See Stehrer et al. (2014) for more details on this database.
[18] See O'Mahony and Timmer (2009) for details on the methodology used to construct the dataset.
[19] See Inklaar and Timmer (2008) for more details.
[20] With the data used in the paper, $\tilde{w}_o^k$ could be recovered only for the UK.
[21] Including measures for trade costs such as distance, RTA's and common language do not change the coefficient values significantly, and it is difficult to interpret their coefficients as they are obtained only after some fixed effects are dropped. Hence, I choose to omit them.

exporter labour market variables. The results are shown in the table below:

Table 1.3: Estimates of $\lambda$

| | (1) OLS | (2) OLS | (3) OLS | (4) 2SLS |
|---|---|---|---|---|
| | **Bilateral Trade Flows** | | | |
| $\lambda$ | 1.120*** | 1.791*** | 1.178*** | 4.934*** |
| | (0.458) | (0.471) | (0.331) | (1.327) |
| China as an Exporter | Yes | - | - | - |
| Labor Market Controls | - | - | Yes | Yes |
| Obs | 6866 | 6194 | 6194 | 6194 |

NOTES: $\lambda$ is the coefficient of the productivity measure $A_o^k$ in equation 1.27, which uses bilateral trade flows at the sector level as the dependent variable and fixed effects for industry, importer-sector and exporter fixed effects. Labour Market Controls is a $4^th$ degree polynomial function of labour compensation, total employment, hourly wage and labour share for each exporter-sector pair. Data is a cross-section of bilateral trade data in 2005 at the WIOD industry-level (roughly ISIC3 2-digit). Data obtained from WIOD, KLEMS and GGDC. Column (4) has the lag of $A_o^k$ (1997 value) as instrument. Clustered standard errors at the exporter-industry level in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Controlling for labour market characteristics decreases the coefficient, while using lagged productivity values as instruments increases it considerably. I use the value of 4.934 in my counterfactuals, which is not far from Costinot et al. (2012) estimates.

### 1.3.2 Counterfactuals

The counterfactuals performed are meant to understand how the rise of China affected other countries in the world, especially the UK. The trade shock I have in mind is one whereby Chinese productivity increases ($A_{k,CHN}$ rises 25%) and all trade costs between China and the rest of the world fall ($d_{k,oCHN}$ and $d_{k,CHNi}$ fall 25%) in all sectors apart from services. This shock implies that China's export shares around the world increases from 0.12 to 0.2 between the two steady states. This corresponds to a growth of 64% in China's share of world exports, a magnitude not very different from the one observed between 2000 (the year before China joined the WTO) and 2004 in the WIOD data (65%). So, my shock aims to mimic the four year period following China's entry into the WTO in terms of percentage change in the its export share. I study how countries respond to this shock during the transition to a new steady state.

To calculate the initial equilibrium, I use the parameters estimated in the previous subsection. My counterfactuals also require values for worker's labour share ($\beta_{k,i}$) and the size of the labour force in each country, both obtained from the WIOD - Socio Economic Accounts.[22] Labour shares are calculated as labour compensation divided by value added

[22] Available at http://www.wiod.org/new$_site/database/seas.htm.$

(at the same level as the WIOD bilateral trade data, roughly the ISIC3 2-digit industry).[23] The expenditure share of each country on goods from a particular sector ($\mu_{k,i}$) is calculated from the WIOD data. The values of $\beta_{k,i}$'s and $\mu_{k,i}$'s can be seen in the Appendix, Table 1.7.

In my counterfactual exercise, I reduce the number of countries to six due to computational reasons. The "countries" chosen are China, US, UK, European Union (EU), the Rest of the World (RoW) Developed and the RoW Developing. The last economies are an aggregation of the remaining WIOD countries, which were separated in high-income (Australia, Japan, Canada, South Korea and Taiwan) and low-income countries (Brazil, India, Indonesia, Mexico, Turkey and Russia). I also aggregate the economy into five sectors: Energy, Agriculture and Mining, Services, and High-Tech, Mid-Tech and Low-Tech Manufacturing. The manufacturing rank of technology is based on R&D intensity in the US in 2005 from OECD STAN database. My sector aggregation is given by:

-*Energy and Others*: Energy, Mining and quarrying; Agriculture, Forestry and fishing;

-*Low-Tech Manufacturing*: Wood products; Paper, printing and publishing; Coke and refined petroleum; Basic and fabricated metals; Other manufacturing.

-*Mid-Tech Manufacturing*: Food, beverage and tobacco; Textiles; Leather and footwear; Rubber and plastics; Non-metallic mineral products.

-*High-Tech Manufacturing*: Chemical products; Machinery; Electrical and optical equipment; Transport equipment.

-*Services*: Utilities; Construction; Sale, maintenance and repair of motor vehicles and motorcycles; Retail sale of fuel; Wholesale trade; Retail trade; Hotels and restaurants; Land transport; Water transport; Air transport; Other transport services; Post and telecommunications; Financial, real estate and business services; Government, education, health and other services; Households with employed persons.

The productivity measure ($A_{k,i}$) are from the GGDC database (described above). I aggregate countries and sectors using value added as weights. The productivity parameters used in the counterfactuals are displayed in Table 1.8, which indicates that China has an absolute advantage in all the sectors. This advantage is most likely because GGDC is based on price data, and China provides the cheapest goods globally. This measure does not take into account, for example, that the UK produces higher quality goods such as airplanes and more advanced cars. Thus, instead of estimating trade costs, I calibrate an additional parameter that *includes* trade costs such that trade shares ($\pi_{k,oi}$) are as close as

[23] I intentionally decrease China's share of value added in agriculture to the second-highest value in agriculture, which in this world is 0.32. The original value corresponded to an extremely high value of 0.8 and was generating problems in my numerical simulations.

possible to the values observed in the WIOD. Put another way, I substitute for $d_{k,oi}$ (the iceberg trade cost described previously) in all my expressions using $\bar{d}_{k,oi} = d_{k,oi} * \omega_{k,oi}$, where $\omega_{k,oi}$ is an unobserved component that accounts, for example, for quality difference across countries. Then, I calibrate the $\bar{d}_{k,oi}$'s such that trade shares are as close as possible to the ones observed in the data. The fact that trade costs are not identified does not play a large role in my counterfactuals, since I am interested in their relative changes (and also in relative income changes).[24]

In my initial steady state equilibrium, I set the unemployment benefit ($b_i$) to a fraction of the average wage in each country: UK 0.36, China 0.18, US 0.4, EU 0.5, RoW Developed 0.5 and RoW Developing 0.14.[25] These values will be fixed throughout my counterfactual exercises, as described in the model. This assumption is not innocuous. It will imply that wages will *not* absorb all the impact from shifts in productivity/prices, and consequently, such shocks will have an effect on the unemployment rate.

My parameter $\zeta$ is held as 36.57 times the average wage in each country in the initial equilibrium, and then kept fixed as well.[26] The summary of all the parameters used are in Table 1.4.

I am then able to find the values of $R_{k,i}$, $u_{k,i}$, $\theta_{k,i}$, $\tilde{w}_{k,i}$ and $L_{k,i}$ in my initial steady state. The model performs relatively well in terms of fitting the size of the labour force in each sector.[27]

Details about the method used to compute the transition path can be found in the Appendix (Subsection 1.B.2). The objective is to find a rational expectations path between the initial and the final steady state. I use a type of multiple shooting algorithm that builds on Artuç et al. (2010) and Lipton et al. (1982). In my algorithm I have to assume a certain number of years for the transition period to occur.[28] I consider 25 years in my numerical exercises, but the higher the number of years assumed the closer the variables of the system

[24] I also assume that $\bar{d}_{k,oo} = 1$ for all countries, as I am able to calibrate only relative values for $\bar{d}$'s. One consequence of calibrating trade costs this way is that China and the RoW developing will have access to the cheapest goods in the world because they are produced by these two countries and their exporting costs are relatively high. This implies that in my initial equilibrium, the rich countries (the UK, US and Eurozone) have a high expenditure on goods around the world but not necessarily the highest real income.

[25] These values are based on Munzi and Salomaki (1999) and Vodopivec and Tong (2008), for the UK, EU, RoW Developed and China. The UK value is relatively low because much of the retained income after a job loss in the UK does *not* come from unemployment benefits, as this is quite small (Job Seekers' Allowance (JSA) nowadays in the UK varies between £57.35 and £113.70 per week and covers a period of approximately 6 months). The US value is based on Shimer (2005), and the value of RoW developing was set slightly below that of China. In my initial steady, state unemployment rates are 0.0479, 0.0575, 0.0256, 0.0399, 0.0391 and 0.0235 in the UK, EU, China, US, RoW Developed and RoW developing, respectively.

[26] This implies that different countries will have different values for this parameters, but all the countries will have the same labour market frictions as the variance of the unobserved preference over sectors will be the same in each country.

[27] The labour force predicted by the model and the labour force observed in the data have a correlation of 63%.

[28] Such types of non-linear systems of equations can only be guaranteed to converge asymptotically - see Lipton et al. (1982).

Table 1.4: Parameters used in the Counterfactuals

| Parameter | Description | Value | How was the Parameter Obtained | Country-Specific | Sector-Specific |
|---|---|---|---|---|---|
| $\rho$ | Constant Rate of Job Destruction | 0.013 | Estimated for the UK and Replicated to other Countries (Table 1.1) | No | No |
| $\kappa$ | Cost of Posting Vacancies | 0.213 | Based on Shimer (2005) | No | No |
| $\zeta$ | Labour Mobility Friction Between Sectors | See Notes Below | Estimated for the UK and Replicated to other Countries (Table 1.2) | Yes | No |
| $\delta$ | Matching Function Elasticity | 0.412 | Based on Borowczyk-Martins et al. (2013) | No | No |
| $m$ | Matching Function Efficiency | 0.190 | Based on Borowczyk-Martins et al. (2013) | No | No |
| $b$ | Unemployment Benefits | See Notes Below | Based on Munzi and Salomaki (1999) and Vodopivec and Tong (2008) | Yes | No |
| $\lambda$ | Trade Elasticity | 4.934 | Estimated for the UK and Replicated to other Countries (Table 1.3) | No | No |
| $d$ | Trade Costs | See Notes Below | Calibrated to Match Trade Flows from WIOD data in 2005 | Yes | Yes |
| $A$ | Countries' Absolute Advantage | See Table 1.8 | GGDC Dataset | Yes | Yes |
| $\beta$ | Labour Share of the Surplus of the Match | See Table 1.7 | WIOD - Socio Economic Accounts Dataset | Yes | Yes |
| $\mu$ | Expenditure Share on a Sector | See Table 1.7 | WIOD Dataset | Yes | Yes |
| $r$ | Annual Interest Rate | 0.031 | Based on Artuç et al. (2010) | No | No |

NOTES: Parameter values used in the main counterfactual. I additionally use unemployment benefits, expressed as a fraction of average wages in each country in the initial equilibrium: UK 0.36, China 0.18, US 0.4, EU 0.5, RoW Developed 0.5 and RoW Developing 0.14. $\zeta = 36.57$ is also expressed as the multiple of average wages in each country in the initial equilibrium. Trade costs and other unobserved components that drive trade (such as unobserved quality of products) are calibrated such that trade flows match WIOD data in 2005, but the two terms cannot be separately observed. See also Tables 1.7 and 1.8 for productivity components and labour and expenditure shares used in the counterfactuals.

are to their new steady state values in the final period of the algorithm. In my numerical simulations approximately 90% of the real income adjustment has taken place in year 25.

**Results**

Real income (or real consumption) is defined as $Y_i/P_i$, where $P_i$ is the price index in country $i$.[29] The analysis will be relative to the initial equilibrium values. Following several papers in the international trade literature, I use real income per capita as a proxy for welfare.[30]

Figure 1.1 shows the evolution of countries' real income per capita (or real consumption per capita) over the 25 years following the fall in trade costs and productivity gains in China. One can see that income instantly increases in all countries, either because the countries are able to export more to China or because consumers have access to cheaper goods.[31] All countries benefit in the new steady state as well. Chinese citizens experience large income gains of more than 24% during the transition period (see Figure 1.2).

Some countries, such as the UK and the EU, experience an initial overshooting in real income (initial gains of approximately 2.4% and 1.3%, respectively). One reason behind this is that after the shock wages (and prices) do the majority of the "heavy-lifting" in the short-run to keep markets cleared, as production is rigid (especially upwards) because it takes time for jobs to be created due to the search and matching frictions in the labour market. Immediately after the shock, nominal wages rise in the exporting sectors and fall in the ones facing fierce import competition from China. Hence, the overshooting of wages accruing to UK/EU workers (together with the fact that consumers have access to cheaper goods) excessively benefits these countries in the short-run. Other countries such as the US exhibit an initial jump in real income (1.35%) and then experience an increasing path toward the new steady state. This is so because the overshooting of wages accruing to workers is mild or non-existent, generating gains that are lower in the short-run.

Overshooting of nominal wages in a sectors occurs whenever the amount of labour used in the final steady state is large relative to its initial equilibrium value. If this is the case, many jobs will have to be created after the shock, and hence, many workers and firms need to be "attracted" to the sector. This implies an overshooting of job surplus

[29] The price index is defined as $P_i = \prod_k (P_{k,i})^{\mu_k}$, where $P_{k,i} = \gamma(\Phi_{k,i})^{(-1/\lambda)}$, and $\Phi_{k,i} = \sum_{o'}(A_{k,o'}/d_{k,o'i}\,\tilde{w}_{k,o'})^{\lambda}$.

[30] In my setup, a more precise welfare calculation would have to incorporate changes workers' utility from switching sectors.

[31] Itskhoki and Helpman (2014) carefully characterize the transition period following a trade shock with imperfect labour markets. They also show that countries gain in the short-run because benefits from trade arise instantaneously after a fall in trade costs.

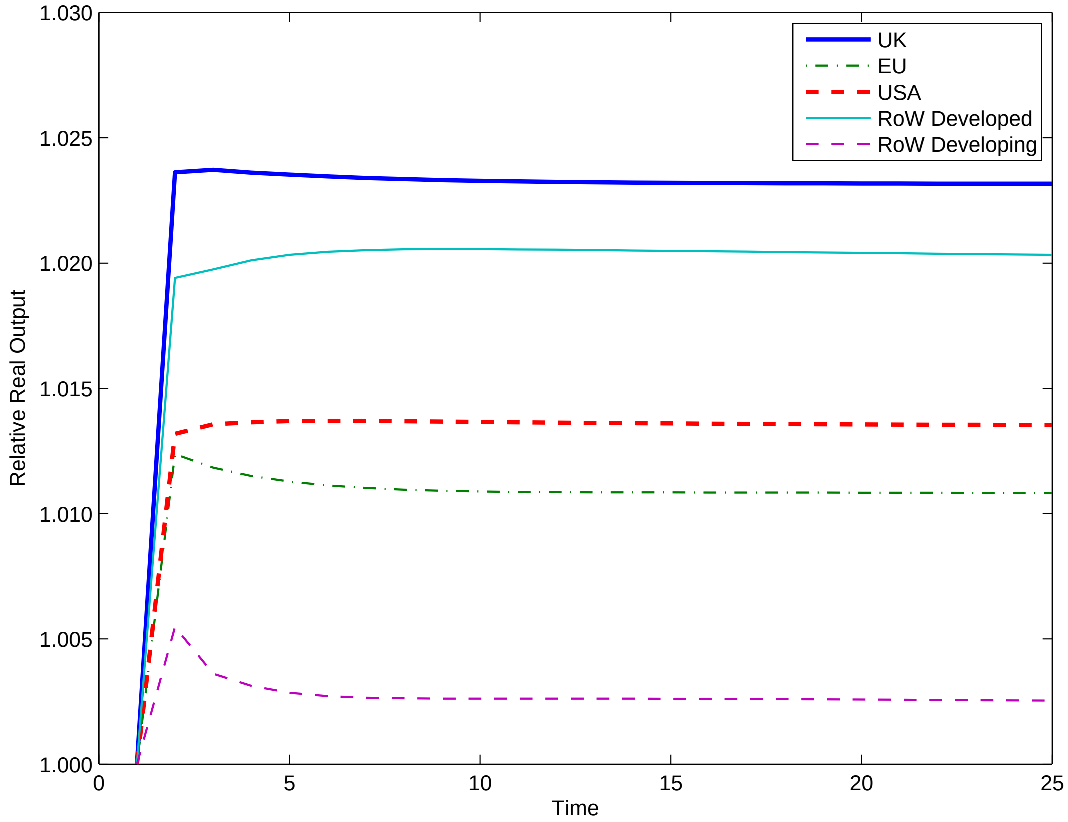



Figure 1.1: World Real Income

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Real income relative to the initial steady state equilibrium.
*EU*: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.
*RoW Developed*: Australia, Canada, Japan, Korea (south) and Taiwan.
*RoW Developing*: Brazil, India, Indonesia, Mexico, Russia and Turkey.

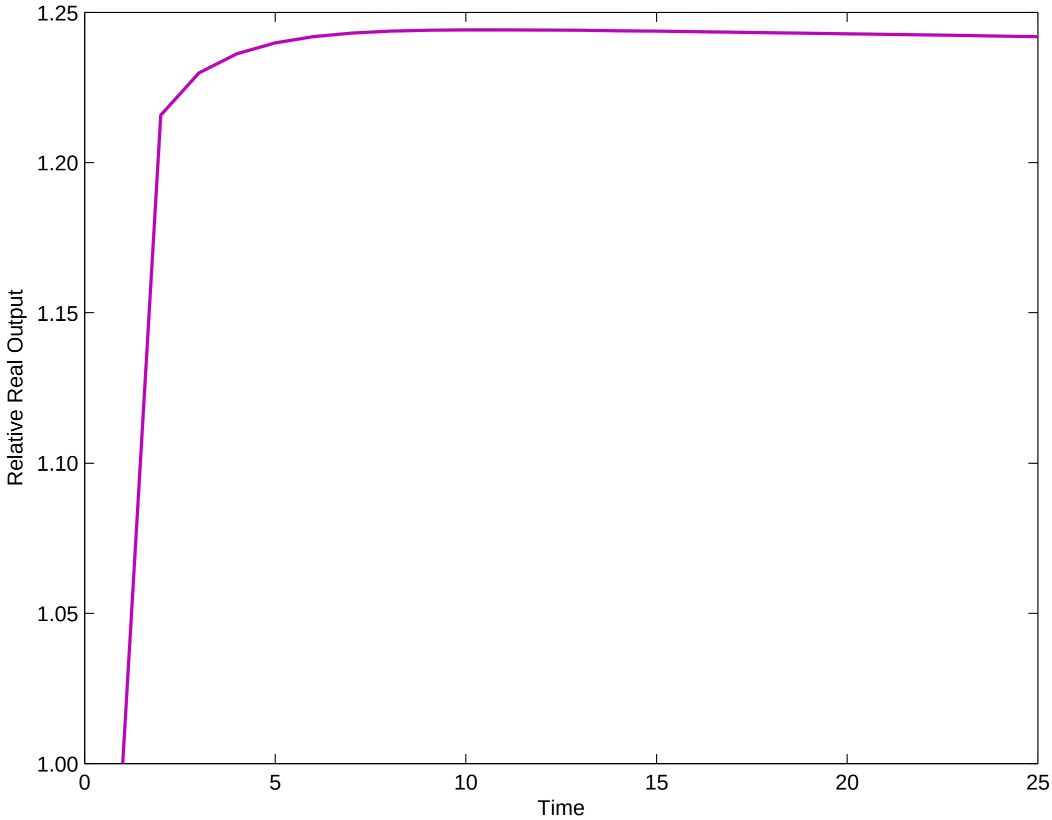



Figure 1.2: China Real Income

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Real income relative to the initial steady state equilibrium.

immediately after the shock, and hence, in wages.[32] The undershooting of wages tends to be less pronounced and it is more difficult to be observed as job destruction can take place faster than job creation.[33] Hence, real income overshooting takes place in countries such as the UK because the number of workers initially in sectors that benefit from more Chinese trade (experiencing overshooting of wages) is sufficiently high (two sectors), while in countries like the US this is not the case (one sector).

Countries experience different levels of income changes. These levels depend on how the shock changes comparative advantages around the globe and on countries' consumption share ($\mu$ in the model) in each sector. For example, after the shock, China's comparative advantages tend to increase for manufacturing goods, especially in Low-Tech manufacturing. This implies that China will be able to export more goods at cheaper prices. If a country has a significant amount of resources allocated to the production of Low-Tech manufacturing products in the initial equilibrium, it will be hurt more severely by China. This seems to be the case for the RoW Developing, i.e., those with the smallest gain in real income.

The effects are not only heterogeneous across countries but also across sectors within countries, as shown in Figures 1.3 and 1.4, which plot the adjustment in real wages in the UK and in the US, respectively. The only sector that experiences a fall in real wages is the Low-Tech Manufacturing one. The competition from Chinese imports is so severe in this area that the positive effects arising from cheaper Chinese goods are not sufficient to offset the negative effects associated with a fall in demand for UK/US goods. The falls in wages can be as high as 1.7% in the US and 1% in the UK. It is also interesting to note that real wages drop and then continue to fall before improving slightly. The rise is mainly because price indexes increase over time in both countries (and also because conditions in the sector improve slightly over time).

Figures 1.3 and 1.4 display unemployment by sector in the UK and in the US. Initially, there is a rise in unemployment in the manufacturing sectors (especially in the Low-Tech and High-Tech in the UK and in all manufacturing in the US), followed by another jump downwards. This pattern occurs because after the initial shock, a mass of jobs is destroyed in these sectors. Then, in period 2, unemployed workers start to move toward sectors in which conditions are better (Energy and Others in the UK; Services and Energy and Others

[32] This overshooting also increases the production cost in the sector and help to keep markets clear in the short-run.

[33] In addition, because the overshooting of wages happens more frequently, and this implies higher costs that are passed-through prices, the price indexes will generally decrease over time until the new steady is reached. This is the case for the US and for the UK, for example.

in the US).[34] The Services industry is almost neutral in terms of labour force change in both countries. Labour moves toward the Energy and Others sector for two reasons. First, in the GGDC dataset countries such as the UK and the US have a comparative advantage in this sector (see Table 1.8).[35] Second, China has a high expenditure share in this sector compared to other countries. So, as China rises, countries with higher comparative advantages in Energy and Others, including the UK and the US, benefit by sending more goods to China.

Figures 1.7 and 1.8 display import exposure to China ($\pi$ in the model) by sector. One can see that negative effects in terms of employment and earnings take place in industries that face stronger import competition from China.

An additional interesting point is illustrated in Figure 1.11 in the Appendix. Wage inequality, the ratio of the maximum to the minimum wage in the UK, falls after the trade shock. In import competing sectors, the least productive (worst paid) jobs are the ones that are destroyed, implying that the intra-sector gap between the minimum and the maximum wages will close.[36] In the exporting sectors, it is possible that the opposite takes place, i.e., the gap between the minimum and the maximum wage may be widening, as lower productive jobs can now exist in this sector due to a rise in demand. Overall, the first effect is the dominant one in the UK, bringing wage inequality down.[37] The fall in wage inequality is small, however.

[34]Figures 1.9 and 1.10 in the Appendix, which present the relative size of the labour force in each sector following the trade shock, show more clearly which sectors grow or shrink relative to the initial size of the labour force.

[35]Considering the way this database is constructed, one can infer that this may also reflect that goods in these industries are cheaper.

[36]This result is common to some models with endogenous job destruction. After a “bad” technology shock in a sector, the least paid jobs destroyed. This will tend to increase overall productivity in any country following an increase in import competition. Moreover, this will always decrease wage inequality within an industry but does not generate clear predictions regarding country overall wage inequality in a multi-sector case.

[37]Wage inequality falls considering also another measure, the ratio between the maximum wage and the unemployment benefit (see Figure 1.12 in the Appendix).

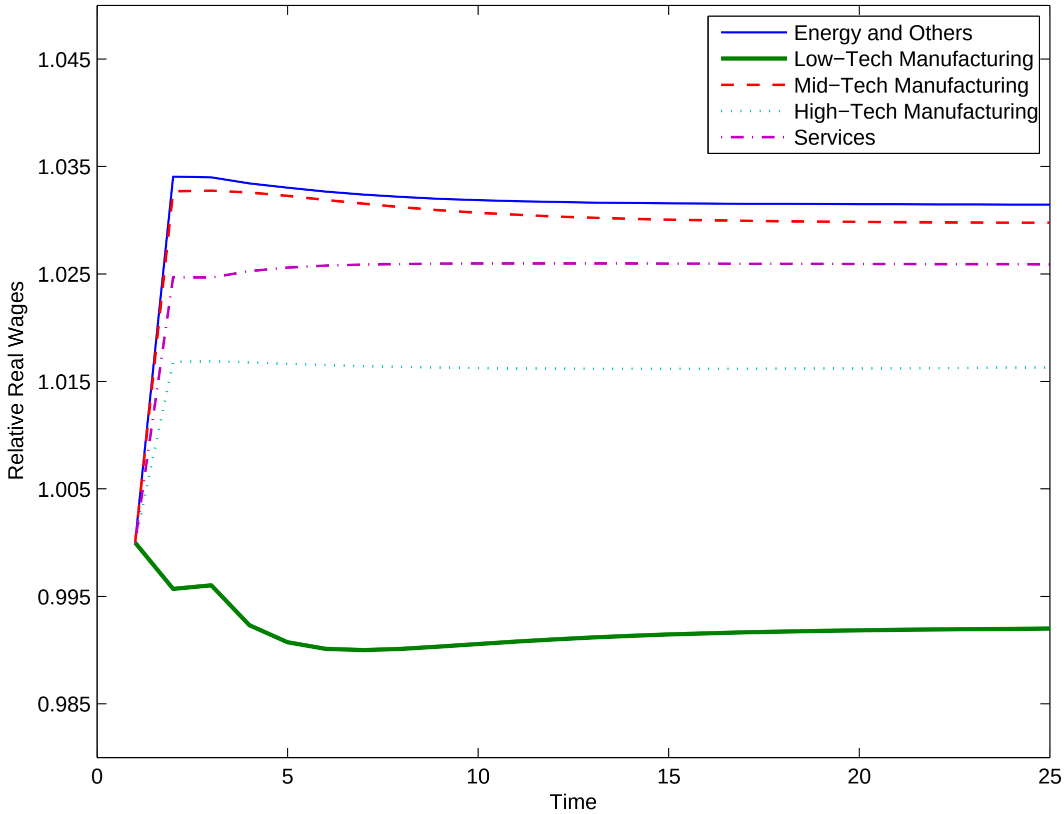



Figure 1.3: UK Relative Real Wages per Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Real wages are relative to the initial steady state equilibrium.

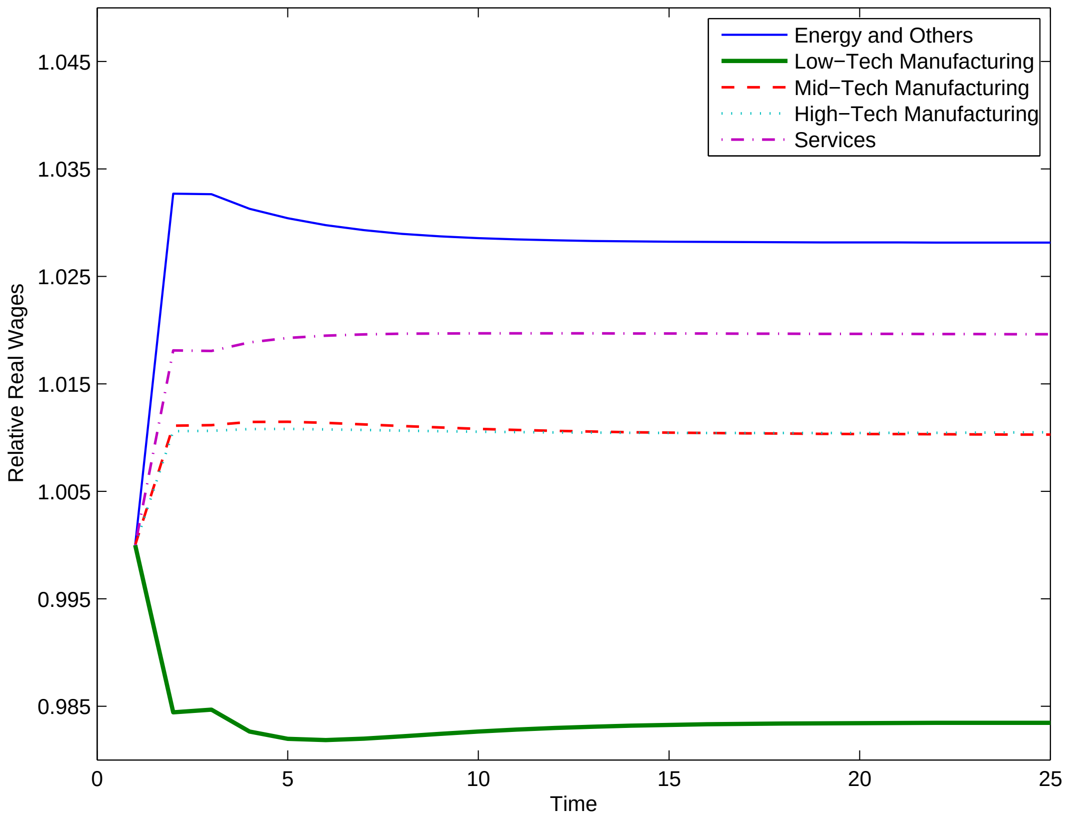



Figure 1.4: US Relative Real Wages per Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services.

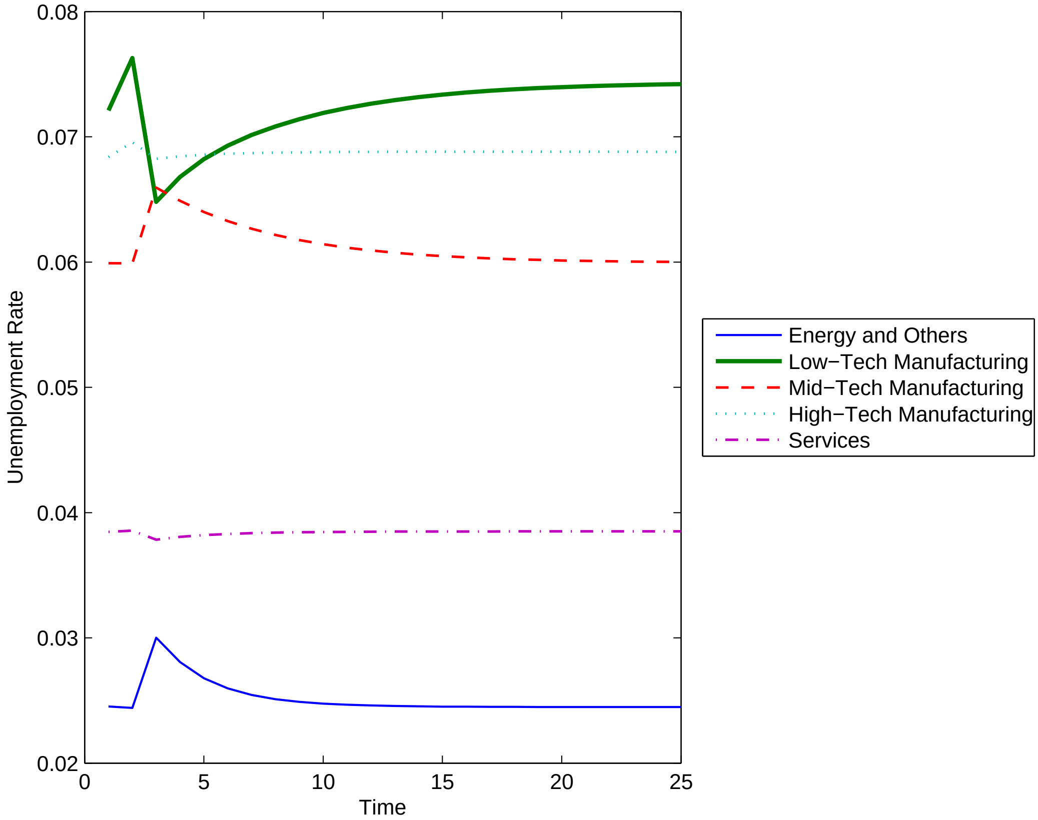



Figure 1.5: UK Unemployment per Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services.

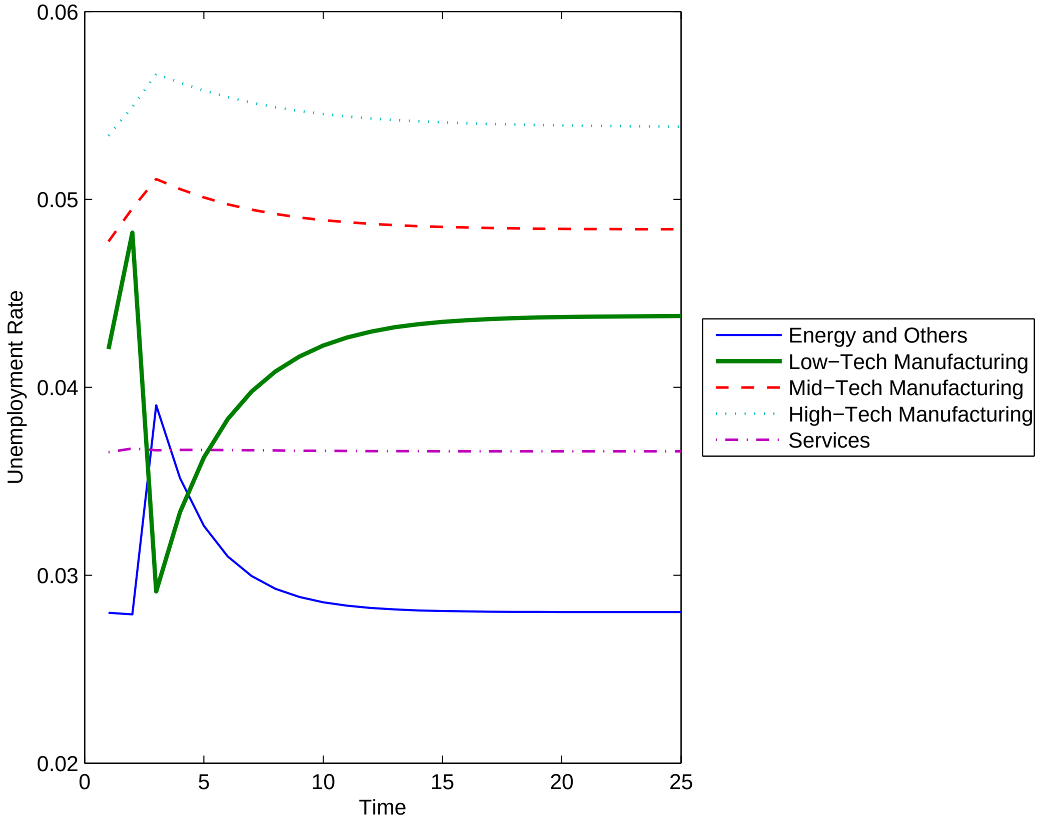



Figure 1.6: US Unemployment per Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services.

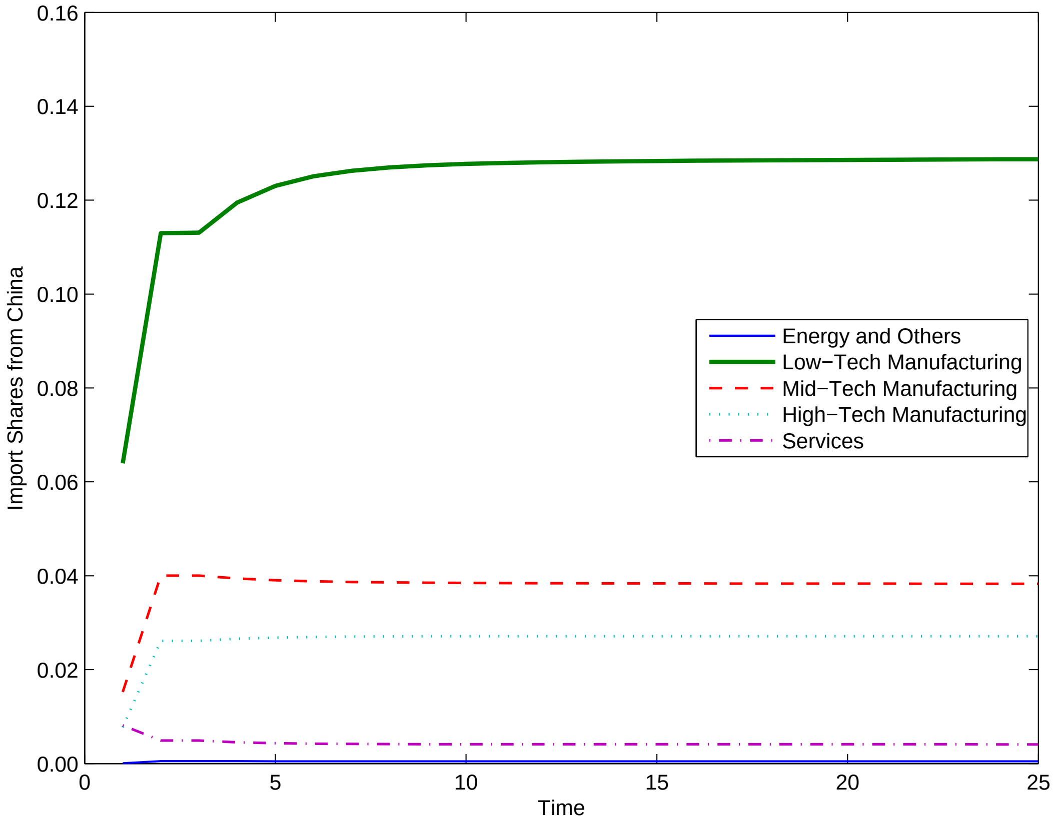



Figure 1.7: UK Import Shares from China by Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Real wages are relative to the initial steady state equilibrium.

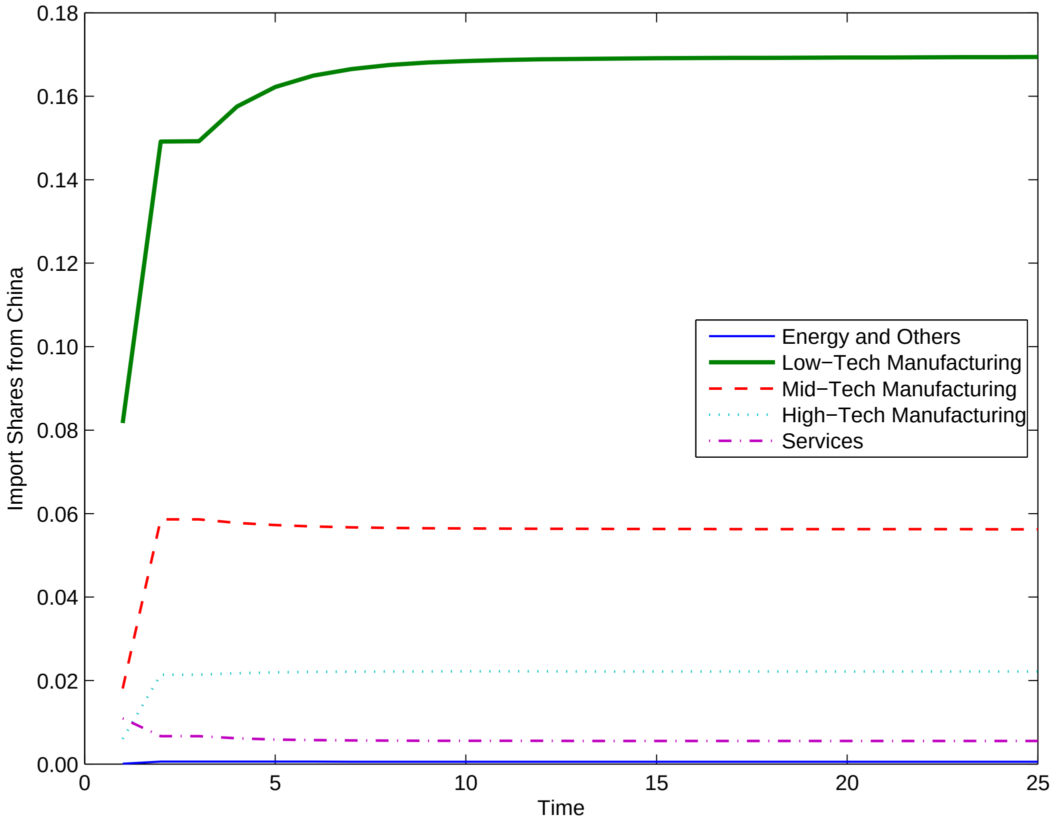



Figure 1.8: US Import Shares from China by Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services.

### Robustness

I also verify the robustness of my results to changes in parameters values. With the exception of the new value of $\lambda$, taken from the Costinot et al. (2012) preferred specification, all the other new parameter values are taken from previous estimates not used in my main exercise. In my robustness exercises, I consider only the aggregate effects by country and the effects by sector in the UK only.

For example, reducing labour mobility frictions across sectors (using $\zeta = 31.25$ from Table 1.2, column 1) indicates that real income levels increase both in the transition and in the new steady state (see Figure 1.13 in the Appendix), but the difference is small. The number of workers that decide to relocate to other sectors is also higher. This exercise suggests that reducing labour mobility frictions allows countries to benefit more from trade shocks.

Increasing the trade elasticity $\lambda$ to 6.453, as in Costinot et al. (2012), reduces overall income gains, as countries benefit less from differences in comparative advantages around the world following the shock (see Figure 1.14).

An increase in job destruction (setting $\rho = 0.0674$ from Table 1.1, column 1) does not change the aggregate results considerably (see Figure 1.15). However, unemployment levels are extremely high at every point in time (including the initial steady state), and the reallocation of workers across sectors is slightly different.

## 1.4 Micro Implications of the Model

The previous counterfactual results show that all countries gain from more trade with China. However, workers in the low-tech manufacturing sector experience a fall in real wages and a rise in unemployment levels following the emergence of China. This occurs because in this sector the levels of import competition are strong, and hence, workers suffer the negative effects from a fall in demand for goods produced domestically. In this particular case, the negative effects generated by more import exposure to Chinese products outweighs the positive effects from a fall in consumption prices.

In this section, I test three micro implications of my model using detailed employer-employee micro-data. I test whether more Chinese import competition: i) decrease worker's earnings; ii) increase worker's number of years spent out of employment; or iii) has a stronger impact on low-paid workers. The last effect is related to the pattern of job destruction in my model, i.e., when a sector receives a bad shock (such as high import competition from China) the low-paid (low-productivity) jobs are destroyed.

Autor et al. (2013a) and Autor et al. (2013b) study the impact of the rise of China on workers in the US and find that more Chinese import competition negatively affected some manufacturing industries, reducing their employment level. More imports from China also reduced manufacturing worker's earnings. In this section, I build on the latter paper to investigate how UK workers are affected by more import competition from China. Quantitative trade exercises usually focus on the US, but as a very large and rich country, I find it useful to test the predictions of my model on a smaller and more open economy, the UK. Drawing on detailed UK data also allows me to investigate outcomes not previously analysed by Autor et al. (2013b), such as hourly earnings. In the rest of the section I describe the data used in my reduced form analysis. I then present my empirical strategy and the results obtained by testing the partial-equilibrium implications of the model.

### 1.4.1 Empirical Strategy

I use a combination of a series of rich data sources in my analysis. At the worker level, my main dataset is the Annual Survey of Hours and Earnings (ASHE). It is an administrative dataset containing one per cent of all workers and the sample is based on the last 2 digits of the National Insurance Number (equivalent to the social security number in the US) every year since 1997.[38] ASHE is a panel dataset and allowed me to extract information

[38]Information is given considering only a reference period, usually some point in April, and includes weekly and hourly earnings, as well as the main industry of activity of the workplace. While limited in terms of personal characteristics compared to other surveys, the responses in ASHE are considered to be more accurate, because they are provided by employers rather than from the employees themselves. ASHE covers neither the self-employed nor individuals without payment in the reference period.

on individuals' earnings and employment history.

To measure UK exposure to China, I use the same import penetration measure derived in my model ($\pi_{k,oi}$), which is the value of imports from a particular country divided by UK total expenditure on all goods:

Chinese Import Exposure $\equiv \frac{Imports_{chi}}{Expenditure}$,

where expenditure equals total imports plus total UK sales (shipments) minus exports. I construct this measure by combining the Business Structure Database (sales per industry) and the UN COMTRADE database (imports and exports). More details about these databases can be found in the Appendix. I consider only China, i.e., I do not include Hong-Kong and Macao in my import exposure measure.[39]

Data on sales, exports and imports are at the 4-digit industry-level (ISIC3) and are expressed in real terms (2005 thousand of GBP) deflated by the most disaggregated Producer Price Index (PPI) provided by ONS (4-digit SIC for local production and 2-digit SIC for imports and exports).[40]

Table 1.9 in the Appendix shows the import exposure measure in the tradable sectors at the 2-digit ISIC3 industry level (agriculture, mining and manufacturing). The highest levels of import exposure occurred in the low-tech manufacturing sectors. Figure 1.16 indicates a negative relationship between changes in $ln(employment)$ and changes in $\frac{Imports_{chi}}{Expenditure}$ from 2000 to 2007 at the 4-digit industry level.[41] The fact that employment falls more in industries more affected by an import shock from China is closely related to my counterfactual results of Section 1.3.

My identification is motivated by Autor et al. (2013b). I observe workers' industry of activity in 2000 and compute its change in import exposure up to 2007. Under a certain level of mobility frictions between sectors (an assumption in my model), import shocks to the workers' initial industry should affect his/her employment and earnings history from 2001 onwards, as workers can spend more time looking for a job in the sector and/or will observe a fall in earnings while employed. My basic estimation equation is:

$$y^{lk01/07} = y^{lk97/00} + \tilde{\beta}_1 \Delta_{00/07} \frac{Imports^{lk}_{chi}}{Expenditure^{lk}} + \tilde{\beta}'_2 Z^{lk} + \epsilon^{lk}.$$

The outcomes I analyze are represented by $y^{lk97/00}$, which will be one of four possible

[39]My results in the next subsection do not change substantially if I include these two Special Administrative Regions.

[40]Imports and exports deflators are available in two categories: European Union and Non-European Union flows.

[41]All my import penetration measures (considering changes or levels) are winsorised at the top 99% and at the bottom 1%.

variables for employee $l$ working in industry $k$ (in 2000) in the period 2001 to 2007: i) Total Working Years - the number of years employed; ii) log of Average Weekly Earnings; iii) log of Average Hourly Earnings; and iv) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings.[42] All earnings measures are in real terms (2005 as the base year) and winsorised at the top 99% and at the bottom 1%, and all regressions consider only workers between 17 and 59 years old in the initial period.

The change in import exposure from China between 2000 and 2007 in the worker's industry of activity in 2000 is given by $\Delta_{00/07}\frac{Imports^{lk}_{chi}}{Expenditure^{lk}}$. The measure is industry specific. The indexes emphasize it corresponds to worker $l$'s initial industry $k$.

I select 2001 as my reference point for workers' outcomes because China joined the WTO at the end of this same year. China's trade liberalisation was a gradual process that started earlier, but to gain access China had to commit to several measures to further liberalize trade, such as the reduction of importing duties. China's entry into WTO also meant that restrictive importing quotas imposed by the European Union (mainly in textiles and apparel) would be lifted. Finally, the entry of China into the WTO also implied a considerable reduction in uncertainty for Chinese exporters. Handley and Limao (2013) show that this reduction in uncertainty in the US indeed contributed to China's export boom to the US after the WTO accession.[43]

The error term, $\epsilon^{lk}$, represents unobserved components that affect workers' outcomes of interest. This term might be correlated with contemporaneous labour demand shocks in the UK. To identify the "real China effect" in the UK labour market caused by productivity gains in China (or falling trade barriers between the two countries), I adopt an instrumental variable (IV) strategy similar to Bloom et al. (2015). My IV is given by:

$$IV_{chi} = \frac{Imports^{lk97}_{chi}}{Expenditure^{lk97}}\Delta_{00/07}IE_{chi,world}.$$

To capture the supply driven Chinese effect I instrument using an interaction between two components. The first one is the industry import exposure to China in 1997 ($\frac{Imports^{lk97}_{chi}}{Expenditure^{lk97}}$ - time invariant). I normalize this measure by the overall exogenous change in Chinese import shares (Chinese imports divided by total imports) in the world (excluding the UK and considering all tradable industries)[44] between 2000 and 2007. The identification assumption is that Chinese exports after 2000 were stronger in industries in which

[42]Average annual earnings is equal to Average Weekly Earnings multiplied by 52, the number of weeks in a year.

[43]Even though tariffs were largely unchanged after 2001, China joining the trading club led the US to implement the permanent most favored nation (MFN) status in the following year, which ended the annual threat to impose high tariffs on Chinese goods. China was not subject to such annual reviews in Europe. On the other hand, China's negotiations with the EU were completed later than with the US and much closer to its accession (2000-2001).

[44]This is simply a normalisation as this component is constant.

China had higher levels of import exposure to China in 1997. The instrument will suffer from reverse causality if trade with China and/or UK production in 1997 are affected by any type of anticipation of post 2000 shocks. To try to mitigate some of these endogeneity concerns, I add a series of additional controls in my regressions, and I also construct two different instruments and analyze the robustness of my results to these alternative IV's - see Subsection 1.4.3 below.

The vector $Z^{lk}$ contains individual and industry controls, depending on each regression specification. All my regressions include average hourly earnings, average weekly earnings and average time employed between 1997 and 2000. Controlling for these lagged variables mitigates the concern that I am only picking up worker-level heterogeneity associated with changes in Chinese imports. I am interested to see how individuals with similar pre-period characteristics (including previous earnings and labour force attachment) working in industries that are affected differently by China performed between 2001 and 2007 in terms of employment and earnings.

I control for some worker's characteristics, in particular age and sex. ASHE does not provide information on individuals' education. To compare individuals with similar educational backgrounds and working in similar jobs, I control for occupation fixed effects at the 4-digit level. I also control for whether the individual was a part-time worker or a full-time worker in 2000.

I am interested in comparing individuals in similar industries. To accomplish this I control for several industry characteristics. I use real (log) industry sales, industry employment level, and real (log) industry exports to China. To rule out that Chinese imports are simply capturing a general increase in the trend of UK imports, I also control for the change in import exposure to China and the rest of the world between 1997 and 1999 and for industry import exposure from the rest of the world in 2000, all at the 4-digit level. I include a very broad measure of outsourcing in 2000: the share of input costs in the output value at the 2-digit industry level. This value is obtained from UK input-output tables. I also control for previous trends in employment by including pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry).

To compare industries with similar levels of technologies, I also include R&D intensity (investment in R&D normalised by value added), real purchase of computer services and real investment in machinery at the 4-digit industry level in 2000. These variables are available at the firm level in the ARD, which I then aggregate to a 4-digit industry average using sample weights.

### 1.4.2 Validation of the Results

I start by testing whether more Chinese imports decreased earnings and/or time out of employment. Table 1.5 presents my main empirical findings. In all the panels, the first column is a simple OLS, and the remaining columns are estimated by IV and using a different set of controls. In particular, I add the lagged dependent variables to all columns (excluding them only makes the results stronger). "Worker Controls" in columns 3 and 5 represent all the individual-level characteristics described previously, while "Industry Controls" in columns 4 and 5 encompass the industry-level ones.

Table 1.5 shows that individuals working in industries more exposed to Chinese imports suffered more negative effects than those who were in industries with a lower exposure. Each one of the four panels A, B, C and D represent a different dependent variable: Log of total earnings, total working year, log of average weekly earnings and log of average hourly earnings, respectively (panels A, C and D exclude individuals with zero years of employment - see table notes for further details and mean value of dependent variable in the full sample). In the first column, which presents the OLS results, one can observe that the coefficients are negative and significant. The IV estimation in column 2 increases the absolute value of the coefficients, indicating that my OLS estimates in column 1 are biased toward zero, possibly because labour demand shocks in the UK are positively correlated with imports from China in this simpler specification without other controls. My first stages are strong, as indicated by the Kleibergen-Paap statistics (significant at all reasonable levels) in the lower part of the panels. When I control for worker's characteristics in column 3, the coefficients fall but remain significant. This fall is mainly due to the addition of the 4-digit occupation fixed effects. Controlling for industry characteristics in column 4 also decreases the coefficients relative to column 2. In column 5, the most demanding specification that includes the full set of controls, the coefficients are smaller but remain significant at standard levels, the exception being the coefficient in Panel B.

In column 5, Panel A indicates a negative effect of imports from China on Total Earnings (defined as the log of the sum of annual earnings between 2001 and 2007). With the help of Table 1.10 in the Appendix, comparing a worker initially employed in an industry at the $90^{th}$ percentile of Chinese import exposure ($\Delta_{00/07}\frac{Imports^{lk}_{chi}}{Expenditure^{lk}} = 0.079$) with a worker employed in an initial industry at the median of Chinese exposure ($\Delta_{00/07}\frac{Imports^{lk}_{chi}}{Expenditure^{lk}} = 0.007$), column 5 shows that an employee in the $90^{th}$ percentile oberved his Total Earnings fall by $4.11\% = 100 * (-0.572) * (0.079 - 0.007)$ more than an employee at the median.

In Panel B, one can see that Chinese import exposure decreases the number of years spent on employment (Total Working Years) between 2001 and 2007. In column 4 of this same panel, a worker initially employed in an industry at the $90^{th}$ percentile of Chinese import exposure spent $0.14 = (-2.005) * (0.079 - 0.007)$ more years without a job when compared to a worker at the median. The only non-significant result in the table is the one in column 5 of the same panel.

Panel C presents the effects on Average Weekly Earnings (defined as the log average of weekly earnings between 2001 and 2007 considering only the years that the individual was employed). Comparing individuals initially employed in industries at the $90^{th}$ and at the median of Chinese import exposure, column 5 shows that the individual in the highly affected industry earned $2.25\% = 100 * (-0.313) * (0.079 - 0.007)$ less when compared to a worker at the median.

Panel D shows the effects on Hourly Earnings (defined as log average hourly earnings between 2001 and 2007 considering only the years that the individual was employed). Comparing the same two groups of workers ($90^{th}$ percentile and median workers), column 5 shows that workers at the $90^{th}$ percentile earned $1.58\% = 100*(-0.220)*(0.079-0.007)$ less. Considering the results presented in Panel B, one can conclude that Chinese exposure had a greater impact on weekly earnings. This suggests that workers may be working fewer hours in industries exposed to more Chinese imports.

In sum, Table 1.5 indicates that more import exposure to China significantly decreases the time spent in employment and real average earnings. This confirms the qualitative predictions shown in my counterfactuals results in Section 1.3, validating some of the partial-equilibrium effects predicted by the model.

I now study the effect of Chinese imports on distinct groups of workers in terms of earnings in the pre-period (1997-2000). I use this as a proxy for the skill level of workers, assuming that a a low wage implies a low skill level. A rise in import penetration should have a greater impact on the low-paid workers, especially in terms of employment as predicted by the model.

My strategy consists of adding an interaction of the change in Chinese import exposure (2000-2007) with average hourly earnings between 1997 and 2000 ($\bar{HE}_{97/00}$). If low-paid workers are more affected in terms of employment and earnings, the coefficient of this interaction should be positive.

Table 1.6 presents the results. All the columns are estimated using the IV and including the full set of controls. In column 2, which considers the effects on Total Working Years, the positive coefficient of the interaction indicate that low-paid workers are more affected by China in terms of employment, validating this other implication of the model. The effects on earnings (columns 1, 3 and 4) do not show any clear pattern, and the coefficients

Table 1.5: Employment and Earnings

| | (1) OLS | (2) 2SLS | (3) 2SLS | (4) 2SLS | (5) 2SLS |
|---|---|---|---|---|---|
| **Panel A** | | | **Total Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.849*** | -1.224*** | -0.804*** | -1.040*** | -0.572** |
| | (0.287) | (0.314) | (0.240) | (0.338) | (0.282) |
| *1st Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 42.504*** | 37.586*** | 41.109*** | 36.881*** |
| | | (8.700) | (7.37) | (9.120) | (7.532) |
| KP F Stat | | 23.867 | 26.009 | 20.319 | 23.974 |
| Observations | 23433 | 23428 | 23427 | 22800 | 22799 |
| **Panel B** | | | **Total Working Years** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -2.003*** | -2.639*** | -2.086** | -2.005* | -1.459 |
| | (0.646) | (0.908) | (0.886) | (1.030) | (1.043) |
| *1st Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 42.441*** | 37.574*** | 41.256*** | 37.162*** |
| | | (8.855) | (7.514) | (9.094) | (7.57) |
| KP F Stat | | 22.97 | 25.007 | 20.582 | 24.099 |
| Observations | 24888 | 24882 | 24881 | 24195 | 24194 |
| **Panel C** | | | **Average Weekly Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.422** | -0.775*** | -0.499*** | -0.648*** | -0.313** |
| | (0.178) | (0.179) | (0.150) | (0.178) | (0.130) |
| *1st Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 42.504*** | 37.586*** | 41.109*** | 36.881*** |
| | | (8.700) | (7.37) | (9.120) | (7.532) |
| KP F Stat | | 23.867 | 26.009 | 20.319 | 23.974 |
| Observations | 23433 | 23428 | 23427 | 22800 | 22799 |
| **Panel D** | | | **Average Hourly Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.343** | -0.566*** | -0.459*** | -0.376** | -0.220** |
| | (0.142) | (0.175) | (0.138) | (0.173) | (0.112) |
| *1st Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 42.505*** | 37.598*** | 41.085*** | 36.846*** |
| | | (8.704) | (7.373) | (9.132) | (7.542) |
| KP F Stat | | 23.845 | 26.006 | 20.242 | 23.87 |
| Observations | 23418 | 23413 | 23412 | 22785 | 22784 |
| $\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $\overline{Working}_{97/00}$ | Yes | Yes | Yes | Yes | Yes |
| Worker Controls | No | No | Yes | No | Yes |
| Industry Controls | No | No | No | Yes | Yes |
| $N_{clusters}$ | 66 | 66 | 66 | 61 | 61 |

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee $i$ working in industry $j$ (in 2000) in the period that goes from 2001 to 2007. Panel A) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings [mean in the full-sample = 11.372]). Panel B) Total Working Years - the number of years employed [mean in the full-sample = 4.540]; Panel C) log of Average Weekly Earnings [mean in the full-sample = 5.97]); Panel D) log of Average Hourly Earnings [mean in the full-sample = 2.335]; Panels A, C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($\overline{Working}_{97/00}$ ) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) between 1997 and 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, $IV_{chi}$, is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

are not statistically significant. This suggests heterogeneous effects of Chinese imports on the unemployment rates of individual workers, not on their wages conditional on having a job.

Table 1.6: Heterogeneous Effects

| | (1) 2SLS | (2) 2SLS | (3) 2SLS | (4) 2SLS |
|---|---|---|---|---|
| | **Total Earnings** | **Total Working Years** | **Average Weekly Earnings** | **Average Hourly Earnings** |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -1.715 | -8.504*** | -0.422 | 0.279 |
| | (1.142) | (3.059) | (0.704) | (0.548) |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure} * \overline{HE}_{97/00}$ | 0.580 | 3.596** | 0.056 | -0.253 |
| | (0.601) | (1.547) | (0.383) | (0.306) |
| $\overline{HE}_{97/00}$ | 0.407*** | 0.186** | 0.375*** | 0.647*** |
| | (0.044) | (0.089) | (0.023) | (0.027) |
| *$1^{st}$ Stage(s) Statistics* | | | | |
| $IV_{chi}$ | 42.477*** | 43.314*** | 42.477*** | 42.475*** |
| | (11.257) | (11.267) | (11.257) | (11.281) |
| $IV_{chi}*\overline{HE}_{97/00}$ | 39.269*** | 39.968*** | 39.269*** | 39.234*** |
| | (7.646) | (7.499) | (7.646) | (7.647) |
| KP F Stat | 12.467 | 12.507 | 12.467 | 12.42 |
| Observations | 22799 | 24194 | 22799 | 22784 |
| $\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $\overline{Working}_{97/00}$ | Yes | Yes | Yes | Yes |
| Worker Controls | Yes | Yes | Yes | Yes |
| Industry Controls | Yes | Yes | Yes | Yes |
| $N_{clusters}$ | 61 | 61 | 61 | 61 |

NOTES: Each column represents a different dependent variable. The last three columns exclude individuals with zero years of employment from 2001 to 2007. All columns estimated by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($\overline{Working}_{97/00}$ ) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) from 1997 to 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, $IV_{chi}$, is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. I also instrument for the interactions above using this same instrument interacted with average hourly earnings. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### 1.4.3 Empirical Robustness

In this subsection, I verify whether the micro implications of my model are robust to different specifications. I also test the implications of the model using BSD firm-level data.

#### Alternative IV's

I make use of another instrument that builds on Bloom et al. (2015). The instrument uses information on pre-period quotas imposed on Chinese products in textiles and apparel industries (see the Appendix for a more detailed description of the IV). Table 1.11 shows that the results are qualitatively similar to the ones in Subsection 1.4.2, giving further support to the implications of my model.

The second alternative IV that I construct is a shift-share type of instrument similar to the one employed by Autor et al. (2013b). It is given by:

$$\tilde{IV}_{chi} = \frac{Imports^{lk97}_{chi}}{Expenditure^{lk97}} \Delta_{00/07} IE^{l\bar{j}}_{chi,world},$$

where $\Delta_{00/07} IE^{l\bar{j}}_{chi,world}$ is the change in Chinese import exposure (defined as imports divided by expenditure) in the world (excluding the UK) between 2000 and 2007 in the worker's initial 2-digit ISIC3 industry.[45] This change in imports is interacted with 1997 Chinese import exposure in the workers' 4-digit initial industry of employment, $\frac{Imports^{lk97}_{chi}}{Expenditure^{lk97}}$. This instrument does not rely solely on pre-existing conditions, and hence, will not satisfy the exclusion restriction if there are demand or technology shocks that shift Chinese exports and are common to all countries in the world. For example, the growth of Chinese imports around the world may only reflect that many countries chose to diminish employment in low-tech labour-intensive sectors in which China had a comparative advantage, and China simply "filled the gap" in these markets. Table 1.12 indicates that the qualitative predictions of my model are generally robust to this alternative IV. For example, comparing the same two groups of workers ($90^{th}$ percentile and median workers), Panel D, column 5, shows that workers at the $90^{th}$ percentile earned 4.45% $= 100 * (-0.618) * (0.079 - 0.007)$ less, and the coefficient is statically significant at 1% level (standard error of 0.169).[46]

**Alternative Specification**

To compare my UK results with those of the US from Autor et al. (2013b), I perform an exercise in which I use a specification more similar to theirs.[47] My estimation equation is now given by:

$$w^{lk01/07}/w^{lk97/00} = \tilde{\beta}_1 \frac{\Delta_{00/07} Imports^{lk}_{chi}}{Expenditure^{lk}_{00}} + \tilde{\beta}_2' Z^{lk} + \epsilon^{lk}.$$

First, I consider in my sample only individuals employed in all fours year between 1997 and 2000 to study only workers with high labour force attachment in the pre-period, as in Autor et al. (2013b). Second, I use a different measure of Chinese import exposure, which is now defined as the change in Chinese imports between 2000 and 2007 divided by the

[45]This measure is constructed using the WIOD database described previously.

[46]Although this second IV hinges on stronger identification assumptions, this specification also allows me to add levels of Chinese exposure in 2000 as a control - see columns 4 and 5 of Table 1.12.

[47]See equation 5 and table 1 in their paper.

expenditure in the UK in 2000 at the 4-digit ISIC3 level in the worker's initial industry of employment in 2000, $\frac{\Delta_{00/07} Imports^{lk}_{chi}}{Expenditure^{lk}_{00}}$. The IV strategy used is the same one from my main results in Table 1.5, as well as the set of controls $Z^{lk}$.

The results are displayed in the Appendix, Table 1.13. In this specification the dependent variable ($w^{lk01/07}/w^{lk97/00}$) is one of four possible outcomes. In Panel A, the dependent variable is defined as total earnings (not log earnings) between 2001 and 2007 divided by average annual earnings between 1997 and 2000 (Normalised Total Earnings). In Panel B, Total Working Years is the total number of working years between 2001 and 2007. In Panel C, Normalised Average Weekly Earnings is equal to average weekly earnings between 2001 and 2007 divided by average weekly earnings between 1997 and 2000. In Panel D, Normalised Average Hourly Earnings is equal to average hourly earnings between 2001 and 2007 divided by average hourly earnings between 1997 and 2000.

The outcomes in Panel A are comparable to the ones in Autor et al. (2013b).*From this point forward, I compare the same groups of workers as they do ($75^{th}$ vs $25^{th}$ percentiles of Chinese import exposure).* In column 5 the coefficient of 2.641 implies that comparing an individual initially employed in an industry at the $75^{th}$ percentile of the Chinese import exposure measure ($\frac{\Delta_{00/07} Imports^{lk}_{chi}}{Expenditure^{lk}_{00}} = 0.026$) to one at the $25^{th}$ percentile ($\frac{\Delta_{00/07} Imports^{lk}_{chi}}{Expenditure^{lk}_{00}} = 0.002$), the implied differential in earnings is $6.33\% = 100 * (-2.641) * (0.026 - 0.002)$ of the worker's initial earnings. Comparing the same two groups of workers in the US, Autor et al. find a value of 45.8% for a 16-year period (between 1992 and 2007). When I divide both coefficients by the number of years used in each analysis (7 and 16), the effects in the UK and in the US are 0.90% and 2.86%, respectively. This comparison is interesting as it corroborates my counterfactual results that indicate that US workers in low-tech manufacturing are also more affected by Chinese imports than employees in the UK in terms of real earnings.

My results show that employment effects in the UK are strong, whereas Autor et al. find almost no effect for the US. In Panel B of Table 1.13, column 5, comparing the same two groups of workers ($75^{th}$ vs $25^{th}$ percentiles), the implied differential in the number of years spent out of employment is $0.06 = (-2.486) * (0.026 - 0.002)$, i.e., 0.71 more months out of employment. In Panel C, the results do not indicate a clear effect on Normalised Average Weekly Earnings, as the coefficients are not significant and switch signs occasionally. Panel D, however, shows a strong significant effect on Normalised Average Hourly Earnings, an outcome not analysed by Autor et al. The earnings differential between a worker at the $75^{th}$ percentile and one at the $25^{th}$ is 0.82% of initial hourly earnings.

Hence, the comparisons between the US and the UK indicate that the earnings effect is stronger in the US, while the employment effect is stronger in the UK. This may be an indication that wages are more flexible in the US than in the UK.

### Firm-Level Data

In the Appendix, I additionally demonstrate using the BSD firm-level dataset (Table 1.14) that plants in industries that faced more Chinese import exposure shut down more frequently and/or reduce their size following an import penetration shock. This implies that the partial-equilibrium effects predicted by my model are robust to firm's outcomes as well.

## 1.5 Conclusion

In this paper, I study how countries responded to the recent rise of Chinese trade. I build a tractable dynamic trade model that delivers simple expressions and incorporates several features that are important when studying the welfare impact of trade shocks, namely, imperfect labour markets, job heterogeneity and partial mobility frictions across sectors. I structurally estimate the model using country-sector level data to quantify both the losses associated with labour market adjustments and the gains to consumers generated by cheaper Chinese goods. My counterfactuals show that a fall in trade barriers between China and the world benefits all countries not only in the new steady state but also along the transition period. In import competing sectors, however, workers bear a costly transition, experiencing lower wages and a rise in unemployment.

I also carry out an empirical analysis using UK employer-employee panel data to validate the micro implications of my model. Consistent with my model predictions, I find that employees in sectors highly affected by Chinese imports spent more time out of employment and experienced a drop in earnings when compared to workers in less affected sectors between 2001 (the year China joined the WTO) and 2007 (the year before the Great Recession). I also find that low-paid workers are more affected by Chinese import exposure.

The results raise important policy questions. The first point is that even facing a fierce competitor such as China brings benefits to developed economies, implying that any policy that aims to restrict trade in the name of more protection for workers should be reconsidered. The trade shock, however, generate winners and losers in the labour market. Hence, it *may* be welfare improving finding a way to compensate the losing individuals, and let the adjustment take place without any type of intervention that hinders trade.

The reader should bear in mind that the gains stemming from trade calculated in my counterfactuals are likely to be lower bounds, because many other GDP per capita improving channels associated with trade such as access to cheaper inputs, immigration, increases in R&D intensity, and vertical production chains, to cite just a few, are not considered in my analysis.

Finally, my tractable theoretical framework allows for studying other questions that were beyond the scope of this paper. For example, it is possible to analyze local implications of foreign labour market policies (minimum wage implementation, change in unemployment benefits and creation/destruction of unions that change workers' bargaining power).

# Appendix

## 1.A Theory

I provide a proof sketch for the fact that $p^t_{k,i}z_{k,i}$ must be equal across markets that produce in equilibrium (see Sub-subsection 1.2.1). First I will show that this holds in Steady State.

Consider two varieties $j$ and $j'$ (all the variables associated with variety $j'$ will be identified with a "$'$"). Note that workers are completely mobile across varieties. Then, using equation 1.3 and condition 1.6 we can write:

$$\theta'_{k,i}q(\theta'_{k,i})(W'_{k,i} - U'_{k,i}) = \theta_{k,i}q(\theta_{k,i})(W_{k,i} - U_{k,i}). \tag{1.28}$$

Now, suppose that $p'_{k,i}z'_{k,i}$ and $p_{k,i}z_{k,i}$ are not equal, and without loss of generality assume that $p'_{k,i}z'_{k,i} > p_{k,i}z_{k,i}$. This implies that the surplus accruing to workers in market $j'$ is higher than in market $j$ ($W'_{k,i} - U'_{k,i} > W_{k,i} - U_{k,i}$), and that wages paid in market $j'$ are also higher. Hence, for equation 1.28 to hold we must have that $\theta_{k,i}q(\theta_{k,i}) > \theta'_{k,i}q(\theta'_{k,i})$, which is satisfied if and only if $\theta_{k,i} > \theta'_{k,i}$.

From Pissarides (2000), page 38, we know that the value of posting a vacancy is increasing in $p_{k,i}z_{k,i}$ and we can also see from equation 1.1 that $V_{k,i}$ is decreasing in $\theta_{k,i}$. Hence, $p'_{k,i}z'_{k,i} > p_{k,i}z_{k,i}$ and $\theta_{k,i} > \theta'_{k,i}$ imply that $V'_{k,i} > V_{k,i}$. Consequently, condition 1.7 cannot be satisfied and no firm will post vacancies in market $j$. This shows that for both markets $j$ and $j'$ to exist in steady state the equality $p'_{k,i}z'_{k,i} = p_{k,i}z_{k,i}$ must hold.

To see that this must also hold outside the steady state, we can rewrite 1.28 considering the time period immediately before the steady state $T$:

$$\theta'^{T-1}_{k,i}q(\theta'^{T-1}_{k,i})(W'^{T}_{k,i} - U'^{T}_{k,i}) = \theta^{T-1}_{k,i}q(\theta^{T-1}_{k,i})(W^T_{k,i} - U^T_{k,i}). \tag{1.29}$$

Given that I showed that $p'^{T}_{k,i}z'_{k,i} = p^T_{k,i}z_{k,i}$ must hold in $T$ (implying that $W'^{T}_{k,i} - U'^{T}_{k,i} = W^T_{k,i} - U^T_{k,i}$), for equation 1.30 to be satisfied we must have that $\theta'^{T-1}_{k,i} = \theta^{T-1}_{k,i}$. And from the firm side (using equation 1.1, condition 1.7 and the fact that $J'^{T}_{k,i} = J^T_{k,i}$), the following must hold:

$$p'^{T-1}_{k,i} z'_{k,i} = q(\theta'^{T-1}_{k,i}) J'^{T}_{k,i}(1)/\kappa(1+r) = q(\theta^{T-1}_{k,i}) J^{T}_{k,i}(1)/\kappa(1+r) = p^{T-1}_{k,i} z_{k,i}. \quad (1.30)$$

Using the same steps, we can also show that this is valid for any previous period $(T-2, T-3, ...)$. This completes the proof sketch.

## 1.B Counterfactuals and Robustness

### 1.B.1 Additional Parameters

Table 1.7: Country-Sector Labour Shares ($\beta_{k,i}$) and Expenditure Shares ($\mu_{k,i}$)

| | Agriculture | Low-Tech Manufacturing | Mid-Tech Manufacturing | High-Tech Manufacturing | Services |
|---|---|---|---|---|---|
| **Panel A:** $\beta_{k,i}$ | | | | | |
| UK | 0.19 | 0.75 | 0.71 | 0.76 | 0.59 |
| EU | 0.32 | 0.55 | 0.61 | 0.50 | 0.55 |
| China | 0.32 | 0.34 | 0.37 | 0.36 | 0.41 |
| US | 0.27 | 0.47 | 0.56 | 0.64 | 0.56 |
| RoW Developed | 0.13 | 0.44 | 0.54 | 0.52 | 0.52 |
| RoW Developing | 0.18 | 0.27 | 0.28 | 0.32 | 0.39 |
| **Panel B:** $\mu_{k,i}$ | | | | | |
| UK | 0.02 | 0.06 | 0.05 | 0.08 | 0.79 |
| EU | 0.03 | 0.09 | 0.07 | 0.11 | 0.70 |
| China | 0.11 | 0.14 | 0.14 | 0.21 | 0.40 |
| US | 0.03 | 0.07 | 0.05 | 0.10 | 0.75 |
| RoW Developed | 0.03 | 0.10 | 0.07 | 0.14 | 0.66 |
| RoW Developing | 0.09 | 0.10 | 0.12 | 0.13 | 0.56 |

NOTES: Panel A shows the labour share of value added in each sector ($\beta_{k,i}$) while panel B show the expenditure share on a particular sector ($\mu_{k,i}$). Author's calculation using WIOD and WIOD - Socio Economic Accounts database. Data is originally disaggregated by country and industry-level (roughly ISIC3 2-digit).
*EU*: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.
*RoW Developed*: Australia, Canada, Japan, Korea (south) and Taiwan.
*RoW Developing*: Brazil, India, Indonesia, Mexico, Russia and Turkey.

Table 1.8: Country-Sector Productivity Parameters: $A_{k,i}$

| | Agriculture | Low-Tech Manufacturing | Mid-Tech Manufacturing | High-Tech Manufacturing | Services |
|---|---|---|---|---|---|
| UK | 1.26 | 1.02 | 1.11 | 1.24 | 0.89 |
| EU | 1.84 | 1.22 | 1.54 | 1.42 | 1.27 |
| China | 2.60 | 2.97 | 2.54 | 2.44 | 2.98 |
| US | 1.79 | 1.38 | 1.23 | 1.20 | 0.94 |
| RoW Developed | 0.70 | 1.28 | 1.19 | 1.44 | 1.11 |
| RoW Developing | 2.51 | 2.02 | 2.53 | 1.31 | 2.58 |

NOTES: Author's calculation using GGDC database. Data is originally disaggregated by country and industry-level (roughly ISIC3 2-digit). Productivity is the inverse of the producer price index, aggregated into sector/countries using value added as weights.
*EU*: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.
*RoW Developed*: Australia, Canada, Japan, Korea (south) and Taiwan.
*RoW Developing*: Brazil, India, Indonesia, Mexico, Russia and Turkey.

### 1.B.2 Transition

I want to find a set of value functions that is consistent with a path that converges to the new steady state. First, one can verify that my wage equation 1.14 holds inside and outside of steady state. Second, $V^t_{k,i} = 0$ will always hold due to the free entry condition.

I will use numerical simulations to find a transition path toward the new steady state. I am neither claiming that this is the first best path nor the unique one. I am simply finding one set of value functions compatible with a rational expectations path.

First, I use equation 1.3, substitute for $W^t_{k,i}(1) - U^t_{k,i}$ using the sharing rule 1.5 and the value of $J^t_{k,i}(1)$ from equation 1.1 (remember that $V^t_{k,i} = 0$) to get:

$$U^t_{k,i} = b_i + \frac{\beta_{k,i}\kappa\theta^t_{k,i}\tilde{w}^t_k}{(1-\beta_{k,i})} + \frac{U^{t+1}_{k,i}}{1+r}. \tag{1.31}$$

To find the transition path I use a type of multiple shooting algorithm that builds on Artuç et al. (2010) and Lipton et al. (1982). Even though this algorithm updates *explicitly* only $U^t_{k,i}$, it implies value functions for workers and firms that are consistent with a rational expectations path (more details below).

The economy is in equilibrium at time t=0. My counterfactuals consider an unanticipated shock where China's productivity increase 25% and Chinese bilateral trade costs around the world decrease 25% in all sectors apart from Services at time t=1.

First I calculate the new steady state equilibrium as described in Subsection 1.2.2. Then I conjecture that the system will converge to a new steady state in a certain amount of time, say $T_{ss} = 25$ years.[48] I guess an initial vector of values $s^t_{k,i}$ for $U^t_{k,i}$ (for all countries, sectors and time $t = 1$ to time $t = T_{ss}$). This will permit me to use equations 1.13, 1.15 and 1.23 to solve for $R^1_{k,i}$, $\theta^1_{k,i}$ and $\tilde{w}^1_{k,i}$, noting that $L^1_{k,i}$ and $u^1_{k,i}$ are fixed at this moment.[49] Before workers move across sectors, job creation and job destruction take place and I can calculate the new number of unemployed individuals in each sector according to equation 1.9. Subsequently, I pin down the share of individuals attached to each sector from equation 1.24 (remembering that now the value function depends on time) and unemployed individuals are reallocated according to such shares.[50] I proceed to $t = 2$ and continue like this up to time $T_{ss}$ to find a time path for $R^t_{k,i}$, $\theta^t_{k,i}$, $\tilde{w}^t_{k,i}$, $L^t_{k,i}$ and $u^t_{k,i}$. I then update values $\tilde{s}^t_{k,i}$ of $s^t_{k,i}$ using equation 1.31, $\tilde{s}^t_{k,i} = b_i + \frac{\beta_{k,i}\kappa\theta^t_{k,i}\tilde{w}^t_k}{(1-\beta_{k,i})} + \frac{s^{t+1}_{k,i}}{1+r}$, and use the

[48] Note that this type of non-linear systems of equations can only be guaranteed to converge asymptotically - see Lipton et al. (1982).

[49] Note that assuming that 1.13, 1.15 and 1.23 hold outside the steady state is an approximation. I later confirm that this approximation is a reasonable one.

[50] I am always using the Gumbel distribution to calculate the total number of individuals attached to each sector and allowing only the unemployed to move such that these shares are satisfied. A possibly more precise (and more complicated) alternative would be to find the distribution of unemployed individuals conditional on individuals previous sector choices and then find the share of individuals moving across sectors.

assumption that the system is in steady state at $T_{ss}$, $\tilde{s}_{k,i}^{T_{ss}-1} = b_i + \frac{\beta_{k,i}\kappa\theta_{k,i}^{T_{ss}-1}\tilde{w}_k^{T_{ss}-1}}{(1-\beta_{k,i})} + \frac{s_{k,i}^{T_{ss}}}{1+r}$. I then compare $\tilde{s}_{k,i}^t$ to $s_{k,i}^t$ and if they are close enough according to my tolerance I stop. Otherwise, I restart the algorithm using my updated values. The algorithm converges quickly to a high degree of precision. Even though this algorithm updates *explicitly* only $U_{k,i}^t$, the transition path found is almost equal to one where I update other value functions as well.[51]

I keep $T_{ss}$ always equal to 25, but the higher its value the closer the variables are to the new steady state counterfactual equilibrium. In my exercises, approximately 90% of the real income adjustment has already taken place by $T_{ss} = 25$.

[51]To verify this I use an algorithm where I update both $J_{k,i}^t(1)$ and $U_{k,i}^t$, and $W_{k,i}^t(1)$ can then be found by the surplus sharing condition. These value functions, together with the endogenous variables are sufficient to calculate all other value functions. In this algorithm I do not assume that 1.13, 1.15 and 1.23 hold outside steady state, but the fact that the two transition paths (the one calculated with this algorithm and the one used in the paper) are almost indistinguishable show this was a reasonable approximation. The downside of this second algorithm is that it is sensitive to the initial guess, converging only for initial values of $J_{k,i}^t(1)$ and $U_{k,i}^t$ around the ones obtained in the final iteration of the first algorithm used in the paper.

### 1.B.3 Labour Movement Across Sectors

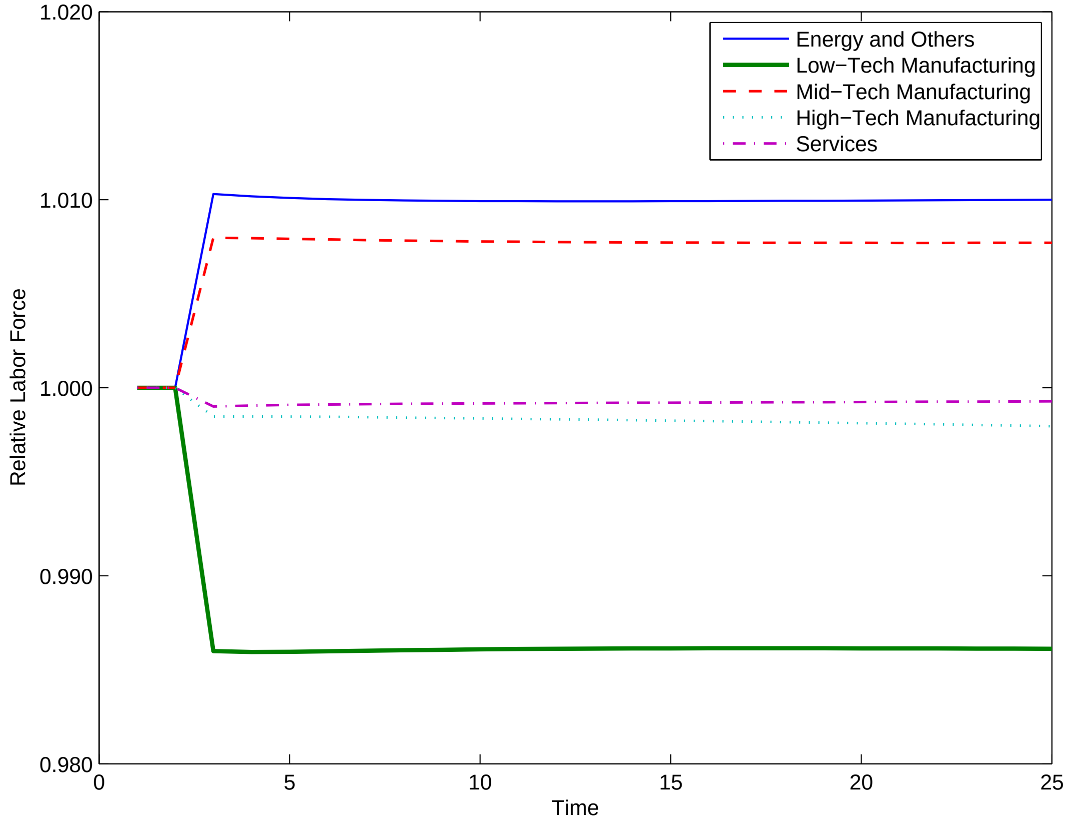



Figure 1.9: UK Relative Labour Force per Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Labour force in each sector is relative to the initial steady state equilibrium.

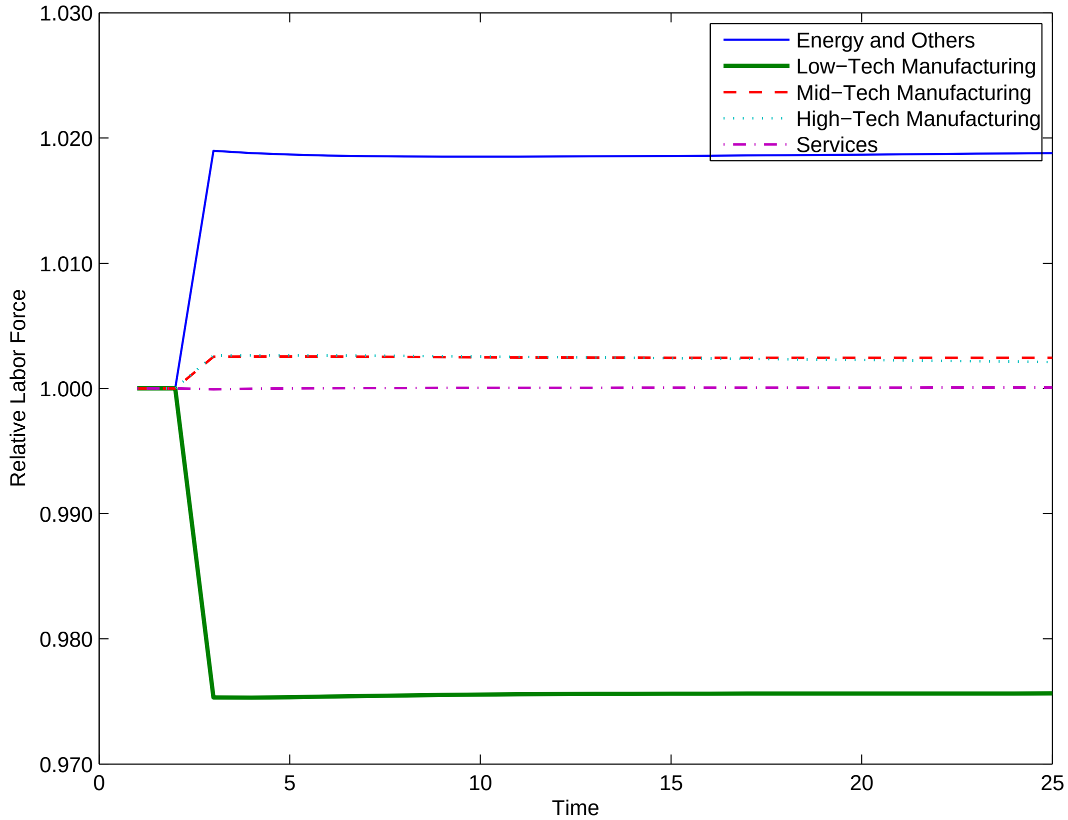



Figure 1.10: US Relative Labour Force per Sector

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Labour force in each sector is relative to the initial steady state equilibrium.

### 1.B.4 Wage Inequality in the UK

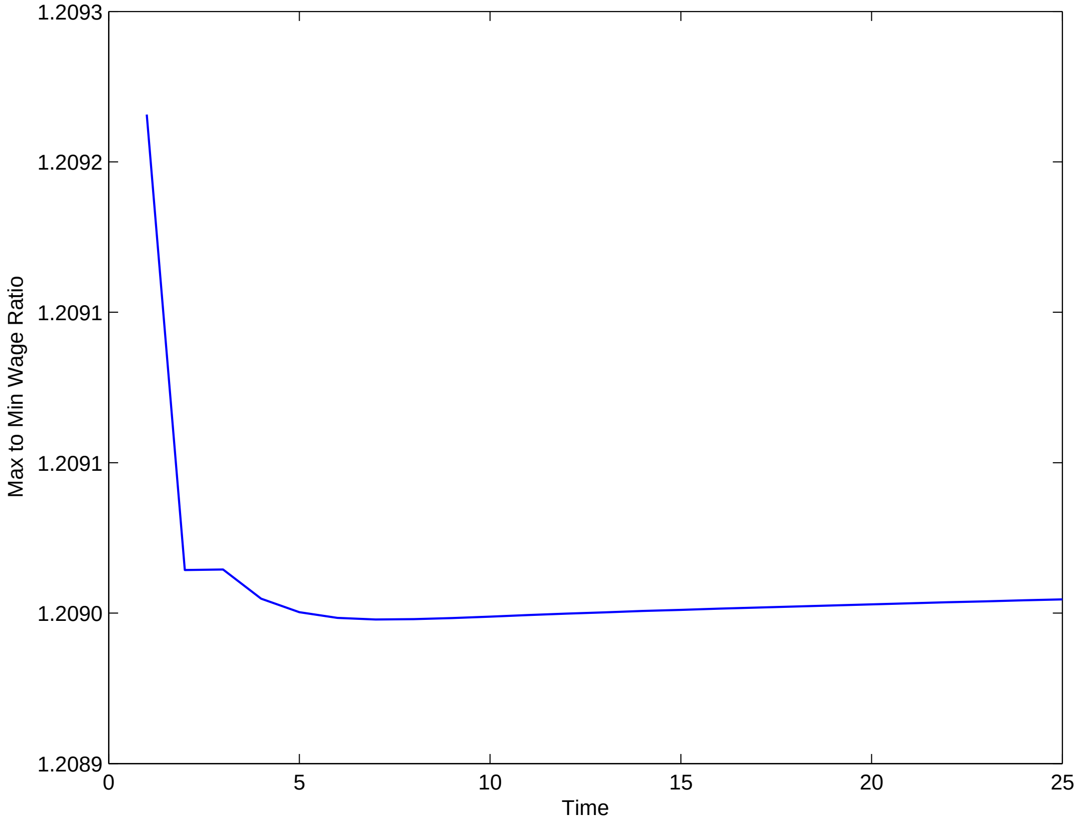



Figure 1.11: UK Wage Inequality

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Wage inequality defined as the ratio between the maximum and the minimum wage in the UK, considering only employed individuals.

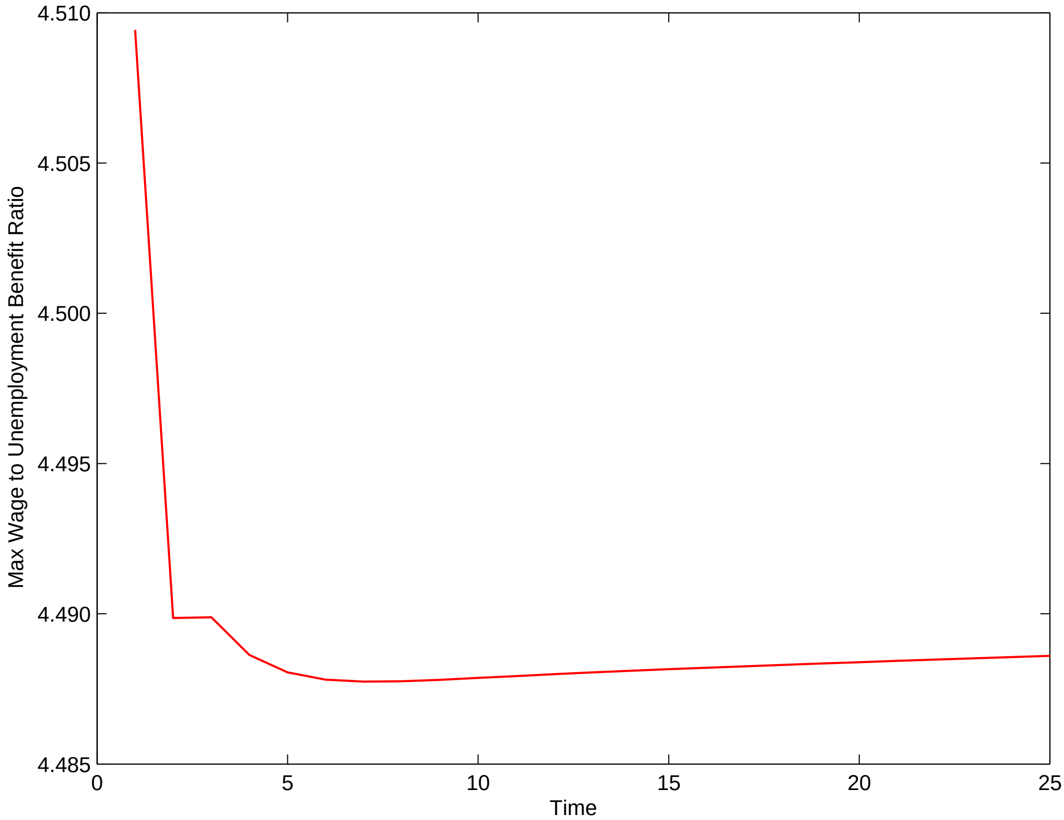



Figure 1.12: UK Alternative Measure of Wage Inequality

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK.

### 1.B.5 Counterfactuals Robustness to Changes in Parameters

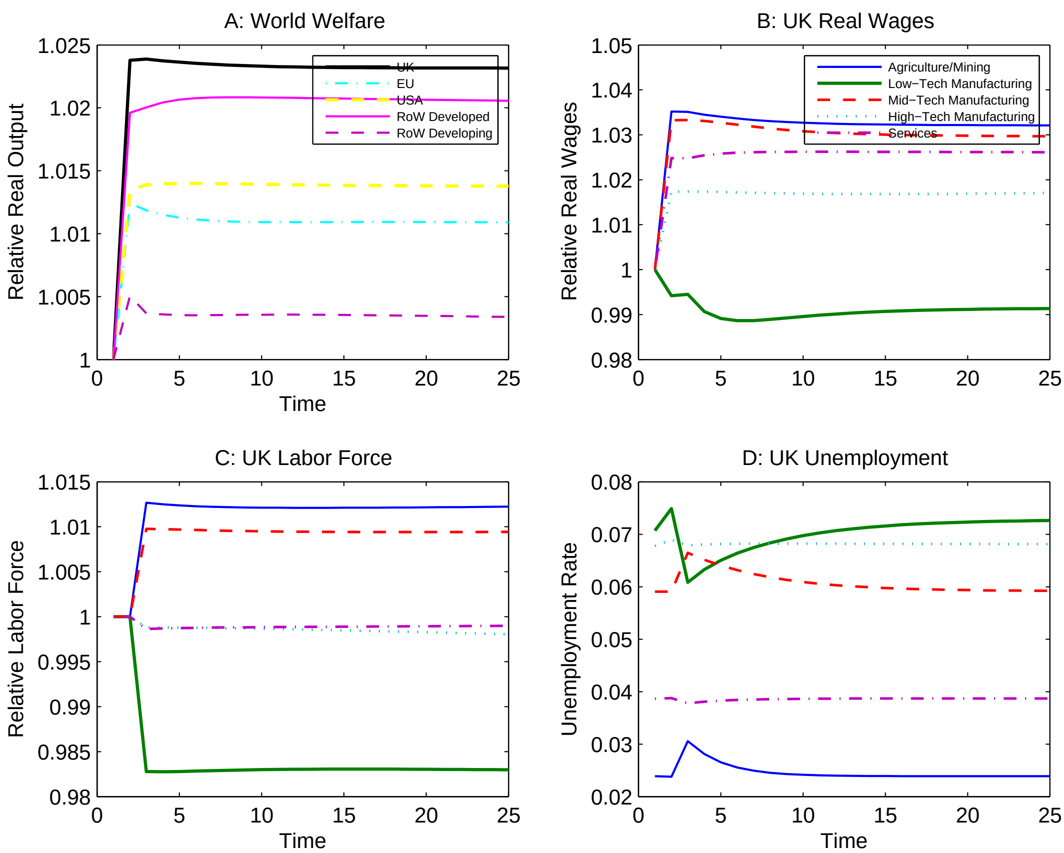



Figure 1.13: Change in parameter: $\zeta = 31.25$

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK. Legends of Panels B, C and D can be found in Panel B.
*EU*: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.
*RoW Developed*: Australia, Canada, Japan, Korea (south) and Taiwan.
*RoW Developing*: Brazil, India, Indonesia, Mexico, Russia and Turkey.

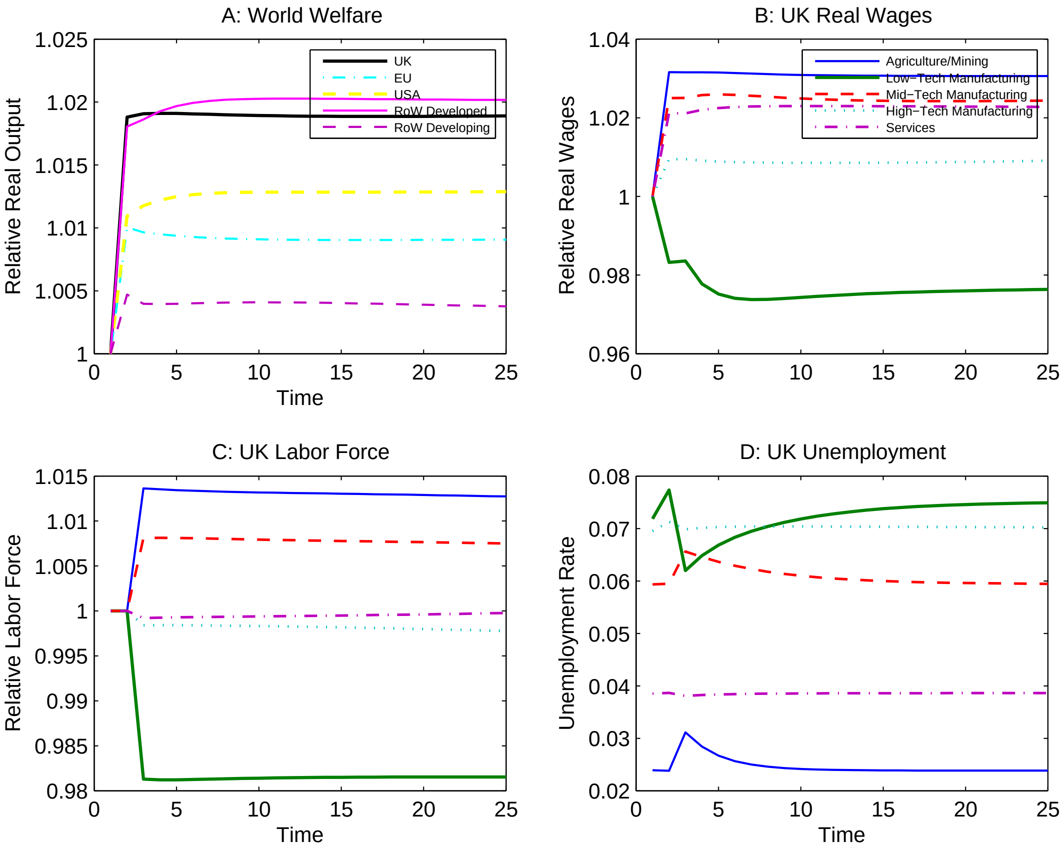



Figure 1.14: Change in parameter: $\lambda = 6.453$

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK. Legends of Panels B, C and D can be found in Panel B.
*EU*: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.
*RoW Developed*: Australia, Canada, Japan, Korea (south) and Taiwan.
*RoW Developing*: Brazil, India, Indonesia, Mexico, Russia and Turkey.

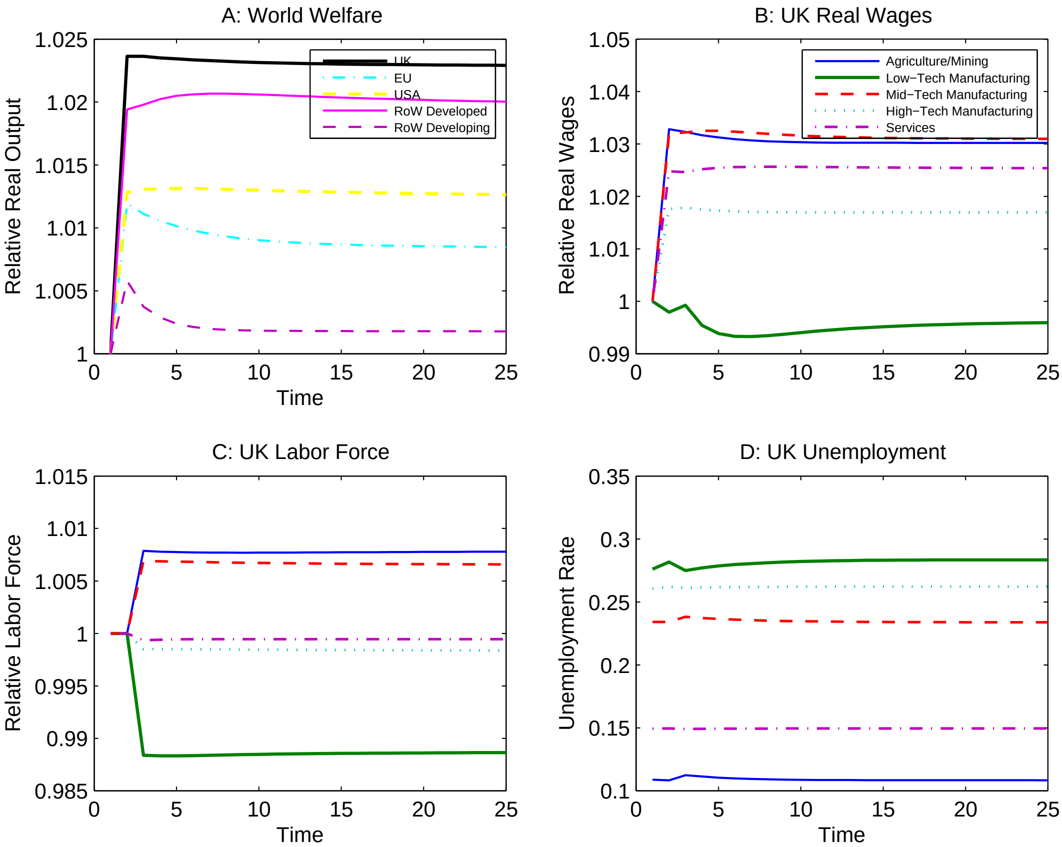



Figure 1.15: Change in parameter: $\rho = 0.0674$

NOTES: Transition path following an unanticipated fall of 25% in trade costs between China and the world and a rise of 25% in Chinese productivity in all sectors apart from Services. Inequality defined as the ratio between the maximum wage and the value of unemployment benefit in the UK. Legends of Panels B, C and D can be found in Panel B.

*EU*: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Poland, Romania, Slovak Republic, Slovenia, Spain and Sweden.

*RoW Developed*: Australia, Canada, Japan, Korea (south) and Taiwan.

*RoW Developing*: Brazil, India, Indonesia, Mexico, Russia and Turkey.

## 1.C Micro Implications of the Model: Data and Results

### 1.C.1 Data Sources

**BSD**

To calculate sales per industry, a measure used in my import penetration variable, I use the Business Structure Database (BSD). It contains information on employment, sales and industry of activity for almost all business organisations in the UK. The BSD is derived mainly from the Inter-Departmental Business Register (IDBR), which is a live register of data collected by HM Revenue and Customs via VAT and Pay As You Earn records. The IDBR data are complimented using business surveys from the Office for National Statistics (ONS). If a business is liable for VAT and/or has at least one member of staff registered for the Pay as you Earn[52] tax collection system, then the business will appear on the IDBR (and hence in the BSD). Businesses listed on the IDBR accounted for almost 99 per cent of economic activity in the UK around 2004. Only very small businesses (such as the self-employed) were not found on the register.

**ARD**

I use another firm data source, the Annual Respondent Database (ARD). The ARD is a census of large businesses, and a sample of smaller ones.[53] The advantage of ARD is that it encompasses much more detailed information than BSD. Hence, I am able to calculate, for example, firm's labour productivity, R&D intensity, wage bill and other important information used also for the structural estimation of my model in Section 1.3.

**UN COMTRADE**

Data on exports and imports use in the validation of the micro implications of the model come from the UN COMTRADE database. It carries information on all bilateral trade flows between any given pair of countries available at the 5-digit standard international trade classification revision 3 (SITC3). To create a correspondence between this trade classification and the industry classification in ASHE, BSD and ARD (5-digit UK standard industrial classification - UK SIC) I considered a third classification: the 4-digit international standard industrial classification revision 3 (ISIC3). Both SITC3 and UK SIC can be easily aggregated to ISIC3, providing a consistent classification for my analysis.

### 1.C.2 UK Import Exposure to China

Table 1.9 shows which industries were affected by China between 2000 and 2007 and the size of those industries in terms of employment in 2000. The greatest increase in import

[52] PAYE is the system that HM Revenue and Customs uses to collect Income Tax and National Insurance contributions from employees.

[53] For more details see http://discover.ukdataservice.ac.uk/catalogue?sn=6644.

penetration occurred in low-tech manufacturing sectors. Several industries that faced more Chinese competition had sizeable shares of the labour force in tradable sectors (agriculture, mining and manufacturing) in 2000. The heavily affected industries are generally linked to textiles, furniture and machinery production. The sectors that observed lower increase in import penetration are inside agriculture and mining.

Table 1.9: Industry Employment and Import Exposure

| Sector | $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | $(\frac{Imports_{chi}}{Expenditure})_{00}$ | $(\text{Employment Share})_{00}$ |
|---|---|---|---|
| Wearing Apparel | 0.173 | 0.069 | 3.21% |
| Tanning and Dressing of Leather | 0.146 | 0.179 | 0.6% |
| Office, Accounting and Computing Machinery | 0.097 | 0.048 | 1.11% |
| Radio, Television and Communication Equipment | 0.081 | 0.023 | 3.04% |
| Textiles | 0.080 | 0.030 | 3.48% |
| Furniture and Manufacturing n.e.c. | 0.071 | 0.063 | 4.97% |
| Electrical Machinery | 0.034 | 0.029 | 4.61% |
| Machinery and Equipment | 0.033 | 0.015 | 9.21% |
| Wood and Cork (except furniture) | 0.030 | 0.010 | 1.86% |
| Basic Metals | 0.029 | 0.004 | 2.40% |
| Fabricated Metal Products $*^A$ | 0.028 | 0.020 | 5.14% |
| Other Non-Metallic Mineral Products | 0.023 | 0.005 | 3.36% |
| Rubber and Plastic | 0.014 | 0.020 | 5.68% |
| Medical, Optical and Other Instruments $*^B$ | 0.009 | 0.016 | 3.61% |
| Paper | 0.009 | 0.003 | 2.53% |
| Forestry and Logging | 0.005 | 0.007 | 0.25% |
| Chemicals | 0.005 | 0.007 | 6.58% |
| Publishing and Printing $*^C$ | 0.004 | 0.004 | 8.20% |
| Other Transport Equipment | 0.003 | 0.005 | 3.81% |
| Other Mining and Quarrying | 0.003 | 0.002 | 0.87% |
| Fishing | 0.003 | 0.001 | 0.28% |
| Motor Vehicles, Trailers and Semi-Trailers | 0.002 | 0.000 | 5.18% |
| Mining of Coal and Lignite | 0.002 | 0.004 | 0.32% |
| Food and Beverages | 0.002 | 0.001 | 11.61% |
| Coke, Refined Petroleum and Nuclear Fuel | 0.000 | 0.001 | 0.66% |
| Tobacco | 0.000 | 0.000 | 0.22% |
| Crude Petroleum and Natural Gas | 0.000 | 0.000 | 0.35% |
| Agriculture and Hunting | -0.000 | 0.004 | 6.86% |
| *Total* | | | *100%* |

NOTES: Table considers only tradable industries (agriculture, manufacturing and mining). Changes in Chines import penetration from 2000 to 2007, Chinese import penetration measure in 2000 and employment shares in 2000 by industry (ISIC3 2-digit). The denominator of this last measure considers only tradable industries.
$*^A$ Excludes machinery and equipment.
$*^B$ Includes watches and clocks.
$*^C$ Includes reproduction of recorded media.

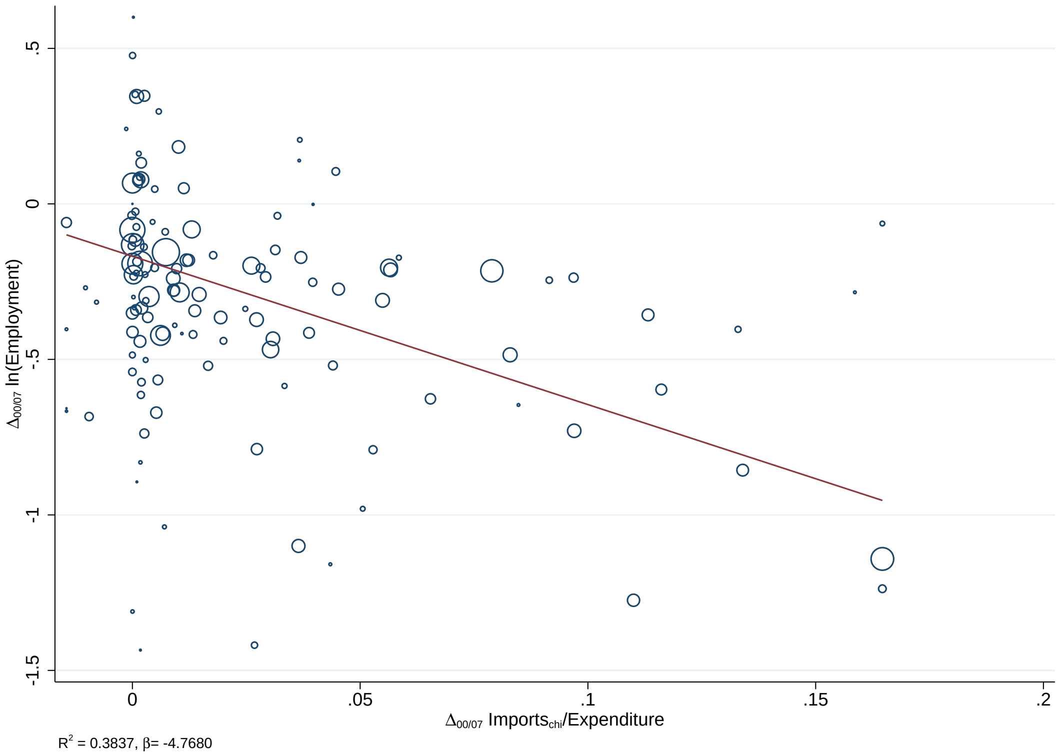



Figure 1.16: Changes in industry log Employment against Chinese Import Exposure

NOTES: Figure plots changes in employment between 2000 and 2007 against changes in exposure to Chinese imports in the UK at the 4-digit ISIC3 industry level. All points (and fitted line) consider industry employment size in 2000 as weights. $\beta$ represents the coefficient of the fitted line (standard error of 0.53).

### 1.C.3 Summary Statistics

Table 1.10: Summary Statistics

| | Average Hourly Earnings | Average Weekly Earnings | Total Earnings | Total Working Years | $\overline{HE}_{97/00}$ | $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | $IV_{quota}$ |
|---|---|---|---|---|---|---|---|
| Obs | 23418 | 23433 | 23433 | 24888 | 24888 | 24888 | 24888 |
| Mean | 2.335 | 5.971 | 11.372 | 4.540 | 2.210 | 0.025 | 0.020 |
| Std. Dev | 0.467 | 0.537 | 0.829 | 2.124 | 0.456 | 0.038 | 0.099 |
| Min | - | - | - | - | - | -0.014 | 0 |
| $10^{th}$ Pctile | 1.791 | 5.341 | 10.227 | 1.000 | 1.659 | 0.000 | 0.000 |
| $50^{th}$ Pctile | 2.281 | 5.984 | 11.510 | 5.000 | 2.180 | 0.007 | 0.000 |
| $90^{th}$ Pctile | 2.957 | 6.600 | 12.271 | 7.000 | 2.798 | 0.079 | 0.000 |
| Max | - | - | - | - | - | 0.165 | 0.603 |

NOTES: Summary statistics for the full sample of individuals from years 2000 to 2007. Some statistics are omitted because of data confidentiality reasons.

### 1.C.4 Empirical Robustness

I also make use of another instrument based on Bloom et al. (2015). This IV uses the idea that many Chinese products in the textile industry had importing quotas until China entered in the WTO (2001). Since these quotas were first implemented in the fifties and their phased abolition negotiations started in the eighties, it is natural to assume that they are exogenous to current demand and supply shocks in the UK. As quotas started to be liberalised, imports in these protected sectors increased significantly. To build my IV I first calculate the fraction of products[54] that were under quota restriction in a given industry $k$ before the liberalisation phase in the 2000's. The number of industries under quotas is extremely small under the ISIC3 classification[55], which makes this simple fraction a poor IV. To add more variability to my instrument, I use the average value of the quota share in the industries where each worker was between 1997 and 2000. My new IV is given by:

$$IV_{quota} = \frac{\sum\limits_{t<2001} quota^{lkt}}{T},$$

where $T$ is the number of years that an individual was employed between 1997 and 2000 and $quota^{lkt}$ is the share of products that had quotas in worker's industry of activity at time $t$. Clearly this IV has its own issues. Even though I use workers' pre-period industry switch, this information may still reflect anticipation to China shocks. In this case my IV would not be strictly exogenous. Bloom et al. (2015) claim that this anticipation effect is unlikely to have had larger effects on R&D investment as there was considerable uncertainty about quota liberalisations at that point.[56]

The results are not qualitatively different from the ones in Subsection 1.4.2, giving further support to my findings. The size of the coefficients in Table 1.11 are larger. For example, the effect on Total Working Years, column 5, implies that an individual in the $90^{th}$ percentile of import penetration experienced 0.36 more years out of employment when compared to a median worker. The first stage statistics are slightly weaker than in Table 1.5, but are still significant at standard levels.

[54]Bloom et al. (2015) use the same idea but have a value weighted share as the instrument.

[55]The 7 industries with non-zero values and respective quota measures are: 1711 Preparation and spinning of textile fibres (0.51); 1721 Manufacture of made-up textiles (0.068); 1722 Manufacture of carpets and rugs (0.087); 1723 Manufacture of cordage, rope, twine and netting (0.5); 1729 Manufacture of textiles n.e.c ( 0.016); 1730 Manufacture of knitted crochet fabrics (0.375); 1810 Manufacturing of wearing apparel (0.603).

[56]The authors find no correlation between their quota instrument and pre-period R&D adjustments. This suggests that this anticipation effect would also be small or nonexistent regarding pre-period labour adjustments.

Table 1.11: Employment and Earnings: Industry Quotas as IV

| | (1) OLS | (2) 2SLS | (3) 2SLS | (4) 2SLS | (5) 2SLS |
|---|---|---|---|---|---|
| **Panel A** | | | **Total Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.849*** | -1.900*** | -1.263*** | -1.760*** | -1.372*** |
| | (0.287) | (0.189) | (0.182) | (0.275) | (0.273) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{quota}$ | | .189*** | .164*** | .193*** | .174*** |
| | | (.045) | (.044) | (.046) | (.043) |
| KP F Stat | | 17.888 | 13.927 | 17.579 | 16.507 |
| Observations | 23433 | 23433 | 23432 | 22805 | 22804 |
| **Panel B** | | | **Total Working Years** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -2.003*** | -4.713*** | -4.667*** | -5.093*** | -5.010*** |
| | (0.646) | (0.810) | (0.924) | (1.155) | (1.136) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{quota}$ | | .189*** | .165*** | .193*** | .175*** |
| | | (.044) | (.044) | (.046) | (.043) |
| KP F Stat | | 18.334 | 13.983 | 17.851 | 16.411 |
| Observations | 24888 | 24888 | 24887 | 24201 | 24200 |
| **Panel C** | | | **Average Weekly Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.422** | -1.048*** | -0.508*** | -0.862*** | -0.566*** |
| | (0.178) | (0.139) | (0.095) | (0.139) | (0.115) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{quota}$ | | .189*** | .164*** | .193*** | .174*** |
| | | (.045) | (.044) | (.046) | (.043) |
| KP F Stat | | 17.888 | 13.927 | 17.579 | 16.507 |
| Observations | 23433 | 23433 | 23432 | 22805 | 22804 |
| **Panel D** | | | **Average Hourly Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.343** | -0.816*** | -0.619*** | -0.744*** | -0.618*** |
| | (0.142) | (0.196) | (0.159) | (0.198) | (0.169) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{quota}$ | | .189*** | .164*** | .193*** | .174*** |
| | | (.045) | (.044) | (.046) | (.043) |
| KP F Stat | | 17.874 | 13.936 | 17.565 | 16.502 |
| Observations | 23418 | 23418 | 23417 | 22790 | 22789 |
| $\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $\overline{Working}_{97/00}$ | Yes | Yes | Yes | Yes | Yes |
| Worker Controls | | | Yes | | Yes |
| Industry Controls II | | | | Yes | Yes |
| $N_{clusters}$ | 66 | 66 | 66 | 61 | 61 |

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee $i$ working in industry $j$ (in 2000) in the period that goes from 2001 to 2007. Panel A) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings [mean in the full-sample = 11.372]). Panel B) Total Working Years - the number of years employed [mean in the full-sample = 4.540]; Panel C) log of Average Weekly Earnings [mean in the full-sample = 5.97]); Panel D) log of Average Hourly Earnings [mean in the full-sample = 2.335]; Panels A, C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($\overline{Working}_{97/00}$ ) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) between 1997 and 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, $IV_{quota}$, is the average value of the quota share in the industries where each worker was between 1997 and 2000. Quota share is the fraction of Chinese products that were under quota restriction in a given industry before the liberalisation phase in the 2000's. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.12: Employment and Earnings: Shift-Share IV

| | (1) OLS | (2) 2SLS | (3) 2SLS | (4) 2SLS | (5) 2SLS |
|---|---|---|---|---|---|
| **Panel A** | | | **Total Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.849*** | -1.376*** | -0.974*** | -1.475*** | -0.930* |
| | (0.287) | (0.301) | (0.244) | (0.569) | (0.550) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 46.78*** | 43.821*** | 41.713*** | 37.676*** |
| | | (5.977) | (6.568) | (8.948) | (8.508) |
| KP F Stat | | 61.256 | 44.507 | 21.734 | 19.608 |
| Observations | 23433 | 23433 | 23432 | 22805 | 22804 |
| **Panel B** | | | **Total Working Years** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -2.003*** | -2.884*** | -2.618** | -2.849 | -2.210 |
| | (0.646) | (0.802) | (0.823) | (1.799) | (2.038) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 46.901*** | 44.08*** | 41.18*** | 37.16*** |
| | | (5.952) | (6.531) | (8.959) | (8.587) |
| KP F Stat | | 62.085 | 45.559 | 21.13 | 18.727 |
| Observations | 24888 | 24888 | 24887 | 24201 | 24200 |
| **Panel C** | | | **Average Weekly Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.422** | -0.710*** | -0.385*** | -0.829*** | -0.487** |
| | (0.178) | (0.175) | (0.099) | (0.273) | (0.224) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 46.78*** | 43.821*** | 41.713*** | 37.676*** |
| | | (5.977) | (6.568) | (8.948) | (8.508) |
| KP F Stat | | 61.256 | 44.507 | 21.734 | 19.608 |
| Observations | 23433 | 23433 | 23432 | 22805 | 22804 |
| **Panel D** | | | **Average Hourly Earnings** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -0.343** | -0.404** | -0.324*** | -0.357 | -0.296 |
| | (0.142) | (0.167) | (0.099) | (0.280) | (0.196) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 46.829*** | 43.903*** | 41.72*** | 37.697*** |
| | | (5.974) | (6.567) | (8.959) | (8.521) |
| KP F Stat | | 61.445 | 44.695 | 21.683 | 19.571 |
| Observations | 23418 | 23418 | 23417 | 22790 | 22789 |
| $\overline{HE}_{97/00}$, $\overline{WE}_{97/00}$ and $\overline{Working}_{97/00}$ | Yes | Yes | Yes | Yes | Yes |
| Worker Controls | No | No | Yes | No | Yes |
| Industry Controls II | No | No | No | Yes | Yes |
| $N_{clusters}$ | 66 | 66 | 66 | 61 | 61 |

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee $i$ working in industry $j$ (in 2000) in the period that goes from 2001 to 2007. Panel A) log of Total Earnings - which is equal to Total Working Years multiplied by average annual earnings [mean in the full-sample = 11.372]). Panel B) Total Working Years - the number of years employed [mean in the full-sample = 4.540]; Panel C) log of Average Weekly Earnings [mean in the full-sample = 5.97]); Panel D) log of Average Hourly Earnings [mean in the full-sample = 2.335]; Panels A, C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. All regressions include average years of employment ($\overline{Working}_{97/00}$ ) and average hourly and weekly earnings ($\overline{HE}_{97/00}$ and $\overline{WE}_{97/00}$) between 1997 and 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls II" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW *and from China*, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, $IV_{chi}$, is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering the worker's initial 2-digit ISIC3 industry of employment. Standard errors clustered by industry (ISIC3 - 3 digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.13: Normalised Earnings

| | (1) OLS | (2) 2SLS | (3) 2SLS | (4) 2SLS | (5) 2SLS |
|---|---|---|---|---|---|
| **Panel A** | | | **Normalized Total Earnings** | | |
| $\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$ | -1.364 | -4.392*** | -2.855** | -3.624** | -2.461 |
| | (1.669) | (1.184) | (1.114) | (1.597) | (1.547) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 48.028*** | 43.616*** | 45.853*** | 42.232*** |
| | | (7.594) | (6.789) | (7.649) | (6.693) |
| KP F Stat | | 39.995 | 41.27 | 35.933 | 39.809 |
| Observations | 20140 | 20137 | 20136 | 19572 | 19571 |
| **Panel B** | | | **Total Working Years** | | |
| $\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$ | -2.774*** | -4.032*** | -3.006*** | -3.272*** | -2.486** |
| | (0.979) | (1.004) | (0.951) | (1.081) | (1.151) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 47.931*** | 43.505*** | 45.807*** | 42.314*** |
| | | (7.707) | (6.941) | (7.630) | (6.694) |
| KP F Stat | | 38.673 | 39.289 | 36.042 | 39.954 |
| Observations | 21412 | 21409 | 21408 | 20791 | 20790 |
| **Panel C** | | | **Normalized Average Weekly Earnings** | | |
| $\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$ | 0.161 | -0.125 | 0.010 | 0.073 | 0.183 |
| | (0.206) | (0.183) | (0.232) | (0.306) | (0.349) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 48.028*** | 43.616*** | 45.853*** | 42.232*** |
| | | (7.594) | (6.789) | (7.649) | (6.693) |
| KP F Stat | | 39.995 | 41.270 | 35.933 | 39.809 |
| Observations | 20140 | 20137 | 20136 | 19572 | 19571 |
| **Panel D** | | | **Normalized Average Hourly Earnings** | | |
| $\frac{\Delta_{00/07} Imports_{chi}}{Expenditure_{00}}$ | 0.124 | -0.266* | -0.193 | -0.409* | -0.344* |
| | (0.246) | (0.150) | (0.140) | (0.215) | (0.191) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 48.024*** | 43.637*** | 45.830*** | 42.210*** |
| | | (7.599) | (6.795) | (7.657) | (6.702) |
| KP F Stat | | 39.939 | 41.240 | 35.828 | 39.668 |
| Observations | 20124 | 20121 | 20120 | 19556 | 19555 |
| Worker Controls. | No | No | Yes | No | Yes |
| Industry Controls | No | No | No | Yes | Yes |
| $N_{clusters}$ | 66 | 66 | 66 | 61 | 61 |

NOTES: Panels A, B, C and D respectively represent the following dependent variables for employee $i$ working in industry $j$ (in 2000) in the period that goes from 2001 to 2007. Panel A) Normalised Total Earnings - total earnings between 2001 and 2007 divided by average annual earnings between 1997 and 2000 [mean in the full-sample = 5.85]). Panel B) Total Working Years - the number of years employed between 2001 and 2007 [mean in the full-sample = 4.58]; Panel C) Normalised Average Weekly Earnings - average weekly earnings between 2001 and 2007 divided by average weekly earnings between 1997 and 2000 [mean in the full-sample = 1.201]); Panel D) Normalised Average Hourly Earnings - average hourly earnings between 2001 and 2007 divided by average hourly earnings between 1997 and 2000 [mean in the full-sample = 1.162].; Panels C and D exclude individuals with zero years of employment from 2001 to 2007. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration (2000-2007) relative to workers' industry of employment in 2000. "Worker Controls" include sex, age, occupation fixed effects (4-digit) and a part-time job dummy. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. Instrument for change in industry Chinese import penetration, $IV_{chi}$, is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. Standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

### 1.C.5 Firms

Using information from the BSD I also investigate firms' outcomes that are tightly related to unemployment and earnings. My empirical approach is similar to the one presented in Subsection 1.4.1, but $i$ indexes firms instead of workers. My initial time period is still 2000, but different from the worker analysis I now include new entrants in my sample, i.e., I also consider firms that entered in any year after (and including) 2001 in some specifications. I allocate to all firms the same import shock (change in import penetration 2000/2007).

My dependent variables are either: i) Activity Status, a dummy variable equals to 1 if a firm was alive in 2007 and 0 otherwise; or ii) Employment Growth, defined as change in $ln(employment)$ between 2000 and 2007 considering only surviving plants.

I focus on local units, which is generally equivalent to plant level data. My set of controls in Table 1.14, "Firm Level Controls", include enterprise birth date fixed effects and a dummy for enterprise foreign ownership in the starting period. "Industry Controls" include the same variables described in the main text.

The results are strong both in the extensive and in the intensive margin of job destruction, giving further support to the partial-equilibrium effects generated by my counterfactuals. Looking at the 5th column, a 1 percentage point increase in Chinese import penetration leads to an increase of 0.96 percentage points in the probability of death of a firm and to a reduction of 2.256 percentage points in the annual employment growth between 2000 and 2007. Hence, plants shut down and/or reduce their size following an import penetration shock.

Table 1.14: Firms - Local Units

| | (1) OLS | (2) 2SLS | (3) 2SLS | (4) 2SLS | (5) 2SLS |
|---|---|---|---|---|---|
| **Panel A** | | | **Activity Status** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | -1.670*** | -2.021*** | -1.364*** | -0.998* | -0.964* |
| | (0.460) | (0.649) | (0.313) | (0.570) | (0.542) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 18.233*** | 17.504*** | 14.345*** | 14.172*** |
| | | (2.222) | (2.552) | (1.976) | (1.982) |
| KP F Stat | | 67.316 | 47.035 | 52.702 | 51.144 |
| Observations | 364814 | 363777 | 297002 | 270819 | 216224 |
| **Panel B** | | | **Employment Growth** | | |
| $\Delta_{00/07}\frac{Imports_{chi}}{Expenditure}$ | 0.375 | -0.335 | -1.879*** | -1.766*** | -2.256*** |
| | (0.568) | (0.939) | (0.509) | (0.593) | (0.453) |
| $1^{st}$ *Stage(s) Statistics* | | | | | |
| $IV_{chi}$ | | 17.602*** | 16.587*** | 13.358*** | 13.308*** |
| | | (2.822) | (3.109) | (2.359) | (2.351) |
| KP F Stat | | 38.909 | 28.457 | 32.074 | 32.03 |
| Observations | 124083 | 123888 | 123888 | 73055 | 73055 |
| Firm Controls | No | No | Yes | No | Yes |
| Industry Controls | No | No | No | Yes | Yes |
| $N_{clusters}$ | 66 | 66 | 66 | 62 | 62 |

NOTES: Estimations considering plant level data. Each panel represents a different dependent variable. Panel A) Activity Status, a dummy variable equals to 1 if a firm was alive in 2007 and 0 otherwise [mean in the full-sample = 0.499]; Panel B) Employment Growth, defined as change in $ln(employment)$ between 2000 and 2007 considering only surviving plants [mean in the full-sample = 1.44]. Panel B considers only surviving plants from 2000 to 2007, while Panel A considers dead and surviving plants, as well as new entrants. Column 1 estimated by OLS and columns 2-5 by 2SLS. Change in import penetration relative to plants' industry of employment in 2000 or plants' industry in its entry year if plant enters after 2000. "Industry Controls" include pre-period employment growth and pre-period employment changes for two different periods, from 1986 to 1991 (2-digit industry) and from 1994 to 1996 (4-digit industry) and a broad outsourcing measure (share of input costs in value added at the 2-digit industry level); and other 4-digit industry measures such as pre-period change (1997-1999) in import penetration from China and the rest of the world (RoW); levels of import penetration from the RoW, real (log) sales, employment level, real (log) exports to China, R&D intensity, real purchase of computer services and real investment in machinery, all in 2000. "Firm Controls" include enterprise birth date fixed effects and a dummy for enterprise foreign ownership in the starting period. Instrument for change in industry Chinese import penetration, $IV_{chi}$, is equal to industry import penetration from China in 1997 interacted with the change in Chinese import share in the world (2000-2007), excluding the UK and considering all tradable industries. Robust standard errors clustered by industry (ISIC3 - 3-digit) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# Chapter 2

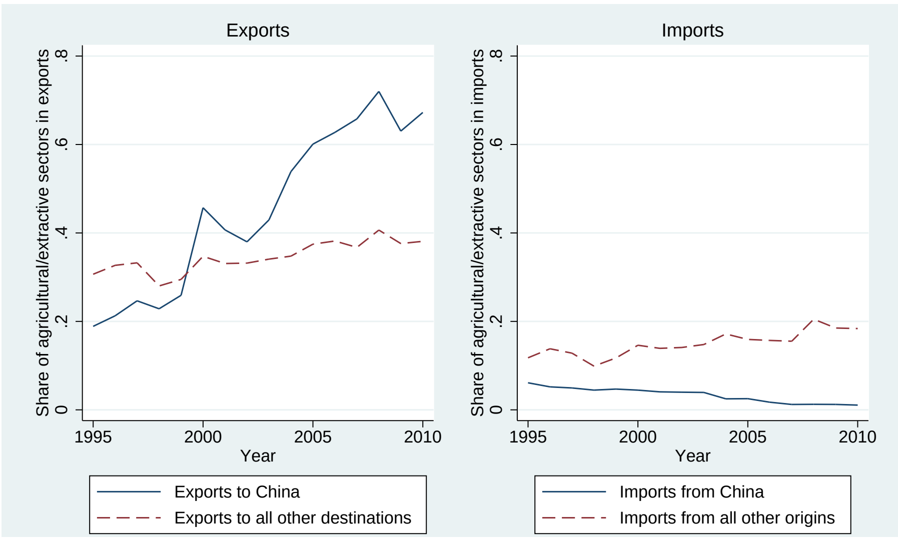
# Winners and Losers from a Commodities-for-Manufactures Trade Boom

## 2.1 Introduction

China's recent emergence as a major force in the world economy is one of the largest economic events of recent times. The combination of China's exceptionally high rates of economic growth, its increasingly deep engagement with the rest of the world via international trade, and the sheer size of its stock of labour, land and capital has generated a set of economic shocks whose influence stretches worldwide. Much of the attention on the effects of China on the economies of other countries has focused on the import competition shock associated with the massive growth of the Chinese manufacturing sector. However, China is also an increasingly large consumer of goods produced abroad: if China has been the source of a large supply shock, it must also have been the source of a large demand shock. We will consider the heterogeneous effects of these supply-side and demand-side 'China shocks' on developing-country labour markets, by examining the case of Brazil.

For developing countries, the 'China demand shock' has taken a distinctive form: increasingly, outside of the manufacturing supply chains of East and Southeast Asia, the goods being sent to China by non-high-income countries are products of the agricultural and extractive sectors. Panel A of Figure 2.1 shows that while there has been a gradual rise in the share of agricultural and extractive sectors in the exports of non-high-income countries (excluding those in East and Southeast Asia) to destinations other than China, the importance of these industries in their exports to China has changed much more dramatically, rising from less than 20% in 1995 to nearly 70% in 2010. Meanwhile, developing countries' imports from China have become increasingly concentrated in manufactures: Panel B of Figure 2.1 shows that the share of products of the agricultural and extractive sectors in the imports of non-high-income countries from China, already small (6%) in 1995, had dwindled to 1% by 2010. This shift towards a commodities-for-manufactures trade relationship with China has coincided with a sharp increase in China's overall importance in developing countries' foreign trade (Panel A of Figure 2.2).

Just as the import side of this boom in trade with China has often been met with suspicion by policymakers and commentators concerned about effects on local industry (see e.g. Economist 2012), China's rising demand for unglamorous agricultural and mining products has similarly not always been treated with enthusiasm. Before a visit to China in 2011, Brazil's president pledged that she would be "working to promote Brazilian products other than basic commodities," amid concern that "overreliance on exports of basic items such as iron ore and soy" might result in 'de-industrialisation' (LA Times 2011). Similarly, a former trade minister of Brazil has spoken of the "need to iron out distortions in the trade relationship, in which Brazil sells commodities and China manufactures" (Bloomberg 2011).




Panel A Panel B

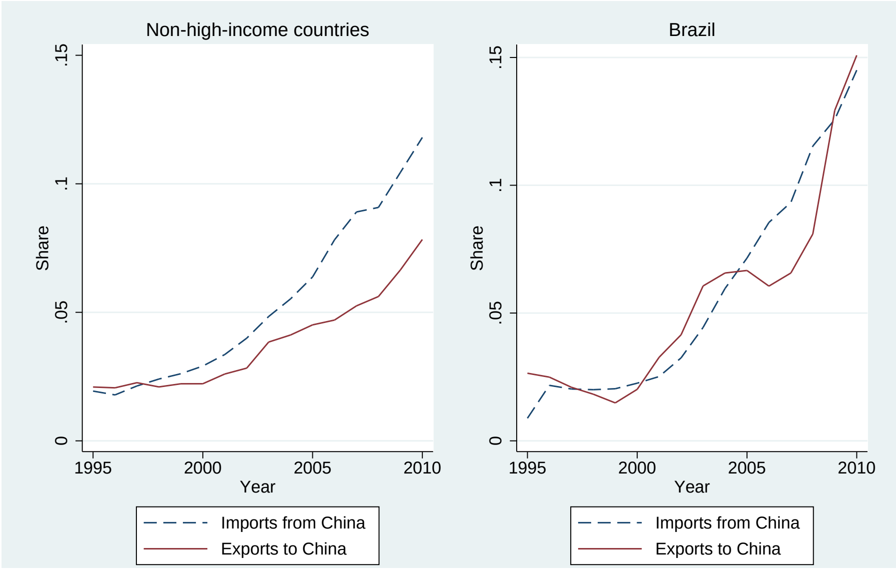
Figure 2.1: Evolution of the share of agricultural and extractive sectors in the exports and imports of non-high-income countries

NOTES: These graphs present the evolution of the share of products of the agricultural and extractive sectors (agriculture, forestry, fisheries/aquaculture and mining) in the exports and imports of non-high-income countries (excluding those in East and Southeast Asia) from 1995 to 2010. *Sources*: CEPII BACI for trade data; definition of high-income countries from the World Bank.

In our study of Brazil, we examine the changing labour market outcomes of regions producing manufactures affected by rising Chinese import supply and localities specializing in raw materials demanded by China. We find that while labour markets in 'loser' regions indeed appear to have suffered from Chinese import competition via slower growth in manufacturing wages and rising wage inequality, it is also the case that 'winner' regions have gained from Chinese export demand, through faster wage growth, lower takeup of social assistance and shifts in the local economy towards 'good jobs'.

Brazil provides an excellent context for a study of China's impact on developing countries' labour markets for several reasons. First, the importance of China in both the imports and exports of Brazil has risen steeply in recent years, as seen in Panel B of Figure 2.2. In 2000, Brazil received approximately 2.3% of its imports by value from China and sent 2.0% of its exports to China; by 2010, these shares were 14.5% and 15.1% respectively. Second, the pattern of Brazil-China trade has followed the broad trends outlined above for the wider set of non-high-income countries: Brazilian exports to China are increasingly products of the agricultural and extractive sectors, while Brazilian imports from China have remained concentrated in manufacturing (see Figure 2.3). Third, Brazil is particularly large and has a diverse geography, generating a set of local labour markets that are highly varied in their comparative advantages, and thus allowing for identification of the heterogeneous effects of trade with China without relying on cross-country regressions. Fourth, the Brazilian population census captures a variable of particular relevance in developing countries: informality. This is important both because the informal sector is large – in Brazil, approximately half of the employed population in 2000 were either informal salaried workers or self-employed – and because the (de-)formalisation of labour markets is a potentially important but understudied effect of trade shocks affecting developing countries.

In order to identify the effects of demand and supply shocks originating from China on local labour markets in Brazil, we use the shift-share methodology of Bartik (1991), which has previously been applied to the study of trade shocks by Topalova (2007), Autor et al. (2013a) and others. This method compares locations with different initial comparative advantages, tracing the fortunes of regions whose basket of industries has been faced with steeper increases in Chinese supply or demand, as compared to locations whose industries have been relatively unaffected by China's emergence. Because some agricultural, extractive and manufacturing industries have been affected more than others by China, we are able to compare regions with identical initial employment shares in each of these three broad categories. For example, our identification strategy relies on comparisons of regions with the same share of employment in agriculture in 2000 but different patterns of specialisation across crops. Our measures of Chinese supply and demand shocks are based on changes in actual trade flows between China and Brazil, but we instrument for these variables to ensure that our results capture neither Brazil-specific shocks nor changes in world prices that are not directly due to China. We also run robustness checks that




Panel A Panel B

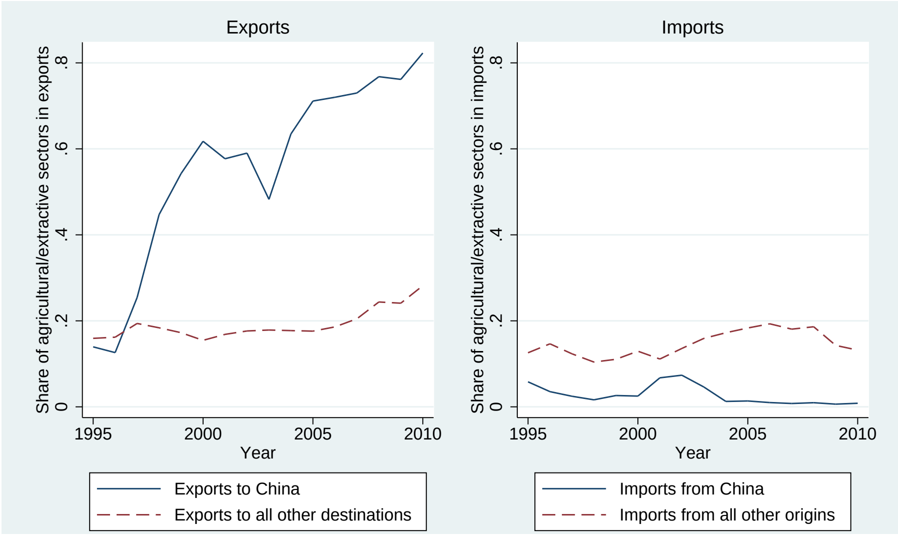
Figure 2.2: Evolution of the share of China in the imports and exports of non-high-income countries and Brazil

NOTES: Panel A presents the evolution of the share of China in the imports and exports of non-high-income countries (excluding those in East and Southeast Asia) from 1995 to 2010. Panel B presents the time series of the share of China in the imports and exports of Brazil from 1995 to 2010. *Sources*: CEPII BACI for trade data; definition of high-income countries from the World Bank.

account for the possibility that our results are driven by other region-specific trends.

We consider the changes between 2000 and 2010 in several key characteristics of local labour markets that can be observed using Brazilian census data: wages, employment rates, in-migration rates, informality and occupational skill level, along with participation in one of the largest cash transfer programs in the world, *Bolsa Família*. We find that locations subject to larger increases in Chinese import competition experienced slower growth in manufacturing wages and in-migration rates during this period, as well as a greater rise in local wage inequality. Our estimates suggest that for a local labour market at the 80th percentile of the 'China supply shock', wage growth in manufacturing sectors was lower by 2.4 percentage points over the ten years between 2000 and 2010, while wage inequality rose by an additional 0.8% relative to average 2000 levels. On the other hand, the supply shock does not appear to have been associated with a fall in employment rates. Instead, there is some evidence of a rise in the employment rates of affected locations, though this appears to have involved a shift in the local structure of employment towards unskilled jobs in nontraded sectors and a decline in the share of the workforce in skilled manufacturing jobs.

Meanwhile, in locations more exposed to rising demand from China, average hourly wages increased more quickly during the period of study: a local labour market at the 80th percentile of the shock to Chinese demand experienced wage growth in the agricultural




Panel A Panel B

Figure 2.3: Evolution of the share of agricultural and extractive sectors in the exports and imports of Brazil

NOTES: These graphs present the evolution of the share of products of the agricultural and extractive sectors (agriculture, forestry, fisheries/aquaculture and mining) in the exports and imports of Brazil from 1995 to 2010. *Sources*: CEPII BACI for trade data; definition of high-income countries from the World Bank.

and extractive sectors that was four percentage points higher over the course of the decade. This wage effect appears to have spilled over to workers in other local industries, and to have occurred without an associated increase in wage inequality. *Bolsa Família* takeup rates were also lower in 2010 in regions benefiting more from Chinese demand. Moreover, while there is little evidence of an effect of demand from China on local employment rates, we do observe positive effects on job quality: an increase in the share of formal employment at the expense of informal jobs, and a rise in the proportion of the local workforce in skilled agricultural or extractive sector occupations.

This chapter contributes to a growing literature on the worldwide effects of the rise of China. This includes papers that have studied the impact of Chinese import competition on economic variables such as manufacturing employment (Pierce and Schott 2013, Autor et al. 2013a), worker earnings (Pessoa 2014), skill upgrading (Hsieh and Woo 2005, Mion and Zhu 2013), firm and product selection (Iacovone et al. 2013) and innovation (Bloom et al. 2011). There are a much smaller number of papers which, like this chapter, also take account of demand-side effects. Dauth et al. (2014) take a reduced-form approach, examining the impact of rising imports from and exports to China and Eastern Europe on local labour market variables in Germany. Dauth et al. study a developed-country context in which agricultural and extractive sectors are relatively unimportant, and so focus on the effects of these trade shocks on the manufacturing and services sectors. General equilibrium analyses of China's effect on the world economy (such as Hsieh and Ossa 2011 and di Giovanni et al. 2014) also take account of both the supply and demand effects of China on other countries, but these studies summarize the impact of China on aggregate welfare rather than distinguishing between the potentially heterogeneous impacts of rising Chinese import competition and export demand.

Our work also relates to the wider literature studying the impact of trade shocks on labour markets. Several other papers investigate the effect of trade on workers in Brazil (e.g. Gonzaga et al. 2006, Menezes-Filho and Muendler 2011, Helpman et al. 2012, Kovak 2013, Dix-Carneiro 2014), with particular attention given to Brazil's early 1990s trade liberalisation. Most research on trade and labour markets, including much of the literature on Brazil, is limited to studying workers in formal employment. Our work also fits into the smaller literature on trade and informality, including Goldberg and Pavcnik (2003), Nataraj (2011), McCaig and Pavcnik (2014) and Paz (2014). Finally, the chapter contributes to the literature on the local labour market effects of shocks involving nonmanufacturing sectors; one particularly relevant study is Aragón and Rud (2013), who examine the local economic impact of a Peruvian gold mine.

The chapter is organised as follows: we first describe our data sources and present our identification strategy in Section 2.2. We then discuss the results of our empirical analysis in Section 2.3, and draw conclusions in Section 2.4. Additional figures and tables are included in an attached appendix.

## 2.2 Data and empirical strategy

This section describes the data used in the study and outlines our empirical strategy, discussing our baseline OLS specification, instrumental variables and robustness checks.

### 2.2.1 Data sources

We use individual-level labour market and socioeconomic data from the long form Brazilian Demographic Census (*Censo Demográfico*) for 2000 and 2010, sourced from the Brazilian Institute of Geography and Statistics (IBGE); some specifications also use individual-level data from the 1991 census. The data contains a number of labour market variables, including employment status, monthly income from employment and hours worked per week, along with information on migration and other demographic variables; we will discuss the variables we use in our analysis in greater depth below. We restrict our sample to the subpopulation most likely to participate in the labour market, defining the workforce as every individual between 18 and 60 years old. We then aggregate the data to the geographical unit 'microregion', a level of aggregation that has been constructed by IBGE by grouping

Brazilian municipalities according to information on integration of local economies. Our sample includes all of the 558 Brazilian microregions, each of which contains an average of 10 municipalities.

We draw information on informality from a question in the census asking employed individuals about their job type: government worker; employee registered at the Brazilian Ministry of Labour and Employment (*com carteira assinada*); employee not registered at the Ministry of Labour and Employment (*sem carteira assinada*); self-employed; or in unpaid work. We include the final three categories in our definition of the informal sector.[1] We also use information on individuals' occupations from the 2000 and 2010 censuses, defining 'skilled occupations' and 'unskilled occupations' using the definition of occupational skill level from the 2008 International Standard Classification of Occupations (ISCO-08). In particular, we define a skilled occupation as one associated with skill level 3 or 4 in the ISCO-08 classification; this covers managers, professionals, technicians and associate professionals. While the occupational classification in the 2010 Brazilian census is almost identical to ISCO-08, we need to use publicly available concordances between the Brazilian occupational classification CBO-02 and ISCO-88, and between ISCO-88 and ISCO-08, to classify the occupations observed in the 2000 census into skilled and unskilled occupations.

Our data on international trade in goods is from the BACI database developed by Centre d'Etudes Prospectives et d'Informations Internationales (CEPII), which reconciles the data separately reported by importers and exporters in the United Nations Statistical Division's COMTRADE database. CEPII BACI contains the total annual value of bilateral trade at the 6-digit level of the Harmonized System classification for more than 200 countries from 1995 to 2010; we use data for 2000 and 2010 in the analysis below. The CEPII data is denominated in thousands of current US dollars; we convert 2000 values to 2010 US dollars using the US GDP deflator from the US Bureau of Economic Analysis.

Our empirical strategy requires us to classify employed individuals in the 2000 census data and products in the 2000 and 2010 trade data into sectors. In the 2000 Brazilian census, individuals are asked to state their sector of activity according to the 5-digit *CNAE Domicílio* classification.[2] We thus construct a concordance assigning products in the trade data to *CNAE Domicílio* sectors, which requires us to combine some of the traded goods

[1]Although a self-employed worker could be registered with the federal government, these cases constitute a small fraction of all self-employed individuals. Publicly available administrative data from the *Relaçao Anual de Informaçoes Sociais* (RAIS) database – the official records of the Ministry of Labour and Employment – show that only 0.9% and 0.8% of the workforce were registered as self-employed in 2000 and 2010, respectively. We observe total rates of self-employment of 18.3% and 15.7% of the workforce in these two years' censuses.

[2]This is defined as the main sector of activity of the firm or other institution of an employed person or the nature of the activity of a self-employed person.

sectors in *CNAE Domicílio* when these cannot be separately identified in the trade data. We are left with a total of 82 traded goods sectors, including 32 agricultural and extractive sectors (22 agricultural sectors, 8 mining sectors, forestry and fishing/aquaculture) and 50 manufacturing sectors; see Table 2.9 for a full list.[3]

### 2.2.2 Baseline specification

To estimate the heterogeneous impacts of supply and demand shocks at the microregion level, we first create sector-level measures of each shock and then define exposure to a shock according to local comparative advantage across sectors, as measured by the sectoral composition of employment in each microregion in 2000. This is the 'shift-share' methodology of Bartik (1991), as applied to trade shocks by Topalova (2007) and to the effect of China on US labour markets by Autor et al. (2013a). Given the existence of migration across microregions, which we will show is correlated with the trade shocks we study, our regression results should be interpreted as identifying effects of China on local labour markets as geographical units varying in their initial comparative advantages, rather than effects on the set of workers present in those labour markets in the year 2000.

Our baseline specification is as follows:

$$\Delta y_m = \beta_I IS_m + \beta_X XD_m + W_m^{'}\gamma + \epsilon_m. \tag{2.1}$$

Here, $\Delta y_m$ is the change in a given labour market outcome between 2000 and 2010 in microregion $m$, $IS_m$ and $XD_m$ are microregion-level measures of the import supply and export demand shocks due to China between 2000 and 2010, and $W_m$ is a set of controls.

To construct $IS_m$ and $XD_m$, we first define an import (export) shock in sector $k$ as the difference in the value of Brazilian imports (exports) from China in sector $k$ between 2000 and 2010, $\Delta I_k = I_{k,2010} - I_{k,2000}$ and $\Delta X_k = X_{k,2010} - X_{k,2000}$, denominated in thousands of 2010 US dollars. We then allocate each shock across microregions according to the fraction of Brazil's workers in sector $k$ sited in a given microregion $m$ in 2000; i.e. $\frac{L_{km,2000}}{L_{k,2000}}\Delta I_k$ and $\frac{L_{km,2000}}{L_{k,2000}}\Delta X_k$, where $L_{km,2000}$ is the number of workers in sector $k$ and microregion $m$ in year 2000, and $L_{k,2000} = \sum_m L_{km,2000}$.[4] Since microregions differ in size, which affects each sector's relevance for the local labour market, we normalize the trade shock by the number of employed workers in each microregion in 2000 (excluding workers employed outside the private sector), giving us the expressions $\frac{L_{km,2000}}{L_{k,2000}}\frac{\Delta I_k}{L_{m,2000}}$ and

[3]Several products from the Harmonized System classification, mostly waste or scrap (e.g. scrap metal, used clothing) could not be concorded to the *CNAE Domicílio* classification; these products make up less than 1% of Brazilian trade by value.

[4]The underlying assumption here is that the trade shock is distributed uniformly across workers in each sector.

$\frac{L_{km,2000}}{L_{k,2000}} \frac{\Delta X_k}{L_{m,2000}}$.[5] Finally, we define the total local exposure per worker to each trade shock as the sum of these expressions across sectors, so that our microregion-level measures of the import supply and export demand shocks are, respectively:

$$IS_m = \sum_k \frac{L_{km,2000}}{L_{k,2000}} \frac{\Delta I_k}{L_{m,2000}}$$
$$XD_m = \sum_k \frac{L_{km,2000}}{L_{k,2000}} \frac{\Delta X_k}{L_{m,2000}}.$$

As measured by $IS_m$ and $XD_m$, the average Brazilian microregion received an import competition shock from China of US\$225 per worker and an export demand shock of US\$594 per worker.[6] The dispersion of the export demand shock is also larger (with a standard deviation of 1.31 for $XD_m$ as compared to 0.27 for $IS_m$), though both distributions are highly skewed to the right, as shown in Figure 2.7. The microregion at the 20th percentile of $IS_m$ received an import supply shock of US\$73 per worker, while the supply shock to the microregion at the 80th percentile of $IS_m$ was US\$313 per worker. The corresponding figures for $XD_m$ are US\$38 and US\$647, respectively. Figure 2.4 shows that the two shocks affected different sets of microregions, as the unconditional distributions of the two measures are nearly orthogonal, with a correlation of 0.07.

Table 2.1 charts the characteristics of microregions in the top 20% of $IS_m$ and $XD_m$ in 2000, while the geographical distribution of microregions in the top 20% of each of the two measures are plotted in Figure 2.5. Table 2.1 shows that the microregions most exposed to Chinese imports tended to have a lower proportion of workers engaged in agriculture and a higher proportion working in manufacturing in 2000 as compared to the average region, as well as a much smaller share of rural residents. On average, these regions also had a larger working-age population, a higher share of the workforce in private sector employment and a greater proportion of workers in skilled occupations than the mean microregion. The average wage in these regions in 2000 was also relatively high.[7]

Table 2.1 also suggests that the microregions most affected by Chinese export demand were somewhat less populous than the mean microregion and much smaller in population than high-$IS_m$ microregions in 2000. At the same time, microregions with large values of $XD_m$ had an average share of the workforce employed in the private sector, share of workers in formal jobs and average hourly wage somewhat higher than that of the mean

[5] The means across microregions of the distributions of these sector-microregion-level variables are shown in columns (3) and (5) of Table 2.9.

[6] These two figures differ in magnitude even though trade between China and Brazil was approximately in balance in both 2000 and 2010; this is because both measures include a microregion-level per-worker normalisation.

[7] Unsurprisingly, the three microregions with the highest $IS_m$ are all major industrial centers: Manaus, São José dos Campos and Santa Rita do Sapucaí. The last of these regions is sometimes referred to as the 'Electronic Valley' due to the size of its electronics industry.

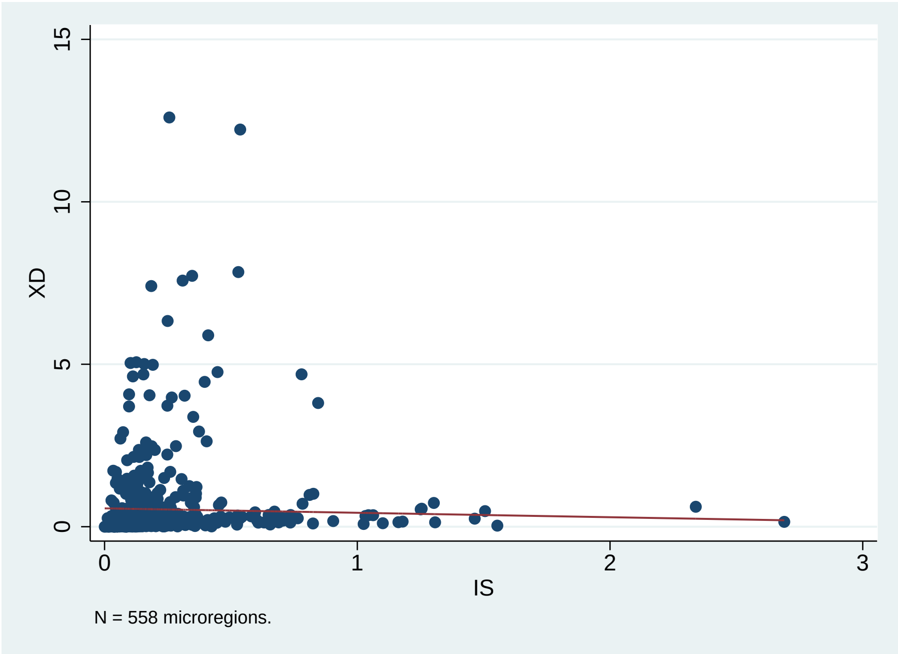
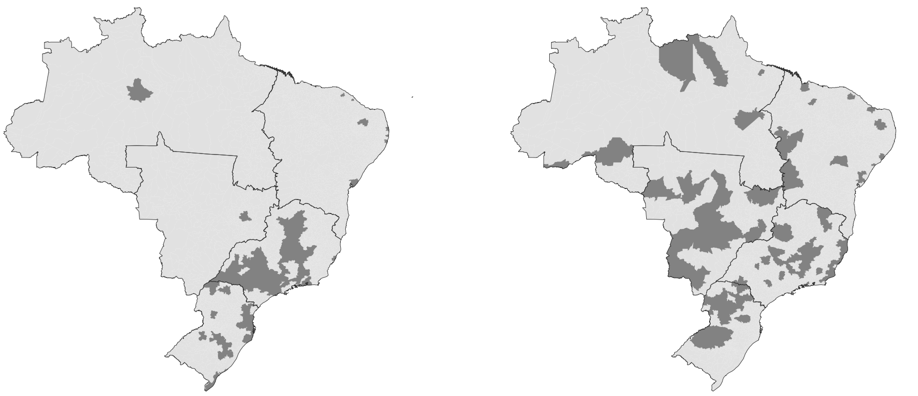



Figure 2.4: Import supply vs export demand measures

NOTES: This graph presents a scatter plot of the export demand shock measure $XD_m$ against the import supply shock measure $IS_m$ at the microregion level. The line plots the results of a linear regression of $XD_m$ on $IS_m$. Both variables are denominated in thousands of 2010 US dollars per worker. *Sources*: 2000 Brazilian Census, and CEPII BACI.



Panel A - Import supply

Panel B - Export demand

Figure 2.5: Geographical distributions of top quintile of import supply and export demand measures

NOTES: These maps display the spatial distributions of microregions in the top quintile of the import supply shock measure $IS_m$ and microregions in the top quintile of the export demand shock measure $XD_m$. The maps also depict the borders between Brazilian regions. *Sources*: 2000 Brazilian Census, and CEPII BACI.

Table 2.1: Brazilian microregion-level summary statistics 2000

| | 2000 | | |
|---|---|---|---|
| | All microregions | Top quintile of $IS_m$ | Top quintile of $XD_m$ |
| | (1) | (2) | (3) |
| Workforce (thousands) | 170.952 | 417.095 | 138.593 |
| Private sector workers | .589 | .624 | .608 |
| Agriculture | .167 | .078 | .161 |
| Extractive | .002 | .002 | .004 |
| Manufacturing | .068 | .123 | .069 |
| Nontraded | .352 | .421 | .375 |
| Formal jobs | .177 | .299 | .205 |
| Informal jobs | .412 | .326 | .403 |
| Skilled occupations | .094 | .124 | .099 |
| Unskilled occupations | .496 | .501 | .509 |
| Rural residents | .313 | .137 | .271 |
| Inmigrated in the last 5 years | .083 | .084 | .088 |
| Average hourly wage (R$) | 2.21 | 3.14 | 2.46 |
| Skilled occupations | 5.07 | 6.72 | 5.55 |
| Unskilled occupations | 1.70 | 2.28 | 1.92 |
| Wage inequality (Gini) | .542 | .528 | .556 |

NOTES: This table displays descriptive statistics of the Brazilian labour market in 2000, averaged at the microregion level. Column (1) includes all microregions, column (2) includes only microregions among the top 20% of $IS_m$, and column (3) includes only microregions in the top 20% of $XD_m$. All figures are shares of the total workforce, except as indicated. The workforce is defined here as the total number of citizens between 18 and 60 years old. Average hourly wage is in current Real. *Sources:* 2000 Brazilian Census, and CEPII BACI.

microregion, though again smaller than the top quintile of $IS_m$. They were relatively more rural than the high-$IS_m$ regions as of 2000, and slightly less rural on average than the mean microregion. Unsurprisingly, the average share of workers in the extractive sector was particularly high in these microregions, though the overall size of the extractive sector relative to total local employment was very small even in these locations. In terms of most other labour market variables, regions in the top 20% of $XD_m$ were similar on average to the mean Brazilian microregion in 2000, and in general they were more similar to the average microregion than were the locations in the top quintile of $IS_m$.[8]

Our baseline specifications also include a set of microregion-level controls $W_m$; key among these are the share of each microregion's workforce employed in agricultural sectors, extractive sectors and manufacturing sectors in 2000.[9] This means that our results depend on comparisons between microregions with the same initial economic structure (in terms of the distribution of local employment across these three broadly defined categories) but specialised in different particular agricultural, extractive and manufacturing sectors.

This strategy is feasible because the distribution of Brazil-China trade growth is skewed

[8]The three microregions with the largest values of $XD_m$ include a major center for the offshore oil industry (Macaé), an important outpost of the iron ore mining complex (Itabira) and a small microregion specialised in soybean production (Não-me-Toque, Rio Grande del Sul).

[9]Forestry and fisheries/aquaculture are defined here as agricultural sectors.

across sectors on both the import and export sides. Approximately 40% of the total growth in Brazil's imports from China between 2000 and 2010 (i.e. $\sum_k \Delta I_k$) is accounted for by electronics (19%), machinery (13%) and electrical equipment (8%). Meanwhile, just three sectors, all of which are agricultural or extractive sectors, were responsible for 82% of the growth in Brazil's exports to China between these two years: mining of nonprecious metals (45%), soybeans (23%) and oil and gas (14%).[10] This breakdown actually understates the level of concentration of Brazil's exports to China, since its exports in the 'mining of nonprecious metals' sector are almost exclusively made up of exports of iron ore. This high degree of concentration in a few commodities is a typical pattern of exports to China among developing countries for whom trade with China is important.[11]

The controls in our baseline regressions also include the workforce size, the share of the workforce employed in nontraded sectors, the share employed in informal jobs, and the proportion of rural residents, all measured at the microregion level for the year 2000, along with a cubic polynomial of 2000 microregion-level income per capita. In all regressions, in order to allow for spatial correlation of errors across microregions, we cluster standard errors at the level of the mesoregion. Like the microregion, this geographical unit has been defined by IBGE according to measures of local market integration; there are 138 mesoregions in Brazil. Also, in order to prevent our regression results from being driven by outliers or very small microregions, we assign values of $IS_m$ and $XD_m$ below the 1st and above the 99th percentiles to the values of the 1st and 99th percentiles, and weight all regressions by the share of the national workforce in each microregion. We include all 558 Brazilian microregions in all regressions.

### 2.2.3 Instrumental variables and robustness checks

Our goal is to identify the causal effect of the two 'China shocks' on local labour market dynamics in Brazil. However, regression equation (2.1) does not capture causality in the presence of any additional shocks that are both relevant for our dependent variables

[10] To calculate these measures, we take the difference between the 2010 and 2000 values of Brazil's imports from China (or exports to China) in each sector and divide by the aggregate difference between 2010 and 2000 Brazilian imports from China (or exports to China). The resulting figures for each of the 82 traded goods sectors may be found in columns (1) and (2) of Table 2.9. The value of imports from China actually decreased in several sectors, but their total decline constitutes a tiny proportion of the total difference in imports, so that the total of all positive values only slightly exceeds 1; the same is true of exports to China. As noted above, some Harmonized System codes (mostly waste and scrap) are not concorded to any sector; trade in these products is included in the denominator but not listed in Table 2.9.

[11] According to the CEPII BACI data, in all 27 non-high-income countries outside East and Southeast Asia for whom exports to China constituted a minimum of 10% of total exports by value in 2010, at least 80% of exports to China were concentrated in three or fewer of the sectors defined in this chapter (82 sectors plus a residual 'waste and scrap' category). In 16 of these 27 countries (including Brazil), at least 80% of exports to China were in agricultural and/or extractive sectors; in a further five, at least 80% of exports were concentrated in up to two agricultural or extractive sectors and either the 'basic metals' manufacturing sector or scrap metal.

and correlated with our exposure measures $IS_m$ and $XD_m$. In particular, given the sector-level variation that underlies our identification strategy, one potential issue would be the existence of Brazil-specific supply or demand shocks in sectors in which Brazil also experienced a relatively large change in trade with China. For example, changes in Brazil-China trade patterns might be capturing sector-specific productivity growth or Engel effects in Brazil rather than changes in China.

Several other studies of the cross-country transmission of shocks have addressed this concern by using an instrumental variables strategy that exploits information on trade between the shocks' country of origin (in this case, China) and countries *other* than the 'destination' country of interest (Brazil).[12] For instance, one might instrument our microregion-level import supply and export demand variables with measures calculated in the same way as $IS_m$ and $XD_m$, but using the change between 2000 and 2010 in imports from China (or exports to China) for a set of countries that does not include Brazil. A key assumption underlying this approach is that the changes in the pattern of trade between China and these other countries are unrelated to Brazil-specific shocks.

The main issue with this strategy is that it does not account for changes in *world* prices or quantities traded that are not due to China: if the world price of a given product rises due to other factors, or all countries trade more intensively in the products of some sector due to a worldwide technology or demand shock, this will be reflected in the trade flows of all countries. This is a particular issue for our study given its focus on commodities, whose world prices were on an upward trajectory over the course of the decade we study. If, for instance, the share of oil by value increased in the import baskets of all countries between 2000 and 2010 due to rises in its world price, both our baseline regression specification and the IV strategy described above would assign this effect to China. However, while China likely played a pivotal role in changes in world prices in many sectors during this period, we do not want to ascribe world price or quantity changes to China when these actually resulted from other factors.

We thus adapt the IV approach described above by considering changes in China's sector-level imports and exports *relative* to those of other countries. To do this, we first define $\tilde{I}_{ikt}$ and $\tilde{X}_{ikt}$ to be the total imports (exports) of country $i$ in sector $k$ in year $t$ from (to) all countries other than Brazil. We then run the following auxiliary regressions, using data on $\tilde{I}_{ikt}$ and $\tilde{X}_{ikt}$ in 2000 and 2010 for all countries available in the CEPII trade

[12]This is a standard approach in the 'China shock' literature; see e.g. Bloom et al. (2011), Autor et al. (2013a) and Iacovone et al. (2013).

data except Brazil:

$$\frac{\Delta \tilde{I}_{ik}}{\tilde{I}_{ik,2000}} = \alpha_k + \psi_{China,k} + \nu_{ik}$$
$$\frac{\Delta \tilde{X}_{ik}}{\tilde{X}_{ik,2000}} = \gamma_k + \delta_{China,k} + \mu_{ik}$$

The left-hand side of the two regressions above is the growth rate of the imports (exports) of a country in a given sector, net of its imports from (exports to) Brazil. The sector fixed effect $\alpha_k$ (or $\gamma_k$) then captures the mean growth rate, across countries, of net-of-Brazil imports (or exports) in that sector. The regressions are weighted by 2000 import (export) volumes, so that the values of these fixed effects are not driven by large positive or negative growth rates in countries with small shares of world trade. This means that the China-specific dummies $\psi_{China,k}$ and $\delta_{China,k}$ represent the deviation in the growth rates of China's imports and exports in sector $k$ excluding trade with Brazil, as compared to this weighted cross-country average.

We then relate the resulting estimates $\hat{\psi}_{China,k}$ and $\hat{\delta}_{China,k}$ to the microregion-level shock measures defined in Section 2.2.2. We first multiply these estimates by the values of Brazil-China imports and exports in 2000, redefining the sector-level 'China shocks' as $\Delta\hat{I}_k \equiv I_{k,2000}\hat{\delta}_{China,k}$ and $\Delta\hat{X}_k \equiv X_{k,2000}\hat{\psi}_{China,k}$. Our instrumental variables are then constructed at the microregion level using these new shock measures in the same way as for $IS_m$ and $XD_m$:[13]

$$ivIS_m = \sum_k \frac{L_{km,2000}}{L_{k,2000}} \frac{\Delta\hat{I}_k}{L_{m,2000}}$$
$$ivXD_m = \sum_k \frac{L_{km,2000}}{L_{k,2000}} \frac{\Delta\hat{X}_k}{L_{m,2000}}.$$

If Chinese trade with the rest of the world (excluding Brazil) had evolved in the same way as that of the (weighted) average country in each sector, all of these shocks would be equal to zero. In practice, however, this is not the case: the two vectors $\Delta\hat{I}_k$ and $\Delta\hat{X}_k$, like the 'raw' measures $\Delta I_k$ and $\Delta X_k$, vary widely across sectors. Indeed, the raw shocks and these IV shock measures are highly correlated, with correlation coefficients of 0.93 for the sector-level import supply shocks $\Delta I_k$ and $\Delta\hat{I}_k$ and 0.86 for the export demand shocks $\Delta X_k$ and $\Delta\hat{X}_k$. Scatter plots of $IS_m$ against $ivIS_m$ and $XD_m$ against $ivXD_m$ are shown in Figure 2.6.

Even if these instrumental variables were to fully capture the sectoral mix of Chinese

[13]The averages across microregions of the sector-microregion-level variables analogous to those in Section 2.2, but constructed using $\Delta\hat{I}_k$ and $\Delta\hat{X}_k$, may be found in columns (4) and (6) of Table 2.9.


Figure 2.6: Raw measures vs instrumental variables measures

NOTES: This graph presents scatter plots of microregion-level import supply and export demand shocks ($IS_m$ and $XD_m$) against the instrumental variables $ivIS_m$ and $ivXD_m$. The lines depict the results of simple regressions of $IS_m$ on $ivIS_m$ (coefficient 1.286, s.e. 0.021 and t-statistic 60.09) and $XD_m$ on $ivXD_m$ (coefficient 2.076, s.e. 0.053 and t-statistic 39.16). *Sources*: 2000 Brazilian Census, and CEPII BACI.

supply and demand shocks, it is naturally still possible that these shocks were correlated to supply and demand shocks in Brazil during this period. The variable $ivXD_m$ might be particularly vulnerable to this problem, since it is driven mainly by export growth in two nonmanufacturing sectors (soybeans and iron ore).[14] It could bias our results, for example, if Brazil discovered major new sources of iron ore just as China began importing it in much larger quantities.

Reassuringly, however, there is evidence that the rise in Brazil-China exports in these two sectors was mainly due to a Chinese demand shock. First, the share of Brazil in world trade by value in the two sectors changed relatively little between 2000 and 2010: Brazil accounted for 23% of world exports of soybeans in 2000 and 27% in 2010, and for 13% of world exports of nonprecious metal ores in 2000 and 17% in 2010. Meanwhile, China's share of world imports in these two sectors rose much more steeply during this period: from 21% to 56% for soybeans, and from 10% to 45% for nonprecious metal ores. Exports to China accounted for 98% of the growth in the total quantity of soybeans exported from Brazil, and 87% of the growth in the quantity of Brazil's exports of nonprecious metal

[14]While the oil and gas sector was responsible for 14% of the growth in exports from Brazil to China between 2000 and 2010 (as noted in Section 2.2), its importance is greatly diminished in the IV shock measure, since $\Delta\hat{X}_{oil}$ accounts for only 2% of $\sum_k \Delta\hat{X}_k$. The point in the upper left of the scatter plot of $XD_m$ against $ivXD_m$ (see Figure 2.6) is the offshore oil center (Macaé) mentioned in Footnote 8.

ores, between the two years.[15]

It is also possible that the outcomes we observe were driven by other circumstances specific to individual Brazilian regions. Indeed, the maps in Figure 2.5 suggest that the incidence of Chinese trade shocks is spatially correlated within Brazil. We thus run a robustness check in which we add fixed effects for Brazil's five regions to our IV specification, so as to check whether the results are robust to accounting for contemporaneous region-specific trends in the dependent variable $\Delta y_m$. That is, in this specification we investigate the within-region effects of the two 'China shocks'.

Finally, we also conduct an additional robustness check to address the concern that any results we observe simply represent the continuation of local labour market trends that began in years before our period of study. For example, Brazil underwent a major trade liberalisation episode in the late 1980s and early 1990s that is known to have had a significant impact on affected local labour markets (see e.g. Menezes-Filho and Muendler 2011, Kovak 2013); adjustments resulting from this shock might still have been occurring between 2000 and 2010. Thus, in order to account for pre-sample-period trends, we use data from the 1991 Brazilian census to add a lagged dependent variable to the right-hand side of specifications for which this data is available; that is, we control for microregion-level changes between 1991 and 2000 in the outcome of interest. Because of likely correlation between the lagged dependent variable and the residual $\epsilon_m$, we instrument for this variable using 1991 levels, as suggested by Anderson and Hsiao (1981).[16]

## 2.3 Results

In this section, we provide empirical evidence of the heterogeneous effects of the import supply shock and export demand shock from China on local labour markets across Brazil. We begin by considering the effects of these shocks on average hourly wages, wage inequality within local labour markets and takeup of the cash transfer program *Bolsa Família*. We then look at the impact of the 'China shocks' on migration, employment rates and the pattern of employment across sectors. Finally, we examine the evolution of 'good jobs' and 'bad jobs' in local labour markets affected by the shocks, considering the proportion of the local workforce in formal and informal jobs, and in skilled and unskilled occupations.

[15] Notably, Bustos et al. (2013) present evidence of non-Brazil-specific technological change in the soybean sector via the development in the US of a genetically modified soybean variety in 1996, and suggest that the adoption in Brazil of this technology in the early 2000s led to increases in agricultural productivity per worker, decreases in the labour intensity of agricultural production, rising manufacturing employment shares and declining manufacturing wages in affected locations. Bustos et al. also discuss a Brazil-specific technological change in the maize sector (*milho safrinha*) which they find is associated with rises in labour intensity, declines in manufacturing employment shares and increases in wages.

[16] Note that the consistency of our estimates then depends on the assumption that 1991 levels are uncorrelated with $\epsilon_m$.

The coefficients and standard errors in all tables are normalised by multiplying by 100, so that they may generally be interpreted as the effect of a US$1000 increase in imports or exports per worker on changes in the dependent variable in percentage points.[17]

### 2.3.1 Wages and wage inequality

Table 2.2 displays the results of microregion-level regressions of differences in log average hourly wages between 2000 and 2010 on $IS_m$, $XD_m$ and controls. In Panel A, the sample of wage-earners includes workers in all sectors, while Panels B, C and D only consider workers in the agricultural and extractive, manufacturing and nontraded sectors respectively. The OLS estimates in column (1) of Panel A suggest that larger export demand shocks are associated with higher growth in wages over these ten years, and that this effect is statistically significant. Columns (2) through (5) of Panel A show that the result is qualitatively unchanged by our instrumental variables strategy and robustness checks, including specifications with region fixed effects (column (3)), a lagged dependent variable (column (4)) and both of these two additional controls (column (5)). In our preferred specification, column (2), a US$1000 per worker increase in exports to China is associated with higher decadal growth in wages of approximately 1.76 percentage points.

Panels B through D suggest that the largest effect of rising export demand from China was on the set of industries most directly affected by this shock: the agricultural and extractive sectors. The baseline IV specification in column (2) of Panel B indicates that a microregion subject to the average demand shock of US$594 per worker saw wage growth in these sectors that was higher by 3.7 percentage points over the course of the decade. Given that the average wage in agricultural and extractive sectors increased by 52% during this period, a back-of-the-envelope calculation would suggest that the estimated effect of the 'China demand shock' is equal to 7.2% of the observed wage increase in these sectors. Panels C and D indicate that growth in wages in agricultural and extractive sectors also spilled over to other industries, as average wages in the manufacturing and nontraded sectors also grew faster in microregions more exposed to Chinese export demand, though only the result for manufacturing is statistically significant in our preferred specification.

Meanwhile, while the results in Panel A suggest that the Chinese import supply shock is not associated with statistically significant changes in average wages overall, Panel C indicates that it did have an effect for manufacturing, the sector most directly affected by Chinese import competition. The IV results in column (2) of Panel C indicate that a microregion exposed to the average import supply shock of US$225 per worker experienced

[17] This interpretation is, of course, approximate when the dependent variable is measured as a long difference of logarithms, but exact when the dependent variable is in long differences of shares.

Table 2.2: Results - log average hourly wages

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. All Sectors** | | | | | |
| $IS_m$ | -3.46 | -3.19 | -.70 | -3.57 | -1.06 |
| | (2.90) | (2.87) | (2.48) | (2.84) | (2.40) |
| $XD_m$ | 1.98*** | 1.76** | 2.26*** | 1.84*** | 2.33*** |
| | (.62) | (.74) | (.73) | (.71) | (.71) |
| **Panel B. Agricultural/Extractive Sectors** | | | | | |
| $IS_m$ | 1.15 | -.92 | 2.40 | -6.39 | .36 |
| | (6.31) | (7.61) | (7.82) | (6.94) | (7.26) |
| $XD_m$ | 5.98*** | 6.31*** | 6.74*** | 7.02*** | 6.96*** |
| | (1.93) | (2.29) | (2.08) | (1.93) | (1.93) |
| **Panel C. Manufacturing Sectors** | | | | | |
| $IS_m$ | -7.84*** | -7.69*** | -7.19*** | -8.51*** | -7.16*** |
| | (1.42) | (1.24) | (1.42) | (1.43) | (1.42) |
| $XD_m$ | 2.93*** | 2.95*** | 3.22*** | 2.78*** | 3.23*** |
| | (.61) | (.64) | (.68) | (.62) | (.69) |
| **Panel D. Nontraded Sectors** | | | | | |
| $IS_m$ | -4.23 | -3.85 | -1.70 | -4.72* | -1.69 |
| | (2.62) | (2.47) | (2.04) | (2.45) | (2.03) |
| $XD_m$ | .94* | .61 | .95* | .93* | .94* |
| | (.49) | (.50) | (.55) | (.51) | (.53) |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in log average hourly wages, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for all sectors, Panel B for agricultural and extractive sectors, Panel C for manufacturing sectors, and Panel D for nontraded sectors. Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the unit of the coefficients is roughly percentage increase. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

Table 2.3: Results - Log Average Hourly Wages by Formality and Occupation

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Formal Jobs** | | | | | |
| $IS_m$ | -6.37*** | -5.83*** | -3.46* | -4.67*** | -2.77 |
| | (1.74) | (1.60) | (1.91) | (1.38) | (1.74) |
| $XD_m$ | 1.45*** | 1.12** | 1.40*** | .91** | 1.23*** |
| | (.48) | (.47) | (.43) | (.46) | (.42) |
| **Panel B. Informal Jobs** | | | | | |
| $IS_m$ | 2.47 | 3.24 | 6.00 | 2.55 | 5.20 |
| | (5.31) | (5.50) | (5.20) | (5.43) | (5.02) |
| $XD_m$ | 2.34** | 2.14* | 2.64** | 2.24** | 2.76*** |
| | (1.03) | (1.17) | (1.08) | (1.13) | (1.03) |
| **Panel C. Skilled Occupations** | | | | | |
| $IS_m$ | -.62 | -.85 | .71 | | |
| | (3.13) | (3.36) | (3.15) | | |
| $XD_m$ | 1.13* | .72 | 1.16** | | |
| | (.60) | (.64) | (.59) | | |
| **Panel D. Unskilled Occupations** | | | | | |
| $IS_m$ | -5.22*** | -5.14*** | -2.22 | | |
| | (1.79) | (1.76) | (2.01) | | |
| $XD_m$ | 2.33*** | 2.24*** | 2.47*** | | |
| | (.72) | (.81) | (.67) | | |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in log average hourly wages, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for workers in formal jobs, Panel B for workers in informal jobs, Panel C for workers in skilled occupations, and Panel D for workers in unskilled occupations. A skilled occupation is defined as an occupation of skill level 3 or 4 according to the ISCO-08 classification. Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the unit of the coefficients is roughly percentage increase. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

Table 2.4: Results - inequality and social assistance

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Wage Inequality (Gini Coefficient)** | | | | | |
| $IS_m$ | 1.34*** | 1.40*** | 1.12** | 1.40*** | 1.11** |
| | (.39) | (.41) | (.46) | (.41) | (.46) |
| $XD_m$ | .07 | .06 | .09 | .06 | .09 |
| | (.11) | (.10) | (.12) | (.10) | (.12) |
| **Panel B. Bolsa Familia** | | | | | |
| $IS_m$ | -.20 | -.15 | .07 | | |
| | (.30) | (.33) | (.19) | | |
| $XD_m$ | -.25* | -.25** | -.14* | | |
| | (.14) | (.13) | (.07) | | |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks, as captured by $\beta_I$ and $\beta_X$ from equation (1), on two outcomes. In Panel A, the dependent variable is the change in microregion-level wage inequality, as measured by the wage Gini coefficient, between 2000 and 2010. In Panel B, the dependent variable is the share of workforce participating in *Bolsa Familia* in 2010. Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors in both panels are multiplied by 100, so that the coefficients in Panel B are in percentage points. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

growth in manufacturing wages that was smaller by 1.7 percentage points over this period.

Table 2.3 breaks down the effects of the shocks on the growth in average wages of workers in formal and informal jobs (Panels A and B), and in skilled and unskilled occupations (Panels C and D). The wage effects of $IS_m$ appear to be concentrated in the formal sector; the estimated coefficient on $IS_m$ is negative for the subcategory of formal jobs and positive (though insignificant) for informal jobs. Also, although the wage effect of Chinese import competition on workers in skilled occupations remains insignificantly different from zero, higher values of $IS_m$ are significantly associated with slower average wage growth for workers in unskilled occupations in the baseline IV specification in Panel D. This result becomes smaller and loses statistical significance after controlling for region-specific trends. Meanwhile, the export demand shock is associated with positive wage growth for all four of these categories – for both skilled and unskilled occupations, and for both formal and informal jobs.

These heterogeneous effects of $IS_m$ on different subgroups of the workforce imply that Chinese import competition may have affected levels of inequality. Indeed, when we consider effects on local wage inequality in Panel A of Table 2.4, we find that import shocks but not export shocks are associated with relatively higher growth in wage inequality, as measured by the microregion-level wage Gini coefficient. Since we multiply all coefficients by 100, the estimate in column (2) implies that in locations experiencing an import competition shock that was greater by US\$1000, the wage Gini coefficient rose by an additional 0.014 between 2000 and 2010; this is equivalent to a 2.6% increase in wage inequality relative to average 2000 levels. The coefficient on $XD_m$ is economically and statistically indistinguishable from zero in each of the specifications; that is, we find no evidence that the demand-side shock contributed to rises in local wage inequality.

In Panel B of Table 2.4, we consider the impact of the 'China shocks' on social assistance in Brazil, by examining the distribution of takeup of the cash transfer program *Bolsa Família* across microregions in 2010. While participation in *Bolsa Família* was on a very large scale in 2010 – according to the census data, more than 7% of the Brazilian workforce received *Bolsa Família* in this year – the program was implemented only after 2002. Thus, in this case, we use levels rather than long differences on the left-hand side of our regressions, so that the dependent variable is the proportion of the local workforce receiving *Bolsa Família* in 2010.[18] The results suggest that a larger export demand shock is associated with lower takeup of *Bolsa Família* in 2010; according to the baseline IV specification, in a microregion experiencing the average export demand shock of US\$594,

[18] As of 2000, Brazil had a similar program on a much smaller scale, *Bolsa Escola*, with a Brazil-wide participation rate of less than 1%. The results are not affected if we instead use differences between *Bolsa Escola* takeup rates in 2000 and *Bolsa Família* takeup rates in 2010 as the left-hand-side variable.

the proportion of the local workforce receiving *Bolsa Família* in 2010 was lower by 0.15 percentage points. The estimated effects of Chinese import competition on participation in *Bolsa Família* are statistically insignificant in all three specifications.

### 2.3.2 Migration and employment

We next consider whether the two 'China shocks' are also associated with changes in the pattern of migration across microregions, and microregion-level employment rates. In Table 2.5, we display the results of regressions whose dependent variable is the long difference in the proportion of the workforce that migrated into the microregion within the five years before the census.[19] Column (2) reports that the change in the share of recent migrants in the local workforce was 0.89 percentage points lower on average in microregions experiencing a \$1000 per worker higher import supply shock; these results are robust across all five specifications. This suggests that in-migration grew by 4.9% less in a microregion exposed to the average increase in import supply from China. The analogous estimate for $XD_m$ is positive, but much smaller in magnitude and statistically insignificant in each of the four IV specifications. The slowdown in local in-migration rates associated with Chinese import competition is reminiscent of the findings of Kovak (2011), who observes a migration response to the Brazilian trade liberalisation of the early 1990s using 2000 census data.

Brazilians' willingness to migrate – the census data indicates that the average share of recent migrants across microregions was 8.3% in 2000 and 12.4% in 2010 – might have served to dampen the effects of the trade shocks on microregion-level employment rates. Indeed, while the damaging impact of Chinese import competition on employment status has been an important finding of studies of high-income countries (e.g. Autor et al., 2013a, for the US), Panel A of Table 2.6 shows that we do not observe a negative correlation between $IS_m$ and changes in private sector employment rates of Brazilian microregions from 2000 to 2010. On the contrary, our preferred specification yields a positive coefficient that is marginally statistically significant. The estimate is magnified and becomes significant at the 1% level in the specifications with region fixed effects; this is a puzzling result. Meanwhile, the effect of the 'China demand shock' on the change in the proportion of the local workforce employed in the private sector is very small and statistically insignificant in all five specifications.[20]

Panels B to D of Table 2.6 provide a breakdown of the changes in employment structure

[19]These regressions thus examine changes in the microregion-level pattern of migration in the five years before 2010 as compared to the five years before 2000.

[20]When comparing these results to our findings on takeup of *Bolsa Família* in Table 2.4, it is important to note that eligibility for *Bolsa Família* is not directly conditional on employment status.

Table 2.5: Results - in-migration

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $IS_m$ | -.86* | -.89* | -.83** | -.92* | -.83** |
| | (.44) | (.46) | (.35) | (.54) | (.41) |
| $XD_m$ | .21** | .11 | .17 | .13 | .17 |
| | (.09) | (.10) | (.12) | (.10) | (.11) |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in the share of the workforce that in-migrated to the microregion in the previous five years, as captured by $\beta_I$ and $\beta_X$ from equation (1). Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the coefficients represent percentage point changes. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

associated with the two 'China shocks', using the difference between 2000 and 2010 in the share of a microregion's working-age population employed in the agricultural and extractive, manufacturing and nontraded sectors as the dependent variables. This analysis yields few statistically significant coefficient estimates. However, Panel D suggests that the finding of rising employment rates in locations competing with Chinese imports appears to have been driven by growth in the share of the workforce employed in nontraded sectors. This result is similar to the findings of Menezes-Filho and Muendler (2011), who observe movement of Brazilian formal sector workers from manufacturing into services after the early 1990s trade liberalisation.

### 2.3.3 Job quality

We now examine the effects of China's emergence on the prevalence of 'good jobs' in affected microregions, using two measures of job quality: informality and occupational skill level. We first consider informality, which is widespread in the Brazilian economy: in 2000, more than half of private sector workers were working in the informal sector as defined in this chapter. Being part of the informal sector brings disadvantages for workers and firms, since they are not granted some legal rights, such as property rights, and do not benefit from some public services linked to employment.

Table 2.7 shows that shocks to export demand from China are associated with a shift

Table 2.6: Results - private sector employment

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. All Sectors** | | | | | |
| $IS_m$ | .56* | .67* | 1.24*** | .28 | .92*** |
| | (.33) | (.34) | (.33) | (.38) | (.34) |
| $XD_m$ | .07 | .08 | .07 | .07 | .08 |
| | (.11) | (.10) | (.10) | (.12) | (.11) |
| **Panel B. Agricultural/Extractive Sectors** | | | | | |
| $IS_m$ | -.39 | -.25 | -.16 | -.01 | .06 |
| | (.26) | (.28) | (.32) | (.25) | (.28) |
| $XD_m$ | .07 | .06 | -.01 | .11 | .06 |
| | (.18) | (.18) | (.15) | (.14) | (.13) |
| **Panel C. Manufacturing Sectors** | | | | | |
| $IS_m$ | -.20 | -.29 | .05 | .34 | .65 |
| | (.52) | (.55) | (.67) | (.56) | (.71) |
| $XD_m$ | -.06 | -.12 | -.10 | -.16 | -.15 |
| | (.10) | (.10) | (.09) | (.10) | (.10) |
| **Panel D. Nontraded Sectors** | | | | | |
| $IS_m$ | 1.18* | 1.21* | 1.34* | 1.39* | 1.43* |
| | (.63) | (.67) | (.73) | (.72) | (.78) |
| $XD_m$ | .11 | .18 | .22 | .04 | .11 |
| | (.15) | (.16) | (.15) | (.12) | (.14) |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in the share of the workforce employed in the private sector, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for all sectors, Panel B for agricultural and extractive sectors, Panel C for manufacturing sectors, and Panel D for nontraded sectors. Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the coefficients represent percentage point changes. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

towards 'good jobs' by this measure: a rise in formal-sector jobs at the expense of the informal sector. The baseline IV results in Panels A and B suggest that a rise in exports to China of US$1000 is associated with an average increase in the proportion of a microregion's workforce in formal jobs that is larger by 0.31 percentage points and an average decline in the share of informal jobs that is greater by 0.24 percentage points, though the result for the informal share is statistically insignificant. The size of these effects is similar across all of the regression specifications in each case.[21]

As discussed in Section 2.2.1, our measure of occupational skill level, which is based on an international definition, is a dummy variable broadly distinguishing between managerial, professional and technical workers and workers directly involved in production. Panel B of Table 2.8 shows that the proportion of the workforce in skilled occupations in the agricultural and extractive sectors rose more quickly in areas more affected by Chinese demand, while this was not the case for unskilled occupations in these sectors. Our estimates suggest that a microregion subject to the mean Chinese export demand shock experienced 18.6% higher growth in the share of the workforce employed in skilled agricultural or extractive sector jobs. The results in Panel A indicate that this led to a positive effect of $XD_m$ on the share of workers in skilled occupations overall, though this estimate is not statistically significant.

Meanwhile, Panel C of Table 2.8 shows that the proportion of the working-age population employed in skilled manufacturing occupations saw a statistically significant decline in locations with higher $IS_m$: an increase of US$1000 in Chinese imports was associated with a reduction of approximately 0.28 percentage points in this share between 2000 and 2010 in the baseline IV specification. Given that the average share of the workforce employed in skilled occupations in manufacturing grew from 0.8% in 2000 to 1% in 2010, a back-of-the-envelope counterfactual exercise suggests that the share of skilled jobs in the manufacturing sector would have grown 31% more on average if it were not for rising import competition from China. Taken together with the results in Table 2.3, it thus appears that local labour markets were affected by the 'China supply shock' through declines in both average unskilled wages and skilled manufacturing employment shares.

Tables 2.7 and 2.8 also provide additional insight on the nature of the shift towards the nontraded sector in locations more affected by Chinese import competition, as documented in Table 2.6. Table 2.8 indicates that growth in the share of nontraded sector employment mainly occurred in relatively unskilled occupations, while Table 2.7 suggests that these

[21] Tables 2.10 and 2.11 show that the estimated effect of $XD_m$ on the proportion of the workforce in formal agricultural or extractive sector jobs is positive in all five specifications, while the estimated impact of $XD_m$ on the share of the workforce in informal jobs in agricultural or extractive sectors is negative in all five specifications. None of these results is statistically significant.

Table 2.7: Results – informality

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Formal Jobs** | | | | | |
| $IS_m$ | .83*** | .80*** | 1.16*** | .88** | 1.25*** |
| | (.29) | (.29) | (.37) | (.36) | (.44) |
| $XD_m$ | .36** | .31** | .31** | .32** | .32*** |
| | (.14) | (.15) | (.12) | (.15) | (.12) |
| **Panel B. Informal Jobs** | | | | | |
| $IS_m$ | -.28 | -.13 | .08 | .11 | .30 |
| | (.38) | (.43) | (.48) | (.39) | (.45) |
| $XD_m$ | -.28** | -.24 | -.24 | -.21 | -.21 |
| | (.14) | (.16) | (.16) | (.16) | (.16) |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in the share of the workforce employed in formal and informal private sector jobs, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for formal jobs and Panel B for informal jobs. Each column corresponds to a different regression with dependent variable and specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the coefficients represent percentage point changes. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

jobs were primarily in the formal sector. This conclusion is supported by the results of regressions with the share of the workforce in formal or informal agricultural/extractive, manufacturing or nontraded jobs on the left-hand side, which may be found in Tables 2.10 and 2.11. Across all of the IV specifications, only the regressions for formal jobs in nontraded sectors yield statistically significant coefficient estimates for $IS_m$.

Table 2.8: Results – occupational skill level

| | **Skilled Occupations** | | | **Unskilled Occupations** | | |
|---|---|---|---|---|---|---|
| | OLS | IV | IV | OLS | IV | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. All Sectors** | | | | | | |
| $IS_m$ | -.21 | -.04 | .10 | .77* | .71 | 1.14** |
| | (.22) | (.33) | (.38) | (.41) | (.50) | (.55) |
| $XD_m$ | .05 | .07 | .07 | .02 | .01 | .00 |
| | (.06) | (.07) | (.08) | (.13) | (.13) | (.14) |
| **Panel B. Agricultural/Extractive Sectors** | | | | | | |
| $IS_m$ | -.03 | -.04* | -.04 | -.36 | -.21 | -.12 |
| | (.02) | (.02) | (.02) | (.25) | (.27) | (.30) |
| $XD_m$ | .06** | .05* | .05* | .01 | .00 | -.06 |
| | (.03) | (.03) | (.03) | (.16) | (.17) | (.14) |
| **Panel C. Manufacturing Sectors** | | | | | | |
| $IS_m$ | -.30** | -.28** | -.26* | .09 | -.00 | .30 |
| | (.12) | (.13) | (.13) | (.43) | (.48) | (.60) |
| $XD_m$ | .01 | .01 | .02 | -.08 | -.13 | -.11 |
| | (.02) | (.02) | (.02) | (.09) | (.09) | (.08) |
| **Panel D. Nontraded Sectors** | | | | | | |
| $IS_m$ | .11 | .27 | .38 | 1.07** | .94* | .96* |
| | (.20) | (.31) | (.35) | (.54) | (.56) | (.58) |
| $XD_m$ | -.02 | .00 | .01 | .13 | .17 | .21 |
| | (.05) | (.06) | (.06) | (.16) | (.18) | (.17) |
| Region Fixed Effects | | | ✓ | | | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | | 334.7 | 250.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in the share of the workforce employed in skilled and unskilled occupations, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for all sectors, Panel B for agricultural and extractive sectors, Panel C for manufacturing sectors, and Panel D for nontraded sectors. Each column corresponds to a different regression with dependent variable and specification indicated. The dependent variable in columns 1 to 3 is the change in the share of workforce in skilled occupations, and in columns 4 to 6 it is the change in the share of workforce in unskilled occupations. A skilled occupation is defined as an occupation of skill level 3 or 4 according to the ISCO-08 classification. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the coefficients represent percentage point changes. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (6) include region fixed effects. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

## 2.4 Conclusion

In this chapter, we investigate the effects of China's ascent into one of the world's largest economies on local labour markets in Brazil. As in other developing countries, Brazil's imports from China are dominated by manufactures while most of the growth in its exports to China has been concentrated in agricultural and extractive sectors. We use data from the Brazilian demographic censuses of 2000 and 2010 to provide empirical evidence of the heterogeneous effects on Brazilian labour markets of shocks to both Chinese import supply and export demand. Using a shift-share methodology, we compare trends in local labour markets with a similar initial employment structure (proportion of workers in agricultural, extractive and manufacturing sectors) but differently exposed to these two 'China shocks' due to specialisation in different specific industries.

We find that local labour markets more affected by Chinese import competition experienced slower growth in manufacturing wages, greater increases in wage inequality and a relative decline in the share of the workforce employed in skilled manufacturing jobs. However, imports from China do not appear to have led to either a fall in employment rates or higher takeup of social assistance (as measured by participation in the *Bolsa Família* program of cash transfers) in affected regions. Meanwhile, in local labour markets experiencing larger growth in Chinese export demand, average hourly wages increased more quickly and without an accompanying increase in wage inequality, while 2010 *Bolsa Família* participation rates were lower. While there is little evidence of an effect of Chinese demand on local employment rates, we do observe positive effects on job quality: an increase in the share of formal employment at the expense of informal jobs, and a rise in the share of the local workforce in skilled agricultural or extractive sector occupations.

Overall, our findings suggest that growth in commodities-for-manufactures trade spurred by the rise of China has created winners as well as losers. Even though the increase in export demand from China has mainly involved the relatively unglamorous agricultural and extractive sectors, local labour markets specialised in these industries appear to have flourished in the presence of this commodity export boom. Moreover, while areas specialised in manufacturing sectors do seem to have suffered from rising Chinese import supply, our findings of slower growth of in-migration rates in more affected regions, along with shifts in the structure of local employment towards nontraded industries, also provide evidence of adjustment in response to competition from China.

# Appendix

## 2.A Additional Figures and Tables

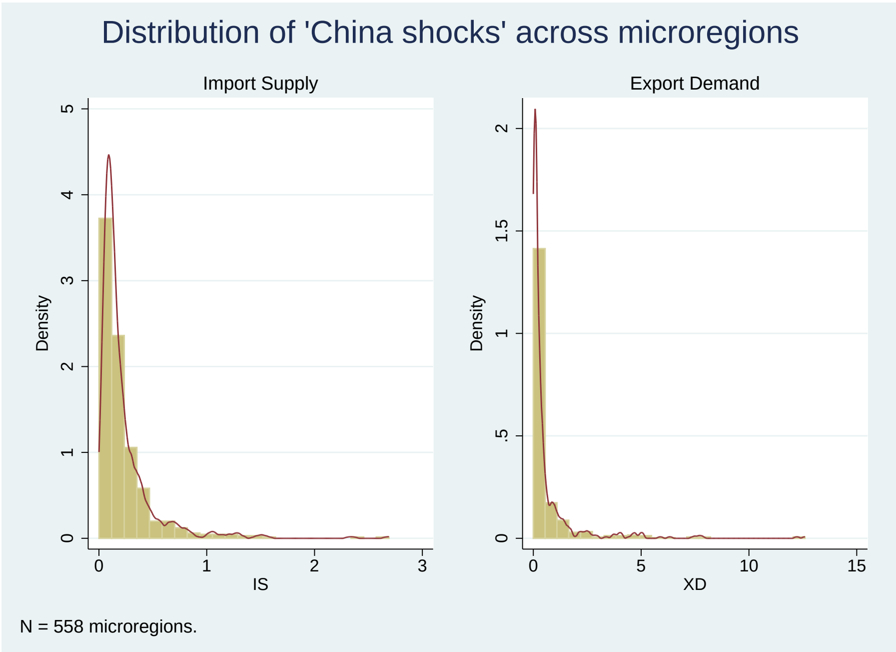



Figure 2.7: Distributions of import supply and export demand measures

NOTES: These graphs show the distributions of the import supply and export demand measures ($IS_m$ and $XD_m$) described in Section 2.2. The solid lines are kernel densities. *Source*: 2000 Brazilian Census, and CEPII BACI.

Table 2.9: List of sectors and additional summary statistics

| | Import Share | Export Share | Import Supply from China | | Export Demand to China | |
|---|---|---|---|---|---|---|
| | | | Mean | IV | Mean | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Agriculture: rice | - | - | - | - | - | - |
| Agriculture: maize | - | .000 | - | - | .000 | - |
| Agriculture: other cereals | .000 | - | .000 | .000 | - | - |
| Agriculture: cotton | .000 | .005 | .000 | .000 | .013 | - |
| Agriculture: sugar cane | - | - | - | - | - | - |
| Agriculture: tobacco | .000 | .010 | .000 | .000 | .022 | .015 |
| Agriculture: soya | - | .229 | - | - | .555 | .259 |
| Agriculture: manioc | - | - | - | - | - | - |
| Agriculture: flowers and ornamentals | .000 | .000 | .000 | .000 | .000 | - |
| Agriculture: citrus fruits | - | .000 | - | - | .000 | .000 |
| Agriculture: coffee | - | .000 | - | - | .000 | .000 |
| Agriculture: cocoa | - | - | - | - | - | - |
| Agriculture: grapes | - | - | - | - | - | - |
| Agriculture: bananas | - | - | - | - | - | - |
| Agriculture: other | .007 | .000 | .006 | .000 | .000 | .000 |
| Agriculture: bovine animals | - | - | - | - | - | - |
| Agriculture: sheep | - | - | - | - | - | - |
| Agriculture: pigs | - | - | - | - | - | - |
| Agriculture: birds | - | - | - | - | - | - |
| Agriculture: beekeeping | .000 | .000 | .000 | - | .000 | .000 |
| Agriculture: silk | .000 | - | .000 | - | - | - |
| Agriculture: other animals | .000 | .000 | .000 | .000 | .000 | - |
| Forestry | .000 | .000 | .000 | .000 | .000 | .000 |
| Fishing and aquaculture | - | .000 | - | - | .000 | .000 |
| Mining: coal | -.001 | .000 | -.002 | -.018 | .000 | - |
| Mining: oil and gas | - | .137 | - | - | .219 | .015 |
| Mining: radioactive metals | - | - | - | - | - | - |
| Mining: precious metals | - | - | - | - | - | - |
| Mining: other metals | .000 | .453 | .000 | -.001 | .917 | .649 |
| Mining: nonmetals for construction | .000 | .001 | .000 | .000 | .001 | .002 |
| Mining: precious stones | .000 | .000 | .000 | .000 | .001 | .001 |
| Mining: other nonmetals | .000 | .000 | .001 | .000 | .000 | .001 |
| Manuf: meat and fish | .004 | .008 | .002 | .000 | .005 | .001 |
| Manuf: fruits and vegetables | .002 | .003 | .002 | .000 | .003 | .000 |
| Manuf: oils and fats | .000 | .026 | .000 | .000 | .045 | .015 |
| Manuf: dairy products | .000 | .000 | .000 | - | .000 | .000 |
| Manuf: sugar | .000 | .018 | .000 | .000 | .019 | - |
| Manuf: coffee | .000 | .000 | .000 | - | .000 | .000 |
| Manuf: other food | .003 | .000 | .001 | .000 | .000 | .000 |
| Manuf: beverages | .000 | .000 | .000 | .000 | .000 | .000 |
| Manuf: tobacco | .000 | - | .000 | .000 | - | - |

Continued on next page.

*List of sectors and additional summary statistics (continued)

| | Import Share | Export Share | Import Supply from China | | Export Demand to China | |
|---|---|---|---|---|---|---|
| | | | Mean | IV | Mean | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Manuf: spinning and weaving | .026 | .000 | .009 | .000 | .000 | .000 |
| Manuf: other textile products | .029 | .000 | .014 | .001 | .000 | .000 |
| Manuf: apparel | .025 | .000 | .008 | .001 | .000 | .000 |
| Manuf: leather processing | .000 | .011 | .000 | .000 | .014 | .000 |
| Manuf: leather products | .001 | .000 | .000 | .000 | .000 | .000 |
| Manuf: footwear | .003 | .000 | .001 | .001 | .000 | .000 |
| Manuf: wood products | .001 | .001 | .001 | .000 | .001 | .002 |
| Manuf: pulp and paper | .003 | .039 | .003 | .000 | .041 | .002 |
| Manuf: paper products | .001 | .000 | .000 | .000 | .000 | .000 |
| Manuf: printing and recording | .003 | .000 | .001 | .000 | .000 | .000 |
| Manuf: coke | .003 | - | .040 | -.119 | - | - |
| Manuf: refined petroleum | .002 | .000 | .001 | .000 | .000 | .000 |
| Manuf: nuclear fuel | - | - | - | - | - | - |
| Manuf: paints and varnishes | .000 | .000 | .000 | .000 | .000 | .000 |
| Manuf: pharmaceuticals | .018 | .001 | .004 | .002 | .000 | .000 |
| Manuf: cleaning and hygiene products | .001 | .001 | .000 | .000 | .000 | .000 |
| Manuf: other chemicals | .065 | .008 | .026 | .014 | .004 | .003 |
| Manuf: rubber products | .014 | .000 | .004 | .001 | .000 | .000 |
| Manuf: plastic products | .025 | .000 | .007 | .001 | .000 | .000 |
| Manuf: glass products | .006 | .000 | .002 | .001 | .000 | .000 |
| Manuf: ceramic products | .009 | .000 | .006 | .000 | .000 | .000 |
| Manuf: other nonmetallic mineral products | .003 | .000 | .001 | .000 | .000 | .000 |
| Manuf: basic metals | .064 | .026 | .027 | .002 | .013 | .003 |
| Manuf: metal products | .029 | .002 | .007 | .001 | .000 | .000 |
| Manuf: machinery | .133 | .005 | .038 | .010 | .002 | .002 |
| Manuf: domestic appliances | .019 | .000 | .009 | .001 | .000 | .000 |
| Manuf: computing | .073 | .000 | .033 | .017 | .000 | .000 |
| Manuf: electrical equipment | .080 | .001 | .023 | .005 | .000 | .000 |
| Manuf: electronics | .192 | .001 | .065 | .024 | .000 | .001 |
| Manuf: medical instruments | .006 | .000 | .002 | .000 | .000 | .000 |
| Manuf: measuring instruments | .008 | .000 | .004 | .001 | .000 | .000 |
| Manuf: optical equipment | .061 | .000 | .030 | .006 | .000 | .002 |
| Manuf: watches and clocks | .002 | .000 | .002 | .000 | .000 | .000 |
| Manuf: motor vehicles | .009 | .000 | .002 | .000 | .000 | .001 |
| Manuf: motor vehicle bodies and parts | .011 | .002 | .003 | .000 | .001 | .001 |
| Manuf: shipbuilding | .018 | - | .016 | .000 | - | - |
| Manuf: railway products | .000 | .000 | .000 | .000 | .000 | - |
| Manuf: aircraft | .000 | .011 | .000 | - | .012 | .005 |
| Manuf: other transport | .009 | .000 | .007 | .001 | .000 | - |
| Manuf: furniture | .005 | .000 | .002 | .000 | .000 | .000 |
| Manuf: other | .026 | .001 | .008 | .001 | .000 | .000 |

NOTES: This table displays the share of each sector in the total growth of Brazil's imports and exports to China between 2000 and 2010 in columns (1) and (2), the means across microregions of the sector-microregion-level variables used to calculate $IS_m$ and $XD_m$ in columns (3) and (5), and the means across microregions of the sector-microregion-level variables used to calculate $ivIS_m$ and $ivXD_m$ in columns (4) and (6). *Source:* 2000 and 2010 Brazilian Census, and CEPII BACI.

Table 2.10: Results - formal private sector jobs

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Agricultural/Extractive Sectors** | | | | | |
| $IS_m$ | .09 | -.00 | .06 | -.01 | .05 |
| | (.12) | (.10) | (.12) | (.11) | (.12) |
| $XD_m$ | .17 | .17 | .17 | .15 | .17 |
| | (.12) | (.13) | (.11) | (.12) | (.11) |
| **Panel B. Manufacturing Sectors** | | | | | |
| $IS_m$ | -.27 | -.28 | -.16 | .45 | .53 |
| | (.55) | (.57) | (.62) | (.65) | (.73) |
| $XD_m$ | -.00 | -.06 | -.06 | -.10 | -.11 |
| | (.08) | (.08) | (.09) | (.08) | (.10) |
| **Panel C. Nontraded Sectors** | | | | | |
| $IS_m$ | 1.04** | 1.09** | 1.26*** | .75 | 1.00** |
| | (.45) | (.50) | (.43) | (.57) | (.45) |
| $XD_m$ | .20* | .21 | .21 | .09 | .11 |
| | (.12) | (.13) | (.13) | (.16) | (.14) |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in the share of the workforce employed in formal private sector jobs, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for agricultural and extractive sectors, Panel B for manufacturing sectors, and Panel C for nontraded sectors. Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the coefficients represent percentage point changes. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

Table 2.11: Results - informal private sector jobs

| | OLS | IV | IV | IV | IV |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Agricultural/Extractive Sectors** | | | | | |
| $IS_m$ | -.48** | -.24 | -.22 | -.12 | -.10 |
| | (.23) | (.23) | (.28) | (.22) | (.26) |
| $XD_m$ | -.10 | -.11 | -.18 | -.07 | -.13 |
| | (.12) | (.14) | (.14) | (.12) | (.13) |
| **Panel B. Manufacturing Sectors** | | | | | |
| $IS_m$ | .07 | -.01 | .20 | -.00 | .21 |
| | (.12) | (.10) | (.13) | (.11) | (.14) |
| $XD_m$ | -.06* | -.06* | -.04 | -.06* | -.04 |
| | (.03) | (.03) | (.03) | (.04) | (.03) |
| **Panel C. Nontraded Sectors** | | | | | |
| $IS_m$ | .14 | .11 | .08 | .28 | .27 |
| | (.35) | (.38) | (.47) | (.36) | (.46) |
| $XD_m$ | -.09 | -.04 | .01 | -.05 | -.02 |
| | (.14) | (.15) | (.12) | (.15) | (.12) |
| Region Fixed Effects | | | ✓ | | ✓ |
| Lag Dep. Variable | | | | ✓ | ✓ |
| 1st Stage (KP F-stat.) | | 334.7 | 250.3 | 245.2 | 195.3 |

NOTES: This table displays estimated effects of Chinese import and export shocks on changes between 2000 and 2010 in the share of the workforce employed in informal private sector jobs, as captured by $\beta_I$ and $\beta_X$ from equation (1). Panel A presents results for agricultural and extractive sectors, Panel B for manufacturing sectors, and Panel C for nontraded sectors. Each column corresponds to a different regression with specification indicated. In the columns marked with IV, we *instrument* imports from (exports to) China using a measure based on growth in Chinese exports to (imports from) all countries, excluding Brazil, relative to a weighted cross-country average. The unit of observation is a microregion (N=558). Coefficients and standard errors are multiplied by 100, so that the coefficients represent percentage point changes. All regressions include a constant and the following *controls*: 2000 workforce, 2000 share of workforce in agricultural sectors, 2000 share of workforce in extractive sectors, 2000 share of workforce in manufacturing, 2000 share of workforce in nontraded sectors, 2000 share of workforce in informal jobs, 2000 share of workforce in rural areas, and a cubic polynomial of income per capita in 2000. Regressions in columns (3) and (5) include region fixed effects, and in columns (4) and (5) include the lag of the dependent variable for the period 1991-2000, instrumented with 1991 levels. All regressions are weighted by share of national workforce. *Standard errors* are clustered by mesoregion, 138 clusters. *Source:* 1991, 2000 and 2010 Brazilian Census, and CEPII BACI. *** p¡.01, ** p¡.05, * p¡.1.

# Chapter 3

# The UK Productivity and Jobs Puzzle: Does the Answer lie in Wage Flexibility?

## 3.1 Introduction

In the long-run productivity growth is the main determinant of material wellbeing. Contrary to popular belief there is a reasonably tight relationship between the growth of real hourly compensation and the growth of GDP per hour over the last 40 years (see Pessoa and Van Reenen, 2012). Figure 3.1 shows that the "decoupling" between average compensation and productivity has been exaggerated, even though some "decoupling" has been observed from the nineties.[1] Given the importance of productivity, it is a serious concern that labour productivity has *fallen* since the onset of the Great Recession in 2008. GDP per worker was about 10% lower at the start of 2013 than it would have been had productivity continued to grow on a trend of 1.5% per annum (1971-2007 average) after 2008Q2 (see Figure 3.2).

There are many possible culprits behind the fall in labour productivity. One popular view that is not supported by many academics but has gained much credence among policy-makers and commentators is "supply side pessimism" (e.g. Giles, 2013; King, 2013). Under this view, the fall of productivity is structural, perhaps linked to the financial crisis or to some kind of mismeasurement of "unsustainable" productivity in the decades leading

[1] The confusion often arises because of a focus in the decoupling literature on the growth of median wages (deflated by the CPI) rather than average compensation (deflated by the GDP deflator). Standard theory points to a long-run relationship between productivity and average compensation with a common deflator in the absence a growth in the profit share of GDP. For example, median wages can diverge from average compensation due to a rise in wage inequality as has happened in the UK. Having said this, there is also some fall in the share of labour compensation in GDP in the 2000s in the US. See Pessoa and Van Reenen (2013) for more details.

up to the crisis. The level of current output is close to potential output and attempts to stimulate the economy with aggressive monetary or fiscal policy simply stokes up inflation.[2]

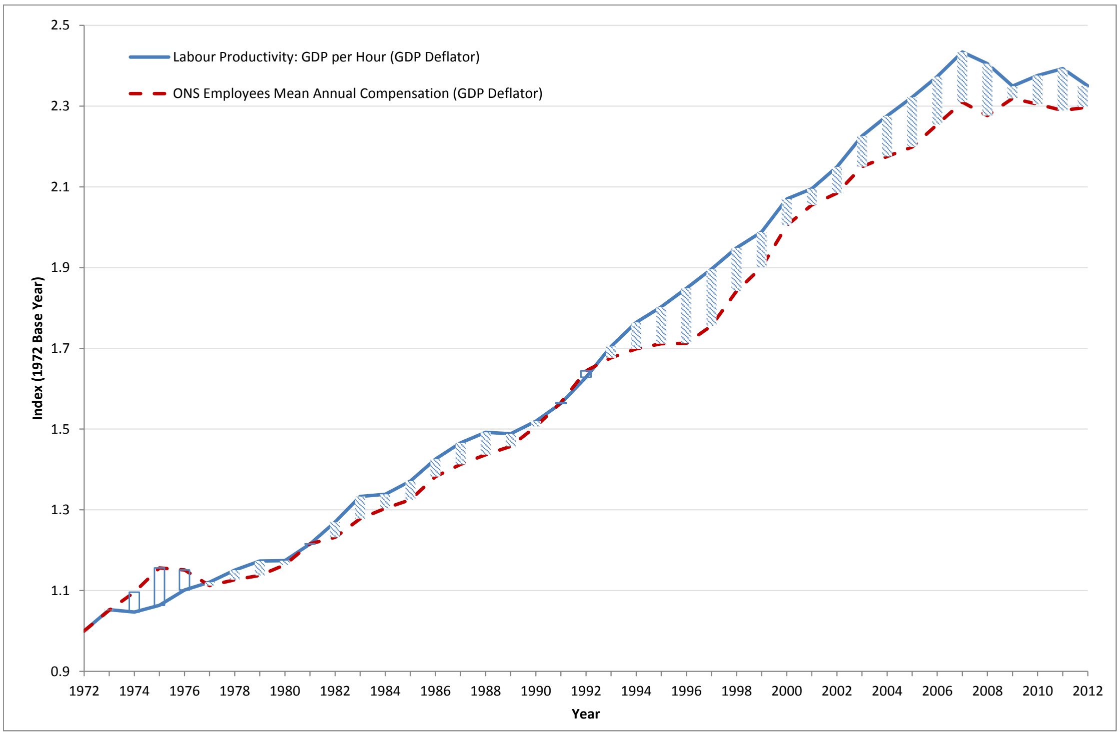



Figure 3.1: Hourly Net Decoupling in the UK: growth in GDP per hour vs. Compensation per hour 1972-2012 (1972=1).

Sources: Updated from Pessoa and Van Reenen (2013), using ONS, OECD and KLEMS data.

In this paper we emphasise one explanation that can potentially account for both the twin puzzles of low productivity and of surprisingly low unemployment given poor GDP growth. This explanation emphasises wage flexibility. Real wages are much more responsive to negative output shocks in the last few years than they have been in previous recessions (see Gregg et al., 2013). This is a secular change over time that is likely to be due to weaker union power and welfare reforms that keep effective labour supply high even when demand is low (e.g. Blundell et al., 2004; Van Reenen, 2004). This flexibility meant that unlike earlier recessions, real wages fell significantly and employers faced lower labour costs than in earlier downturns. As real wages fall there is likely to be downward pressure on the capital-labour ratio ("capital shallowing") as people are substituted for structures and equipment. A second force increasing capital shallowing is the fact that this

[2] By contrast Bagaria *et al.* (2012) argued that fiscal stimulus through higher public investment would be welfare enhancing.

recession stemmed from a global financial crisis that increased the effective cost of capital, especially for small and medium sized enterprises (SMEs). Banks have been reluctant to lend as they repair their balance sheets.

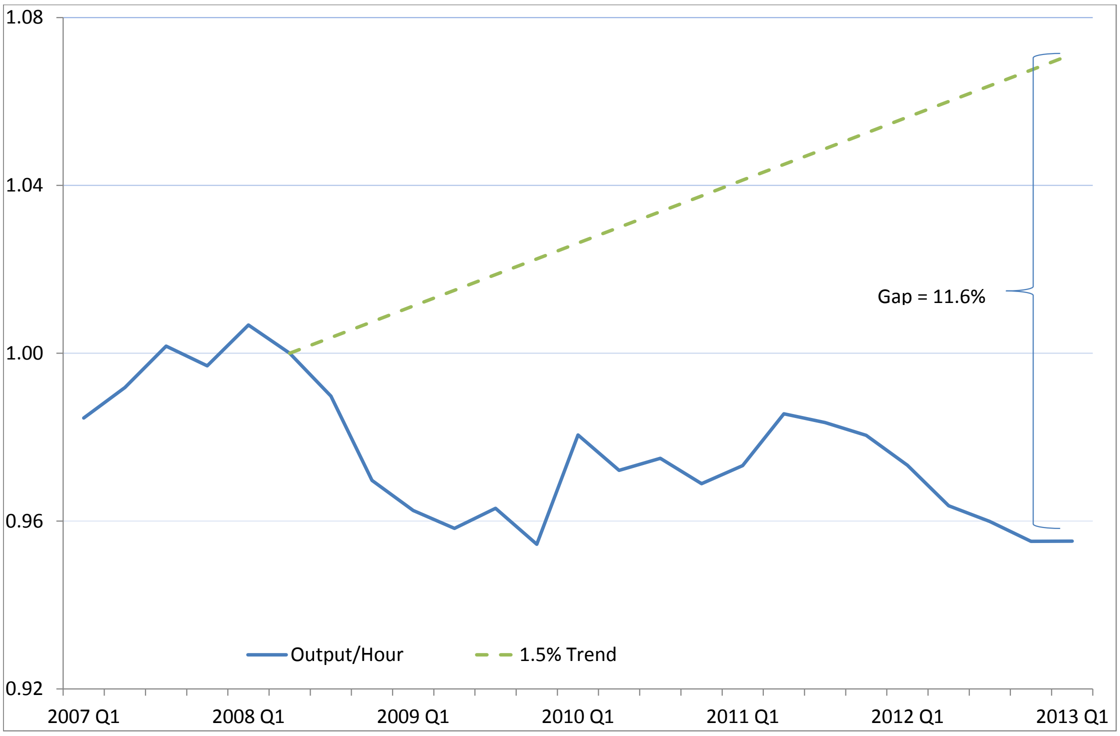



Figure 3.2: UK labour productivity: output per hour (2008 Q2 = 1).

Sources: ONS, July 2013.

Falling capital-labour ratios in response to changing factor prices, mean that labour productivity will fall, but not necessarily Total Factor Productivity (TFP). Since it is TFP that determines long-run economic growth, our view is that this more important measure of productivity has been more resilient than usually thought. Although there are many difficulties in accurately measuring the capital stock, especially in recent years, some simple simulations show that most of the fall of labour productivity could be accounted for by the fall in effective capital per worker. In these productivity decompositions (subject to many caveats) TFP trends over the recession look much more like those in the 1970s and 1980s and are not so surprising given the magnitude of the global shock.

We believe that it is important to consider the relevant counterfactual for the last five years is *not* to simply extrapolate a pre-recession trend line as in Figure 2. First, given that the output shock was huge, financially based and accompanied by severe austerity in the UK and its main trading partner (the Eurozone), a better counterfactual is to look at previous recessions. Second, when considering the collateral damage to the economy we should consider TFP which tries to remove the impact of changes in other inputs such as capital and hours rather than GDP per worker. When these adjustments are done, the current recessions looks more like previous deep post-war recessions than an event that should cause a change in potential growth.

The structure of the paper is as follows. Section 2 describes the basic facts, Section 3 sketches our main theory, Section 4 discusses other explanations of the productivity mystery, Section 5 offers some preliminary quantitative estimates and Section 6 concludes.

## 3.2 Some Basic Facts

In an accounting sense the productivity puzzle is easily explained. GDP is still about 3% below the level it stood at the start of the crisis in 2008 whereas employment levels have recovered. Consequently, as a matter of arithmetic, GDP per worker fell. Figure 3.3 shows the cumulative change of GDP since the start of the downturn (black line) compared to its evolution in all other major recessions in the last century. The current recovery is worse than all of them as by this point of the business cycle; GDP had made a stronger recovery in the Great Depression between the wars.

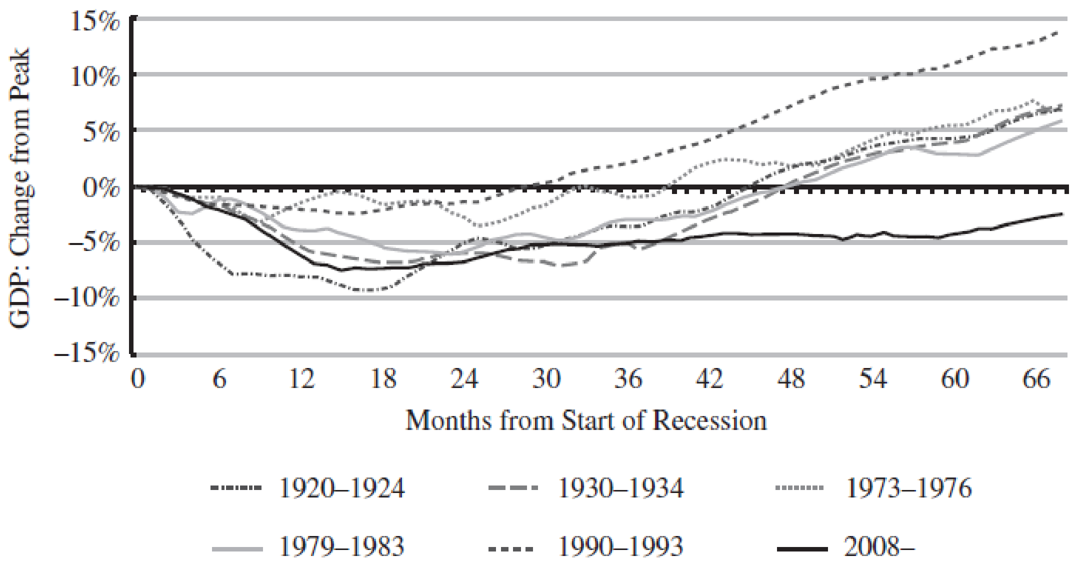



Figure 3.3: The profile of recession and recovery.

Notes. Calculated from centred three-month moving averages of monthly GDP, the effect of the miners' strike in 1921 is excluded from the 1920-1924 profile (the strike started on 31st March 1921and ended on 28th June 1921). Sources: National Institute of Economic and Social Research estimates of monthly GDP, October 2013.

Figure 3.4 produces the analogous figure for labour productivity for post-war recessions. It is clear that productivity stalls or drops in all recessions. The fall was likely to be larger in this recession because the magnitude of the 2008/09 shock was larger. Indeed, two years after the start of the current recession, labour productivity was at a similar level to the mid 1970s recession. What is more surprising is that over four years later productivity has still not recovered and appears worse than all other post-war downturns.

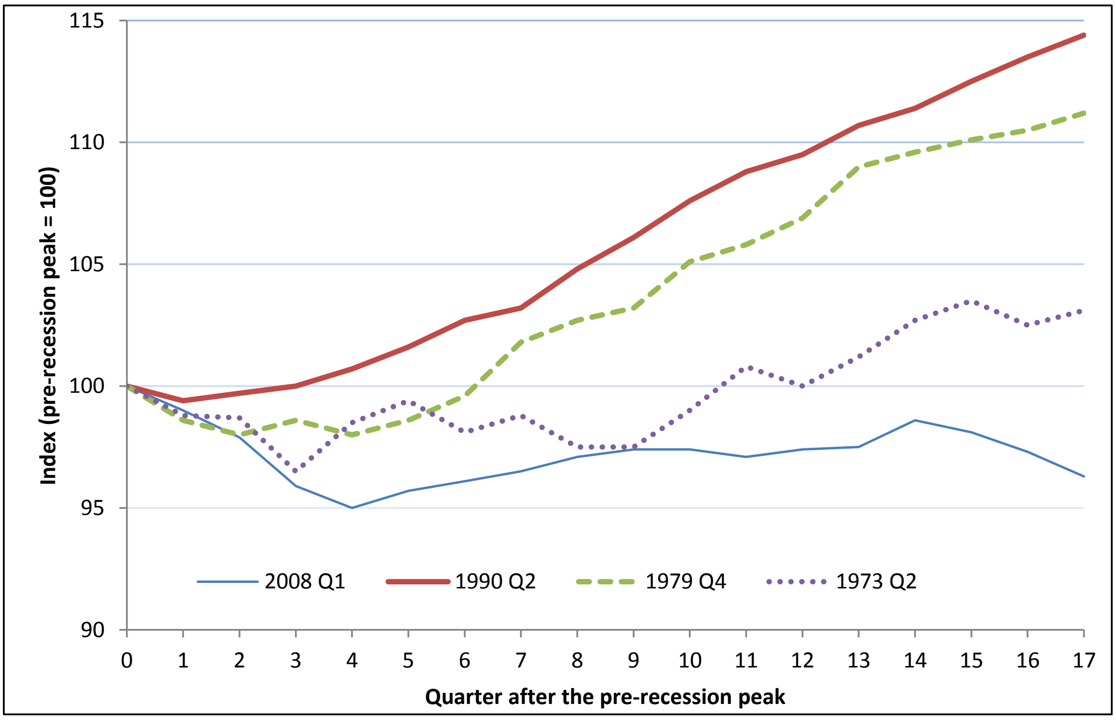



Figure 3.4: UK productivity levels, output per worker during UK recessions, seasonally adjusted.

Sources: Patterson (2012).

The fall of GDP per hour looks worse than the fall of total GDP because the labour market has recovered more quickly than the output market. The fall in GDP per worker is worse than the fall in GDP per hour as there has been a move to more part-time work, self-employment and zero hours contracts which has caused hours per worker to fall. This is explored more deeply by Blundell et al. (2013) and Wadsworth (2013) and we will examine the quantitative importance of hours in Section V. The key fact though is that labour productivity has fallen on both a per worker and a per hour basis.

There are two pieces of evidence that suggest that the fall in productivity may be temporary rather than permanent. Firstly, the UK is not unique in having a "productivity puzzle" as other European countries also experienced a fall in labour productivity (see Figure 3.5). US productivity did do much better than in Europe, but again this is the flipside of what happened in the jobs market. Although the magnitude of the initial GDP shock was similar in the US and the European countries, American unemployment rose much more severely (from 4.4% in late 2006 to 10% in late 2009) compared to the UK and Germany. Part of the reason for the faster rise in US unemployment in than in the UK may be because of lower US firing costs, the extensions of unemployment benefit and deeper problems in the housing market.

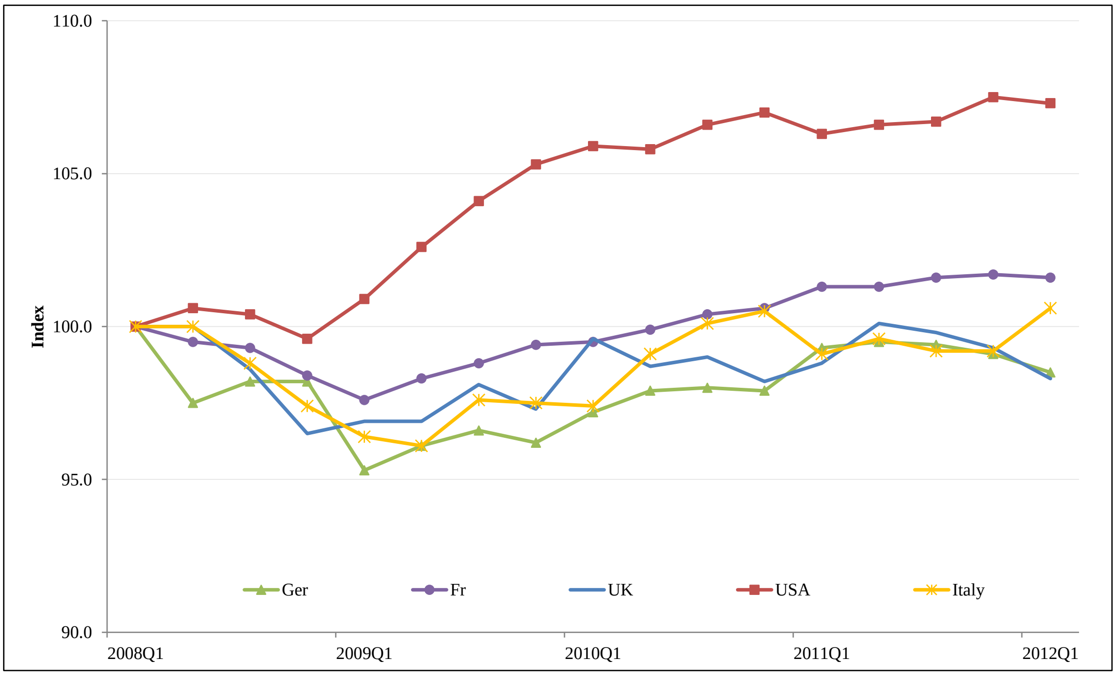



Figure 3.5: Output per hour (2008 Q1 = 100), seasonally adjusted.

Sources: Sources: Aghion et al. (2013). US output per hour covers only the business sector.

A second cause for possible optimism is that the fall in UK productivity is surprising in the light of recent economic history. As shown in Aghion et al. (2013), the UK reversed a century of economic decline in the three decades after the end of the 1970s. Figure 3.6 shows that the advantage in per capita GDP enjoyed by the UK in 1870 over our American and European counterparts had evaporated by 1979 with the US, France and Germany all ahead of the UK. In the next three decades however, things changed. On the eve of the crisis, the UK had again overtaken France and Germany and made inroads into the lead of the US.

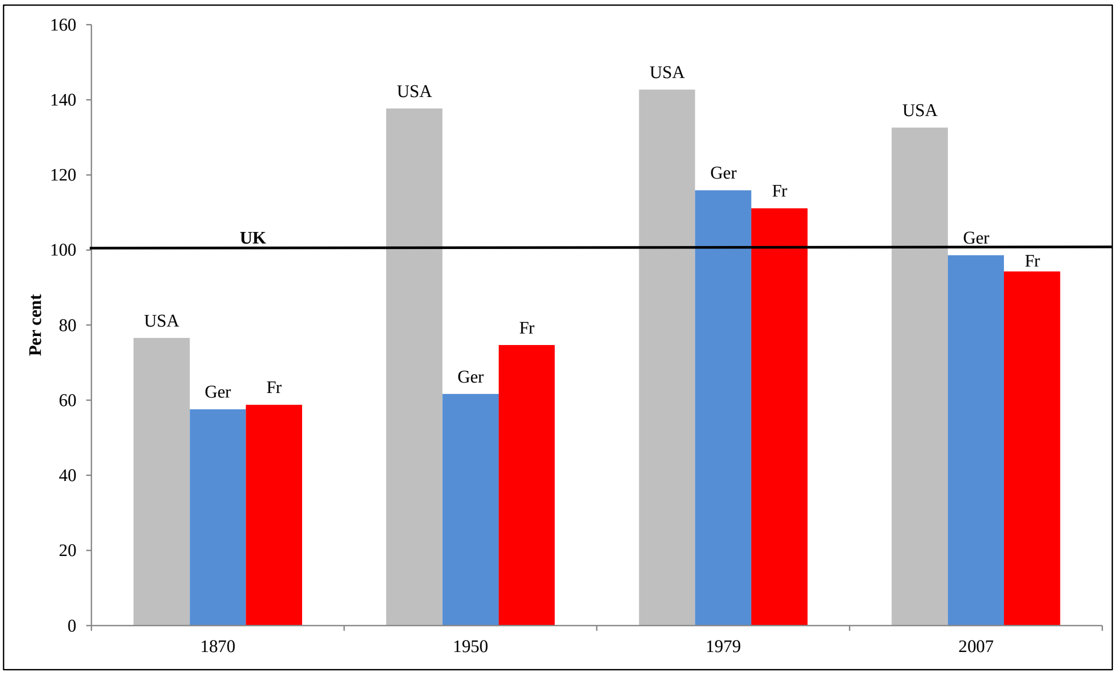



Figure 3.6: GDP per capita 1870–2007 (UK = 100).

Sources: Sources: Aghion et al. (2013) and Crafts (2012). Notes. In each year the base is UK = 100 and each country's GDP per capita is relative to this. So a value of US = 120, for example, implies the US has a 20% higher GDP per capita than the UK. GDP per capita is expressed in 1990 International Geary–Khamis dollars.

Some of this was due to improvements in the labour market with employment rates rising. But a good part was due to an improvement in productivity growth. Figure 3.7 shows that UK productivity growth outstripped the other countries after 1979 under both Conservative and Labour governments. With the exception of the US this is true even taking the Great Recession into account. Nor was this strong productivity growth simply due to unsustainable booms in finance, oil, property or the government sector. Corry et al. (2012) show that value added per hour growth in the market sector (dropping the public and property sectors) was about 2.7% per annum 1979-2007 and only around a tenth of this productivity growth was accounted for by the financial services sector.[3]

[3] Oulton (2013) shows that given the way GDP is measured in the UK finance cannot have caused a large bias in the measurement of GDP growth in the pre-crisis period. This is essentially because finance is an intermediate input so is no counted in GDP which is value-added.

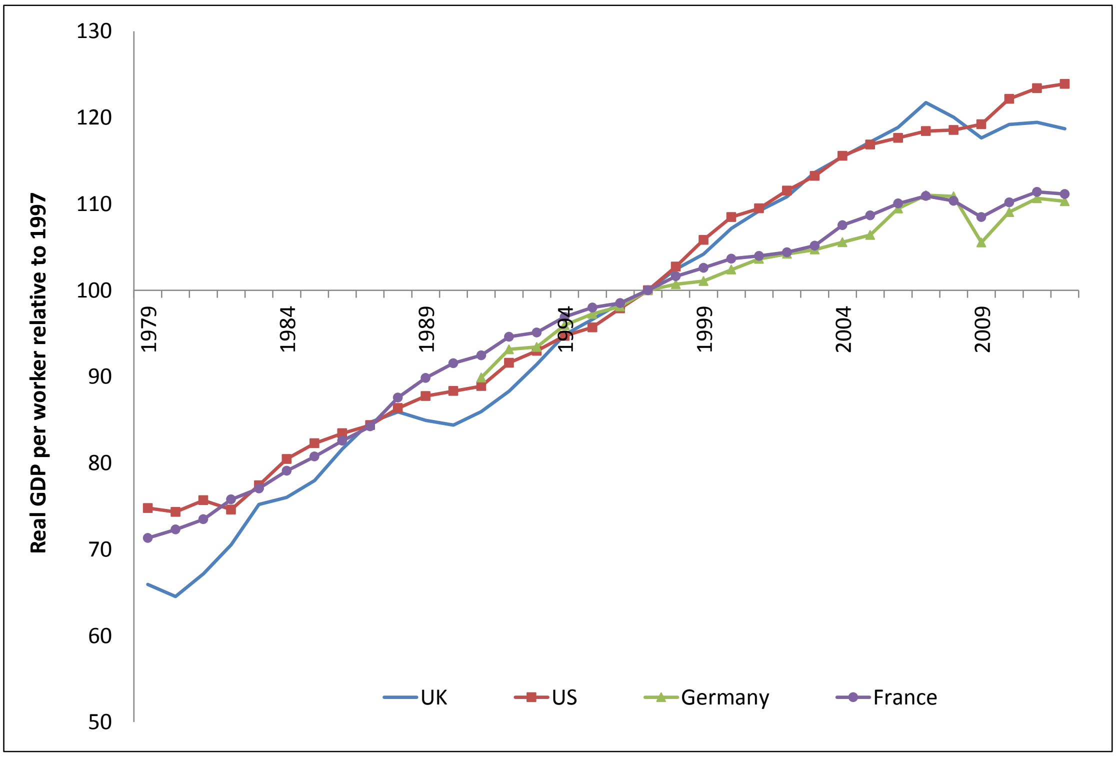



Figure 3.7: Trends in real GDP per worker relative to 1997, from 1979 to 2012.

Sources: Sources: Analysis based on Conference Board data (extracted on 19 of February 2013). GDP is measured in US dollars, at constant prices and constant purchasing power parity, with a Conference Board base year of 2011. 'Adult' refers to working age adults; data obtained from US Bureau of Labor Force Statistics and includes the civilian population aged over 16. Data for unified Germany from 1991. For each country the logged series is set to 100 in 1997, so the level of the line in any year indicates the cumulative growth rate (for example, a value of 110 in 2001 indicates that the series has grown by $\exp(10/100) - 1 = 11\%$ between 1997 and 2001). The steeper the slope of the line, the faster growth has been over that period.

Aghion et al. (2013) argue that these productivity improvements can be linked to policy reforms such as enhanced product market competition (e.g. privatisation and tougher anti-trust policies), labour market flexibility (due to weakening union power and welfare reforms) and the growth of independent institutions such as utility regulators, the Monetary Policy Committee and the National Institute for Health and Care Excellence (NICE). If these improvements to UK economic capacity were real, it seems unlikely that they would quickly disappear.

Having said this, it is of course possible that a large part of the productivity loss is permanent and/or that the UK is on a much lower trend growth path for the foreseeable future even though this would be a break with historical experience. To explore this we turn to a simple model and empirical evidence in the next two sections.

## 3.3 Theory

### 3.3.1 Flexibility of the Labour Market

Consider a representative firm facing competitive market conditions with a constant returns production function of the form:

$$Q = AL^{\alpha}K^{1-\alpha}, \tag{3.1}$$

where $Q$ is output, $L$ is labour, $K$ is capital and $A$ is TFP. From the first order conditions, labour productivity is related to the real product wage, i.e. nominal wages $(W)$ deflated by the output price deflator $(P)$

$$\frac{Q}{L} = \frac{1}{\alpha}\frac{W}{P}. \tag{3.2}$$

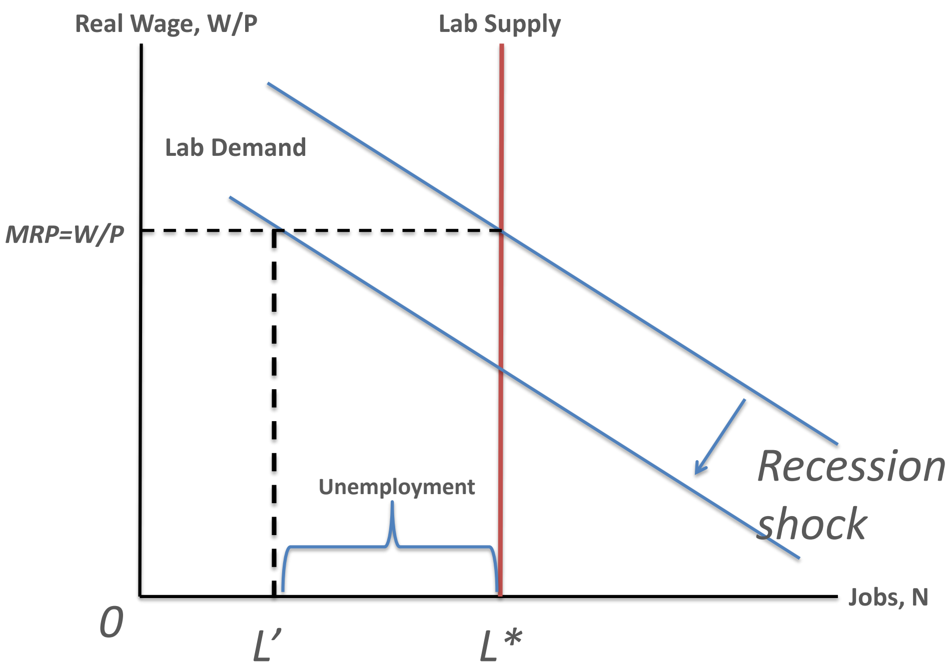



Figure 3.8: Negative output shock and rigid wages – labour productivity stable ("Normal time"). MRP = marginal revenue product of labour. Fixed real wages.

Sources: Sources: Aghion et al. (2013). US output per hour covers only the business sector.

This gives us a conventional downward sloping labour demand curve as illustrated in Figure 3.8. For simplicity we consider an inelastic supply curve which generates an equilibrium wage with full employment $L = L*$ where $L*$ is the labour force.

Now consider a recession which is a negative output shock ($Q$ to $Q$') shifting the labour demand curve to the left. In a "normal" recession real wages are downwardly rigid, hence employment will fall and unemployment will emerge ($L$*- $L$'). Notice that equation 3.2 still holds as even though output and employment are lower their ratio remains the same ($Q$'/$L$'). Because real wages are unchanged labour productivity is also unchanged.

The polar opposite case of a classical labour market where real wages are completely flexible in Figure 3.9. In this case real wages fall to ensure full employment, but now labour productivity has fallen $Q'/L = 1/\alpha(W/P)' < Q/L$. The greater flexibility of real wages has protected jobs, but measured productivity is lower.

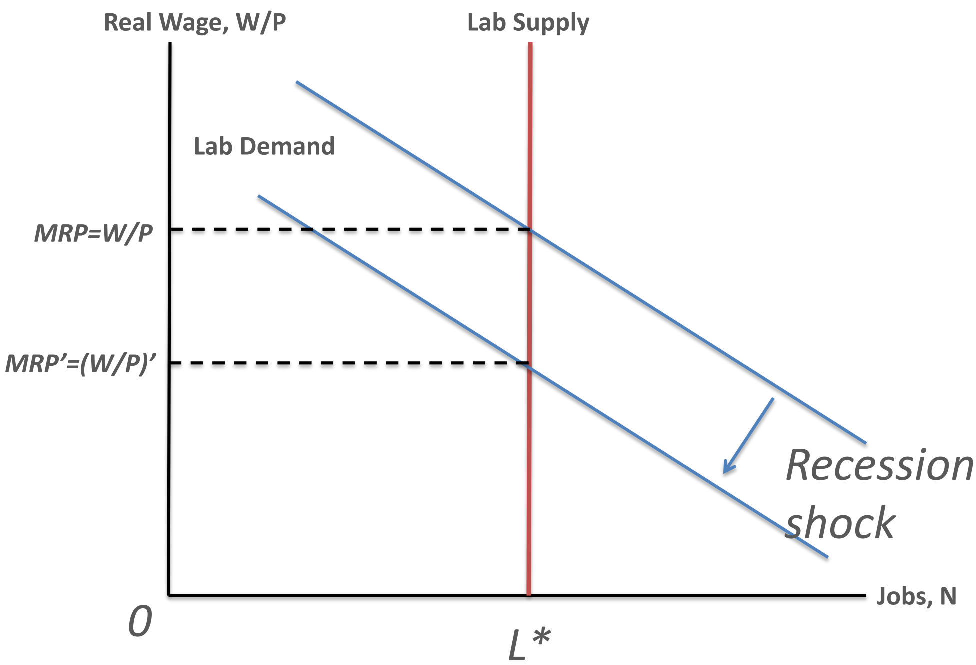



Figure 3.9: Negative output shock and flexible wages – labour productivity fall. Flexible real wages.

Sources: Sources: Aghion et al. (2013). US output per hour covers only the business sector.

One way the adjustment takes place is through changes in the capital-labour ratio. Combining the first order conditions for labour and capital we obtain $K/L = [(1-\alpha)/\alpha](W/R)$ where $R$ is the cost of capital. Assuming that the cost of capital is unchanged, the fall in W means an offsetting fall in K. This fall in the capital-labour ratio will depress labour productivity, the output to labour ratio.

Another way to see this is to re-write the production function in logarithmic changes and solve for TFP growth:

$$\Delta lnA = \Delta ln(Q/L) - (1-\alpha)\Delta ln(K/L). \tag{3.3}$$

TFP growth is the difference between labour productivity growth and the change in the (weighted) capital-labour ratio. A pure demand shock causes a fall in $\Delta ln(Q/L)$ and $\Delta ln(K/L)$ but leaves TFP unchanged.

This is obviously an extreme model as real wages are not really fully flexible and will not fall by as much as suggested in Figure 3.9. Nevertheless, if the most recent recession is closer to Figure 3.9 and previous recessions were closer to Figure 3.8, then this may explain why employment has fallen by less in this recession than in previous recessions, but labour productivity has fallen by more.

The qualitative evidence gives some support for this simple model. In the four years after 2008Q2 real product wages fell by 4% (and CPI deflated wages by 8%). This is unprecedented for a post-war recession and is likely linked to policy reforms that have weakened unions, lowered the replacement rate and kept up work search pressure on benefit claimants (those claiming Job Seekers Allowance, but also Incapacity and Lone Parent Benefits). The sensitivity of wages to negative shocks has increased over time: Gregg et al. (2013) show that the "wage curve" (Blanchflower and Oswald, 1994) has become more elastic, i.e. an increase in unemployment has a more depressing effect on real wages today than in the 1980s or 1990s.

### 3.3.2 Other Causes of a Fall in the Effective Capital to Labour Ratio

In addition to falls in real wages, other factors may have depressed the capital-labour ratio. Even though this may be a temporary effect, according to Bank of England (2012) the cost of capital for large firms has risen by about a quarter from 8% in the pre-crisis period to 10% in 2012 (see Figure 3.10). The increase in the cost of capital for SMEs is even higher (e.g. Armstrong et al., 2013). Despite a fall in the Bank of England's base rate banks have been re-building their balance sheets and are so very reluctant to lend. Various government credit easing schemes such as Project Merlin, the National Loan Guarantee Scheme and Funding for Lending do not seem to have made a significant impact.

Investment has been held back by low demand expectations and a higher cost of capital. But a third factor is that uncertainty has also risen. This always tends to increase in recessions (see Bloom et al., 2013) but the increase in uncertainty in this recession may

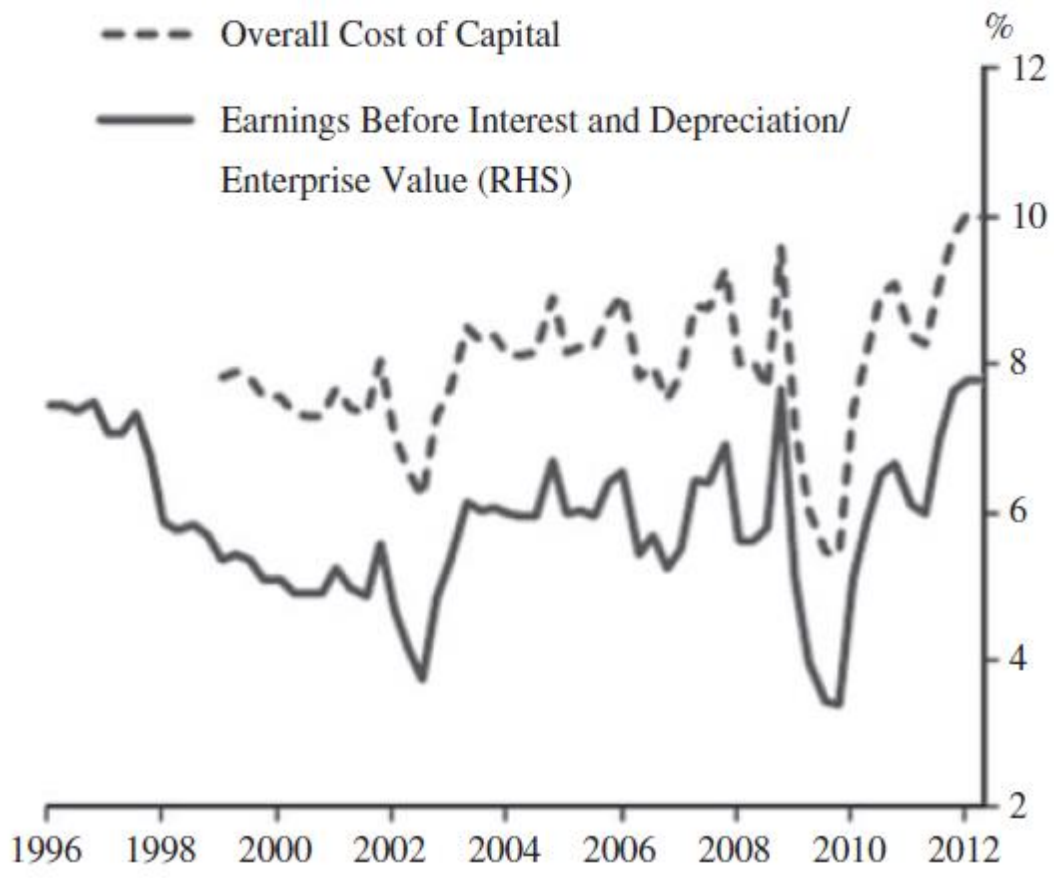



Figure 3.10: Increasing cost of capital for large firms.

Sources: Bank of England (2012): Consensus Economics, Thomson Reuters Datastream and Bank of England calculations. Ratio of earnings before interest and depreciation to enterprise value calculated for all UK listed companies, as defined by Datastream code TOTMKUK; enterprise value sums the market values of firms' equities and outstanding debt. The overall measure is calculated by adding an estimate of expected long-run growth of earnings.

have been particularly severe due to the size of the demand shock. Although fiscal policy was aggressive in the first year of the recession, in subsequent years policy-makers have struggled to find a consistent way to tackle the problem of low growth and high deficit. In 2010 the new government accelerated an already tough austerity programme inherited from the previous Labour administration, and has had to constantly revise its estimates of growth downwards and budget deficits upwards. The crisis in the Eurozone has a strong effect on the UK as almost half of all exports go there. The chaos over the fiscal cliff, debt ceiling and sequester in the US has also added to policy uncertainty. Since uncertainty can be an important barrier to investment (Bloom *et al.*, 2007; Bloom, 2009), this policy risk may further reduce investment.[4]

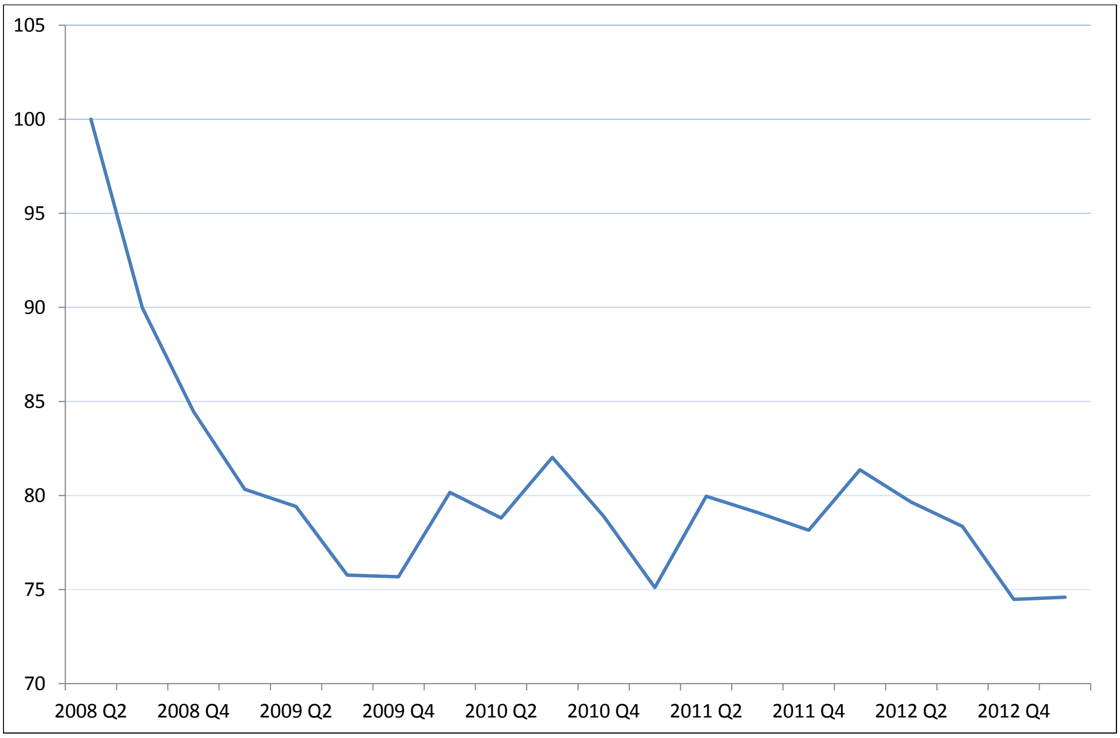



Figure 3.11: The collapse of real investment, 2008Q2-2013Q1 (2008 Q2=100). Investment defined as gross fixed capital formation, in constant prices, seasonally adjusted.

Sources: ONS data, July 2013.

Together these factors may explain the collapse of investment in the UK as shown in Figure 3.11. The UK has had a problem of low investment for many decades (Aghion et al., 2013) and this has taken a severe turn for the worse since 2008. In Section V we

[4] Of course, uncertainty will also reduce hiring, but since labour has lower adjustment costs than capital the impact is likely to be less severe.

show how this helps resolve much of the productivity puzzle as it leads to a fall in capital intensity and therefore output.

## 3.4 Other Explanations of the Productivity Slowdown

### 3.4.1 Mismeasurement

One mundane explanation for the puzzle is simply mismeasurement. The denominator of labour productivity is simply employment or hours and measurement error is not a major concern (although there could be some contribution coming from the increasing number of self-employed and those on zero-hours contracts). A more serious concern is that GDP may be understated. The GDP number is subject to very large revisions, but Grice (2012) shows that the magnitude of these revisions is not usually large enough to explain away the puzzle and future revisions may *lower* the GDP number rather than raise them.[5]

### 3.4.2 Under-utilisation of Resources

As Wadsworth (2013) points out, the UK population has risen by about a million since 2008, so the absolute number of jobs is a poor measure of labour market tightness. As expected - there has been a significant rise in unemployment and fall in the employment rate (employees as a proportion of working age population) during the recession. So there is clear under-utilisation of human resources. Labour productivity measures account for this, however, as only employed or hours are in the denominator. It may well be, however, that people are not being used to their full potential when in work. This is usually described as "labour hoarding" whereby firms will not reduce employment by as much as expected as they hope that demand will pick up later and do not want to pay the cost of re-hiring the laid off workers (e.g. if they have firm-specific human capital). This is the usual explanation of why productivity is pro-cyclical.

The labour hoarding story has become less plausible as time goes by. This is because employment rates have been rising for the last two years and it is hard to square this with labour hoarding. There is some evidence that the increase in employment has been in some low productivity sectors, however, so the hoarding may still be happening in some firms and sectors where demand remains depressed but employers are reluctant to shed as many workers even though output has fallen (e.g. Martin and Rowthorn, 2012).

[5] Still the disruption of the ONS move to Newport and severe nature of the recession leaves room for concern. For example, if service exports were severely understated this would help resolve both the puzzle of both why productivity and exports are so surprisingly low despite a large sterling depreciation.

### 3.4.3 Zombies: Misallocation of Capital

Representative firm models are a poor reflection of economic reality as firms differ considerably in their productivity, efficiency and management quality (Bloom *et al.*, 2013). Modern theories of heterogeneous firms emphasise that much of aggregate productivity growth is caused by the reallocation of capital from less productive to more productive firms. A given aggregate quantity of capital may be allocated in different ways across firms of heterogeneous efficiency. Allocating too much capital to inefficient firms for example will diminish aggregate productivity. This has been shown to be of first order importance when considering aggregate productivity differences across countries (e.g. Bartelsman *et al.*, 2013; Hsieh and Klenow, 2009; Bloom *et al.*, 2013). Some have argued that this could account for the fall in UK productivity (Bank of England, 2012). Another way of saying this is that the *effective* amount of aggregate capital has fallen due to increased misallocation.

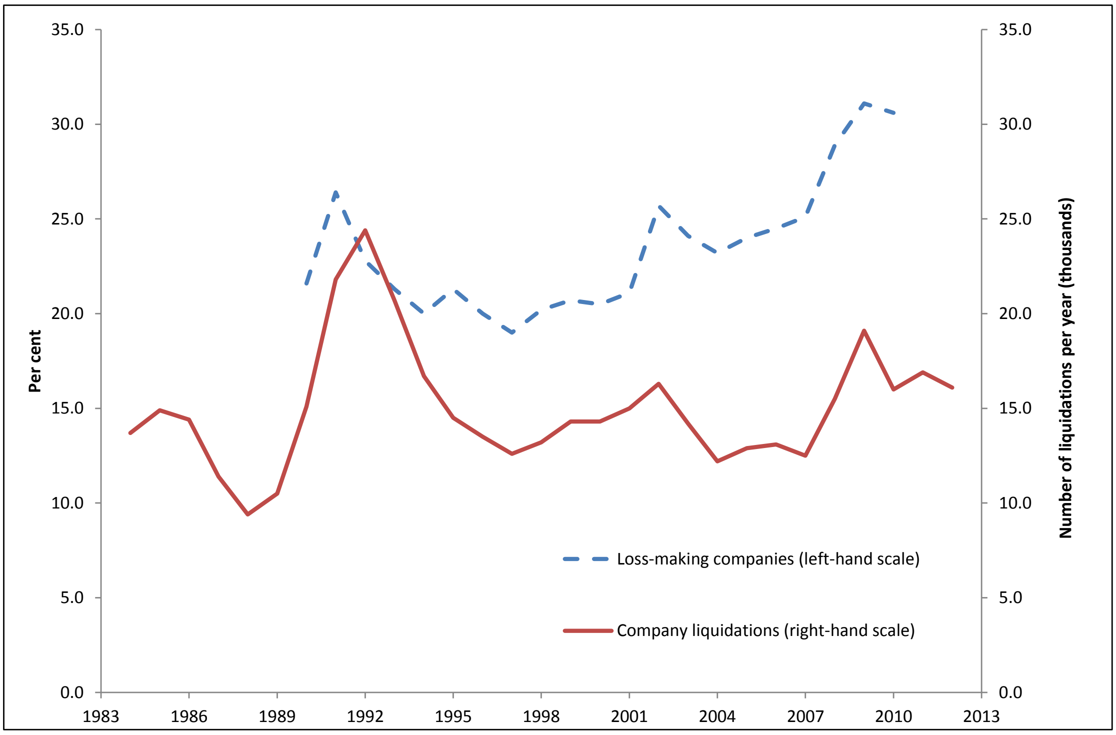



Figure 3.12: Company liquidations from 1984 to 2012.

Sources: Bureau van Dijk, The Insolvency Service and Bank calculations. The number of companies that reported negative pre-tax profits in each year as a percentage of the total number of private non-financial companies in the Bureau van Dijk data set that report data on pre-tax profits.
Companies in the mining and quarrying, electricity and gas supply, and water supply sectors and extra-territorial organisations are excluded from the calculations.

There is some suggestive evidence of these capital misallocation forces having got worse in the recession. First, the rate of bankruptcies and liquidations appears to be particularly low given the macro-economic climate (See Figure 3.12). Second, the cross sectional variance of employment, output and prices has increased across sectors (see Figure 3.13). Finally, Field and Franklin (2013) point to the increased variance of productivity across establishments even within sectors.

Why should misallocation have become worse? First, Bloom et al. (2013) argue that increased uncertainty is pervasive in all recessions and that this is responsible for a substantial fraction of aggregate productivity falls. As noted above, uncertainty may be particularly severe in the current recession.

A second set of reasons focuses more directly on the dysfunctionality of the financial system – after all, a massive banking crisis was the catalyst for the 2008/9 Great Recession. The major issue here is of bank "forbearance", i.e. that banks are reluctant to call in underperforming loans to firms and projects that can no longer make their interest payments. Hence low productivity projects and firms that in "normal times" should have exited the economy do not, and their persistence pulls down aggregate productivity. Why should banks behave in such a manner? It may be rational to allow debt restructuring/forgiveness if lenders believe that projects are ultimately viable and demand will recover (analogous to labour hoarding). However, lenders may be sure that a project will not be viable and still not call in their loans if they are reluctant to admit the true state of the under-performing loans on their balance sheet as this may force them into bankruptcy or regulatory intervention. This seems to have been a pervasive feature of Japan following the bust of the asset bubble in the 1980s (e.g. Cabellero et al., 2008). A second reason for forbearance may be political pressure, especially when many banks are fully or partially owned by the public sector (e.g. RBS) as politicians are reluctant to push SMEs into bankruptcy and be seen to be making workers redundant.

These under-performing companies are often pejoratively called "zombies". If output could be swiftly reallocated from low productivity zombies to other projects this would tend to raise productivity. However, if some of the value of the assets were lost this is a cost to be born in mind. For example, there may be firm-specific capital that is lost or workers may spend considerable time in non-employment before they are reallocated to more productive firms. Since these problems may be particularly severe in deep recessions, it is not obvious that faster closing down of the zombies is welfare enhancing. Although it is often assumed in Austrian economics that recessions are the best time for cleansing the economy of low productivity firms, the evidence on this is unclear. For example, in a financially driven recession many productive firms may also be closed down during a sharp downturn if they are credit constrained (e.g. smaller actual and potential innovators as in Garicano and Steinwender, 2013).

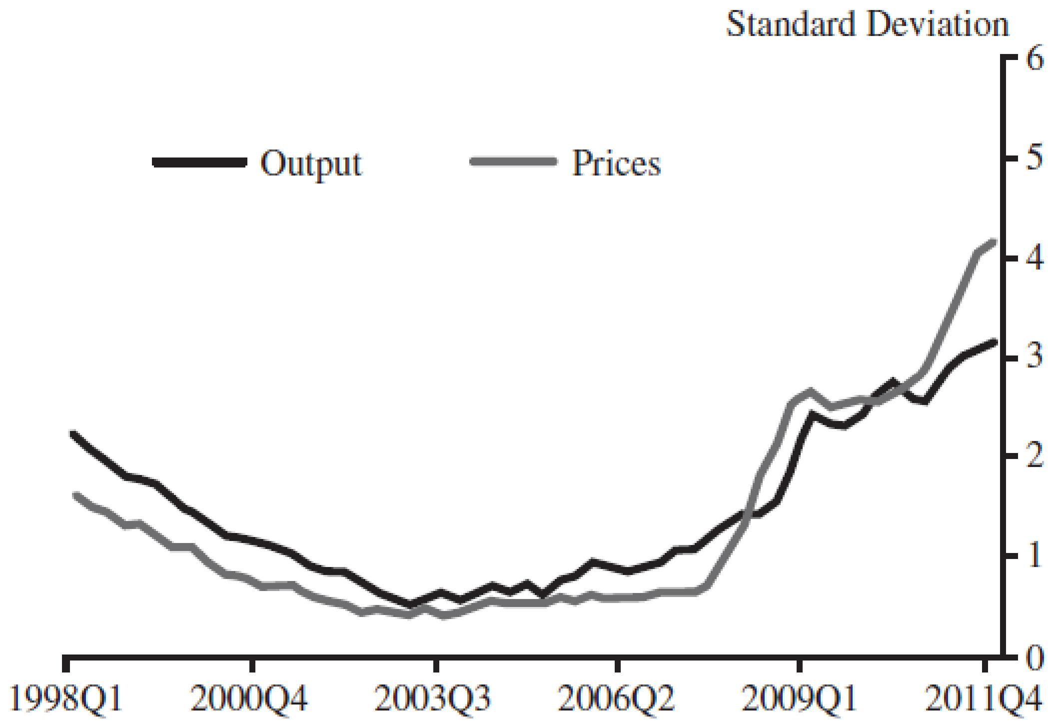



Figure 3.13: Misallocation across sectors.

Sources: Bank of England (2012), ONS and Bank of England calculations.

The direct micro-evidence on zombies is rather mixed. In the early part of the recession in 2008-2009 it seemed as if most of the fall in productivity was confined to small firms who may be most susceptible to forbearance. However, after 2009 it appears that productivity also fell in larger firms. Furthermore, decompositions of the aggregate fall in labour productivity suggest it is a within establishment rather than a between establishment phenomenon (Bank of England, 2013). However, the fall in labour productivity in these surviving firms is all accounted for by falls in real wages and investment (Crawford et al., 2013)

Since the forbearance story is mainly on the exit/entry dimension, this suggests that the problem is with ongoing plants rather than zombies. Consequently, the role of zombies seems less important than changes in factor prices.

### 3.4.4 Intangible Capital

Our focus so far has been on tangible capital, but an influential line of research suggests that intangible capital such as scientific know-how, business practices, advertising, etc. may be as important as more conventional equipment and structures. Goodridge *et al.* (2013) allow for intangible capital in analysing UK productivity growth through 2010 and argue that about a third of the productivity slowdown could be due to mismeasurement of intangible capital. The essential problem is that output growth is mismeasured when intangible capital is ignored. Intangible investment should be part of GDP but is instead treated only as an intermediate input and therefore not included in GDP (which is a value added based measure net of intermediate inputs). During times when intangible investment is growing fast (as in the late 1990s and early 2000s) GDP growth and therefore productivity is over-estimated. During periods when intangible investment is growing more slowly (as today) GDP and productivity growth is under-estimated.

### 3.4.5 Labour Quality

Another explanation of the fall in labour productivity is that the quality of the workforce could have deteriorated: for example, older workers may be delaying retirement because of the fall in house prices. In fact, labour quality tends to rise during recessions as unskilled and less experienced workers are more likely to be unemployed. The current recession is similar in this regard. But the relevant counterfactual is what happened in previous recessions. It does not appear that there is much of a difference in the increase in labour quality in this recession compared to previous recessions, however (Blundell et al., 2013). This may seem surprising given the more flexible labour market, but it appears that the main reason for the fall in aggregate real wages is that incumbent workers are accepting more nominal wage freezes which are eroding aggregate real wages.

## 3.5 Putting it All Together

Table 3.1 gives some examples of some growth accounting estimates over the recession where we are just using 3.3 to decompose the growth of GDP per worker: $\Delta ln(Q/L) = \Delta lnA + (1-\alpha)\Delta ln(K/L)$. These are very crude, back of the envelope estimates in order to examine whether the labour market flexibility story might matter in a quantitative sense. We focus on the period from the start of the Great Recession in 2008Q2 (just before Lehman's collapse) to the latest data at the time of writing (2013Q1). Over this period whole economy real GDP fell by 3.1% (column (1)), employment rose by 0.8% and so labour productivity (GDP per worker) fell by 3.9% (column (2)). This is the productivity puzzle we are trying to explain.

Table 3.1: Example of Aggregate Productivity Growth Accounting Exercise

| | (1) Change in GDP | (2) Change in labour productivity (GDP per worker) | (3) Change in effective capital-labour ratio | (4) Contribution of capital to change in labour productivity | (5) % Labour productivity change accounted for by capital-labour changes |
|---|---|---|---|---|---|
| 1. Baseline (2008Q2-2013Q1) | -3.1 | -3.9 | -9.1 | -3.1 | 79% |
| 2. Use changes in factor prices (2008Q2-2013Q1) | -3.1 | -3.9 | -6.1 | -2.1 | 52% |
| 3. Baseline (2008Q2-2012Q2) | -3.8 | -4.0 | -7.1 | -2.4 | 59% |
| 4. Lower depreciation rate (2008Q2-2013Q1) | -3.1 | -3.9 | -6.8 | -2.3 | 59% |

Notes: Assumes labour costs are two-thirds of value added & Constant Returns to Scale ; Capital stock estimated from ONS 2009 whole economy net capital stock updated with real investment series as ONS has not published capital stock estimates since 2010 (depreciation=2.2% per quarter except in row 4 where it is 2.06%).

Unfortunately, estimating the change in the capital stock is extremely hard as the ONS have suspended the series and have not produced a measure of the UK capital stock since 2009 (ONS, 2010). Presumably concerns over data quality were particularly fierce during the severe downturn. Aggregate capital stocks are very hard to measure even in the best circumstances so the calculations in Table 3.1 should be regarded as very rough exercises to give the reader an idea of the magnitudes of capital shallowing that would be needed to account for the productivity fall.

A series for the volume of real investment is produced by ONS so we update the net capital stock in 2008 with this quarterly investment series using the perpetual inventory method.[6] Our baseline estimates suggest that capital per worker has declined by just over 9% (column (4)). Assuming that GDP is split two-thirds to labour costs and one third to capital costs implies that capital shallowing has made a contribution of -3.1 percentage points to declining labour productivity (column (4)). Hence, changes in capital can account for almost four fifths of the decline in labour productivity. This is obviously a much smaller proportion of the gap between current labour productivity and what it might have been “but for” the recession (recall Figure 2), but we have argued that this is a poor counterfactual. A more plausible counterfactual would be the productivity experience of previous severe recessions.

To examine this we use the estimates of Table 3.1 row 1 to produce a crude TFP index for the whole economy for the current recession and compare this to the 1970s and 1980s

[6] To be precise we use the whole economy current net capital stock for 2008 as the initial value of the capital stock in 2008Q2 (CIXM from ONS, 2010). We then uprate this using the PIM with the first value of seasonally adjusted gross fixed capital formation (GFCF) from 2008Q3 onwards. The constant price investment series is rebased to be in 2008Q3 prices (instead of 2010) using the current and constant values of GFCF (series NPQT and NPQS). We use a quarterly depreciation rate of 2.2%, slightly higher than normal to reflect capital scrapping in the baseline results, but check the sensitivity of this assumption to alternative depreciation rates.

recessions in Figure 3.14.[7] This figure shows that in TFP terms the current recession is not so unusual compared to severe recessions in the past. In 2010 the TFP performance was actually better than the previous recessions, but it then stalled so by the end of 2012 it was worse than the 1980s recession (but still better than the 1970s). Given that the GDP fall was worse than in both these recessions, there is much less of a mystery to be explained in TFP terms. The fall of measured TFP in recessions is likely to be a more standard combination of labour hoarding and misallocation – there is no compelling evidence of a permanent structural change in underlying potential output growth according to these estimates.

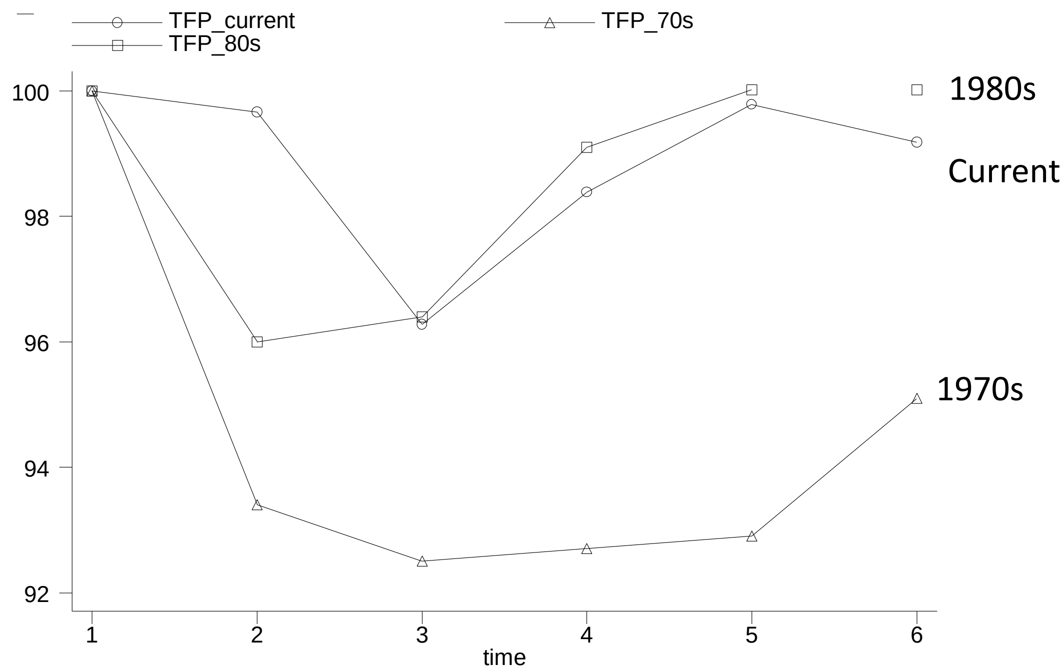



Figure 3.14: Change of TFP in recessions over time.

Notes: 1970s and 1980s derived from EU KLEMS data by Goodridge *et al.* (2013) . 1970s recession is 1973-1978.
1980s recession is 1979-1984; Current is 2007-2012. 2000s authors' estimates.

Our estimates of the fall in the aggregate capital stock are larger than others have used on shorter runs of data (e.g. ONS, 2013; Goodridge et al., 2013) so we performed some checks on the plausibility of the estimates. The model presented earlier implies that the evolution of relative factor uses could be described as $\Delta ln(K/L) = \Delta ln(W/R)$. The real product wage fell by 4.1% in the four years after 2008Q2 and the Bank of England (2012)

[7] It is crude because *inter alia* we are not making adjustments for heterogeneous types of capital or labour services. For a much more sophisticated analysis over a shorter period of the recession see Goodridge et al. (2013).

suggests an increase in the cost of capital of 2%. This implies a fall in the capital-labour ratio of 6.1% and therefore 52% the fall in row 2 of Table 3.1. So this is smaller than our baseline, but still more than half of the fall.

There is an arbitrariness in using 2013Q1 as the end date and this will shift of course as more data becomes available. We checked that too much hinges on this by re-estimating over different sample periods. Row three looks at a four year window from 2008Q2 to 2012Q2 and shows that 59% of the fall is accounted for. In the final row we use a lower depreciation rate of capital (equal to 8% annual following Oulton, 2013) and find a similar result to the previous row. We also considered using an adjustment for hours.[8] Although hours per worker fell at the start of the recession, by the start of 2013 hours had recovered so this adjustments makes no discernible difference.

Taking Table 3.1 as a whole capital shallowing caused by changes in factor prices seems to account for over half of the fall in labour productivity in the period since the start of the Great Recession.

As noted at the start of this sub-section, considerable uncertainty surrounds these estimates due to the difficulty of measuring the capital stock. Oulton (2013), for example, finds no fall in the capital stock from 2007Q4. The reasons for the differences include (i) he looks at the market sector where inputs and outputs are better measured than our focus on the whole economy[9]; (ii) he uses a lower depreciation rate (we have used a higher depreciation rate to reflect greater capital scrapping and lower capital quality due to forbearance and weaker entry) and (iii) he calculates the initial capital stock in a different way. This may be a more reasonable approach and as time goes on we will hopefully get improved capital stock measures which should help sort out whether declining effective capital is as important as we think it is.

## 3.6 Conclusion

We have argued that the twin puzzles of the fall in labour productivity (GDP per worker) and the good performance of the labour market may both have their source in greater wage flexibility compared to earlier recessions (probably because of labour market policy reforms over the last 30 years). The big difference of this recession is (i) its severity and (ii) that real wages have fallen dramatically. The fall in the price of labour coupled with the rise in the cost of capital is likely to cause a fall in the capital to labour ratio which means that labour productivity falls substantially even though TFP has barely fallen at

[8] In other words we look at including a correction for the change in average hours worked ($\Delta ln(H/L)$): $\Delta ln(Q/L) = \Delta lnA + (1-\alpha)\Delta ln(K/L) + \alpha\Delta ln(H/L)$

[9] The market economy drops the public sector and property. Dwellings are a problematic category for productivity analysis.

all. The fall in TFP is similar to other (less severe) post-war recessions from which the economy eventually recovered. The fall in measured TFP in recessions is likely to be due to factors such as under-utilisation of factors and uncertainty-driven misallocation. These are real costs but rather are more a feature of a typical cyclical downturn rather than permanent, structural changes.

This analysis suggests that UK economy was not fundamentally the victim of a large supply side shock, but rather a very severe demand side shock (exacerbated by the ongoing problems of the financial system). We should not be complacent – the longer the recession goes on, the greater risks of structural damage through hysteresis effects (e.g. DeLong and Summers, 2012). However, these demand problems are amenable to conventional solutions of fiscal and monetary stimulus as they imply a substantial output gap. In other words, the argument of supply side pessimists that such stimulus programmes would simply lead to higher inflation do not, in our view, appear to be strongly supported by the data.

The message of this paper is *not* that structural policies are unnecessary. For example, strategies to improve the functioning of credit markets are vital. Long-run policies to improve investment in human capital, infrastructure and innovation are also extremely important for long-run economic health as argued by Aghion et al. (2013).

# Chapter 4

# Decoupling of Wage Growth and Productivity Growth? Myth and Reality

## 4.1 Introduction

It is widely believed that in the US wage growth has fallen massively behind productivity growth. Recently, it has also been suggested that the UK is starting to follow the same path. Analysts point to the much faster growth of GDP per hour than median wages. The purpose of this paper is to look at the decoupling between wages and productivity in the UK and compare this with other countries, in particular the US. We do this by defining what is meant by decoupling and then examining trends in these variables between 1972 and 2010.

We distinguish between "net decoupling" – the difference in growth of GDP per hour deflated by the GDP deflator and average compensation deflated by the same index - and "gross decoupling" – the difference in growth of GDP per hour deflated by the GDP deflator and median wages deflated by a measure of consumer price inflation (CPI-U-RS in the US and RPI in the UK). Basic economics would predict that real compensation growth deflated by the producer price (the labour costs that employers face) should follow real labour productivity growth (value added per hour), so net decoupling should only occur if labour's share falls as a proportion of gross GDP, something that rarely happens over sustained periods. So net decoupling would be a real surprise.

We show that over the past 40 years that there is almost no net decoupling, although there is evidence of substantial gross decoupling in the US and, to a lesser extent, the UK. This difference can be accounted for essentially by three factors (i) compensation inequality (which means the average compensation is growing faster than the median one), (ii) "benefits" - the wedge between compensation (which includes employer-provided benefits like pensions and health insurance) and wages which do not and (iii) differences in the GDP deflator and the CPI-U-RS/RPI deflator (i.e. producer wages and consumption wages). These three factors explain basically ALL of the gross decoupling leaving only a small amount of "net decoupling". The first two factors are important in both countries, whereas the difference in price deflators is only important in the US.

This is illustrated in the Figure 4.1 for the UK. Looking at the 1972-2010 period as a whole productivity grew almost 42.5% faster than median wage – this is "gross decoupling". But there was almost zero net decoupling (the blue bar at -0.8%). The diagonally hatched bar and the dotted bar are inequality (a 16.6% contribution) and "benefits" (a 16% contribution) which explain just about all the divergence between gross and net decoupling. Benefits are the difference between compensation (which includes health and pension benefits) and wages which do not.

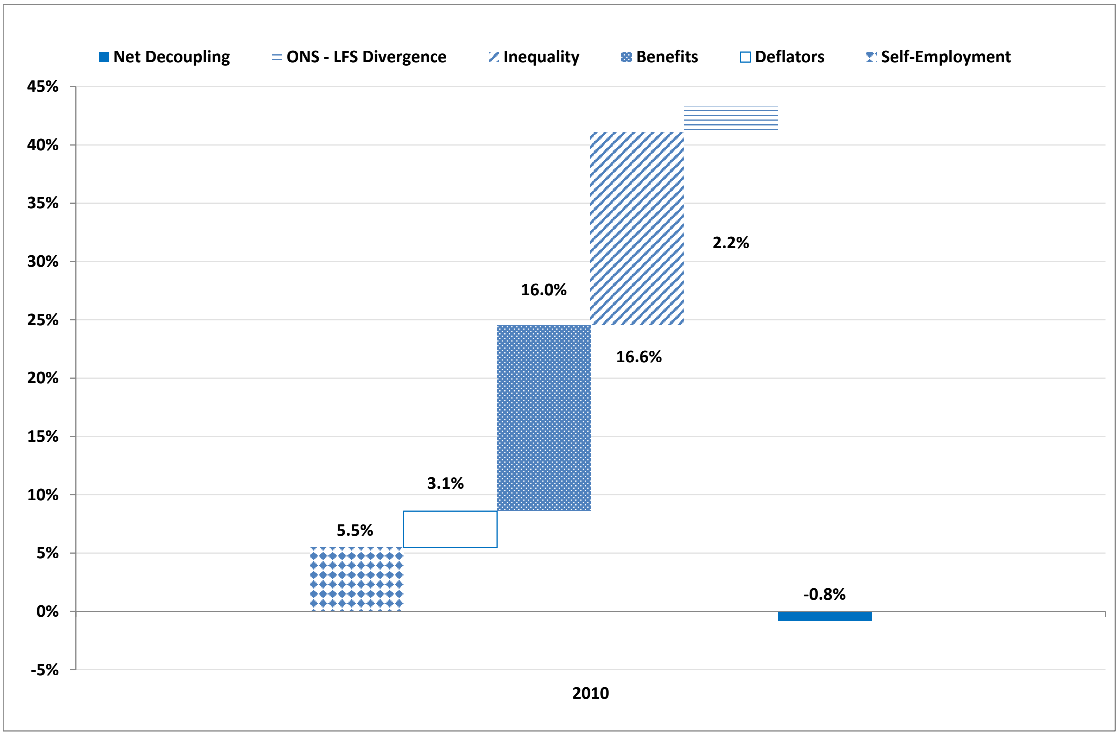



Figure 4.1: Decoupling Decomposition in the UK, 1972-2010

We also look at the share of labour in national income as a cross check. These trends are consistent with our analysis. Labour's share has fallen only slightly as a share of GDP in the US and UK. Interestingly, there is more of a fall in this “functional” share of income in Continental EU nations and Japan, so there might be evidence of capitalists doing a lot better than workers in these nations whereas the latter group have done a lot better in the US and UK.

Although we focus at the macro level we also analyse trends in productivity and wages at the industry level. Again, we find no evidence of net decoupling here except (paradoxically) in the “non-market” sectors of real estate, health, education and public administration. We suspect this is because of poor measurement of value added in these sectors. In other sectors (“the market economy) compensation growth has tended, if anything, to outstrip productivity growth.

In terms of policy, there has been a lack of clarity over what specifically is meant by decoupling. Our results suggest that net decoupling is essentially a myth and cannot be used to justify redressing the overall balance between wages and profits. Inequality within the group of employees however, is a major issue and the existing literature has been correct to focus on the causes of this and what could be done to improve matters. Improvements in the quantity and quality of skills and education for people in the bottom half of the distribution are the most important.

In terms of research questions, we need to understand a lot better why there is divergence between the wage series and compensation series. In the US this is driven by the rapid inflation in healthcare insurance costs, something that healthcare reform is seeking to tackle. This is not the case in the UK where pension costs seem to be more of the dominant force. Of course, the underlying reasons for the growth of wage inequality, especially the recent polarisation of the labour market remain very important research topics.

The structure of this report is as follows. Section 4.2 examines the theory of decoupling, section 4.3 looks at decoupling in the UK and section 4.4 looks at decoupling in the US. In section 4.5 we turn to examine labour’s share of GDP across many countries so we can see the UK and US in comparison with other OECD nations. Finally we return to the UK to look at industry-level trends in wages and productivity in Section 4.6. Sections 4.7 and 4.8 draws some conclusions for policy and for future research.

## 4.2 Decoupling Theory

Decoupling has had no precise definition, but loosely it refers to the difference between wages and productivity, or rather the idea that wage growth is substantially lagging behind productivity growth. Appendix 4.A shows what we would expect from some basic economic relationships.

We define the notion of **Net Decoupling** (ND) as the difference between the growth of GDP per hour (labour productivity) deflated by the GDP deflator and average compensation deflated by the same index. We would normally expect labour productivity and compensation to grow at the same rate in long-run. Appendix 4.A gives a model which shows the conditions under which we would expect this to happen. In particular, if the production function parameters and preferences are stable across time then we would expect a 10% growth in GDP per hour to lead to a 10% growth in real compensation.

Of course, net decoupling could certainly occur for a number of reasons. For example:

- In the short run there could be shocks that disturb the long-run equilibrium.
- Technological changes that are biased against labour as a whole.
- An increase in the profit mark-up (for example if product market competition weakens).
- A fall in the bargaining power of workers compared to firms[1].
- Changes in effective labour supply – for example the growth of globalisation, immigration, female participation.

It is worth noting that examining the net decoupling relationship is robust (in principle) to changes in the composition of the workforce. If the quality of the workforce increases because workers gain more human capital, this will increase their productivity and their wages by an equal amount, according to the marginal revenue productivity condition. Similarly, if there is an influx of low skilled immigrants then average productivity and wages will fall together.

By contrast, **Gross Decoupling** (GD) is the measure more frequently looked at in policy circles. It is not so easy to relate this to basic theory, but a common definition would be to use the same measure of productivity as net decoupling but instead of average real compensation use median wage deflated by a consumer price deflator such as the CPI. Thus, the difference in gross vs. net decoupling can be defined as:

$$GD - ND = Inequality + Wage\_wedge + Price\_wedge.$$

The first term ("inequality") is the difference between the average compensation and the median one, the second term ("wage wedge") is the difference between compensation

[1] This will only happen in some models. In basic models of bargaining over wages, a fall in worker power implies a lower nominal wage at a firm, but no change in the wage bill share of value added, because employers increase employment to exactly offset the wage bill (i.e. move up the labour demand curve. Even in efficient bargaining models the aggregate share of labor may not change - see Blanchard and Giavazzi (2003); Layard and Nickell (1998).

and wages and the third term ("price wedge") is the difference between the GDP deflator and the consumer price index. These can all change even if gross decoupling stays the same.

Gross decoupling is an important economic indicator since it measures how the productivity growth is accruing to the *middle* worker in the economy and it considers wages (*not* compensation), a variable that is more tightly related to workers' static material wellbeing. Moreover, the changes in the true cost of living faced by individuals seem to be better represented by the consumer price index than by the GDP deflator, increasing the importance of this measure.

Economists would tend to be more surprised by systematic net decoupling, though. For one thing, net decoupling would imply that the share of labour in GDP should be falling, and the stability of labour's share is generally taken (rightly or wrongly) as one of the stylised facts of the US and UK economies. We will examine the trends in labour's share in this report explicitly and show that the results are consistent with what we find when looking at the productivity and compensation trends. In fact, the labour share of GDP for the UK and US look relatively stable, whereas the share has declined significantly in Japan and many Continental Europe and countries.

## 4.3 Macro Analysis of Decoupling in the UK

### 4.3.1 Data Sources

We use several sources of data to compute hourly compensation and productivity (see Data Appendix for more details). We measure labour productivity by examining GDP per hour based on national accounts from the ONS. The information on total number of hours worked in the economy is provided by the OECD. Hours is obviously a more appropriate measure of labour input than total workers because of part-time working. But may be subject to greater measurement error so in subsection 4.3.5 below we also consider GDP per worker and annual compensation.

The basic measure of wage (w) is the basic payments, allowances, tips, and bonuses that workers receive pre-tax. This is recorded from representative samples of households in the General Household Survey (GHS) and the Labour Force Survey (LFS). The LFS is a quarterly sample of 60,000 households living at private addresses[2] and is the main source of UK micro-data on the labour market. It has been running since 1976 but comprehensive wage information was only asked in 1992 and subsequent quarters. The GHS has been

[2] From 1992 onwards, all the UK is included, but before this year only Great Britain was included in the database.

running since 1972, and although the sample size has varied a lot between years it is much smaller than the LFS. In order to get the longest time series we splice the series together using the GHS prior to 1992 and the LFS after 1992.

We also cross checked the wage results with the Annual Survey of Hours and Earnings (ASHE) - formerly known as the New Earnings Survey (NES) – which is an administrative dataset covering 1% of the working population. Employers are asked to provide detailed information on the hours and earnings of their employees to ASHE (note that it does not include self-employed workers).

A wider measure to appropriately look at decoupling is workers compensation (c). This includes non-pay benefits that are received by the worker such as pension contributions, employer's payroll tax (NI), health benefits, etc. Obviously these are costs to the employer and benefits to the employee, but they will not be captured by the standard surveys.

The advantage of compensation is that it is a theoretically more appropriate measure to examine decoupling. The disadvantage is that there is no dataset that can track the inequality of compensation over time in the UK (in the US this is possible – see Pierce, 2001). By contrast, with the more narrow measure of wages from LFS we can examine how wages have changed at different points of the distribution. In particular, we can look at how median wages have done compared to the mean. As inequality rises, the mean worker will be increasingly richer than the median worker.

The widest measure of employers' costs is labour costs. This is the same as compensation but also adds on other labour-related costs that may not be regarded as direct benefits to the worker such as payroll taxes and training costs. Trends in this look rather similar to compensation, so we will focus on compensation and use labour costs only as a cross check in Section 4.5. Our approach follows the majority of the literature – see Krueger (1999) or Gollin (2002) for example.

Without further assumptions, it is not possible to compute the self-employed wage and compensation directly from the ONS national accounts data. A common practice is to assume that employees and self-employed earn the same on average. Although we explicitly assume this in Section 4.5, in Sections 4.3 and 4.4 this assumption would not change the analysis since we consider only growth rates in them. Note that computing wage and compensation per hour using data from the ONS also requires information on the total number of hours worked by all employees (excluding self-employed) in the economy, which is provided by the EU KLEMS.

Labour productivity is computed as:

*Labour Productivity = volume measure of output / measure of labour input*

The OECD uses gross domestic product (GDP) or gross value added (GVA) as a volume measure of output. The UN System of Accounts (SNA) defines GDP (measured at market prices) as the sum of the GVA estimates, plus taxes on products (for example, value added tax, alcohol duty), less subsidies on products. It is important to point out that GVA and GDP are highly correlated over time within a country, as reported by the OECD. More specifically, from 1972 to 2010, the correlation between the two measures is 0.99 in the UK. Although we use GVA as our measure of output in Sections 4.6 (and in Appendix 4.E) due to restrictions in the KLEMS database, we will focus on the more standard GDP measure.

### 4.3.2 Trends in Compensation and Wages

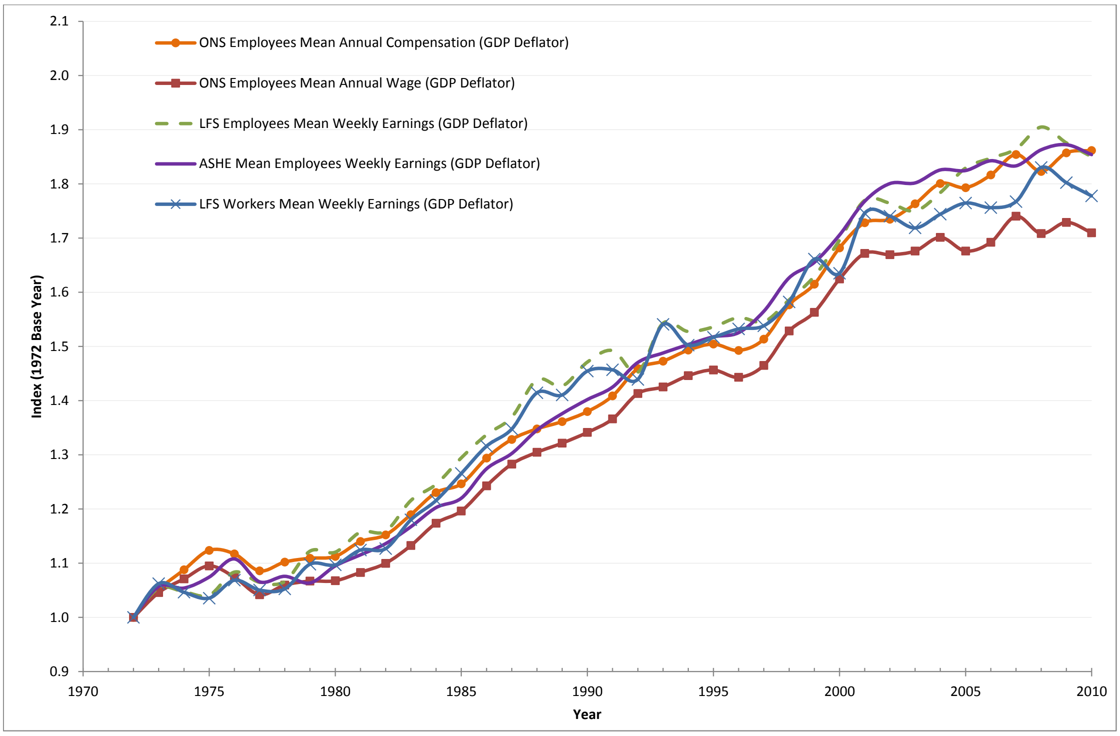



Figure 4.2: Real Mean Weekly Earnings in UK

Sources: ONS, GHS/LFS Survey, ASHE. "Workers" includes both Employees and Self-Employed.

Figure 4.2 and Figure 4.3 plot the growth over time for compensation and some wage series mentioned above (all series consider the mean and are deflated by the GDP deflator). The legend in the graph describes the source, the definition of the series, and the deflator to convert the series to real terms. If the name of the series is related to "workers", then it includes both employees **and** self-employed. By contrast "employees" excludes the self-employed. The structure of most of the figures in this paper is that we normalize the level of the series to be 1 in the base year (usually 1972) so the number on the vertical axis can be read as a growth rate. For example, the fact that the ONS wage series (red squares) reached 1.7 in 2010 indicates that real hourly compensation was 70% higher in 2010 than in 1972. An arithmetic growth rate of 1.84% per annum (70/(2010-1972)).

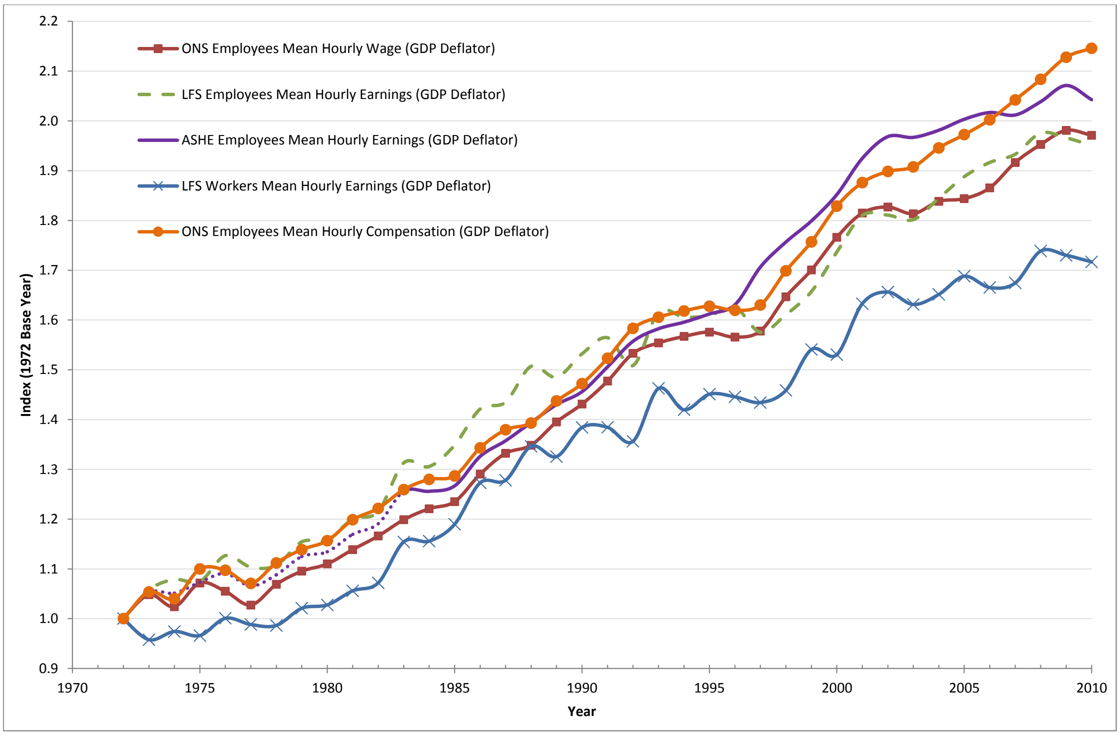



Figure 4.3: Real Mean Hourly Earnings in the UK/GB

Sources: ONS, GHS/LFS Survey, ASHE. "Workers" includes both Employees and Self-Employed.

Figure 4.2 shows that employees' real weekly earnings from ASHE and LFS follow each other quite closely and indeed are identical in growth rates over the 1972-2010 period as a whole. The LFS workers' wage has grown more slowly than the employees' earnings series because it includes the self-employed and measured earnings of the self-employed appears to have grown more slowly since 1993. We should be cautious about this as self-employed earnings are hard to define as some of the compensation may be taken directly in the form of dividends, profits or in other ways[3]. Wages computed by the ONS seem to be growing much less than the other series, but this is due to the fact that ONS wages are in annual terms, while other series are weekly. The growth of part-time and temporary work will be

[3] Note also that workers' earnings growth after 1993 is based on the GHS survey (and not *only* on the LFS survey as the in the employees series), which becomes noisy after 2005. This is another reason why the workers series should be interpreted carefully.

reflected in annual earnings more than it is in weekly earnings.

Figure 4.3 considers the same five series but now in terms of hourly earnings[4]. Note first that, as in the weekly case, including self-employed earnings drops the growth rate of wages. The self-employed are facing slower earning growth than other groups and the difference is greater in hourly terms than in weekly ones (although the caveats about data must still be taken into account, especially over hours now). Second, in this figure the ONS wage presents a similar growth when compared to the LFS series as we are measuring things on a common basis. Third, ASHE seems to have faster growth in hourly wages than the other series, but this may be due to needing to make more imputations regarding hours. In what follows we will focus on the ONS and LFS series.

Note that in both figures the ONS compensation is growing faster than the ONS wage. Moreover, it is growing faster than all wage series in Figure 4.3 (except for the ASHE measure with its approximation). Note that the difference in growth starts to increase in the beginning of the last decade, increasing ever since. Obviously, some components included only in the compensation measure are growing much faster than wages. More on the reasons behind this growth difference in Subsection 4.3.5 below.

### 4.3.3 Labour Productivity Trends

Figure 4.4 shows GDP (and GVA) per hour and per worker using the GDP deflator. GDP per hour has more than doubled between 1972 and 2010 (a factor of 2.14) whereas GVA per hour has about doubled. Note that this is faster than the growth of wages discussed above which is the first sign of decoupling. The per worker equivalents of these productivity measures have grown more slowly which reflects the increase in part-time work (fewer hours per worker).

Note that either in annual or hourly terms, computing labour productivity using the GVA instead of the GDP decreases the labour productivity growth in the period as a whole by approximately 8%. Hence, since we consider GDP per Hour in our analysis, keep in mind that the decoupling would be smaller (or inexistent) if we considered GVA per hour instead. We show in Appendix 4.C results using gross value added which show even less decoupling on this measure – thus using GDP is actually more "conservative" and gives decoupling a better chance of working, as will become clear.

[4] Although the ASHE hourly earnings are available only from 1982, we included it here considering that before this period its growth was the average between the LFS and the ONS wage growth.

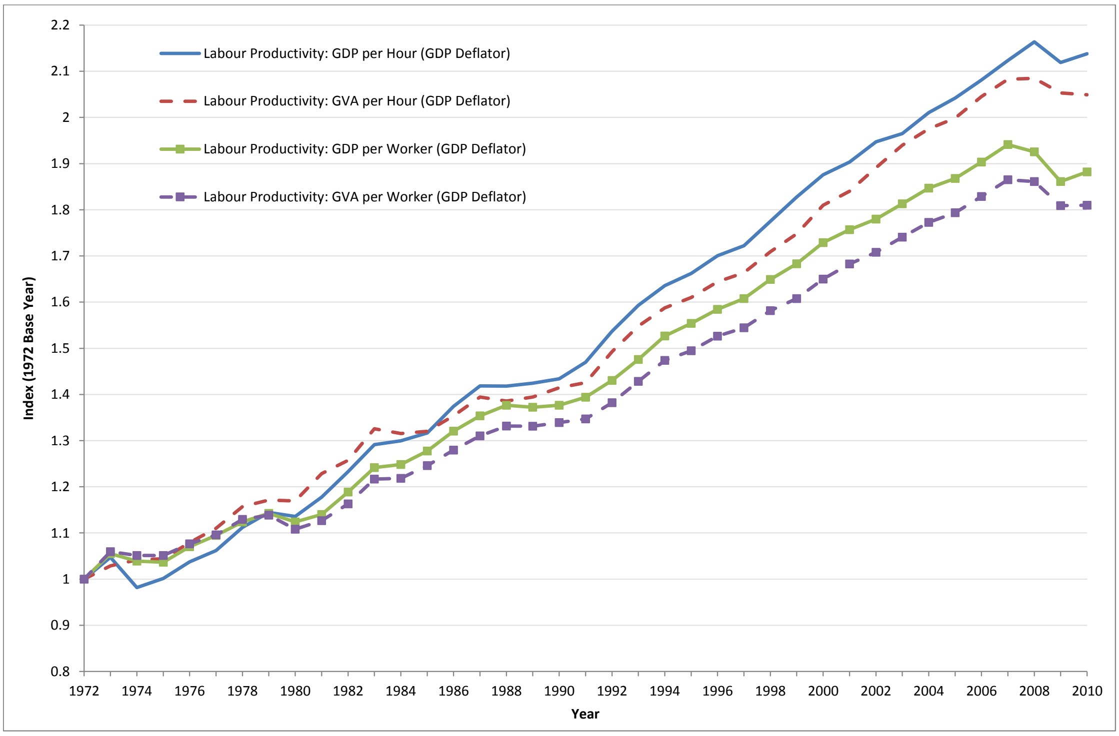



Figure 4.4: Labour Productivity in the UK

Sources: ONS, OECD.

### 4.3.4 Decoupling between Hourly Productivity and Compensation in the UK?

*No Net Decoupling in the UK*

We start our analysis considering hourly measures since they are more robust to some kinds of shifts in the labour market composition. Figure 4.5 describes the basic story behind the decoupling in the UK. Looking at the 1972-2010 period as whole both labour productivity and hourly compensation have doubled, so there is not much sign of net decoupling. Having said this, there are periods when the two series diverge. During the recession periods of the late 1970s and early 1990s wage growth outstripped productivity growth which is consistent with the idea of some labour hoarding – firms holding on to workers even when their productivity is low because demand is low (inverse decoupling if you will). There is even some sign of this in the current recession where wage falls have been outstripped by productivity falls[5]. By contrast, during boom periods, especially the long upswing from 1994-2007 productivity growth was faster than compensation growth leading to some decoupling.

[5] It is worth mentioning that the 2008 crisis brought a lot of noise to the data and this data may be revised at some point by the ONS.

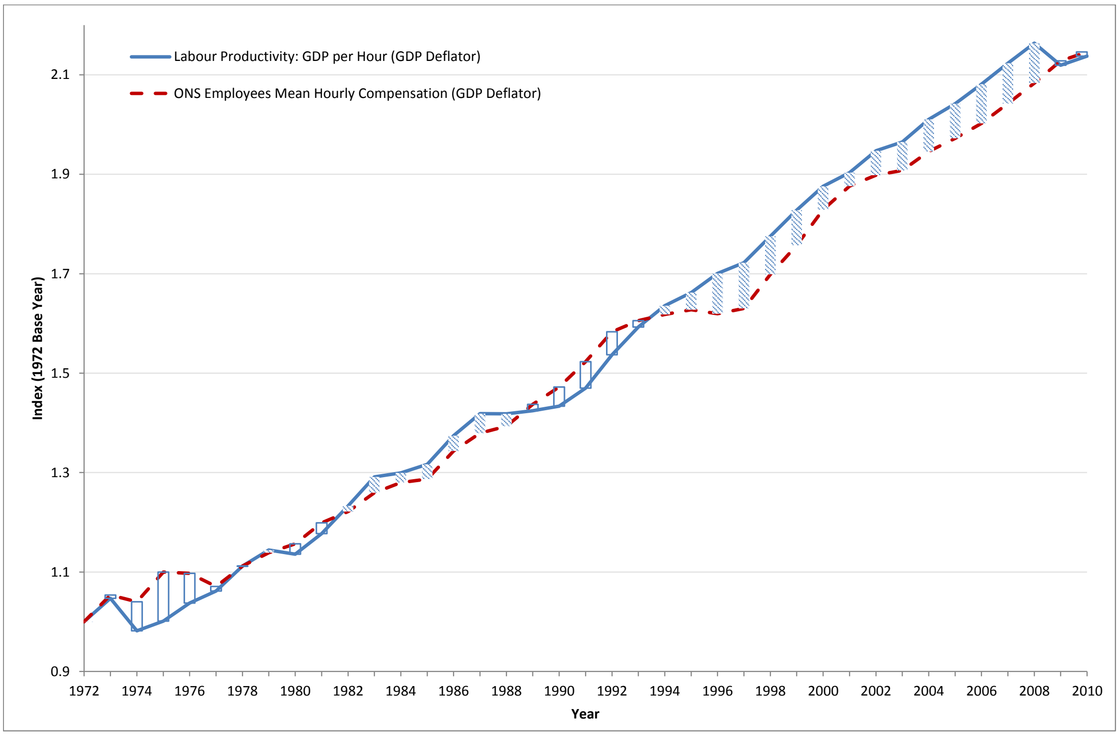



Figure 4.5: Hourly Net Decoupling in the UK

Sources: ONS, OECD.

*Explaining Gross and Net Decoupling*

Given the absence of net decoupling one might legitimately ask "why so much debate around decoupling in the UK"? The reason is that some policy analysts have been focused on other important measures of median wages, in particular what we call gross decoupling. Rather than look at the real hourly average compensation series, the focus has been more on the median hourly wage series. We plot the productivity and compensation curves again in Figure 4.6, but now we add to them some alternative wage and compensation measures[6].

Looking at the median LFS worker wage (including self-employed and deflated by the Retail Price Index -RPI). This has only increased by a factor of 1.71 over our sample period, compared to a factor of 2.14 for productivity and compensation. So there is something like a 43% difference between productivity and median wage growth on this measure of gross decoupling which disappears when we consider net decoupling. Figure 4.6 shows us why this is the case. Looking at the curve for LFS median compensation we can see that the line is more than one third way between the mean compensation/productivity by the

[6] Our LFS compensation measure is calculated assuming that the growth in benefits is proportional to the one observed in the ONS series, i.e., we multiply the LFS earnings series by a factor equals to the ratio of ONS compensation to ONS wages. This approach is similar to the one used in Mishel and Gee (2012).

end of the period. This implies about one third of the gap is due to inequality. The other half is essentially due to the faster growth of compensation than wages.

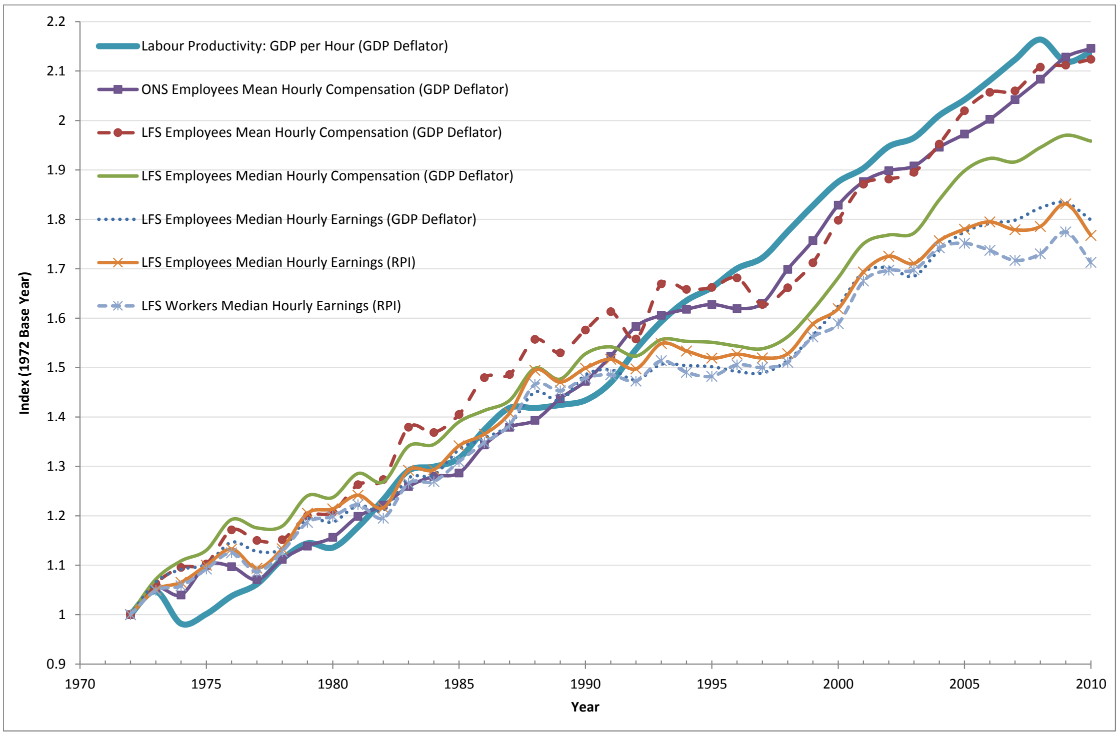



Figure 4.6: Hourly Decoupling in the UK

Sources: GHS/LFS Survey, OECD, HM Treasury, and ONS. “Workers” includes both Employees and Self-Employed.

This divergence between wages and compensation is surprising – it is showing us that the employer provided benefits such as pensions have been growing much faster than wages (the difference between the ONS average wage measure and LFS average wage measure is trivial). Even though the compensation growth level is greater than the wages one throughout the period, we can observe that the difference increases significantly in the 2000s. What would be behind this?

The ONS description of the national accounts system clearly shows us which are the components responsible for the fast growth of compensation compared to wages. The non-wage compensation is decomposed in Table 4.1 from 1999 to 2007. The accounts that are included in compensation (but not in wages) are employers' contributions to national insurance schemes and employers' contributions to pension schemes (funded and unfunded). The first component grew 67% (from £31bn to £52.3bn) in nominal terms between 1999 and 2007. The second grew considerably more: 98% (from £ 32.9 to £ 65.3 billions) in nominal terms in this same period (from which the relevant part corresponds to growth in funded pension schemes).

In the meantime, wages and salaries grew at a modest rate of 47% (not shown in the Table). Hence, contributions to pension schemes are the major component behind this disparity. This fact might reflect the various legal acts that affected pension schemes during the 1990s[7].

Table 4.1: Non-Wage Compensation Decomposition (millions of GB Pounds)

| Year | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|---|---|---|---|
| National Insurance Contributions | 31,286 | 34,028 | 35,706 | 35,735 | 39,890 | 43,586 | 46,741 | 49,552 | 52,300 |
| Notionally Funded Pension Schemes | 2,115 | 2,369 | 2,754 | 3,045 | 5,177 | 5,616 | 6,028 | 6,472 | 7,003 |
| Funded Pension Schemes | 19,128 | 20,891 | 21,836 | 26,025 | 32,054 | 38,473 | 42,963 | 47,527 | 45,995 |
| Imputed Social Contributions* | 11,670 | 12,536 | 12,920 | 13,977 | 11,692 | 11,031 | 11,931 | 11,739 | 12,328 |

Sources: ONS - United Kingdom National Accounts: The Blue Book 2008 edition.
*This last account includes employers' imputed contributions to unfunded government pension schemes.

In the Appendix 4.C we show the decoupling in terms of GVA per hour (and not GDP). Even the net decoupling observed from 1993 almost disappears when we consider the GVA as our measure of output, showing an even closer correlation between compensation and productivity growth.

Figure 4.7 decomposes the difference between gross and net decoupling more formally. It compares the contribution of each of the components listed to the final difference between labour productivity (measured as GDP per hour) deflated by the GDP deflator and the LFS median hourly earnings (including self-employment) deflated by the RPI. The numbers behind each element are in Appendix 4.D, Table 4.3.

Looking at the entire four decades of data, we see that gross decoupling reaches a maximum in 2010 of 42.5%. Yet, as we noted net decoupling is zero (actually it is slightly negative). As noted above, the two largest components of this are inequality (the bar) which accounts for 16.6 percentage points and non-wage benefits (the horizontal lines, the difference between compensation and wages) which accounts for 16 percentage points. So between them, inequality and benefits account for 32.5% of the 42.5 percentage points gross decoupling. Other components that make some minor contribution are the difference between the GDP deflator and the RPI (3.1%) arising from the faster growth of the RPI than the GDP deflator and the gap between employees and self-employed earnings in the UK (5.5%). Next, the ONS wage series growth was slightly faster than the LFS wage series

[7] The Welfare Reform and Pensions Act 1999, the Pensions Act 1995 and the Pension Schemes Act 1993.

(2 percentage points). Nevertheless, these last three components are minor – inequality and benefits are basically the story taking the last 4 decades together.

Figure 4.7 also performs the same decomposition for other years. As Figure 4.6 showed, there is some net decoupling in some periods, especially in the Labour years of 1997-2010, although it is still very small compared to the headline gross decoupling figures. Net decoupling takes its maximum value in 2007. In this year gross decoupling was 40.6% and net decoupling was 8.1%. Inequality contributed 14.4% and benefits 11.8% so they were still both more important.

Looking over the sample period, as noted above there are times when compensation has outstripped productivity growth. From 1990 inequality started to make an important contribution to gross decoupling and "benefits" became much more important from the mid-nineties, although they have always made a contribution throughout the last 40 years.

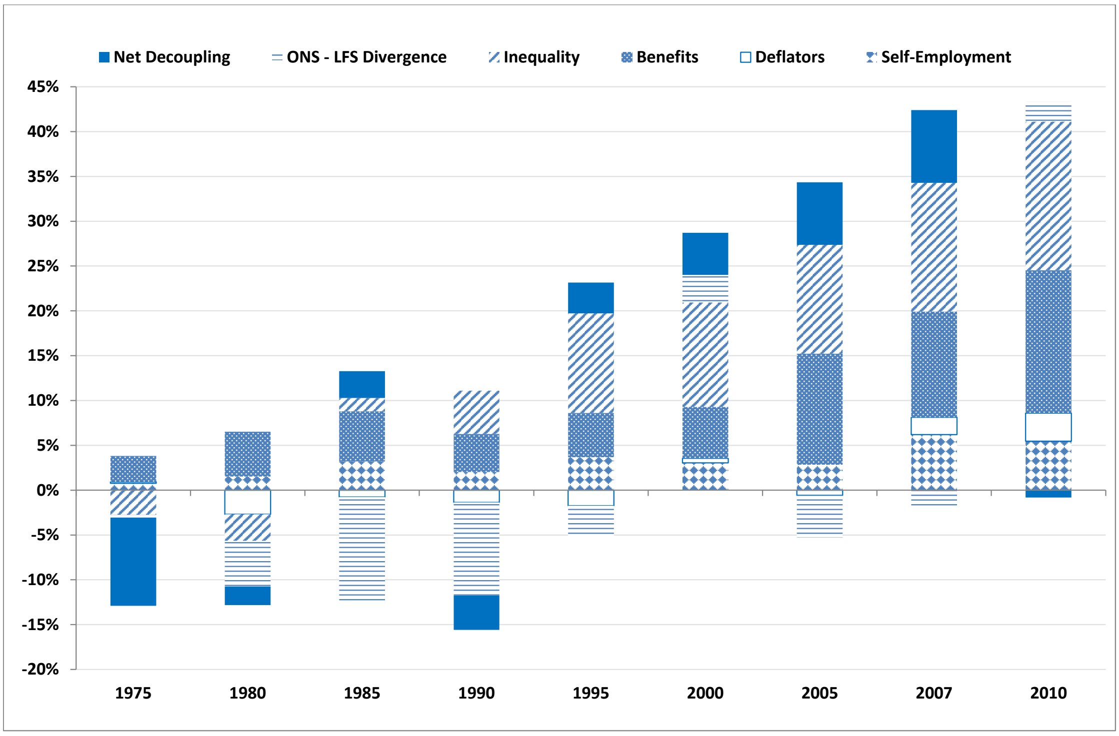



Figure 4.7: Decoupling Decomposition in the UK

Sources: GHS/LFS Survey, OECD, HM Treasury, and ONS.

### 4.3.5 Weekly and Annual Measures of productivity and wages

Figure 4.8 summarizes the decoupling analysis in the UK in terms of compensation and labour productivity per worker, and weekly earnings. As a measure of labour productivity we use GDP divided by the total number of employed individuals (including self-employed). Once more, the analysis here is robust to the hypothesis that employees and self-employed earn on average the same amount. Focusing on the net decoupling, i.e., the difference between labour compensation and labour productivity, Figure 4.8 is a lot like Figure 4.6, with the excepetion that LFS figures seem a bit overstaded when compared to the ONS ones.

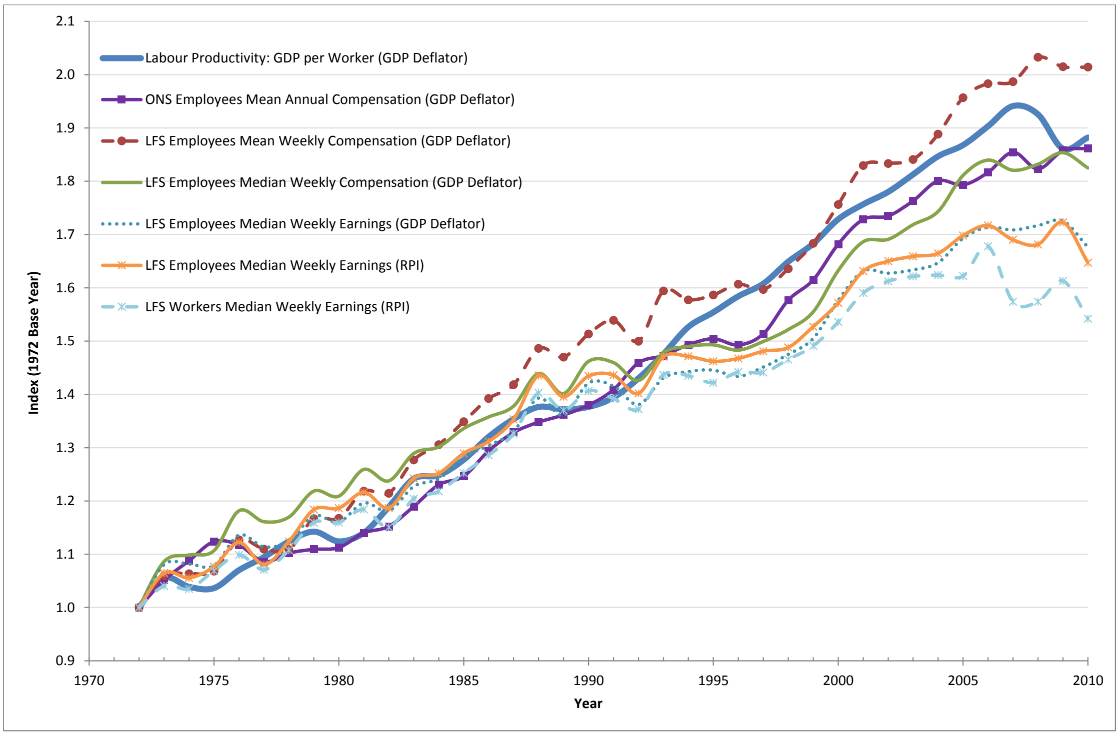



Figure 4.8: Weekly/Annual Decoupling in the UK

Sources: GHS/LFS, OECD, HM Treasury and ONS. “Workers” includes both Employees and Self-Employed.

### 4.3.6 Summary on UK Decoupling

The data tell a pretty straightforward story. Over the 1972 to 2010 period compensation and productivity grew as the same rate – a factor of 2.14 compared to 1972. There was no net decoupling as economists would generally think of it. Although the series diverge over some periods, the consistency is striking, no matter how these are measured (in hours compared to weeks; in value added or GDP).

On the other hand a large wedge did open up between the growth of median wages and productivity (gross decoupling). The main reason for this is (i) the growth of inequality which causes the mean compensation to grow faster than the median and (ii) the faster growth of compensation (which includes non-pay benefits like pensions and healthcare) compared to wages. The first reason is expected given the extensive empirical literature about the subject, the second is more surprising. Van Reenen (2011) shows how the inequality is evolving in the UK. Inequality is rising since the early eighties, but the "lower tail" inequality (comparing the $50^{\text{th}}$ percentile gains with the $10^{\text{th}}$ percentile ones) stabilised in the 2000s while the upper tail inequality (comparing the $90^{\text{th}}$ percentile gains with the $50^{\text{th}}$ percentile ones) continued to grow during this period. These facts support the findings of this section, showing that the mean-median inequality has risen since the eighties with significant increases both in the nineties and in the last decade.

## 4.4 Macro Analysis of Decoupling in the US

### 4.4.1 Data Sources in the US

As in the UK case, we use more than one data source to compute workers' wages and compensation. The first database is from the Bureau of Economic Analysis (BEA) who has information on wages and compensation in order to compute the National Income and Products Account (NIPA) tables. This is the equivalent of our ONS measures.

The second database is the Current Population Survey (CPS) March supplement, which is the US equivalent of the LFS survey. It is a survey conducted by the Bureau of Labor Statistics (BLS) and the Census Bureau of about 50,000 households per annum representing the civilian non-institutional population. It includes individuals of 16 years and older. Even though the earning computed in this survey does not include some types of compensation included in the NIPA tables, it permits us to analyse self-employed earnings and the median earnings of workers and employees. We also collected information on employment and hours worked from the BLS and the OECD.

As with the UK we obtain measures of labour productivity from the NIPA and OECD and focus on GDP (although we also compare with GVA).

### 4.4.2 Trends in Compensation and Wages in the US

Figure 4.9 plots the growth over time for some annual wage and compensation series and Figure 4.10 does the same for their hourly equivalents. Only the "CPS Workers" series include self-employment. We can observe that the NIPA annual wages are growing slower than the CPS annual employees earnings. In hourly terms, however, the two wage series seem to track each other fairly well.

In contrast with the UK, the self-employed earnings appear to be growing faster than employees in both in hourly and annual terms. We also observe a lot of noise in the CPS hourly earnings series that includes the self-employed. Note that, as in the UK, compensation is growing faster than the wage series in general.

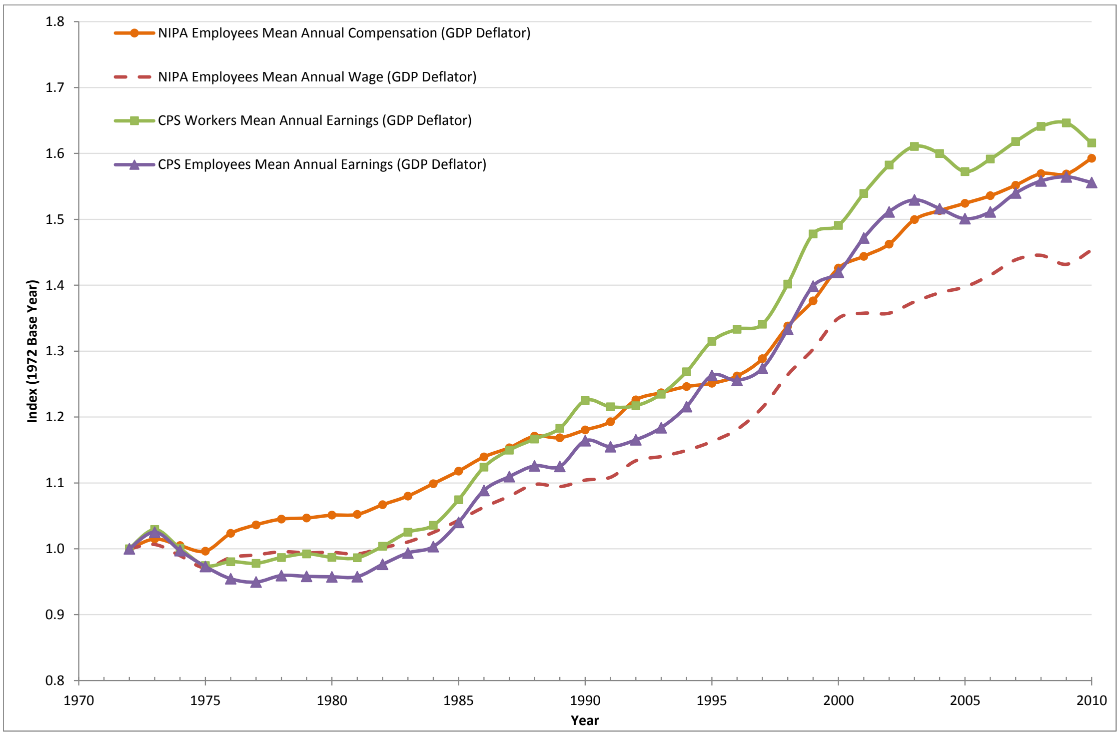



Figure 4.9: Real Mean Annual Earnings in the US

Sources: BEA, OECD and CPS Survey. “Workers” includes both Employees and Self-Employed.

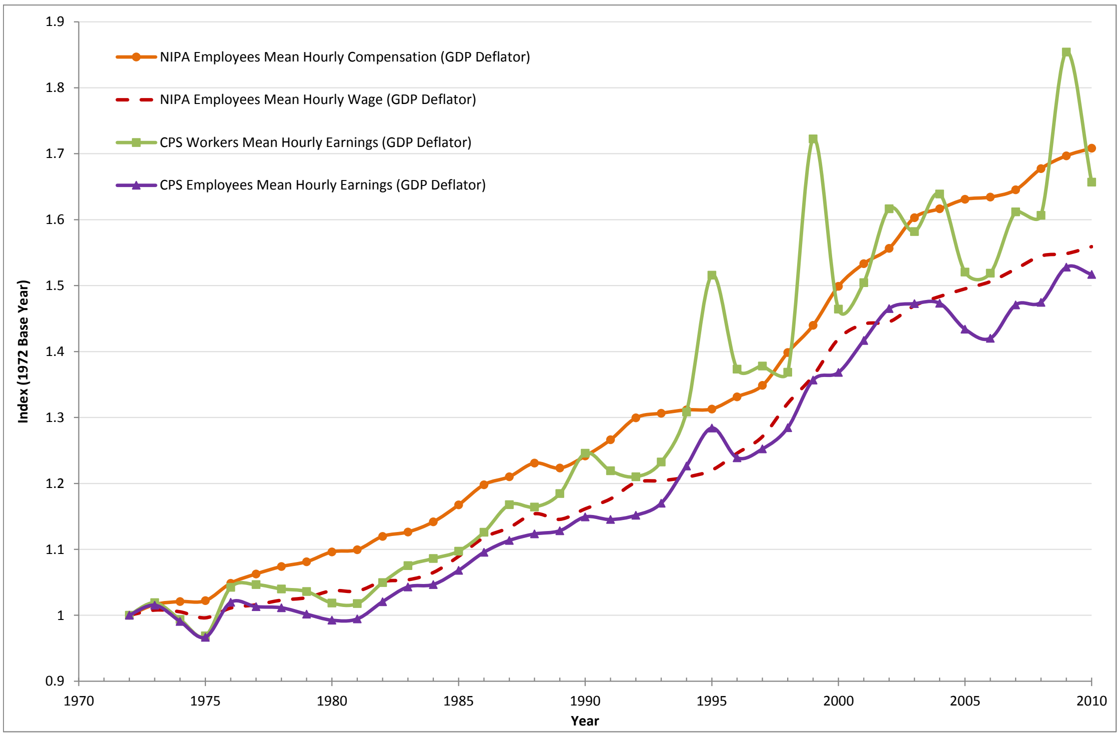



Figure 4.10: Real Mean Hourly Earnings in the US

Sources: BEA, OECD and CPS Survey. "Workers" includes both Employees and Self-Employed.

### 4.4.3 Labour Productivity Trends in the US

Figure 4.11 plots out productivity measured in per hour terms and per worker terms. As with the UK the hourly-based measure has grown faster than the per worker measure, which again reflects falls in average hours worked (although this is less marked in the US than in the UK). GDP per hour has risen by a factor of 1.84 since 1972, less than the UK's productivity growth. This reflects some catch-up growth of the UK with the US (although UK productivity levels remain well below those of the US even by the end of the sample).

We can see in Figure 4.11 that GDP per Hour and GVA per hour have a similar growth, apart from some minor divergence that starts in the late eighties and ends in the late nineties. As in the UK case, the correlation between GVA and GDP is extremely high (approximately 0.99)

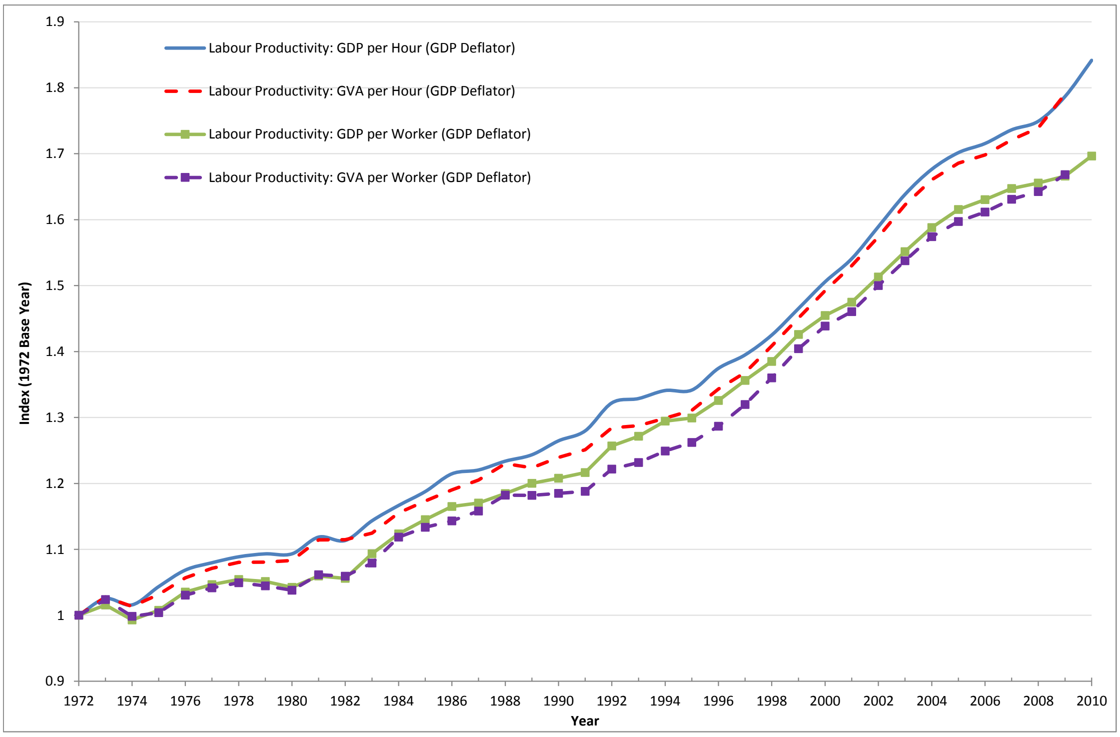



Figure 4.11: Labour Productivity in the US

Sources: BEA and OECD.

### 4.4.4 Decoupling between Hourly Productivity and Compensation in the US

The measures we use are analogous to the ones used in the previous section. In Figure 4.12 labour productivity is measured as GDP per hour and we use hourly compensation. Both are deflated by the GDP deflator. There is some evidence of net decoupling throughout the period especially during cyclical upswings (as in the UK). Unlike the UK, however, the faster growth of productivity during the 2000s has not been fully reversed by the Great Recession.

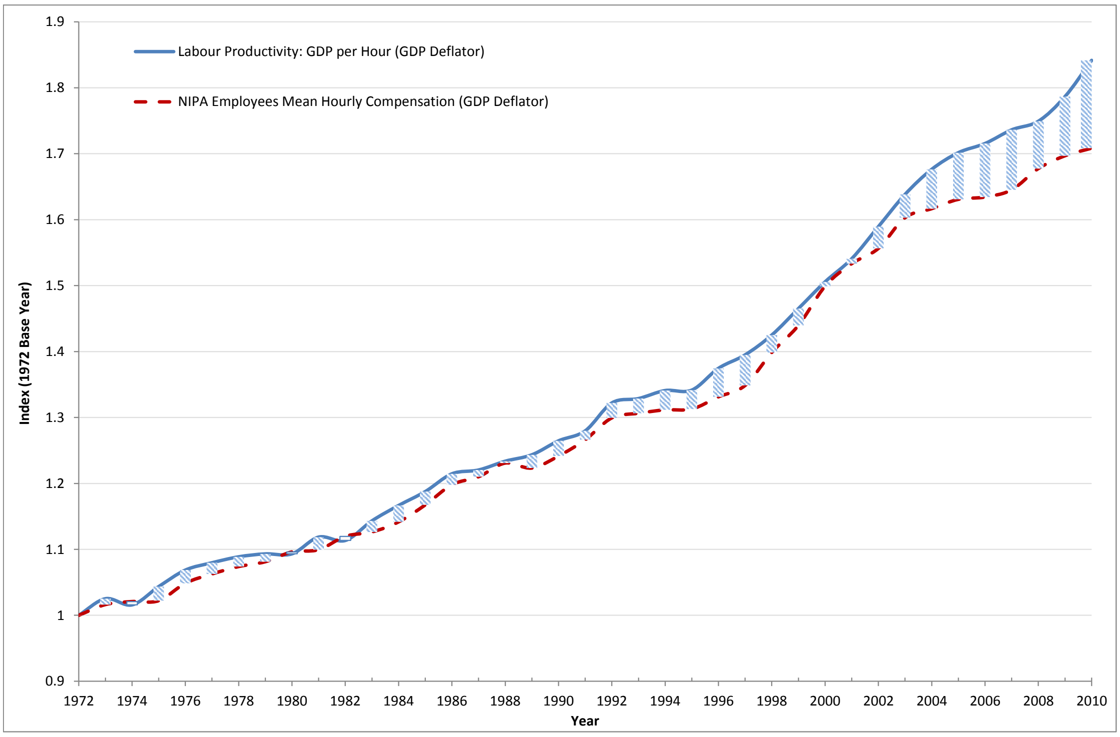



Figure 4.12: Hourly Net Decoupling in the US

Sources: BEA and OECD.

In Figure 4.13 we add five other wage series: NIPA mean wages, CPS mean employees' wages (deflated both by the GDP deflator and by the CPI-U-RS), CPS median wages (deflated by the CPI-U-RS) and CPS median workers' wages (deflated by the CPI-U-RS). It is clear that gross decoupling is much more dramatic in the US than in the UK. The gap between productivity and median wages is about 63% compared to only 42% in the UK over the 1972-2010 period as a whole[8].

[8] Similar to the UK analysis, our CPS compensation measure is constructed assuming that the growth in benefits is proportional to the one observed in the NIPA series, i.e., we multiply the CPS earnings by a factor equals to the ratio of NIPA compensation to NIPA wages. This approach is similar to the one used in Mishel and Gee (2012).

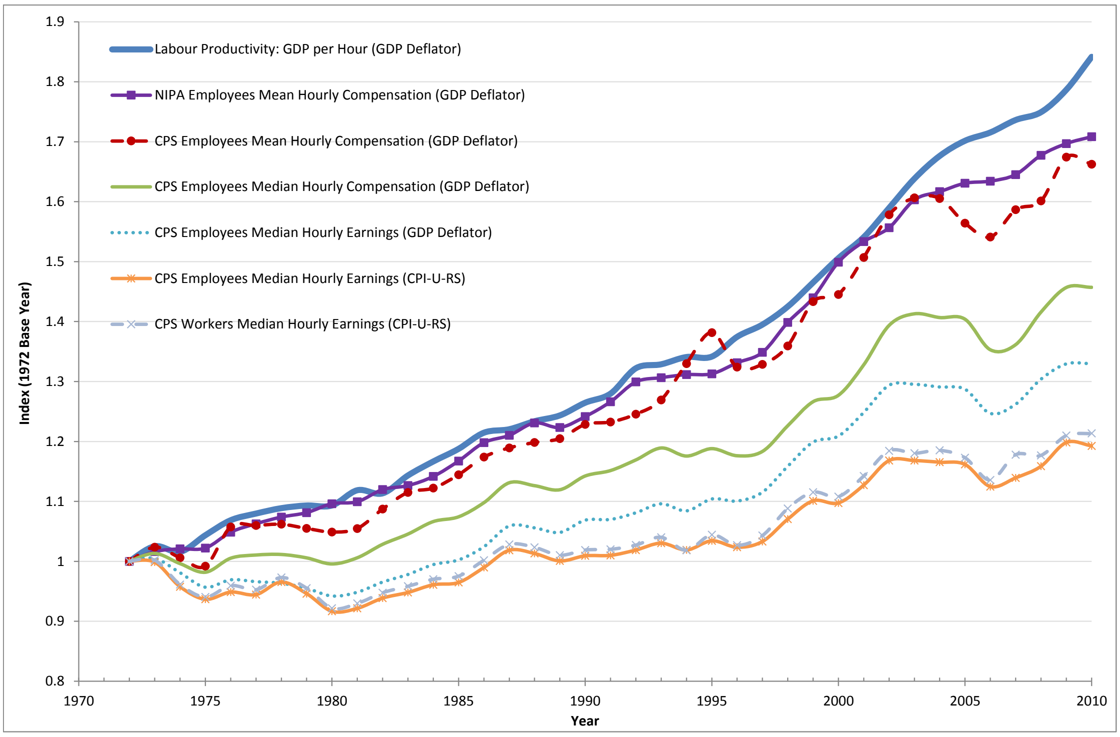



Figure 4.13: Hourly Decoupling in the US

Sources: BEA, OECD, CPS Survey and BLS. “Workers” includes both Employees and Self-Employed.

Looking at the cumulative change as indicated by where the lines finish, it is clear that the net decoupling in Figure 4.13 is pretty small compared to the overall change: only 13.3 percentage points relative to the 63% change. Just as with the UK, “benefits” (the difference between compensation and wages) and “inequality” (the difference between mean and median wages) are large components of the difference. Unlike the UK, however, the difference between the CPI-U-RS and GDP deflator also accounts for a substantial chunk of the difference.

Figure 4.14 decomposes the decoupling. It compares the contribution of each of the components listed to the difference between the labour productivity measure and CPS workers' median hourly earnings (deflated by the CPI-U-RS). Looking at 2010, the second largest component of gross decoupling is the divergence between the two measures of inflation (13.7%). Since this is puzzling and different from the UK we will discuss this explicitly in the next subsection. The first and the third components are inequality and benefits accounting for 20.5% and 12.7%, respectively. This is similar to the UK. The benefit which matters most in the US is health insurance which is generally provided by the employer. There has been substantial cost inflation for health insurance which is a major part of why compensation has risen faster than wages. Net decoupling is more important in the US than in the UK as already mentioned. There is a larger discrepancy between NIPA wages and CPS wages than their equivalents in the UK, contributing to 4.6%. Finally, unlike the UK, the self-employed have had faster income growth which reduces the decoupling.

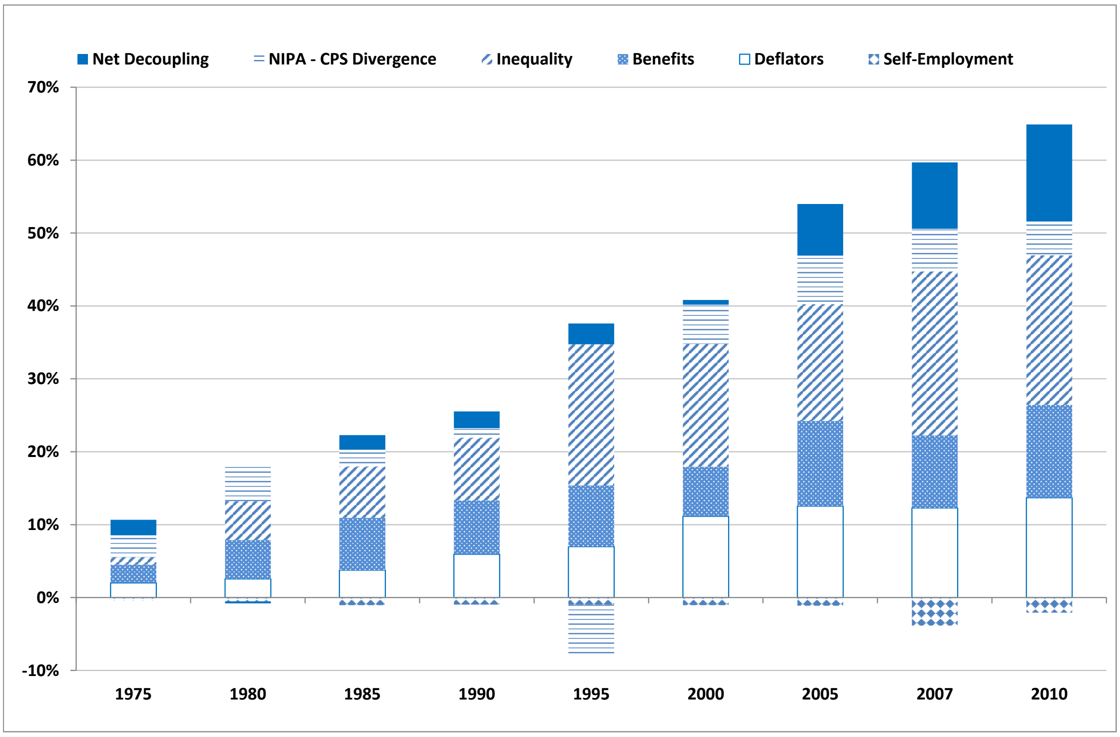



Figure 4.14: Decoupling Decomposition in the US

### 4.4.5 Deflator Discrepancies

In our main analysis in this section we consider the CPI for all urban consumers – research series (or CPI-U-RS). We prefer to use the CPI-U-RS because it incorporates most of the improvements made to the CPI over the last 33 years, i.e., the CPI-U-RS is measured consistently over the entire period while the CPI is not (the CPI historical series would not be adjusted for modifications made from today onwards, for example). Unfortunately, the CPI-U-RS is available only from 1977. So, in our main analysis we actually considered a composition of the CPI and the CPI-URS: we used the former series for the period 1972-1976 and the latter for the post 1976 years.

We also take into account different price deflators in our US analysis as it appears that, in contrast with the UK, different price deflators play an important role here. There are two alternatives to the CPI-U-RS - the non-consistent CPI for all urban consumers (or CPI) series and the Personal Consumption Expenditure (PCE) deflator series.

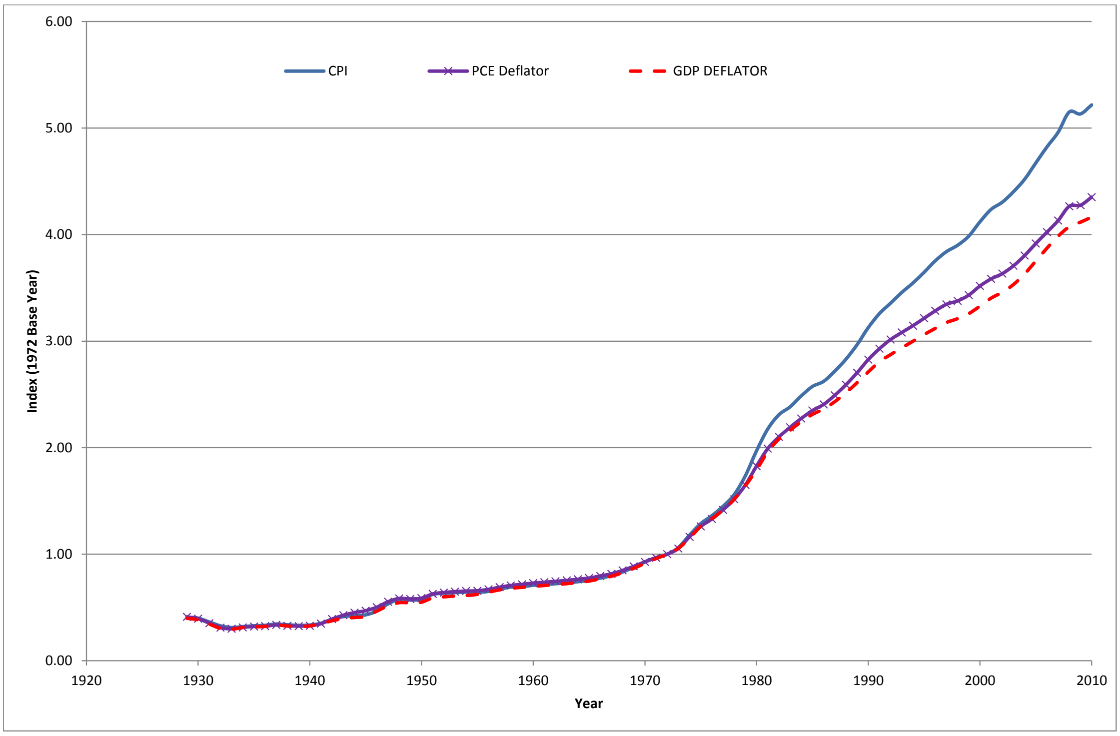



Figure 4.15: GDP Deflator, PCE Deflator and CPI over Time in the US

Sources: BEA and BLS.

In Appendix 4.E we show that using the non-consistent CPI and considering the 1977-2010 period, the gross decoupling is 14 percentage points higher when compared to the one obtained using the CPI-U-RS. In other words gross decoupling after 1977 was 57.2% using the CPI whereas it was only 43.2% using the CPI-U-RS. The difference is simply because the CPI-U-RS has not risen as fast as the CPI and is therefore closer to the GDP deflator (net decoupling was equal to 9.8% and is unchanged of course as this is in terms of the GDP deflator). In terms of a decomposition analogous to the one seen in Figure 4.14, looking at the 1977-2010 period the breakdown of gross decoupling using the CPI was 9.8% due to inequality, 27.5% due to difference in deflators, 7.3% due to the difference in mean compensation vs. mean wages, 3.7% due to the NIPA-CPS divergence and self-employment contributed with -1%

We also show in Appendix 4.E that gross decoupling falls when we consider the PCE deflator during the 1977-2010 period (37.8%). In terms of gross decoupling decomposition, now only 6.5% of the gross decoupling is explained by differences in deflators. The part explained by inequality is 11.5% and the other components do not change relative to the values obtained using the CPI described in the previous paragraph.

It is not completely clear which deflator is best to use. Because we want to look over as long a period in the US as possible to compare with the UK (where we can do this for all years after 1972) we have used a mixed CPI/CPI-U-RS index in the main part of this section, since for the period after 1977 the CPI-U-RS does include many improvements relative to the CPI.

*Explaining the differences between deflators*

As we mentioned previously, the CPI and the CPI-U-RS differ because the latter series is measured consistently over time, incorporating modifications made to the CPI since the late seventies. An example of a methodological difference between the two series is the treatment given to homeowner cost. In 1983 the homeownership component of the CPI was changed from the cost of purchase of a home to a “rental equivalence” approach. The CPI-U-RS incorporates this modification for the pre 1983 years, while the CPI does not. Several modifications like this[9] since 1978 led to significant divergence between the two series, with the CPI rising faster than the CPI-U-RS.

The difference between the CPI and the GDP deflator is more complex. Figure 4.15 below plots the GDP deflator, Personal Consumption Expenditure[10] (PCE) deflator and the Consumer Price Index for all urban consumers (CPI). We can observe that the CPI increases steeply after the late seventies, diverging significantly from the two other series

[9] For a complete list of the improvements to the CPI between 1978 and 1998 see Stewart and Reed (1999).

[10] Personal consumption expenditures (PCE) measures the goods and services purchased by households and by non-profit institutions serving households who are resident in the United States. The implicit PCE deflator is calculated in a similar way to the implicit GDP deflator.

after this same period. This faster growth of the CPI compared to the GDP deflator is also common to other countries – see Figure 4.36 in Appendix 4.E.

There are several papers that try to explain the differences between the three deflators seen below[11]. Here we summarise the possible channels of divergence and indicate which of them might be responsible for such a gap. To understand the difference between the CPI and the GDP deflator we decompose our analysis in two steps. First we explain potential differences between the GDP deflator and the PCE deflator, and then mention the reasons behind the PCE deflator and the CPI differences.

Consumer expenditure and GDP are obviously not exactly equal, but they are similar, with the former accounting for two thirds of the latter. The PCE and the GDP differ because of the composition of the aggregate purchases by consumers relative to the composition of the total GDP. An important source of potential differences between the two measures is that the PCE includes imported goods, while the GDP deflator includes only domestic production. Apparently, the greater weight given to energy in the PCE associated with increased costs of this product since the mid-seventies, account for a significant part of the divergence between the two deflators.

The difference between the CPI and the PCE deflator comes from four main potential sources[12]. First, they have different formulae. The CPI is based on a modified Laspeyres formula, while the PCE is based on a Fisher-Ideal formula (which is a geometric average of the Laspeyres and Paasche price relatives). The major practical difference between the two formulas is the substitution among items as the relative price of those items change. Consumers *tend* to substitute away from products that are increasing in prices, and the Fisher price index better reflects this type of changes.

A second source of divergence is the relative weights assigned to comparable items in the two indexes. The weights are different because they are not based on the same data source. For example, Bosworth (2010) points out that the CPI final weight on housing is considerably higher than that of the PCE deflator. Additionally, he highlights that different weights to housing and energy, whose prices have risen faster than average, account for a significant part of the divergence observed in the last decade.

Third, there are differences in the scope of the two measures. A significant example regards medical care. The CPI includes only medical expenses actually paid by individuals. On the other hand, the PCE includes medical expenses paid by third parties (public and private insurers) on behalf of individuals.

A final potential source of divergence regards different methodologies for computing

[11] See Triplett (1981); Fixler and Jaditz (2002); McCully et al. (2007); Bosworth (2010).
[12] There are other sources not mentioned here – for example, seasonal adjustment.

price changes, especially for owner-occupied housing. Triplett (1981) finds that different approaches for estimating owners' equivalent rent accounts for approximately 65% of the cumulative difference between the CPI and the PCE deflator from 1972 until 1980 (the weighting effect is also responsible for a significant 30% chunk).

In sum, the many potential sources of divergence (formula, weight, scope and price changes) between the CPI and the PCE deflator makes it difficult to elect a main responsible for the pattern observed in Figure 4.15. Fixler and Jaditz (2002) reach a similar conclusion in a more detailed analysis considering a five year period in the mid-nineties (1992-97). They attribute most part of the difference between the PCE deflator and the CPI to formula and price change effects, but highlight that "... there is no "smoking gun" that accounts for the entire discrepancy between the two indexes."

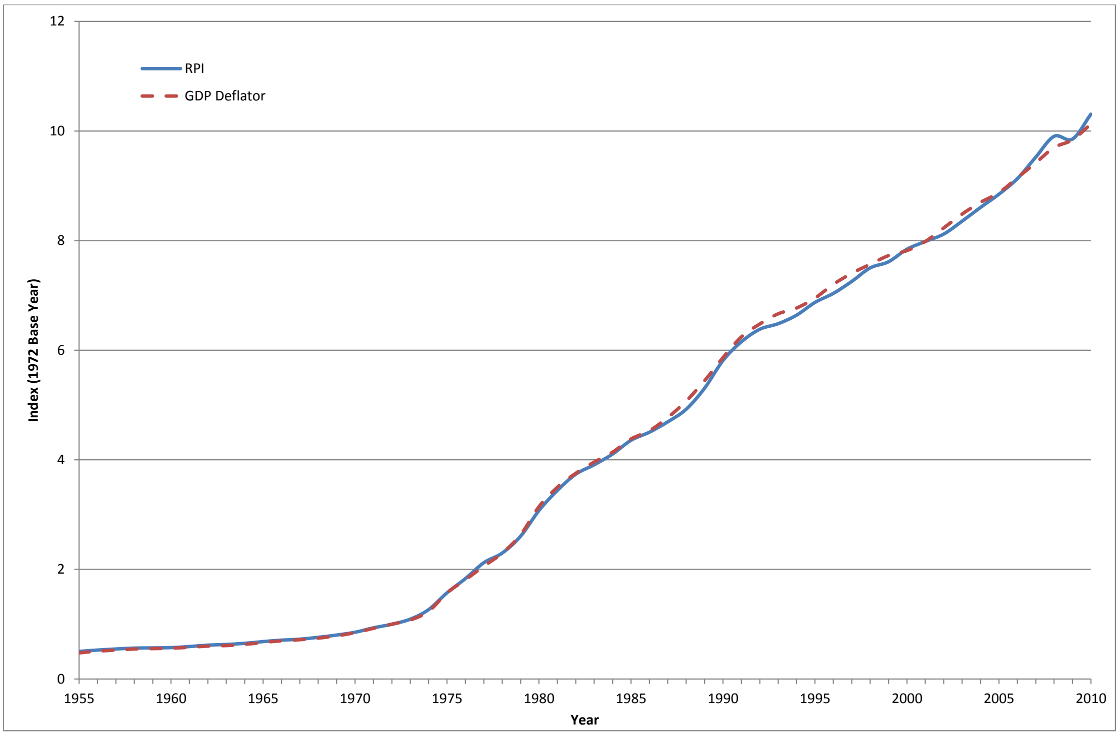



Figure 4.16: GDP Deflator and RPI over Time in the UK

Sources: ONS and HM Treasury.

*UK Deflators*

For the sake of comparison we also put in the UK numbers since 1955. There is no CPI equivalent inflation measure available in the UK before 1988, but we show in Appendix 4.E that the CPI grew at slower rate compared to the above two deflators in the period available for analysis. Hence, we plot the Retail Price Index (RPI) against the GDP deflator. Figure 4.16 shows that the two inflation measures are not exactly equal, but the divergence between them is trivial.

### 4.4.6 Annual Measures of Productivity and Wages in the US

In contrast to the UK case, with the US data it is possible to compute all measures in annual (or per worker) terms so we present these in Figure 4.17. Labour productivity is measured as GDP per worker. The decoupling characteristics are relatively similar to the ones presented earlier, but we can observe that the CPS measures are growing faster relatively to the NIPA ones.

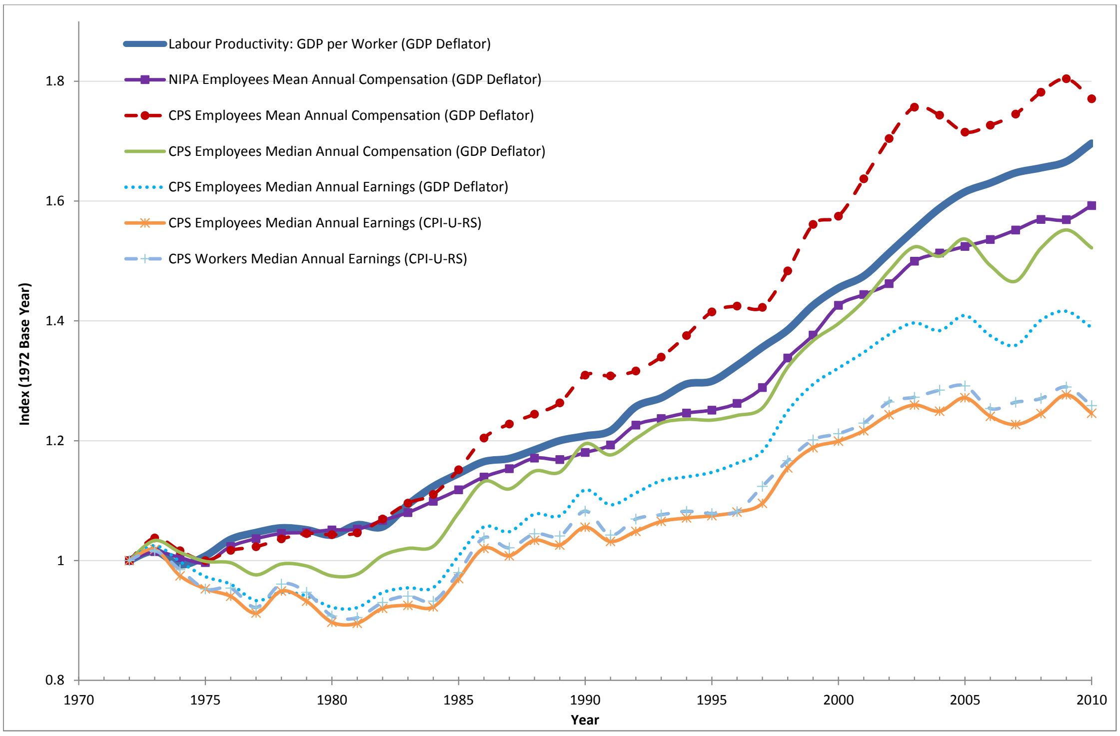



Figure 4.17: Annual Decoupling in the US

Sources: BEA, OECD, CPS Survey and BLS. "Workers" includes both Employees and Self-Employed.

### 4.4.7 Summary on US Decoupling

The policy debate on decoupling started in the US. However, like the UK the headline numbers that focus on gross decoupling: the difference between median workers' wages deflated by the CPI and productivity deflated by the GDP deflator. This gross decoupling appears to be 1.5 times the size of that in the UK (approximately 63% vs. 42%). However, only about 13% is due to net decoupling: the difference between compensation and labour productivity using common deflators. Much of gross decoupling in the US is driven by increases in inequality and the growing wedge between compensation (which includes employer provided health and pension benefits) and wages (which do not). These account for approximately 33% of the gross decoupling. Unlike the UK, however, the wedge between the CPI-U-RS and GDP price deflator accounts for a great part of gross decoupling, approximately 12.7%, a phenomenon that requires deeper investigation. Part of this seems to be due to discrepancies in the measures of consumer price inflation used. If we use the PCE deflator then the contribution of deflator differences falls from 12.7% to 5.7%. On the other hand, If we use the non-consistent version of the CPI the contribution of deflator differences rises to 26.8%.So differences in deflators can account for between 5.7% to 26.8% of the difference between net and gross decoupling in the US – quite a large range[13]. Given the problems of comparability of the CPI over time we would tend to guess that the deflator difference is more towards the bottom of this range and therefore the US looks more like the UK.

## 4.5 Trends in the Labour Share of Income: Evidence from the UK, US and other OECD Countries

Theory predicts that labour productivity should follow average wages (or average compensation) in a given economy. If this is not happening, i.e., if labour productivity is actually decoupling from average compensation, than we should observe a fall in labour income share over time. In this section we investigate if there is any indication of decoupling in some of the major economies of the world by analysing labour income shares.

The OECD computes the labour income share as total labour costs divided by the GVA of the economy, where labour costs include wages, allowances, bonuses, payments in kind, benefits paid by the employer, costs associated with training of the workers, taxes regarded as labour costs, and other labour associated costs. So unlike compensation, payroll taxes (like employer NI in the UK) and training costs are also factored in.

Here we assume that employees and self-employed earn the same on average (in hourly terms). Hence, before computing the labour share we multiply compensation by a factor equals to the total hours worked in the economy divided by hours worked only by employees

[13]Baker (2007) also finds that inequality and inflation are important in explaining differences between wage growth and productivity growth. He claims that the slow growth in productivity after 1973 (when compared to the post war period growth) is one of the main *causes* behind the slow wage growth, i.e., he is implicitly assuming that net decoupling should be always zero (that compensation growth should always reflect productivity growth).

(excluding self-employed)[14]. The OECD measure considers a similar approximation.

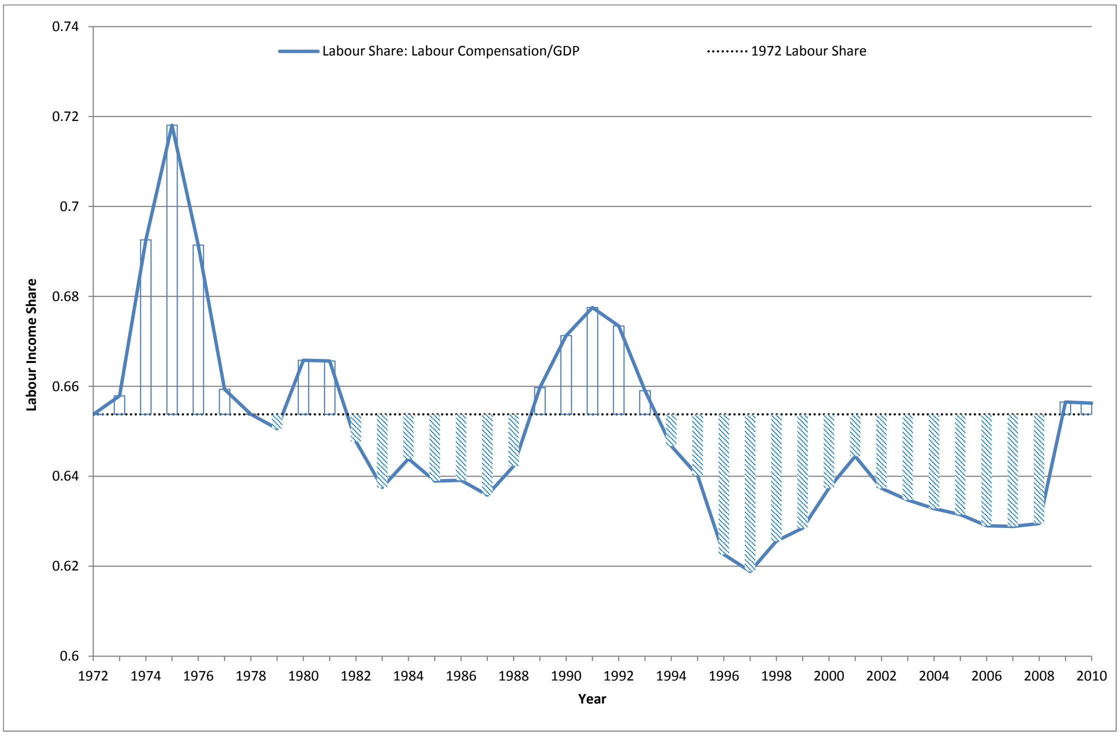



Figure 4.18: Labour Income Share in the UK

Sources: ONS, OECD, and KLEMS. All Measures Adjusted for Self-Employment.

We begin by using compensation. Figure 4.18 plots the UK share of compensation in GDP and Figure 4.19 does the same for the US. Unsurprisingly (since there is an identity between them) these figures show the same information as the compensation and productivity trends. The labour share in the UK in 2010 is essentially identical to that in 1972 at just under two thirds of GDP, although it did fall during the long-boom after 1993. The US share is also around 65% of GDP, although as noted above, the fall in the labour share in the 2000s was not reversed in the Great Recession.

[14] In Appendix 4.F we plot the labour shares for the UK and for the US dropping the self-employed (i.e. assuming they have a wage of zero). This is obviously the wrong thing to do because it is assuming that the self-employed have a zero wage and all their return should be counted as capital (since large numbers of the measured self-employed work as builder on construction sites this is obviously misleading). Since the proportion of self-employed is increasing, this artificially makes it appear as if labour's share is falling.

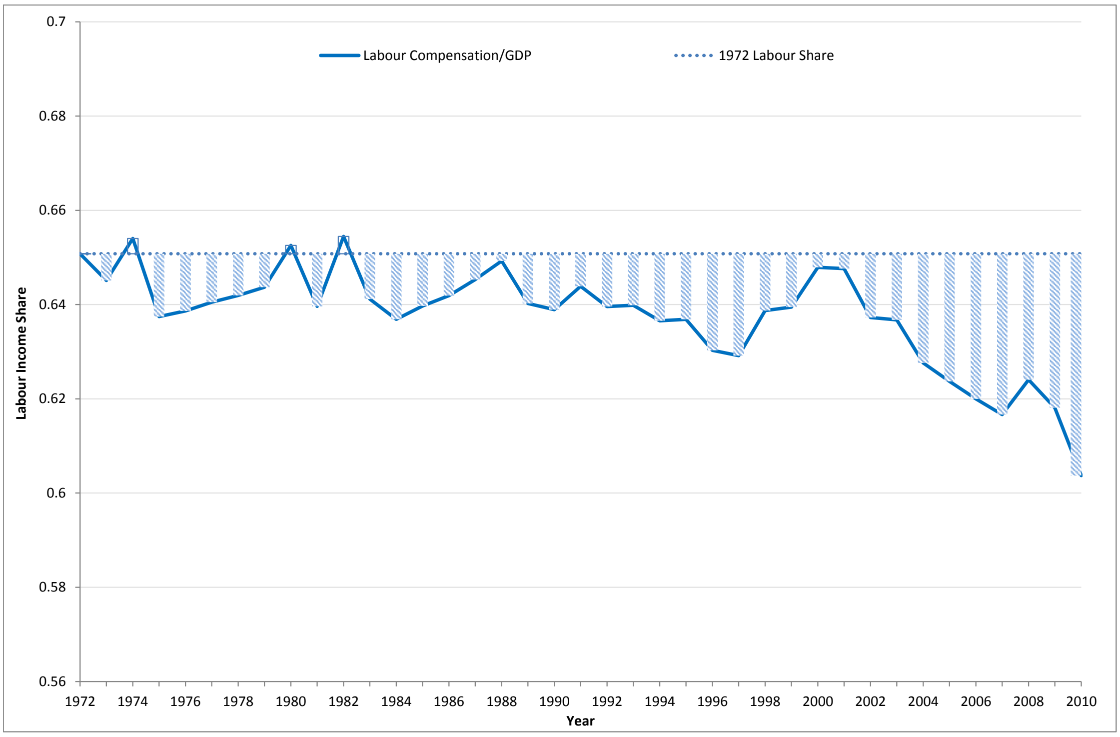



Figure 4.19: Labour Income Share in the US

Sources: BEA and OECD. All Measures Adjusted for Self-Employment.

Figure 4.20 and Figure 4.21 show again the compensation share compared with the wider concept of the labour share in the UK and US. Obviously, since the labour cost share includes more items than compensation (like payroll taxes and training costs) it takes up a larger share of GVA (which is also smaller than the GDP), the difference is not great (e.g. about 70% of GDP rather than 65% for the UK) and the trends are near identical.

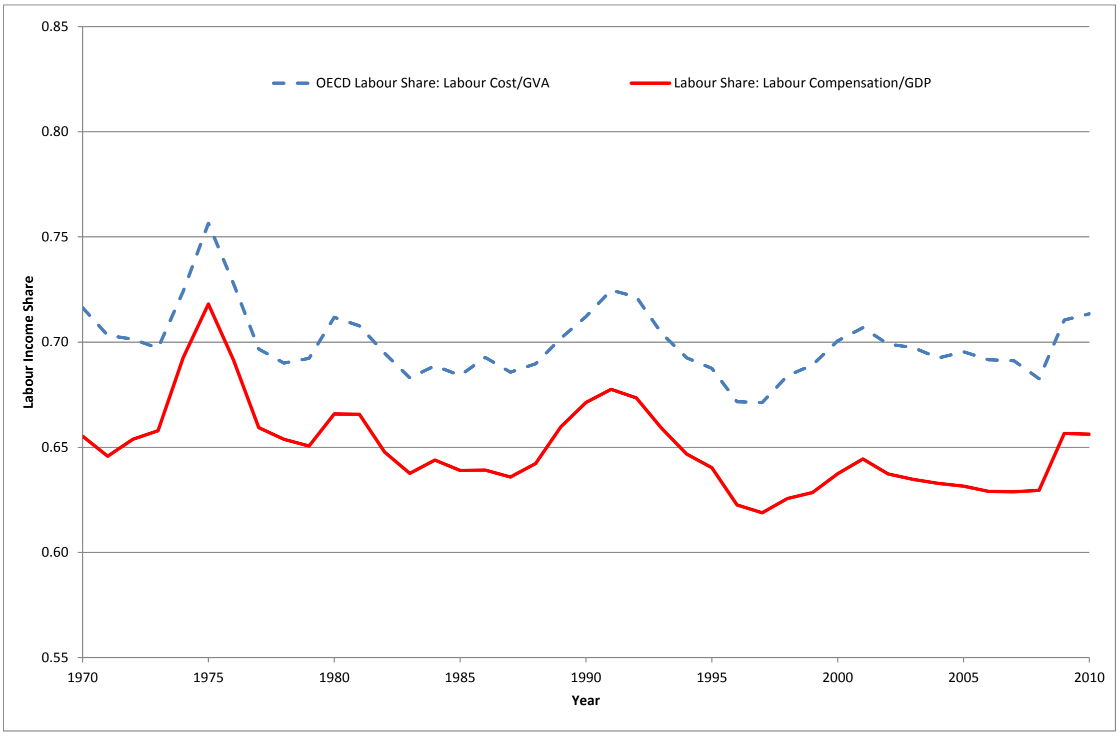



Figure 4.20: Labour Income Share over Time in the UK

Sources: OECD, ONS, and KLEMS. All Measures Adjusted for Self-Employment.

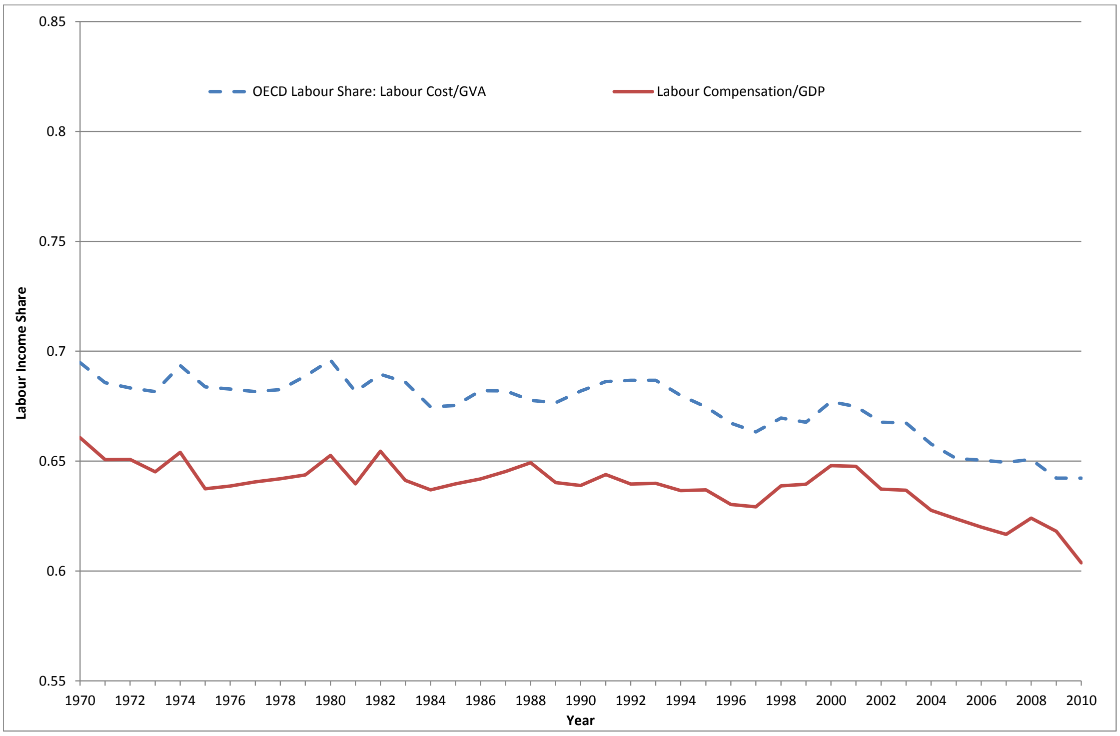



Figure 4.21: Labour Income Share over Time in the US

Sources: OECD and BEA. All Measures Adjusted for Self-Employment.

Figure 4.22 and Figure 4.23 show the labour share for a number of other OECD countries. What is striking is that many of these countries *have* seen substantial falls in labour's share of income, so therefore substantial net decoupling. The German share fell from about 75% in 1975 to 65% in 2006, Japan from 73% in 1975 to 57% in 2006 and France from 80% in 1975 to 67% by the end of the period. Italy saw a fall in labour's share from 80% in 1970 to 67% by 2006. This net decoupling is vastly greater than the changes that have been seen in the US and UK and suggests workers have fared badly in the Continental EU countries and Japan which are usually regarded as being much more worker-friendly. This is not news, of course. The decline of the labour share especially in the Continental EU countries is the source of a considerable (and unsettled) literature (e.g., Azmat et al., 2011; Blanchard and Giavazzi, 2003). Globalisation, decline of worker bargaining power and privatisation have all been seen as possible (multiple) culprits. What is less widely realised is that the UK and US have been relatively immune to these negative trends against the labouring classes as a whole.

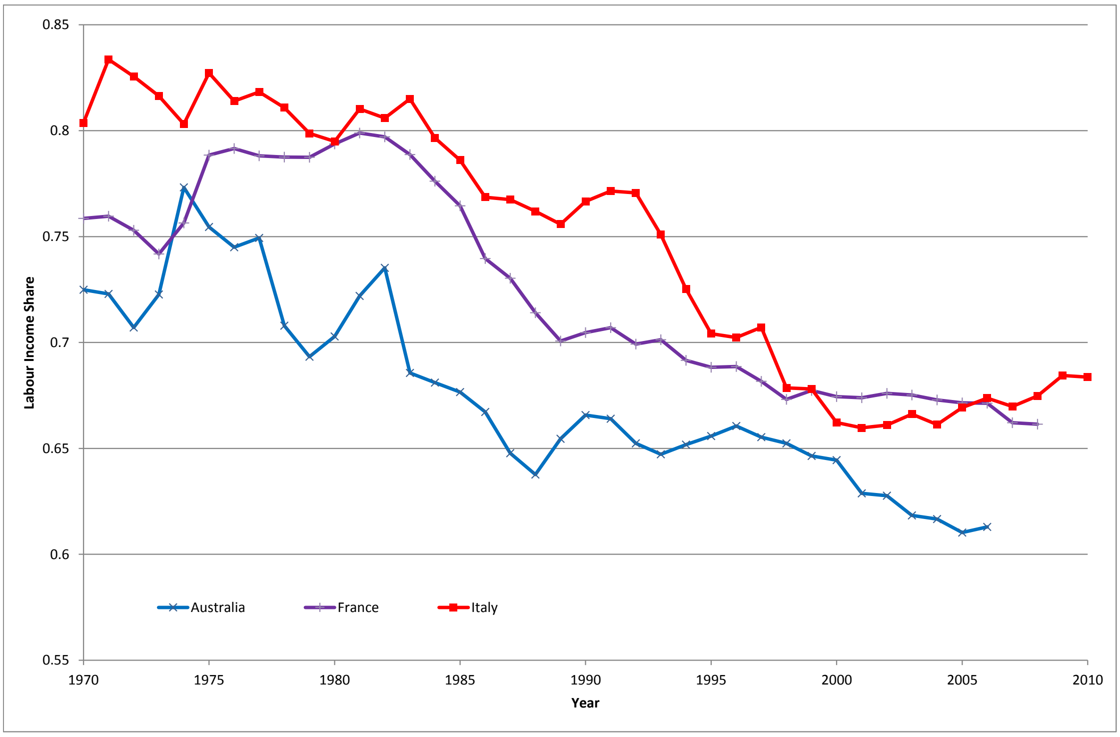



Figure 4.22: Labour Income Share over Time in Australia, France and Italy

Source: OECD. All Measures Adjusted for Self-Employment.

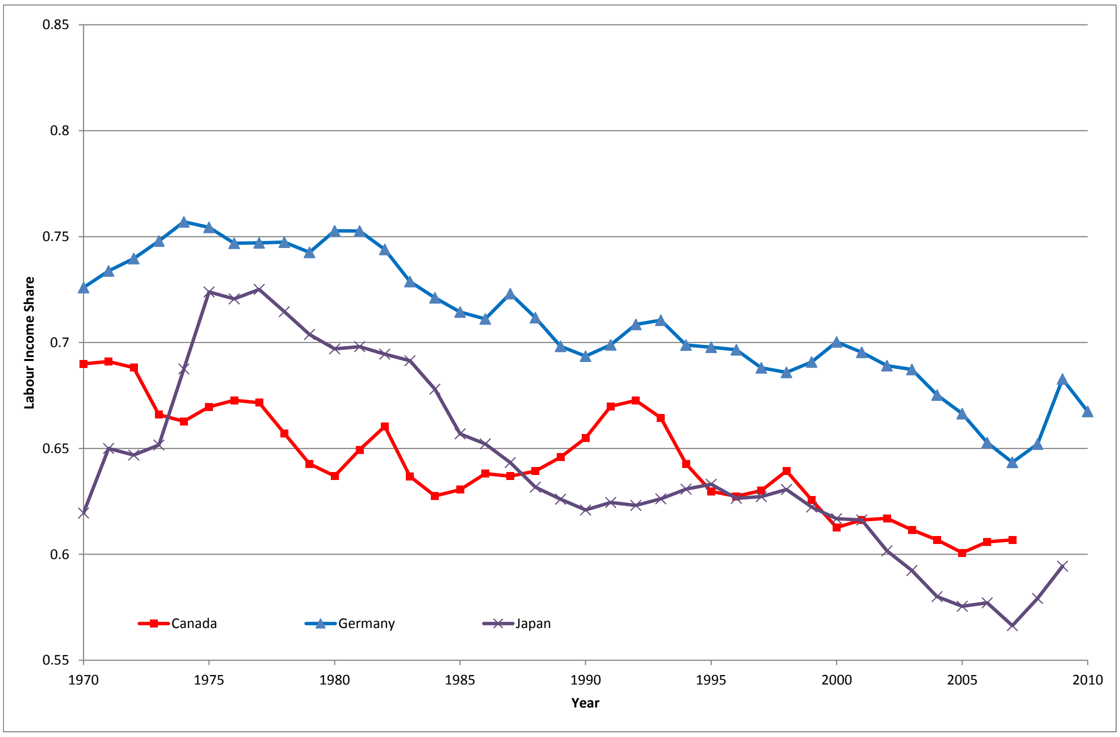



Figure 4.23: Labour Income Share over Time in Canada, Germany and Japan

Source: OECD. All Measures Adjusted for Self-Employment.

## 4.6 Industry- Level Analysis of Decoupling in the UK

We examined some disaggregation of the trends by industry. Of course, there is no reason to expect that compensation growth should match productivity growth at the industry (or firm) level. In the standard economic model workers' wages will depend on aggregate demand and supply, not the productivity of a specific firm or sector. Of course, when there is imperfect competition a positive shock to an industry's (or firm's) productivity might increase wages. But one might expect this to be only a short-run effect.

### 4.6.1 Data

For the "micro" analysis we use the EU KLEMS database. This is the best available internationally comparable database on productivity measures at the industry level. In the UK, the data is available from 1970 to 2007, but we start our analysis from 1972 in order to keep some consistency with the analysis made previously.

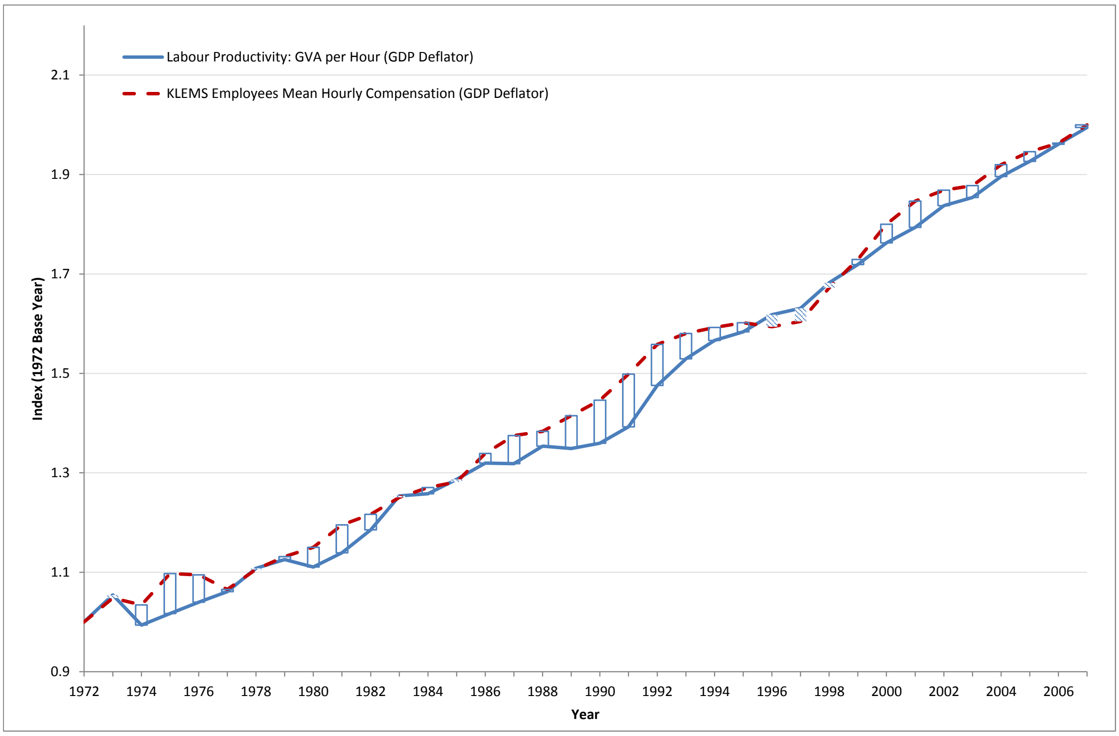



Figure 4.24: Hourly Net Decoupling in the UK considering GVA

Source: KLEMS.

### 4.6.2 Overall Trends

We begin by taking another look at net decoupling using only KLEMS data in Figure 4.24. There is even less net decoupling here than in the ONS data with compensation growth slightly ahead of productivity growth through much of the period and almost exactly equal in 2007. The reason (as noted above) is that KLEMs used gross value added which has grown slightly more slowly than GDP.

### 4.6.3 Changes in the Shares of Sectors

The KLEMS data permits us to separate the economy into two different levels of disaggregation. In a first level, we separate the economy into a Market and a Non-Market Services sectors. The latter includes public services like administration, education, health, and defence; it also includes private education, health and social work, and real estate activities. These are sectors where value added is hard to measure and dominated by public sector services.

The Market sector comprises the rest of the private economy. We separate the Market sector into the following industries:

1. Electrical Machinery, Post and Communication Services – This classification includes electrical and optical equipment, and post and telecommunication services.

2. Goods Producing (excluding electrical machinery) – Includes manufacturing, agriculture, mining, construction, and supply of electricity, gas, and water.

3. Distribution Services - This is associated to retail and wholesale trade, transport, and storage.

4. Financial and Business Services (except real estate) – comprises financial intermediation, renting of mergers and acquisitions, and other business activities.

5. Personal Services – Composed by services like hotels and restaurants, private households with employed persons, and other community, social, and personal services.

Figure 4.25 splits GVA into market and non-market and shows that the non-market sector has increased from 18.3, to 26.4%, much of this is driven by increases in health and real estate.

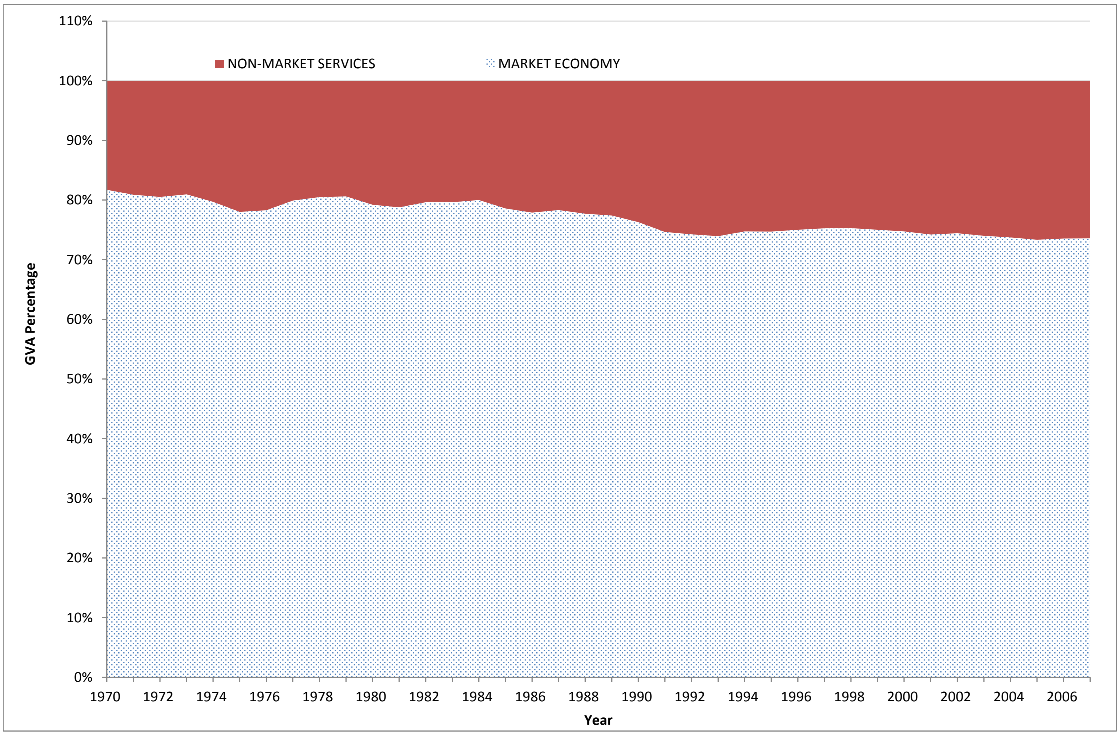



Figure 4.25: GVA Decomposition between Market and Non-Market Economies in the UK

Source: KLEMS.

Looking within the market economy in Figure 4.26, we see that the Financial and Business Services grew considerably along time, going from approximately 11% of the Market economy GVA, to 31% in 2007. In contrast, the Goods Producing sector fell from 55% to 31% during the same period. The Personal Services also increased significantly, changing from 6% to 11% with stability in the other two sectors.

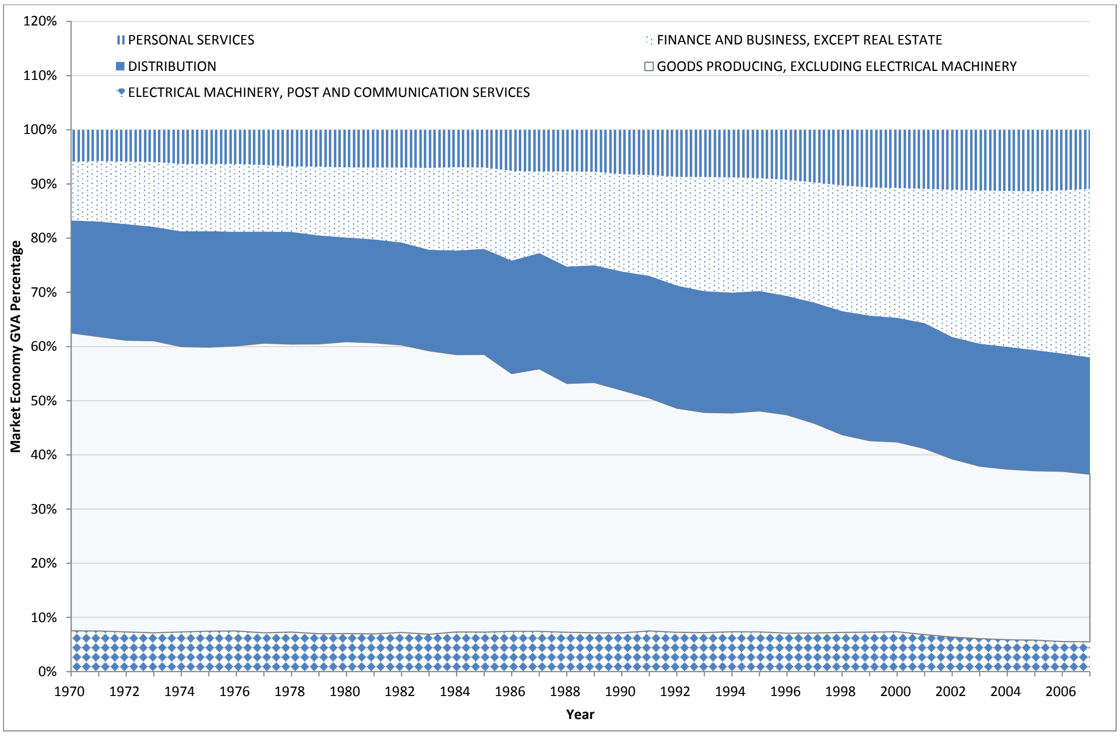



Figure 4.26: Market Economy GVA Decomposition between main Sectors in the UK

Source: KLEMS.

### 4.6.4 Changes within Sectors

Figure 4.27 shows that compensation grew more slowly than productivity in the non-Market services whereas the reverse was true in the market economy. We may doubt the accuracy of value added measures in the non-market sector, but what is remarkable is that in the better-measured market economy there is no sign of decoupling at all – workers compensation appears to outstrip productivity growth

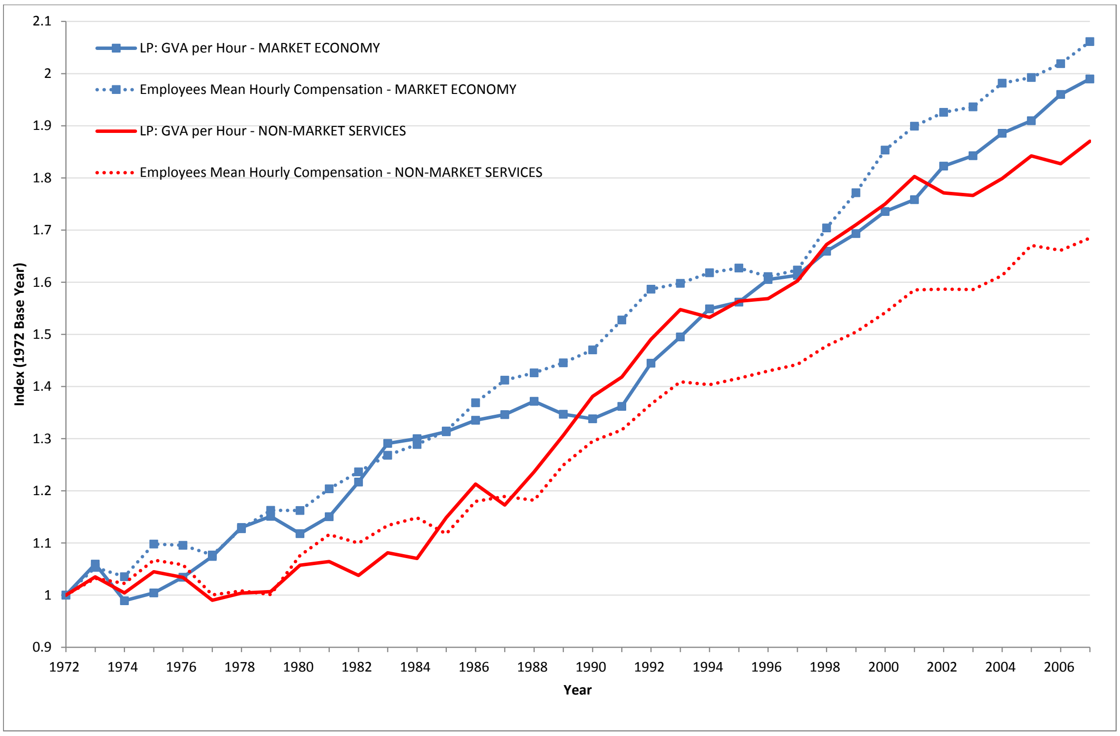



Figure 4.27: Hourly Net Decoupling in the UK considering GVA for Market and Non-Market Economies

Source: KLEMS. All Measures Adjusted for Self-Employment.

Disaggregating the Market economy, Figure 4.28 below shows that labour productivity tracks labour compensation reasonably well in the Goods Producing and in the Electrical Machinery sectors. The same is true for Distribution. In Finance, however, there is some "negative decoupling" in the sense that compensation appears to grow faster than productivity. Personal services (Figure 4.30) are the most extreme example where compensation appears to have grown much faster than productivity. Again, this may be due to measurement issues, although it is worth remembering that this is an important component of total GVA by the end of the sample.

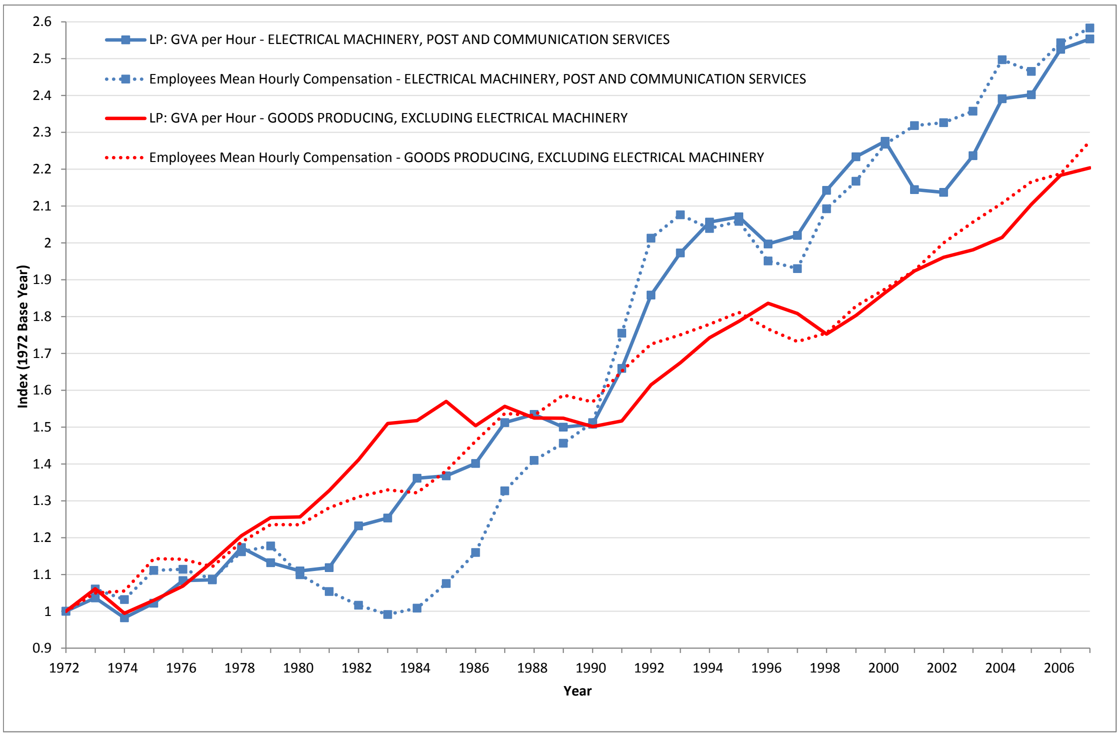



Figure 4.28: Hourly Net Decoupling per Sector in the UK considering the GVA; Production and Services

Source: KLEMS.

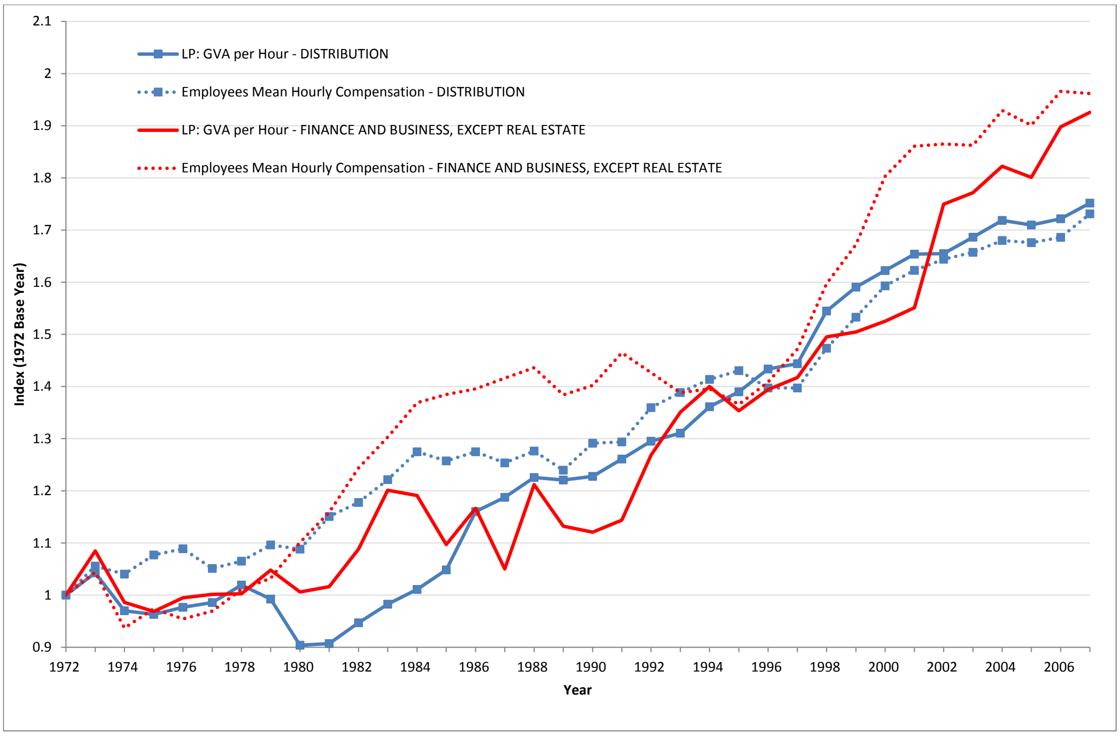



Figure 4.29: Hourly Net Decoupling per Sector in the UK considering the GVA; Services

Source: KLEMS.

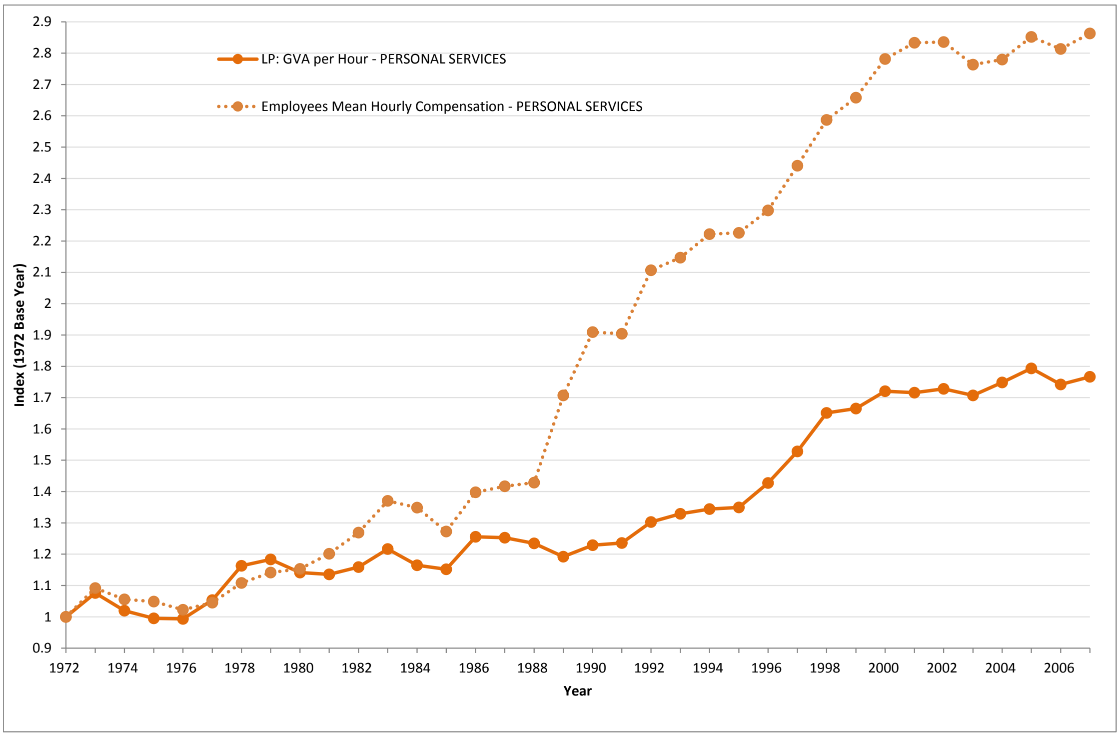



Figure 4.30: Hourly Net Decoupling per Sector in the UK considering the GVA; Personal Services

Source: KLEMS.

### 4.6.5 Summary on industry-specific analysis

Using industry data to obtain a more disaggregated view of decoupling does not give a very clear picture. Overall, using value added per hour as our productivity measure there is no aggregate net decoupling in the UK over the 1972-2007 period, so in one sense there is not much "to explain" when we disaggregate by sector. The only major decoupling we find is in the non-market economy which is dominated by the public sector. In the market economy, compensation appears to have generally growth faster than productivity, especially in personal services and (to a lesser extent) in finance.

It is perhaps unsurprising that there should be less of a clear picture at the industry level than at the national level as noted in the introduction to this section. There is certainly no sign of net decoupling.

## 4.7 Research and Policy Implications

### 4.7.1 Research Implications

The decoupling literature has been more popular in policy circles than in academic research. Perhaps this is because some economists are blinkered and find it hard to understand how net decoupling could be a long-term phenomenon when labour's share of GDP has not changed so much (at least in the US and UK). In fact, we have found that there is not much evidence for net decoupling in the UK or US, so an investigation of the functional distribution of income is unlikely to excite much analysis.

There have been some interesting new puzzles thrown up by our analysis:

1. Why has compensation grown so much faster than wages in the UK and the US?
2. Why in the US have the CPI and GDP deflators diverged so much, whereas they (RPI and CPI) have not in the UK?
3. Why has there been net decoupling in Continental European countries and Japan (but not the UK and US)?
4. ....And the same old question of what has caused the massive increase in inequality between workers?

### 4.7.2 Policy Implications

If (net) decoupling were a major fact in the UK (or US) it would lead to a concern that the shares of economic growth are not going to workers. This may not matter if shares were evenly distributed, but that is not the case. Assets are distributed even more unequally than wages. However, we have seen that there is not much, if any, net decoupling in the UK.

The fact that we see gross decoupling raises some issues, but of a different sort:

1. The fact that compensation has followed productivity growth over the long run highlights the importance of a growth policy to boost productivity. Reforms supporting productivity will lead to higher compensation which is good for workers (Corry et al., 2011).

2. What can be done about the increase in inequality between workers as indicated by the growing divergence between the mean and the median wage? This is the classic policy issue that has been discussed by economists for the last three decades when the rise in wage inequality first started to be properly documented, showing that inequality is rising since the eighties in the UK with significant increases along the past two decades (although the "lower tail" inequality seems to have stabilised in the 2000s – see Van Reenen, 2011). Dealing with wage (or compensation) inequality is fundamentally about dealing with inequality in the acquisition of human capital. There is a major need in the US and UK to improve education and skills for those in the lower half of the distribution and in the long-term this has to be done through public school (and early years) reform and the school to work transition (e.g. apprenticeships).

3. Is the increasing divergence between wages and compensation a problem? Since this is driven by pensions in the UK, this is an issue of whether the wedge is sufficiently *large* (See the Turner Report). There is evidence that people are not saving enough for retirement and that the current pension regime is unsustainable without significant changes to the generosity of pensions (such as the raising of the retirement age).

4. In the US, a major issue is the cost of healthcare which is outstripping wage inflation by a considerable degree. The issue here is whether the new healthcare act will be sufficient to tackle this problem. At the moment, the Act does not look like it has sufficient cost control elements in it even though it extends entitlements.

## 4.8 Conclusion

This paper seeks to shed some light on a confused debate around decoupling. We have focused on the following question: has the growth of workers' compensation and wages fallen behind the growth of labour productivity in the UK? We start with the growth of GDP per hour (deflated by the GDP deflator) and compare this to (i) the growth of median wages per hour deflated by the CPI (net decoupling) and (ii) the growth of mean compensation per hour (deflated by the GDP deflator).

We find no evidence of net decoupling in the UK over the 1972-2010 period as a whole. There is some evidence of net decoupling in the US of the order of 13% (i.e. productivity grew by 13% more than compensation since 1972), but it is small compared to gross decoupling (about 63%) . This means that workers' compensation and productivity growth have tracked each other fairly well since the seventies in both countries. This is consistent with generally used, simple economic models.

The reason for the confusion in some policy circles is that there certainly has been some "gross decoupling", i.e. median workers' wages (deflated by consumer prices) have been growing more slowly that GDP per hour (deflated by the GDP deflator). In the UK this gross decoupling is 42% and in the US this was 63% (although this falls or rises if different consumer deflators are used such as the PCE deflator or the non-consistent CPI). In the UK the difference between gross and net decoupling is because of increased inequality (mean wages have grown much faster than median wage) and because compensation (which includes non-wage benefits like employer pension contribution) has grown faster than wages. In the US these two factors are also important (health premiums are another big driver of the wedge between wages and compensation) but so is a third: an increased divergence between the consumer and producer price index (this deflator difference can account for between 6 and 27 percentage points of gross decoupling). We introduce a decomposition method to clarify where these differences between gross and net decoupling comes from.

Our conclusion is that the debate around net decoupling in the UK and US is rather a distraction (it is actually more important in Continental Europe and Japan). Obtaining faster productivity growth is a highly desirable policy goal in the current climate of near recession as it will ultimately lead to faster wage growth and consumption. On the other hand, the clear presence of gross decoupling shows that the real issues are inequality within the class of workers, not between workers and firm profits and the challenge of health and retirement benefits.

# Appendix

## 4.A Decoupling Theory

Consider a firm who maximises profits

$$\Pi = PQ - cL - rK.$$

Where P is producer prices, Q is output, c is worker compensation (wages plus employer costs), L is labour, r is the cost of capital and K is capital. Assume also that the firm faces a Cobb-Douglas production function (this can be relaxed).

$$Q = AL^{\alpha}K^{1-\alpha}.$$

Where A is an efficiency parameter. We can allow for imperfect competition in the product market so the firm can have market power by letting the demand curve facing the firm be downward sloping with elasticity $\eta$. This implies that the firm will potentially enjoy a mark-up, $\mu$, which will be falling in the elasticity of demand (perfect competition is when the demand elasticity facing the firm is infinite).

The firm will choose a level of employment by maximising profits given the technological constrains and factor prices it faces. This leads to a first order condition for the demand for labour that can be written as:

$$\frac{c}{P} = \frac{\alpha\mu Q}{L}.$$

Or in logarithmic differences (i.e. a growth rate approximation):

$$\Delta ln(c/P) = \Delta ln(Q/L) + \Delta ln(\alpha) + \Delta ln(\mu).$$

This equation shows the basic forces at work. If the factor bias of technology and consumer preferences does not change (i.e. $\Delta ln(\alpha) = \Delta ln(\mu) = 0$ ), then the growth of compensation deflated by product prices ($\Delta ln(c/P)$) should equal the growth of real productivity ($\Delta ln(Q/L)$).

We define **Net Decoupling** as:

$$ND \equiv \Delta ln(Q/L) - \Delta ln(c/P).$$

Of course, technology and preferences may change in a way that is unfavourable to workers. For example, if firm mark-ups increase because (for example) consumers become less sensitive to price increases then $\Delta ln(\mu) > 0$ and there will be some net decoupling. Behind much of the analysis is the view that firms are enjoying more market power and this is allowing them to gain "excess profits".

**Gross decoupling** is what is usually analysed in the policy literature. It can be defined as

$$GD \equiv \Delta ln(Q/L) - \Delta ln(Medw/CPI).$$

Where $Medw$ is the MEDIAN wage rather than the AVERAGE compensation. $CPI$ is the consumer (rather than producer) price index. There is no theoretical reason to expect the two measures to be the same. In particular there is no reason why we would think GD should be constant over time. A simple way to see the difference is to write:

$$GD - ND = (\Delta ln(c) - \Delta ln(Medc)) + (\Delta ln(Medc) - \Delta ln(Medw)) + (\Delta ln(CPI) - \Delta ln(P))$$

or

$$GD - ND = Inequality + Wage\_wedge + Price\_wedge.$$

The first term (inequality) is the difference between the average compensation and the median one, the second term ("wage wedge") is the difference between compensation and wages and the third term is the difference between the consumer price index and the GDP deflator.

## 4.B Data Sources

Table 4.2: Data Sources

| Source | Name | Description | Country | Modified? | Self-Employed? | Notes | Website |
|---|---|---|---|---|---|---|---|
| ONS | Wages | Basic wages, cost-of-living allowances, and other guaranteed and regularly paid allowances. It also includes:<br>i) enhaced rates of pay for overtime, night work, hazardous circumstances.<br>ii) bonuses and gratuities regularly paid<br>iii) remuneration for time not worked<br>iv) bonuses and gratuities paid (productivity, Christmas, holydays, transport, etc)<br>v) payments in kind (meals, vehicles, provision of workplace creches, etc) | UK | No | No | Definition of this wage measure and the others (ASHE, GHS/LFS and CPS) are similar. Differences between them must be due to sample bias, differences in the way surveys are conducted, Scott's modifications in the surveys, and adjustments made in the ONS/NIPA measures that are not explicit. | http://www.ons.gov.uk/ons/datasets-and-tables/index.html |
| | Compensation | It is equal to Wages plus social contributions (incurred by employers in order to ensure their employees are entitled to social benefits). This latter account includes:<br>vi) employer contribution to statutory social security schemes or to private funded social insurance schemes<br>vii) unfunded employee social benefits paid by employers in the form of: (a) children's, spouse's, family, education or other allowances in respect of dependants; (b) payments made to workers because of illness, accidental injury, maternity leave, etc.; (c) severance payments | UK | No | No | - | |
| | GDP (nominal) | Nominal gross domestic product | UK | No | Yes | - | |
| NIPA | Wages | See ONS description above | US | No | No | Minor differences between ONS and BEA descriptions; not relevant. | http://www.bea.gov/national/nipaweb/SelectTable.asp?Selected=N |
| | Compensation | See ONS description above | US | No | No | Minor differences between ONS and BEA descriptions; not relevant. | |
| | GDP (nominal) | See ONS description above | US | No | Yes | - | |
| OECD | Labour Cost | It is equal to Labour Compensation plus (see NIPA and ONS definitions above):<br>viii) cost of vocational training<br>ix) cost of welfare training (i.e. cost of canteens)<br>x) labour cost not elsewhere classified (i.e. costs of transport of workers, cost of work clothes, cost of recruitment)<br>xi) taxes regarded as labour costs (i.e. taxes on employment or payrolls) | All | No | No | - | http://stats.oecd.org/Index.aspx |
| | GVA (nominal) | GVA is equal to GDP, minus taxes on products (for example, value added tax, alcohol duty), plus subsidies on products. Also excludes FISIM (financial intermediation services indirectly measured). | All | No | Yes | The examples of taxes deducted from the GDP were taken from the ONS website, since the OECD does not clarify tthis point. See: http://www.ons.gov.uk/ons/guide-method/user-guidance/index-of-services-methodology/conceptual-basis/index.html | |
| KLEMS | Compensation | See ONS/NIPA descriptions above | All | No | No | - | http://www.euklems.net/ |
| | GVA (nominal) | See OECD description above | All | No | No | - | |
| ASHE | Earnings | -Defined as "...gross pay before tax, national insurance or other deductions and exclude earnings in kind".<br>-Similar to ONS wages, although it does not include benefits in kind. | UK | No | No | Includes only GB;<br>Different from GHS/LFS and CPS, it is derived from employers' records (not from survey over workers). | Provided by ONS staff |
| GHS/LFS | Earnings | -Similar to ASHE. Also does not include benefits in kind. | UK | Yes | Yes;<br>We separate it when convenient | Part of the time series include all the UK, while part includes only GB. | Available upon request |
| CPS | Earnings | -Similar to GHS/LFS and ASHE. Also does not include benfits in kind.<br>-Defined as: "Money wage or salary income is the total income people receive for work performed as an employee during the income year. This category includes wages, salary, armed forces pay, commissions, tips, piece-rate payments, and cash bonuses earned, before deductions are made for items such as taxes, bonds, pensions, and union dues." | US | Yes | Yes;<br>We separate it when convenient | - | Available upon request |

## 4.C Net Decoupling in Terms of Gross Value Added (GVA)

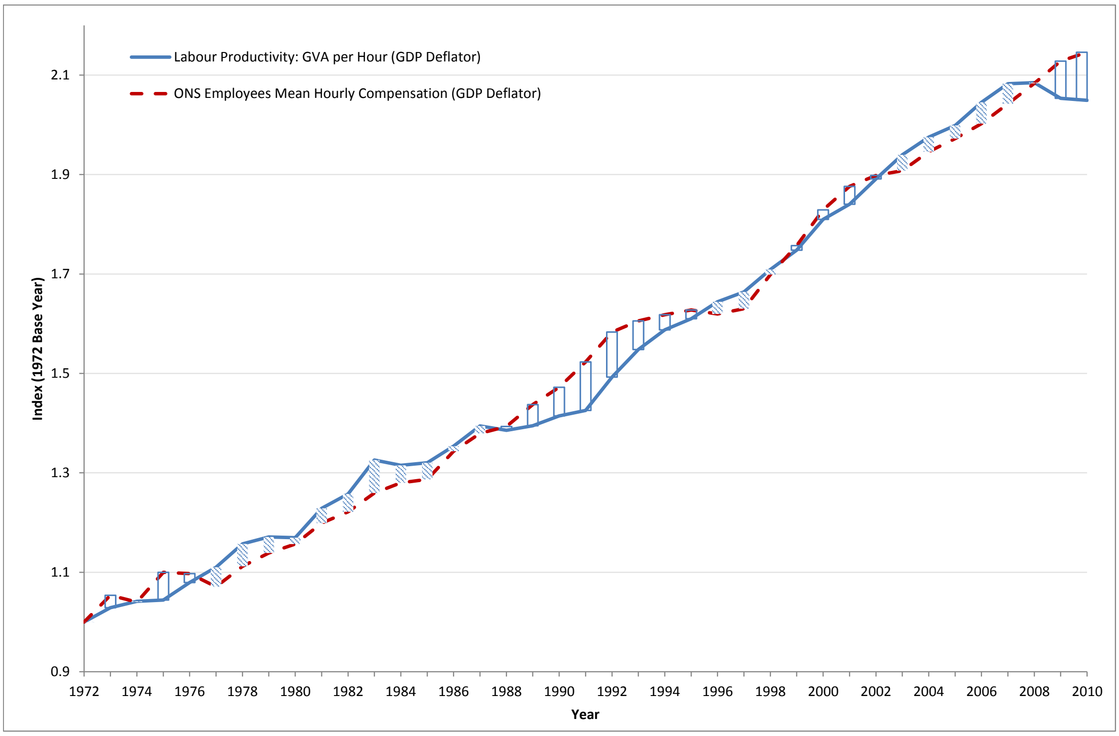



Figure 4.31: Labour Productivity and Labour Compensation per Hour Growth over Time in the UK

Sources: ONS and OECD and KLEMS.

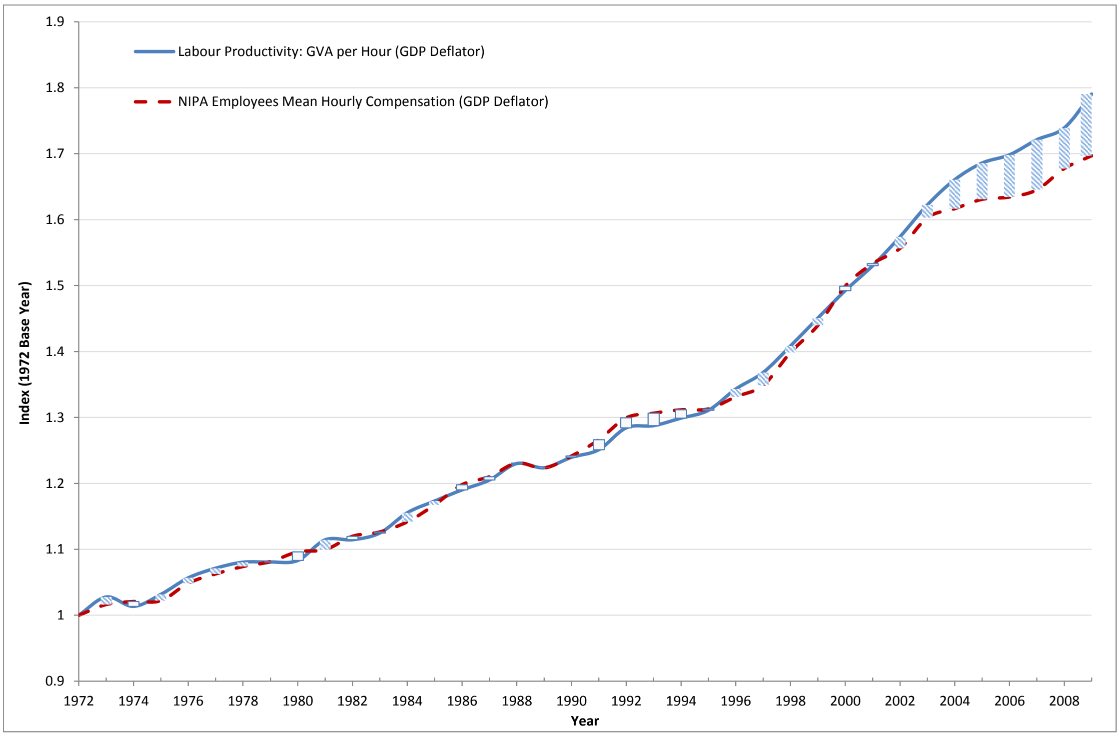



Figure 4.32: Labour Productivity and Labour Compensation per Hour Growth over Time in the US

Sources: BEA and OECD.

## 4.D Decoupling Decomposition Tables

Table 4.3: Decoupling Decomposition in the UK

| Year | Net Decoupling | ONS - LFS Divergence | Inequality | Benefits | Deflators | Self-Employment | Gross Decoupling |
|---|---|---|---|---|---|---|---|
| 1975 | -9.85% | -0.30% | -2.76% | 2.88% | 0.17% | 0.76% | -9.10% |
| 1980 | -2.09% | -5.08% | -2.97% | 4.99% | -2.68% | 1.52% | -6.31% |
| 1985 | 2.98% | -11.83% | 1.49% | 5.59% | -0.75% | 3.21% | 0.69% |
| 1990 | -3.84% | -10.39% | 4.82% | 4.25% | -1.36% | 2.04% | -4.49% |
| 1995 | 3.44% | -3.45% | 11.11% | 4.94% | -1.73% | 3.67% | 17.98% |
| 2000 | 4.70% | 3.07% | 11.65% | 5.74% | 0.51% | 3.03% | 28.71% |
| 2005 | 6.96% | -4.73% | 12.16% | 12.38% | -0.57% | 2.85% | 29.04% |
| 2007 | 8.10% | -1.75% | 14.37% | 11.79% | 1.94% | 6.19% | 40.64% |
| 2010 | -0.81% | 2.20% | 16.57% | 15.95% | 3.12% | 5.47% | 42.51% |

Table 4.4: Decoupling Decomposition in the US

| Year | Net Decoupling | ONS - LFS Divergence | Inequality | Benefits | Deflators | Self-Employment | Gross Decoupling |
|---|---|---|---|---|---|---|---|
| 1975 | -9.85% | -0.30% | -2.76% | 2.88% | 0.17% | 0.76% | -9.10% |
| 1980 | -2.09% | -5.08% | -2.97% | 4.99% | -2.68% | 1.52% | -6.31% |
| 1985 | 2.98% | -11.83% | 1.49% | 5.59% | -0.75% | 3.21% | 0.69% |
| 1990 | -3.84% | -10.39% | 4.82% | 4.25% | -1.36% | 2.04% | -4.49% |
| 1995 | 3.44% | -3.45% | 11.11% | 4.94% | -1.73% | 3.67% | 17.98% |
| 2000 | 4.70% | 3.07% | 11.65% | 5.74% | 0.51% | 3.03% | 28.71% |
| 2005 | 6.96% | -4.73% | 12.16% | 12.38% | -0.57% | 2.85% | 29.04% |
| 2007 | 8.10% | -1.75% | 14.37% | 11.79% | 1.94% | 6.19% | 40.64% |
| 2010 | -0.81% | 2.20% | 16.57% | 15.95% | 3.12% | 5.47% | 42.51% |

## 4.E Inflation

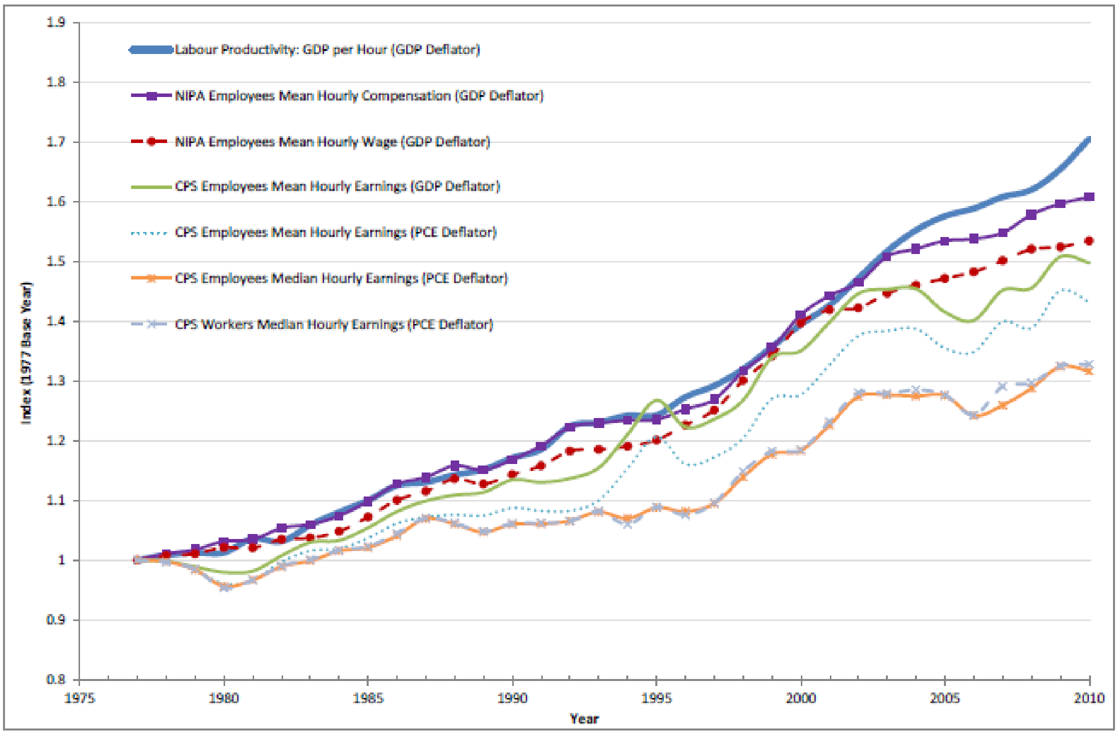



Figure 4.33: Hourly Decoupling in the US after 1977 considering the PCE Deflator

Sources: BEA, OECD, CPS Survey and BLS. “Workers” includes both Employees and Self-Employed.

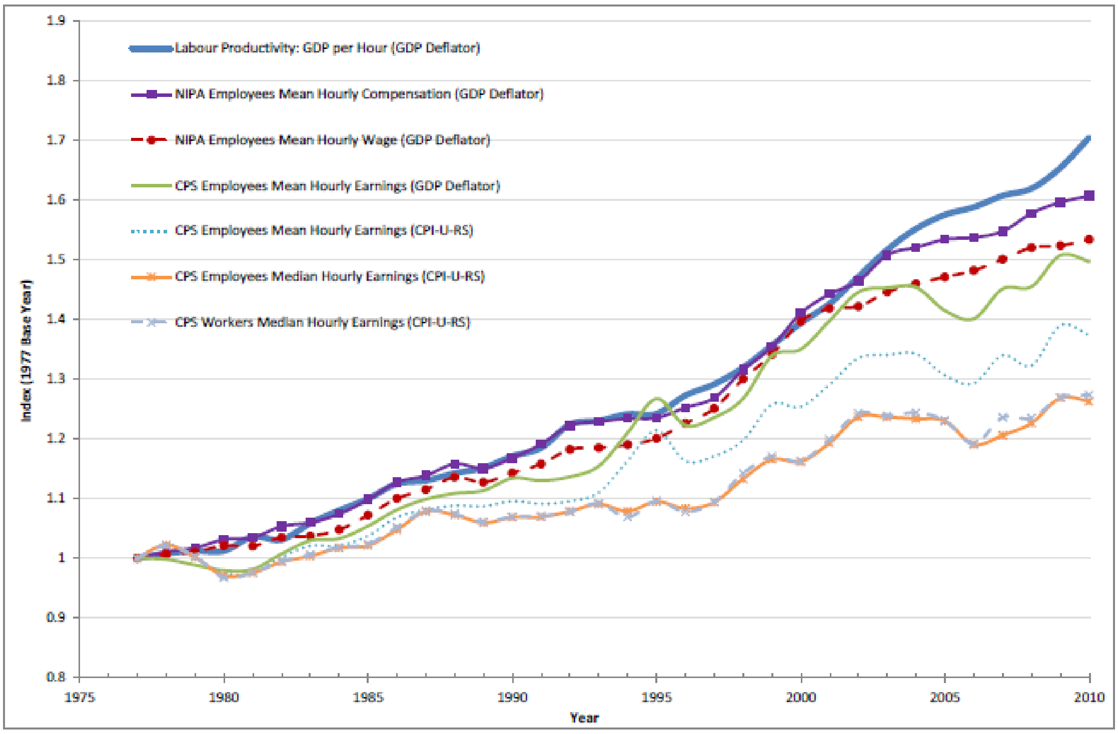



Figure 4.34: Hourly Decoupling in the US after 1977 considering the CPI-U-RS

Sources: BEA, OECD, CPS Survey and BLS. “Workers” includes both Employees and Self-Employed.

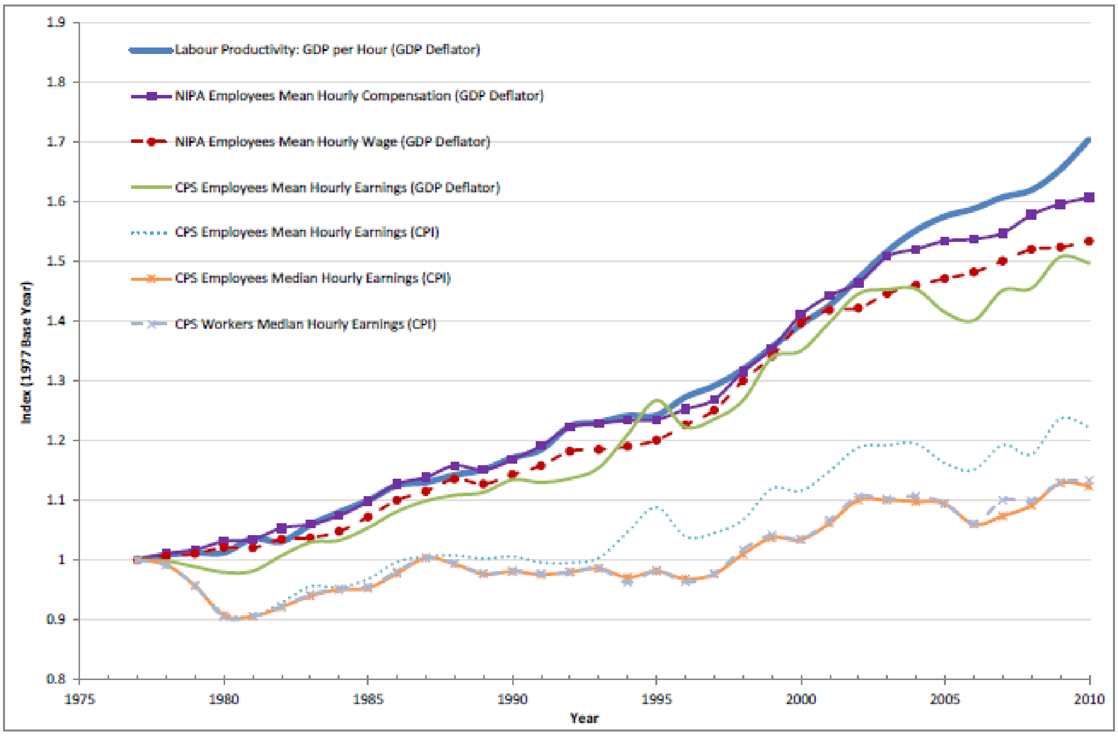



Figure 4.35: Hourly Decoupling in the US after 1977 considering the CPI

Sources: BEA, OECD, CPS Survey and BLS. “Workers” includes both Employees and Self-Employed.

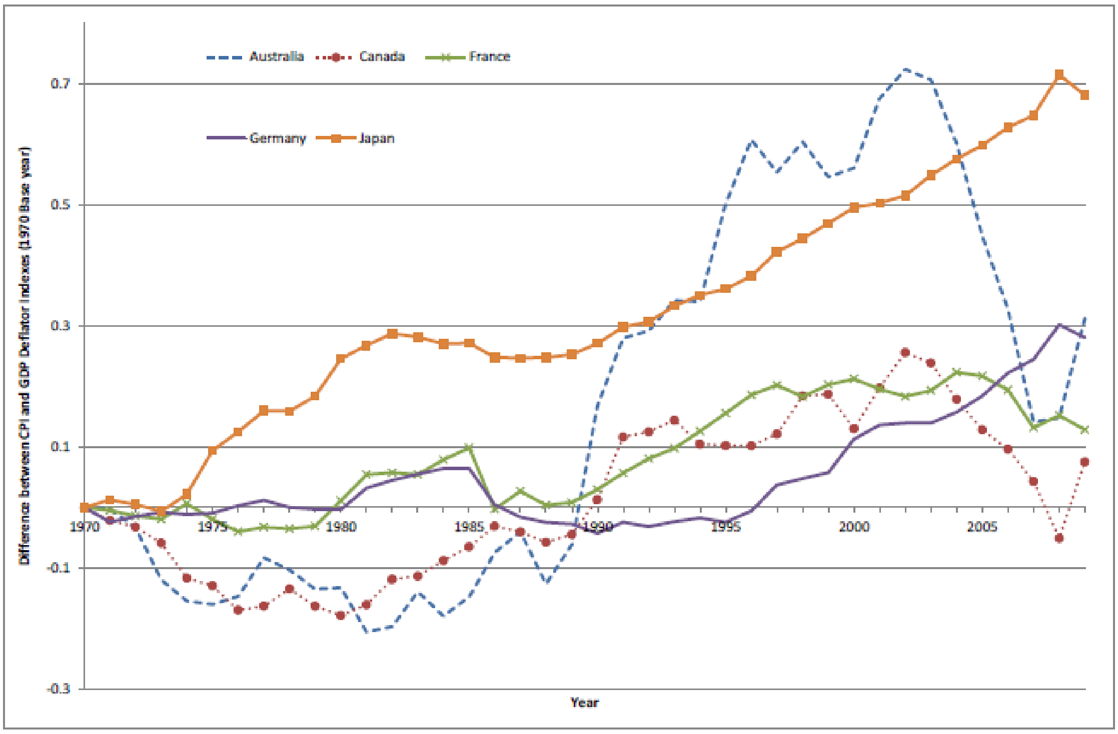



Figure 4.36: Difference between the CPI growth and the GDP Deflator growth for some OECD countries

Source: OECD.

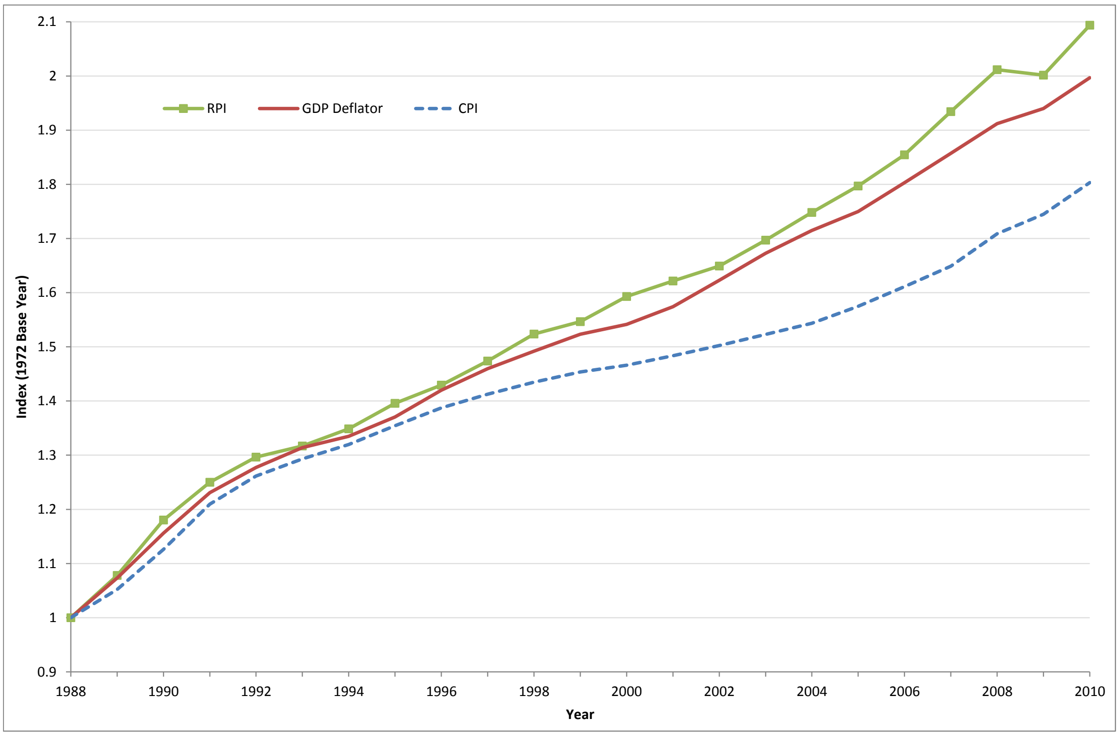



Figure 4.37: CPI, GDP Deflator and RPI over Time in the UK

Sources: ONS and HM Treasury.

# 4.F Labour Income Shares

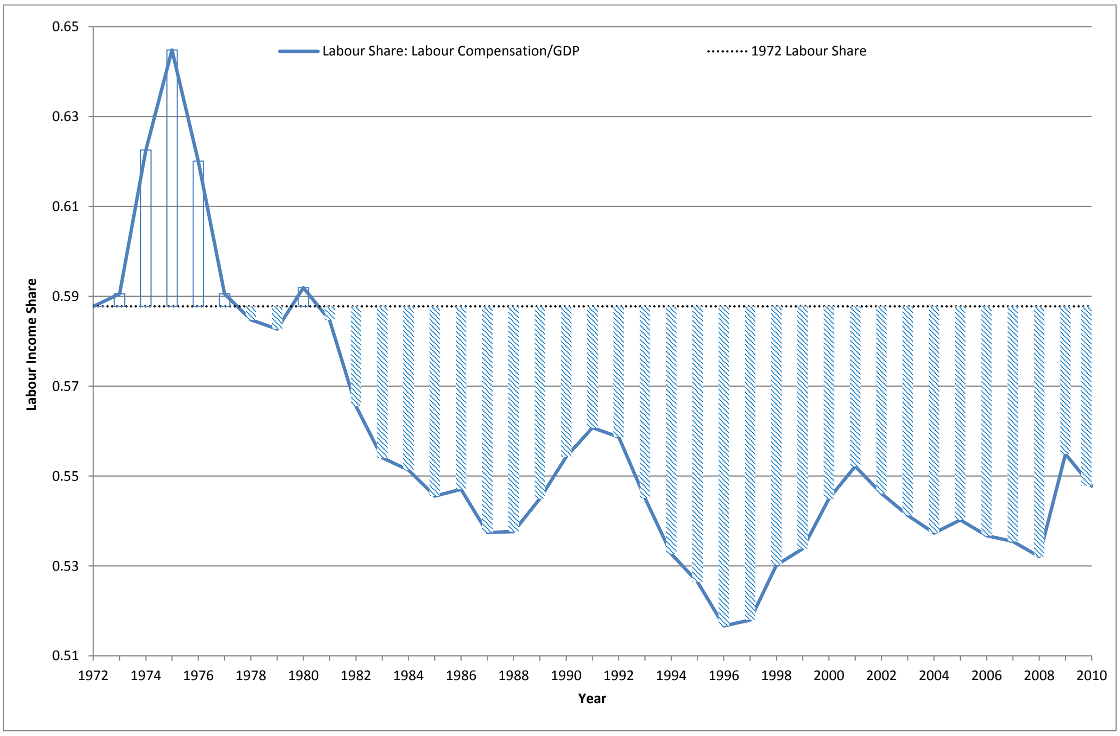



Figure 4.38: Labour Income Share in the UK

ONS, OECD, and KLEMS. *No* adjustment for Self-Employment.

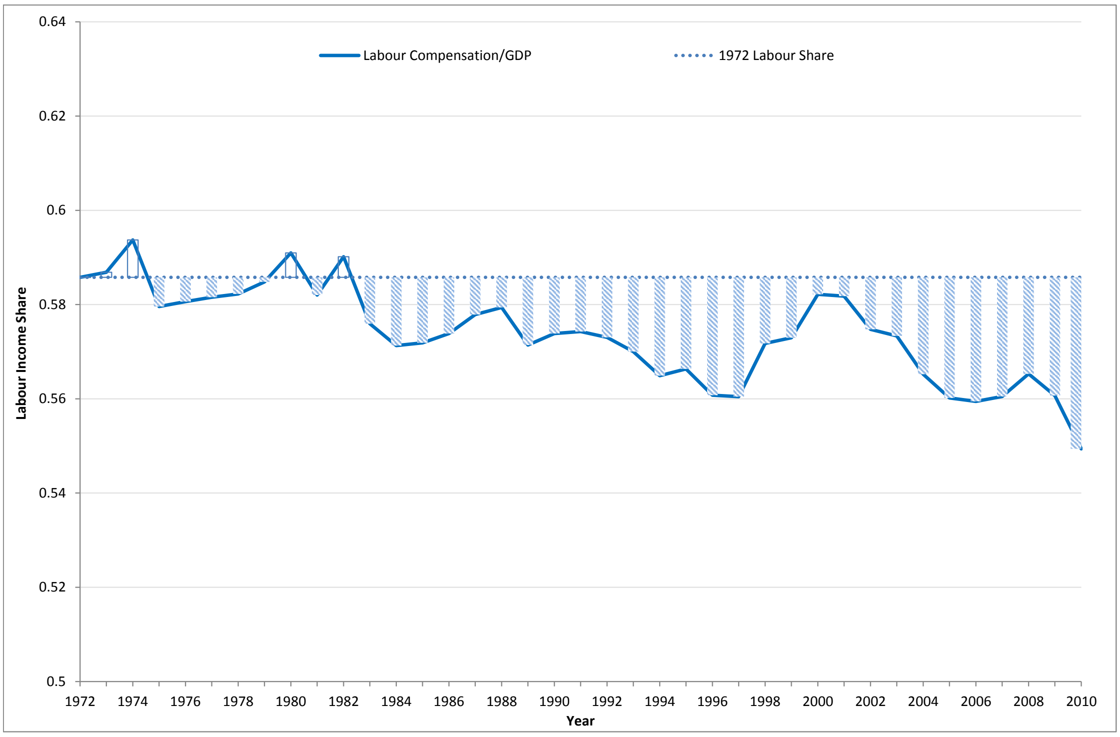



Figure 4.39: Labour Income Share in the US

Sources: BEA and OECD. *No* adjustment for Self-Employment.

# Bibliography


Aghion, P., Besley, T., Browne, J., Caselli, F., Lambert, R., Lomax, R., Stern, N., Van Reenen, J., 2013. Investing for prosperity: skills, infrastructure and innovation. In: Besley, T., Van Reenen, J. (Eds.), Investing for Prosperity. LSE Academic Publishing, London, pp. 1–50.

Anderson, T. W., Hsiao, C., 1981. Estimation of dynamic models with error components. Journal of the American Statistical Association 76 (375), 598–606.

Aragón, F. M., Rud, J. P., 2013. Natural resources and local communities: Evidence from a peruvian gold mine. American Economic Journal: Economic Policy 5 (2), 1–25.

Arkolakis, C., Costinot, A., Rodriguez-Clare, A., February 2012. New trade models, same old gains? American Economic Review 102 (1), 94–130.

Armstrong, A., Davis, P., Liadze, I., Rienzo, C., 2013. Evaluating changes in bank lending to smes over 2001-2012. Discussion Paper 408, National Institute for Economic Social Research.

Artuç, E., Chaudhuri, S., McLaren, J., June 2010. Trade shocks and labor adjustment: A structural empirical approach. American Economic Review 100 (3), 1008–45.

Autor, D. H., Dorn, D., Hanson, G. H., October 2013a. The china syndrome: Local labor market effects of import competition in the united states. American Economic Review 103 (6), 2121–68.

Autor, D. H., Dorn, D., Hanson, G. H., Song, J., July 2013b. Trade adjustment: Worker level evidence. NBER Working Papers 19226, National Bureau of Economic Research, Inc.

Azmat, G., Manning, A., Van Reenen, J., 2011. Privatization and the decline of labour's share: International evidence from network industries. Economica 79(315), 1–23.

Bagaria, N., Holland, D., Van Reenen, J., 2012. Fiscal consolidation during a depression. National Institute Economic Review 221, R38 – R50.

Baker, D., 2007. The productivity to paycheck gap: What the data show. CEPR working paper, Center for Economic and Policy Research.

Bank of England, 2012. Productivity and the allocation of resources. , Speech by Ben Broadbent, Available at http://www.bankofengland.co.uk/publications/Pages/news/2012/082.aspx (last accessed: 15 October 2013).

Bank of England, 2013. Inflation report, february 2013. , Available at http://www.bankofengland.co.uk/publications/Pages/inflationreport/2013/ir1301.aspx (last accessed: 15 October 2013).

Bartelsman, E., Haltiwanger, J., Scarpetta, S., 2013. Cross country differences in productivity: the role of allocation and selection. American Economic Review 103(1), 305–334.

Bartik, T. J., 1991. Who Benefits from State and Local Economic Development Policies? W.E. Upjohn Institute for Employment Research, Kalamazoo, Michigan.

Bernard, A. B., Jensen, J. B., Schott, P. K., January 2006. Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of u.s. manufacturing plants. Journal of International Economics 68 (1), 219–237.

Blanchard, O., Giavazzi, F., 2003. Macroeconomic effects of regulation and deregulation in goods and labor markets. The Quarterly Journal of Economics 118, 879–907.

Blanchflower, D., Oswald, A., 1994. The Wage Curve. MIT Press, Cambridge.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77, 623–685.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and company investment dynamics: empirical evidence for uk firms. Review of Economic Studies 74, 391–415.

Bloom, N., Draca, M., Van Reenen, J., 2015. Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. Review of Economic Studies, forthcoming.

Bloom, N., Floetotto, M., Jaimovich, N. Saporta-Eksten, I., Terry, S., 2013a. Really uncertain business cycles. CEP Discussion Paper 1195, CEP.

Bloom, N., Romer, P., Terry, S., Reenen, J. V., Mar. 2014. Trapped Factors and China's Impact on Global Growth. CEP Discussion Papers dp1261, Centre for Economic Performance, LSE.

Bloom, N., Sadun, R., Van Reenen, J., 2013b. Management as a technology. LSE mimeo, Available at http://cep.lse.ac.uk/textonly/_new/staff/vanreenen/pdf/mat_2012fmar16_ucb.pdf (last accessed: 15 October 2013).

Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and countries. Quarterly Journal of Economics 122 (4), 1341–1408.

Bloomberg, April 2011. Rousseff wants china buying more than soybeans, vale's iron ore April 10.

Blundell, R., Crawford, C., Jin, W., 2013. Employment composition, hourly wages and the productivity puzzle. IFS mimeo.

Blundell, R., Dias, M. C., Meghir, C., Van Reenen, J., 2004. Evaluating the employment impact of a mandatory job search assistance programme. Journal of the European Economics Association 2 (4), 569–606.

Borowczyk-Martins, D., Jolivet, G., Postel-Vinay, F., July 2013. Accounting For Endogeneity in Matching Function Estimation. Review of Economic Dynamics 16 (3), 440–451.

Bosworth, B., 2010. Price deflators, the trust fund forecast, and social security solvency. Working Paper 2010, Center for Retirement Research.

Bureau of Economic Analysis, 2011. Nipa handbook: Concepts and methods of the u.s. national income and product accounts. , Available at http://www.bea.gov/methodologies/index.htm#national_meth.

Bustos, P., Caprettini, B., Ponticelli, J., 2013. Agricultural productivity and structural transformation: Evidence from brazil, mimeo.

Caballero, R., Hoshi, T., Kashyap, A., 2008. zombie lending and depressed restructuring in japan. American Economic Review 98 (5), 1943–77.

Corry, D., Valero, A., Van Reenen, J., 2011. Uk economic performance since 1997. Cep special paper, Centre for Economic Performance, LSE.

Corry, D., Valero, A., Van Reenen, J., 2012. Uk economic performance under labour. Renewal 20 (1), 56–69.

Cosar, A. K., Guner, N., Tybout, J., Nov. 2013. Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy. IZA Discussion Papers 7718, Institute for the Study of Labor (IZA).

Costa, F., Garred, J., Pessoa, J. P., May 2014. Winners and losers from a commodities-for-manufactures trade boom. CEP Discussion Papers CEPDP1269, CEP.

Costinot, A., Donaldson, D., Komunjer, I., 2012. What goods do countries trade? a quantitative exploration of ricardo's ideas. Review of Economic Studies 79 (2), 581–608.

Crafts, N., 2012. British relative economic decline revisited: the role of competition. Explorations in Economic History 49, 17–29.

Crawford, C., Jin, W., Simpson, H., 2013. Firmsproductivity, investment and training: what happened during the recession and how was it affected by the national minimum wage? , IFS Report to the Low Pay Commission.

Dauth, W., Findeisen, S., Suedekum, J., Jun. 2012. The rise of the east and the far east: German labor markets and trade integration. IZA Discussion Papers 6685, Institute for the Study of Labor (IZA).

Dauth, W., Findeisen, S., Suedekum, J., 2014. The rise of the east and the far east: German labor markets and trade integration. Journal of the European Economic Association 12 (6), 1643–1675.

Davis, S. J., Haltiwanger, J. C., August 1992. Gross job creation, gross job destruction, and employment reallocation. The Quarterly Journal of Economics 107 (3), 819–63.

Delong, B., Summers, L., 2012. Fiscal policy in a depressed economy. Brookings papers on economic activity.

Dew-Becker, I., Gordon, R. J., 2005. Where did the productivity growth go? inflation dynamics and the distribution of income. NBER Working Papers 11842, National Bureau of Economic Research.

di Giovanni, J., Levchenko, A. A., Zhang, J., July 2014. The Global Welfare Impact of China: Trade Integration and Technological Change. American Economic Journal: Macroeconomics 6 (3), 153–83.

Dix-Carneiro, R., 2014. Trade liberalization and labor market dynamics. Econometrica 82 (3), 825–885.

Donaldson, D., Oct. 2010. Railroads of the raj: Estimating the impact of transportation infrastructure. NBER Working Papers 16487, National Bureau of Economic Research, Inc.

Eaton, J., Kortum, S., September 2002. Technology, geography, and trade. Econometrica 70 (5), 1741–1779.

Economist, T., 2012. Seeking protection January 14th.

Felbermayr, G., Impullitti, G., Prat, J., 2014. Firm Dynamics and Residual Inequality in Open Economies. Tech. rep.

Felbermayr, G., Prat, J., Schmerer, H.-J., August 2011. Trade and unemployment: What do the data say? European Economic Review 55 (6), 741–758.

Felbermayr, G. J., Larch, M., Lechthaler, W., 2013. Unemployment in an interdependent world. American Economic Journal: Economic Policy 5 (1), 262–301.

Field, S., Franklin, M., 2013. Micro-data perspectives on the uk productivity conundrum. ONS, Available at http://www.ons.gov.uk/ons/dcp171766_295470.pdf (last accessed: 15 October 2013).

Filho, N. A. M., Muendler, M.-A., 2007. Labor reallocation in response to trade reform. CESifo Working Paper Series 1936, CESifo Group Munich.

Fixler, D., Jaditz, T., 2002. An examination of the difference between the cpi and the pce deflator. Working Paper 361, Bureau of Labor Statistics.

Freeman, R., 2008. Comparison of two oecd databases productivity differentials & the balassa-samuelson effect. , Available at http://www.oecd.org/dataoecd/57/15/41354425.pdf, OECD Labour Productivity Indicators.

Garicano, L., Steinwender, C., 2013. Survive another day: does uncertain financing affect the composition of investment? CEP Discussion Paper 1188, Centre for Economic Performance, LSE.

Giles, C., 2013. Sir mervyn takes a walk on the supply side. Financial Times January 23rd.

Goldberg, P. K., Pavcnik, N., 2003. The response of the informal sector to trade liberalization. Journal of Development Economics 72 (2), 463–496.

Gollin, D., 2002. Getting income shares right. Journal of Political Economy 110, 458–474.

Gomme, P., Rupert, P., 2004. Measuring labor's share of income, policy Discussion Papers, Federal Reserve Bank of Cleveland.

Gonzaga, G., Menezes-Filho, N., Terra, C., 2006. Trade liberalization and the evolution of skill earnings differentials in brazil. Journal of International Economics 68 (2), 345–367.

Goodridge, P., Haskel, J., Wallis, G., May 2013. Can intangible investment explain the productivity puzzle? National Institute Economic Review 224, R48–R58.

Gregg, P., Machin, S., Salgade, M., 2013. Real wages and unemployment in the big squeeze. CEP mimeo.

Grice, J., 2012. The productivity conundrum, interpreting the recent behaviour of the economy. ONS, Available at http://www.ons.gov.uk/ons/dcp171766_277262.pdf (last accessed: 15 October 2013).

Handley, K., Limao, N., August 2013. Policy uncertainty, trade and welfare: Theory and evidence for china and the u.s. Working Paper 19376, National Bureau of Economic Research.

Head, K., Mayer, T., Jan. 2013. Gravity equations: Workhorse, toolkit, and cookbook. CEPR Discussion Papers 9322, C.E.P.R. Discussion Papers.

Heid, B., Larch, M., 2012. International trade and unemployment: A quantitative framework. CESifo Working Paper Series 4013, CESifo Group Munich.

Helpman, E., Itskhoki, O., Muendler, M.-A., Redding, S., Apr. 2012a. Trade and Inequality: From Theory to Estimation. CEP Discussion Papers dp1138, Centre for Economic Performance, LSE.

Helpman, E., Itskhoki, O., Muendler, M.-A., Redding, S., Apr. 2012b. Trade and inequality: From theory to estimation. CEP Discussion Papers dp1138, Centre for Economic Performance, LSE.

Helpman, E., Itskhoki, O., Redding, S., 07 2010. Inequality and unemployment in a global economy. Econometrica 78 (4), 1239–1283.

Hopwood, P., 2005. Developments in ons earnings statistics: an overview. Labour Market Trends 113, 327–328.

Hsieh, C.-T., Klenow, P. J., November 2009. Misallocation and Manufacturing TFP in China and India. The Quarterly Journal of Economics 124 (4), 1403–1448.

Hsieh, C.-T., Ossa, R., 2011. A global view of productivity growth in china. Working Paper 16778, National Bureau of Economic Research.

Hsieh, C.-T., Woo, K. T., 2005. The impact of outsourcing to china on hong kong's labor market. American Economic Review 95 (5), 1673–1687.

Iacovone, L., Rauch, F., Winters, L. A., 2013. Trade as an engine of creative destruction: Mexican experience with chinese competition. Journal of International Economics 89 (2), 379–392.

Inklaar, R., Timmer, M. P., 2008. GGDC Productivity Level Database: International Comparisons of Output, Inputs and Productivity at the Industry Level. Tech. rep.

Itskhoki, O., Helpman, E., June 2014. Firms, trade and labor market dynamics. Mimeo, Princeton.

King, S., 2013. Putting lower unemployment ahead of higher productivity risks long-term economic damage. The Times March 19th.

Kovak, B. K., 2011. Local labor market effects of trade policy: Evidence from brazilian liberalization, mimeo.

Kovak, B. K., August 2013. Regional effects of trade reform: What is the correct measure of liberalization? American Economic Review 103 (5), 1960–76.

Krause, M. U., Lubik, T. A., April 2007. The (ir)relevance of real wage rigidity in the new keynesian model with search frictions. Journal of Monetary Economics 54 (3), 706–727.

Krueger, A. B., 1999. Measuring labor's share. American Economic Review 89, 45–51.

Layard, R., Nickell, S., 1998. Labour market institutions and economic performance. CEP Discussion Papers dp0407, Centre for Economic Performance, LSE.

Levchenko, A. A., Zhang, J., 2013. The global labor market impact of rmerging giants: a quantitative assessment. Tech. rep.

Lipton, D., Poterba, J., Sachs, J., Summers, L., 1982. Multiple shooting in rational expectations models. Econometrica 50 (5), pp. 1329–1333.

Los Angeles Times, 2011. Brazil's commodities-heavy trade with china gives some pause July 16th.

Manova, K., September 2008. Credit constraints, equity market liberalizations and international trade. Journal of International Economics 76 (1), 33–47.

Martin, W., Rowthorn, R., 2012. Is the uk economy supply constrained ii. , Centre for Business Research and UK IRC, Available at http://www.cbr.cam.ac.uk/pdf/BM_Report3.pdf (last accessed: 15 October 2013).

McCaig, B., Pavcnik, N., 2014. Export markets and labor allocation in a low-income country. Working Paper 20455, National Bureau of Economic Research.

McCully, C. P., Moyer, B. C., Stewart, K. J., November 2007. Comparing the consumer price index and the personal consumption expenditure price index. Survey of Current Business, 26–33.

McLaren, J., Hakobyan, S., Nov. 2010. Looking for local labor market effects of nafta. NBER Working Papers 16535, National Bureau of Economic Research, Inc.

Melitz, M. J., November 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71 (6), 1695–1725.

Menezes-Filho, N. A., Muendler, M.-A., 2011. Labor reallocation in response to trade reform. Working Paper 17372, National Bureau of Economic Research.

Mion, G., Zhu, L., 2013. Import competition from and offshoring to china: A curse or blessing for firms? Journal of International Economics 89 (1), 202–215.

Mishel, L., Bernstein, J., Shierholz, H., 2009. The State of Working America 2008/2009. Economic Policy Institute. Cornell University Press.

Mishel, L., Gee, K.-F., 2012. Why aren't workers benefiting from labour productivity growth in the united states? International Productivity Monitor 23, 31–43.

Mitra, D., Ranjan, P., July 2010. Offshoring and unemployment: The role of search frictions labor mobility. Journal of International Economics 81 (2), 219–229.

Munzi, T., Salomaki, A., February 1999. Net replacement rates of the unemployed. comparisons of various approaches. Tech. Rep. 133, European Commission.

Nataraj, S., 2011. The impact of trade liberalization on productivity: Evidence from india's formal and informal manufacturing sectors. Journal of International Economics 85 (2), 292–301.

National Institute of Economic and Social Research, 2013. Estimates of monthly gdp. , October, http://niesr.ac.uk/press/october-2013-gdp-estimates-11608#.Ul5m8Gxwb5o (last accessed: 16 October 2013).

Office for National Statistics, 1998. United kingdom national accounts concepts, sources and methods. , Available at http://www.ons.gov.uk/ons/publications/index.html.

Office for National Statistics, 2008. United kingdom national accounts: The blue book 2008 edition. , Available at http://www.ons.gov.uk/ons/publications/index.html.

Office for National Statistics, 2010. Capital stocks, capital consumption and non-financial balance sheets. , Edition No. 8, Available at http://niesr.ac.uk/press/october-2013-gdp-estimates-11608.Ul5m8Gxwb5o (last accessed: 16 October 2013).

O'Mahony, M., Timmer, M. P., 2009. Output, input and productivity measures at the industry level: The eu klems database*. The Economic Journal 119 (538), F374–F403.

Ornelas, E., Jan. 2012. Preferential trade agreements and the labor market. CEP Discussion Papers dp1117, Centre for Economic Performance, LSE.

Oulton, N., 2013a. A comment on pessoa and van reenen. mimeo.

Oulton, N., 2013b. Has the growth of real gdp in the uk been overstated because of mismeasurement of banking output? National Institute Economic Review 224, R59–R65.

Patterson, P., 2012. The productivity conundrum, explanations and preliminary analysis. ONS, Available at http://www.ons.gov.uk/ons/dcp171766_283259.pdf (last accessed: 15 October 2013).

Paz, L. S., 2014. The impacts of trade liberalization on informal labor markets: A theoretical and empirical evaluation of the brazilian case. Journal of International Economics 92 (2), 330–348.

Pessoa, J. P., Van Reenen, J., Oct. 2013. Decoupling of Wage Growth and Productivity Growth? Myth and Reality. CEP Discussion Papers dp1246, Centre for Economic Performance, LSE.

Pfaffermayr, M., Egger, P., Weber, A., 2007. Sectoral adjustment of employment to shifts in outsourcing and trade: evidence from a dynamic fixed effects multinomial logit model. Journal of Applied Econometrics 22 (3), 559–580.

Pierce, B., 2001. Compensation inequality. The Quarterly Journal of Economics 116, 1493–1525.

Pierce, J. R., Schott, P. K., 2013. The surprisingly swift decline of U.s. manufacturing employment, mimeo.

Pissarides, C. A., December 2000. Equilibrium Unemployment Theory, 2nd Edition. Vol. 1 of MIT Press Books. The MIT Press.

Ranjan, P., 2012. Trade liberalization, unemployment, and inequality with endogenous job destruction. International Review of Economics & Finance 23 (C), 16–29.

Revenga, A. L., 1992. Exporting jobs? the impact of import competition on employment and wages in u.s. manufacturing. The Quarterly Journal of Economics 107 (1), 255–84.

Rho, H. J., Schmitt, J., 2010. Health-insurance coverage rates for us workers, 1979-2008. Tech. rep., Center for Economic and Policy Research.

Schreyer, P., 2001. Measuring productivity - measurement of aggregate and industry-level productivity growth. , Available at http://www.oecd.org/dataoecd/59/29/2352458.pdf, OECD Manual.

Shimer, R., March 2005. The Cyclical Behavior of Equilibrium Unemployment and Vacancies. American Economic Review 95 (1), 25–49.

Stehrer, R., de Vries, G. J., Los, B., Dietzenbacher, H., Timmer, M., 2014. The World Input-Output Database: Content, Concepts and Applications. Tech. rep.

Stewart, K. J., Reed, S. B., 1999. Consumer price index research series using current methods, 1978-98. The Monthly Labor Review, 29–38.

Topalova, P., 2007. Trade liberalization, poverty and inequality: Evidence from indian districts. In: Globalization and Poverty. NBER Chapters. National Bureau of Economic Research, Inc, pp. 291–336.

Trigari, A., 2006. The Role of Search Frictions and Bargaining for Inflation Dynamics. Tech. rep.

Triplett, J. E., September 1981. Reconciling the cpi and the pce deflator. Monthly Labor Review, 3–15.

Utar, H., Dec. 2006. Employment Dynamics and Import Competition. 2006 Meeting Papers, Society for Economic Dynamics 298, Society for Economic Dynamics.

Utar, H., Aug. 2011. Adjusting to Trade Liberalization: Reallocation and Labor Market Policies. Mimeo, University of Chicago Booth School of Business.

Van Reenen, J., 2004. Active Labor Market Policies and the British New Deal for the Young Unemployed in Context. In: Seeking a Premier Economy: The Economic Effects of British Economic Reforms, 1980-2000. NBER Chapters. National Bureau of Economic Research, Inc, pp. 461–496.

Van Reenen, J., 2011. Wage inequality, technology and trade: 21st century evidence. Labour Economics 18 (6), 730–741.

Vodopivec, M., Tong, M. H., 2008. China: improving unemployment insurance. Social Protection Discussion Papers 44779, The World Bank.

Wadsworth, J., 2013. Whats up now? the behaviour of uk employment over recent recessions. CEP mimeo.