FACULTY OF SOCIAL SCIENCES
UNIVERSITY OF COPENHAGEN

PhD Thesis

Damoun Ashournia

Essays in International Trade

Labor Market Outcomes and Competition Dynamics

Academic Advisor: Jakob Munch

Submitted: September 3, 2013

To Nanna.

This mustn't make much sense to you.
But without you, it wouldn't make sense to me either.

Contents

Acknowledgments

The present dissertation is the product of four years of work done since I was enrolled in the PhD program in Economics at the University of Copenhagen in September 2009.

I owe thanks to a number of people, who have been helpful in the process of writing the dissertation. First of all, I would like to thank my advisor, Professor Jakob Munch, for helpful discussions, guidance, encouragement, and inspirational coauthorship. Jakob's comments and advice have significantly improved the quality of this dissertation. My coauthors Per Svejstrup Hansen, Jonas Worm Hansen, and Dan Nguyen deserve thanks for great collaboration over the years. During my studies, I had the great fortune to visit Professor David Hummels at Purdue University, and would like to thank him and the PhD students there for hospitality and comments on my work.

The Centre for Applied Microeconometrics (CAM) at the Department of Economics has provided an inspirational environment for PhD students to present and receive comments on their work. The feedback I have received at these seminars have been of great help, and I would like to thank everyone associated with CAM.

My fellow PhD students (none mentioned, none forgotten) in and around the applied microeconometrics corner of the department have made the past four years a more fun experience than I could have imagined. Besides all the commenting on each others work (for which I am grateful), the jokes have been uncountable, and the volume of coffee we have consumed immeasurable.

Finally, I would like to thank my family, friends, and my girlfriend Nanna, who have all stood by me and encouraged me throughout the process. To you I owe more than you could imagine.

Damoun Ashournia

Copenhagen, September 2013

Summary

This dissertation consists of three self-contained chapters. The first two are empirical papers on the labor market outcomes of international trade, using data from the administrative records of Statistics Denmark. The final chapter contributes to the theoretical literature on the impact of trade liberalization on competition when firms are imperfectly competitive.

Chapter 1, *"A Dynamic Analysis of Globalization and Unemployment"*, aims to estimate the mobility costs involved when workers change from one sector to another, for example due to globalization. Developed countries have experienced increasing foreign competition, particularly from low wage countries, since the early 1990s. This has been coupled with a shift in production away from the manufacturing sector towards non-traded goods and services. In so far as this reallocation is costly for workers, estimating the mobility costs is important in understanding how the labor market adjusts to increased foreign competition. The mobility costs are estimated in a structural model of the Danish labor market, and found to be in the range of 1.2 to 2.4 average annual wages for the median worker, thus comprising a significant barrier to intersectoral mobility.

Chapter 2, *"The Impact of Chinese Import Penetration on Danish Firms and Workers"* (joint with Jakob Munch and Daniel Nguyen), uses the recent surge in imports from China as a natural experiment to investigate how low wage country imports affect domestic firms and workers. Since the 1980s several developed economies have experienced contemporaneous increases in imports and in the wage gap between high- and low-skilled workers. The paper measures Chinese import penetration at the firm level, and finds that greater exposure to Chinese imports corresponds to a negative firm-level demand shock, which is biased towards low-skill intensive products. Consistent with this,

an increase in Chinese import penetration results in lower wages for low-skilled workers.

Finally, Chapter 3, *"Trade Liberalization and the Degree of Competition in International Duopoly"* (joint with Per Svejstrup Hansen and Jonas Worm Hansen), build a theoretical model to analyze how a reduction in trade costs influences the possibility for firms to engage in international cartels, and hence how trade liberalization affects the degree of competition. By amending the 'reciprocal dumping' model of Brander and Krugman (1983) to allow for differentiated products, the paper finds that trade liberalization may have an anti-competitive effect, though there is no monotone relation between reducing trade costs and the degree of competition. The paper has been accepted for publication at the *Review of International Economics*.

Resumé (Summary in Danish)

Denne afhandling består af tre separate kapitler. De to første er empiriske papirer omhandlende effekten af international handel på arbejdsmarkedet. Begge gør brug af registerdata fra Danmarks Statistik. Det sidste kapitel bidrager til den teoretiske litteratur om effekten af handelsliberalisering på graden af konkurrence, når virksomheder er imperfekte konkurrenter.

Kapitel 1, *"A Dynamic Analysis of Globalization and Unemployment"*, søger at estimere den mobilitetsomkostning, der for lønmodtagerne er forbundet med at skifte fra én sektor til en anden. Udviklede lande har oplevet stigende udenlandsk konkurrence, især fra lavtlønslande, siden 1990erne. Denne stigning er sket samtidigt med et skifte i produktionen fra fremstilling til ikke-handlede goder og service. I det omfang at denne reallokation er forbundet med omkostninger for lønmodtagerne, er estimation af mobilitetsomkostningerne vigtigt for forståelsen af, hvordan arbejdsmarkedet tilpasser sig stigende udenlandsk konkurence. Mobilitetsomkostningerne bliver i papiret estimeret i en strukturel økonometrisk model af det danske arbejdsmarked, og fundet til at være i størrelsesordenen 1,2 til 2,4 gange årslønnen for medianlønmodtageren, og dermed en signifikant barriere for intersektoral mobilitet.

Kapitel 2, *"The Impact of Chinese Import Penetration on Danish Firms and Workers"* (skrevet i samarbejde med Jakob Munch and Daniel Nguyen), bruger den nylige stigning i importen fra Kina som et naturligt eksperiment for at undersøge, hvordan import fra lavtlønslande påvirker danske virksomheder og lønmodtagere. Siden 1980erne har flere udviklede lande oplevet samtidige stigninger i importen og i løngabet mellem højt- og lavtuddannede lønmodtagere. Papiret måler kinesisk importkonkurrence på virksomhedsniveau og finder, at stigende udsættelse for kinesisk import svarer til et neg-

ativt efterspørgselsstød for virksomheder. Stødet er biased mod produkter, der gør intensivt brug af ufaglært arbejdskraft, og i overensstemmelse med dette findes, at en stigning i kinesisk importkonkurrence resulterer i lavere løn for lavtuddannede lønmodtagere.

Kapitel 3, *"Trade Liberalization and the Degree of Competition in International Duopoly"* (skrevet i samarbejde med Per Svejstrup Hansen and Jonas Worm Hansen), bygger slutteligt en teoretisk model for at analysere, hvordan en reduktion i handelsomkostninger påvirker virksomheders mulighed for at indgå i internationalt kartelsamarbejde, og dermed hvordan handelsliberalisering påvirker graden af konkurrence. Ved at udbygge den reciprokke dumping model i Brander og Krugman (1983) for dermed at tillade differentierede produkter, finder papiret, at handelsliberalisering kan have en anti-kompetitiv effekt, selvom der ikke er et monotont forhold mellem reducering af handelsomkostninger og graden af konkurrence. Papiret er blevet accepteret til udgivelse i *Review of International Economics*.

Chapter 1

A Dynamic Analysis of Globalization and Unemployment

Abstract

This paper builds and estimates a dynamic structural model of the labor market with heterogeneous workers accumulating sector specific human capital. The model features mobility costs of switching sectors and a formal model of the institutional setting facing the unemployed in Denmark. Estimating the reallocation costs by Simulated Minimum Distance on administrative data covering the population of Danish workers and firms, mobility costs are found to be in the range of 1.2 to 2.4 times average annual wages, providing a significant barrier to mobility. By conducting counterfactual policy experiments, it is shown that the mobility costs are instrumental in explaining the slow adjustment of the labor market following globalization.

1.1 Introduction

Developed countries have experienced increasing foreign competition, particularly from low wage countries, since the early 1990s. This has been coupled with a shift in production away from the manufacturing sector towards non-traded goods and services. The reallocation process has naturally involved decline of some industries and the expansion of others. While the public debate on globalization often focuses on the destruction jobs rather than the gains, economists and policy makers insist that the gains from trade outweigh the losses, at least in the long run as resources are allocated towards comparative advantage industries. But focusing only on long term gains does not address questions on the sluggishness and costs of the reallocation process. As globalization continues, this tension between workers concerned by short term outcomes and policy makers focused on aggregate long term outcomes is bound to increase, making estimation of the adjustment costs following globalization an ever more present concern.

This paper attempts to do just that for Denmark. Among Continental European countries Denmark is special as the flexibility of the Danish labor market is very high, comparable even to the United States.[1] With weak employment protection and high unemployment insurance (UI) benefits being two of three pillars of the 'flexicurity' system (active labor market policies is the third) firms are relatively free to hire and lay off workers as they desire. That firms are free to lay off workers does not mean that it is without costs for workers to reallocate to new firms and sectors, however. Workers may experience spells of unemployment, they might lose part of their sector specific human capital, or they may have a distaste for switching sectors for other reasons. The main purpose of this paper is to quantify these reallocation costs following globalization.

To this end I build and estimate a dynamic structural model of the Danish economy, where heterogeneous workers of overlapping generations accumulate human capital specific to the sector in which they are employed. In every period of time, workers receive wage offers from all sectors of the economy after which they choose to work in the sector that maximizes expected lifetime utility. The choice takes into account the possibility of becoming unemployed and receiving unemployment benefits. If the worker wishes to switch sectors from one year to the next, he faces different costs. Firstly, he may not be able to offer the same amount of human capital to all sectors as part of his human capital is sector specific. Secondly, the worker faces a utility cost of switching sectors that depends on characteristics such as gender, education and age. The production side of the model is characterized by perfect competition, where sectoral representative firms demand human and physical capital in order to produce output according to a Cobb-Douglas production function.

The structural parameters of the model are estimated using Simulated Minimum Distance (SMD) on a matched worker-firm dataset covering the population of Danish workers and the universe of firms from 1996 to 2008. Employing SMD on this dataset, I fit a

[1]See Botero, Djankov, La Porta, Lopez-De-Silanes, and Shleifer (2004) for a cross country comparison of labor market flexibility.

set of Auxiliary Parameters (AP) that provide a detailed description of the data. The SMD estimator finds the set of structural parameters such that the distance between APs estimated on actual data and APs estimated on data simulated from the model is minimized.

The main estimation result is that the mobility cost of switching sectors for the median worker is between 1.2 and 2.4 times average annual wages, providing a significant barrier to inter-sectoral mobility. The median mobility cost covers substantial heterogeneity over the population of workers: Female, less-educated, and in particular older workers face higher mobility costs.

Once the model parameters are estimated, I use it to explore the dynamic adjustment processes following a globalization shock to the economy. While globalization manifests itself in numerous ways, this paper focuses on two of these. Firstly, by causing some sectors to expand and others to contract, globalization can increase the probability of becoming unemployed for workers in the contracting sectors, particularly if workers are unable to reallocate immediately. The second way that this paper considers that globalization affects the economy is through trade liberalization, which lowers the output price of the liberalizing sector.

Consider increased globalization of the manufacturing sector. Then, the globalization shock consists of two separate shocks: i) An unemployment shock increasing the probability of becoming unemployed for workers employed in the manufacturing sector; ii) A trade liberalization episode lowering the output price of the manufacturing sector. First, the unemployment and trade liberalization shocks are studied in isolation before turning to the impact of a joint shock. In the simulations, I find that: i) The labor market reallocation process is sluggish, so that only 50% of the reallocation is completed after 7 years in case of the unemployment shock, and 49% after 9 years in case of the trade liberalization; ii) The unemployment shock leaves human capital prices unchanged since physical capital is free to flow in and out of the sectors; iii) Trade liberalization lowers human capital prices in the affected sectors.

Recent empirical papers have studied how international trade affects domestic labor markets. In an influential paper, Autor, Dorn, and Hanson (2013) find that increasing import competition from China increases unemployment in local labor markets: For every $1,000 increase in imports per worker, the share of employed manufacturing workers falls by 0.7 percentage points. Examples of other reduced form studies are the papers by

Autor, Dorn, Hanson, and Song (2012), and Ebenstein, Harrison, McMillan, and Phillips (forthcoming). Recently, efforts have been made to estimate the transition costs of labor reallocation in structural models, e.g. Artuç, Chaudhuri, and McLaren (2010), Artuç and McLaren (2012), Coşar (2013), Coşar, Guner, and Tybout (2011). The paper closest to mine in the structural literature is Dix-Carneiro (2013), who estimates a similar model on Brazilian worker data. He is focused on the distributional effects of trade liberalization on high and low skilled workers. In contrast, although my model allows workers to be highly educated, this affects only the *amount* of human capital they can offer, not the *type*. In addition, the key feature of my model is the formal modeling of the institutional setting facing unemployed workers in Denmark, a feature we know from the theoretical literature on labor markets and international trade to be crucial.[2]

The remainder of the paper is organized as follows. The next section presents a dynamic structural model of the labor market allowing for observed and unobserved heterogeneity on the worker side. Section 1.3 describes the matched worker-firm data and the aggregate data used for estimation. Section 1.4 gives an overview of the estimation procedure and presents the results. Section 1.5 examines the dynamic adjustments following different shocks to the economy and conducts policy experiments. Finally, Section 1.6 concludes.

1.2 Empirical Model

The objective is to design and estimate a general equilibrium model of the labor market that allows for an assessment of the transition costs of labor reallocation across sectors while allowing workers to be unemployed. Building on the framework developed in Keane and Wolpin (1994), Lee (2005), Lee and Wolpin (2006), and Dix-Carneiro (2013), the strategy is to estimate a dynamic Roy (1951) model.[3]

At each period of time the economy is populated by overlapping generations of workers aged 30 to 65. Workers supply their human capital to one of five sectors: (1) Agruculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation

[2]A growing body of theoretical papers studies the effect of international trade on unemployment. In Davidson, Martin, and Matusz (1999), Helpman and Itskhoki (2010), Helpman, Itskhoki, and Redding (2010), and Helpman, Itskhoki, and Redding (2011), the equilibrium unemployment rate may rise following trade liberalization.

[3]See Heckman and Sedlacek (1985, 1990), and Heckman and Honoré (1990).

/Communication, or (5) Services. Workers have different levels of human capital to offer different sectors as a worker might be an able economist whilst being a less able construction worker. To capture this, workers accumulate work experience, part of which is transferable to other sectors. Changing sectors from one period to the next is costly for the worker for two reasons: First, not all experience is transferable across sectors, and second, the worker faces a utility cost of switching. In addition to the five productive sectors there is an unproductive unemployment sector (0) where workers sit idle, receiving unemployment insurance benefits or welfare assistance. Workers cannot choose the unemployment sector as unemployment arrives with individual specific probability. Thus, all unemployment is involuntary.

In the following I describe the production and worker sides of the model before discussing how the model is solved and estimated.

1.2.1 Sectoral Production

Representative firms in each sector demand the human capital supplied by workers in order to produce output. The production technology is assumed to be of a Cobb-Douglas form so that the value added of sector s becomes

$$Y_t^s = p_t^s A_t^s (S_t^s)^{\alpha_t^s} (K_t^s)^{1-\alpha_t^s}, \tag{1.1}$$

where p_t^s is the output price, A_t^s is productivity, S_t^s is the human capital employed in the sector, and K_t^s is physical capital. Notice that α_t^s is allowed to vary over time, and that the aggregate human capital, S_t^s, is not observed.

Given the production technology, the unit prices of human capital and physical capital are

$$\begin{aligned} r_t^s &= \alpha_t^s \frac{Y_t^s}{S_t^s}, \\ r_t^{s,K} &= \left(1-\alpha_t^s\right) \frac{Y_t^s}{K_t^s}. \end{aligned} \tag{1.2}$$

1.2.2 Workers

At every period of time, a worker chooses to work in the sector that maximizes the present value of lifetime utility. He must consume his entire contemporaneous income in the current period as there is no saving. If the worker, previously employed in sector s_{t-1}, chooses to work in $s \neq s_{t-1}$, he incurs a utility cost. However, regardless of the sectoral choice, the worker with a set of characteristics Ω_{iat} faces unemployment probability $\delta(\Omega_{iat})$. Unemployed workers receive either unemployment insurance benefits or welfare assistance.

Let $\mathbf{V}_{at}(\Omega_{iat})$ be the value function of a worker. This value function represents the maximum expected present value of lifetime utility in year t over the choice alternatives. The Bellman equations of worker i of age a in year t are

$$\mathbf{V}_{at}(\Omega_{iat}) = \max_{s} \left\{ \mathbf{V}^{s}_{at}(\Omega_{iat}) \right\}, \tag{1.3}$$

with alternative-specific value functions

$$\mathbf{V}^{s}_{at}(\Omega_{iat}) = \begin{cases} (1-\delta(\Omega_{iat}))\left[w^{s}(\Omega_{iat}) + \rho \mathbb{E}\mathbf{V}_{a+1,t+1}(\Omega_{i,a+1,t+1}|\Omega_{iat}, d_{it}=s) \right] + & \\ \delta(\Omega_{iat})\left[w^{0}(\Omega_{iat}) + \rho \mathbb{E}\mathbf{V}_{a+1,t+1}(\Omega_{i,a+1,t+1}|\Omega_{iat}, d_{it}=0) \right] + & \text{if } a < 65 \\ \eta^{s}_{it} - \mathbf{C}^{s_{t-1},s}(\Omega_{iat}) & \\ & \\ (1-\delta(\Omega_{iat}))\, w^{s}(\Omega_{iat}) + \delta(\Omega_{iat})\, w^{0}(\Omega_{iat}) + \eta^{s}_{it} - \mathbf{C}^{s_{t-1},s}(\Omega_{iat}) & \text{if } a = 65 \end{cases} \tag{1.4}$$

In the value functions of Equation (1.4), $w^{s}(\Omega_{iat})$ is the real wage offer in sector s, $w^{0}(\Omega_{iat})$ is the unemployment benefit, η^{s}_{it} is a zero mean random sectoral preference shock, $\mathbf{C}^{s_{t-1},s}(\Omega_{iat})$ is a utility cost incurred by a worker switching from sector s_{t-1} to sector s, and ρ is the discount factor.

The state space, Ω_{iat}, is given by all variables that are relevant for the determination of the real wage the worker would get in any sector and any other variables relevant for the formation of expectations.

$$\Omega_{iat} = \left\{ \text{Female}_{i}, \text{Educ}_{i}, \text{Elig}_{it}, \text{Exper}_{it}, \{\mathbf{r}_{t+\tau}\}_{\tau=0}^{65-a}, s_{t-1}, w_{t-\tau}, \boldsymbol{\eta}_{it}, \boldsymbol{\varepsilon}_{it} \right\}. \tag{1.5}$$

These include gender, level of education, eligibility for UI benefits, experience, the sequence of future human capital prices, previous sector including unemployment, wage in last employment, and current idiosyncratic shocks. In the following I describe each of the components of the value function.

1.2.2.1 Wages

As is common in the literature, the wage offer a worker receives in a sector is the product of the unit price of human capital in that sector and the amount of sector specific human capital that the worker possesses.[4] The sector specific human capital of a worker can be decomposed into a deterministic part and an idiosyncratic shock. The deterministic part depends on worker characteristics such as gender, education, and experience. The wage offer in sector s is given by

$$\begin{aligned} w^s(\Omega_{iat}) = r_t^s \cdot \exp\Big[&\beta_1^s \text{Female}_i + \beta_2^s \text{Educ}_i + \beta_3^s \text{Exper}_{it} + \beta_4^s \left(\text{Exper}_{it}\right)^2 + \\ &\beta_5^s \text{Exper}_{it} \cdot \mathbf{1}\{s_{t-1} \neq s\} + \varepsilon_{it}^s\Big], \end{aligned} \tag{1.6}$$

where r_t^s is the unit price of human capital, Female_i indicates whether the worker is a woman, Educ_i indicates if the worker has completed college education, and ε_{it}^s is the idiosyncratic human capital shock. Work experience, Exper_{it}, is gained for each year of employment. This means that Exper_{it} and its square term capture the component of experience that is transferable across productive sectors. However, if the worker chooses to switch sectors, not all experience is transfered. This is captured by the interaction term between Exper_{it} and $\mathbf{1}\{s_{t-1} \neq s\}$, an indicator for switching.

1.2.2.2 Unemployment

Workers become unemployed with individual specific probability, $\delta(\Omega_{iat})$. These probabilities are allowed to vary with gender, education level, age, and previous sector of employment, meaning that workers for whom these attributes are identical face the same probability of becoming unemployed. The probabilities are set to the empirical frequencies as observed in the data.

During spells of unemployment, the worker receives unemployment benefits, the size of which depends on whether the worker is eligible for UI benefits or has to rely on welfare assistance:

$$w^0(\Omega_{iat}) = \begin{cases} \min\left\{\gamma \cdot w_{t-\tau}, \overline{\text{UI}}\right\} & \text{if } \text{Elig}_{it} = 1, \\ \text{WA} & \text{if } \text{Elig}_{it} = 0, \end{cases} \tag{1.7}$$

where γ is the degree of compensation for the insured, $w_{t-\tau}$ is the wage received in the most recent employment, $\overline{\text{UI}}$ is the maximum UI benefits, Elig_{it} is an indicator of whether

[4] See e.g. Dix-Carneiro (2013), Heckman and Sedlacek (1985), Lee (2005), and Lee and Wolpin (2006)

the worker is eligible for UI benefits, and WA is the welfare assistance. $\overline{\text{UI}}$, WA, and γ are set to values that matches what unemployed Danish workers are facing.[5] Eligibility for UI benefits depends on two criteria. First, the worker must be member of a UI fund. Second, the worker must not have received UI benefits for more than 4 years.

1.2.2.3 Mobility Costs

The utility cost that a worker switching sectors faces depends on gender, education, and age and is given by

$$\mathbf{C}^{s_{t-1},s}(\Omega_{iat}) = \exp\left[\xi^{s_{t-1}} + \kappa_1 \text{Female}_i + \kappa_2 \text{Educ}_i + \kappa_3(a-30) + \kappa_4(a-30)^2\right], \tag{1.8}$$

where $\xi^{s_{t-1}}$ is a parameter depending on the previous sector. The costs are only incurred if the worker switches productive sectors from one year to the next, meaning that $\mathbf{C}^{s_{t-1},s}(\Omega_{iat}) = 0$ if $s_{t-1} = s$ or $s = 0$. Since all unemployment is involuntary it is not possible to identify mobility costs from switching to and from unemployment. The mobility costs represent workers' distaste for switching to a new sector, that may arise for any number of reasons, e.g. due to the existence of search costs. This paper remains agnostic as to the exact source of the mobility costs, and leaves exploring this important issue to future research.

1.2.2.4 Expectations of Future Human Capital Prices

For a worker to be able to decide in which sector to work at a given point in time, he must compute what wage offers he expects to receive in the future. These wage offers depend not only on the idiosyncratic sector specific shocks to his human capital $\boldsymbol{\varepsilon}_{i\tau}$, which is unknown to him at time $t < \tau$, but also on the unit price of human capital in all sectors, $\mathbf{r}_\tau$. Following Lee (2005), it is assumed that workers have perfect foresight with respect to the future sequence of human capital prices, a sequence that is computed endogenously when the model is solved.

1.2.2.5 Idiosyncratic Shocks

The vectors of idiosyncratic shocks, $\boldsymbol{\varepsilon}_{it}$ and $\boldsymbol{\eta}_{it}$, comprise the components of the state space that are unobserved by the researcher. In order to solve the model, assumptions

[5] Appendix 1.A describes the institutional setting facing unemployed workers in Denmark in some detail.

on their distributions are necessary. It is assumed that they are independent and drawn from a normal distribution and the Extreme Value Type I distribution, respectively:

$$\begin{aligned} \varepsilon_{it}^{s} &\overset{\text{iid}}{\sim} \mathcal{N}\left(0, \sigma^{s}\right), \\ \eta_{it}^{s} &\overset{\text{iid}}{\sim} \text{Extreme Value Type I.} \end{aligned} \tag{1.9}$$

The iid extreme value assumption on the preference shocks yields a convenient closed for solution when taking the expectation, contributing to computational tractability. Given these distributional assumptions, it is possible to solve the model.

1.2.3 Model Equilibrium

At age a and time t, each worker solves his optimization problem given by Equations (1.3) and (1.4) in order to decide what sector to work in. Once all workers have made their choices, the total supply of human capital to sector s is

$$S_t^{s,sup}\left(\{\mathbf{r}_{t+\tau}\}_{\tau=0}^{35}\right) = \sum_{a=30}^{65} \sum_{i=1}^{n_{at}} S^s\left(\Omega_{iat}\right) \cdot \mathbf{1}\left\{d_{iat} = s\right\}, \tag{1.10}$$

where $S^s(\Omega_{iat})$ is the individual sector specific human capital of worker i at age a, $\mathbf{1}\{d_{iat} = s\}$ is an indicator function for sectoral choice s, and n_{at} is the number of workers of age a at time t. The current aggregate supply of human capital in sector s, $S_t^{s,sup}$, is a function of the entire sequence of human capital prices in all sectors, $\{\mathbf{r}_{t+\tau}\}_{\tau=0}^{35}$.

In equilibrium, sectoral supply of human capital, from Equation (1.10), equals sectoral demand, which is found from Equation (1.2) to be

$$S_t^{s,dem} = \alpha_t^s \frac{Y_t^s}{r_t^s}.$$

Combining the aggregate supply and demand for human capital yields the equilibrium condition for sector s

$$S_t^{s,sup}\left(\left\{\mathbf{r}_{t+\tau}^{*}\right\}_{\tau=0}^{35}\right) = \alpha_t^s \frac{Y_t^s}{r_t^{s,*}}, \tag{1.11}$$

whose solution determines the equilibrium human capital prices. As my sample period is finite, I am able to impose perfect foresight only between the initial and final sample years. Therefore it is assumed that workers have static expectations from the the final year onwards. Thus, when deciding where to work in, say, the final sample year, a worker of age 30, who forms expectations on the future sequence of human capital prices from now until he retires at age 65, assumes that future human capital prices remain at their contemporaneous level.

As the aggregate sectoral value added series, Y_t^s, and wage bill series, $\alpha_t^s Y_t^s$, are observed in the data, I impose these during estimation. This entirely removes the need to make assumptions on the evolution of physical capital.

1.2.4 Solving the Model

The set of structural model parameters consists of the discount factor, ρ, the full set of 30 wage offer function parameters for all sectors, $\{\boldsymbol{\beta}^s\}_{s=1}^5$ and $\{\sigma^s\}_{s=1}^5$, the 9 mobility cost parameters, $\{\boldsymbol{\xi}^s\}_{s=1}^5$ and $\boldsymbol{\kappa}$, the 3 unemployment benefit parameters, γ, $\overline{\text{UI}}$, and WA, and finally the 864 unemployment probability parameters, $\boldsymbol{\delta}$.

Solving the model for a given set of structural parameters involves computing the expected values in the Bellman equations (1.3) and (1.4), which presents several computational challenges. First, taking the expectation involves integrating over the distributions of η_{it}^s and ε_{it}^s. The distributional assumptions on these in (1.9), means that the integral over η_{it}^s has a convenient closed form solution (Rust, 1994). The integral over ε_{it}^s does not have a closed form, and therefore has to be numerically approximated. Here the integration is done by Monte Carlo methods.[6] The second difficulty concerns the "curse of dimensionality". The state space in (1.5) is large and contains continuous variables ($\{\mathbf{r}_{t+\tau}\}_{\tau=0}^{65-a}$ and $w_{t-\tau}$). To address this issue, I employ the Keane and Wolpin (1994) method of computing the expectations only at a subset of the state space and then inter- and extrapolating over this subset by regression. Here, that is done by second order polynomial regression. To obtain the equilibrium sequence of of human capital prices, I use the perfect foresight algorithm developed by Lee (2005).

Define

$$\begin{aligned}&\text{Emax}_{at}\Big(g, ed, el, s_{t-1}, \text{Exper}, \mathbf{r}, \{\mathbf{r}_{t+\tau}^*\}_{\tau=1}^{65-a}, w_{t-\tau}\Big) =\\&\mathbb{E}_{\boldsymbol{\varepsilon},\boldsymbol{\eta}}\mathbf{V}_{at}\Big(g, ed, el, \text{Exper}, \mathbf{r}, \{\mathbf{r}_{t+\tau}^*\}_{\tau=1}^{65-a}, w_{t-\tau}, \boldsymbol{\varepsilon}, \boldsymbol{\eta} \mid d_{t-1} = s_{t-1}\Big)\end{aligned}$$

to be the expected value, prior to drawing contemporaneous shocks of $\boldsymbol{\varepsilon}$ and $\boldsymbol{\eta}$, of a worker of age a at time t, who were in sector s_{t-1} in the last period, where s_{t-1} can also

[6]Other integration methods can be used such as Gauss-Hermite quadrature (Judd, 1998), but these methods are computationally expensive for high-dimensional problems. Although the dimensionality problem can be somewhat alleviated by sparse grid or monomial methods, this comes at the cost of precision.

be 0, in which case the worker was unemployed. Here, g is gender, ed education, el eligibility for UI benefits, $\mathbf{r}$ is the current human capital prices, and $\{\mathbf{r}^*_{t+\tau}\}_{\tau=1}^{65-a}$ are the future human capital prices. Now, let

$$\Delta = \left\{\left(\text{Exper}, \mathbf{r}, w_{t-\tau}\right) \mid \text{Exper} \leq 35;\ \underline{r} \leq r^s \leq \overline{r};\ \underline{w} \leq w_{t-\tau} \leq \overline{w}\right\},$$

where $\underline{r}$, $\overline{r}$, $\underline{w}$, and $\overline{w}$ are lower and upper bounds for human capital prices and wage in previous employment, respectively. $\text{Emax}_{at}(g, ed, el, s_{t-1}, \{\mathbf{r}^*_{t+\tau}\}_{\tau=1}^{65-a}, .)$ is approximated for all $g \in \{\text{Male}, \text{Female}\}$, $ed \in \{0,1\}$, $el \in \{0,1\}$, and $s_{t-1} \in \{0,1,2,3,4,5\}$ by the backward recursion algorithm:

1. Start at the final period $t = T$ and the final age $a = A = 65$. Draw $N = 1500$ random values of $\{\mathbf{d}^n = (\text{Exper}^n, \mathbf{r}^n, w^n_{T-\tau})\}_{n=1}^N \in \Delta$.

2. For each n draw $\boldsymbol{\varepsilon}$ and integrate over $\boldsymbol{\eta}$. Then integrate over the $\boldsymbol{\varepsilon}$ draws to get an approximation of $\text{Emax}_{AT}(g, ed, el, s_{T-1}, \mathbf{d}^n)$.

3. Approximate $\text{Emax}_{AT}(g, ed, el, s_{T-1}, .)$ by a second order polynomial regression of $\text{Emax}_{AT}(g, ed, el, s_{T-1}, \mathbf{d}^n)_{n=1}^N$ on $\{1, \text{Exper}^n, \mathbf{r}^n, w^n_{T-\tau}\}_{n=1}^N$. This polynomial regression gives a very good fit, as for all a, t, g, ed, el, and s_{t-1} I have $R^2 > 0.96$.

4. Repeat steps 1 to 3 recursively for $a = 64$ through $a = 31$ to get an approximation for $\text{Emax}_{aT}(g, ed, el, s_{T-1}, .)$. Since this is the final period workers have static expectations over the future human capital prices.

5. Repeat steps 1 to 4 for periods $t = T - 1$ to $t = 1$ using equilibrium skill prices such that $\mathbf{r}_t = \mathbf{r}^*_t$.

Once the model is solved, it can be estimated. The paper proceeds with a section describing the dataset used for estimation before turning to estimation strategy and results.

1.3 Data

Estimating the empirical model from above puts certain requirements on the data. It necessitates the use of panel data on the worker side, including observations of outcomes for the unemployed. It also requires panel data on sectoral real value added and income shares for the factors of production. Both such datasets are available from Statistics Denmark for the period 1996 to 2008. This section documents each of the sources of these data, and gives some descriptive statistics.

1.3.1 Worker Data

For each year in the sample period, the worker data is taken from the administrative register "Integrated Database for Labor Market Research" (IDA), which covers the entire Danish population aged 15-74. At birth, or when becoming a permanent resident, every individual is given a unique personal identification number, used by the local and central government to record a variety of individual level information. Likewise, the universe of Danish firms, each with a unique identifier, are recorded in the "Firm Statistics Register" (FirmStat), whose information allows me to assign each firm to the five productive sectors that are defined in accordance with the NACE Rev. 2 statistical classification of economic activities in the European Union. Workers and firms can then be matched using the "Firm-Integrated Database for Labor Market Research" (FIDA) database.

From this matched worker-firm dataset I extract data on age, sex, labor market status (employed or unemployed), UI fund membership, work experience, firm tenure, sector tenure, and hourly wages for workers aged 30 to 65. The entry age of 30 is chosen since almost all workers have completed their education at this age. For workers who are employed I observe hourly wage rates, while for the unemployed I observe unemployment benefits, which can be decomposed into UI benefits for those eligible and welfare assistance for others. It is possible to match workers with firms only from 1995 onwards, so I use the 1995 data to construct initial conditions for estimating the model.

The dataset allows me to track individual workers over the sample period, which makes it possible to construct sectoral transition rates as well as transitions to and from unemployment. Table 1.1 shows average yearly transition rates between the five productive sectors as well as the unemployment sector. Several features are worth noting. First, a key feature of the data that the model must be able to replicate is the high degree of persistence in sectoral choices: The diagonal elements of the transition matrix are all much larger than the off-diagonals, which may be the result of workers being unable to arbitrage wage differentials. Second, although there is persistence in unemployment, the persistence is smaller than that of the productive sectors. Third, workers initially unem-

Table 1.1: Average Yearly Transition Rates

From ↓ , To →	(0)	(1)	(2)	(3)	(4)	(5)
(0)	0.4794	0.0141	0.1053	0.0436	0.1046	0.2531
(1)	0.0409	0.8447	0.0281	0.0228	0.0265	0.0370
(2)	0.0294	0.0017	0.9090	0.0080	0.0249	0.0271
(3)	0.0290	0.0042	0.0208	0.9009	0.0191	0.0261
(4)	0.0227	0.0016	0.0226	0.0063	0.9144	0.0324
(5)	0.0182	0.0009	0.0075	0.0026	0.0111	0.9596

Sectors: (0) Unemployment, (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

ployed are less likely to find a job in the agriculture/mining sector and the construction sector than they are of finding a job in the other sectors, with the service sector being the most likely employer. Moreover, workers initially employed in agriculture/mining are those most likely to become unemployed, while those from the service sector are least likely.

A final observation is timely here. The transition rates to unemployment from any sector can be further decomposed into rates as a function of worker characteristics such as age, gender, and education level. This decomposition gives exactly the unemployment probabilities, $\delta(\Omega_{iat})$, from Section 1.2, which is then fixed throughout the estimation procedure.

1.3.2 Aggregate Series

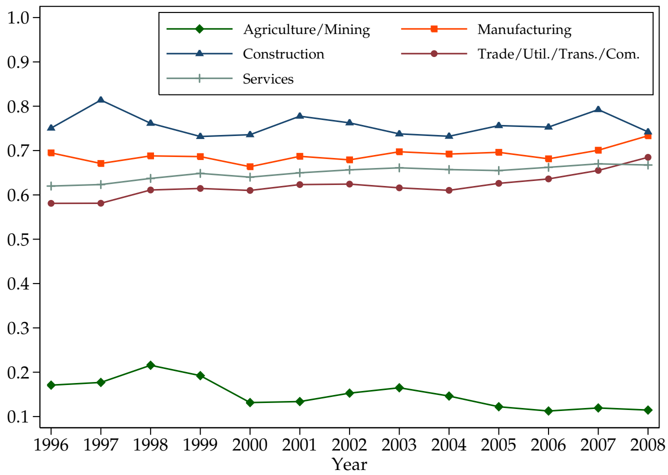
The aggregate series used for estimation and simulation are taken from the online databases of Statistics Denmark.[7] From the PRIS8 database I extract the Consumer Price Index (CPI) and set the base year to 2000. Gross value added series on the sectoral level are obtained from NATE101, while income shares for human capital and physical capital, also on the sectoral level, are constructed from data from NATE102 as

$$\alpha_t^s = \frac{\left(\text{Wage bill}\right)_t^s}{(\text{Gross value added})_t^s - (\text{Production taxes})_t^s},$$

with the physical capital share being $1-\alpha_t^s$. Figure 1.1 shows the evolution of human capital income shares.

[7] Statistikbanken (http://statistikbanken.dk)

Figure 1.1: Evolution of Labor Income Shares



From NAT09N I extract data on sectoral capital stocks, which together with income shares of capital allows me to compute the return to capital in sector s as

$$r_t^{s,K} = \left(1 - \alpha_t^s\right) \frac{Y_t^s}{K_t^s} = \frac{\left(\text{Gross surplus from production}\right)_t^s}{\left(\text{Capital stock}\right)_t^s}.$$

Finally, using Input-Output tables for the Danish economy in 2008, I construct expenditure shares as

$$\mu^s = \frac{(\text{Total uses})^s}{\sum_{k=1}^5 (\text{Total uses})^k},$$

shown in Table 1.2.

Table 1.2: Expenditure Shares

	μ^s
Agriculture/Mining	0.0114
Manufacturing	0.1757
Construction	0.0610
Trade/Util./Trans./Com.	0.2748
Services	0.4770

1.4 Estimation Strategy and Results

The structural parameters of the model, θ, are estimated using Simulated Minimum Distance (SMD), also known as Indirect Inference (see Hall and Rust (2002) and Gourieroux and Monfort (1996) for details). As the name suggests, this is a simulation based estimation technique that minimizes the distance between a set of simulated and sample moments, known as Auxiliary Parameters (APs). The sample APs are calculated once and for all, and stored in a vector, α^D. Then, for a trial value of θ, the APs are calculated on data from one or more simulations of the model, and stored in $\alpha^S(\theta)$. The SMD estimator of θ is the vector that minimizes a quadratic form of distance between the two sets of APs:

$$\widehat{\theta}_{SMD} = \arg\min_{\theta} \left[\alpha^S(\theta) - \alpha^D\right]' \mathbf{A} \left[\alpha^S(\theta) - \alpha^D\right],$$

where $\mathbf{A}$ is a positive definite matrix. So long as the APs are well enough specified, $\widehat{\theta}_{SMD}$ is a consistent estimator (asymptotically) of the true structural parameters, even when computing $\alpha^S(\theta)$ using a single simulation. As shown in Appendix 1.C, using a single simulation effectively doubles the asymptotic variance of the SMD estimator compared to a situation where the number of simulations approaches infinity. In the present context, this is a fairly small price to pay when compared to the significant computational gain of simulating data from the model only once.

1.4.1 Auxiliary Parameters

The purpose of the APs is to capture statistical relationships that allows for identification of the structural parameters of the model. Therefore, although the researchers choice of APs may seem rather *ad hoc*, the choice should be motivated by identification reasons. As the parameters to be estimated here relate to the human capital production functions and the mobility costs, the APs are simply chosen to be the coefficients of OLS regressions of the form

$$Y_{it} = X_{it}'\zeta + \lambda_t + \eta_{it},$$

where Y_{it} is the outcome, X_{it} is a vector of regressors excluding a constant, ζ is a parameter vector, and λ_t are year fixed effects for each of the years from 1996 to 2008. The regressors X_{it} are the same for all regressions: a female dummy, a tertiary education dummy, age, age squared, experience, and experience times an indicator for sectoral switching.

In order to identify the parameters of the human capital production functions in Equation (1.6), the first set of regressions are chosen to be log wage regressions for each of the five productive sectors. In addition to recording the coefficients, I also record the standard error of the regressions to help in the identification of the standard error of the shock to human capital. The next set of regressions are linear probability models (LPMs) for sectoral choices (five regressions), and LPMs for transitions between any pair of productive sectors (25 regressions). These regressions are crucial for identifying the mobility cost parameters in Equation (1.8), but the LPMs for sectoral choices also help identify parameters of the human capital production functions.

The APs are comprised of the ζ's and λ's from the regressions, as well as the root mean squared error of the log wage regressions, making a total of 670 APs. Appendix 1.D shows the results of their estimation on the sample data. The efficient choice of the weighting matrix, $\mathbf{A}$, is the inverse covariance matrix of the APs, which I bootstrap also using the matched worker-firm data.

1.4.2 Estimation Procedure

The estimation procedure involves searching over the 39 human capital production function and mobility cost parameters. The remaining parameters (unemployment probabilities, unemployment benefit parameters, and the discount factor) are calibrated. The

Table 1.3: Calibrated Parameters

Parameter		Equation	Value	USD
Discount factor,	ρ	(1.4)	0.95	
Compensation rate,	γ	(1.7)	0.90	
Maximum benefit,	$\overline{\text{UI}}$	(1.7)	101	\$22.47
Welfare assistance,	WA	(1.7)	75	\$16.69

The values for $\overline{\text{UI}}$ and WA are hourly real benefits in 2000 DKK, calculated by dividing deflated annual figures by 1,702 work hours per year. The last column shows the benefits in current US dollars using Danish CPI of 1.288 to convert to 2012 DKK and then the exchange rate of 5.79 DKK/\$.

parameters concerning unemployment benefits are set to mimic the institutional setting faced by Danish workers (see Appendix 1.A).

The estimation procedure follows the steps:

1. From the data, obtain series for real value added, Y_t^s, and human capital income shares, α_t^s. These are imposed throughout the estimation procedure.

2. Obtain the 670 sample auxiliary parameters, α^D, and get their covariance matrix by a bootstrap procedure.

3. Solve the structural model and simulate sectoral choice paths that resembles those observed in the data with respect to e.g. age, gender and education profiles. Obtain simulated auxiliary parameters, $\alpha^S(\theta)$, using the simulated data.

4. Search for the structural parameter vector, $\widehat{\theta}_{SMD}$, that minimizes the quadratic distance between the simulated and sample auxiliary parameters using the bootstrapped covariance matrix as the weighting matrix.

Once the structural model parameters are estimated, the covariance matrix is computed at their optimized values. As shown in Appendix 1.C, the covariance matrix for the estimated parameters is computed using the bootstrapped covariance matrix of the sample auxiliary parameters. Thus, the precision of the structural estimates are a function of the precision of the auxiliary estimates.

1.4.3 Estimation Results

Table 1.4 gives the results of simulated minimum distance estimation of the human capital production function parameters. As expected, human capital grows with work

Table 1.4: Human Capital Production Functions

	(1)	(2)	(3)	(4)	(5)
Female	-0.2628	-0.1747	-0.2361	-0.2150	-0.1667
	(0.0003)	(0.0001)	(0.0003)	(0.0003)	(0.0002)
Educ	0.1454	0.3180	0.1710	0.2361	0.2533
	(0.0001)	(0.0005)	(0.0002)	(0.0003)	(0.0003)
Exper	0.0254	0.0220	0.0337	0.0263	0.0229
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper^2	-0.0004	-0.0002	-0.0004	-0.0001	-0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	-0.0007	-0.0250	-0.0425	-0.0336	-0.0214
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
σ^s	0.2721	0.2735	0.2816	0.3360	0.2875
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)

Standard errors in parenthesis. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

experience. However, experience is generally not completely transferable across sectors, as seen from the negative coefficients on Exper($s_{t-1} \neq s$). The transferability of experience varies over the sector of entry with experience being almost entirely transferable to the agriculture/mining sector and least transferable to construction.

That barriers to mobility are potentially large is clear from Table 1.5, which also shows that mobility costs are heterogeneous over worker characteristics with women, older, and less educated workers facing higher costs.

Table 1.5: Mobility Costs

	(1)	(2)	(3)	(4)	(5)
ξ	7.0009	5.3759	6.2341	4.7008	6.0461
	(0.0747)	(0.0178)	(0.0350)	(0.0201)	(0.0120)
	Female	Educ	Age	Age^2	
κ	0.2117	-0.1987	0.0696	-0.0003	
	(0.0008)	(0.0002)	(0.0000)	(0.0000)	

Standard errors in parenthesis. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

To interpret the mobility cost estimates, Table 1.6 computes (counterfactual) median mobility costs for all workers in terms of average annual wages. The trade/util./tran./com. sector is most costly to enter with a median cost of 2.4 times average annual wages, while the services sector is least costly to enter at 1.2 times annual wages. These estimates are very much in line with those found by Dix-Carneiro (2013), and much smaller than the mobility costs of around 6 times annual average wages as found by Artuç, Chaudhuri, and McLaren (2010) using CPS data from the United States.[8] When restricting focus to the workers who switch sectors, the median mobility costs are much lower at between 0.4 and 0.9 times average annual wages.

Figure 1.2 shows the non-parametric density of the counterfactual mobility costs of entering each sector. These densities differ because of the different demographic characteristics of workers employed in the sectors.

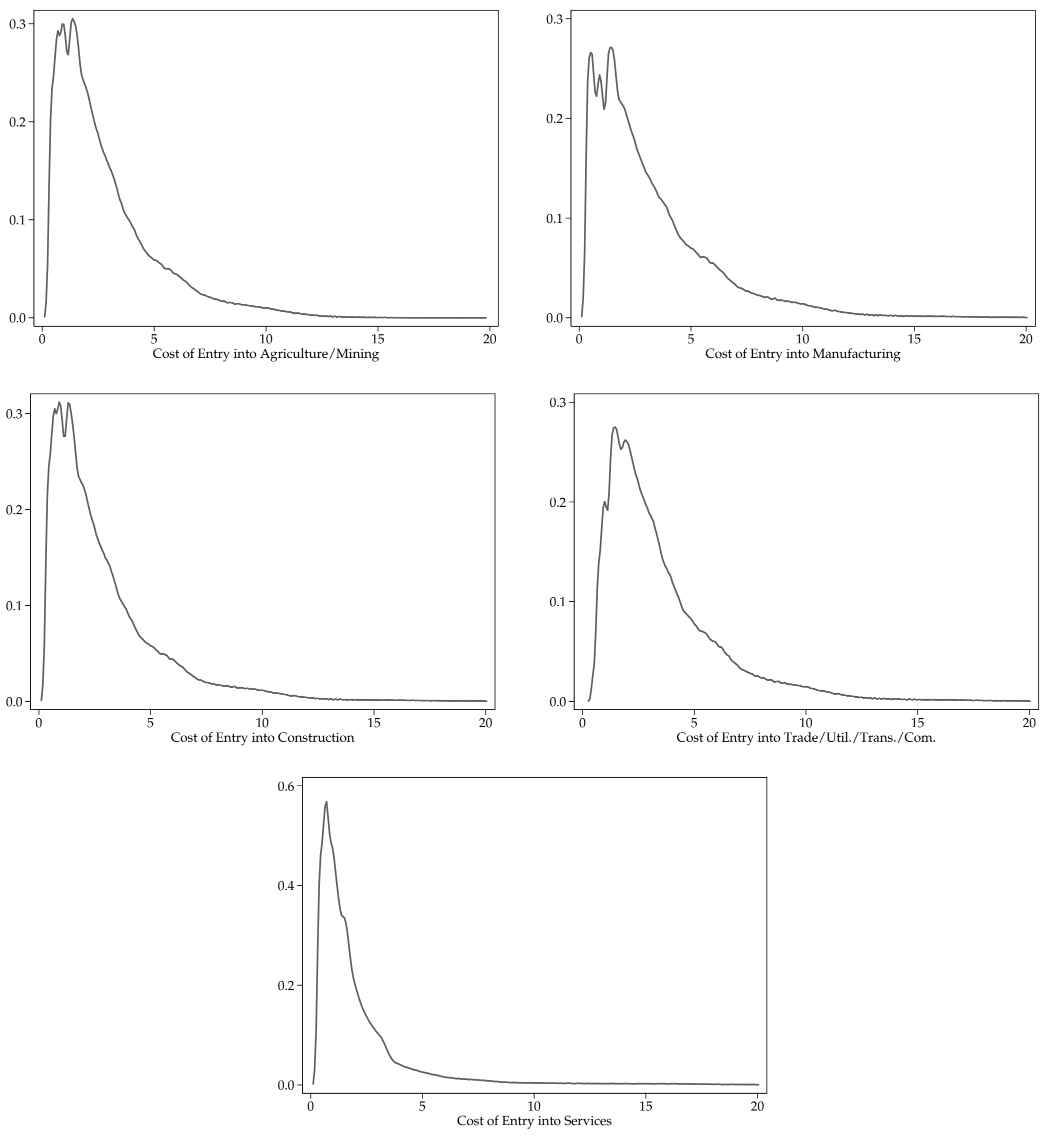
[8]See Dix-Carneiro (2013) for a discussion of the methodological source of this difference.

Table 1.6: Mobility Costs in Terms of Wages

	All workers	Conditional on switching
Agriculture/Mining	1.9262	0.4895
Manufacturing	2.1938	0.4235
Construction	1.9005	0.4985
Trade/Util./Tran./Com.	2.4494	0.9016
Services	1.1686	0.5609

Median costs of entry to the indicated sector is computed as $\mathbf{C}^{ss'}(X_i)/\hat{w}(X_i)$, where $\hat{w}(X_i)$ is an estimate of the average annual wage of a worker with characteristics X_i.

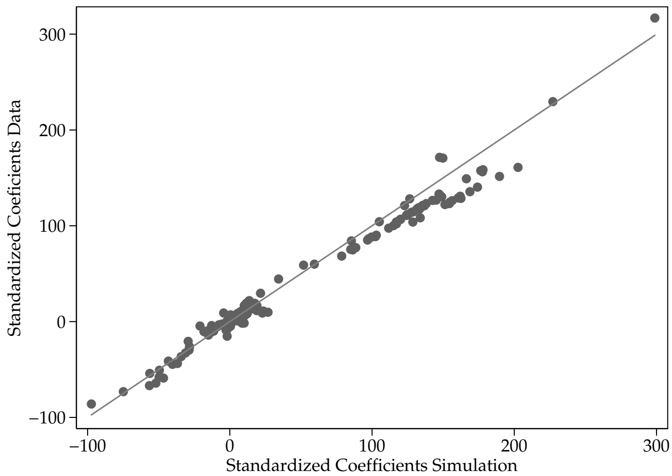
Figure 1.2: Kernel Densities of Mobility Costs



1.4.4 Goodness of Fit

To asses the goodness of fit of my model, I plot the auxiliary parameters from the data against auxiliary parameters simulated from the model. A perfect fit would result in all point lying on the plotted 45 degree line. Though all points are not on the 45 degree line,

Figure 1.3: Goodness of Fit – Scatter over 45 degree line



the estimated model does a sensible job of matching the moments from the observed data.

Table 1.7 shows average sectoral choices in actual and simulated data. The model is able to match sectoral choices remarkably well.

Table 1.7: Average Sectoral Choices

	Actual Data	Simulated Data
Unemployment	0.0397	0.0438
Agriculture/Mining	0.0132	0.0227
Manufacturing	0.1861	0.1817
Construction	0.0591	0.0624
Trade/Util./Tran./Com.	0.1948	0.2122
Services	0.5071	0.4772

1.5 Simulations

Now that the parameters of the model are estimated, it can be used to evaluate the effects of counter-factual structural changes in the model economy. The focus here is to study the dynamics following a globalization shock to the manufacturing sector that both increases the probability of becoming unemployed for workers there and, at the same time, reduces the output price of the sector. Before doing that, however, it will be useful to consider the shocks in isolation in order to compare the differential way in which they affect the economy. This section therefore considers the dynamics following three shocks: (i) Unemployment shock only, (ii) Trade Liberalization shock only, and (iii) Globalization (both unemployment and trade liberalization shocks). All shocks occur to the manufacturing sector. A maintained assumption through all simulations is that only the outputs of the agriculture/mining sector and the manufacturing sector are traded globally at exogenous world market prices. The output prices of the remaining non-traded sectors are endogenously determined by the model.

The unemployment shock is modeled as a permanent unanticipated doubling of the unemployment probability for workers employed in manufacturing, such that a worker previously facing a one percent probability of becoming unemployed now faces a two percent unemployment probability. Trade liberalization is modeled as a permanent 30% decline in the output price of the manufacturing sector.

1.5.1 Additional Assumptions

In estimating the model in Section 1.4, no assumptions were made on the accumulation of physical capital. All that was needed was the sectoral real value added series and income shares, both of which were observed.[9] When simulating the model this no longer suffices: Further assumptions are necessary in order to endogenize output prices for the non-traded sectors. I assume that the sectoral returns to physical capital, which are observed in the sample period (see Section 1.3), remain fixed at their 2008 level. This has two consequences: (i) Physical capital cannot flow across sectors, so physical capital is sector specific, and (ii) Sectoral physical capital levels adjust freely in order for physical capital returns to remain constant.

The instantaneous utility from consuming is given by the Cobb-Douglas function

$$u(\mathbf{C}) = \prod_{s=1}^{5} C_s^{\mu^s},$$

where the expenditure shares, $\boldsymbol{\mu}$, are those from Table 1.2. The indirect utility of a worker with nominal wage w_t is then $w_t / \prod_{s=1}^{5} \left(p_t^s\right)^{\mu^s}$. The real income of capital owners is $\sum_{s=1}^{5} r_t^{s,K} K_t^s$.

[9]This is an implicit assumption that capital is allocated efficiently during the estimation procedure.

All output from the non-traded sectors must be consumed domestically, which identifies the output prices of these sectors:

$$\begin{aligned}
&\mu^s \sum_{k=1}^{5} Y_t^k = Y_t^s \iff \\
&p_t^s = \frac{\mu^s}{1-\mu^s}\left[\frac{\left(\sum_{k=1}^{5} Y_t^k\right) - Y_t^s}{A_t^s\left(S_t^s\right)^{\alpha_t^s}\left(K_t^s\right)^{1-\alpha_t^s}}\right]
\end{aligned} \quad \text{for } s = 3,4,5.$$

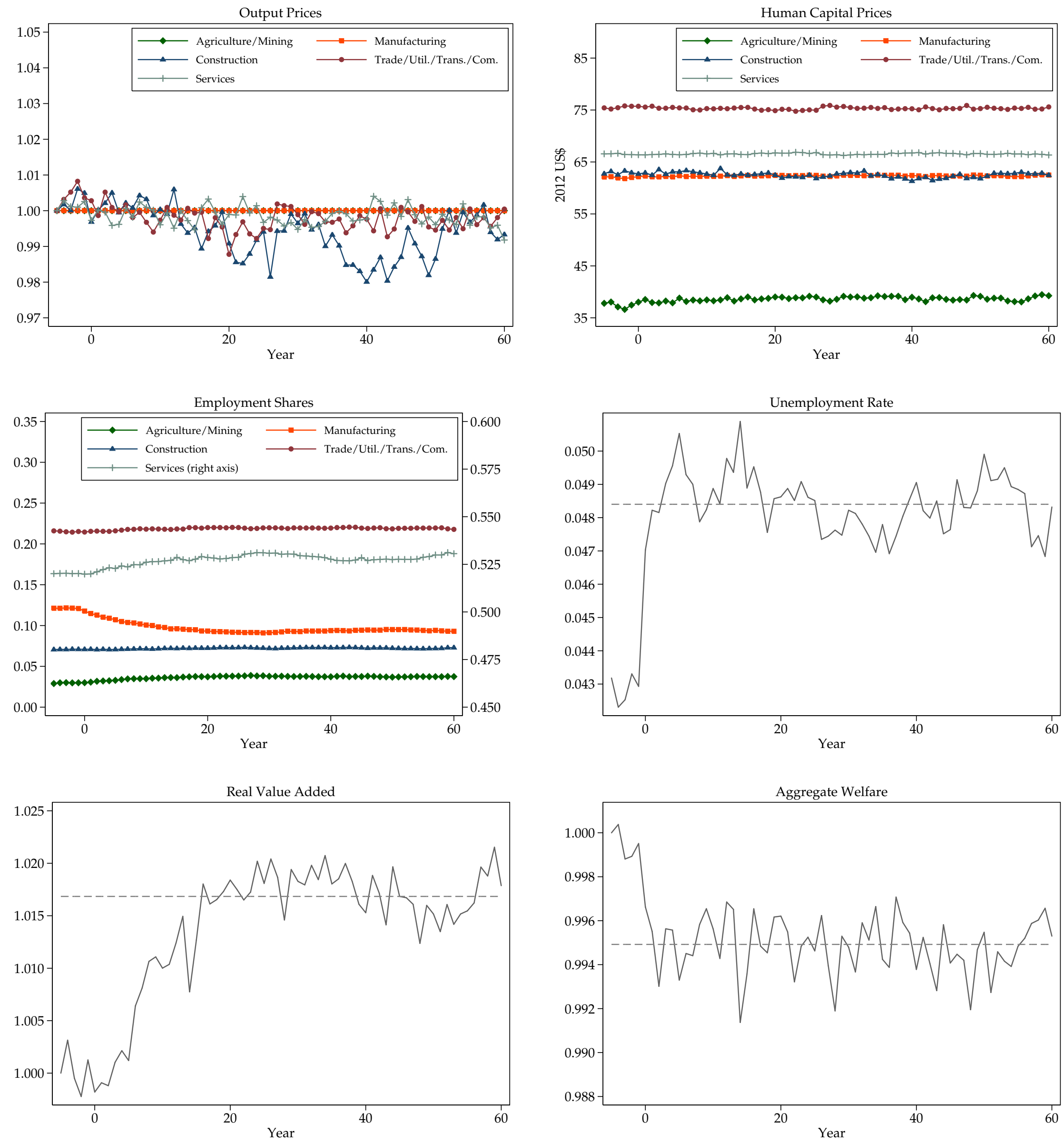
Finally, the unemployed are compensated by lump-sum transfers from employed workers and capital owners. With these assumptions, the dynamics following counter-factual shocks to unemployment and to the output price of the manufacturing sector can now be examined.

1.5.2 Unemployment Shock

Consider the effect of a permanent shock to the probability of becoming unemployed for workers in the manufacturing sector. The share of manufacturing workers who become unemployed increases, leading to a higher unemployment rate. The manufacturing sector is now less attractive, which leads workers to seek out opportunities in other sectors, lowering the share of the workforce employed in manufacturing. Due to the reallocation cost, however, the adjustment process is sluggish: 50% of the reallocation is completed after 7 years, and 90% after 17 years. The employment share of manufacturing drops by 25% compared to the initial steady state. However, this adjustment in the labor market leaves both output prices and human capital prices virtually unaffected. As manufacturing workers are reallocated elsewhere, production drops, putting downward pressure on wages. But, as the price of physical capital is assumed to be fixed, the physical capital level drops proportionally to human capital in order to hold constant the rental price of physical capital. As the ratio of physical to human capital remains unchanged, so do the human capital prices.

In the new steady state, the real value added of the economy has increased by 1.7%. The gradual labor market adjustment is clear: After 10 years real value added is adjusted by only 59% of new steady state level. Despite the increase in real value added, aggregate welfare is 0.005% lower in the new steady state. The reason for this drop in welfare is that the new equilibrium unemployment rate is higher, meaning greater transfers from the employed to the unemployed.

Figure 1.4: Simulation – Unemployment Shock

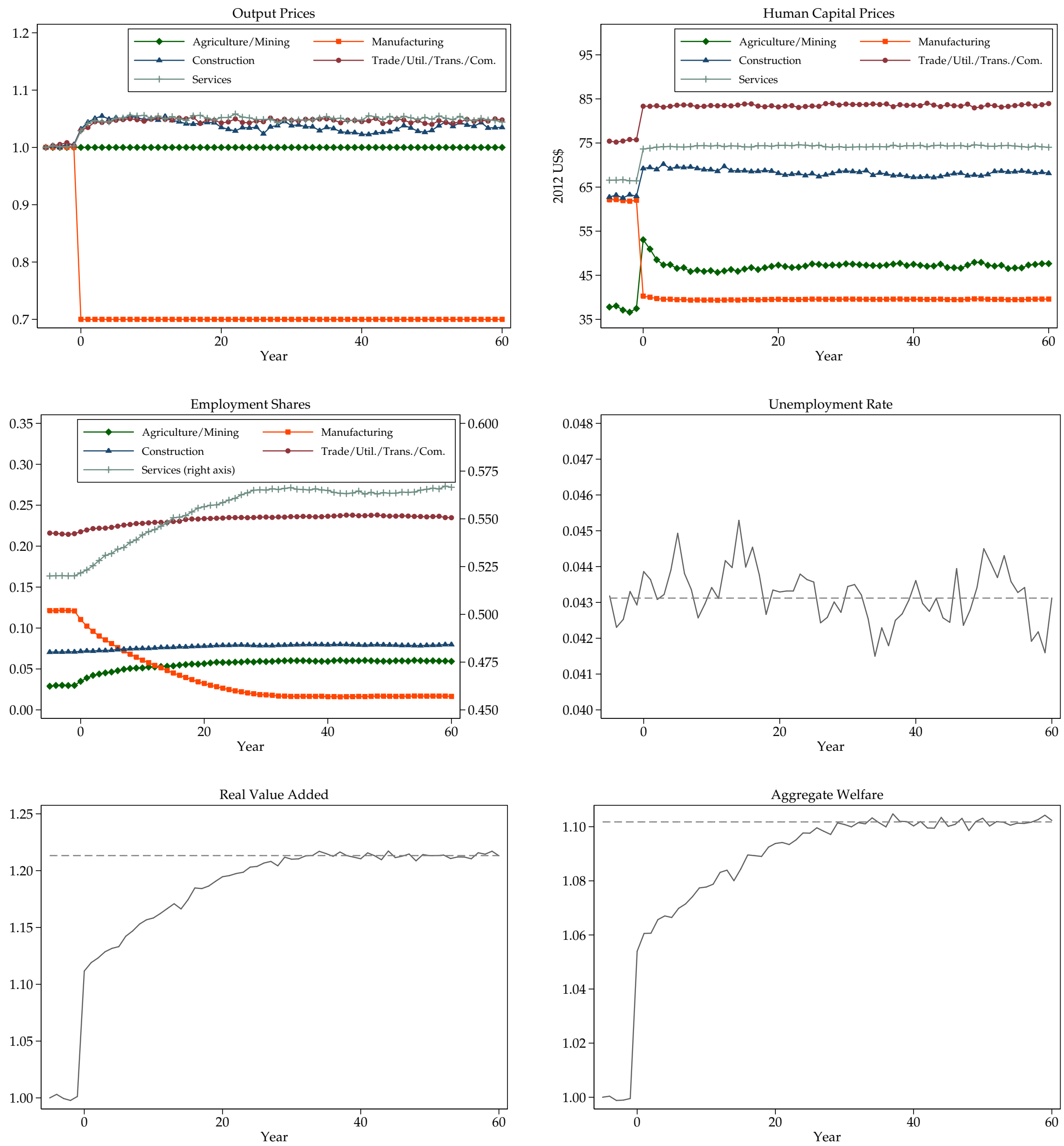


1.5.3 Trade Liberalization

Now consider the effects of a 30% decrease in the output price of the manufacturing sector due to trade liberalization. The output price of the agriculture/mining sector remains constant as it is assumed that its output is traded internationally. The output prices of the remaining non-traded sectors adjust endogenously. Human capital prices in the manufacturing sector drop with the output price shock. The manufacturing sector all but disappears as workers reallocate towards the other sectors. 49% of the reallocation is complete after 9 years, while 91% is complete only after 24 years.

Human capital prices are affected by trade liberalization for two reasons. First, lowering output prices reduces the marginal product of human capital, putting downward pressure on human capital prices. Second, in order to keep the physical capital return fixed, the ratio of physical to human capital drops, further lowering human capital prices. When the economy reaches the new steady state, real value added has increased by 21%, albeit gradually: After 10 years 74% of the adjustment is complete. The welfare gains are smaller at 10%, due to the presence of unemployment.

Figure 1.5: Simulation – Trade Liberalization



1.5.4 Globalization Shock

Focus now on the dynamics following a joint shock; that is, both a doubling of the unemployment probabilities facing manufacturing workers, and a 30% decrease in the manufacturing output price. Again, the output price of the agriculture/mining sector remains constant while the prices of the remaining non-traded sectors adjust endogenously. Human capital prices in the manufacturing sector drop with the output price shock and workers reallocate towards other industries.

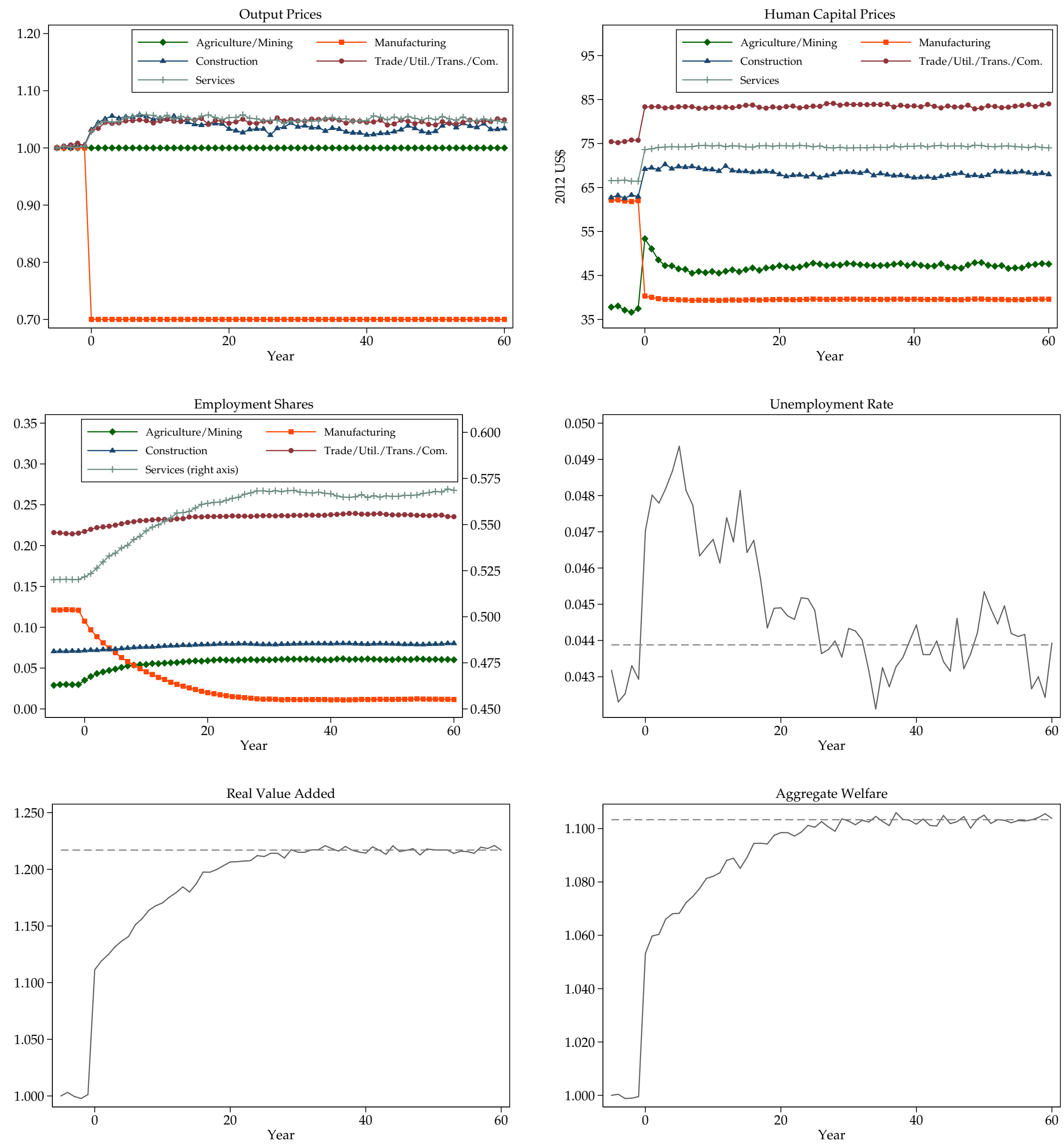
The unemployment rate initially jumps as it is now more likely for manufacturing workers to become unemployed. However, as the labor market adjusts, the unemployment rate gradually drops towards its initial level. This drop happens even though the rise in unemployment probability for manufacturing workers was assumed to be permanent. But as the manufacturing employment share declines from about 12% of the workforce to less than 2%, the number of workers affected by the increase in unemployment probabilities is dramatically reduced.

1.5.5 The Role of the Mobility Costs

In order to examine how the mobility costs affect the dynamic adjustment process, it is useful to consider a situation in which the utility cost of switching sectors is zero. Figure 1.7 plots the cumulated labor market reallocation as a percent of the final year for the globalization shock. This is done for two scenarios: One where the mobility cost is set to zero for all workers, and one where the mobility cost is the one estimated above.

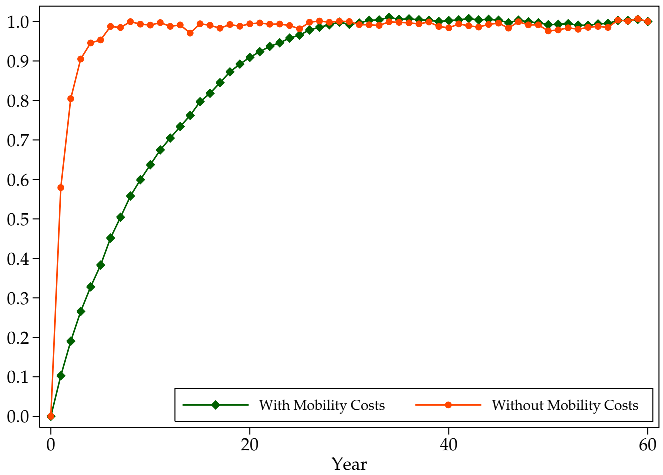
The green line in the figure shows the reallocation process described in the simulation above where mobility costs are estimated. The reallocation process is very sluggish and takes several years to complete: One year after the shock 10% of the reallocation process is completed and 90% completion is reached only after 20 years. In absence of the mobility costs, the reallocation is much faster: 58% of the reallocation is completed by the end of the first year and 90% completion is done during the fourth year. The reallocation is not immediate when the mobility costs are zero. This is due to the fact that the existence of sector specific human capital makes it costly to switch sectors even when mobility costs are zero. Also note that the reallocation process is much more volatile when the mobility costs are zero as workers become much more likely to switch sectors from one year to the next.

Figure 1.6: Simulation – Globalization Shock



This would suggest that, in so far as policy makers wish to minimize the length of the reallocation period, focus should be on policies that minimize the mobility costs. One such policy may be educating workers through job training programs, as the estimation results show that more educated workers face smaller mobility costs. Modeling and assessing the impact of such policies is important and left for future research.

Figure 1.7: Speed of Labor Reallocation Following Globalization Shock



1.6 Conclusion

This paper built and estimated a dynamic structural model of the Danish labor market in order to compare the different adjustment mechanism in force when the economy is respectively hit by an unemployment shock and a trade liberalization episode, both to the manufacturing sector. The unemployment shock lead workers to reallocate away from manufacturing towards more productive sectors. Although this reallocation increased the real value added of the economy, aggregate welfare dropped as the new steady state unemployment rate increased. The labor market adjustment left human capital prices unaffected as physical capital levels adjusted in order to keep the ratio of physical to human capital constant. Trade liberalization also lead to reallocation of manufacturing workers. Unlike the unemployment shock, both real value added and aggregate welfare increased in the new equilibrium, and the price of human capital in the manufacturing sector dropped, both due to the lower output price and due to a lower equilibrium ratio of physical to human capital.

In both cases, the labor market adjustment process was sluggish: After 10 years real value added had adjusted by 59% when hit by the unemployment shock, and 74% when exposed to trade liberalization. There are two explanations for the sluggishness. First, as part of the human capital of a worker is specific to the sector in which he works, human capital is not entirely transferable across sectors. This means that it takes time for reallocated workers to build up human capital in the new sectors. Secondly, workers face substantial mobility costs when switching sectors, resulting in postponement of reallocation. The estimation shows that the mobility costs are large and provide a substantial barrier to reallocation with median costs in the range of 1.2 to 2.4 times average annual wages.

In case of the unemployment shock, it is important to bear in mind that the only source of gains is from a more efficient allocation of resources. If the unemployment shock proxies a trade shock such as offshoring, additional gains, such as productivity increases or lower intermediate input prices, may exist. These are not modeled here, and the estimating gains from these sources is left for future work.

The mobility costs turn out to be crucial in understanding the slow adjustment following globalization shocks. When these costs are absent, the labor market reallocates to the new steady state within 2 to 3 years. As more educated workers face smaller mobility costs, policy makers wishing to minimize the adjustment period could focus on implementing policies such as job training for workers. Assessing the efficiency of such policies is important, but lies outside the scope of the current paper, which is focused on estimating the reallocation costs.

The paper can be seen as an attempt to take seriously some arguments often encountered in the public debate on globalization, which often focuses the costs rather than the gains. By measuring the costs and showing that they are potentially large, the paper is able to illustrate the trade offs faced by individual workers worried by the prospect of reallocating to new sectors, and those faced by policy makers focused on attaining aggregate gains. As the process of globalization continues, this conflict is bound to become ever more present.

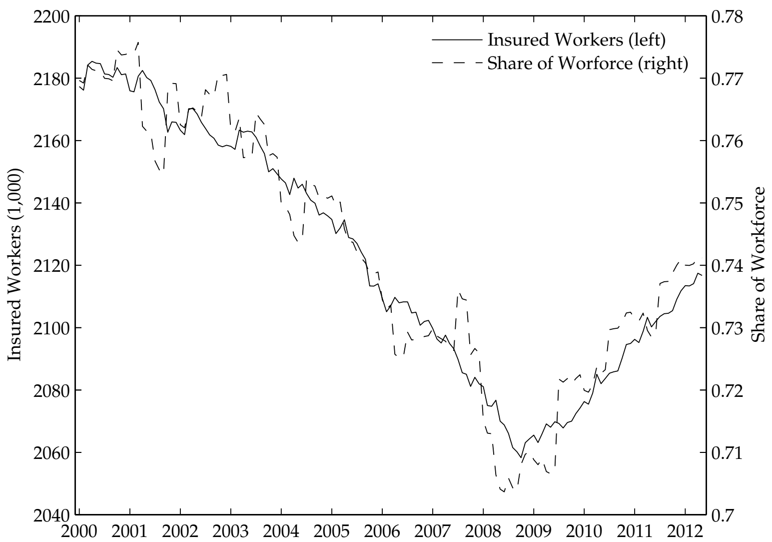
Appendices

1.A Unemployment Benefits in Denmark

This section describes the institutional setting for the unemployed in Denmark as applicable to the period from 1996 to 2008. The structural model in Section 1.2 includes a model of the institutional setting presented here.

All unemployed workers who wish to receive benefits must be registered as "seeking employment" at local job-centers run by the government. Then there are two separate systems: One for members of unemployment insurance (UI) fund, and one for those who are not.

Figure 1.8: Insured Workers



The figure shows that the vast majority of the workforce are members of a UI fund; the membership rate is about 70-77 percent in the period shown.

1.A.1 Benefits for the Insured

The UI system is administered by government approved UI funds ("A-kasser"). In order to be eligible for UI benefits, a worker must satisfy certain criteria. The worker must

1. have been member of an UI fund for at least one year,
2. satisfy the employment criterion,
3. satisfy the availability criteria,
4. not be unemployed by self-infliction.

The employment criterion states that full-time insured must have been employed for at least 52 weeks out of the last 3 years while the part-time insured must have been employed for at least 34 weeks out of the last 3 years in order to be eligible for UI benefits. Some of the availability criteria are that the worker must actively seek any employment opportunities and reside in Denmark.

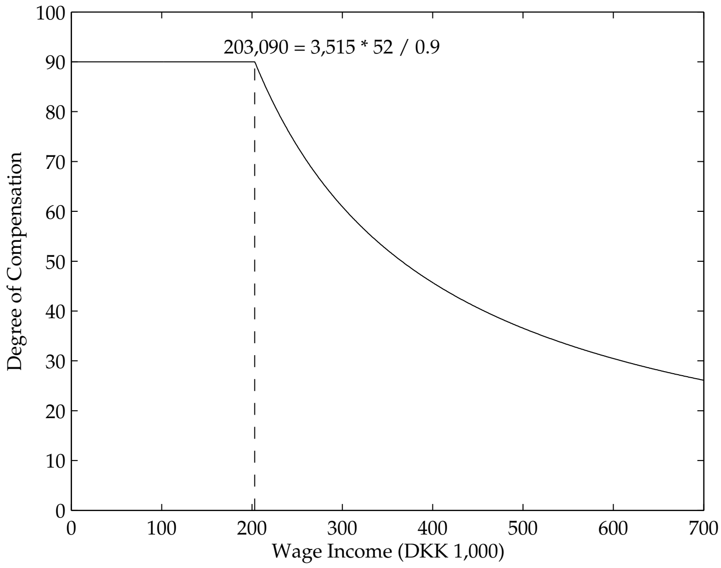
If the worker is eligible for UI benefits, then the weekly benefit is calculated as 90 percent of the worker's labor income for the past 3 months or 12 weeks, depending on whether the wage was paid on a monthly basis, or weekly of biweekly basis. However, the maximum benefit is DKK 3,515 per week from January 1, 2008. This number is regulated once a year by a factor that takes into account the general development of wages for the employed. The UI benefits are paid out for a maximum of four years after which the benefits expire.

Since the maximum UI benefit is capped at DKK 203,090 a year in 2008, the degree of compensation drops in incomes above this level. The resulting compensation degree is 61 and 46 percent for yearly incomes of DKK 300,000 and DKK 400,000, respectively.

1.A.2 Benefits for the Uninsured

The unemployed workers who are either uninsured or ineligible for UI benefits may apply for welfare assistance ("kontanthjælp"). The size of the assistance depends on a number of factors. For workers of age 25 and above that are caretakers of children, the monthly maximum assistance is DKK 13,732 in 2012, while that figure is DKK 10.335 for those without children. For workers under the age of 25 the maximum assistance is DKK 6,660 for caretakers and DKK 5,662 for others.

Figure 1.9: Compensation Rate



However, workers are only eligible for assistance if their assets do not exceed a total value of DKK 10,000. Furthermore, spousal income is deducted from the assistance.

1.B Sectors

Table 1.8: Mapping from NACE Rev. 2 to Sectors

Agriculture/Mining	Agriculture and Horticulture (01); Forestry (02); Fishing (03); Extraction of Oil and Gas (06); Extraction of Gravel and Stone (08); Mining Support Service Activities (09)
Manufacturing	Food Products (10); Beverages (11); Tobacco Products (12); Textiles (13); Wearing Apparel (14); Leather and Related Products (15); Wood and Wood Products (16); Paper and Paper Products (17); Printing and Reproduction of Recorded Media (18); Coke and Refined Petroleum Products (19); Chemicals and Chemical Products (20); Pharmaceuticals (21); Rubber and Plastic Products (22); Other Non-Metallic Mineral Products (23); Basic Metals (24); Fabricated Metal Products (25); Computer, Electronic and Optical Products (26); Electrical Equipment (27); Machinery and Equipment (28); Motor Vehicles (29); Other Transport Equipment (30); Furniture (31); Other Manufacturing (32); Repair and Installation of Machinery and Equipment (33)
Construction	New Buildings (41); Civil Engineering (42); Specialized Construction Activities (43)
Trade/Utilities/ Transportation/Communication	Electricity, Gas, Steam and Air Conditioning Supply (35); Water Collection, Treatment and Supply (36); Sewerage (37); Waste and Recycling (38); Wholesale and Retail Trade and Repair of Motor Vehicles and Motorcycles (45); Wholesale Trade (46); Retail Trade (47); Land Transport and Transport via Pipelines (49); Water Transport (50); Air Transport (51); Support Activities for Transportation (52); Postal and Courier (53); Publishing (58); Motion Picture and TV Program Production (59); Programming and Broadcasting (60); Telecommunications (61); Computer Programming and Consultancy (62); Information Services (63)
Services	Accommodation (55); Food and Beverage Services (56); Financial Services (64); Insurance and Pension Funding (65); Other Financial Activities (66); Real Estate (68); Legal and Accounting (69); Business Consultancy (70); Architecture and Engineering (71); Scientific Research and Development (72); Advertising and Market Research (73); Other Professional, Scientific and Technical Activities (74); Veterinary Activities (75); Renting and Leasing (77); Employment (78); Travel Agency (79); Security and Investigation (80); Services to Buildings and Landscapes (81); Other Business Services (82); Public Administration (84); Education (85); Human Health (86); Residential Care (87); Social Work (88); Creative, Arts and Entertainment (90); Libraries and Museums (91); Gambling and Betting (92); Sports (93); Activities of Membership Organizations (94); Repair of Personal Goods (95); Other Personal Services (96); Activities of Households as Employers of Domestic Personnel (97)

1.C Asymptotic Distribution of the SMD Estimator

Define the SMD estimator[10] as

$$\widehat{\theta}_{SMD} = \arg\min_{\theta} \left[\alpha^S(\theta) - \alpha^D\right]' \mathbf{A} \left[\alpha^S(\theta) - \alpha^D\right], \tag{1.12}$$

where the positive definite weighting matrix $\mathbf{A}$ is assumed to converge to a non-stochastic matrix. If the model is well specified $\alpha^S(\theta)$ converges to α^D. Then, by using $\text{plim}\,\alpha^S(\theta) = \alpha^\infty(\theta)$ and $\text{plim}\,\alpha^D = \alpha^0(\theta)$, we have

$$\text{plim}\,\widehat{\theta}_{SMD} = \theta_0.$$

Let

$$\begin{aligned}
\alpha^S(\theta) - \alpha^D &= \alpha^S(\theta) - \alpha^D + \alpha^\infty(\theta_0) - \alpha^\infty(\theta_0) + \alpha^0(\theta_0) - \alpha^0(\theta_0) \\
&= \left[\alpha^S(\theta) - \alpha^\infty(\theta_0)\right] + \left[\alpha^0(\theta_0) - \alpha^D\right] + \left[\alpha^\infty(\theta_0) - \alpha^0(\theta_0)\right],
\end{aligned}$$

where the last term cancels out when the model is well specified. Now, apply the Central Limit Theorem and evaluate at $\theta = \theta_0$ to get

$$\sqrt{n}\left[\alpha^S(\theta_0) - \alpha^D\right] = \sqrt{n}\left[\alpha^S(\theta_0) - \alpha^\infty(\theta_0)\right] + \sqrt{n}\left[\alpha^0(\theta_0) - \alpha^D\right],$$

and

$$\sqrt{n}\left[\alpha^S(\theta_0) - \alpha^D\right] \longrightarrow^d \mathcal{N}\left(0, \frac{S+1}{S}\mathbf{V}_0\right). \tag{1.13}$$

The first order condition of the optimization problem in (1.12) is

$$\left[\alpha^S(\theta) - \alpha^D\right]' \mathbf{A} \nabla \alpha^S(\theta) = 0,$$

and a Taylor series expansion around θ_0 gives

$$\alpha^S(\theta) = \alpha^S(\theta_0) + \nabla \alpha^S(\theta_0)\left[\theta - \theta_0\right].$$

Substitute back into the first order condition and solve for $[\theta - \theta_0]$ to get

$$[\theta - \theta_0] = -\left[\nabla \alpha^S(\theta)' \mathbf{A} \nabla \alpha^S(\theta)\right]^{-1} \nabla \alpha^S(\theta)' \mathbf{A} \left[\alpha^S(\theta_0) - \alpha^D\right].$$

Using this and (1.13) we get

$$\sqrt{n}\left[\widehat{\theta}_{SMD} - \theta_0\right] \longrightarrow^d \mathcal{N}\left(0, \frac{S+1}{S}\mathbf{G}_1^{-1}\mathbf{G}_2\mathbf{G}_1^{-1}\right),$$

[10] See Hall and Rust (2002), Browning, Ejrnæs, and Alvarez (2010), and Alan (2006).

where

$$\mathbf{G}_1 = \left[\operatorname{plim} \nabla \alpha^S(\theta_0)\right]' \mathbf{A}_\infty \left[\operatorname{plim} \nabla \alpha^S(\theta_0)\right],$$
$$\mathbf{G}_2 = \left[\operatorname{plim} \nabla \alpha^S(\theta_0)\right]' \mathbf{A}_\infty \mathbf{V}_0 \mathbf{A}_\infty \left[\operatorname{plim} \nabla \alpha^S(\theta_0)\right].$$

With the optimal weighting matrix $\mathbf{A} = \mathbf{V}_0^{-1}$, the asymptotic distribution of the Simulated Minimum Distance Estimator is

$$\sqrt{n}\left[\widehat{\theta}_{SMD} - \theta_0\right] \longrightarrow^d \mathcal{N}\left(0, \frac{S+1}{S}\mathbf{G}^{-1}\right),$$

where

$$\mathbf{G} = \left[\operatorname{plim} \nabla \alpha^S(\theta_0)\right]' \mathbf{V}_0^{-1} \left[\operatorname{plim} \nabla \alpha^S(\theta_0)\right].$$

1.D Auxiliary Parameters

Table 1.9: Log-Wage Regressions

	(1)	(2)	(3)	(4)	(5)
Female	-0.225770	-0.169741	-0.166993	-0.198295	-0.209311
	(0.0018)	(0.0003)	(0.0009)	(0.0004)	(0.0002)
Educ	0.160424	0.316571	0.215302	0.290197	0.226375
	(0.0019)	(0.0004)	(0.0008)	(0.0005)	(0.0002)
Age	0.038571	0.013350	0.018009	0.018789	0.012954
	(0.0008)	(0.0002)	(0.0003)	(0.0002)	(0.0001)
Age^2	-0.000445	-0.000184	-0.000225	-0.000266	-0.000172
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	0.004641	0.006850	0.006529	0.008335	0.006877
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	-0.001951	-0.002840	-0.003274	-0.003691	-0.004709
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	4.217619	4.824655	4.704604	4.738534	4.838578
	(0.0180)	(0.0037)	(0.0067)	(0.0043)	(0.0025)
1997	4.214235	4.814332	4.693450	4.735317	4.827604
	(0.0180)	(0.0037)	(0.0067)	(0.0043)	(0.0025)
1998	4.236790	4.857475	4.716918	4.759405	4.855633
	(0.0180)	(0.0037)	(0.0067)	(0.0043)	(0.0025)
1999	4.230793	4.845266	4.724120	4.760118	4.857312
	(0.0180)	(0.0037)	(0.0067)	(0.0043)	(0.0025)
2000	4.241672	4.851834	4.729479	4.763529	4.863007
	(0.0180)	(0.0037)	(0.0067)	(0.0043)	(0.0025)
2001	4.257276	4.865525	4.749059	4.778822	4.882439
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2002	4.271265	4.869439	4.749296	4.779176	4.880082
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2003	4.235850	4.853705	4.732755	4.756843	4.862623
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2004	4.235780	4.851975	4.731816	4.747835	4.872738
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2005	4.282241	4.894966	4.773812	4.789896	4.909219
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2006	4.310018	4.918123	4.801449	4.810689	4.931857
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2007	4.336668	4.940444	4.825477	4.840149	4.953328
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
2008	4.338527	4.934240	4.815024	4.842222	4.967502
	(0.0180)	(0.0037)	(0.0066)	(0.0043)	(0.0025)
Root MSE	0.373303	0.276544	0.284388	0.336371	0.305798
R^2	0.995	0.997	0.997	0.996	0.997
Observations	268224	3791930	1204452	3968220	10331959

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 1.10: LPMs for Sectoral Choices

	(1)	(2)	(3)	(4)	(5)
Female	-0.012603	-0.105754	-0.082464	-0.086120	0.288068
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Educ	-0.007912	-0.099011	-0.047300	-0.133806	0.316794
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Age	-0.000378	-0.000129	-0.000754	-0.012433	0.015647
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age^2	0.000005	-0.000035	0.000002	0.000091	-0.000130
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	-0.000394	0.002072	-0.000033	0.002935	0.001086
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	0.000429	-0.001663	0.000447	-0.000830	-0.008370
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	0.035880	0.311438	0.133809	0.577965	-0.188614
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
1997	0.035511	0.314994	0.134018	0.579744	-0.177914
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
1998	0.035490	0.318760	0.136030	0.583498	-0.173233
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
1999	0.035470	0.316217	0.137536	0.585554	-0.169940
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2000	0.035606	0.316729	0.139924	0.584328	-0.170248
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2001	0.035931	0.315354	0.140495	0.583353	-0.166604
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2002	0.036282	0.312481	0.140331	0.583231	-0.166076
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2003	0.036060	0.306324	0.140641	0.584214	-0.169382
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2004	0.036200	0.301354	0.141749	0.586223	-0.165607
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2005	0.036200	0.298510	0.144899	0.590177	-0.161753
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2006	0.036111	0.299514	0.148197	0.592117	-0.157089
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2007	0.036659	0.300686	0.148819	0.595435	-0.153928
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
2008	0.036267	0.291473	0.146335	0.598015	-0.141547
	(0.0007)	(0.0022)	(0.0013)	(0.0022)	(0.0026)
R^2	0.018	0.220	0.099	0.233	0.604
Observations	20373918	20373918	20373918	20373918	20373918

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 1.11: LPMs for Transitions from Agriculture/Mining

	(1)	(2)	(3)	(4)	(5)
Female	-0.011452	-0.000318	-0.000435	-0.000230	-0.000107
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Educ	-0.006931	-0.000171	-0.000155	-0.000158	-0.000065
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age	-0.000262	-0.000056	-0.000055	-0.000069	-0.000002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age^2	0.000003	0.000000	0.000000	0.000001	0.000000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	-0.000270	-0.000014	-0.000007	-0.000013	-0.000033
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	-0.000553	0.000196	0.000181	0.000190	0.000262
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	0.028636	0.002369	0.002093	0.002448	0.000990
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
1997	0.029337	0.002132	0.001962	0.002311	0.000795
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
1998	0.029377	0.002360	0.001951	0.002289	0.000781
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
1999	0.029420	0.002138	0.001958	0.002303	0.000769
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2000	0.029531	0.002112	0.001953	0.002271	0.000758
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2001	0.029835	0.002091	0.001935	0.002254	0.000812
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2002	0.029881	0.002123	0.001920	0.002267	0.000730
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2003	0.030211	0.002050	0.002059	0.002230	0.000894
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2004	0.030263	0.002011	0.001995	0.002263	0.000739
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2005	0.030220	0.002117	0.001991	0.002315	0.000854
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2006	0.030045	0.002161	0.002093	0.002387	0.000814
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2007	0.030106	0.002155	0.001998	0.002395	0.000827
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
2008	0.030259	0.002200	0.001903	0.002292	0.001232
	(0.0006)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R^2	0.016	0.003	0.003	0.003	0.004
Observations	20373918	20373918	20373918	20373918	20373918

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 1.12: LPMs for Transitions from Manufacturing

	(1)	(2)	(3)	(4)	(5)
Female	-0.000260	-0.101225	-0.001873	-0.001851	0.000190
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Educ	-0.000157	-0.096667	-0.000625	-0.000533	0.002204
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Age	-0.000045	0.001358	-0.000234	-0.000727	-0.000598
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Age^2	0.000000	-0.000048	0.000002	0.000005	0.000004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	-0.000008	0.002640	-0.000008	0.000008	-0.000084
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	0.000177	-0.008974	0.000939	0.002900	0.003071
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	0.001891	0.244658	0.009520	0.027120	0.021760
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
1997	0.001737	0.254299	0.008510	0.023993	0.018710
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
1998	0.001698	0.257294	0.008650	0.023932	0.018976
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
1999	0.001697	0.258194	0.008668	0.023775	0.019413
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2000	0.001688	0.256321	0.008667	0.023263	0.018974
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2001	0.001712	0.256139	0.008362	0.023710	0.019223
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2002	0.001742	0.255075	0.008277	0.023923	0.018439
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2003	0.001662	0.251187	0.008516	0.023358	0.017925
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2004	0.001656	0.245282	0.008125	0.022984	0.018030
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2005	0.001642	0.240967	0.008515	0.024136	0.018598
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2006	0.001713	0.240073	0.008800	0.023923	0.018686
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2007	0.001708	0.240325	0.008467	0.024170	0.021088
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
2008	0.001638	0.233704	0.008248	0.024198	0.027396
	(0.0001)	(0.0021)	(0.0002)	(0.0004)	(0.0004)
R^2	0.003	0.216	0.017	0.049	0.051
Observations	20373918	20373918	20373918	20373918	20373918

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 1.13: LPMs for Transitions from Construction

	(1)	(2)	(3)	(4)	(5)
Female	-0.000354	-0.001557	-0.075572	-0.001134	-0.001356
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Educ	-0.000123	-0.000455	-0.044517	-0.000470	0.000060
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Age	-0.000025	-0.000152	-0.000175	-0.000196	-0.000105
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Age^2	0.000000	0.000001	-0.000003	0.000002	0.000001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	-0.000008	-0.000023	0.000198	-0.000009	-0.000035
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	0.000148	0.000730	-0.003030	0.000679	0.000907
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	0.001204	0.006806	0.104159	0.007436	0.006387
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
1997	0.001077	0.006198	0.108415	0.006687	0.004672
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
1998	0.001059	0.006245	0.110164	0.006652	0.004638
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
1999	0.001080	0.006078	0.112107	0.006640	0.004470
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2000	0.001060	0.006087	0.113990	0.006565	0.004489
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2001	0.001128	0.006278	0.115385	0.006657	0.004803
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2002	0.001445	0.006204	0.115562	0.006693	0.004743
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2003	0.001079	0.005905	0.115695	0.006658	0.004698
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2004	0.001070	0.005870	0.116647	0.006482	0.004876
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2005	0.001071	0.005847	0.118801	0.006811	0.004683
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2006	0.001133	0.006118	0.121589	0.006855	0.004814
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2007	0.001126	0.006325	0.123313	0.007148	0.005347
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
2008	0.001102	0.006152	0.122501	0.006843	0.005415
	(0.0001)	(0.0002)	(0.0013)	(0.0002)	(0.0002)
R^2	0.003	0.013	0.093	0.012	0.015
Observations	20373918	20373918	20373918	20373918	20373918

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 1.14: LPMs for Transitions from Trade/Util./Tran./Com.

	(1)	(2)	(3)	(4)	(5)
Female	-0.000221	-0.001902	-0.001185	-0.082729	0.000816
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
Educ	-0.000141	-0.000586	-0.000520	-0.130861	0.001058
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
Age	-0.000049	-0.000773	-0.000223	-0.010165	-0.001235
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Age^2	0.000000	0.000006	0.000002	0.000071	0.000011
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	-0.000009	-0.000007	-0.000002	0.003541	-0.000114
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	0.000175	0.002670	0.000789	-0.009273	0.003609
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	0.001903	0.027499	0.007959	0.491174	0.038590
	(0.0001)	(0.0004)	(0.0002)	(0.0022)	(0.0004)
1997	0.001642	0.024942	0.007270	0.501879	0.035346
	(0.0001)	(0.0004)	(0.0002)	(0.0022)	(0.0004)
1998	0.001642	0.025297	0.007512	0.504817	0.035580
	(0.0001)	(0.0004)	(0.0002)	(0.0022)	(0.0004)
1999	0.001669	0.024703	0.007363	0.508281	0.035770
	(0.0001)	(0.0004)	(0.0002)	(0.0022)	(0.0004)
2000	0.001729	0.025786	0.007496	0.508207	0.036599
	(0.0001)	(0.0004)	(0.0002)	(0.0022)	(0.0004)
2001	0.001660	0.025113	0.007515	0.507108	0.036498
	(0.0001)	(0.0004)	(0.0002)	(0.0022)	(0.0004)
2002	0.001645	0.024614	0.007319	0.506942	0.035925
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
2003	0.001639	0.023816	0.007096	0.508482	0.035088
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
2004	0.001648	0.023837	0.007170	0.510063	0.035717
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
2005	0.001685	0.024508	0.007490	0.511498	0.035896
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
2006	0.001723	0.025652	0.007931	0.512749	0.038365
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
2007	0.001745	0.026169	0.007620	0.515293	0.038947
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
2008	0.001664	0.025030	0.007239	0.519633	0.038889
	(0.0001)	(0.0004)	(0.0002)	(0.0021)	(0.0004)
R^2	0.003	0.045	0.014	0.228	0.057
Observations	20373918	20373918	20373918	20373918	20373918

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 1.15: LPMs for Transitions from Services

	(1)	(2)	(3)	(4)	(5)
Female	-0.000093	0.000126	-0.001010	0.000596	0.282797
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Educ	-0.000035	0.001727	-0.000068	0.001076	0.314987
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Age	-0.000010	-0.000547	-0.000144	-0.001054	0.017336
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Age^2	0.000000	0.000004	0.000001	0.000009	-0.000150
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper	-0.000023	-0.000119	-0.000032	-0.000136	0.002675
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exper($s_{t-1} \neq s$)	0.000264	0.001990	0.000791	0.003052	-0.019566
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1996	0.000927	0.019755	0.006239	0.034345	-0.271674
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
1997	0.000682	0.017986	0.005207	0.030822	-0.247749
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
1998	0.000713	0.018347	0.005355	0.031371	-0.244333
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
1999	0.000656	0.017863	0.005235	0.031523	-0.238903
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2000	0.000703	0.018477	0.005487	0.031330	-0.238573
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2001	0.000668	0.018481	0.005274	0.031110	-0.236467
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2002	0.000726	0.017819	0.005330	0.031063	-0.232733
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2003	0.000626	0.017207	0.005082	0.031213	-0.235069
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2004	0.000623	0.016953	0.005228	0.030593	-0.235287
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2005	0.000646	0.017595	0.005576	0.031739	-0.231899
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2006	0.000699	0.018459	0.005781	0.032783	-0.228649
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2007	0.001279	0.020078	0.006159	0.034190	-0.227186
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
2008	0.001080	0.019947	0.005471	0.033890	-0.219947
	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0025)
R^2	0.004	0.030	0.013	0.047	0.602
Observations	20373918	20373918	20373918	20373918	20373918

Standard errors in parentheses. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Chapter 2

The Impact of Chinese Import Penetration on Danish Firms and Workers

joint with Jakob Munch and Daniel Nguyen

Abstract

The impact of imports from low-wage countries on domestic labor market outcomes has been a hotly debated issue for decades. The recent surge in imports from China has reignited this debate. Since the 1980s several developed economies have experienced contemporaneous increases in the volume of imports and in the wage gap between high- and low-skilled workers. However, the literature has not been able to document a strong causal relationship between imports and the wage gap. Instead, past studies have attributed the widening wage gap to skill biased technological change. This paper finds evidence for the direct impact of low wage imports on the wage gap. Using detailed Danish panel data for firms and workers, it measures the effects of Chinese import penetration at the firm level on wages within job-spells and over the longer term taking transitions in the labor market into account. We find that greater exposure to Chinese imports corresponds to a negative firm-level demand shock, which is biased towards low-skill intensive products. Consistent with this an increase in Chinese import penetration results in lower wages for low-skilled employees.

2.1 Introduction

In the last quarter century, the United States and several other advanced economies have experienced greater income inequality between skilled and unskilled workers. The simultaneous rise in imports from China and other developing countries triggered a lively early debate among trade and labor economists about whether increased trade caused the higher skill premium. One example is the survey by Freeman (1995) entitled "Are your wages set in Beijing?". This study concluded that increased trade contributed to, but was not the primary cause behind the rising wage gap. The skepticism was fueled in part by the fact that, in the mid 1990s, trade still only constituted a small percentage of total consumption in most advanced countries, so the factor contents of trade were only small fractions of the domestic supplies of labor.

Since then, the establishment of the WTO and trade liberalizations enacted during the Uruguay Round has led to a boom in imports from developing countries and from China in particular. This has once again ignited interest in how imports affect workers in advanced countries. For example, Krugman (2008) concludes: "...there has been a dramatic increase in manufactured imports from developing countries since the early 1990s. And it is probably true that this increase has been a force for greater inequality in the United States and other developed countries." However, there is still a lack of studies documenting a causal relationship between increased import competition from low-wage countries and the skill wage gap.

Among low-wage countries, the rise of China has been remarkable. When the Chinese government enacted market reforms in 1978, China was the 11th largest economy in the world, accounting for only 2% of global GDP. Thirty years later, China has overtaken Japan as the second largest economy in the world, accounting for 10% of global GDP. Its growth rate over these decades have been unmatched by any other nation. Much of this economic success has been driven by international trade. Since opening its borders in 1978, China has grown from a closed economy to the world's largest exporter.

In this paper we use matched worker-firm data from Denmark covering the universe of firms and workers merged with domestic sales by product for the period 1997–2008. We make three main contributions. First, using the domestic sales by product, we document that domestic firms are exposed to Chinese import penetration to very different degrees. For example, in most industries the firm at the 25th percentile is unaffected by

Chinese imports while the 75th percentile firm in many cases has a Chinese import penetration measure at least double that of the median firm. This is in line with the literature on heterogeneous firms showing that firms, even within narrow industries, differ with respect to, e.g. size, productivity, capital intensity, wages, exports and imports. In contrast, the traditional approach in the literature has been to use industry-level measures of import penetration.

Second, we provide evidence for how firm-level Chinese imort penetration correlates with domestic sales. We first decompose changes in firm-level domestic sales into increases or decreases in sales of products sold throughout the period as well as entry and exit of products. We then relate these components to changes in import competition and find that all three components contribute to lower domestic sales when the firm is exposed to increasing Chinese imports. In an extension we show that the skill intensity of products matter. Domestic sales in low-skill intensive products contract faster than high-skill intensive products in response to increased Chinese import penetration. This suggest that imports from China correspond to negative demand shocks with a bias toward low-skilled workers.

Third, we show a causal relationship between Chinese import penetration and the rising wage gap. We estimate within job spell wage equations using over time changes in the firm-level Chinese import penetration measure as the source of variation. We instrument for Chinese import penetration using China's world export supply in order to mitigate endogeneity concerns. Greater exposure to Chinese imports lowers the share of low-skilled workers within firms, but our within job spell approach has the advantage that changes in the composition of workers is controlled for. We find that the rise in Chinese imports increases the wage gap between low and high skilled Danish workers. A low skilled worker loses 0.48% of his wage for each percentage point increase in Chinese imports.

Our results when using firm-level Chinese import competition measures contrast those of studies using industry-level measures. When measured at the industry level, we find that Chinese import penetration does not have a negative effect on wages. This mirrors to some extent the findings in the earlier literature on trade and wages, see, e.g., Feenstra and Hanson (1999). These lack of results also mirror those of two contemporary papers: Autor, Dorn, and Hanson (2013) and Ebenstein, Harrison, McMillan, and Phillips (forthcoming).

Autor, Dorn, and Hanson (2013) use local labor markets instead of industries to analyze the effects of imports. They find that increased exposure to import competition from China depresses manufacturing employment, but no wage effects are found in the manufacturing sector. Instead wages fall in the service sector. They attribute the absent manufacturing wage effects to rigid wage setting or compositional changes. Ebenstein, Harrison, McMillan, and Phillips (forthcoming) examine the impact of offshoring and import penetration on wages both within the manufacturing sector and across sectors and occupations. They use data on worker-level wages and occupations and find that workers in occupations most exposed to import penetration experience slower wage growth. However, Ebenstein, Harrison, McMillan, and Phillips (forthcoming) also find negligible within industry effects. One of their main contributions is to show that workers that leave manufacturing are the ones who experience wage reductions.

Unlike Autor, Dorn, and Hanson (2013) and Ebenstein, Harrison, McMillan, and Phillips (forthcoming), this study finds significant wage effects within the manufacturing sector. We do this by exploiting firm-level import penetration measures for a panel of manufacturing firms, while controlling for more aggregate wage effects at the level of industries and local labor markets. Our firm-level measure is more representative of the import competition that firms face and is not attenuated by aggregation, as is the industry level measure.

Our study examines the wage effects of Chinese import penetration both within job-spells, that is, for the workers who remain employed within the same firm and over an eight-year period taking into account effects on transitions between jobs and out of employment. Increased import competition may also lead to earnings losses associated with unemployment and earnings changes related to change of firm, industry or occupation. Autor, Dorn, Hanson, and Song (2012) find that workers initially employed in U.S. manufacturing industries experiencing high subsequent levels of import growth show lower employment rates and cumulative earnings over ensuing years, and are more likely to swich industries. They do not find differences in these patterns across skill groups. In contrast, we do find a clear skill-wage correlation in the impact of import competition for both workers who remain employed in the firm and over the longer term taking labor market transitions into account.

While Autor, Dorn, and Hanson (2013), Autor, Dorn, Hanson, and Song (2012) and Ebenstein, Harrison, McMillan, and Phillips (forthcoming) focus on more aggregate labor market outcomes, several recent papers analyze how *firms* adjust in response to increased import competition. Bernard, Jensen, and Schott (2006) show that American plant survival and growth are negatively correlated with industry exposure to imports from low wage countries.[1] Iacovone, Rauch, and Winters (2013) find that Chinese import penetration reduces sales of smaller Mexican plants and more marginal products and they are more likely to cease.[2] Bloom, Draca, and Van Reenen (2012) use the number of computers, the number of patents, or the expenditure on R&D as measures of innovation and find that Chinese import penetration correlates positively with within-plant innovation in the UK.[3] Finally, using Belgian firm-level data, Mion and Zhu (2013) find that industry-level import competition from China reduces firm employment growth and induce skill upgrading in low-tech manufacturing industries. For a survey of recent firm-level empirical research on trade, see Harrison, McLaren, and McMillan (2011). In summary, there has been a revival in studies looking at firm-level outcomes, but none of these papers focus on wages as the outcome. In this paper we attempt to fill this gap.

The rest of the paper is structured as follows. Section 2.2 describes the data on firms and workers and constructs a measure for firm-level Chinese import penetration. Section 2.3 presents a model of how imports affect wages through firms. Section 2.4 shows how Chinese import penetration affects components of firm-level domestic sales. Section 2.5 first motivates and outlines our worker level wage regression framework and then presents the estimation results. Section 2.6 shows the results of long term worker outcomes. Finally, Section 2.7 concludes.

2.2 Data Description

In this section we describe the Danish labor market, our data sources and show that the rise of China in the global economy has reached Denmark. We then define our measure of Chinese import competition that Danish firms face at home. Finally our instrument

[1] Greenaway, Gullstrand, and Kneller (2008) show similar patterns in Swedish firms.

[2] Consistent with this, Liu (2010) finds that import competition leads multi-product US firms to drop peripheral products to refocus on core production.

[3] In a related study Teshima (2010) finds that Mexican plants increase R&D expenditure in response to tariff reductions.

for Chinese import penetration is described.

2.2.1 The Danish Labor Market

Botero, Djankov, La Porta, Lopez-De-Silanes, and Shleifer (2004) classify the Danish labor market as one of the most flexible in the world. Employment protection is relatively weak, and as compensation workers receive relatively generous UI benefits when unemployed. Incentives to search for jobs during unemployment are reinforced by required participation in active labor market programs.

The Danish labor market is strongly unionized even by European standards. More than three quarters of all workers are union members and bargaining agreements are extended to cover most of the labor market. However, even if most workers are covered by bargaining agreements, firm-specific demand shocks may often easily influence wages. This is because wage formation in the Danish labor market to a great extent takes place at the firm level.

There are three different levels at which wages can be negotiated: the Standard-Rate System, the Minimum-Wage and Minimum Pay System; and Firm-level Bargaining. Under the Standard-Rate System the wages of workers are set by the industry collective agreement and the wages are not modified at the firm level. The Minimum-Wage System and the Minimum-Pay System are two-tiered systems in which wage rates negotiated at the industry level represent a floor which can be supplemented by local firm-level negotiations. Under Firm-Level Bargaining wages are negotiated at the firm level without any centrally bargained wage rates. Since 1991 less than 20% of the private labor market is covered by the Standard-Rate System and an increasing share of wage contracts are negotiated exclusively at the worker-firm level. As a consequence, wages are more in accordance with individual workers' marginal productivity. Dahl, le Maire, and Munch (2013) show that decentralization has increased wage dispersion in the Danish labor market.

2.2.2 Register Data

The microdata in our sample period from 1997 to 2008 are drawn from several registers in Statistics Denmark. We describe each in turn. The "Firm Statistics Register" (FirmStat) covers the universe of Danish firms and provides us with annual data on firms' activities and characteristics, such as industry affiliation in accordance with the six-digit

NACE classification, total wage bill, employment, output, value added and capital stock. There is also information about the firm's municipality code such that we can classify all firms into local labor markets based on commuting patterns. There are 36 so-called commuting zones defined such that internal commuting is significantly higher than external commuting. All firms in FirmStat are associated with a unique firm id.

Data on the imports and exports of every Danish firm are taken from the "Danish Foreign Trade Statistics"-database. These are compiled in two systems: Extrastat and Intrastat. Extrastat covers all trade with countries outside the European Union and is recorded by customs authorities while Intrastat covers trade with EU countries. Firms are only required to report intra-EU imports and exports if these exceed time-varying thresholds. When comparing to official aggregate statistics, the coverage rate of Extrastat is nearly complete, whereas the coverage rate of Intrastat is around 90%. For every firm, trade flows are recorded according to the eight-digit Combined Nomenclature classification, which amasses to roughly 9,000 products a year. In our main specifications we aggregate these to about 5,000 six-digit HS products, so that we are able to match with the COMTRADE world export supply data, which we use to create our instruments. As the firm identifier is identical to that used in FirmStat, we can match the trade data with our firm data.

From the PRODCOM-database we observe total sales (domestic sales and exports) for each manufacturing firm by ten-digit product codes, which we aggregate to the six-digit Harmonized System (HS) to match the aggregation levels of our trade data and instruments.[4] Subtracting exports from total sales then gives us each firm's domestic sales by products measured in Danish Kroner (DKK). Firms whose employment level or sales are below time-varying thresholds are not required to report sales, and so the coverage rate of the value of sales data is less than complete (around 90%) when comparing with official aggregate statistics. Since the firm id in PRODCOM is the same as the FirmStat identifier, we can match the domestic sales data to the firm statistics.

The worker data comes from the "Integrated Database for Labor Market Research" (IDA). This database covers the entire Danish population aged 15–74. To match every worker in IDA to every firm in FirmStat we use the "Firm-Integrated Database for Labor Market Research" (FIDA). From IDA we obtain worker's hourly wage rate, which is

[4] The PRODCOM database has also been used by Bernard, Blanchard, Van Beveren, and Vandenbussche (2012) to study so-called carry along trade (goods exported but not produced) by Belgian firms.

calculated as total labor income plus mandatory pension payments divided by the number of hours worked in the worker's job. Educational attainment is recorded according to the International Standard Classification of Education (ISCED), from which we define high-skilled workers as having a tertiary education corresponding to ISCED categories 5 and 6.[5] All other workers are classified as low-skilled. In addition there is information about the workers four-digit occupation (recorded according to the International Standard Classification of Occupations, ISCO-88), labor market experience, union membership and marital status.

2.2.3 The Rise of China

China's emergence as a global economic heavyweight over the course of the last three decades has been intertwined closely with its rise on the scene of international trade, manifested by its accession to the WTO in 2001. While accounting for a negligible 1% of world exports in 1980, by late 2009 that share had increased to 10%, and on the road there, China has overtaken Germany as the world's largest exporter. This increase in world exports has been paralleled by in an increasing presence on the Danish market. From 1990 to 2009, China's share of Danish manufacturing imports grew from 1% to 6.8%. Other low wage economies, notably the Central and Eastern European Countries (CEEC), have also increased their share in Danish imports. The CEEC countries increased their import share from 1.6% in 1990 to 6.5% in 2009, which in part may be attributed to the accession of several of these countries into the European Union in 2004 and 2007. Since the growth in Chinese exports is more dramatic we focus on China, but we also show results for imports from CEEC countries. For comparison, Autor, Dorn, and Hanson (2013) report that the low-income-country share of U.S. was 28% in 2007, while the Chinese import penetration ratio measured as Chinese imports as a share of U.S. consumption was 4.6% reflecting that the U.S. is not a small open economy like Denmark. For comparison, we define in the next section the Chinese import penetration ratio as the imports of goods from China divided by the total consumption of goods in the Danish economy (imports+production-exports). In our data, this ratio has increased from 1.8% in 2001 to 5% in 2008.

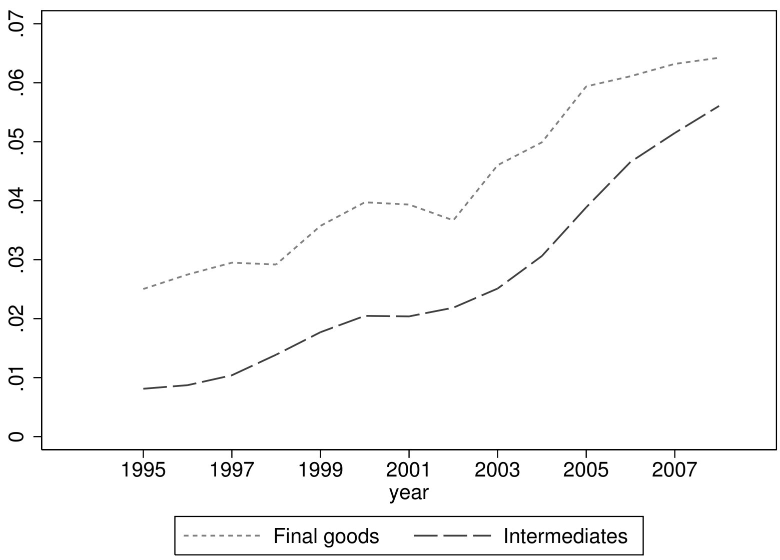
[5] A limited number of workers switch educational group during job spells. To get a clean identification we fix the educational attainment of these workers to the value in the first year of the job spell.

Table 2.1 contains top ten lists of CN8 products imported from China in 1993 and 2009 respectively, while Table 2.2 shows how Chinese imports have hit manufacturing industries very differently. Manufacture of textiles (NACE industry 17–19), Iron and Metal (28) and Transportation and Furniture (35-36) stand out as industries with the highest growth in Chinese imports. This expansion creates a natural experiment which we, via firms, can map onto individual workers in the Danish manufacturing sector. This is done by our Chinese import penetration measure, which we discuss in the next section.

2.2.4 Chinese Import Penetration

We want to measure the level of competition that each individual manufacturing firm faces from China. To do so, we characterize all imports by manufacturing firms as intermediate inputs in line with the "broad offshoring" measure of Hummels, Jørgensen, Munch, and Xiang (2011). Imports of intermediate inputs constitute roughly a quarter of all manufacturing imports from all origin countries. The remaining three quarters are final goods imported by non-manufacturing firms. Figure 2.1 shows that China's share of both intermediate and final goods imports have increased over time, most rapidly from 2002 onwards.

Figure 2.1: China's Import Share



In the literature it is common to use industry measures of import competition, see e.g. Bernard, Jensen, and Schott (2006), implying that all firms within an industry face the

Table 2.1: Top 10 Imports From China

Rank	Year	CN8	Product	Value (bio. DKK)	China's share
1	1993	61091000	T-shirts, singlets and other vests, knitted or crocheted	12.6	0.20
2	1993	62112000	Ski suits	10.4	0.79
3	1993	95039031	Tricycles, scooters... [other toys]	8.48	0.42
4	1993	62052000	Men's shirts – of cotton	6.23	0.22
5	1993	62064000	Women's blouses, shirts and shirt-blouses	5.09	0.17
6	1993	39269099	Other articles of plastics	4.66	0.07
7	1993	62034235	Trousers, bib and brace overalls, breeches and shorts	4.61	0.34
8	1993	61101091	Jerseys, pullovers, cardigans, waistcoats and similar articles of cotton	4.54	0.27
9	1993	61046210	Trousers, bib and brace overalls, breeches and shorts	4.37	0.28
10	1993	42029291	Traveling-bags, toilet bags, rucksacks and sports bags	4.31	0.47
1	2009	89012010	Tankers – Seagoing	176	0.47
2	2009	84713000	Portable automatic data-processing machines	58.5	0.15
3	2009	61103099	Jerseys, pullovers, cardigans, waistcoats and similar articles of man made fibers, women's	45.8	0.63
4	2009	62046239	Women's trousers, bib and brace overalls, breeches and shorts of cotton	42.6	0.54
5	2009	62029300	Women's overcoats, car coats, capes, cloaks [and similar] of man made fibers	33.9	0.80
6	2009	61102099	Jerseys, pullovers, cardigans, waistcoats and similar articles of cotton, women's	31.6	0.47
7	2009	61102091	Jerseys, pullovers, cardigans, waistcoats and similar articles of cotton, men's	27.1	0.40
8	2009	62046231	Women's trousers, bib and brace overalls, breeches and shorts of denim	25.5	0.31
9	2009	94016100	Seats of cane, osier, bamboo or similar materials – Upholstered	24.6	0.22
10	2009	73089099	Structures and parts of structures (for example, bridges [...])	24.5	0.10

Table 2.2: Chinese Import Shares by Danish Manufacturing Industries

Industry	Name	CIS 2001	CIS 2008	Δ CIS	Employment share 2001
15	Food and drinks	0.0080	0.0137	0.0056	0.169
16	Tobacco	0.0000	0.0000	0.0000	0.002
17	Textiles	0.0696	0.2171	0.1475	0.012
18	Clothing	0.2405	0.3375	0.0970	0.000
19	Leather	0.1239	0.2079	0.0841	0.000
20	Wood	0.0181	0.0416	0.0235	0.035
21	Paper	0.0036	0.0155	0.0120	0.016
22	Graphics	0.0164	0.0424	0.0260	0.044
23	Mineral oil	0.0000	0.0001	0.0001	0.002
24	Chemistry	0.0085	0.0162	0.0077	0.128
25	Rubber and plastics	0.0358	0.0558	0.0200	0.059
26	Stone, clay, and glass	0.0391	0.0708	0.0317	0.045
27	Metals	0.0075	0.0150	0.0076	0.018
28	Iron and metal	0.0539	0.1035	0.0497	0.080
29	Machinery	0.0184	0.0535	0.0351	0.192
30	Office and IT	0.0213	0.0468	0.0255	0.002
31	Other elect. machinery	0.0372	0.0837	0.0466	0.045
32	Tele industry	0.0384	0.0806	0.0421	0.012
33	Medical equip., clocks, etc.	0.0371	0.0759	0.0389	0.045
34	Car	0.0013	0.0120	0.0106	0.021
35	Other transportation	0.0740	0.1201	0.0460	0.022
36	Furniture and other manuf.	0.1231	0.2510	0.1280	0.049
37	Recycling	0.0000	0.0000	0.0000	0.001
Total		0.0375	0.0676	0.0302	1.000

same exposure to imports from China. For comparison, we construct import penetration CIP_{lt} for four-digit NACE industry l for year t:

$$CIP_{lt} = \frac{M_{lt}^{CH}}{M_{lt} + D_{lt}}, \tag{2.1}$$

where M_{lt}^{CH} and M_{lt} are the values of final good imports from China and all countries in industry l at time t respectively, and D_{lt} is total domestic sales by Danish firms in industry l.

While CIP_{lt} can describe the variation across industries, our data allows us to measure Chinese import penetration at a finer aggregation. We construct a firm-level Chinese import penetration measure CIP_{jt} for firm j in year t:

$$CIP_{jt} = \sum_{k \in \Omega_j} s_{jk} \frac{\left(M_{kt}^{CH} - M_{jkt}^{CH}\right)}{\left(M_{kt} - M_{jkt}\right) + D_{kt}}, \tag{2.2}$$

where M_{kt}^{CH} and M_{kt} are the values of imports from China and all countries for HS6 product k at time t respectively. From these we subtract firm j's own imports, M_{jkt}^{CH} and M_{jkt}. D_{kt} is total domestic sales of product k by Danish firms at time t. That is, the import penetration for firm j is defined as the weighted average of the Chinese import penetration in the set of firm j's products, Ω_j. The weights, s_{jk}, are defined as the shares of product k in firm j's total domestic sales over the presample period 1999–2000.[6] This definition keeps constant the product mix in the presample period to measure the extent to which firms subsequently are hit by surges in imports from China.[7] Firms may adjust the product mix to increased import competition, but such (endogenous) responses are outcomes we will later investigate.

Notice that imports by competing domestic manufacturing firms are included in the definition of CIP_{jt} as these will tend to improve the performance of firm j's competitors e.g. through access to cheaper inputs. We also report results for a version of the import penetration measure where we include only final goods as a robustness check. That is, imported intermediate inputs by all manufacturing firms are excluded from the definition of the measure.

Table 2.3 summarizes the changes in CIP_{jt} across industries in our sample. Several points are worth noting. First, as was the case with the industry-level Chinese import penetration measure in Table 2.2, our firm-level measure varies greatly across industries with the same industries standing out. Second, the level of the firm-level import penetration measure is generally lower than the industry-level measure. This reflects mainly that a substantial part of the presample product bundle is unaffected by imports from China. Third, and most importantly, Chinese import penetration exhibits substantial variation across firms within industries. For example, in most industries the firm at the 25th percentile is unaffected by Chinese imports while the 75th percentile firm in many cases has a CIP_{jt} at least double that of the median firm.

After merging our worker-firm data with the constructed CIP_{jt} variable we select all full time manufacturing workers aged 20–60 years in the period 2001–2008. As explained above, the wage rate is calculated as labor income divided by hours worked, so to ensure that our results are not influenced by noisy observations, we trim the data by drop-

[6] In defining the presample period there is a trade-off between the length of the sample window (2001–2008) and the range of products sold by domestic firms before the surge in Chinese imports.

[7] This way of defining the import penetration measure is consistent with Autor, Dorn, and Hanson (2013). At the level of local labor markets they use initial period employment weights for industries.

Table 2.3: Dispersion in Firm-Level Chinese Import Penetration, 2008

Industry	Name	Mean	sd	p25	p50	p75
15	Food and drinks	0.002	0.007	0.000	0.000	0.001
16	Tobacco	0.000	0.000	0.000	0.000	0.000
17	Textiles	0.111	0.160	0.001	0.026	0.170
18	Clothing	0.231	0.128	0.132	0.243	0.342
19	Leather	0.095	0.003	0.092	0.097	0.097
20	Wood	0.011	0.037	0.001	0.001	0.004
21	Paper	0.012	0.008	0.007	0.014	0.017
22	Graphics	0.004	0.017	0.000	0.001	0.002
23	Mineral oil	0.000	.	0.000	0.000	0.000
24	Chemistry	0.004	0.014	0.000	0.000	0.004
25	Rubber and plastics	0.028	0.029	0.003	0.029	0.040
26	Stone, clay, and glass	0.016	0.044	0.000	0.000	0.004
27	Metals	0.028	0.032	0.004	0.016	0.042
28	Iron and metal	0.025	0.041	0.007	0.012	0.025
29	Machinery	0.017	0.033	0.001	0.006	0.017
30	Office and IT	0.056	0.057	0.000	0.054	0.082
31	Other elect. machinery	0.043	0.057	0.002	0.013	0.063
32	Tele industry	0.052	0.075	0.000	0.017	0.055
33	Medical equip., clocks, etc.	0.023	0.037	0.003	0.008	0.025
34	Car	0.014	0.035	0.000	0.001	0.014
35	Other transportation	0.020	0.026	0.000	0.009	0.033
36	Furniture and other manuf.	0.075	0.058	0.018	0.070	0.128
37	Recycling	0.000	0.000	0.000	0.000	0.000

ping wage rate observations that are deemed to have a low quality by Statistics Denmark (77,159 obs.). In addition, observations in the upper and lower 0.5 percentiles of the wage distribution are deleted (21,924 obs.). Also, to avoid that extreme values of the firm-level import penetration measure influence the results we drop the top percentile of these values (19,718 obs.). Finally, we drop the job-spells that only exist in one year (176,649) since these will be absorbed by job spell fixed effects. With these restrictions our final sample contains about 1.7 million worker–year observations and accounts for 85% of aggregate manufacturing employment among 20-60 year olds. Summary statistics of the data are displayed in Table 2.4.

Table 2.4: Descriptive Statistics: Worker Sample

	Mean	Std. Dev	P25	Median	P75
Wage	218.35	78.11	168.26	201.48	247.20
Output (mio. DKK)	3,586	7,329	1,172	4,388	2,306
Size	1632.51	2957.26	92	313	1122
Cap./Labor (1,000 DKK)	432.25	449.36	181.33	305.30	496.01
Shr. High Skill	0.21	0.15	0.10	0.17	0.27
Exports/Sales	0.52	0.34	0.19	0.58	0.84
Imports/Sales	0.18	0.16	0.05	0.14	0.27
Experience	19.07	9.66	11.19	18.98	26.66
Experience^2	456.75	387.04	125.13	360.05	710.86
Married	0.58	0.49	0	1	1
Union Member	0.86	0.35	1	1	1

Note: Number of observations is 1688249.

2.2.5 Instruments

A potential concern in our empirical specification is that unobserved factors such as technology shocks are correlated with both changes in product-level Chinese imports and labor demand. To address this problem, we use Chinese world export supplies as an instrument that is correlated with Danish imports from China but uncorrelated with the firm's wage setting.[8] The instrument I_{jt} for firm j in time t is

$$I_{jt} = \sum_{k \in \Omega_j} s_{jk} WES_{kt},$$

where WES_{kt} is China's total supply of product k to the entire world, minus exports to Denmark, in period t. The world export supplies are based on COMTRADE data at the HS6 product level. WES_{kt} is weighted by presample shares s_{jk} of product k in firm j's total domestic sales. WES_{kt} measures changes in China's comparative advantage that are exogenous to Danish firms and workers. The causal relationship between WES_{kt} and CIP_{jt} arises from the correlation between Denmark's imports for product k and China's comparative advantage in that product. This approach requires that the main driver behind Chinese world export supplies is not import demand by the rest of the world but rather changes in Chinese comparative advantage arising due to e.g. an increase in China's productivity in producing k or a decrease in transportation costs/tariffs.

[8] Autor, Dorn, and Hanson (2013) and Hummels, Jørgensen, Munch, and Xiang (2011) use similar identification strategies.

A salient example of the latter is the expiration of textile tariffs in 2001 and 2005 that led to huge increases in textiles imports seen in Table 2.2.

2.3 Theory

This section outlines the main components of a simple partial equilibrium trade model showing how increases in Chinese import penetration affect firms' product demand and worker specific wages.[9] We use the model as a motivation for our subsequent empirical approach and as a theoretical derivation of our empirical regression specification.

Three main features of the model are required to fit our matched worker-firm data. First, since we observe product specific domestic sales by domestic firms, we rely on recents models of heterogenous firms producing multiple products such as Bernard, Redding, and Schott (2011). Since we do not examine product or firm entry/exit we can simplify the heterogeneity and focus on the price and wage effects. We assume that each firm produces two products indexed by k, and that within each product category firms supply unique product varieties that are imperfect substitutes for each other. The demand for each variety follows from standard CES preferences with elasticity of substitution, σ_k, between varieties:

$$q_j^k = \alpha_k \frac{\left(p_j^k\right)^{-\sigma_k}}{\Phi_k + \Phi'_k}, \tag{2.3}$$

where $\Phi_k + \Phi'_k$ quantifies the "toughness" of market competition present in standard CES demand functions. We decompose this "toughness" of competition into that arising from domestic and from foreign varieties, Φ_k and Φ'_k respectively. We can think of Φ'_k as the effect on demand due to comparative advantages and trade costs for product substitutes emerging from China. That is, an increase in Chinese import penetration reduces the demand for varieties sold by domestic firms. α_k is the Cobb-Douglas proportion of income spent on all varieties of product k.

Second, to capture differential impacts of Chinese import competition across firms and workers we assume that each firm, j, is born with a firm-product specific productivity, φ_j^k (which follows Bernard, Redding, and Schott (2011)) and that each product k is

[9] The details of the model are relegated to the theory appendix.

produced with a specific type of labor, high and low skilled workers.[10] These assumptions lead to differences across firms in their product (and worker) mix and thus to differences in their exposure to Chinese import penetration.

Third, for wages to differ across firms we need imperfections in the labor market. If labor markets are fully competitive, employers who cut wages slightly will see all their workers quit immediately. By contrast, if there are frictions in the labor market, firms will face an upward sloping labor supply curve, and wages are possibly specific to the firm.

Frictions in the labor market may arise for a variety of reasons. Search models rely on the assumption that it takes time and effort for workers to change jobs because information about the labor market is imperfect. However, even with full information and no mobility costs firms may have monopsony power if jobs are differentiated due to e.g. commuting distances or non-monetary aspects. Rents in the employment relationship may also arise due to institutions in the labor market such as unions, specific wage setting mechanisms such as efficiency wages or the accumulation of specific human capital.[11] We remain ambivalent as to the exact cause behind imperfections in the labor market, and simply assume that firms face an upward sloping labor supply curve with elasticity λ_k by pointing to the ample evidence for the existence of rents in the employment relationship (reviewed in e.g. Manning (2011)).

With these assumptions, we show in the theory appendix that profit maximization leads to the following revenue equation for firm j and product k

$$\log p_k^j q_k^j = \left(\frac{\sigma_k - 1}{\sigma_k}\right)\kappa_k + \frac{(\sigma_k - 1)(\lambda_k + 1)}{\sigma_k \lambda_k + 1}\log\varphi_j^k - \frac{\lambda_k + 1}{\sigma_k \lambda_k + 1}\log\left(\frac{\Phi_k + \Phi'_k}{\alpha_k}\right), \tag{2.4}$$

where κ_k is a constant. Clearly, growth in Chinese import penetration reduces domestic sales. Similarly, we can derive the wages for high and low skilled workers in firm j;

$$\log w_k^j = \lambda_k \kappa_k + \left(\frac{\lambda_k(\sigma_k - 1)}{\sigma_k \lambda_k + 1}\right)\log\varphi_j^k - \frac{\lambda_k}{\sigma_k \lambda_k + 1}\log\left(\frac{\Phi_k + \Phi'_k}{\alpha_k}\right). \tag{2.5}$$

Assuming the firm's labor demand curve is upward sloping ($\lambda_k > 0$), an increase in Chinese import competition in a product reduces the wages of the workers used to produce that product. Since Chinese imports are primarily products produced with low-skilled

[10] This means that k represents both the skill-intensity of the product or the skill intensity of the worker producing k.

[11] An emerging literature on trade and labor markets has modeled imperfections such as rent sharing (Amiti and Davis, 2012), efficiency wages (Davis and Harrigan, 2011), fair wages (Egger and Kreickemeier, 2009) and search costs (Davidson, Matusz, and Shevchenko, 2008; Helpman, Itskhoki, and Redding, 2010).

labor, the theory predicts that low skilled workers' wages will fall in those firms facing higher Chinese import penetration.

2.4 Import Penetration and Firm Outcomes

Before we proceed to the main outcome of interest, worker-level wages, we show how our import penetration measures correlate with firm outcomes. The first column of Table 2.5 show results from regressions of a firm-level outcome (value added, domestic sales, employment, wage bill etc.) on the industry-level Chinese import penetration measure, where year dummies and firm fixed effects are included as controls. None of the correlations are significantly different from zero. The second column uses our firm-level import penetration measure. Here we find that firms, that are more exposed to import competition see value added and employment drop. Also, sales decrease, which is consistent with equation (2.4) above. Interestingly, the fall in employment is more pronounced for low-skilled workers than for workers in general. This reduction in the share of low-skilled workers highlights the need to control for within-firm compositional changes when analyzing wages.

Table 2.5: Firm-Level Effects of Chinese Import Penetration

	Industry CIP	Firm CIP
log...		
profits	-0.116	-0.644
value added	0.230	-0.782***
domestic sales	0.479	-0.455**
exports	0.426	-1.905***
imports	0.932	-0.372
employment	0.544*	-0.520***
low skill employment	0.352	-0.939***
wage bill	0.432	-0.590***
capital/labor	-0.463	-0.880**
Year dummies	Yes	Yes
Firm fixed effects	Yes	Yes

Notes: Standard errors adjusted for clustering at the firm level. Both columns are from regressions of each firm outcome variable on a single Chinese Import Penetration variable. *** p< 0.01, ** p< 0.05, * p< 0.10.

Given that the firm-specific import penetration measure is strongly correlated with firm outcomes and the industry specific measure is not, we will proceed using the firm-specific version in what follows, while we report some results for the industry-specific measure in the appendix.

2.4.1 Decomposition of Domestic Sales Changes

The main channel through which Chinese import penetration affects domestic firms is by reducing their demand in the local market. Consistent with the theory model in section 2.3, Table 2.5 shows declining domestic sales for firms facing increased Chinese import penetration, and lower demand for a firm's products leads to lower labor demand, which is also evident from Table 2.5. The aim of this section is to establish a more detailed picture of how firms adjust their domestic sales along different margins and to identify how Chinese import penetration affects this adjustment process. Firm-level domestic sales may change due to increases or decreases in sales of products sold throughout the period, and due to entry and exit of products in the firm's product mix. Decomposing firm-level domestic sales changes this way allows us to subsequently relate these firm components to changes in firm-level Chinese import penetration. Importantly, we will also be able to investigate if firms change their domestic sales of certain product types as measured by the product-level skill intensity. This allows us to derive predictions about how wages of different worker types may be affected.

Our decomposition of firm-level domestic sales follows the approach taken in Bernard, Jensen, Redding, and Schott (2009), who decompose U.S. imports and exports into the increase due to the entry of new trading firms, the decrease due to the exit of existing trading firms, and the change due increases or decreases in trade at continuing firms. Instead we consider continuing firms only and calculate for each firm the following components of the overall percentage change in domestic sales, D_{jt}, for firm j between time $t-1$ and t:

$$\frac{\Delta D_{jt}}{D_{j,t-1}} = \frac{1}{D_{j,t-1}} \sum_{k\in\Omega_j^C} \Delta D_{kjt} + \frac{1}{D_{j,t-1}} \sum_{k\in\Omega_j^N} D_{kjt} - \frac{1}{D_{j,t-1}} \sum_{k\in\Omega_j^X} D_{kj,t-1}.$$

The first term on the right hand side capture sales changes for products that are sold by the firm in both year t and year $t-1$ (denoted C for continuing). The second term is the contribution of new products sold in the last year (denoted N for new products), and the last term measures the contribution of products sold only in the first year (denoted X for exit).

The first column of Table 2.6 performs the decomposition for the period 2001-2008. The average firm experienced an 18% increase in domestic sales over this period, where 13% was due to the intensive margin increase in sales of continuing products, 20% was attributed to entry of new products, while sales dropped 15% due to exit of products.

Table 2.6: Decomposing Firm-Level Sales Changes, 2001-2008

	(1)	(2)
Total	0.1840	-1.990***
		(0.57)
Intensive Margin	0.1336	-1.379***
		(0.34)
Low Skill Intensity	0.0480	-0.975***
		(0.28)
High Skill Intensity	0.0847	-0.403**
		(0.16)
Residual Skill Intensity	0.0008	-0.000
		(0.00)
Entry	0.2019	-2.290***
		(0.47)
Low Skill Intensity	0.0496	-0.966***
		(0.21)
High Skilled Intensity	0.0394	-0.584*
		(0.35)
Residual Skill Intensity	0.1130	-0.741***
		(0.14)
Exit	-0.1515	1.679***
		(0.17)
Low Skill Intensity	-0.0430	1.098***
		(0.15)
High Skill Intensity	-0.1024	0.581***
		(0.09)
Residual Skill Intensity	-0.0060	0.000
		(0.00)

Notes: Column (1) shows averages of the decompositions of firm-level sales changes across firms. The coefficients in column (2) are obtained from firm-level regressions of the change in Chinese import penetration on each component of the domestic sales decompositions. $N = 2,037$. *** p< 0.01, ** p< 0.05, * p< 0.10.

To investigate the direction of skill bias in Chinese import penetration shocks to domestic demand we split each component into high- and low skill intensive products.[12] The first column of Table 2.6 shows that roughly two-thirds of the intensive margin change is due to rising sales of high-skill intensive products while the rest is due to rising sales of low-skill intensive products. Likewise, the entry component is split into entry of high skill intensive products, low skill intensive products and a residual category that captures products that were not produced by any Danish firms in the presample period. Most of the entry component consists of completely new products, while high- and low skill intensive products accounted for 4 and 5% respectively. Finally, most of the exit component is due to firms dropping high-skill intensive products.

How do these components of the growth in firm-level domestic sales relate to Chinese import penetration? The second column of Table 2.6 shows simple firm-level regressions of each of the calculated components on the change in firm level Chinese import penetration over the period 2001-2008. Consistent with Table 2.5 there is a clear negative correlation between Chinese import penetration and the total change in firm-level domestic sales. Each of the three main components contribute to lower sales, so firms that are more exposed to imports reduce sales of continuing products, enter fewer new products and exit more initially sold products. Bloom, Draca, and Van Reenen (2012) find that innovation as measured by patenting and R&D rises within European firms (including Danish firms) who were more exposed to increases in Chinese imports. This appears not to transmit into greater entry into new products.

The division of products into high- and low skill intensity reveals a stronger correlation between Chinese imports and the low skill intensive products of all three components. That is, Chinese import penetration has a stronger negative correlation with the domestic sale of continuing low-skill intensive products, on entry into new low-skill intensive products and a stronger positive effect on exit out of low-skill intensive products. These patterns suggest that we should expect to see lower demand for workers and in particular for low-skilled workers.

[12] We calculate each product's intensity in the use of high skilled labor as a weighted average of each firm's skill intensity in the presample years, 1999-2000. That is, the skill intensity of product k is defined as $s_k = \sum_j s_j \frac{V_{jk}}{V_k}$, where s_j is firm j's share of high skilled workers in total employment and $\frac{V_{jk}}{V_k}$ is firm j's share of total foreign and domestic sales in product k. We then classify all products with a skill intensity higher than the median product as high skill intensive products.

2.5 Import Penetration and Worker Outcomes

Having established how firms adjust their domestic sales in response to increased Chinese import penetration this section moves on to study the main outcome of interest, worker-level wages. We first specify the empirical model motivated by the theory in section 2.3. Next we present the estimation results, and finally we perform several robustness exercises.

2.5.1 Empirical Specification

As argued in section 2.3, if there are frictions in the labor market, firms will face an upward sloping labor supply curve, and wages are possibly specific to the firm. This, in turn, will leave room for demand shocks due to e.g. changes in import competition to affect wages at the level of the firm. To examine the effect of Chinese import penetration, CIP_{jt}, on wages, we take equation (2.5) to the data by extending it with controls for observable and unobservable worker and firm characteristics and by allowing for CIP_{jt} to have a differential impact on wages for high- and low-skilled worker through an interaction term with a high-skill indicator variable, H_i. That is, we adopt a standard worker-level Mincer wage equation framework of the form

$$\log w_{ijt} = \gamma_L CIP_{jt} + \gamma_H CIP_{jt} \cdot H_i + x_{it}\beta_1 + z_{jt}\beta_2 + \alpha_{ij} + \varphi_{IND,t} + \varphi_{REG,t} + \varepsilon_{ijt}, \quad (2.6)$$

where w_{ijt} is the wage rate of worker i employed by firm j at time t. The high skill indicator, H_i, takes the value 1 for workers with a college degree and 0 otherwise. We are ultimately interested in the effect of firm-level Chinese import penetration, CIP_{jt}, on worker wages as indicated by the sign and magnitude of γ_L and γ_H, where γ_H measures the increase in the wage gap between high and low skilled workers in response to a percentage point increase in Chinese import penetration.

x_{it} are observed time varying worker characteristics (experience, experience squared and indicators for marriage and union membership) and z_{jt} are observed time varying firm controls. In accordance with equation (2.5) we should control for firm productivity, which we capture by including log output, log size, log capital-labor ratio and share of high skilled workers. We also include import and export intensities measured as imports and exports divided by sales.

The term α_{ij} is a worker-firm match fixed effect that controls for time invariant unobserved characteristics specific to the worker-firm job spell. In the literature on wages using matched worker-firm datasets pioneered by Abowd, Kramarz, and Margolis (1999) it is common to estimate worker and firm fixed effects separately. Such a specification relies on the assumption of conditional exogenous worker mobility, implying that, conditional on time-varying worker and firm characteristics and worker and firm fixed effects, workers are assigned randomly to firms. In our context it is likely that increased import penetration affects the mobility of workers through unobserved worker-firm match quality, thus violating the assumption of exogenous worker mobility.[13] We therefore include worker-firm match fixed effects to control for endogenous worker mobility.

We also include industry by time dummies, $\varphi_{IND,t}$, and region by time dummies, $\varphi_{REG,t}$, to capture general macroeconomic trends in wages as well as time varying shocks to industries or local labor markets that affect wages. This captures that firms in industries exposed to imports may grow slower than firms in other industries as found by e.g. Bernard, Jensen, and Schott (2006) and changes in wages working at the level of local labor markets as documented by Autor, Dorn, and Hanson (2013).

2.5.2 Estimation Results

To begin, we examine how Chinese import penetration affects workers' wages without correcting for endogeneity. Results from the estimations of equation (2.6) using the firm-specific measure of Chinese import penetration in equation (2.2) are presented in Table 2.7. In columns (1) and (2) we estimate the model controlling only for individual worker characteristics and entering CIP_{jt} alone and interacted with the high-skill dummy respectively. Column (1) shows that a percentage point increase in Chinese import penetration for a firm reduces hourly wages at that firm by 0.137%. This reduction is concentrated in the wages for low-skilled workers, who experience a drop of 0.181% per percentage point increase in CIP_{jt}. On the other hand, high-skilled workers benefit from Chinese import penetration. The wage gap between high and low skilled workers increases by 0.288% for each percentage point increase in CIP_{jt}, resulting in a net gain

[13] Krishna, Poole, and Senses (2011) study the impact of trade liberalization in Brazil using matched worker-firm data. They reject the assumption of exogenous worker mobility by applying the test developed by Abowd, McKinney, and Schmutte (2010). Once they control for worker-firm match fixed effects, they find no effect of trade reform on wages.

of 0.107% for high skilled workers. In columns (3)-(6) we succesively add firm more controls, which reduces the magnitude of the coefficients slightly, while the net gain for high-skilled workers remain largely unchanged.

Table 2.7: Mincer Wage Regressions, Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
CIP	-0.137***	-0.181***	-0.169***	-0.168***	-0.166***	-0.165***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
CIP * High Skill		0.288***	0.269***	0.270***	0.268***	0.268***
		(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
Experience	0.009***	0.009***	0.008***	0.008***	0.008***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Union	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Output			0.031***	0.032***	0.032***	0.032***
			(0.00)	(0.00)	(0.00)	(0.00)
Log Size			0.002	0.001	0.001	0.001
			(0.00)	(0.00)	(0.00)	(0.00)
Log Cap./Lab.			0.002***	0.002***	0.002**	0.002**
			(0.00)	(0.00)	(0.00)	(0.00)
Shr. High Skill			-0.017	-0.018	-0.017	-0.017
			(0.01)	(0.01)	(0.01)	(0.01)
Imports/Sales				0.011**		0.010**
				(0.00)		(0.00)
Exports/Sales					0.013***	0.012***
					(0.00)	(0.00)
R-squared (within)	0.126	0.126	0.129	0.129	0.129	0.129
Observations	1688249	1688249	1688249	1688249	1688249	1688249
Job-Spell FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns show regressions on log wages. Standard errors, clustered at the firm-year level, in parentheses. *** p< 0.01, ** p< 0.05, * p< 0.10.

Previous studies (e.g. Bernard, Jensen, and Schott (2006)) use industry level import penetration measures, but effects working at this level are absorbed by the industry-time fixed effects. To investigate if such effects are important in our data we estimate a version of the model where the industry-time and region-time fixed effects are replaced with time dummies and where we use the industry measure of import competition in equation (2.1). We find no significant negative relationship between industry measures of Chinese import penetration and wages of low-skilled workers. This is in line with other studies (e.g., Autor, Dorn, and Hanson (2013), Ebenstein, Harrison, McMillan, and Phillips (forthcoming)) that find negligible effects of industry level import penetration measures on workers in that industry. In fact, we find a positive effect of industry-level Chinese import penetration on the wages of high-skilled workers indicating an increased wage gap. In contrast, the negative wage effects of firm-level import penetration found for low-skilled workers in Table 2.7 are exclusively attributable to over-time changes within the firm, and so this suggests that most of the wage reductions are occurring within firms.

2.5.3 Instrumental Variable Analysis

In equation (2.6), the error term, ε_{ijt}, may contain unobserved shocks that affect both Chinese import penetration and the workers' wages. An example would be a positive shock to firm j's productivity that increases its domestic sales, which mechanically lowers CIP_{jt}. The productivity shock simultaneously increases wages for workers at firm j. To identify the causal effect of Chinese import penetration on wages, we instrument CIP_{jt} with Chinese world export supply. Insofar as Chinese world export supply proxies for Chinese comparative advantage, it should affect wages only through CIP_{jt}. We address the endogeneity of CIP_{jt} in a two stage estimation procedure. In the first stage, CIP_{jt} and the interaction term, $CIP_{jt} \cdot H_i$, are regressed on the instrument, I_{jt}, (and $I_{jt} \cdot H_i$) and the other controls. The results of the first-stage regressions are shown in Table 2.8. In all cases the instruments are strong and have the expected signs.

Employing predicted values from the first stage, we estimate the models in equation (2.6) in the second stage. The two first columns of Table 2.9 display the results controlling only for individual worker characteristics and entering CIP_{jt} alone and interacted with the high-skill dummy respectively. Again we find that the effect of import competition differs across skill types and that low-skilled workers see their wages decline. The IV results have the same signs as in the OLS regression, but the negative wage effect from CIP is more than doubled for low-skilled workers. However, there is now no longer any wage gain for high-skilled workers from increased import penetration. In columns (3)-(6) we succesively add more firm controls, which tends to increase the negative impact

Table 2.8: First Stage Regressions

	(1a)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
CIP WES	0.186***	0.189***	-0.005***	0.190***	-0.005***	0.190***	-0.005***	0.190***	-0.005***	0.190***	-0.005***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
CIP WES * High Skill		-0.018***	0.183***	-0.018***	0.183***	-0.018***	0.183***	-0.018***	0.183***	-0.018***	0.183***
		(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)
Experience	-0.000	0.000	0.000**	0.000	0.000**	0.000	0.000**	0.000	0.000**	0.000	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.000	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	-0.000**	-0.000**	0.000**	-0.000**	0.000**	-0.000**	0.000**	-0.000**	0.000**	-0.000**	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Union	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Output				-0.000	-0.000	-0.001	-0.000	-0.001	-0.000	-0.001	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Size				-0.002**	0.000	-0.002**	0.000	-0.002**	0.000	-0.002*	0.000
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Cap./Lab.				0.000	0.000*	0.000	0.000*	0.000	0.000*	0.000	0.000*
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Shr. High Skill				0.002	-0.000	0.002	-0.000	0.002	-0.000	0.002	-0.000
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Imports/Sales						-0.005***	-0.001**			-0.005***	-0.001**
						(0.00)	(0.00)			(0.00)	(0.00)
Exports/Sales								-0.001	0.000	-0.001	0.000
								(0.00)	(0.00)	(0.00)	(0.00)
R-squared (within)	0.416	0.417	0.248	0.418	0.248	0.418	0.248	0.418	0.248	0.418	0.248
Observations	1688249	1688249	1688249	1688249	1688249	1688249	1688249	1688249	1688249	1688249	1688249
F-stat. for instr.	540	274	86	278	87	282	88	277	87	281	88
Job-Spell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable in columns marked 'a' is CIP, and in columns marked 'b' it is CIP * High Skill. Standard errors, clustered at the firm-year level, in parentheses. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$.

on low-skilled workers slightly. In the most comprehensive specification in column (6) wages low-skilled workers fall by 0.478% for each percentage point increase in Chinese import penetration, and the wage skill gap now significantly rises by 0.422% per percentage point.

Table 2.9: Mincer Wage Regressions, IV

	(1)	(2)	(3)	(4)	(5)	(6)
CIP	-0.388**	-0.457***	-0.485***	-0.488***	-0.475***	-0.478***
	(0.18)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)
CIP * High Skill		0.462**	0.422**	0.424**	0.421**	0.422**
		(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Experience	0.009***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Union	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Output			0.031***	0.032***	0.032***	0.032***
			(0.00)	(0.00)	(0.00)	(0.00)
Log Size			0.001	0.001	0.000	0.000
			(0.00)	(0.00)	(0.00)	(0.00)
Log Cap./Lab.			0.002***	0.002***	0.002**	0.002**
			(0.00)	(0.00)	(0.00)	(0.00)
Shr. High Skill			-0.018	-0.018	-0.017	-0.018
			(0.01)	(0.01)	(0.01)	(0.01)
Imports/Sales				0.010*		0.009*
				(0.00)		(0.00)
Exports/Sales					0.011**	0.011**
					(0.00)	(0.00)
R-squared (within)	0.126	0.126	0.129	0.129	0.129	0.129
Observations	1688249	1688249	1688249	1688249	1688249	1688249
Job-Spell FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns show regressions on log wages. Standard errors, clustered at the firm-year level, in parentheses. *** p< 0.01, ** p< 0.05, * p< 0.10.

These results of course cover the vast variation in import competition changes faced by firms across and within industries. For example, consider the furniture industry (two-digit NACE industry 36), which employ roughly 5% of all Danish manufacturing workers.

The firm at the 25 percentile has a firm-level import penetration of 1.8%, while the firm at the 75 percentile has an exposure corresponding to 12.8% (Table 2.3). Low-skilled workers in the most exposed firm would then, everything else equal, earn 5.3% lower wages than low-skilled workers in the least exposed firm.

2.5.4 Occupational Characteristics and Wages

Globalization may have a differential impact on workers not only across but also within skill groups. For example, Hummels, Jørgensen, Munch, and Xiang (2011) find that offshoring shocks to Danish firms leads to lower wages among workers within skill groups performing tasks with high routine contents. We follow their approach and merge occupational characteristics from O*NET via the four-digit occupation codes in our data. We consider routine and non-routine characteristics, choosing O*NET characteristics that are closest to the ones employed by Autor, Levy, and Murnane (2003). We compute the principal component, which we then normalize to have mean 0 and standard deviation 1.

Table 2.10 holds the results. Workers with average routineness scores (i.e., the routineness variables is zero) are now not significantly affected by Chinese import penetration. This is consistent with the previous results as educational attainment is negatively correlated with routineness (the correlation coefficient is -0.54). Workers whose occupations are characterized by higher than average routineness experience greater wage losses. On the other hand, occupations that are characterized by non-routine tasks are affected positively by Chinese import penetration.

2.5.5 Robustness

As a robustness check this section compares the effects of import competition from China to imports from other origin countries using the full model specification from column (6) in Table 2.9. Over the period 2001–2008 imports from the Central and Eastern European Countries (CEEC) have also increased substantially but not quite to the same extent as the more dramatic rise in imports from China. The first column of Table 2.11 show that the effect of imports from China and CEEC combined is negative for low-skilled workers, but the point estimate is somewhat closer to zero. In column (2) Chinese imports

Table 2.10: Mincer Wage Regressions, IV: Task Characteristics

	(1)	(2)
CIP	-0.197	-0.277
	(0.21)	(0.20)
CIP * High Skill	-0.178	-0.198*
	(0.12)	(0.11)
CIP * Routine	-0.297***	
	(0.06)	
CIP * Non-Routine		0.315***
		(0.06)
R-squared (within)	0.130	0.130
Observations	1657783	1657783
F-stat CIP	187	189
F-stat CIP*High	175	130
F-stat CIP*OCC	168	109
Other controls	Yes	Yes

Notes: Columns show regressions on log wages. Standard errors, clustered at the firm-year level, in parentheses. Other controls are log firm output, log firm size, log firm cap./lab., share high skill workers in firm, imports/sales, exports/sales, experience experience^2, married dummy, and union membership dummy, as well as job-spell fixed effects, region-year and industry-year dummies. *** p< 0.01, ** p< 0.05, * p< 0.10.

are lumped together with imports from other low-income countries.[14] Here the results for low-skilled workers are similar to those of Table 2.9 while high-skilled workers appear to be hurt more. This suggests that Chinese import penetration is special amongst low-wage countries in that it affect the wages of high-skilled workers to a lesser extent. In column (3) we estimate the impact of import penetration from high-income countries defined as EU-15 plus USA and Japan. Here there is no significantly negative effect for the low-skilled workers, but the sign is now significantly negative for high-skilled workers such that they see their wages drop relatively more in response to increasing imports from these countries. This is in line with a Stolper-Samuelson interpretation, since the factor content of trade here presumably is more skill-intensive.

In the next two columns of Table 2.11 we impose more strict sample selection criteria. We first drop small firms with fewer than 50 employees, and in the next column

[14]We use the World Bank definition in 1989 to classify countries as being low-income.

Table 2.11: Mincer Wage Regressions, IV: Robustness

	China + CEEC	China + Poor Countries	Rich Countries	Exclude Small Firms	Exclude Zero-CIP Spells	Alternative CIP Definition
	(1)	(2)	(3)	(4)	(5)	(6)
IP	-0.293***	-0.465**	-0.020	-0.503**	-0.498***	-0.892***
	(0.09)	(0.22)	(0.01)	(0.20)	(0.17)	(0.27)
IP * High Skill	0.251**	0.102	-0.049***	0.514**	0.429**	0.765***
	(0.12)	(0.28)	(0.02)	(0.23)	(0.19)	(0.29)
R-squared (within)	0.129	0.129	0.129	0.132	0.131	0.129
Observations	1688249	1688249	1688249	1438045	1598425	1688249
F-stat IP	204	79	257	184	279	237
F-stat IP*High	32	43	247	78	86	95
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns show regressions on log wages. Standard errors, clustered at the firm-year level, in parentheses. Other controls are log firm output, log firm size, log firm cap./lab., share high skill workers in firm, imports/sales, exports/sales, experience experience^2, married dummy, and union membership dummy, as well as job-spell fixed effects, region-year and industry-year dummies. CEEC: Cyprus, Estonia, Lithuania, Latvia, Malta, Poland, Czech Republic, Slovakia, Slovenia, Hungary, Romania, Bulgaria. Poor countries: Afghanistan, Albania, Angola, Armenia, Azerbaijan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Burma, Cambodia, Central African Republic, Chad, Comoros, Republic of the Congo, Equatorial Guinea, Eritrea, Ethiopia, The Gambia, Georgia, Ghana, Guinea, Guinea-Bissau, Guyana, Haiti, India, Kenya, Laos, Lesotho, Madagascar, Maldives, Mali, Malawi, Mauritania, Moldova, Mozambique, Nepal, Niger, Pakistan, Rwanda, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Sierra Leone, Somalia, Sri Lanka, Sudan, Togo, Uganda, Vietnam, Yemen. Rich countries: EU15, United States, Japan. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$.

we exclude job-spells where the firm-level Chinese import penetration variable is zero throughout. The results show that, if anything, the estimates from our main specification in column (6) in Table 2.9 are conservative. In the final column of Table 2.11 we change the definition of Chinese import penetration such that imported intermediates by manufacturing firms no longer are included. Qualitatively, we find the same effects, but the parameter estimates are now roughly doubled. However, in terms of economic significance there is not much of a change, since the mean value of the alternative import penetration measure (and the avereage change in import penetration) is substantially lower (the mean drops from 0.020 to 0.012).

2.6 Long Term Impacts of Chinese Import Penetration

The preceding analysis has focused on the impact of import penetration on wages within job-spells. However, our data allows us to track workers over time as they move across job-spells and spells of unemployment. In this section we use this information to study how import penetration has impacted workers over our sample period along dimensions that are not identified when focusing on within job-spell effects. We adapt the approach taken in Autor, Dorn, Hanson, and Song (2012) to our data. Unlike Autor, Dorn, Hanson, and Song (2012) we can estimate effects for high- and low-skilled workers separately and we can define the import competition measure at the level of the firm instead of the level of the industry.

We start with a cohort of workers who were full-time employees of manufacturing firms in 2001. These workers are then tracked throughout the sample period from 2001 to 2008, as they move between firms, industries, occupations, and spells of unemployment. We then run regressions of the form

$$y_{ij} = \alpha + \gamma_1 \Delta CIP_j + \gamma_2 CIP_{j,01} + x'_{i,01}\beta_1 + z'_{j,01}\beta_2 + \varphi_l + \delta_r + \varepsilon_{ij}, \tag{2.7}$$

where y_{ij} is some outcome variable for worker i initially employed at firm j, ΔCIP_j is the change in CIP from 2001 to 2008 for firm j, $CIP_{j,01}$ is the initial CIP for firm j (in year 2001), $x_{i,01}$ is a set of initial worker characteristics (experience, experience squared, and marriage and union dummies), $z_{j,01}$ is a set of initial firm characteristics (log initial output, log capital-labor ratio, log size, share of high skill workers, and export and import intensities), φ_l are two-digit NACE industry dummies, and δ_r are region dummies (so-called commuting zones as defined in the data section). Both the worker and the initial firm must be observed throughout the sample period in order for us to be able to estimate the above model.

We run the regression for different dependent variables. In line with the preceding focus on wage outcomes, we start by examining the impact of an increase in CIP for firm j on the cumulative earnings of workers initially employed by the firm. Cumulative earnings are defined as the sum of annual labor incomes, Y, normalized by the initial income of the worker, $\sum_{t=2001}^{2008} Y_{it}/Y_{i,2001}$. The results are displayed in Table 2.12. Column (1) shows that OLS fails to find any significant impact of Chinese import penetration. In column (2) we instrument for Chinese import penetration using the Chinese world export supply variable described earlier and find a negative and statistically significant effect of changes in import competition on the cumulative earnings of low-skilled workers. That is, low-skilled workers initially employed at firms who subsequently face increasing import competition from China, have lower earnings from 2001 to 2008. This is qualitatively in line with the within-job spell results found in Table 2.9. To quantify these results consider a low-skilled worker employed by the firm at the 25th percentile of the change in import competition (no change) and a low-skilled worker employed by the 75th percentile firm (1.49 percentage points). The estimates in column (2) suggest that the worker at the 75th percentile firm has experienced 4% lower earnings of initial annual labor earnings over the period from 2001 to 2008 ($2.725 \times (1.49 - 0)$). High-skilled workers do not seem to be affected negatively; if anything, their earnings are increased by changes in Chinese import penetration. Column (3) shows that controlling for initial firm CIP does not significantly alter the estimates. Finally, columns (4) and (5) add interaction terms between the change in Chinese import penetration and workers' occupational characteristics. The earnings of workers performing tasks characterized by routineness are affected negatively by changes in CIP, while the reverse is true for workers performing non-routine tasks. Again, these results are consistent with the within job-spell wage results found in Table 2.10.

To better understand why the earnings of low-skilled, but not high-skilled, workers are lowered by increased exposure to import competition, we next focus on three different outcomes. The first three columns of Table 2.13 show the results for regressions where we use cumulative income transfers (the sum of UI benefits and welfare assis-

Table 2.12: Cumulative Earnings

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
Δ CIP	-0.677	-2.725**	-2.692**	-1.198	-1.500
	(0.60)	(1.26)	(1.24)	(1.24)	(1.21)
Δ CIP * High Skill	1.834	5.849	5.930	2.959	2.478
	(1.54)	(4.05)	(4.04)	(4.08)	(3.95)
Δ CIP * Routine				-1.833**	
				(0.84)	
Δ CIP * Non-Routine					2.065**
					(0.94)
CIP 2001			-1.022	-1.478*	-1.332
			(0.95)	(0.88)	(0.90)
R-squared	0.027	0.027	0.027	0.028	0.028
Observations	178386	178386	178386	174847	174847
F-stat CIP		65	78	52	52
F-stat CIP*High		41	45	47	38
F-stat CIP*OCC				48	30
Other controls	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors, clustered at the firm level, in parentheses. Other controls are 2001 values of log firm output, log firm size, log firm cap./lab., share high skill workers in firm, imports/sales, exports/sales, experience experience^2, married dummy, and union membership dummy. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$.

tance), normalized by initial income, as the dependent variable. High-skilled workers initially employed at firms that were subsequently hit by Chinese import penetration have less cumulative transfers over the sample period than do other high-skilled workers. On the other hand, conditioning on education workers performing routine tasks have higher transfers. The remaining six columns of Table 2.13 show results where the dependent variable is the share of the sample period spent in unemployment and employment, respectively. High-skilled workers, and workers doing non-routine tasks, who face increasing import competition in their initial firms are less unemployed, and spend more time in employment, while workers doing routine tasks are more unemployed and spend less time in employment. It is also interesting to note increased import competition does not increase the time spent in unemployment for low-skilled workers (column 4). This suggests that the negative earnings effects found in Table 2.12 mainly must be ascribed to lower wage rates.

The magnitudes of these effects are modest: Column (7) shows that a high-skilled worker at the 75th percentile firm spends 1% more of the sample period in employment than a high-skilled worker at the 25th percentile firm ($0.767 \times (1.49 - 0.00)$). These results should be considered in light of the fact that the Danish economy achieved close to full employment from 2006 to 2008, resulting in fewer than normal transitions to unemployment.

In order to understand the employment effect of changes in Chinese import penetration, we decompose the cumulative employment effect from column (7) of Table 2.13 into the share of the period spent in the initial industry and occupation, in the initial industry and a new occupation, in a new industry and the initial occupation, and finally in a new industry and occupation. The results of the regressions using these as outcomes are shown in Table 2.14, where the coefficients in columns (2) to (5) sum to the corresponding coefficient in column (1). High-skilled workers facing increases in import competition are less likely to remain in their initial industry and occupation, as they seek towards, in particular, new occupations. On the other hand, low-skilled workers exposed to higher import competition are more likely to remain in their original industry and occupation.

To summarize the results of this section, low-skilled workers whose initial firms are hit by increased Chinese import penetration do not experience increased unemployment and tend to remain in their initial industries and occupations. This lack of mobility is translated into lower earnings through lower wage rates over the sample period. High-skilled workers are much more mobile, in particular across occupations, giving them an advantage when their initial firm is hit by Chinese competition.

2.7 Conclusion

It is often claimed that the economic rise of China has cascading effects on the rest of the world. Rising comparative advantages in particular products has made China the largest exporter in the world. Domestic firms must now compete with Chinese product in their own local markets. This may have pronounced effects on firms' production structure and the wages of its workers. However, previous literature has been unable to find evidence for an increasing skill-wage gap.

In this paper, we have documented this process for Danish firms. Imports from China

Table 2.13: Other Cumulative Regressions: 2SLS

	Cumulative Transfers			Cumulative Unemployment			Cumulative Employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ CIP	-0.134	-0.792**	-0.647*	-0.012	-0.051**	-0.040*	-0.063	0.061	0.027
	(0.40)	(0.35)	(0.36)	(0.02)	(0.03)	(0.02)	(0.05)	(0.05)	(0.05)
Δ CIP * High Skill	-2.909***	-1.192	-1.049	-0.145**	-0.059	-0.059	0.767***	0.461***	0.448***
	(1.00)	(0.76)	(0.70)	(0.06)	(0.05)	(0.04)	(0.21)	(0.17)	(0.14)
Δ CIP * Routine		0.757***			0.044***			-0.146***	
		(0.20)			(0.01)			(0.04)	
Δ CIP * Non-Routine			-0.823***			-0.043***			0.150***
			(0.25)			(0.02)			(0.05)
CIP 2001	0.472	0.462	0.403	0.020	0.017	0.014	-0.032	-0.035	-0.024
	(0.50)	(0.49)	(0.50)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
R-squared	0.032	0.031	0.031	0.036	0.035	0.035	0.049	0.046	0.046
Observations	178386	174847	174847	178386	174847	174847	178386	174847	174847
F-stat CIP	78	52	52	78	52	52	78	52	52
F-stat CIP*High	45	47	38	45	47	38	45	47	38
F-stat CIP*OCC		48	30		48	30		48	30
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors, clustered at the firm level, in parentheses. Other controls are 2001 values of log firm output, log firm size, log firm cap./lab., share high skill workers in firm, imports/sales, exports/sales, experience experience^2, married dummy, and union membership dummy. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$.

Table 2.14: Employment Decomposition: 2SLS

	Cumulative Employment	Ini. Industry Ini. Occupation	Ini. Industry New Occupation	New Industry Ini. Occupation	New Industry New Occupation
	(1)	(2)	(3)	(4)	(5)
Δ CIP	-0.063	0.829***	-0.097	-0.393***	-0.402***
	(0.05)	(0.27)	(0.19)	(0.14)	(0.14)
Δ CIP * High Skill	0.767***	-1.144**	1.345**	-0.039	0.605**
	(0.21)	(0.54)	(0.54)	(0.11)	(0.24)
CIP 2001	-0.032	0.503***	-0.290***	-0.025	-0.220**
	(0.04)	(0.19)	(0.10)	(0.12)	(0.11)
R-squared	0.049	0.080	0.021	0.044	0.066
Observations	178386	178386	178386	178386	178386
F-stat CIP	78	78	78	78	78
F-stat CIP*High	45	45	45	45	45
Other controls	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes

Notes: Columns (2) through (4) decompose cumulative employment into its components. Standard errors, clustered at the firm level, in parentheses. Other controls are 2001 values of log firm output, log firm size, log firm cap./lab., share high skill workers in firm, imports/sales, exports/sales, experience experience^2, married dummy, and union membership dummy. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.10$.

has increased substantially, rising from around 2% of all imports in 1997 to almost 7% in 2009. These increases are concentrated in a handful of industries, notably textiles and furniture. Within an industry, these increases exposes only a subset of the firms. For example, in most industries the firm at the 25th percentile is unaffected by Chinese imports while the 75th percentile firm in many cases has a Chinese import penetration measure at least double that of the median firm.

Consistent with the predictions from a simple multi-product heterogenous firm model with imperfect labor markets we find that firms exposed to increasing Chinese import penetration contract domestic sales. This sales reduction has a clear skill bias as sales low-skill intensive products drop relatively more. Again relying on the simple theoretical framework this suggests that wages of low-skilled workers in particular should fall. We confirm this prediction in two ways. First, within job-spells we find that low-skilled workers lose around 0.48% of their wages for each percentage point increase in Chinese import penetration, while the wages of high-skilled workers are affected to a lesser extent. Second, we estimate the long-term impacts of Chinese import penetration on earnings over an eight-year period taking into account transitions between jobs and into unemployment. This approach confirms the finding that low-skilled workers see their labor earnings fall in response to increased Chinese import penetration, while high-skilled workers tend to be unaffected. Further, we show that low-skilled workers do not experience increased unemployment and tend to remain in their initial industries and occupations in response to increase import competition pointing to wages being the most important adjustment channel for these workers.

Appendices

2.A Theory appendix

In order to understand the mechanism by which Chinese import penetration affects firm outcomes, we present a partial equilibirum model with heterogeneous firms, multiple inputs and outputs, and an increasing labor supply curve for workers.

2.A.1 Demand

Each firm produces two products, indexed by $k \in \{l, h\}$.[15] Within each product category, firms indexed by j supply unique varieties k_j that are imperfect substitutes for each other. The demand x_j^k for variety k_j is dual-staged, mirroring that of Helpman and Krugman (1985):

$$\begin{aligned} q_j^k &= \alpha_k \frac{\left(p_j^k\right)^{-\sigma_k}}{\Phi_k + \Phi_k'} \\ \Phi_k &= \int_{k_j \in J_k} \left(p_j^k\right)^{1-\sigma_k} \\ \Phi_k' &= \int_{k_j \in J_k'} \left(p_j^k\right)^{1-\sigma_k}, \end{aligned} \tag{2.8}$$

where p_j^k is the price of variety k_j of product k, σ_k is the Dixit-Stiglitz elasticity of substitution between varieties of product k, and α_k is the Cobb-Douglas proportion of income spent on all varieties of k ($\alpha_l + \alpha_h = 1$). Φ_k and Φ_k' are the toughness of competition for product k arising from domestic and foreign varieties, respectively. This distinction between domestic and foreign captures the effect of Chinese import penetration, which will increase Φ_k'. We assume that individual varieties are differential and the characteristics of

[15] We limit our discussion to two products to facilitate exposition. However, the model can encompass any number of products since there are no supply side interactions among the products.

any single variety does not change the overall Φ_j. As in Autor, Dorn, and Hanson (2013), an increase in Φ_k or Φ'_k will result in lower demand for variety k_j. To proceed, we find the inverse demand function from equation (2.8):

$$
\begin{aligned}
p_j^k &= \left(\frac{\Phi_k + \Phi'_k}{\alpha_k}\right)^{-\frac{1}{\sigma_k}} \left(x_j^k\right)^{-\frac{1}{\sigma_k}} \\
\log p_j^k &= -\frac{1}{\sigma_k} \log\left(\frac{\Phi_k + \Phi'_k}{\alpha_k}\right) - \frac{1}{\sigma_k} \log x_j^k \qquad (2.9)
\end{aligned}
$$

2.A.2 Production and Labor Demand

Products are supplied by firms indexed by j. Products l and h are produced by labor specific to that product. Specifically low skilled workers are used to produce product l while high skilled workers are used to produce product h.[16] The firm also has a firm-product specific productivity φ_j^k denoting the efficiency of its workers. Firm j can transform one unit of labor of type $k \in \{l, h\}$ into φ_j^k units of product k. Therefore, to produce q_j^k units, firm j demands L_k^j units of labor, where

$$L_k^j = \frac{q_k^j}{\varphi_j^k}. \qquad (2.10)$$

Since we will not model firm entry and exit in this model, we assume firms are fully aware of their productivities φ_j^k for each product k.[17]

2.A.3 Firm level labor supply

As discussed in the theory section, firms face an upward sloping firm-specific labor supply curve due to imperfections in the labor market. For each type of worker $k \in \{l, h\}$, the labor supply curve is described by the function $w\left(L_k^j\right)$, where:

$$w_k^j = w\left(L_k^j\right) = \left(L_k^j\right)^{\lambda_k}. \qquad (2.11)$$

[16]This partitioning of workers allows us to generate explicit predictions concerning the effects of Chinese import penetration. However, we must abstract from product interactions to maintain simplicity. An extension to this model would include a HOV style production function where some high skilled workers are required to manufacture the low-skilled product.

[17]Firm-product specific productivities are introduced in Bernard, Redding, and Schott (2011), although they call it firm ability and firm-product attributes.

2.A.4 Profit Maximization

Given the inverse demand function in equation (2.9), the firm's unit labor requirement in equation (2.10), and the firm's labor supply curve in equation (2.11), the firm must choose the quantities of each product it will supply to the market. The firm's maximization problem can be written as:

$$
\begin{aligned}
\max_{q_1,q_2} \pi_j &= \sum_{k=l,h} \left[p_k^j q_k^j - w_k\left(L_k^j\right) L_k^j \right] \\
&= \sum_{k=l,h} \left[\left(\frac{\Phi_k + \Phi_k'}{\alpha_k} \right)^{-\frac{1}{\sigma_k}} \left(q_k^j\right)^{1-\frac{1}{\sigma_k}} - \left(\frac{q_k^j}{\varphi_j^k} \right)^{\lambda_k+1} \right]
\end{aligned}
$$

with first order conditions:

$$
\frac{d\pi_j}{dq_k} = \left(1 - \frac{1}{\sigma_k}\right) \left(\frac{\Phi_k + \Phi_k'}{\alpha_k} \right)^{-\frac{1}{\sigma_k}} \left(q_k^j\right)^{-\frac{1}{\sigma_k}} - \frac{(\lambda_k+1)}{\varphi_j^k} \left(\frac{q_k^j}{\varphi_j^k} \right)^{\lambda_k}.
$$

By setting $\frac{d\pi_j}{dq_k} = 0$, we find the profit maximing outputs for each product $k \in \{l, h\}$:

$$
\begin{aligned}
q_k^j &= \left(\frac{\sigma_k - 1}{\sigma_k(\lambda_k+1)} \right)^{\frac{\sigma_k}{\sigma_k\lambda_k+1}} \left(\varphi_j^k\right)^{\frac{\sigma_k(\lambda_k+1)}{\sigma_k\lambda_k+1}} \left(\frac{\Phi_k + \Phi_k'}{\alpha_k} \right)^{-\frac{1}{\sigma_k\lambda_k+1}} \\
\log q_k^j &= \kappa_k + \frac{\sigma_k(\lambda_k+1)}{\sigma_k\lambda_k+1} \log \varphi_j^k - \frac{1}{\sigma_k\lambda_k+1} \log\left(\frac{\Phi_k + \Phi_k'}{\alpha_k} \right),
\end{aligned}
$$

where $\kappa_k = \frac{\sigma_k}{\sigma_k\lambda_k+1} \log\left(\frac{\sigma_k-1}{\sigma_k(\lambda_k+1)} \right)$. Revenues can be obtained by adding the log inverse demand from equation (2.9):

$$
\log p_k^j q_k^j = \left(\frac{\sigma_k - 1}{\sigma_k} \right) \kappa_k + \frac{(\sigma_k-1)(\lambda_k+1)}{\sigma_k\lambda_k+1} \log \varphi_j^k - \frac{\lambda_k+1}{\sigma_k\lambda_k+1} \log\left(\frac{\Phi_k + \Phi_k'}{\alpha_k} \right) \tag{2.12}
$$

which shows a negative relationship between the revenues of product k and level of imports Φ_k'.

The wages for workers of type k can also be determined by combining the profit maximizing quantity with the labor supply curve:

$$
w_k^j = \left(L_k^j\right)^{\lambda_k} = \left(\frac{q_k^j}{\varphi_j^k} \right)^{\lambda_k}
$$

and log linearizing:

$$
\log w_k^j = \lambda_k \kappa_k + \left(\frac{\lambda_k(\sigma_k-1)}{\sigma_k\lambda_k+1} \right) \log \varphi_j^k - \frac{\lambda_k}{\sigma_k\lambda_k+1} \log\left(\frac{\Phi_k + \Phi_k'}{\alpha_k} \right). \tag{2.13}
$$

The revenue equation and the wage equation describe the effects of Chinese import penetration on firm and worker level outcomes.

2.B Wage Effects using Industry-Level CIP

Table 2.15 shows the results of using industry-level CIP instead of the firm-level CIP in equation (2.6).

Table 2.15: Mincer Wage Regressions: Industry CIP

	Fixed Effects		IV	
	(1)	(2)	(3)	(4)
Δ CIP	-0.079***	-0.105***	0.089	0.022
	(0.03)	(0.03)	(0.07)	(0.07)
Δ CIP * High Skill		0.173***		0.364***
		(0.02)		(0.04)
R-squared	0.129	0.129	0.129	0.129
Observations	1643447	1643447	1643447	1643447
F-stat CIP			167	208
F-stat CIP*High				74
Other controls	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes

Notes: Standard errors, clustered at the firm-year level, in parentheses. Other controls are log firm output, log firm size, log firm cap./lab., share high skill workers in firm, imports/sales, exports/sales, experience experience^2, married dummy, and union membership dummy, as well as job-spell fixed effects, region-year and industry-year dummies. *** p< 0.01, ** p< 0.05, * p< 0.

Chapter 3

Trade Liberalization and the Degree of Competition in International Duopoly

joint with Per Svejstrup Hansen and Jonas Worm Hansen

(Accepted for publication at the *Review of International Economics*)

Abstract

This paper analyzes how a reduction in trade costs influences the possibility for firms to engage in international cartels, and hence how trade liberalization affects the degree of competition. We consider an intra-industry trade model of the Brander and Krugman (1983) type, but amended to allow for firms producing differentiated products. Our main finding is that trade liberalization may have an anti-competitive effect. We find that there is no unique relation between a reduction in trade costs and the degree of competition. When products are differentiated, a lowering of trade costs is pro-competitive if trade costs are initially high, but anti-competitive if trade costs initially are low. Hence, trade policy is not necessarily a substitute for competition policy.

3.1 Introduction

The aim of this paper is to analyze how a reduction in trade costs influences the possibility for firms to engage in international cartels, and hence how trade liberalization affects the degree of competition. Conventional trade theory suggests that trade liberalization – interpreted as a reduction in trade costs – will increase competition since trade costs typically shelter the domestic market from foreign competition. Hence, lowering trade costs should increase competition by easing access to the domestic market. This conclusion is trivial in models of perfect competition but needs to be considered more carefully once competition is imperfect. In models of oligopoly with a homogeneous product – or the simpler version of duopoly – intra-industry trade might emerge if trade costs are not too large as shown by Brander and Krugman (1983). But it also raises the possibility of collusion to emerge where firms maximize their joint profit by refraining from exporting to each other's market as shown by Pinto (1986). Hence, competition is reduced. Clearly, such collusive or cartel behavior is not necessarily stable. If cartel stability is modeled as an infinitely repeated game, whether international cartels can be upheld or not depends critically on firms' discount factor that again depends on trade costs. There are two opposing forces at work: the lower the trade costs, the larger the incentive to break out of the cartel and export to the rival's market; on the other hand, when trade costs are lowered it is also easier for your rival to export to your market, and hence in the future punishment for breaking the cartel, your profit is lower. Which effect dominates depends on the market structure and analysis of this is the aim of our paper [1].

We consider an intra-industry trade model of the Brander and Krugman (1983) type but amended to allow for firms producing differentiated products. By varying the degree of product differentiation we are able to analyze products ranging from "perfect complements" over independent products to perfect substitutes (a homogeneous product). We follow a well-established tradition when analyzing these types of models working with linear demand and constant marginal costs of production (see e.g. Pinto (1986), Fung (1991, 1992), Clarke and Collie (2003), Lommerud and Sørgaard (2001), Friberg and Ganslandt (2005), Bond and Syropoulos (2008), and Schröder (2007)). In contrast to much of the literature, we find no unique relation between a reduction in trade costs and the degree of competition when firms compete in quantities. The most striking result is that the relationship is hump-shaped and depends on the degree of product differentiation. With

[1] Some evidence of international collusive behavior has been reported. Recently (Nov. 2007), the European Commission fined YKK, Prym, Coats, and four other companies for, among other things, having shared markets and coordinated prices in the market for zip fasteners. Another example is the European cement industry, where the European Commission in 1994 fined 42 cement producers for having secret cartel agreements aimed at limiting the sales of cement between EU member-countries. A third example concerns the synthetic fiber industry, where Japanese and English producers had agreed not to export to each other's markets as disclosed by the Japanese antitrust authorities in 1972. In fact, there is a plethora of evidence of international cartel behavior.

differentiated products, a lowering of trade costs is pro-competitive if trade costs are initially high, but anti-competitive if trade costs initially are low. The anti-competitive effect is greater when products are more differentiated. Hence, trade policy is not necessarily a substitute for competition policy.

The intuition for the results follows from the fact that the joint profit maximizing solution (the cartel solution) is not necessarily each firm acting as a monopolist in its own market, when products are imperfect substitutes. In fact, the joint profit maximizing solution involves intra-industry trade (also called collusive trade) if transport costs are not too high as demonstrated by Fung (1991). The reason is that consumers are assumed to have love of variety. Hence, when considering breaking out of a cartel, a firm should not compare the gain and future discounted losses to the monopoly profit, but instead compare it to the cartel solution with collusive trade. The cartel solution with collusive trade is simply more attractive when transport costs are relatively low, and this makes it easier for the cartel to be sustained when transport costs are lowered from an initial low level. The opposite is true if transport costs are initially high.

There are a number of papers related to our paper. The one closest in spirit and in model setup is Lommerud and Sørgaard (2001). But in contrast to our paper they consider a homogeneous good duopoly model of intra-industry trade, and it can therefore be seen as a special case of our paper. They show that if firms compete in quantities, a lowering of trade costs will always reduce the critical discount factor that allows collusion to be sustained, and hence trade liberalization is pro-competitive. The difference in the results between their paper and our paper lies in the fact that we allow for differentiated products.

As indicated above, Fung (1991) considers a model with differentiated products. His interest in that paper is to explain when intra-industry trade emerges as the cartel solution. He does not investigate the cartel stability issue. This is done in Fung (1992), but unlike our model he only considers competition in the domestic market and not competition in both the domestic and in the foreign market – a distinction we know from Brander and Krugman (1983) is essential. Another paper that deals with cartel stability in international duopoly is Pinto (1986). He considers a homogeneous good duopoly, and is as such much closer to Lommerud and Sørgaard (2001) than to our paper, though the results in Pinto (1986) turn out to be a special case here.

Bond and Syropoulos (2008) extend the analysis of Lommerud and Sørgaard (2001) by allowing firms to produce differentiated products. However, in contrast to our paper, they only consider the case where products are substitutes. They find that trade liberalization may reduce welfare. The trade liberalization effects of Bond and Syropoulos (2008) are a subset of our more general analysis.

Schröder (2007) has shown in a model with homogeneous goods how cartel stability depends on the specification of trade costs. It turns out that the results from Lommerud and Sørgaard (2001) do not always carry over if trade costs are ad valorem instead of specific. The focus in our paper is on the degree of product differentiation and cartel stability, and not as much on the exact nature of trade costs. Therefore, we follow the tradition in this strand of literature and work with specific trade costs.

Papers that also consider a Brander and Krugman (1983) type model with differentiated products are Clarke and Collie (2003) and Friberg and Ganslandt (2005). However, they do not study the issue of cartel stability but are solely focused on the welfare implications of trade in static games with Bertrand competition.[2]

The paper is organized as follows. The next section introduces the model setup. Following that are the profit solutions under quantity competition. These are used in section 4 to discuss the concept of cartel stability, which allows us to present the main results in section 5. The final section concludes.

3.2 The Model

To analyze the impact of trade liberalization on the sustainability of collusion, we use a Brander and Krugman (1983) type model of intra-industry trade between two countries, 1 and 2. The only difference between the model of Brander and Krugman (1983) and our model is that we allow for products to be differentiated. There are two firms who compete in quantities (Cournot competition), where firm 1 is based in country 1, and firm 2 is based in country 2. It is assumed that the markets are segmented, so the decisions of the firms for the home market are independent of the decisions for the foreign market. The firms produce using constant returns to scale technologies, and there is a unit

[2] The effects of trade liberalization continues to remain at the heart of much theoretical and empirical work in international trade. Recently, the focus has been on firm-level entry and exit responses, see e.g. Gustafsson and Segerstrom (2010), or welfare effects of quota removal, see e.g. Dadakas and Katranidis (2010). This paper abstracts from these responses as the focus is on cartel stability.

transportation cost of t associated with exporting. We assume that the demand structure is similar to the differentiated duopoly model of Dixit (1979), and hence we work with linear demand curves[3]. The inverse demands are given by:

$$p_{x_i} = \alpha_1 - \beta_1 x_i - \gamma y_i \tag{3.1}$$

$$p_{y_i} = \alpha_2 - \beta_2 y_i - \gamma x_i, \tag{3.2}$$

where $i = 1,2$ denotes country 1 and 2, respectively. Firm 1 produces x, whereas firm 2 produces y. The parameter γ represents the degree of product differentiation. If $0 < \gamma < \beta_j$, goods are imperfect substitutes and as $\gamma \to \beta_j$, goods become perfect substitutes. If $-\beta_j < \gamma < 0$, goods are imperfect complements and as $\gamma \to -\beta_j$, goods become perfect complements. If $\gamma = 0$, goods are independent of each other.

In order to show most clearly that it is the inclusion of differentiated products that accounts for our results, we work with complete symmetry between firms and countries. Hence, marginal costs are normalized to zero, $c = 0$, for both firms, and transportation costs are identical in the two countries, $t_1 = t_2 = t$. For the sake of clarity and in accordance with the existing literature, we simplify our model by setting $\alpha_1 = \alpha_2 = 1$ and $\beta_1 = \beta_2 = 1$[4].

Hence, the inverse demand functions become:

$$p_{x_i} = 1 - x_i - \gamma y_i \tag{3.3}$$

$$p_{y_i} = 1 - y_i - \gamma x_i. \tag{3.4}$$

Since we consider products ranging from perfect substitutes to perfect complements, non-negativity of the inverse demand functions require that:

$$x_i \leq 1 - \gamma y_i \tag{3.5}$$

$$y_i \leq 1 - \gamma x_i. \tag{3.6}$$

These constraints are possibly binding in cases where products are highly complementary and trade costs are low.

[3]There is a well-established tradition of working with linear demand curves in models of repeated games of the type we consider. Nevertheless, the assumption of linearity is still restrictive but generally not known to be a crucial simplification unless demand is very convex.

[4]Our results are still valid if these simplifications are not made. However, the derivations are complicated significantly and nothing is gained in terms of results, so we use the simplified model here. An appendix showing the derivations for the more general case is available upon request.

Since we are interested in analyzing the conditions under which collusion can be sustained in an infinitely repeated game, we begin by stating the game that is played. The game is of the prisoner's dilemma type. Initially firms collude and somehow share the markets, obtaining higher profits than if they competed. But each firm has a unilateral incentive to deviate from collusion by charging individually optimal quantities, given that the other firm still sets the collusive quantities. If, however, the firm deviates from collusion it will be punished by the other firm in the future. We assume that the punishment is to revert to the competitive (Nash) equilibrium in all future periods, and hence firms employ the grim trigger strategy[5]. The firm then has to weigh the short run gain from deviating, against lower future profits. Whether collusion can be upheld or not depends on the firm's discount rate, which in turn depends on the transport costs. These transport costs are at the core of our analysis, as we try to answer how a change in the transportation cost affects the incentive for firms to collude. Trade liberalization is interpreted as a lowering of the unit transport cost, which has an ambiguous effect on the profits of the firms. It may increase the short term gains from deviating, but can also make the subsequent punishment harsher. Trade liberalization can therefore be pro- or anti-competitive.

Collusion can be sustained if the discounted value of all future collusive profits is equal to or greater than the sum of the one-shot deviation profits and the discounted value of all the future punishment profits. That is, the following expression must hold true:

$$\begin{aligned} \frac{1}{1-\delta}\pi_1^C \geq \pi_1^D + \frac{\delta}{1-\delta}\pi_1^P &\Longleftrightarrow \\ \delta \geq \delta^* = \frac{\pi_1^D - \pi_1^C}{\pi_1^D - \pi_1^P}, & \end{aligned} \tag{3.7}$$

where the superscript denotes collusion (C), deviation (D), and punishment (P), respectively. δ is the firms' (common) discount rate. If δ is larger than some critical discount rate, δ^*, collusion can be sustained.

The profits of the firms are given by:

$$\pi_1 = \pi_{11} + \pi_{12} = p_{x_1} x_1 + \left(p_{x_2} - t\right) x_2 \tag{3.8}$$

$$\pi_2 = \pi_{21} + \pi_{22} = \left(p_{y_1} - t\right) y_1 + p_{y_2} y_2, \tag{3.9}$$

[5]Many possible punishment strategies can be considered. The aim of our paper is not to consider these different punishment strategies, so we work with the grim trigger strategy.

where the first subscript denotes the firm and the second denotes the market. Since demand is symmetric between the two countries, is suffices to analyze the model from the viewpoint of one of the firms. In the following we analyze it from the viewpoint of firm 1.

To find the critical discount factor and determine how it changes with transportation costs, we need the relevant profit expressions.

3.3 Profit Solutions

The profit in the punishment phase (the Nash equilibrium) is straightforward to calculate. Firm 1 maximizes its profits, π_1, taking the output level of firm 2 as given. The resulting profit expressions for the markets in country 1 and 2 are:

$$\pi_{11}^P = \frac{\left(2-\gamma(1-t)\right)^2}{\left(4-\gamma^2\right)^2}, \tag{3.10}$$

$$\pi_{12}^P = \frac{\left(2-2t-\gamma\right)^2}{\left(4-\gamma^2\right)^2}, \tag{3.11}$$

and the total profit on both markets is thus: $\pi_1^P = \pi_{11}^P + \pi_{12}^P$. We note that for exporting to be profitable, the resulting exporting quantity of firm 1 to market 2 should be positive. This requires that:

$$t \leq \bar{t}^P = \frac{2-\gamma}{2}, \tag{3.12}$$

where $\bar{t}^P$ is the prohibitive cost of transportation in the punishment phase.

If goods are perfect substitutes, collusion simply means that each firm is a monopolist in its own market. Since exporting involves a transport cost, there is no reason to transport the exact same good to another country. This is, however not the case when goods are imperfect substitutes or complements as shown by Fung (1991). Precisely because goods are imperfect substitutes or complements, it might be beneficial for firms to actually trade during collusion; the so-called collusive trade. Collusive trade will only emerge if transport costs are not too high. This possibility has to be taken into account and will together with the assumption of differentiated goods contribute to the novel results of this paper.

Firms will trade under collusion if

$$\pi_1^T \geq \pi_1^M,$$

where π_1^T denotes the profit the firm obtains under collusive trade, whereas π_1^M is the monopoly profit.

During collusive trade, firms maximize their joint profits, $\pi_1 + \pi_2$. This gives us the collusive trade quantity, price and profit of firm 1:

$$x_1 = \frac{1-\gamma(1-t)}{2\left(1-\gamma^2\right)}, \quad p_{x_1} = \frac{1}{2}, \qquad \pi_{11}^T = \frac{1-\gamma(1-t)}{4\left(1-\gamma^2\right)}, \tag{3.13}$$

$$x_2 = \frac{1-t-\gamma}{2\left(1-\gamma^2\right)}, \qquad p_{x_2} = \frac{1+t}{2}, \quad \pi_{12}^T = \frac{(t-1)\left(t+\gamma-1\right)}{4\left(1-\gamma^2\right)}, \tag{3.14}$$

where the first line shows the home market expressions of firm 1, and the second line gives us the foreign market expressions for firm 1. The total collusion profits of firm 1 is the sum of the home market profit and the foreign market profit: $\pi_1^T = \pi_{11}^T + \pi_{12}^T$. If firms share the market by not exporting to each other, they have a monopoly in their own market, and we obtain the monopoly quantity, price and profit of firm 1:

$$x_1 = \frac{1}{2}, \quad p_{x_1} = \frac{1}{2}, \quad \pi_{11}^M = \frac{1}{4}, \quad \pi_{12}^M = 0,$$

where the superscript M denotes monopoly.

By comparing the two profit expressions $\pi_1^M = \pi_{11}^M$ and π_1^T we can find the level of transport costs t_s that makes collusive trade viable. This gives us

$$t \leq t_s = 1-\gamma.$$

That is, if transport costs are not too high, firms trade during collusion, which is also what is found in Fung (1991).

When finding the deviation profits, we assume that the deviating firm takes the rival's output as given. That is, the rival is sluggish in reacting and only reacts in the following period. In the period of deviation, the rival produces either the monopoly quantity or the collusive trade quantity depending on the setting firms are in. The resulting expressions regarding quantity, price, and profit for firm 1 in the monopoly setting ($t > t_s$) are:

$$x_1 = \frac{1}{2}, \qquad p_{x_1} = \frac{1}{2}, \qquad \pi_{11}^{DM} = \frac{1}{4}, \tag{3.15}$$

$$x_2 = \frac{2-2t-\gamma}{4}, \quad p_{x_2} = \frac{2+2t-\gamma}{4}, \quad \pi_{12}^{DM} = \frac{\left(2-2t-\gamma\right)^2}{16}. \tag{3.16}$$

The total deviation profit for firm 1 is the sum of the profits of market 1 and 2, $\pi_1^{DM} = \pi_{11}^{DM} + \pi_{12}^{DM}$. Superscripts denote deviation and monopoly setting, respectively.

When firms are in the collusive trade setting ($t \leq t_s$), firm 1 breaks the collusive agreement by maximizing its own profit. Firm 2 is assumed to be sluggish in adjusting its quantity, and it therefore still produces the collusive quantities. Since demand is symmetric, we know from (3.13) and (3.14) that firm 2 produces $y_2 = \frac{1-\gamma(1-t)}{2(1-\gamma^2)}$ for its home market (market 2) and exports $y_1 = \frac{1-t-\gamma}{2(1-\gamma^2)}$ to its foreign market (market 1). Note, however, that the non-negativity constraints (3.5) and (3.6) may be binding for firm 2's prices in the deviation phase of the collusive trade setting. Specifically, the non-negativity constraints are binding in the deviation phase if both of the following conditions are satisfied:

$$-1 < \gamma < 1 - \sqrt{3},$$

and

$$t < \begin{cases} \bar{t}_{p_{y_1}} = \frac{3\gamma^2-\gamma^3-2}{2-\gamma^2} & \text{for firm 2's export price, } p_{y_1} \\ \bar{t}_{p_{y_2}} = \frac{2+\gamma^3-3\gamma^2}{\gamma^3} & \text{for firm 2's domestic price, } p_{y_2}. \end{cases}$$

That is, the non-negativity constraints are only binding if the products of firm 1 and 2 are highly complementary and transport costs are sufficiently low.

Figure 3.1 shows all constraints for quantity competition in (γ, t)-space.

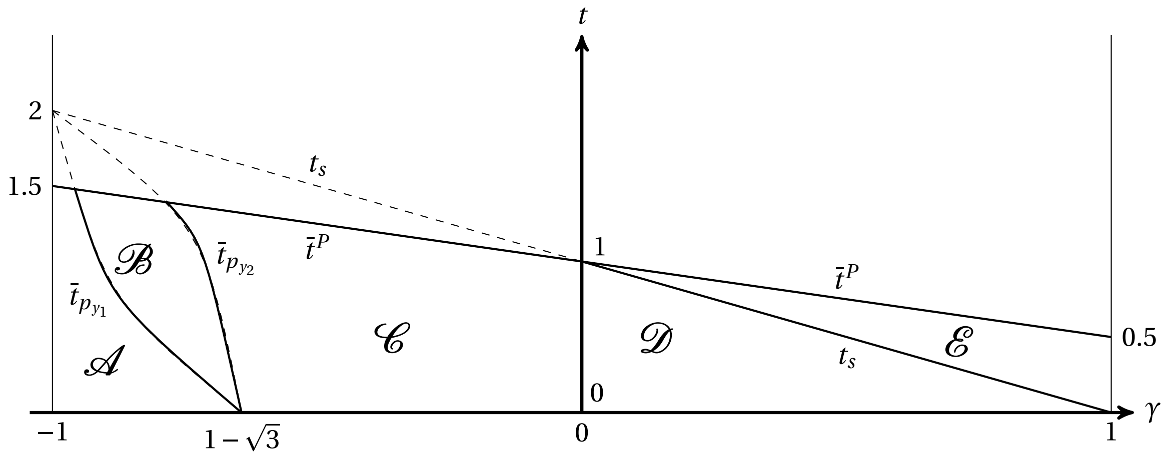


Figure 3.1: Constraints in (γ, t)-space.

First note that for transport costs greater than $\bar{t}^P$ all trade is impeded, and firms are monopolists in their home markets. For values of γ and t in area $\mathscr{A}$, the non-negativity constraints on firm 2's domestic prices (p_{y_2}) and export prices (p_{y_1}) are both binding. For combinations in area $\mathscr{B}$, only the constraint on firm 2's domestic prices are binding, while the constraint on its exports are not. In areas $\mathscr{C}$, $\mathscr{D}$ and $\mathscr{E}$, none of non-negativity constraints are binding.

When we are in area $\mathscr{E}$, the firms are monopolists in their home markets during collusion as $t > t_s$, and the relevant profit expressions are given by (3.15) and (3.16).

The deviation quantities, prices and profits of firm 1 when we are in areas $\mathscr{C}$ or $\mathscr{D}$ become:

$$x_1 = \frac{2-\gamma(1-t)-\gamma^2}{4\left(1-\gamma^2\right)}, \qquad p_{x_1} = \frac{2-\gamma(1-t)-\gamma^2}{4\left(1-\gamma^2\right)}, \qquad \pi_{11}^{DT} = \frac{\left(2-\gamma(1-t)-\gamma^2\right)^2}{16\left(1-\gamma^2\right)^2}, \quad (3.17)$$

$$x_2 = \frac{2-2t-\gamma-\gamma^2+t\gamma^2}{4\left(1-\gamma^2\right)}, \quad p_{x_2} = \frac{3t\gamma^2+\gamma^2+\gamma-2t-2}{4\left(1-\gamma^2\right)}, \quad \pi_{12}^{DT} = \frac{\left(\gamma^2+\gamma+2t-t\gamma^2-2\right)^2}{16\left(1-\gamma^2\right)^2}, \quad (3.18)$$

where superscript T denotes the collusive trade setting. The total deviation profit for firm 1 is the sum of the profits of market 1 and 2, $\pi_1^{DT} = \pi_{11}^{DT} + \pi_{12}^{DT}$.

When we are in area $\mathscr{B}$, firm 2's constraint on p_{y_2} is binding, while the constraint on p_{y_1} is not. Hence, firm 1's domestic quantity, price and profit are still given by (3.17). Its export quantity, price and profit change to:

$$x_2 = \frac{2\gamma^2+t\gamma-\gamma-1}{2\gamma\left(\gamma^2-1\right)}, \quad p_{x_2} = \frac{t\gamma+\gamma-1}{2\gamma}, \quad \pi_{12\mathscr{B}}^{DT} = \frac{\left(1+\gamma(t-1)\right)\left(2\gamma^2+\gamma(t-1)-1\right)}{4\gamma^2\left(1-\gamma^2\right)}, \quad (3.19)$$

where subscript $\mathscr{B}$ indicates the area. Total profits are $\pi_{1\mathscr{B}}^{DT} = \pi_{11}^{DT} + \pi_{12\mathscr{B}}^{DT}$

In area $\mathscr{A}$ both constraints are binding, and firm 1's quantities, prices and profits are:

$$x_1 = \frac{1+\gamma+t-2\gamma^2}{2\gamma\left(1-\gamma^2\right)}, \quad p_{x_1} = \frac{\gamma-t-1}{2\gamma}, \quad \pi_{11\mathscr{A}}^{DT} = \frac{\left(\gamma-t-1\right)\left(1+\gamma+t-2\gamma^2\right)}{4\gamma^2\left(1-\gamma^2\right)}, \quad (3.20)$$

$$x_2 = \frac{1+\gamma-t\gamma-2\gamma^2}{2\gamma\left(1-\gamma^2\right)}, \quad p_{x_2} = \frac{\gamma+t\gamma-1}{2\gamma}, \quad \pi_{12\mathscr{A}}^{DT} = \frac{\left(1+\gamma(t-1)\right)\left(2\gamma^2+\gamma(t-1)-1\right)}{4\gamma^2\left(1-\gamma^2\right)}, \quad (3.21)$$

where subscript $\mathscr{A}$ indicates the area. Total deviation profits are $\pi_{1\mathscr{A}}^{DT} = \pi_{11\mathscr{A}}^{DT} + \pi_{12\mathscr{A}}^{DT}$.

3.4 Cartel Stability

The monopoly setting, $t > t_s = 1-\gamma$

In the monopoly setting, that is in area $\mathscr{E}$, collusion can be sustained if $\delta \geq \delta_M^* = \frac{\pi_1^{DM}-\pi_1^M}{\pi_1^{DM}-\pi_1^P}$, where δ_M^* is the critical discount rate when firms maximize their joint profits by being monopolists in their home markets. Substituting in the profit expressions from above yields:

$$\delta_M^* = \frac{\left(\gamma^2-4\right)^2\left(\gamma+2t-2\right)}{\gamma\left(\gamma^4+2t\gamma^3-2\gamma^3-4\gamma^2-24t\gamma+24\gamma-32\right)}.$$

To determine how trade liberalization, interpreted as a reduction in trade costs, affects the critical discount rate in the monopoly setting, differentiate δ_M^* with respect to t:

$$\frac{\partial \delta_M^*}{\partial t} = \frac{16\left(\gamma-2\right)^3\left(\gamma+2\right)^3}{\gamma\left(\gamma^4+2t\gamma^3-2\gamma^3-4\gamma^2-24t\gamma+24\gamma-32\right)^2}.$$

The collusive trade setting, $t \leq t_s = 1-\gamma$

In the collusive trade setting, collusion can be sustained in areas $\mathscr{C}$ and $\mathscr{D}$ if $\delta \geq \delta_T^* = \frac{\pi_1^{DT}-\pi_1^T}{\pi_1^{DT}-\pi_1^P}$, where δ_T^* is the critical discount rate when firms maximize their joint profits by trading under Cournot competition. The partial derivative with respect to transport costs is $\frac{\partial \delta_T^*}{\partial t}$.

In area $\mathscr{B}$, collusion can be sustained if $\delta \geq \delta_{T\mathscr{B}}^* = \frac{\pi_{1\mathscr{B}}^{DT}-\pi_1^T}{\pi_{1\mathscr{B}}^{DT}-\pi_1^P}$, where $\delta_{T\mathscr{B}}^*$ is the critical discount rate. Its partial derivative is $\frac{\partial \delta_{T\mathscr{B}}^*}{\partial t}$.

Lastly, collusion can be sustained in area $\mathscr{A}$ if $\delta \geq \delta_{T\mathscr{A}}^* = \frac{\pi_{1\mathscr{A}}^{DT}-\pi_1^T}{\pi_{1\mathscr{A}}^{DT}-\pi_1^P}$, where $\delta_{T\mathscr{A}}^*$ is the critical discount rate. Its partial derivative is $\frac{\partial \delta_{T\mathscr{A}}^*}{\partial t}$.

3.5 Results

With the calculations above we are now ready to state the main results.

Proposition 1. *In a Cournot duopoly, trade liberalization (a reduction in t):*

i) will be anti-competitive for values of (γ, t) in area $\mathscr{A}$,

ii) will be pro-competitive for very high t and anti-competitive for most t in area $\mathscr{B}$

iii) will be pro-competitive for values of (γ, t) in area $\mathscr{C}$,

iv) will be anti-competitive for values of (γ, t) in area $\mathscr{D}$,

v) will be pro-competitive for values of (γ, t) in area $\mathscr{E}$.

Proof. i) $\frac{\partial \delta_{T\mathscr{A}}^*}{\partial t} > 0$ in area $\mathscr{A}$. Hence, trade liberalization increases the range of discount factors that make collusion sustainable, and thus is anti-competitive. *ii)* $\frac{\partial \delta_{T\mathscr{B}}^*}{\partial t} \gtrless 0$ depending on t. Trade liberalization can therefore be both pro- or anti-competitive in area $\mathscr{B}$; however, t has to be near the upper boundaries, $\bar{t}^P$ or $\bar{t}_{p_{y2}}$, if it is to be pro-competitive, so trade liberalization is mostly anti-competitive. *iii)* $\frac{\partial \delta_T^*}{\partial t} < 0$, so trade liberalization is pro-competitive in area $\mathscr{C}$. *iv)* $\frac{\partial \delta_T^*}{\partial t} > 0$ since $0 < \gamma < 1$, so trade liberalization is anti-competitive in area $\mathscr{D}$. *v)* $\frac{\partial \delta_M^*}{\partial t} < 0$, and so trade liberalization is pro-competitive in area $\mathscr{E}$. $\square$

Figure 3.2 illustrates the proposition for a particular positive γ.

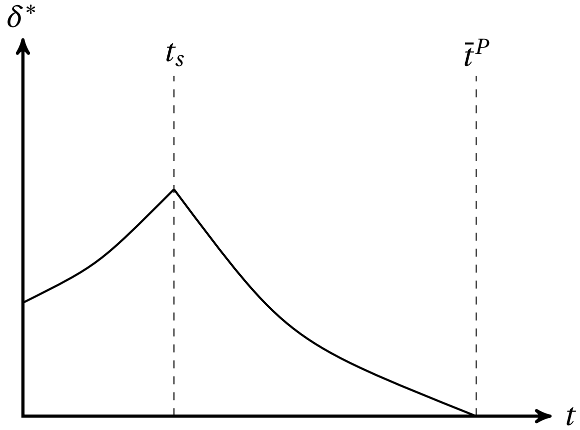


Figure 3.2: Critical discount rate with imperfect substitutes ($0 < \gamma < 1$).

Proposition 1 says that the effect of trade liberalization is ambiguous when products are imperfect substitutes since t intersects both areas $\mathscr{D}$ and $\mathscr{E}$ for a particular positive γ. Particularly, for $0 < t \leq t_s$ we are in area $\mathscr{D}$, while for $t_s < t \leq \bar{t}^P$ we are in area $\mathscr{E}$. Thus, the effect of trade liberalization depends on the initial transport costs. If initially transport costs are sufficiently low such that firms trade during collusion, a lowering of the transport cost will reduce the incentive to deviate, and hence reduce competition. The intuition is straightforward: If it pays off to trade during collusion, reducing the costs of trade will strengthen the collusive behavior. If, on the other hand, transport costs are initially so high that firms are in a monopoly setting during collusion, a lowering of trade costs will increase the incentive to deviate and export to the rival's market.

As the degree of product substitutability increases (i.e. when γ increases), t_s decreases and the range of transport costs that make trade liberalization anti-competitive decreases. That is, the peak of the critical discount rate, δ^*, in figure 3.2 moves towards the vertical axis.[6]

[6]However, this convergence is not continuous in the limit. Specifically,

$$\lim_{\gamma\to 1, t\to 0} \delta_M^* = \frac{9}{13},$$
$$\lim_{\gamma\to 1, t\to 0} \delta_T^* = \frac{9}{17}.$$

Thus, monopoly profit levels can be sustained in the limit, where products are perfect substitutes, at lower discount rates when firms trade during collusion, than if they do not. Hence, trade can facilitate collusion

The picture is not as clear cut when products are complements. Here, trade liberalization is pro-competitive unless the non-negativity constraints are binding. When in area $\mathscr{C}$, and when transport costs are not too high such that firms trade during collusion, $\left(0 \leq t \leq \bar{t}^P\right)$, a lowering of trade costs makes breaking out of collusion more likely. The opposite was true with substitute products. The reason is that with Cournot competition and substitute goods, the choice variables are strategic substitutes. A firm can gain by exporting at the expense of its rival. When goods are complements, the choice variables are strategic complements and the opposite is true. Both firms would benefit from increasing production and exports. But trade costs prevent firms from doing so. Hence, lowering the transport costs would make breaking out of collusion more attractive. Thus, competition will be increased.

But this effect only dominates up to the point where the non-negativity constraints become binding. Trade liberalization is mostly anti-competitive in area $\mathscr{B}$, and purely anti-competitive in $\mathscr{A}$. The change occurs since when the non-negativity constraints are binding, firm 1 would like to produce more than it is able to do. Thus, its profit becomes lower than it would have been in the absence of binding constraints. As a direct consequence, the incentive of the firm to break the collusive agreement drops sharply. Hence, trade liberalization becomes anti-competitive when products are highly complementary and trade costs are sufficiently low.

3.6 Conclusions

In this paper we have analyzed how a reduction in trade costs influences the possibility for firms to engage in international cartels, and hence how trade liberalization affects the degree of competition. By constructing an intra-industry trade model of the Brander and Krugman (1983) type, we have been able to analyze the effects of trade liberalization on the entire range of product differentiation when firms compete in quantities. We are therefore able to synthesize most of the existing literature into our model (Fung (1991, 1992), Lommerud and Sørgaard (2001), and Bond and Syropoulos (2008) among others).

Our main finding is that trade liberalization may have an anti-competitive effect when goods are imperfect substitutes. This result is in contrast to the paper most closely related

even with homogeneous products.

to ours – Lommerud and Sørgaard (2001). They consider a model where goods are homogeneous and find that a lowering of trade costs will always be pro-competitive under Cournot competition. As our model shows, this is indeed a limiting case. When goods are imperfect substitutes, a reduction of trade costs is pro-competitive if trade costs are initially high, but anti-competitive if trade costs are initially low. This shows just how restrictive the assumption of homogeneous goods can be.

Schröder (2007) has shown that the results of Lommerud and Sørgaard (2001) are not robust when considering other forms of trade costs such as ad valorem costs. This is a natural way of extending the results in our paper. It could also be interesting to extend our analysis by adopting other punishment paths, such as the maximum punishment, to see whether our results are robust in that aspect. We assume linear demand functions in constructing our model, it would therefore be interesting to know if this assumption is crucial for our results, or whether our results are more generally applicable. We have not looked at the welfare effects of liberalizing trade. We do know however, from Brander-Krugman type models that welfare is not necessarily maximized with free trade. The same is obviously true when we consider collusive trade with differentiated products as demonstrated by Fung (1992). An analysis of how welfare depends on the trade costs and the critical discount factor is however beyond the scope of this paper and is left for future research (a number a papers study welfare effects of collusion in more general industrial economics models (e.g. Gaudet and Salant (1992), Kamien and Zang (1990)), and Bond and Syropoulos (2008), Colombo and Labrecciosa (2007), and Fung (1992) among others in models with international cartels).

Though the extensions mentioned could possibly alter conclusions, we remain confident that the essence of our results will survive; namely that there is no clear-cut relation between industry structure, trade liberalization and the degree of competition.

References

Abowd, J., F. Kramarz, and D. Margolis (1999): “High Wage Workers and High Wage Firms,” *Econometrica*, 67, pp. 251–333.

Abowd, J., K. McKinney, and I. Schmutte (2010): “How Important is Endogenous Mobility for Measuring Employer and Employee Heterogeneity?,” .

Alan, S. (2006): “Entry Costs and Stock Market Participation Over the Life Cycle,” *Review of Economic Dynamics*, 9, 588–611.

Amiti, M., and D. Davis (2012): “Trade, Firms, and Wages: Theory and Evidence,” *Review of Economic Studies*, 79, pp. 1–36.

Artuç, E., S. Chaudhuri, and J. McLaren (2010): “Trade Shocks and Labor Adjustment: A Structural Empirical Approach,” *American Economic Review*, 100(3), 1008–45.

Artuç, E., and J. McLaren (2012): “Trade Policy and Wage Inequality: A Structural Analysis with Occupational and Sectoral Mobility,” NBER Working Paper 18503.

Autor, D., D. Dorn, and G. Hanson (2013): “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, forthcoming.

Autor, D., D. Dorn, G. Hanson, and J. Song (2012): “Trade Adjustment: Worker Level Evidence,” mimeo.

Autor, D., F. Levy, and R. Murnane (2003): “The Skill Content of Recent Technological Change: An Empirical Exploration,” *Quarterly Journal of Economics*, 118, pp. 1279–1334.

Bernard, A., E. Blanchard, I. Van Beveren, and H. Vandenbussche (2012): "Carry-Along Trade," NBER Working Paper 18246.

Bernard, A., B. Jensen, S. Redding, and P. Schott (2009): "The Margins of US Trade," *American Economic Review: Papers & Proceedings*, 99, pp. 487–493.

Bernard, A., B. Jensen, and P. Schott (2006): "Survival of the Best Fit: Exposure to Low Wage Countries and the (Uneven) Growth of US Manufacturing Plants," *Journal of International Economics*, 68, pp. 219–237.

Bernard, A., S. Redding, and P. Schott (2011): "Multiproduct Firms and Trade Liberalization," *Quarterly Journal of Economics*, 126, pp. 1271–1318.

Bloom, N., M. Draca, and J. Van Reenen (2012): "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," .

Bond, E. W., and C. Syropoulos (2008): "Trade costs and multimarket collusion," *RAND Journal of Economics*, 39(4), 1080–1104.

Botero, J. C., S. Djankov, R. La Porta, F. Lopez-De-Silanes, and A. Shleifer (2004): "The Regulation of Labor," *Quarterly Journal of Economics*, 119, pp. 1339–1382.

Brander, J., and P. Krugman (1983): "A 'Reciprocal Dumping' Model of International Trade," *Journal of International Economics*, 15, 313–321.

Browning, M., M. Ejrnæs, and J. Alvarez (2010): "Modelling Income Processes with Lots of Heterogeneity," *Review of Economic Studies*, 77(4), 1353–1381.

Clarke, R., and D. Collie (2003): "Product differentiation and the gains from trade under Bertrand duopoly," *Canadian Journal of Economics*, 36(3), 658–673.

Colombo, L., and P. Labrecciosa (2007): "Sustaining Collusion Under Economic Integration," *Review of International Economics*, 15(5), 905–915.

Coşar, A. K. (2013): "Adjusting to Trade Liberalization: Reallocation and Labor Market Policies," Mimeo, University of Chicago.

Coşar, A. K., N. Guner, and J. Tybout (2011): "Firm Dynamics, Job Turnover, and Wage Distributions in an Open Economy," NBER Working Paper 16326.

Dadakas, D., and S. D. Katranidis (2010): "The Effects of Trade Liberalization in Textiles and Clothing on the Greek Market for Cotton Yarn: A Multi-Market Analysis," *Review of International Economics*, 18(1), 138–152.

Dahl, C., D. le Maire, and J. Munch (2013): "Wage Dispersion and Decentralization of Wage Bargaining," *Journal of Labor Economics*, 31, pp. 501–533.

Davidson, C., L. Martin, and S. Matusz (1999): "Trade and Search Generated Unemployment," *Journal of International Economics*, 48(2), 271–299.

Davidson, C., S. Matusz, and A. Shevchenko (2008): "Globalization and Firm Level Adjustment with Imperfect Labor Markets," *Journal of International Economics*, 75, pp. 295–309.

Davis, D., and J. Harrigan (2011): "Good Jobs, Bad Jobs, and Trade Liberalization," *Journal of International Economics*, 84, pp. 26–36.

Dix-Carneiro, R. (2013): "Trade Liberalization and Labor Market Dynamics," mimeo, University of Maryland.

Dixit, A. (1979): "A Model of Duopoly Suggesting a Theory of Entry Barriers," *Bell Journal of Economics*, 10(1), 20–32.

Ebenstein, A., A. Harrison, M. McMillan, and S. Phillips (forthcoming): "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys," *Review of Economics and Statistics*.

Egger, H., and U. Kreickemeier (2009): "Firm Heterogeneity and the Labor Market Effects of Trade Liberalization," *International Economic Review*, 50, pp. 187–216.

Feenstra, R., and G. Hanson (1999): "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States," *Quarterly Journal of Economics*, 114, pp. 907–940.

Freeman, R. (1995): "Are Your Wages Set in Beijing?," *Journal of Economic Perspectives*, 9, pp. 15–32.

Friberg, R., and M. Ganslandt (2005): "Reciprocal dumping with Bertrand competition," SSE/EFI Working Paper Series in Economics and Finance no. 592.

Fung, K. C. (1991): "Collusive Intra-Industry Trade," *Canadian Journal of Economics*, 24(2), 391–404.

——— (1992): "Economic Integration as Competitive Discipline," *International Economic Review*, 33(4), 837–847.

Gaudet, G., and S. W. Salant (1992): "Mergers of Producers of Perfect Complements Competing in Price," *Economics Letters*, 39(3), 359–364.

Gourieroux, C., and A. Monfort (1996): *Simulation-Based Econometric Methods*. Oxford University Press.

Greenaway, D., J. Gullstrand, and R. Kneller (2008): "Surviving Globalisation," *Journal of International Economics*, 74, pp. 264–277.

Gustafsson, P., and P. Segerstrom (2010): "Trade Liberalization and Productivity Growth," *Review of International Economics*, 18(2), 207–228.

Hall, G., and J. Rust (2002): "Econometric Methods for Endogenously Sampled Time Series: The Case of Commodity Price Speculation in the Steel Market," NBER Technical Working Paper 278.

Harrison, A., J. McLaren, and M. McMillan (2011): "Recent Perspectives on Trade and Inequality," *Annual Review of Economics*, 3, pp. 261–289.

Heckman, J., and B. Honoré (1990): "The Empirical Content of the Roy Model," *Econometrica*, 58(5), 1121–49.

Heckman, J., and G. Sedlacek (1985): "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market," *Journal of Political Economy*, 93, 1077–1125.

——— (1990): "Self-Selection and the Distribution of Hourly Wages," *Journal of Labor Economics*, 8(1), S329–63.

Helpman, E., and O. Itskhoki (2010): "Labour Market Rigidities, Trade and Unemployment," *Review of Economic Studies*, 77(3), 1100–1137.

Helpman, E., O. Itskhoki, and S. Redding (2010): "Inequality and Unemployment in a Global Economy," *Econometrica*, 78(4), 1239–1283.

——— (2011): “Trade and Labor Market Outcomes,” NBER Working Paper 16662.

Helpman, E., and P. Krugman (1985): *Market Structure and International Trade*. MIT Press.

Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2011): “The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data,” NBER Working Paper 17496.

Iacovone, L., F. Rauch, and L. Winters (2013): “Trade as an Engine of Creative Destruction: Mexican Experience with Chinese Competition,” *Journal of International Economics*, 89, pp. 389–392.

Judd, K. (1998): *Numerical Methods in Economics*. MIT Press.

Kamien, M., and I. Zang (1990): “The Limits of Monopolization through Acquisition,” *Quarterly Journal of Economics*, 105(2), 465–499.

Keane, M., and K. Wolpin (1994): “The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence,” *Review of Economics and Statistics*, 76, 648–672.

Krishna, P., J. Poole, and M. Senses (2011): “Wage Effects of Trade Reform with Endogenous Worker Mobility,” NBER Working Paper 17256.

Krugman, P. (2008): “Trade and Wages, Reconsidered,” *Brookings Papers on Economic Activity*, pp. pp. 103–137.

Lee, D. (2005): “An Estimable Dynamic General Equilibrium Model of Work, Scholing, and Occupational Choice,” *International Economic Review*, 46(1), 1–34.

Lee, D., and K. Wolpin (2006): “Intersectoral Labor Mobility and the Growth of the Service Sector,” *Econometrica*, 74(1), 1–46.

Liu, R. (2010): “Import Competition and Firm Refocusing,” *Canadian Journal of Economics*, 43, pp. 440–466.

Lommerud, K. E., and L. Sørgaard (2001): “Trade Liberalization and Cartel Stability,” *Review of International Economics*, 9, 345–355.

Manning, A. (2011): “Imperfect Competition in the Labor Market,” in *Handbook of Labor Economics*, vol. 4B. Amsterdam: North Holland.

Mion, G., and L. Zhu (2013): “Import Competition from and Offshoring to China: A Curse or Blessing for Firms?,” *Journal of International Economics*, 89, pp. 202–215.

Pinto, B. (1986): “Repeated Games and the ‘Reciprocal Dumping’ Model of Trade,” *Journal of International Economics*, 20, 357–366.

Roy, A. (1951): “Some Thoughts on the Distribution of Earnings,” *Oxford Economic Papers*, pp. 135–146.

Rust, J. (1994): “Structural Estimation of Markov Decision Processes,” in *Handbook of Econometrics*, chap. 51, pp. 3081–3143.

Schröder, P. J. H. (2007): “Cartel Stability and Economic Integration,” *Review of International Economics*, 15(2), 313–320.

Teshima, K. (2010): “Import Competition and Innovation at the Plant Level: Evidence from Mexico,” .