THREE ESSAYS IN INTERNATIONAL ECONOMICS

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A DISSERTATION
PRESENTED TO THE FACULTY
OF PRINCETON UNIVERSITY
IN CANDIDACY FOR THE DEGREE
OF DOCTOR OF PHILOSOPHY

RECOMMENDED FOR ACCEPTANCE
BY THE DEPARTMENT OF
ECONOMICS
Adviser: Stephen Redding

May 2016
Abstract

This dissertation consists of three essays on the impact that import competition and importing opportunities can have on households. Specifically, I aim to quantify the effects that reductions in trade costs and access to new inputs have on income and on the menu of options available to consumers. I achieve these goals by focusing on the differential impact of import competition on workers with different occupations and different skill levels, and by examining the extent to which import opportunities change firms’ output decisions.

Chapter 1 examines the role of occupations in understanding who gains and who loses from changes in import costs. From estimating a structural model of the Danish labor market, I find that a substantial portion of the variation in income changes induced by the decline in import costs from 1996 to 2005 is accounted for by one’s occupation at the time that costs decrease. Moreover, I find that when workers must engage in costly occupational reallocation, the short run variation in changes to workers’ incomes can be substantially larger than in the long run.

While chapter 1 explores how workers’ incomes respond to changes in import costs, chapter 2 focuses on how firms respond to new importing opportunities. This chapter, co-authored with Valerie Smeets and Frederic Warzynski, uses data on Danish apparel firms to estimate how firms change the quality of their goods when trade costs decrease. We find that access to imports from poorer countries tends to lead firms that produce lower quality goods to upgrade their products, and firms that produce higher quality goods to downgrade theirs. Thus, import competition tends to reduce the dispersion in quality of domestically produced goods.

Finally, in the third chapter, I return my focus to workers to explore how the elasticity of substitution between imported intermediates and workers of different skill levels varies across industries. I find significant heterogeneity in this parameter across industries and build a model to demonstrate how this elasticity of substitution can affect how wages between skilled and unskilled workers responds to changes in import costs.
I will be forever indebted to my first adviser, Stephen Redding. He has been unfathomably generous with his time, advice, encouragement and, above all, his patience over the last six years. Steve taught me the difference between knowing and understanding, between a student and a researcher. He continues to inspire me as an economist and a researcher every day. I also thank my second adviser, Jan De Loecker. In terms of the methods I use in my work, no one at Princeton has had a deeper influence on me than Jan. His seemingly boundless optimism also helped me through many of the most difficult parts of this process. Aside from my advisers, several professors have served an outsized role in my progress as a student here. I am particularly thankful to Bo Honore, Alex Mas, Kirill Evdokimov, Esteban Rossi-Hansberg, Gene Grossman, Oleg Itskhoki, Eduardo Morales, and Myrto Kalouptsidi.

For sitting through many talks, I thank the participants of the Graduate Trade, Labor, and IO Lunch Groups. I’d also like to single out my fellow adventurers in international economics: Mark Razhev, Kevin Lim, David Nagy and especially Ricardo Reyes-Heroles. Their friendship is only matched by their insight.

I would like to express my gratitude to my co-authors, Valerie Smeets and Frederic Warzynski, and to the researchers and staff at Aarhus University. Without Valerie and Fred’s guidance and support this dissertation would not have been possible.

I thank Sharon Ernst and Laura Hedden for their wonderful administrative support. I also gratefully acknowledge financial support from Princeton University, the International Economics Section at Princeton University, the Dean’s Fund for Scholarly Travel, and Aarhus University.

Without friends, I think I would have given up many years ago. And for countless memories I thank Pauline Leung, Mark Li, Pedro Olea, Gabriel Tenorio, Christian vom Lehn, and Dan Zeltzer. I would like to especially thank my former roommates, Moshe Katzwer, Inessa Liskovich, and Diane Alexander, for keeping me sane and grounded. Of course, economics is not life, and I thank James Somers, Noemi Garcia, Sam Espahbodi, and Jimmy Li for helping me remember that.

Before I came here I spent time as a research assistant to Julie Mortimer. I thank her and
Chris Conlon for teaching me about research, introducing me to structural estimation, and doing everything they could to get me into graduate school.

I would have nothing if not for the care and sacrifices of my parents, Genia and Gennadi, and if not for the friendship and encouragement of my sister, Tanya. This work is dedicated to her. Finally, and above all else, I thank Katherine Cheng. For reasons unexplained, she has stuck by me for 7 years. And without her loving support, endless encouragement and boundless faith, this dissertation would not have been possible.
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Chapter 1

Occupations and Import Competition: Evidence from Danish Matched Employee-Employer Data

1.1 Introduction

Free trade creates winners and losers, both in the short and long term. These distributional consequences arise from economic activity shifting across industries, firms and occupations. Recent theoretical work (Grossman and Rossi-Hansberg, 2008) and empirical evidence (Autor et al., 2014) suggest that much reallocation is not only across sectors, but also across occupations within sectors—e.g., substitution from routine to knowledge-intensive tasks. Hence, work ignoring the occupational dimension may underestimate the potential costs of trade liberalization. Yet, extant literature has focused solely on the role of either industries or firms. To address this gap, I investigate the distributional consequences and dynamic costs of trade across different occupations.

In order to measure the dynamic and distributional impact of trade shocks, I build and estimate a model of occupational choice: in each period, workers choose their occupation weighing their menu of wages against the costs of switching occupations and the inability to transfer skills across

* I thank my advisers Stephen Redding and Jan De Loecker for their support and guidance in this project. I also thank Rafael Dix Carneiro, Kirill Evdokimov, Gene Grossman, Bo Honore, Oleg Itskhoki, Ilyana Kuziemko, Alex Mas, Eduardo Morales, Ezra Oberfield, John Shea, Valerie Smeets, Frederic Warzynski and participants in Econ Con at the University of Pennsylvania, the Eleventh Danish International Economics Workshop, and various student lunch workshops. I am also thankful to Henning Bunzel and Labor Market Dynamics Group (LMDG) at Aarhus University for tremendous data help. Finally, I have received funding from Princeton University, the Princeton IES Summer Fellowship and Aarhus University.
jobs. In the model, trade shocks reduce the demand for labor in some occupations while increasing it in others, inducing workers to engage in costly readjustment. I have two major findings: first, I demonstrate that occupational mobility frictions are large and as, if not more, important than sectoral mobility frictions; second, I quantify heterogeneity in the effects of globalization across occupations. I also make a methodological contribution by combining several techniques from the industrial organization and labor literatures in order to estimate a dynamic choice model with a large choice set.

I find that the costs of trade shocks can be large and vary substantially with one’s initial occupation. In my model, the median observed utility cost of switching occupations is on the same order of magnitude as five years of income, while the interquartile range is two years of income. Moreover, I find that intrasectoral switching to be much costlier than moving across sectors. For example, amongst switching workers, intrasectoral switching is twice as costly on average as switching sectors but not occupations. Despite the steep cost, intrasectoral movement accounts for a full third of all reallocation. The most expensive transitions are those that require moving across both sectors and occupations; but costs are sub-additive, so the marginal cost of switching sectors conditional on switching occupations is small. These costs also vary with the worker's characteristics. For example, costs grow by an additional percent with each additional year of age, implying larger adjustment costs for older workers.

In addition to the costs of switching occupations, I find that the returns to occupational specific tenure can be large and are equally important to workers’ life cycle profile as general labor market experience. My results echo recent findings in the literature (e.g., Kambourov and Manovskii (2009b)) on the importance of occupation specific capital. The mix of occupational specific human capital and high switching frictions point to a potential bias in models that focus exclusively on intersectoral movement. In particular, these models ignore the potential effects of trade on intrasectoral patterns of production. Moreover, they average together relatively low-cost pure-sectoral transitions (i.e., no occupational movement) with workers moving across both occupations and sectors. This will underestimate the potentially large transition costs to the latter group.
Steep frictions to switching occupations, a result of switching costs and foregone specific human capital, have two effects: (1) adjustment to external shocks can be slow, as workers wait for favorable idiosyncratic shocks to compensate for costs; (2) workers are motivated to move within a narrow band of similar occupations. To explore the importance of these frictions for understanding trade liberalization, I embed my estimated labor supply model in a small open economy. The economy features a highly disaggregated input-output matrix, which yields substantial heterogeneity in the elasticity of substitution between imported inputs and occupations.

I find a sharp distinction in outcomes between the short and long run. In the short run the impacts of trade shocks are more dispersed across occupations. High switching costs, paired with the tight correlation between wages in similar occupations, imply that trade shocks can trap workers into bouts of extended low wages. The effects of these shocks vary substantially across occupations and workers. In terms of percentage changes in income, the interquartile range of effects across occupations is nearly as large as the total gains from trade. While the aggregate effects on labor income are sensitive to assumptions about capital, I still find substantial heterogeneity within workers, but negative effects are tempered as workers adjust over time.

In order to estimate the model, and in particular switching costs, I exploit variation in different career trajectories. The intuition of my approach is simple: workers’ patterns and rates of occupational movement, controlling for income, reveal information about costs and benefits of changing occupations, as well as information about the size of shocks facing workers. The actual procedure is complicated by the presence of worker heterogeneity and continuation values, both of which are unobserved. The latter arise as a consequence of state-dependent switching costs, which add a dynamic consideration to the worker’s problem. These two considerations create two sources of bias that my procedure surmounts. First, workers select into occupations, so that switching is not randomly assigned. Second, the dynamic component of the worker’s problem leads to the existence of unobservable, time-varying, worker-specific, compensating differentials across occupations. That is, income differentials are not a sufficient statistic for the relative value of occupations. To deal with unobservable comparative advantage that may drive selection, I use an empirical likelihood
method to separate workers into a finite set of types. To overcome the presence of unobserved
dynamic components of a worker's problem, I exploit the fact that identical workers moving into
the same occupation face the same continuation values. My method builds on Scott (2014), and
is closely related to the concept of finite dependence proposed by Arcidiacono and Miller (2011).
They demonstrate formally that focusing on workers that start and end in the same state effectively
controls for unobservable initial conditions and continuation values.

My procedure reduces estimation to a series of non-linear regressions, avoiding the need to
solve the model directly. This simplification is important for three reasons. First, the structural
parameters can be estimated without specifying workers’ expectations or solving their dynamic
problem. Hence, results are not sensitive to a particular specification of beliefs. Second, the
computational burden of solving the model with many choices makes repeated solutions infeasible.
For example, even a simple forecasting rule for wages adds over 100 parameters to the model
that must be calibrated for every guess of parameters. For this reason, I cannot use the indirect
inference strategy pursued by Dix-Carneiro (2014) and others. Third, my estimation strategy leads
to transparent identification. In particular, my structural parameters can readily be interpreted as
reduced form semi-elasticities, which are of interest independently of any particular model. In
order to implement this strategy, I need to precisely estimate the occupational switching rates
across highly disaggregated states and choices. Because it covers the entire universe of workers,
the Danish employee-employer matched data that I use can meet the demands of the estimation
strategy.

I face one final obstacle: the dimensionality of the parameter space. This is a problem endemic
to models with a large choice set. For example, the number of pairwise switching costs grows
quadratically in the size of the choice set—so that an unrestricted matrix of costs would lead to
over one thousand parameters in my model. To circumvent this issue, I use the idea of projecting
goods onto an attribute space, suggested first by Lancaster (1966), and used extensively in the
industrial organization literature, for example in Berry et al. (1995). In my context, I treat occu-
pations as a bundle of elementary tasks, each with a different importance weight. For example,
machine workers spend substantial time on routine tasks involving manual dexterity and spatial acuity and less time on tasks involving mathematics or information processing. After projecting onto task space, I estimate switching costs by pricing movement across different levels of tasks. For example, there is a price of moving to a more math-intensive occupation that varies with the math intensiveness of one’s initial occupation as well as other state variables.

My paper also contributes to the growing literature on the importance of occupational reallocation for understanding labor markets more generally. For example, Kambourov and Manovskii (2009a) discuss the importance of occupational transitions for more general macroeconomic phenomena, such as inequality. My paper estimates a large set of parameters that are useful beyond understanding trade shocks. For example, I can estimate the elasticity of occupational flows with respect to wage differentials across occupations, as well as estimates of the value of occupational human tenure and the importance of comparative advantage in explaining observed patterns of movement. As I discuss further in the main text, these parameters are interesting in their own right if one wants to understand how occupations factor into the incidence of labor market shocks.

I estimate my model using a linked employee-employer dataset of the Danish labor market. The Danish data have two distinct qualities that make them ideal for my setting. First, the dataset is large, with about 2.5 million observations per year. This is crucial for estimating transitions across a large number of occupations. Second, the data are of very high quality, providing details on workers’ occupations and information on their firm and industry of employment. In addition to the quality and breadth of the dataset, the Danish setting has two additional advantages. As a small open economy, Denmark allows me to focus on the direct impact of trade shocks without modeling the entire global economy. In particular, I am able to treat changes in trade costs as well as the price of foreign goods as plausibly exogenous. Also, as a developed economy with a highly flexible labor market, the lessons of Denmark can be applied broadly to other developed economies. As an example, Denmark has experimented with its own set of retraining programs for displaced workers—a policy that echoes the push for more vocational training and community colleges in the United States. However, uptake of this program has been weak. My model helps understand
this outcome: retraining costs, even if partially subsidized, may be too high or too difficult for workers, inducing them to either accept lower wages or exit the labor market altogether.

The rest of this paper proceeds as follows. In section 1.2 I briefly describe some characteristics of the Danish labor market and present some stylized facts about trade and occupational mobility. In Section 1.3 I present the dynamic occupational choice model that serves as the labor supply side of my economy. In section 1.4 I outline the estimation strategy used to recover key parameters of this supply side. These two sections do not rely on specifying labor demand as the data generating process on income differentials, the source of variation in the model, need not be explicitly determined. Then in Section 2.3 describes how I map my highly granular data to the variables I need in estimation. After defining the model and the data, I turn in section 2.6 to describing the results of my labor supply model. Here I describe the parameters that will govern workers’ responses to general labor market shocks. Finally in section 1.7 I close my labor demand model in order to perform my counterfactual analysis. The last section concludes.

1.2 Stylized Facts on Occupational Switching and Trade

Before discussing details of the structural model, I provide some reduced form facts about the importance of occupations for the wage structure in Denmark. I also discuss occupational transitions in Denmark and how they are influenced by trade. In the remainder of the paper, unless otherwise stated, I focus on ISCO 2 digit occupations and 4 broad sectors of economy activity. The four broad sectors are Manufacturing, FIRE (Finance, Insurance, Real Estate), Public Services (Health and Education), and remaining Services.

1.2.1 Occupations in Denmark

In this subsection I briefly outline some of the features of occupational movement in Denmark. The Danish labor market relies on a system referred to as “flexicurity” that aims to provide generous welfare benefits to workers and especially unemployed workers. The tradeoff for the populace is
that firms are relatively free to hire and fire workers. Moreover, even though Denmark is characterized by very high rates of unionization, labor market reforms beginning the 1990s have sought to greatly liberalize Danish labor markets. This has given the Danish labor market a reputation as very fluid, albeit still rigid compared to the United States.\footnote{For example, the OECD 2013 Employment Outlook OECD (2013) places Denmark between the UK and the US for difficulty of dismissing workers, suggesting high fluidity. On the other hand, the same article notes that Denmark has large severance pay requirements which may make dismissal harder. On the whole, the OECD ranks Denmark as average in its total protection for workers against dismissal.}

The vibrancy of the Danish labor market can be seen in the rates of occupational switching in Denmark over time. Table 1.2 plots the time series of transitions over time. Even at the 2-digit level, workers move across occupations at a rate of 8-10\% per year (adding movement within and across sectors). The exact breakdown of within and across sectoral switching depends, of course, on the aggregation of sectors. Nevertheless, the plot suggests that occupational movement is occurring at least as frequently as sectoral switching. These numbers are relatively close to the United States.\footnote{Kambourov and Manovskii (2009a), in the working paper version of their work, find a switching rate for the US of about 15\% for similarly disaggregated occupational codes.} Figure 1.3 breaks out switching by age and skill and demonstrates the substantial heterogeneity in switching patterns by demographics.

To conclude this subsection, I demonstrate the importance of occupations to understanding income dynamics in Denmark. In particular, I focus on a variance decomposition of log income. While there is a large literature on decomposition approaches, I use the following relatively simple regression setup:

\[
\log w_{it} = \beta X_{it} + \varphi_{o(i)t} + \varphi_{f(i)t} + \varepsilon
\]

where \(i\) indexes individuals, \(t\) is time, \(X\) is a host of flexibly specified control variables, and \(\varphi\) are fixed effects for occupation and firm. I include firm fixed effects in the above regression. This has two benefits: first, it corrects for the fact that there may be compositional effects if certain occupations are more likely to appear in high wage industries or high wage firms; second, it allows me to contrast the relative importance of occupations and firms. This latter point is important in light of the recent work focusing on the importance of firms to understand wage differentials.
Figures 1.4 and 1.5 plot the time series of the growth in the variance in earnings and the ratio of the across occupational variation to total variance over time. Two things stand out. First, much like in other developed countries, there has been a rise in income inequality in Denmark—albeit, it is more modest than that in the US and some other countries. Second, even at a coarse 2-digit level, occupations are nearly as informative as firm fixed effects in explaining variation in income.

1.2.2 Occupational Reallocation and Trade

In this subsection, before turning to the model, I briefly relate trade and occupational reallocation. Since one cannot easily observe productivity shocks to occupations and sectors, causally identifying the effect of foreign productivity shocks or trade cost changes on occupational demand can be difficult. Thus, I leave deeper arguments about this relationship to my model and counterfactual analysis. Nevertheless, here I present the correlations between occupational demand, occupational transitions and import competition in order to present a picture of the variation in the data.

First I explore the relationship between import competition and occupational demand. To do this, I need a measure of import competition at the occupation level. I construct a measure inspired by Autor et al. (2013). In particular, I construct the change in imports per head in each industry and then allocate these changes to occupations by that industry’s weight in the occupation’s overall industry representation. So, for example, if occupation A is 50% in industry A and 50% in industry B, and industry A experiences no change in imports per head while industry B experiences a 100 unit increase in this measure, then occupation A has a 50 unit increase in their measure of import exposure. Mathematically,

$$exposure_o = \sum_{i \in Inds} \frac{L_{oi} - L_{oi-1}}{L_{ot} - L_{ot-1}} \times \frac{\Delta Imps_i}{L_{it} - L_{it-1}}$$

where I used lagged weights to help mitigate, partially, endogeneity concerns.

Figure 1.6 plots the relationship between changes in imports per head and changes in occupational shares in total employment, focusing on the time span of 1995-2007. Here I use occupations
crossed with sectors in order to more precisely measure the exposure to workers in potentially aggregated occupations.\textsuperscript{3} The slope is negative and statistically significant, suggesting that those occupations most exposed to trade may have experienced a decrease in their demand. A regression with only 38 observations is going to be low-powered, but the results are robust, and actually substantially more well-estimated, if one uses three digit occupations.\textsuperscript{4}

In addition to the relationship between trade and occupational demand, I explore how import competition interacts with occupational transitions. Specifically, I ask if workers facing import competition in period $t$ move to occupations facing less import competition. To that end, I run regressions of the following form:

$$\log(\pi_{oo't}) = \log(\pi_{oo'}) + \beta \times (\text{exposure}_{ot} - \text{exposure}_{o't}) + u_{oo't}$$

where $\pi$ is the transition probability of moving from $o$ to $o'$. Because transitions occur at an annual frequency, I use year on year changes in imports per head to construct the exposure measure. I also include fixed effects to deal with different levels of switching rates. Thus, the above regression asks: within a transition pair, $(o, o')$, do differences from mean differences in growth rates of imports per head lead to more transitions.

Figure 1.7 plots this relationship. The slope is negative and statistically significant. That $\beta$ is negative suggests in fact that workers are pushed out of occupations with large import exposure and pulled into those with less. The relationship in the data is messy because of how much is missed in aggregating across different workers. The model attempts to more precisely and formally measure these forces, controlling for heterogeneity in workers as well as for other economic factors. Having demonstrated both that occupations play an important role in understanding worker and income dynamics in Denmark, as well as the connection between import competition and occupational

\textsuperscript{3}For example, workers who are coded at the two digit level as drivers are almost entirely truck drivers or fork lift operators when in manufacturing, or taxi drivers in services. One can see this by looking at more refined codes. In section 2.3 I discuss in more detail exactly how my occupation codes and sector codes are defined, and how they interact.

\textsuperscript{4}At this more disaggregated level, one can also observe substantial heterogeneity in the effects of import competition on occupations. In particular, occupations inside of 1 digit occupations that map to “routine” occupations experience severe declines in demand while those in other kinds of occupations see a muted response.
reallocation, I turn to my structural model and counterfactual analysis in order to more precisely explain the relationship between occupations and trade.

1.3 Econometric Model and Framework

In this section I describe the labor supply model that I take to the data. The basic setup is a discrete choice model: in each period, a worker chooses an occupation, \( o \in O \), comparing the benefits of her current occupation against the costs of switching to an occupation with a higher present value. While conceptually simple, enriching the model to make it realistic has the consequence of introducing many parameters and state variables. To that end, I break the presentation down into several pieces: first, I present the general environment; second, I introduce timing and information in some detail; then, I describe the state space in more detail; next I describe the parametrization of occupational switching costs; finally, I discuss non-employment.

Environment

Before describing the model in detail, I briefly introduce notation and the general environment. Time is indexed by \( t \) and a period is equal to one year. Workers are indexed by \( i \), and each worker has a state, \((o, \omega)\), that reflects her most recent occupation and a vector of observable and unobservable traits that govern her productivity across occupations. The model features a life cycle component, and I assume that all workers enter at 23 and retire at 60. I index occupations by \( o \in O \), a discrete and finite set. In the succeeding discussion I refer to the workers’ decision as being over occupations, however in general they can be sector-occupation pairs.

I assume that worker income is determined by two components: a competitively determined skill price, and an occupation-specific human capital function. Human capital is supplied inelastically and workers consume their income within the period. At the beginning of a period, each workers chooses an occupation, including the possibility of staying in their current occupation. In order to switch occupations, workers must pay a switching cost which enters into the utility function.
A worker enters her new occupation in the same period that she pays switching costs; thus, upon paying the switching cost workers can consume the income in their new occupation before making the decision again next period. In the remainder of this section I describe the components of the model in detail, including a description of the shocks that workers face.

**Information and the Worker’s Problem**

There are two sources of randomness in each period, revealed at different times. Upon entering the period, the worker receives a switching cost shock that differs across occupations; after making her decision she receive an additional income shock. The first set of shocks capture any transitory forces that lowers or increases the burden of switching, such as a promotion or a layoff. The latter shocks reflect idiosyncratic negative health shocks or serendipitous *ex-post* productivity shocks.

Treating workers as risk neutral and letting switching costs, including shocks, be additive leads to the following recursive formulation for the worker’s problem:

\[
v_t(o_{it-1}, \omega_{it}, \epsilon_{it}) = \max_{o' \in O} C(o_{it-1}, o', \omega) + \rho \epsilon_{o'it}
+ \eta_{o'} + w_{o't} E_t h_{o'}(\omega_{it}, \varsigma_{iot}) + \beta E_t V_{t+1}(o', T(\omega_{it}, o'))
\]

where \(C\) are switching costs, \(\eta\) are the non-pecuniary benefits of occupations, common to all workers, \(w_{o't}\) is a skill price, \(h_{o'}\) is a human capital function specific to each occupation, \(V_{t+1}\) is a continuation value and \(T(\omega, o')\) is the transition map on states, which I describe in detail below. Finally, \(\epsilon_{o'it}\) are the moving cost shocks while \(\varsigma_{iot}\) are *ex-post* productivity shocks. The problem is written from the perspective of the worker at the beginning of the period—so that expectations over human capital and future prices need to be formed, but skill prices and moving cost shocks are observed. As a final point on notation, I use an uppercase \(V\) to represent \(v\) integrated over moving cost shocks.\(^5\)

Despite the heavy notation, the problem is straightforward. The first two terms represent the cost

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\(^5\)Keane et al. (2011) refer to this as the EMAX function and offer a complete, rigorous introduction to the DCDP framework.
of switching occupations, if these are large and negative then the worker will demand substantial compensation in order to switch her occupation. The second two terms reflect the total benefits of each occupation, including those that are unobserved and captured in \( \eta \). Finally, pairwise varying switching costs as well as occupational specific human capital lend a dynamic element to the worker’s problem. The dynamic component is captured in the continuation value \( V \).

I assume that all components of the worker’s state are fully known by the worker, even if not to the econometrician. This contrasts with other models, such as Farber and Gibbons (1996), that allow for worker learning. As discussed in Altonji et al. (2013), it is essentially impossible to write down a structural model of the labor market that describes all the features of the data at once. In focusing on worker over 23, I try to alleviate some bias resulting in workers’ education and leaning. Nevertheless, in aiming to estimate the parameters of a particular model, I shut down well-documented aspects of workers’ career paths. Instead, I focus on those features of the labor market that I think matter most when considering the impacts of trade shocks.

**State Variables and Human Capital**

The worker’s state \( \omega \) can be partitioned into an *observable* (to the econometrician) component and an *unobservable* (to the econometrician) component. The observable state consists of a worker’s age, her current occupational tenure, and her skill level. Each worker enters the labor market at 23 so that I can abstract from any education choices. I partition workers into three education groups. Occupational tenure accumulates with continued work but is non-transferable across occupations. I discuss the evolution of human capital further at the end of this subsection.

The worker’s *unobservable* state is a vector of time-invariant talent shocks denoted by \( \theta \). These shocks allow for otherwise-identical workers to be better at different occupations. For example, some workers may be more well suited to office jobs such as management or law while others are more well suited to hands on work in research laboratories or manufacturing. This parameter governs both comparative advantage and absolute advantage. To see this, compare the value of \( \theta \) across occupations for two different workers. If \( \theta_{io}/\theta_{i'o'} > \theta_{jo}/\theta_{j'o'} \) then clearly worker \( i \) has
comparative advantage in occupation \( o \); but if \( \theta_{io} > \theta_{jo} \) for all or many \( o \) then worker \( i \) also has an absolute advantage over \( j \).

The human capital function is assumed to be log-linear, as in a Mincer regression. The exact expression is given by

\[
h_o(\omega_{it}, \vartheta_{it}) = \exp \left\{ \beta_o^1 \times age_{it} + \beta_o^2 \times age_{it}^2 + \beta_o^3 \times ten_{it}
+ \beta_o^4 \times 1\{skill_i = med\} + \beta_o^5 \times 1\{skill_i = high\} + \theta_{oi} + \sigma_{o\varsigma_{iot}} \right\}
\]

where \( \varsigma_{it} \) is the worker’s ex-post productivity shock. The first 5 parameters in this equation are standard covariates: a quadratic function in age, human capital returns and differential returns to skill. Notice that I allow all of these to differ by occupation. This captures that labor market experience, proxied by age, as well as occupation-specific experience, matter more in some occupations than in others. As discussed above, \( \theta \) captures unobservable absolute and comparative advantage. I treat \( \theta \) as constant over the lifecycle.\(^6\)

For workers that switch occupations, I assume that conditional on paying the full cost of changing occupations, there is no additional transferability of occupation-specific human capital. Thus, there can be no persistent effects of one’s human capital on future wages, conditional on switching. To capture the idea of skill transferability, I allow for switching occupations to vary pairwise across occupations. Moreover, one can allow for this cost to depend on one’s current talents and other state variables. As an example, the model posits that a confectioner and an economist may face different costs of learning to bake, but conditional on paying switching costs and other observables, they are equally skilled bakers at the outset. This assumption, it should be noted, does not rule out human capital accumulation, as I still allow for returns to age.

In principle, one could track a worker’s history for some finite length (pursued, for example, Dix-Carneiro (2014)). I do not do this for two reasons. First, with such a large state space it places extreme demands on the data, as few workers have exactly identical long term career trajectories.

\(^6\)In principle, one could allow for a Markov chain on the unobservable state. While possible in theory, it is difficult to identify this underlying process given my panel length.
Second, my focus is on precisely estimating a rich set of occupational switching costs. It is difficult to credibly, separately identify a very large set of parameters governing experience, selection and switching costs, especially in a short panel. Previous work has economized on parameters by sacrificing flexibility in moving costs and focusing on small choice sets, I have opted to build a rich cost side that allows heterogeneity in source occupation, target occupation as well as one's state.

**Switching Costs**

To understand switching costs in this model, first consider the full cost borne by a worker moving from \textit{o} to \textit{o}':

\[
\text{Costs}(o, o', \omega) = C(o, o', \omega) + \rho \epsilon_{oo'}
\]

This cost has two components. The first is the baseline moving cost, while the second is the moving cost shock facing workers. Artuc et al. (2010) point out that if switching were random, then \(C\) would reflect the mean cost of switching across workers while \(\rho\) would capture the variance. Of course, switching is not random. In fact, because workers always have the option of waiting for favorable cost draws, the actual cost of switching conditional on switching will be lower than \(C\). This is a crucial distinction that will return in the results section. In the remainder of this section I expand on \(C\) and then describe the role that \(\rho\) plays in governing worker movement. This second parameter is important as it ultimately governs the elasticity of worker flows with respect to wage differentials.

Turning to the first component, I specify the following multiplicatively separable form which I refer to as the moving cost function:

\[
C(o, o', \omega) = f(\omega)C(o, o')
\]

The first function, \(f(\omega)\), is an occupation-invariant, inverse moving productivity. This captures how quickly workers can pick up new skills and the lifetime monetary costs of moving. In the esti-
mated model I allow \( f \) to vary by age, skill, and type. There is also an unobservable component to switching costs which, notationally, I include as part of the vector \( \theta \). This unobservable component allows for some workers to be more adept at career changes than others. For example, there may be “quick-learners” in the population, who find changing occupations easier all else held equal. In terms of the actual functional form I use a log-linear specification:

\[
f(\omega_{it}) = \exp \left\{ \alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2 \\
+ \alpha_3 \times 1\{skill_i = med\} + \alpha_4 \times 1\{skill_i = high\} + \theta_{fi} \right\}
\]

where \( \theta_{fi} \in \theta \). The productivity term varies across workers on unobservables as well as their general human capital and education level. It does not include occupational specific human capital. I do this for two reasons: (1) to be interpretable it would require an occupation-pair specific component, which is exactly the situation we wish to avoid; (2) variation in returns to occupational tenure generate variation in wage differentials that aid identification of key parameters. The second point reflects the notion that conditional on knowing the returns to occupation specific human capital, the hazard rate of occupational switching with respect to tenure is actually informative about the elasticity of switching with respect to wages.

The second function, \( C(o, o') \) is a worker-invariant cost function across occupations. In order to specify the cost function, I first project occupations onto task space. To that end, suppose that each occupation is associated with a vector, \( \nu^o \in \Upsilon \subset \mathbb{R}_+^{\lvert \Upsilon \rvert} \). Tasks should be thought of as “a unit of work activity that produces output” (Acemoglu and Autor, 2011). Examples could be writing reports, communicating with colleagues or operating a CNC lathe. The value of \( \nu \) is an importance weight of a task to a particular occupation. For example, economists spend little time operating CNC lathes but substantial time communicating with colleagues. This projection allows costs to incorporate a learning or dis-learning component. Continuing with the example from the last section, an economist becoming a baker must learn to operate an oven or how to follow recipes; a confectioner, on the other hand, may need to learn very little. I will describe in the Data section
how I observe occupational characteristics and their loadings.

Estimating switching costs are at the heart of my paper and I use the following specification:

\[ C(o, o') = \exp \left( \Gamma^M + \Gamma^S \delta_{in-sector} + \Gamma^O \delta_{out-sector} + \sum_{i=1}^{\left| \Gamma \right|} \left( \psi_i^{o'} - \psi_i^o \right) \left( \Gamma_i^+ \delta_+ + \Gamma_i^- \delta_- \right) \right) \]

The first three terms are an intercept and coefficients on dummies for switching sectors only and switching occupations only. These terms accomplish two goals: first, they reflect general search costs and labor market frictions associated with switching sectors and occupations in general. For example, in Denmark they may require the cost of changing licenses or other search frictions. Second, they allow for a clear comparison with existing methods that focus only on pricing inter. The remaining \( \Gamma \) terms are the coefficients on linear distance in each component of the characteristics vector. The \( \delta_{\pm} \) terms are indicators for whether the change in task space is positive or negative—so that the coefficients may depend on whether a worker is up-tasking or down-tasking.\(^7\) That \( \Gamma \) is different for each \( i \) reflects that some tasks are easier to learn than others.

Moving on to the second component of the full costs, \( \rho \) is the variance of the mean zero cost-shock. It serves two purposes: (1) it governs the probability of receiving sufficiently favorable cost draws; (2) conditional on switching, it determines the relative importance of moving costs and wage differentials. Both points can be understood by considering the extreme cases of 0 and infinite values of \( \rho \). In the case that \( \rho = 0 \), switching is entirely deterministic, implying a sparse transition matrix across occupations consisting entirely of 1s and 0s. In the case where \( \rho \to \infty \), costs play no role, and one’s future occupation is a draw from a uniform distribution. This would lead to a very dense transition matrix with every entry simply being equal to \( 1/|O| \).

As a result of its role as the variance of shocks, \( \rho \) governs the semi-elasticity of worker movement with respect to wage differentials. A number of recent papers have examined the importance of worker adjustment in understanding labor market outcomes, and in many of these papers this elasticity plays an important role. For example, both Caliendo et al. (2015) and Bryan and Morten (2015) look at reallocation across space. Despite presenting different models, both papers ulti-

\(^7\)I also experimented with quadratic terms, but found they added little explanatory power in the final estimation.
mately arrive at estimating equations that require estimation of this parameter. This elasticity is also useful to anyone wishing to understand the extensive margin response to labor market shocks.

To understand this, consider the case where cost shocks are distributed logistically. Then one can show that the elasticity of switching with respect to transient aggregate shocks to skill prices is given by,

$$\frac{\partial \log \pi_{\text{switch}}}{\log \partial w_o} = -\frac{w_o h_o}{\rho} \pi_{\text{stay}}$$

Hence, a larger $\rho$ implies that workers are less responsive to changes in wages. As already pointed out, in the extreme that $\rho \to \infty$, wages are completely uninformative about the transition matrix.

**Non-Employment**

To model non-employment I construct a virtual payout as a simple quadratic function of age, skill and type:

$$w^N(\omega, o) = \beta_{\text{skill}} + \beta_\theta + \beta_a \times a + \beta_{a^2} \times a^2$$

The model is silent on the reason for entering non-employment. A shock that pushes an agent into non-employment could reflect a choice on the part of the worker, but also could reflect an unanticipated separation shock, maternity leave or any other reason for removing oneself from employment. Similarly, this value of non-employment reflects a variety of different forces affecting workers. Aside from capturing the Danish social safety net, non-employment can pick up tastes for leisure, having a family or the value of home production relative to wages.

To re-enter the workforce, workers pay the moving cost associated with their most recent occupation and an additional cost $f_U$. The state transitions in non-employment are the same as in employment with the following exception: I assume that workers keep their accumulated occupational tenure for one period of non-employment and then lose it. This is an ad hoc assumption chosen to fit the data, as most unemployment spells are either a single period or forever (i.e., labor force exit).
Shocks

Finally, to finish the labor supply model I describe the distribution of worker shocks. I mostly follow the extant literature and specify the following distributions:

\[ \epsilon \sim \text{Logistic}(0, \rho) \]
\[ \vartheta \sim \mathcal{N}(0, 1) \]
\[ \theta \sim (q_1, q_2, \ldots, q_K) \]

The Logistic assumption on shocks is standard as it yields a closed form for the value function conditional on \( \theta \). This distribution has a location parameter and scale parameter, normalized to (0,1), implying a symmetric distribution about 0 with variance \( \rho \). The logistic distribution, well known from standard binary outcome models, has a fatter tail than the Gaussian distribution. I model income as log Gaussian. Not only is this a standard assumption, but, as I’ll discuss below, is particularly attractive for estimation. Finally, I model the worker’s unobserved type as coming from a discrete distribution with \( K \) types. In the actual estimation I estimate a separate distribution of types for each skill level — thus there are \( S \times K \) possible groups of workers, where \( S \) is the number of skill types. The value of \( \theta \) is free to vary across occupations. Thus, the estimation of types adds \( (O + 1) \times (K - 1) \) parameters to the estimation.

1.4 Estimation

This section outlines my estimation procedure. I exploit the model’s structure to transform estimation into a series of non-linear regressions. The full estimation procedure occurs in two stages: in a first stage, I estimate the distribution of time-invariant unobservables as well as the wage parameters; then in a second stage, I use a series of non-linear least squares regressions to extract the structural parameters. This is similar to the method of Scott (2014) building on Arcidiacono and Miller (2011) (henceforth, AM). The latter paper is particularly important as it outlines pre-
cisely how one can exploit renewal actions (described below), in conjunction with conditional 
choice probability techniques first explored in Hotz and Miller (1993), to tractably and transpar-
ently estimate models like mine. I demonstrate how their method can be used in the occupational 
choice setting and bring in projection onto characteristic space to reduce the dimensionality of the 
estimation problem. For clarity’s sake, I present the estimation stages in reverse order of their 
implementation: first, I outline the second stage procedure as if the worker’s state were fully ob-
servable; second, I explain how I use the empirical distribution function of occupational switching 
and the Gaussian structure on income to estimate the income parameters as well as the distribution 
of unobserved heterogeneity.

Traditionally, papers in this literature first solve the model and then use either maximum like-
lihood or simulated method of moments to estimate parameters. Two major roadblocks prevent 
me from employing these methods. First, the large state and parameter space means that solving 
and simulating the model for every guess of parameters is prohibitively expensive—including un-
observed heterogeneity in the Mincer regressions, my model has over 900 parameters. My two 
stage approach separates the parameters of the income equations, nearly 850 parameters, from the 
remaining structural parameters, of which there less than 80. Second, workers in this model have 
to solve a very complicated forecasting problem. By exploiting the idea of renewal actions, the 
workers’ forecast error will ultimately appear as the residual in a system of non-linear regressions. 
Once part of the regression error, the worker’s expectations no longer play a role in estimation.

1.4.1 Occupational Flows and Selection

To motivate the procedure that follows, I first briefly discuss the reduced form moments that would 
identify my parameters in an idealized setup. To that end, consider a world of homogeneous agents 
with no switching costs and no occupational human capital. In this case, the probability of a worker 
switching occupations would be given by

\[ P(o \rightarrow o') = P\left(\frac{w_o' - w_o}{\rho} + \epsilon_{oo'} \geq \max_{o''} \frac{w_{o''} - w_o}{\rho} + \epsilon_{oo''}\right) \]
Such a model could be estimated for any well-behaved particular distribution on $\epsilon$. The logistic is particularly attractive for such problems as it leads to the following simple estimating equation:

$$\log \left( \frac{\pi_{o'0,t}}{\pi_{00,t}} \right) = \frac{1}{\rho} (w_{o't} - w_{ot}) + u_{o'0,t}$$

where $\pi$ are transition rates and $u$ is measurement error from the estimated left hand side. If a researcher were interested in measuring the extent of reallocation in response to a shock they would either run the regression above directly, or instrument wage differentials with a direct measure of the shock. However, now suppose that there are fixed costs to switching occupations. In this case, the above equation would become,

$$\log \left( \frac{\pi_{o'0,t}}{\pi_{00,t}} \right) = -C_{o'0} + \frac{1}{\rho} (w_{o't} - w_{ot}) + \beta (V_{o',t+1} - V_{o,t+1}) + u_{o'0,t}$$

where $C$ is the cost and $V$ are continuation values that arise whenever $C_{\text{switch}} > C_{\text{stay}}$. Even in this simple setting one cannot regress flows on wage differentials because of the unobserved continuation values. Finding instruments that are correlated with current wage differentials but do not impact future differences would pose serious challenges. To circumvent this issue, Hotz and Miller (1993) and Arcidiacono and Miller (2011) exploit further properties of the logistic distribution in order to remove unobservable continuation values. The next subsection describes how I apply their techniques to my setting.

### 1.4.2 Estimating Structural Parameters with Renewal Actions

Given the problems above, the key to identification is renewal actions: decisions that return workers to the same state. By focusing on workers who begin and end in the same state with a mediating period of divergent trajectories, I can exploit differences in the probability of these trajectories to pin down parameters. Before moving on, I introduce some terminology to help keep the presentation organized. I collect moving costs and incomes into a flow payoff denoted by $u_t(o, o', \omega)$. Next
I define the **inclusive value** as:

$$D_t(\omega, o) = \sum_{o' \in \mathcal{O}} \exp \left[ u_t(o, o', \omega) + \beta E_{t+1} T(\omega, o, o', o') \right]$$

This term plays the role of the denominator in the worker’s transition probability and, as shown in Rust (1987), plays a prominent role in the analytic solution to the worker’s dynamic problem.

Moving on to the procedure, Hotz and Miller (1993) show that the probability of observing a career path from time $t$ to $\tau$ can be written as the discounted sum of stage payoffs, the discounted sum of worker’s expectation errors, the inclusive value and an unobserved future continuation value.

The particular equation is given by,

$$\tau \sum_{s=t}^\tau \beta^{(s-t)} \log \pi_s(\omega_s, o_{s-1}, o_s) = \tau \sum_{s=t}^\tau \beta^{(s-t)} u_s(\omega_s, o_s, o_{s-1}) + \tau \sum_{s=t}^\tau \beta^{(s-t)} \zeta_s + E_{\tau} V_{\tau+1} (\omega_{\tau+1}, o_{\tau}) - \log D_t(\omega_s, o_{s-1})$$

where $\zeta_s$ is the worker’s forecast error on future continuation values. Despite the large number of components, this equation has a natural economic interpretation. The first term, a discounted sum of stage payoffs, implies that workers are more likely to move from occupation $o$ to $o'$ if the actual payoff from doing so is high. The second term, a discounted sum of forecast errors, is a measure of worker optimism. If workers are optimistic then an econometrician will observe workers moving into an occupation at a high rate. Crucially, I assume that workers are rational so that the expectational errors are mean zero. The first unobservable term is the worker’s continuation value at time $\tau$. The last term is the inclusive value in the initial period—which reflects lost option value in committing to a particular career path.

To operationalize this insight for estimation, take the difference in the discounted probability of

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8In the technical appendix I review these steps in more depth, especially as they pertain to my particular problem.
observing two different career trajectories for workers, \( i \) and \( j \):

\[
\sum_{s=t}^\tau \beta^{(s-t)} \log \frac{\pi_s(\omega_{is}, o_{i,s-1}, o_{i,s})}{\pi_s(\omega_{js}, o_{j,s-1}, o_{js})} = \sum_{s=t}^\tau \beta^{(s-t)} \left[ u_s(\omega_{is}, o_{is}, o_{i,s-1}) - u_s(\omega_{js}, o_{js}, o_{j,s-1}) \right] \\
+ \sum_{s=t}^\tau \beta^{(s-t)} \left[ \zeta_{is} - \zeta_{js} \right] \\
+ \left[ E_{\tau} V_{\tau+1}(\omega_{i,\tau+1}, o_{i,\tau}) - E_{\tau} V_{\tau+1}(\omega_{j,\tau+1}, o_{j,\tau}) \right] \\
- \left[ \log D_t(\omega_{is}, o_{i,s-1}) - \log D_t(\omega_{js}, o_{j,s-1}) \right]
\]

Notice that if workers have the same initial inclusive values and the same terminal continuation values, then the unobservable terms disappear. This is the central insight of AM and Scott (2014) that I bring into my paper. The left hand side of the above equation can be non-parametrically estimated and the right hand side is a non-linear function of observables with an additive error term. In the next subsection I outline my identification strategy. First, I identify which career paths lead to an estimable regression equation, then I discuss the actual variation in the data that identifies the structural parameters.

### 1.4.3 Identification

To make use of the AM insight, I exploit the fact that after paying switching costs, workers moving into the same occupation face identical continuation values, conditional on their demographics and productivity. Two assumptions about worker behavior underly this fact:

1. The worker’s occupational choice is orthogonal to the \textit{ex-post} income shock

2. Occupational switching is a \textit{renewal} action—the new state only inherits the deterministic part of the prior state

The first assumption simply reiterates that the income shock is only realized after the worker makes a decision. This is a weaker assumption than exogenous mobility, as I allow for rich selection on a host of observable variables and explicitly model unobservable selection. As an example, I allow
for workers to have comparative advantage in certain occupations and to select their occupation based on this fact. The second assumption reasserts that when workers switch occupations, their occupation specific capital does not transfer. As discussed in the modeling section, this does not imply that workers cannot exploit their talents when transferring occupations. These two assumptions imply that occupational switching is, in the language of AM, a renewal action. These are actions that allow for initially identical workers who have diverged to return to an identical state.

In order to generate a regression equation, I focus on career trajectories that I call one shot deviations. Figure 1.1 contains an example of such movement:

![Figure 1.1: Example of One Shot Deviation](image)

Here, two workers in occupation $o$ with the same level of human capital diverge at $t + 1$—one continues working in $o$ while another goes to $o'$. At $t + 2$ they both move to yet another occupation $o''$. This resets their human capital levels so that the workers are, once again, identical. Because the terminal continuation values are the same, the only reason that the econometrician can observe the two paths above is if identical workers received different idiosyncratic, independent shocks. Thus, I can exploit deviations between observed probabilities of these paths and those implied by logit-shocks to estimate the structural parameters. Mathematically, I use the following final estimating equation:

$$\log \frac{\pi_t(\omega, o, o')}{\pi_t(\omega, o, o)} + \beta \log \frac{\pi_{t+1}(\omega', o', o'')}{\pi_{t+1}(\omega'', o', o'')} = C(\omega, \omega', \omega'', o, o', o'') + \frac{1}{\rho} (w_{o'\sigma} h_{\sigma}(\omega) - w_{o\sigma} h_{\sigma}(\omega)) + \frac{1}{\rho} (\eta_{o'} - \eta_o) + \tilde{\zeta}_{o\sigma} + m_{t\omega'\sigma''}$$

(1.1)

where the $\zeta$ terms collect expectation errors, $m$ is measurement error as a result of an estimated left
hand side and $\tilde{C}$ is a function of occupational characteristics and state variables. While functional form assumptions yield the particular estimating equation, it is nevertheless intuitive. In particular, variation in a worker’s occupational choices given wages determines switching costs, while worker responsiveness to wage differentials, controlling for occupational characteristics, identifies responsiveness to wages. The special case of non-employment identifies the non-pecuniary value of occupations, since here costs are normalized to be zero.\(^9\)

1.4.4 Estimating Mincer Regressions and Unobserved Heterogeneity

In order to model unobserved heterogeneity I suppose that workers’ comparative advantage is a vector $\theta$ drawn from a finite distribution $Q_{\Theta}$. This approach is common in the structural literature and was first suggested by Heckman and Singer (1984). In the particular case of dynamic discrete choice, Crawford and Shum (2005), Dix-Carneiro (2014) and others make this assumption.\(^{10}\) The particular estimation strategy I use is the Expectation-Maximization and CCP hybrid approach described in Arcidiacono and Miller (2011). As I use their approach essentially without modification, I omit many details here and relegate the direct mapping between my model and theirs to the technical appendix. Nevertheless, I present a broad overview of the algorithm I employ.

The method begins with the likelihood function over the data including unobserved types:

$$L = \prod_{i=1}^{N} \left( \sum_{k=1}^{K} q_k \prod_{t=1}^{T} f \left( w_{it} | \omega_{it}, o_{it}, k; \Xi \right) \pi \left( \omega_{it}, o_{it} | H_{it-1}, k; \Xi \right) \right)$$

where $q_k$ is the probability of being type $k$, $f$ is the Gaussian pdf on wages and $\pi$ is the probability of being in state $\omega_{it}, o_{it}$ conditional on the initial state summarized by $H_{it-1}$. If one could easily solve the model, then he or she could maximize this likelihood function to solve for unobserved

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\(^9\)This normalization is without loss of generality since one cannot identify a constant term in a discrete choice model. However, an implicit assumption carried into the counterfactual analysis is that the value of non-employment relative to employment is invariant to different equilibria.

\(^{10}\)Heckman and Singer actually prove that under certain conditions, a finite distribution is the solution to a non-parametric likelihood problem for an arbitrary distribution. However, since many estimation procedures for large structural models, including mine, are not strictly maximum likelihood this proof may not hold. Instead, it is an attractive assumption from the view of computational feasibility and numerical stability.
states. To see how, notice that the model provides a formula for both $f$ and $\pi$, thus allowing one to calculate the likelihood of the data. The unobserved heterogeneity presents an issue by breaking the log separability of the likelihood function. However, this could be overcome with the EM algorithm.\(^{11}\) Thus, if one could solve the model explicitly, he or she could use standard likelihood techniques to back out all structural parameters including the distribution of unobserved heterogeneity.

Arcidiacono and Miller’s insight is that if the model can be factored into separate pieces where one component contains some subset of model parameters and the other component contains transition rates, then one can use the empirical distribution of transitions instead of the model probabilities. In my context, income shocks are Gaussian and independent of moving cost shocks. Thus, conditional on the observed choice of workers and their unobserved state, the likelihood for income is just the Gaussian pdf. On the other hand, the transition rates are very complicated objects. So, consider a modified likelihood given by:

$$\tilde{L} = \prod_{i=1}^{N} \left( \sum_{k=1}^{K} q_k \prod_{t=1}^{T} f \left( w_{it} | \omega_{it}, o_{it}, k; \Xi \right) \hat{\pi} \left( \omega_{it}, o_{it} | \mathcal{H}_{it-1}, k; \Xi \right) \right)$$

where the only difference between the true likelihood is the hat on the transition rates, implying that I estimate transition rates from the data directly, rather than using the model-implied transition rates. The actual algorithm now proceeds as in the standard EM algorithm. An important piece of the algorithm is that if one specifies $\hat{\pi}$ as a linear probability model and assumes Gaussian income shocks then the entire procedure reduces to iterating on a set of OLS regressions, allowing for a very large number of parameters to be handled tractably.

Identification for this method relies on three ideas. First, workers’ inability to select on idiosyncratic wage shocks implies that the wage equation coefficients are identified essentially off of a regression of person-occupation fixed effects. Second, unexplained persistence in the wages of a worker in a particular occupation identifies the talent shock of a worker in that occupation. Third,

\(^{11}\)As a brief reminder, the EM algorithm works by alternating on a guess of types (yielding an expectation) and maximizing the likelihood conditional on this guess. One updates the guess of type probabilities with each parameter update. This procedure monotonically increases the likelihood, and will converge to the maximum.
the finite types assumption allows me to use different workers who span the full set of occupations to identify the full vector of talent shocks. This last point is crucial. The underlying assumption is that if two workers, \( i \) and \( j \) are both in occupation \( o \), and have a similar wage profile that cannot be explained by observables then they must be of the same type. Thus, if worker \( j \) moves to occupation \( o' \), their wage in that occupation is the wage that \( i \) would receive if \( i \) also switched (up to an idiosyncratic shock).

1.4.5 Comparison with Current Methods

As mentioned previously, the strength of my approach is the ability to estimate a rich model without having to explicitly model the workers’ expectations. In particular, I demonstrate how even with a large state space, I can still estimate all model parameters with a series of regressions. Interestingly, my regression equations bear resemblance to the estimating equation of Artuc et al. (2010) (ACM). This is because both rely on observed probabilities of movement to cancel out unobservable continuation values. However, our procedures differ in one key dimension. Letting \( i, j, k \) generically refer to choices, ACM regresses current flows from \( i \rightarrow j \) on future flows from \( i \rightarrow j \). I explicitly avoid this case and focus on transitions \( i \rightarrow j \rightarrow k \) where \( k \neq j \). Arcidiacono and Miller, to the best of my knowledge, were the first to highlight that one can iterate the worker’s Bellman equation forward on an arbitrary sequences of choices in order to generate estimating equations like mine. This subtle difference allows me to extend the initial insights of ACM in two key ways.

First, in recognizing the explicit role of finite dependence in the model, I am able to capture the effects of human capital and other state variables, which is a first order concern when considering the worker’s dynamic problem. Their model only feature a static state space—losing the importance of the life cycle, tenure and comparative advantage. If, like ACM, I had focused on the same transitions in the past and present I would lose this orthogonality as well as the ability to handle human capital. To see this very clearly, consider a Head and Ries (2001) inspired approach towards
estimating moving costs and ignore all state variables but tenure:

\[
\log \left( \frac{\pi(o, o', ten)}{\pi(o, o, ten)} \right) = \frac{- (C(o, o') + C(o', o)) + (w_0 h(0) - w_0 h(ten) + w_0 h(0) - w_0 h(ten))}{\rho} + \beta E \frac{(V(o', 1) - V(o, ten + 1) + V(o, 1) - V(o', ten))}{\rho}
\]

In a setup without human capital accumulation, so that the tenure variable vanished, all terms that were not explicitly moving costs would also vanish. Then one could estimate switching costs (scaled by shock variance) by regression as long as one had a sufficiently large number of choices. The above formula also makes explicitly clear why any state variable with a path affected by workers’ choices becomes problematic in the ACM setup.

The second benefit is that by projecting moving costs onto observable characteristics, I can estimate a flexible moving cost function that remains parsimonious. Work in this literature has continued to struggle with the curse of dimensionality, while projection offers a solution.\(^{12}\) Moreover, in tying together the likelihood and the conditional choice probabilities as in Arcidiacono and Miller, I can control for unobservable comparative advantage which enriches the model and also helps with selection problems.

### 1.4.6 Possible Sources of Bias and Threats to Identification

Before moving to the results, I wish to discuss the bias resulting from one weakness of the model: the inability for workers to select on non-additive, time-varying idiosyncratic shocks. This does not mean that there is no selection on unobservables in the model. Indeed, I allow for rich differences in comparative advantage both across workers and through the life cycle, but idiosyncratic shocks pose difficulties. This is a departure from standard Roy models (e.g., Heckman and Honore (1990)) as well as previous papers in the structural labor literature. Unfortunately, when choice sets become very large, even fully specifying beliefs and solving the model make dealing with unobservable, time-varying multiplicative shocks difficult. This is because the solution to the value function

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\(^{12}\)For example, Artuc and McLaren (2012) attempt to model occupational movement but focus on three occupations and impose substantial symmetry restrictions in their cost functions.
would require very high dimensional integrals which even the best numerical methods cannot yet tackle. While incorporating this level of selection may be intractable, that does not validate ignoring it. To that end, one may think of the bias that arises from excluding this kind of selection. I work out the details in an appendix, but I consider two special cases here.

First, suppose that occupations are symmetric in the sense that wages are the same in every occupation and there is one cost of switching, $C$. If this were the case, workers would only move if they received a favorable shock as it is clear that there is no other benefit to switching occupations. In this case, one can solve for the main regression equation as,

$$\log \frac{P(o'|o; \sigma)}{P(o|o; \sigma)} = -\frac{C}{\rho} + \frac{w^2 \sigma^2}{\rho^2} \times \frac{NP(o|o; 0) - 1}{N - 1}$$

where $N$ is the number of occupations and $\sigma$ is the variance of the observed multiplicative income shocks. The bias term is positive so that if $C > 0$, moving costs will be biased to 0. To the extent that one believes this approximation, it means that the costs will be underestimated and thus any estimated impact on workers can be viewed as a lower bound. The intuition for this result is that the probability of receiving a positive moving cost shock and a positive wage shock is increasing in the number of occupations. Thus, workers will move with a higher probability than in the presence of only additive moving cost shocks—leading to underestimation of moving costs.

In the asymmetric case, there is no closed form solution. However, by taking second order approximations around the variance of income shocks, one can demonstrate that the conditions for negative bias are quite stringent. In particular, for the bias to not work in my favor, low paying occupations must have substantially higher shock variances than high paying occupations. While the correlation between variance and levels is negative, it is quite mild. Thus, it seems plausible that in empirically relevant cases, ignoring multiplicative shocks will tend to push cost estimates to zero, underestimating the impact to workers.
1.5 Data Description

The Danish administrative data contains several databases that can be woven together to provide information on workers, such as income, occupation and place of employment. This breadth of coverage, covering the universe of Danish workers from 1997 to 2007, is what allows me to estimate the model. In this section I discuss those ingredients essential to estimation of the worker’s dynamic decision problem. First, I briefly mention the datasets that I use and provide some summary statistics. Then I outline the two key aggregations from raw data to model inputs: (1) a mapping from highly disaggregated occupational and industry codes to a tractable number of occupations; (2) the construction of task space, which play the role of occupational characteristics. In the interest of brevity, I omit some details; however, a more complete description of the data and the methodology can be found in an appendix available upon request.

1.5.1 Aggregating Occupational Codes

Denmark uses the ISCO system developed by the ILO in order to classify workers into occupations. The system’s primary tenet is that “the basis of any classification of occupations should be the trade, profession or type of work performed by an individual, irrespective of the branch of economic activity to which he or she is attached or of his or her status in employment.” That is to say, the system strives to classify occupations based on tasks and work activity.

At the most disaggregated 4 digit level there are nearly 1000 codes. However, in the structural estimation, I must aggregate both for computational reasons and because many occupations only employ a few workers. While my strategy can handle large choice sets, it is still limited by the need to have reliable estimates of transition probabilities. My aggregation strategy proceeds in two cuts. First I move from the ISCO 4 digit level to the ISCO 2 digit level. This leads to 23 occupations. These occupations are still quite specific and should be thought of as separating, for example, machinists, plant operators, drivers and craftsmen but not differentiating between type of machine. I actually disaggregate these codes by crossing them with four sectors: manufacturing, health and
education, FIRE and other services. While my focus is primarily on occupations, I do this disaggregation for two important reasons. First, while two digit codes often span multiple sectors, more disaggregated occupation codes are often found in only one sector. For example, workers coded at the two digit level as drivers in manufacturing are almost always fork lift operators while in services they are almost always taxi drivers. Thus, sectoral divisions are often a stand-in for more disaggregated occupational divisions. In this sense, they provide a bridge between an intractably large number of disaggregated codes and a more manageable level of disaggregation. Second, including sectors allows me to benchmark my results against the literature that has focused on sectoral reallocation. By including this dimension directly in my estimation I can separately identify those costs associated with moving across sectors but keeping the same occupation, the costs of switching occupations within sectors and the combined costs. This allows for a direct test of the relevance of the occupational margin in thinking about worker adjustment: if occupations are irrelevant than only intersectoral movement should be costly. This procedure yields 38 total occupations, as many occupations only appear in one sector (for example, machinists are only present in manufacturing).

1.5.2 Occupational Characteristics

I model occupations as bundles of tasks. As mentioned above, I think of tasks as abstract objects that represent a single unit of work output. I assume there are a finite number of elementary tasks, $|\mathcal{V}|$, and that an occupation is a vector in $\mathbb{R}^{|\mathcal{V}|}$ that gives loadings on these tasks. As a concrete example, suppose there were three elementary tasks in the world—dexterity, communication and problem solving; then an occupation such as restaurant worker would have a high loading on communication with low weights elsewhere while an economist may have relatively high weight on the latter two tasks but not the first.

Tasks offer a way to put a metric on the space of occupations. If an occupation is a vector, $v_o \in \mathbb{R}^{|\mathcal{V}|}$, then one can measure the distance between occupations $d(v_o, v'_o)$. To construct occupational characteristics, I need a notion of tasks that is observable. Following the labor literature, I use the
O*NET database. The US Department of Labor asks detailed questions of workers on the task content of their occupations. Workers are asked to rank the importance of a task on a scale of 1 to 5. Examples of tasks include “Active Learning,” “Writing,” “Equipment Maintenance,” and “Assisting and Caring for Others.” For each occupation the value recorded is an average across many workers. I standardize these values to quantiles and then treat them as cardinal. Drawing together various surveys yields 128 questions covering 983 occupations. I relegate details of the questions and aggregation across occupations to the data appendix.

A large number of survey questions is almost as problematic as a large number of occupations. Reducing the dimensionality of the parameter space from the thousands to the hundreds is a huge step forward but remains unwieldy. Thus, I use principal components analysis (PCA) to collapse the set of tasks to 10 attributes. Table 1.1 lists several examples of tasks and the survey questions with the largest loadings.

1.6 Results

In this section I present the major findings from my estimation. First, I discuss the parameters governing workers’ income and benefits. Then, I turn to discussing the costs of occupational transitions and explore the empirical distribution of costs in the economy. Finally, I look at some out-of-sample predictions of the model to assess goodness of fit.

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13The dataset also contains information on the variance in tasks within occupations, as well as changes in task composition over time. While I do not use this information, there is nothing methodologically preventing a researcher from incorporating this information into the cost function.

14In the results in this version this is what I am doing. However, in a newer draft I am doing the standardization only after aggregating. In this sense, the cost function is fully general in that it prices movement along quantiles of the tasks. I treat the pricing function as linear, but it can be specified more flexibly without creating a substantial burden.

15PCA uses the covariance matrix across survey responses to construct linearly independent combinations of the original data. It selects those linear combinations that explain the most variation in the data. To determine the optimal number of attributes, I follow the methodology and estimation strategies set forth in Bai and Ng (2002) and Stock and Watson (2002). In the data appendix, I review this strategy as it applies to my problem.
1.6.1 Income and Other Benefits

In this section I discuss results of the income regressions, including how coefficients vary across occupations, as well as the value of non-employment. Table 1.2 presents all income parameters, including the value of the comparative advantage for each skill group and unobserved type (high or low). Tables 1.4 and 1.5 display the occupation fixed effects and the coefficients of the linearly specified non-employment payoff, respectively.

All coefficients in the Mincer regressions are allowed to vary by occupation. And indeed, there is substantial variation in these coefficients. First turning to occupational tenure, at the low end, agriculture work has a flat profile with respect to career length. An additional year of tenure only raises the wage by 3.8%. At the other extreme, there is a surprisingly steep tenure profile for personal workers in the services sector, with an additional year of occupational tenure yielding gains of nearly 10%. Occupations with steeper tenure profiles lead to large consequences of involuntary job switching, especially for experienced workers: a highly tenured worker can lose up to half a years of income when switching occupations.

A natural follow up question is how numbers on specific capital relate to more general labor market experience. The model in fact allows for limited transferability of human capital by tracking age, proxying for lifetime experience. Comparing the coefficients on age and tenure cannot be directly done because of the quadratic term in age, however comparing the linear terms gives an upper bound on the importance of general human capital because all quadratic terms are negative. The linear coefficients are of the same magnitude, implying that not modeling occupational specific human capital can bias both estimates of the value of labor market experience as well as the cost of job displacement. In fact, if one actually calculates the returns to general experience for 30 year olds, then the returns to occupational specific human capital are on average 2.4 times larger. This highlights an important channel by which switching occupations can carry costs for workers.

Moreover, the costs of foregone human capital discourage workers from voluntarily switching occupations, which slows labor market adjustment.

One interesting comparison is that only in manufacturing is specific capital on average more
valuable than general experience. If indeed manufacturing workers are more vulnerable to trade shocks, then ignoring the value of their specific human capital risks underestimating the effects on workers, especially experienced and older workers. In a similar vein, there seems to be some skill-bias in the transferability of tenure. In particular, managers and other professional workers tend to face smaller returns to tenure relative to experience. One can interpret this as reflecting that occupational specific capital in management is less important than other factors (one’s skill level and general level of experience) or as reflecting that there is substantially more learning-by-doing in traditionally lower skilled occupations. In either case the implication is the same: in terms of foregone human capital, disruption affects those in traditionally lower and middle skilled occupations more than those in higher skilled occupations.

An important feature of the model is capturing unobservable comparative advantage across workers. The last five columns of Table 1.2 present these comparative advantage terms for all six types of workers in the sample\(^{16}\), while 1.3 displays the distribution of types in the population. Two facts jump out from this table. First, within educational categories there appear to be a low productivity and a high productivity worker. That is to say, there are low income earners and high income earners within broad educational categories. Second, there is substantial motivation for self-selection in the model—easily seen from the variation in the size of the coefficients both within and across occupation. For example, high type, middle skilled workers actually have a higher productivity at several occupations than college educated workers; this is especially pronounced in the manufacturing sector.

Up to now, the discussion has focused on worker income; however, the estimation also yields measures of the non-pecuniary value of various occupations. Table 1.4 displays the occupation fixed effects across sectors—with the value of non-employment normalized to 0. The unconditional mean income in this economy is normalized to 1, so that \(\eta\) can be interpreted relative to this number. Thus merely being employed is worth on the order of approximately two years of income. Of course, the value of non-employment changes over time and so, as workers age, the

\(^{16}\)The value of \(\theta\) for high-skilled, low-types is normalized to zero as this is not separately identified from the constant term in a regression.
gap between the value of employment and non-employment shrinks. To see this, table 1.5 displays the parameters governing workers’ outside option. Here one sees that non-employment is more costly for higher skilled workers and that the value of non-employment increases with age.

### 1.6.2 The Costs of Occupational Switching

This section discusses occupational switching costs, the recovery of which was a central goal of estimation. I focus on three major points: first, switching costs can be large—on the order of several years of income; second, switching costs are heterogeneous across workers’ states and workers’ occupations; finally, intrasectoral adjustment costs are as large, if not larger, than intersectoral adjustment costs, thus ignoring the occupational margin leads to underestimates of the impact of trade shocks on worker adjustment. This last point is particularly important—the trade literature has traditionally focused on intersectoral adjustment. Yet at my level of aggregation, intrasectoral adjustment accounts for 31% of all worker switches in a given year.

Turning to the first point, Figure 1.8 presents the histogram of costs of observed switches relative to unconditional mean income, while Figure 1.9 presents the same figure relative to the income (in the initial occupation) of workers. Before moving onto the results recall that switchers face both mean switching costs and a logit moving cost shock:

$$\text{Costs}(o, o', \omega) = f(\omega)C(o, o') - \rho(\epsilon_{oo'} - \epsilon_{oo})$$

Dubin and McFadden (1984) show that under the GEV assumption on shocks, the expected costs borne by a switching worker is given by,

$$E(\text{Costs}(o, o', \omega)|o \rightarrow o') = f(\omega)C(o, o') + \rho \left( \log \pi(o, o', \omega) + \frac{\pi(o, o, \omega)}{1 - \pi(o, o, \omega)} \log \pi(o, o, \omega) \right)$$

(1.2)

Discussing costs clearly requires discussing both $C$ and $\rho$. I will refer to the first component in the above expression as the cost of switching occupations. This is because $C$ is the policy-relevant variable in understanding costs: any subsidy to switching or any retraining program that targets
particular tasks operates through effects on $C$. On the other hand, $\rho$ governs the likelihood of large shocks. While I do not ever observe workers’ particular draws of shocks, I will refer to the expression in (1.2) as the realized cost of switching. Figure 1.10 plots the distribution of realized costs.

Turning to $C$, the median cost of switching is on the order of 5-8 years of income. These numbers are well within the range of numbers estimated by Dix-Carneiro (2014) and Artuc et al. (2010), who find numbers in the range of 3 years and 10 years of income respectively. Nevertheless, two points are crucial in interpreting these numbers. First, these are the costs exclusive of realized moving cost shocks. As is clear from figure 1.10, realized costs are closer to a quarter years of income with substantial spread\textsuperscript{17} Second, many switchers are young, implying that their incomes are low. This makes the costs relative to income seem high when they may actually reflect a worker’s natural career decisions. Table 1.8 displays summary statistics for the cost of switching broken down by age group. The median cost of switching relative to income is decreasing in age—reflecting high income. Nevertheless, these numbers make a clear point: labor market adjustment can be sluggish and this is a direct consequence of the fact that workers treat occupational movement as a very costly enterprise.

These costs are not only large, but vary substantially across one’s initial occupations. This variation can drastically change the distributional consequences of trade shocks. To see why, consider a world where switching costs were the same across occupations. In such a world, workers in lower-demanded occupations would be worse off in the short ran than in the long run as an over supply would push down wages. Over time this would correct. Thus, uniform switching costs would lead to qualitatively similar effects in the short run as in the long run. However, when costs vary two things change. First, differences in costs factor into the value of an occupation, which can interact with occupational demand to either increase or decrease wages. Second, if costs of switching are correlated with the shock (e.g., adversely affected occupations are also costly to exit), then het-

\textsuperscript{17}Interpreting negative moving costs can be difficult, however one may think of them as a disemployment shock. Losing one’s occupation makes switching “easier.” This is not important for the purposes of identification but whether these shocks are treated as positive or negative shifts the level of the value function and can matter in welfare analysis.
erogeneity in switching costs can lead to much larger short run effects across workers. Together, this suggests that policy makers interested in helping workers smooth consumption along their transition path may want to target their efforts to the most sluggishly moving occupations.

Before presenting results, we need a meaningful notion of an occupation’s overall cost. To that end, I focus on the cost of exiting an occupation. This is the mean cost of moving to a new occupation holding the source occupation fixed. One can also consider the entry cost of an occupation, the mean cost across source occupations for a target occupation. Turning to the model’s results, Figure 1.11 plots the density of the mean cost of exiting an occupation. The density is unweighted by the composition of workers to avoid conflation with equilibrium outcomes. Instead, this figure reflects the level of costs that a worker in some occupation will face when deciding to move. It’s clear from the figure that even with only 38 occupations, there is substantial heterogeneity in the mean cost of moving out of an occupation. For example, the least costly and the most expensive occupation differ by a factor of 2.11. The implication is not necessarily that workers in these occupations actually realize higher costs of moving; rather, some workers will wait longer for good shocks to come around, and may accept lower pay in the interim. Thus, this heterogeneity in costs implies that many workers face longer adjustment times than others.

A natural question for trade economists is whether those occupations that face the highest adjustment costs are more or less vulnerable to trade shocks. While I quantify the full effects of trade shocks in the counterfactual analysis, previous work has highlighted that the most vulnerable occupations are routine occupations, predominantly, but not exclusively, in manufacturing. With this in mind, Table 1.6 contains the mean switching costs across aggregated occupational groups. Machinists and crafts workers face some of the highest costs of leaving those professions. With occasional exceptions, they face the highest costs of entering management fields, professional fields, clerical work and technician work. The lowest cost professions for these workers to switch into are agricultural work or menial labor, which tend to either pay lower wages or also be vulnerable to import competition.

Turning to the second component of realized costs, recall that $\rho$ governs the importance of ob-
servable benefits in determining flows relative to shocks. In particular, $\rho$ determines the importance of wage differentials for flows across occupations. It does so by determining the variance of moving cost shocks. I estimate a value of $\rho$ at 1.38, implying a standard deviation of 2.5 years of income for the logistically distributed moving costs. Unfortunately, there is no real benchmark for this number. The two most closely related studies, Dix-Carneiro (2014) and Artuc et al. (2010), find higher values of $\rho$ in between 2 and 3 using a similar specification. However, one expects $\rho$ to fall as choice sets become more granular since wage differentials become more informative. Thus, the value of $\rho$ is close but understandably smaller than extant estimates of the importance of wage differentials in describing worker movement. To put this number in perspective, one can calculate that for the median worker (in terms of income), a 1% decrease in the skill price of an occupation, holding other skill prices fixed, raises the probability of switching occupations by 3%. In general equilibrium, all skill prices move simultaneously, and we will see in the counterfactual analysis that worker adjustment can be quite slow.

Moving on to heterogeneity across workers’ states, Table 1.7 displays the estimates of the inverse productivity function. There are two major takeaways from this table. First, tying to the introductory discussion of the life cycle, switching occupations becomes more costly with age. From the first two rows, a forty year old faces 14% higher moving costs than a thirty year old. With the magnitudes under discussion, this can amount to nearly one additional years of income. This increased cost manifests itself in the decisions of actual workers. Older workers tend to choose occupations nearer to them in task space—another contributing factor to the pattern of decreasing costs observed in Table 1.8. Moreover, they simply switch less than younger workers. For example, workers in their fifties switch at half the rate of workers in their thirties.

Workers’ skill and unobserved type matter as much as age. Looking again at the point estimates in Table 1.7, the data selects a high type and a low type within each skill level. This sets up an additional channel through which unobservable heterogeneity affects outcomes. The actual point estimates suggest that frequently moving workers may actually not be as adversely affected by a shock as workers who move little. This is because these low type workers face 8 to 10% lower
costs than other workers in the same skill group. Moreover, while it’s true that in general more skilled workers face lower moving costs, the unobservables imply a reversal in some cases. Table 1.9 summarizes the distribution of costs relative to income by skill and type. Low types face higher costs relative to income, implying that their absolute disadvantage relative to others trumps their lower mobility costs. The most startling numbers are in the first row, displaying moving costs on the order of twenty years of income for low type, unskilled workers. In interpreting this large number, remember that this implies low type workers will await a good shock rather than actually face the burden of high costs. Moreover, this is estimated to be a relatively small group in the total population.

Finally, I compare my results for occupational movement with intersectoral movement. Many models have focused on sectoral movement in order to model workers’ adjustment to trade shocks while ignoring the occupational dimension. Here I argue that this lack of a focus misses substantial heterogeneity within sectors. This heterogeneity matters as intrasectoral adjustment constitutes a large fraction of total worker flows across occupations. My model actually offers a natural way to tease apart costs across the sectoral and occupational dimension. And my results demonstrate that occupational movement is at least, if not more, important than movement across sectors. Figure 1.12 plots the densities of costs for workers switching sectors but not occupations, workers switching occupations but not sectors, and workers switching both. Costs for workers switching sectors is very tight while costs for workers switching occupations is very spread out. Table 1.11 summarizes the disparity in both magnitudes and spread. Intrasectoral occupation movement is associated with median costs that are 28% larger than pure sectoral movement.

At the level of aggregation in the model, pure intrasectoral movement accounts for 32% of transitions. Extant work has averaged together the remaining two groups of workers—those facing relatively low costs of intrasectoral movement while keeping their occupation and the substantial costs of switching both sectors and occupations. To shed light on how this can bias results quantitatively, Table 1.10 displays the matrix of switching costs across sectors. These numbers are constructed without adjusting for workers’ state spaces and are simply unweighted averages of the
costs of movement. In other words, these are the baseline multipliers on costs that a worker would face if they were forced into some occupation at random. The reason that the diagonal is non-zero is because this averages costs across occupations within sectors as well. Thus, the diagonal elements reflect average intrasectoral costs while the off-diagonal elements reflect intersectoral costs. These baseline costs are on the same order of magnitude for both intra- and inter-sectoral mobility. From this matrix one can draw two conclusions: first, switching occupations within sectors can be as costly as switching across sectors; second, the fact that the observed switching costs are higher within sectors reflects a worker composition effect. In particular, for observed intrasectoral costs to be higher it must be that the workers engaging in intrasectoral movement are either systematically moving to occupations far apart in task space, or are precisely those workers who are less productive at moving. In either scenario, failing to take into account intrasectoral moving costs misses what is possibly a substantial burden facing many workers.

### 1.6.3 Goodness of Fit

In this last subsection, I assess the fit of the model. I focus on two dimensions, standard in the literature: in-sample fit and out-of-sample performance. First, I use the $R^2$ of my second stage fitting procedure to determine the in-sample fit. That is to say, this is the $R^2$ from the regression described in 2.4. The centered and uncentered $R^2$ from my second stage estimation are .5353 and .9184, respectively. In interpreting these two numbers one should keep in mind that the model allows for 78 parameters to explain several million observations. Thus, unlike in a moment-matching procedure, the disparity between the number of parameters and number of targets is several orders of magnitude. Moreover, recall that the residual has a structural interpretation; it reflects worker uncertainty and ought to have positive variance in the absence of perfect foresight. Because the variance of expectation errors is unknown, interpreting the $R^2$ is difficult. However, it's magnitude is large and suggestive that this relatively parsimonious model can explain a substantial amount of variation.

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18I report the uncentered $R^2$ because a non-linear model lacks a natural interpretation for the $R^2$. 
The second, and more telling, model assessment comes from looking at an out-of-sample prediction. A natural choice is the model’s predictions for the distribution of occupational switches. The model is fit to discounted relative differences in switching probabilities, but the actual distribution of switches is a separate set of moments that can be used to benchmark performance. Figure 1.13 plots actual unconditional transition rates against the log of predicted unconditional transition rates. The dotted line is the 45 degree line, which would reflect a perfect fit, while the black line is the best fit line explaining the relationship between data and model predictions. There are three takeaways. First, the overall fit of the empirical distribution is very good, with a regression of actual switches on predicted switches having an $R^2$ of .8557 and a coefficient of .747. Second, the fit is dramatically improved when weighting observations by their empirical likelihood—the $R^2$ increases and the slope coefficient is .889. The fit is clearly imperfect. Moreover, the error is systematic with a regression coefficient of less than 1. This is a consequence of the multinomial logit approach, which tends to equalize choice probabilities. Hence, multinomial logit models will under predict the diagonal and imply overly uniform transitions across choices. This is because the multinomial logit approach precludes zero transitions, even though these are observed empirically (especially with large choice sets). This could be remedied by arbitrarily limiting choice sets (i.e., setting mobility costs to infinity), but the model’s fit is good without imposing these restrictions and allowing for this movement might be relevant in counterfactuals.

As a final point in this section, I stress that the model has been identified solely off income and transition data. Importantly, I have not had to make any strong assumptions about labor demand beyond the assumption of a market-level skill price. In the next section, when I present counterfactuals, I posit a particular labor demand system and assess the model’s equilibrium predictions against observed outcomes. However, any assumptions made in subsequent sections have no bearing on the results presented here.

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19 In order to perform this exercise I fed in the path of skill prices from 1996 to 2007 and compared the actual changes from 1996 to 1997 against those predicted by the model. To do this I had to take a stand on worker’s beliefs. For the purposes of this exercise I assumed that workers had perfect foresight from 1996 to 2007 and then assumed that skill prices would remain at their 2007 levels forever.
1.7 Counterfactuals

In this section I summarize my procedure for counterfactuals and how changes in import costs affected the Danish labor market. To close the model, I specify a labor demand system based on a model of industry spillovers. In particular, I model many narrow industries within each of my sectors. The input-output structure allows for rich heterogeneity in the occupational response to trade shocks. After outlining the model, I describe how I calibrate key parameters of the demand side. Finally, I simulate the Danish economy as if foreign prices were constant at their 1996 levels and compare this to a simulation where the economy faces the time series of observed import prices from 1996 to 2005.

1.7.1 Closing the Model

In this subsection, I describe consumer preferences, the production side of the economy, and finally the model’s equilibrium. In order to be consistent with the dynamic model in which workers maximize income, I propose a simple homothetic demand structure for consumers. The production side features the aforementioned industry spillovers.

Consumer’s Preferences and Final Demand

I assume that workers live for a finite number of periods, 1, ..., T. In each period they choose an occupation (potentially non-employment) and supply their time inelastically. I abstract from savings decisions and assume that agents consume their entire income within each period. Thus workers’ consumption decisions are static and decoupled from their working decision. The consumers’ utility function is a three-tiered utility function as in Broda and Weinstein (2006). The top tier is a Cobb-Douglas aggregator over industry-level outputs:

\[ U = \prod_{i \in I} C_i^{\alpha_i} \]
where $i \in I$ indexes industries or goods and $C$ is consumption of industrial aggregate $i$. The second tier is an Armington aggregator over domestic and foreign varieties:

$$C_i = \left(\left(C_i^D\right)^{\rho_i} + \left(C_i^F\right)^{\rho_i}\right)^{1/\rho_i}$$

where $\rho_i \in (0, 1)$ is an industry specific parameter and $D$ and $F$ refer to Denmark and Foreign respectively. Finally, the third tier is a CES aggregator over foreign varieties to construct the foreign aggregate.

Let $\sigma_i = \frac{1}{1-\rho_i}$ be the industry-specific elasticity of substitution. In this case, for a given level of expenditure in industry $i$, $E_i$, expenditure on domestic varieties, $E_i^D$ will be given by,

$$E_i^D = E_i \frac{\left(P_i^D\right)^{1-\sigma_i}}{\left(P_i^D\right)^{1-\sigma_i} + \left(P_i^F\right)^{1-\sigma_i}}$$

In addition to domestic households, foreigners can demand Danish goods. I treat export demand as exogenous and given by, $A_i^F \left(P_i^D\right)^{-\sigma_i}$ where $A_i$ is a demand shifter. Putting these pieces together yields the demand curve for domestic final production:

$$E_i^{D,final} = W\alpha_i \times \frac{\left(P_i^D\right)^{1-\sigma_i}}{\left(P_i^D\right)^{1-\sigma_i} + \left(P_i^F\right)^{1-\sigma_i}} + A_i^F \left(P_i^D\right)^{-\sigma_i}$$

where $W$ is aggregate income.

**Labor Demand: Representative Firm’s Problem**

I use a model of inter-industry linkages and heterogeneous elasticities of substitution between domestic and foreign varieties to generate labor demand curves: a system of industry-level Cobb-Douglas production functions give rise to complex and varied substitution patterns across occupations. In the bulk of my paper, I have referenced broad sectors in the economy. Now I allow for highly disaggregated industries within each sector. Implicitly, this means I assume that work-
ers switching across narrow industries within a sector face no costs of doing so if they do not switch their occupation. The benefit of this modeling approach is that the highly disaggregated input-output matrix interacts with the labor supply model to capture very rich aggregate substitution patterns, as well as heterogeneity in the response of occupations to shocks. Both ingredients are actually crucial: non-unit elasticities between domestic and foreign varieties creates disparate substitution elasticities between foreign inputs and different occupations; adjustment costs affect the ability of the economy to respond to shocks, generating heterogeneity in the elasticity of substitution between occupations. With this in mind, I posit “roundabout” production as in Foerster et al. (2011):

\[ Y_i = z_i K^{\beta K} \prod_{o \in O} H_{o}^{\beta H} \prod_{j \in I} M_{i}^{\beta M} \]

where \( K \) is capital, \( H \) is human capital and \( M \) refers to an industry aggregate used as an intermediate. Here, \( i \) and \( j \) index industries, and \( o \) indexes occupations. I assume that \( \sum \beta = 1 \) (but \( \beta \) can be 0 for some occupations and industries). As before, \( M_i \) is an aggregator across domestic and foreign goods and the foreign good itself is an aggregator across foreign varieties. I assume the same elasticities of substitution are used by producers and consumers. I posit a perfectly competitive representative firm in each industry. Finally, I treat capital as a non-tradable, fixed endowment in this economy. I discuss this assumption more at the end of this section and highlight its implications for counterfactuals when discussing results.

The above production function and assumptions on competition leads to the following demand for industry output:

\[ E_{i}^{D} = \left( \alpha_i W + \sum_{j \in I} \beta_{kj} R_{j} \right) \times \frac{(P_{i}^{D})^{1-\sigma_i}}{(P_{i}^{D})^{1-\sigma_i} + (P_{i}^{F})^{1-\sigma_i}} + A_{i}^{F} (P_{i}^{D})^{-\sigma_i} \]

where \( E_{i}^{D} \) is domestic on industry \( i \). To illustrate the flexibility of this approach, consider the market demand for occupations. The Cobb-Douglas system implies the following market expenditure

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20Baqaee (2015) discusses a macroeconomic model in which an IO matrix can lead to non-trivial labor supply elasticities at an aggregate level. He also provides conditions under which an interconnected economy cannot be collapsed into a composite commodity economy.
where again $E_i^D$ is domestic expenditure in industry $i$ and $H_o$ is total demand for occupation $o$.

Now consider a change in the price of foreign good $i$ and hold all other prices (including wages) fixed. Then, by substituting in the expression for domestic expenditure and totally differentiating with respect to $P_k^F$ one has:

$$w_o dH_o = \beta_{ok}^H (\sigma - 1) \times \left[ \left( \alpha_i^D W + \sum_{j \in I} \beta_{kj}^M R_j \right) \left( \frac{P_k^D}{P_k} \right)^{1-\sigma} \times \left( \frac{P_k^F}{P_k} \right)^{-\sigma} \right] dP_k^F$$

where the first effect maps out the impact of import competition on demand for industry $k$ while the second effect maps out how various industries substitute from labor to other inputs as a result of changes in the relative price of inputs. Given that $\sigma > 1$, the direct effect of a drop in the price of $k$ from $F$ will be to lower demand for occupation $o$. However, the change in $P_k^F$ changes the revenues in other industries who likewise adjust their demand for $o$. Thus, even the partial equilibrium effect of foreign prices on occupational demand can be arbitrary.

**Equilibrium**

Despite the complex economy-level substitution patterns between foreign supply and labor demand, this set up gives rise to a very simple equilibrium characterization. An equilibrium is defined by a set of domestic prices, $\{ P_i^D \}_{i \in I}$, wages $\{ w_o \}_{o \in O}$, labor stocks, $\{ H_o \}_{o \in O}$ and revenues, $\{ R_i \}_{i \in I}$ such that:

1. Representative firms choose intermediates, labor and capital optimally

2. Workers act optimally with respect to their static preferences over consumption and dynamic
3. Goods Market Clearing (for each $i \in \mathcal{I}$):

$$
R_i = \frac{\left( \alpha_i^D W + \sum_{j \in \mathcal{I}} \beta_{ij}^M R_j \right)}{\left( P_i^D \right)^{1-\sigma} + \left( P_i^F \right)^{1-\sigma}} \left( P_i^D \right)^{1-\sigma} + A_i^F \left( P_i^D \right)^{1-\sigma}
$$

4. Labor Market Clearing (for each $o \in \mathcal{O}$):

$$
w_o \times \left( \sum_{\{n:o(n) = o\}} h_{on} \right) = \sum_{i \in \mathcal{I}} \beta_{oi}^H R_i
$$

5. Capital Market Clearing

$$
K = \sum_{i \in \mathcal{I}} \beta_i^K R_i
$$

6. Balanced Trade:

$$
\sum_{i \in \mathcal{I}} A_i^F \left( P_i^D \right)^{1-\sigma_i} \left( P_i^D \right)^{1-\sigma_i} + A_i^F \left( P_i^F \right)^{1-\sigma} = \sum_i \left[ \left( \alpha_i^D W + \sum_{j \in \mathcal{I}} \beta_{ij}^M R_j \right) \left( P_i^D \right)^{1-\sigma} + \left( P_i^F \right)^{1-\sigma} \right]
$$

1.7.2 Demand Side Calibration

Calibration proceeds in several steps. I discuss the details of the Danish IO matrices and how I handle changes over time in the Data Appendix, but I outline the procedure here. First, if inputs are flexible from the perspective of each representative firm, then production function coefficients on intermediates, capital and total labor can be estimated from expenditure shares and the IO matrix published in the Danish national accounts. To construct the parameters for occupational expenditures I proceed in two steps. First, as discussed above, I use the Danish IO matrices to calculate the total share of expenditure on labor
(i.e., $\sum_o \beta^H_{io}$ for each industry $i$). Then I use relative wage bills within industries to calculate $\beta^H_{io}$. And so, indexing workers by $j$, industries by $i$ and occupations by $o$,

$$\beta^H_{io} = \beta^L_i \times \frac{\sum_{j \in O \cap i} w_j}{\sum_{j \in i} w_j}$$

where $\beta^L_i$ is the total expenditure in labor as given by the IO tables. In principle, the numerator that calculates $\beta^L_i$ should be the denominator in the occupational share term. This is not the case because I dropped workers with imputed or missing occupational information, so $\beta^L_i$ is a rescaling factor.

To estimate foreign prices, I use Danish customs data and a slightly modified version of the procedure described in Broda and Weinstein (2006).\(^{21}\) This method allows one to construct a CES price index for imported industry aggregates while taking explicit account of the fact that different countries produce goods of different quality and variety.

Finally, to calibrate the relative price of domestic goods to foreign goods, notice that relative expenditure shares are a sufficient statistic for relative prices:

$$\frac{E^D_i}{E^F_i} = \left(\frac{P^F_i}{P^D_i}\right)^{1-\sigma_i}$$

An important parameter is the Armington elasticity, $\sigma_i$ across domestic and foreign imported aggregates. Properly disciplining this parameter is a well known problem in the trade literature and attempting to estimate industry-specific elasticities would lay outside the scope of this paper. To that end, I use the elasticity of substitution proposed by Simonovska and Waugh (2014) and set $\sigma_i = 4$ for all industries. As a final point, I define tradable industries to be industries in manufacturing, agriculture and mining. These industries comprise 85% of Danish imports and 65% of Danish exports.

\(^{21}\)More precisely, I use a geometric mean of the naive estimator arising from a change in industry prices over time (this is part of the IO tables), the CES estimator as described in Broda and Weinstein using Danish customs data, and the same CES estimator using UN COMTRADE data. This is necessary because a few changes in the units of goods (from quantity to weight) leads to some radical price swings for some industries in the early 2000s. By taking a geometric mean across these different sources, I smooth out these noisy years.
1.7.3 Procedure for Counterfactuals

Before turning to results, in this section I briefly describe the algorithm which I use to perform counterfactuals. Solving the model essentially proceeds in four steps: (1) define an initial equilibrium; (2) guess a set of nominal wages; (3) use the constant returns to scale production system and perfect competition to back out real prices and thus real wages; (4) use new wages and new prices to solve for equilibrium labor supplies and demands respectively. In this section first I describe step (3) and then step (4) in some detail before writing out more precisely the algorithm and its convergence criterion.

To initiate the equilibrium, one can demonstrate that the production side of the economy can be rewritten in a way that allows one to solve for changes in endogenous equilibrium objects as a function of changes in exogenous parameters. Moreover, the resulting system only depends on the relative price of foreign to domestic goods and changes in sectoral price indices—and requires no information on relative prices of goods between industries. Mathematically, given an initial equilibrium and changes in exogenous variables as well as changes in wages one can derive the following formula for changes in production side variables:
\[
\Delta \begin{bmatrix}
\log r_{ti} \\
\ldots \\
\log P_{ti}
\end{bmatrix} = \left( I_{N \times N} - \begin{bmatrix}
B_{T,T}^M \circ \frac{r_1^{1-\sigma}}{1+r_1^{1-\sigma}} & B_{T,NT}^M \\
\ldots & \ldots \\
B_{NT,T}^M \circ \frac{r_1^{1-\sigma}}{1+r_1^{1-\sigma}} & B_{NT,NT}^M
\end{bmatrix} \right)^{-1} \times (1.3)
\]

\[
\begin{bmatrix}
\begin{bmatrix}
B_{T,T}^M - I_{|T|}
\end{bmatrix} \\
\ldots \\
\begin{bmatrix}
B_{NT,T}^M
\end{bmatrix}
\end{bmatrix} \\
\begin{bmatrix}
\Delta \log z + \Delta \log P_i^F + B^K \Delta \log p_k + B^L \Delta \log w \\
\Delta \log z + \Delta \log P_i^F + B^K \Delta \log p_k + B^L \Delta \log w
\end{bmatrix}
\]

Exogenous

\[
\begin{bmatrix}
E_T \\
\ldots \\
E_{NT}
\end{bmatrix} = \left( I_{N \times N} - \begin{bmatrix}
(B_{T,T}^M)' \circ \frac{r_1^{1-\sigma}}{1+r_1^{1-\sigma}} & (B_{NT,T}^M)' \circ \frac{r_1^{1-\sigma}}{1+r_1^{1-\sigma}} \\
\ldots & \ldots \\
\alpha_T' \circ \frac{r_1^{1-\sigma}}{1+r_1^{1-\sigma}} & (X \circ r_1^{1-\sigma})
\end{bmatrix} \right)^{-1} \times (1.4)
\]

where \(\circ\) refers to appropriate element-wise multiplication, \(T\) collects tradable industries while \(NT\) collects those that are not. Looking first at (1.3), notice that all changes in exogenous variables are readily observed, so that given an initial wage and a guess of current wages one can solve this matrix system for changes in sectoral price indices. With changes in prices solved and information on original prices one can solve for the levels of expenditure and thus labor demand.\(^{22}\) This summarizes the crux of the algorithm. As a final point, the Cobb-Douglas system implies that one can solve for the levels of expenditures without needing information on the relative prices across industries. This is important because in the data one rarely observes long time series of relative prices across goods—only the changes in these relative prices. To conclude I summarize the algo-

\(^{22}\)This equation is actually a log-linearization in order to speed up solution time. Thus, one market (capital as this is what I do not clear explicitly) will only approximately clear. In actual simulations the tolerance for market clearing in labor is 1e-16 and the consequent relative error in capital markets (i.e., \((K_{sup} - K_{dem})/K_{sup}\)) is on the order of 1e-6.
Algorithm in more detail below:

**Algorithm:** Given information on initial wages in *levels* and initial *relative* prices, \( \{ r_{i,t-1}, w_{t-1} \} \), as well as information on *changes* in exogenous variables \( \{ \Delta P^F_i, \Delta z_i, \Delta r_K \} \), and a current guess of equilibrium wages, \( w_{ot}^{(j)} \):

1. Solve the agent’s dynamic problem given \( w_{t}^{(j)} \) in order to construct labor demand \( \{ H^D_o \} \) and
   \[
   W_t = \sum_i w_{o(i)} h_{o(i)}(\omega_i)
   \]
2. Solve for new levels of relative prices, \( r_t \) using (1.3)
3. Solve for counterfactual export demand by
   \[
   X_{it} = D^F_{it} \left( P^F_{it} \right)^{1-\sigma} \times r_{it}^{1-\sigma}
   \]
4. Solve for new levels of expenditure using (1.4)
5. Construct labor demand from the expenditure system:
   \[
   H^D_{ot} = \frac{\sum_i \beta_i L_{\gamma i o} E_{it}}{w_{ot}}
   \]
6a. If \( \| H^D_{ot} - H^S_{ot} \| < \varepsilon^{tol} \) STOP
6b. If \( \| H^D_{ot} - H^S_{ot} \| > \varepsilon^{tol} \) update wages to \( w_{t}^{(j+1)} = \chi w_{t}^{(j)} + (1-\chi) \kappa \left( \frac{H^D_{ot} - H^S_{ot}}{H^S_{ot}} \right) \) where \( \kappa \) is an increasing function such that

   \[
   \kappa(x) = \begin{cases} 
   < 0 & \text{if } x > 0 \\
   0 & \text{if } x = 0 \\
   > 0 & \text{if } x < 0 
   \end{cases}
   \]

There are three points left to discuss: (1) workers need to form expectations about continuation values in order to solve the worker’s problem; (2) the role of capital in this model; and (3) this algorithm relies on an observed initial equilibrium.
To the first point, I assume that workers have perfect foresight of shocks from an initial steady state. That is to say, I start the model by simulating to steady state with zero changes. Then I assume that there is an unanticipated new set of foreign prices. However, I assume that workers fully predict the transition dynamics induced by this change and I use a shooting algorithm to solve for the transition to the new steady state. I compare this transition to a longer simulation in order to generate a comparison point.

As in Dix-Carneiro (2014), assumptions about capital play a crucial role in the counterfactual analysis. Currently, I am holding capital stocks fixed while allowing the price of capital to adjust endogenously in order to maintain trade balance. I am currently exploring an alternative where capital stocks can adjust freely in order to maintain an exogenously determined capital price. In between these two extremes lay the aggregate consequences of trade.

Finally, in all counterfactual experiment, I start from the following initial steady state: I begin the model at the 1996 observed variables, feed in observed 1996 to 1997 changes in all variables and then simulate forward assuming no changes in variables thereafter until a steady state is reached. I do this so that the model’s performance can be compared with observed 1997 changes in wages and occupational allocations. The model performs well as one can see in figures 1.14 and 1.15.

When I perform a counterfactual experiment I feed in a price series for changes to foreign price indices holding fixed all other exogenous variables. I run this through actual data until 2005 and then simulate towards a new steady state. While in principle one could immediately shock the economy with the full changes from 1997 to 2005, I choose to allow for a smooth transition. This is because in a model with fixed costs of transitions, the level of shocks may magnify the negative or positive effects on workers. I do not want to conflate the effects of a series of small to medium observed shocks with an artificially large one-time shock. Nevertheless, conceptually and computationally there is nothing stopping one from exploring alternative assumptions on timing.

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^23A true steady state in this model would take thousands of periods to reach because of the large state space across workers. As this is infeasible computationally, I define a steady state to be when all prices and stocks of variables do not move more than .05% from period to period. This takes 20-30 periods (essentially the time for the initial cohort to fully retire).
1.7.4 The Labor Market Impacts of Lower Import Prices

In this section I ask what happens to the composition of workers and their wages had the rapid fall in trade costs between 1996 and 2005 not occurred. In this counterfactual, I hold all variables besides foreign trade prices fixed at their 1996 levels and let foreign prices progress as they do in the data. In order to demonstrate more concretely what this experiment entails, Figure 1.16 plots the time series of all foreign price changes while 1.17 plots an import weighted price index. In this time period, energy prices (in particular, oil and coal) are actually increasing. However, there is a general downward trend in prices—especially of machinery. By the end of the period, import prices decrease 10%. I break the discussion of my results into three pieces. First, I discuss long run changes to aggregates in the economy—including GDP, total labor income and the reallocation of workers across occupations. Second, I look at transition dynamics in this economy and discuss the length of adjustment. I also perform a variance decomposition of wage dynamics as a way to assess the relative contribution of occupations and sectors to dynamics in this economy. Third and finally, I discuss heterogeneity in the impacts of trade across workers. In this final discussion I look at wage differences across occupations both in the short run and long run, as well as changes in the lifetime well being of workers, measured by the value, $V$, of workers.

Turning first to aggregate variables, I focus on two variables: total GDP and total labor income. Figure 1.18 plots the time series of GDP in the economy. As a point of notation, period 0 refers to the first period in which trade prices in the model no longer move, so this corresponds to 2006. The overall change in GDP is relatively modest, and the 10% decrease in import prices ultimately leads to a .3% increase in GDP. While small, this number is comparable to other estimates in the literature. For example, Costinot and Rodriguez-Clare (2014) find that, for Denmark, the losses from a uniform 40% increase in worldwide tariffs yields losses from less than 1% to around 4% of GDP, depending on modeling assumptions. While there may be asymmetries from price increases versus declines, the fact that a 4 times larger shock in a similar but different model yields changes in welfare from 4 to 10 times suggests that my numbers are reasonable. Two other reasons for small changes in aggregate GDP are that I do not allow capital to grow and I do not model the
increase in export demand that occurred alongside the decrease in import prices. I did this to focus on the importance of import competition, but future research may wish to explore the interaction of these forces more closely. Nevertheless, the figure makes clear that there are aggregate gains from decreased import prices.

I plot the time series of total labor income in figure 1.19. In the figure, two facts stand out. First, total labor income adjusts quickly to its steady state value. As I will show below, this makes substantial heterogeneity. Second, total labor income declines in this model. Given that aggregate GDP increases, this implies that the gains from trade largely accrue to capital in this model. This is possibly also related to the assumptions on capital in the model, and the fact that it cannot adjust to changes in import prices. When I present results related to workers I will focus on their labor earnings and the results on lifetime welfare only refer to changes in earnings. However, if capital is rebated to workers in a lump sum fashion, then on average workers must gain from trade.

Changes in aggregate GDP and income are important, but do not speak to the reallocation induced by changes in import prices. To get at this question, figure 1.20 plots the percent change in occupation shares in the long run steady state compared to steady state without changes in trade costs. The top line represents plant operators in manufacturing. This large growth is driven by their over representation in petroleum refinement, growth that is itself driven by changes in energy costs. Nevertheless, for most manufacturing occupations there is a steep decline in occupations. Figure 1.21 shows this by looking at percent changes in the share of each sector in total employment. The model suggests that lower import prices caused a large decline in manufacturing. In the actual data, this sector loses close to but less than 15% of their workforce, so the model slightly over predicts exit from manufacturing. The health and education experiences the most growth, with many workers in manufacturing becoming personal care workers or clerks in the health sector. This, intuitively, suggests that most reallocation is from tradable industries to non-tradable industries. Having examined the model’s predictions for long run changes both in aggregate variables and the composition of workers, I turn now to transition dynamics in this economy.

From the above discussion, one can see that aggregate variables respond quickly to trade shocks.
However, transition dynamics may still matter for different workers. That is, even if the average effect on income reacts quickly to changes in trade costs, there may be heterogeneity in how long it takes workers’ individual incomes to adjust. To understand the role of occupations in transition dynamics in the economy, I perform a variance decomposition of the difference between worker income in the equilibrium with decreasing import costs and in the equilibrium with fixed import costs. That is to say, I look at a variance decomposition of changes in outcomes across workers. The exercise is useful because as workers reallocate, the variance in this difference in outcomes will decrease over time. To understand why, note that if switching costs were zero, then workers would reallocate immediately and all dispersion in outcomes would be dictated by differences in comparative advantage and changes in occupational demand. However, in the presence of switching costs, some workers may either wait for sufficiently favorable idiosyncratic shocks or accept a lower income rather than transition. Thus looking at this variance decomposition over time is informative about the speed of adjustment. The exact decomposition is given by,

$$\sum_{i=1}^{n} s_i (\Delta w_i - \Delta w)^2 = \sum_{o \in O} s_o (\Delta w_o - \Delta w)^2 + \sum_{i=1}^{n} s_i (\Delta w_i - \Delta w_o(i))^2$$

(1.5)

where $i$ indexes worker types, $s$ refers to the share of those types in the economy and $o$ indexes occupations. As weights of workers changes between equilibrium, a choice of weighting needs to be made. I use the weights in the equilibrium with changing trade costs.

The results of this decomposition are shown in figure 1.22, which plots, for each year, the fraction of total variance explained by the across component of equation (1.5). In addition to performing this decomposition for the 23 ISCO occupations in Denmark, I also plot it for the 38 occupation-sector pairs, as well as for the four sectors I defined in the economy. From the decomposition by occupation one can see that in the long run, the occupation of a worker can account for 60% of changes in income across workers. There will always be some explanatory power of occupations due to changes in wage differentials across occupations and worker sorting. However, in the short run, workers’ occupations account for nearly 75% of the variation in outcomes, and it
takes 15 years for the importance of occupations to reach their steady state level.

This variance decomposition also speaks to the importance of modeling occupations in addition to sectors. To see this, look at the dynamics of the same variance decomposition across sectors. Two things stand out. First, sectors explain less variation in outcomes than occupations. This is almost mechanical as sectors are more aggregated. However, it is also clear that there are little dynamics in this decomposition. In period 0, sectors account for approximately 45% of the variance in outcomes and they account for the same amount in the long run. This means that sectoral income differentials change over across equilibria, but that these adjustments occur rapidly. This is not true of occupations. The implication of these two facts is that while sectoral income differentials adjust quickly, this aggregation masks substantial sluggishness in the adjustment of occupational income differentials. While this outcome is dependent on the particular shocks facing an economy, to the extent that the Danish experience is similar to other countries’, these results suggest that ignoring occupational adjustment may lead to underestimates of the length of adjustment to changes in trade prices. What remains unanswered is whether this sluggish adjustment actually translates into meaningful differences in short run and long run effects across workers. I now turn to exactly this question.

To understand the outcomes across workers, I break the discussion up into looking at skill prices in the short and long run, as well as changes in the lifetime welfare of workers. In this part, I focus on manufacturing as this sector undergoes the largest changes in terms of employment. Looking at skill prices, figure 1.23 plots the time series of skill prices in each occupation. Notice the wide dispersion both in the short and long runs. In the short run, at one extreme, agricultural workers experience a 1% decline in their skill price, while at the other extreme, plant operators see a .6% increase. Recall that the total gains from trade were on the order of .3% and so this spread in changes in wages is actually 5 times larger than average. Even ignoring plant operators, as they are something of an outlier, the spread in changes in skill prices is more than twice the mean change. Thus, ignoring occupations masks substantial heterogeneity. In the long run, there is still substantial dispersion in changes in skill prices—but this is heavily attenuated due to worker
adjustment. Moreover, one can see that it can take several years for skill prices to adjust, mirroring the findings from the variance decomposition above.

Finally, I turn attention to changes in the welfare of workers, which I measure with workers’ value functions. These value functions pick up the net changes in worker utility taking income, costs and all shocks into effect. Because I treat workers as risk neutral, so that income enters linearly, the units on the value function are dollars (which I converted from Danish kroner). Thus, by comparing the value function of a worker in the trade equilibrium and the equilibrium holding prices fixed, one can calculate the financial transfer that would make this worker indifferent between either situation. Figure 1.24 plots the distribution of the changes in workers’ value function in manufacturing at period 0. I also plot this distribution separately for older (40+) and younger workers. The average loss to workers in manufacturing is 850 dollars, but with a very large spread. Some workers gain slightly, even in the short run, but most workers lose. The most negatively effect workers can lose several thousand dollars. Young workers in particular lose, largely because they are further from retirement. Figure 1.25 plots the same distribution in other sectors. Two things should be apparent: first, the effect on workers in non-manufacturing sectors is much smaller than in manufacturing (the mean loss is now 400 USD); second, the spread in outcomes within sectors is substantial, even in non-manufacturing sectors. The numbers in this graph are particularly interesting from the standpoint of policy, as these reflect the transfers that would have to be given to make workers in the trade equilibrium at least as well off as they would be without import prices decreasing. These transfers could be paid for by rebating increased capital income back to workers.

In this subsection, I have shown that changes in import prices not only explain a great deal of changes in the composition of the Danish economy, but they also have a substantial impact on income. The substantial reallocation and adjustment in the model should temper discussion of the overall gains from trade. While national income ultimately increases, many workers face welfare costs of transitioning as well as long term costs. These transition costs may translate into negative lifetime effects on workers, even when total GDP increases.
1.8 Conclusion

This paper employs a rich micro data set on the Danish labor market in order to assess the impact of changes in import prices on workers. I develop and employ a dynamic model of occupational choice that measures occupational switching costs, as well as returns to occupation specific human capital, across a large set of occupations. A key feature of my model is that it allows a large degree of heterogeneity across workers. In particular, I account for the life cycle profile of workers, differences in skill, as well as difference in unobservable comparative advantage across occupations.

My main findings can be divided into two parts: first, I discuss the parameters and implications of my structural model; second, I embed my labor supply model into an open economy setting and analyze the impact of lower import prices on workers’ incomes in the short and long runs.

From my model I draw two important lessons. First, that the costs of occupational switching are large. These costs come in two forms: foregone human capital and bilateral costs of moving across occupations. In terms of human capital, I find that occupational tenure is as important as general human capital for explaining income profiles over the life cycle. Thus, shocks that move workers across occupations can actually decrease short run productivity through a decrease in human capital. In terms of bilateral moving costs, I find that costs are on the order of several years’ of income, which translates to very sluggish adjustment. Low productivity, uneducated and older workers face particularly high barriers to occupational mobility. This echoes recent findings in the literature on the importance of understanding workers’ occupational choices. It also suggests that labor shocks that induce reallocation of workers across occupations may actually destroy substantial human capital, more so than one might estimate in a model ignoring the occupational dimension.

Second, I find that moving costs are larger for workers moving across occupations, even within sectors, than for workers moving across sectors but keeping their occupation. This means that researchers focusing on intersectoral movements are actually averaging together the costs of two distinct kinds of workers—those undergoing an occupational transition and those that are not. This averaging implicitly underestimates both the negative effects and the adjustment times for those workers who transition across occupations. This finding speaks to a growing empirical and
theoretical literature which suggests that in modern economies, with highly disintegrated production processes, one’s occupation plays a crucial role in one’s response to labor market shocks—perhaps more important than one’s industry. This is particularly important for policy makers and researchers hoping to identify workers who lose in response to trade shocks.

With the estimates of my structural model in hand, I am able to simulate the effect of changes in trade costs on the labor market in Denmark. More precisely, I simulate the Danish economy holding productivity and export demand fixed in 1996 and feeding in the observed price changes from 1996 to 2005 of imports in a large number of disaggregated industries. Through a rich input-output structure, my model generates dispersion in the elasticity of substitution between different occupations and imported goods. I draw three major lessons from this exercise.

First, I find that aggregate variables respond quickly to changes in import costs. In particular, I find small changes in total output and total labor income that adjust almost completely within a period or two of changes in trade costs subsiding. I also find that in the long run changes in import costs can account for a substantial proportion of the decline in manufacturing employment in Denmark. Specifically, I find that employment in manufacturing decreases by 15% due to declines in import costs, with most workers moving into the health and education sector. This mirrors similar findings on the very large effects of trade shocks on manufacturing employment. However, I also demonstrate which occupations account for the majority of this decline, and which occupations seem relatively insulated.

Second, I find that these aggregate and long run changes mask a great deal of heterogeneity among workers. For example, I find that in the short run, one’s occupation can account for three quarters of the variation in outcomes between an equilibrium where import costs move, and one where they do not. However, in the long run one’s occupation can only account for 60% of this variation. This gap between the short run and long run, which takes 15 years to close, suggests that large switching costs induces workers to remain in their initial occupations, even if this occupation now offers lower wages. Despite no market failure in my economy, the costs of transition open up scope for policy makers interested in compensating workers dislocated by trade shocks. For exam-
ple, the sluggish response of workers suggests a role for retraining programs or direct subsidies to occupational switching. These are important questions for future research.

Finally, in my simulations I am able to demonstrate exactly how the sluggish adjustment discussed above maps into gains and losses for different workers. For example, I show that in the short run the spread in changes in income across workers is 5 times the magnitude of changes in total income. However, this spread attenuates in the long run. The fact that wages across occupations can take several years to reach their steady state level is seemingly at odds with the finding that average income in the economy reaches its steady state level quickly. To reconcile these facts, it must be that the gains to those who gain from trade roughly offset the losses to other workers along the entire transition path, but the gap in gains and losses is larger in the short run. This finding may partially help make sense of the perceived dissatisfaction that many workers in developed countries have with globalization. It may be that the long run benefits simply do not accrue to a great deal of workers.

My paper opens up several avenues for future work. In terms of modeling, recent work on dynamic discrete choice has opened up the door to allowing for a richer specification of the process governing wage and moving cost shocks. It would be interesting to test if these extensions, for example a Markov chain on worker types, changes the analysis. The model as it stands also can be used to answer a host of related questions that I did not answer. In particular, one can use my model to explore not simply the effects of changes in import costs, but also the, likely positive, effects of increased export demand for the Danish economy. Understanding the extent, if any, to which export demand may offset the effects of import competition is crucial to researchers and policy makers analyzing changes in trade costs. One could also use the model to simulate actual labor market policies.
### Appendix A: Tables

#### Table 1.1: Examples of Tasks

<table>
<thead>
<tr>
<th>Task 1: Communicative Activities</th>
<th>Task 2: Monitoring</th>
</tr>
</thead>
<tbody>
<tr>
<td>Written Expression</td>
<td>Far Vision</td>
</tr>
<tr>
<td>Written Comprehension</td>
<td>Operation Monitoring</td>
</tr>
<tr>
<td>Writing</td>
<td>Perceptual Speed</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Task 3: Facetime Tasks</th>
<th>Task 8: Routine Maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performing for or Working Directly with the Public</td>
<td>Installation</td>
</tr>
<tr>
<td>Assisting and Caring for Others</td>
<td>Repairing</td>
</tr>
<tr>
<td>Resolving Conflicts and Negotiating with Others</td>
<td>Equipment Maintenance</td>
</tr>
</tbody>
</table>

Tasks calculated from PCA on the US Department of Labor’s O*Net surveys for US SOC 2000 occupational codes. This presents the survey questions receiving the highest loadings in several example tasks.
Table 1.2: Income Regression Coefficients

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Age²</th>
<th>Tenure</th>
<th>High School L</th>
<th>H</th>
<th>Some Coll. L</th>
<th>H</th>
<th>College+ H</th>
</tr>
</thead>
<tbody>
<tr>
<td>MANU.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Managers</td>
<td>5.74</td>
<td>-0.06</td>
<td>3.85</td>
<td>-58.16</td>
<td>42.44</td>
<td>48.18</td>
<td>-26.84</td>
<td>53.12</td>
</tr>
<tr>
<td>Science Professional</td>
<td>6.46</td>
<td>-0.07</td>
<td>7.42</td>
<td>0.00</td>
<td>0.00</td>
<td>15.79</td>
<td>-23.48</td>
<td>17.97</td>
</tr>
<tr>
<td>Science Assc. Professional</td>
<td>6.18</td>
<td>-0.06</td>
<td>4.60</td>
<td>-22.86</td>
<td>35.23</td>
<td>38.42</td>
<td>-0.34</td>
<td>48.08</td>
</tr>
<tr>
<td>Other Assc. Professional</td>
<td>6.47</td>
<td>-0.07</td>
<td>6.54</td>
<td>-24.93</td>
<td>28.12</td>
<td>32.90</td>
<td>-4.89</td>
<td>37.91</td>
</tr>
<tr>
<td>Clerks</td>
<td>7.40</td>
<td>-0.08</td>
<td>6.74</td>
<td>-21.41</td>
<td>43.78</td>
<td>50.07</td>
<td>9.11</td>
<td>52.62</td>
</tr>
<tr>
<td>Agriculture</td>
<td>3.83</td>
<td>-0.04</td>
<td>1.59</td>
<td>-2.95</td>
<td>105.43</td>
<td>115.12</td>
<td>13.86</td>
<td>100.42</td>
</tr>
<tr>
<td>Building Trades</td>
<td>5.04</td>
<td>-0.05</td>
<td>4.70</td>
<td>-3.93</td>
<td>59.40</td>
<td>65.45</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Metal Trades</td>
<td>4.23</td>
<td>-0.05</td>
<td>4.85</td>
<td>39.80</td>
<td>91.07</td>
<td>98.57</td>
<td>52.40</td>
<td>85.28</td>
</tr>
<tr>
<td>Other Crafts</td>
<td>5.11</td>
<td>-0.05</td>
<td>6.45</td>
<td>-18.42</td>
<td>40.29</td>
<td>56.98</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Plant Operator</td>
<td>6.69</td>
<td>-0.07</td>
<td>6.55</td>
<td>-45.58</td>
<td>79.34</td>
<td>89.90</td>
<td>47.36</td>
<td>66.86</td>
</tr>
<tr>
<td>Machine Operator</td>
<td>4.14</td>
<td>-0.04</td>
<td>5.98</td>
<td>-22.99</td>
<td>33.55</td>
<td>44.35</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Drivers</td>
<td>4.10</td>
<td>-0.04</td>
<td>6.96</td>
<td>-3.50</td>
<td>29.63</td>
<td>32.97</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Laborers</td>
<td>3.85</td>
<td>-0.04</td>
<td>6.90</td>
<td>-35.64</td>
<td>46.11</td>
<td>52.22</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Mean</td>
<td>5.33</td>
<td>-0.06</td>
<td>5.62</td>
<td>-9.95</td>
<td>48.80</td>
<td>5.17</td>
<td>35.56</td>
<td></td>
</tr>
</tbody>
</table>

| SERVICES              |       |       |        |               |   |              |   |            |
| Managers              | 5.58  | -0.06 | 3.60   | -23.70        | 86.34 | 89.90        | 9.48   | 90.77      |
| Science Professional  | 8.54  | -0.09 | 7.22   | -29.00        | 96.04 | 103.79       | 14.42  | 95.45      |
| Other Professional    | 9.99  | -0.10 | 5.99   | -39.49        | 68.44 | 72.05        | -28.22 | 69.20      |
| Science Assc. Professional | 6.61  | -0.07 | 4.41   | -14.07        | 83.70 | 86.06        | 31.66  | 88.49      |
| Other Assc. Professional | 6.46  | -0.07 | 4.66   | -29.50        | 60.51 | 64.72        | 19.29  | 55.74      |
| Clerks                | 6.87  | -0.07 | 5.15   | -14.38        | 82.74 | 87.13        | 36.20  | 68.55      |
| Personal Workers      | 9.36  | -0.10 | 9.99   | -5.21         | 77.02 | 91.52        | 14.69  | 52.27      |
| Retail Workers        | 9.80  | -0.11 | 5.37   | -38.72        | 36.77 | 58.20        | 0.00   | 0.00       |
| Metal Trades          | 4.82  | -0.05 | 4.17   | -24.08        | 57.96 | 65.99        | 0.00   | 0.00       |
| Drivers               | 4.88  | -0.05 | 5.64   | -20.40        | 41.83 | 47.46        | 0.00   | 0.00       |
| Elementary Occupations| 7.62  | -0.08 | 5.76   | 0.32          | 76.85 | 92.19        | 21.88  | 62.55      |
| Laborers              | 6.30  | -0.07 | 9.21   | -33.04        | 56.45 | 63.03        | 0.00   | 0.00       |
| Mean                  | 7.24  | -0.08 | 5.93   | -22.61        | 68.72 | 9.95         | 76.84  | 48.59      |

| FIRE                  |       |       |        |               |   |              |   |            |
| Managers              | 6.38  | -0.06 | 2.97   | -9.85         | 107.25| 114.57       | -1.44  | 119.05     |
| Science Professional  | 7.72  | -0.08 | 6.62   | -118.39       | 28.76 | 35.37        | -15.98 | 32.72      |
| Other Professional    | 10.46 | -0.11 | 6.87   | -66.71        | 33.96 | 41.11        | -24.49 | 38.61      |
| Science Assc. Professional | 7.42  | -0.08 | 5.86   | -42.08        | 40.53 | 42.79        | -3.43  | 44.83      |
| Other Assc. Professional | 6.75  | -0.07 | 5.21   | -33.70        | 38.83 | 46.54        | -4.06  | 47.00      |
| Clerks                | 9.53  | -0.10 | 7.70   | -23.08        | 63.63 | 72.71        | 17.63  | 64.52      |
| Customer Service      | 5.92  | -0.06 | 3.84   | -35.83        | 40.34 | 49.54        | 0.00   | 0.00       |
| Mean                  | 7.74  | -0.08 | 5.58   | -47.09        | 50.47 | 5.47         | 57.52  | 49.53      |

| HEALTH & EDUC.        |       |       |        |               |   |              |   |            |
| Health Professional   | 6.75  | -0.07 | 3.79   | 0.00          | 0.00  | 0.00         | 0.00   | 46.03      |
| Teachers              | 9.12  | -0.09 | 6.61   | -30.61        | 76.84 | 80.09        | -18.63 | 88.98      |
| Health Assc. Professional | 6.14  | -0.06 | 4.13   | -58.42        | 24.92 | 53.18        | -7.30  | 51.05      |
| Teaching Assc. Professional | 7.78  | -0.08 | 6.38   | -38.01        | 27.71 | 55.88        | -54.59 | 53.16      |
| Clerks                | 7.01  | -0.07 | 9.17   | -2.84         | 67.36 | 76.47        | 27.87  | 49.92      |
| Personal Workers      | 5.23  | -0.05 | 7.39   | -17.96        | 62.60 | 67.27        | 22.30  | 52.79      |
| Mean                  | 7.00  | -0.07 | 6.25   | -24.64        | 43.24 | -5.06        | 56.82  | 56.99      |

Presents coefficients of a mincer regression on workers in Denmark. Unobserved types identified from an EM algorithms described in the text. Coefficients are presented x 100%. Mean refers to the unweighted average across occupations. College educated low type is the reference group for unobserved types and normalized to 0. Zeroes in the comparative advantage imply that the occupation is not in the choice set of that skill group.
Table 1.3: Type Distribution

<table>
<thead>
<tr>
<th>Type</th>
<th>Unconditional Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>No College: L</td>
<td>0.025</td>
</tr>
<tr>
<td>No College: H</td>
<td>0.237</td>
</tr>
<tr>
<td>Some College: L</td>
<td>0.056</td>
</tr>
<tr>
<td>Some College: H</td>
<td>0.396</td>
</tr>
<tr>
<td>College+: L</td>
<td>0.031</td>
</tr>
<tr>
<td>College+: H</td>
<td>0.255</td>
</tr>
</tbody>
</table>

Presents the distribution of unobservable types in the population estimated from an EM algorithm on wages, taking into account worker selection into occupations.

Table 1.4: Occupation Fixed Effects

<table>
<thead>
<tr>
<th>SECTOR</th>
<th>Occupation</th>
<th>$\eta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MANUFACTURING</td>
<td>Managers</td>
<td>2.06</td>
</tr>
<tr>
<td></td>
<td>Science Professional</td>
<td>2.02</td>
</tr>
<tr>
<td></td>
<td>Science Assc. Professional</td>
<td>1.93</td>
</tr>
<tr>
<td></td>
<td>Other Assc. Professional</td>
<td>1.97</td>
</tr>
<tr>
<td></td>
<td>Clerks</td>
<td>1.93</td>
</tr>
<tr>
<td></td>
<td>Agriculture</td>
<td>1.98</td>
</tr>
<tr>
<td></td>
<td>Building Trades</td>
<td>1.90</td>
</tr>
<tr>
<td></td>
<td>Metal Trades</td>
<td>2.19</td>
</tr>
<tr>
<td></td>
<td>Other Crafts</td>
<td>1.19</td>
</tr>
<tr>
<td></td>
<td>Plant Operator</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>Machine Operator</td>
<td>1.89</td>
</tr>
<tr>
<td></td>
<td>Drivers</td>
<td>2.10</td>
</tr>
<tr>
<td></td>
<td>Laborers</td>
<td>2.31</td>
</tr>
<tr>
<td></td>
<td><strong>Mean</strong></td>
<td><strong>1.87</strong></td>
</tr>
<tr>
<td>SERVICES</td>
<td>Managers</td>
<td>2.33</td>
</tr>
<tr>
<td></td>
<td>Science Professional</td>
<td>2.53</td>
</tr>
<tr>
<td></td>
<td>Other Professional</td>
<td>2.44</td>
</tr>
<tr>
<td></td>
<td>Science Assc. Professional</td>
<td>1.94</td>
</tr>
<tr>
<td></td>
<td>Other Assc. Professional</td>
<td>2.29</td>
</tr>
<tr>
<td></td>
<td>Clerks</td>
<td>2.51</td>
</tr>
<tr>
<td></td>
<td>Personal Workers</td>
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</tr>
<tr>
<td></td>
<td>Retail Workers</td>
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</tr>
<tr>
<td></td>
<td>Metal Trades</td>
<td>2.71</td>
</tr>
<tr>
<td></td>
<td>Drivers</td>
<td>2.42</td>
</tr>
<tr>
<td></td>
<td>Elementary Occupations</td>
<td>2.29</td>
</tr>
<tr>
<td></td>
<td>Laborers</td>
<td>2.16</td>
</tr>
<tr>
<td></td>
<td><strong>Mean</strong></td>
<td><strong>2.34</strong></td>
</tr>
<tr>
<td>FIRE</td>
<td>Managers</td>
<td>2.57</td>
</tr>
</tbody>
</table>

Continued on next page
### Table 1.4: Occupation Fixed Effects

<table>
<thead>
<tr>
<th>SECTOR</th>
<th>Occupation</th>
<th>η</th>
</tr>
</thead>
<tbody>
<tr>
<td>Science Professional</td>
<td>2.46</td>
<td></td>
</tr>
<tr>
<td>Other Professional</td>
<td>2.43</td>
<td></td>
</tr>
<tr>
<td>Science Assc. Professional</td>
<td>2.15</td>
<td></td>
</tr>
<tr>
<td>Other Assc. Professional</td>
<td>2.09</td>
<td></td>
</tr>
<tr>
<td>Clerks</td>
<td>2.29</td>
<td></td>
</tr>
<tr>
<td>Customer Service</td>
<td>1.45</td>
<td></td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td><strong>2.21</strong></td>
<td></td>
</tr>
<tr>
<td>HEALTH &amp; EDUC.</td>
<td>Health Professional</td>
<td>1.98</td>
</tr>
<tr>
<td>Teachers</td>
<td>2.26</td>
<td></td>
</tr>
<tr>
<td>Health Assc. Professional</td>
<td>2.06</td>
<td></td>
</tr>
<tr>
<td>Teaching Assc. Professional</td>
<td>2.44</td>
<td></td>
</tr>
<tr>
<td>Clerks</td>
<td>2.40</td>
<td></td>
</tr>
<tr>
<td>Personal Workers</td>
<td>3.22</td>
<td></td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td><strong>2.39</strong></td>
<td></td>
</tr>
</tbody>
</table>

Presents non-pecuniary value of an occupation. All values are relative to the value of non-employment of college-educated low types, as one constant must always be normalized to 0. Mean refers to the unweighted average across occupations.

### Table 1.5: Non-Employment Virtual Wage

\[ w^N(\omega) = \beta_0^f + \beta_1^f \omega + \beta_2^f \omega^2 + \sum_i \beta_i^f \times D_i \]

**Age Params.**
- \( \beta_0^f \): .011
- \( \beta_2^f \): \(-4.19 \times 10^{-4}\)

**Type Params.**
- \( \beta_1^f \): .441
- \( \beta_2^f \): .411
- \( \beta_3^f \): .037
- \( \beta_4^f \): .328
- \( \beta_5^f \): 0
- \( \beta_6^f \): -.283

Presents the parameters governing non-employment calculated from the structural model. The dummies refer to types. Types 1 and 2 are high school educated low and high type respectively; Types 3 and 4 are some college educated workers, low and high type respectively; Types 5 and 6 are low and high type educated workers respectively. Educated low types are the baseline.
Table 1.6: Switching Cost Matrix Across Occupations

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Managers</td>
<td>3.76</td>
<td>6.65</td>
<td>6.05</td>
<td>4.40</td>
<td>5.70</td>
<td>5.97</td>
<td>5.62</td>
<td>6.62</td>
<td>5.16</td>
</tr>
<tr>
<td>Professionals</td>
<td>4.63</td>
<td>5.75</td>
<td>5.13</td>
<td>3.89</td>
<td>5.08</td>
<td>6.15</td>
<td>5.30</td>
<td>6.44</td>
<td>5.07</td>
</tr>
<tr>
<td>Technicians</td>
<td>5.05</td>
<td>6.10</td>
<td>5.29</td>
<td>3.71</td>
<td>5.25</td>
<td>6.13</td>
<td>5.34</td>
<td>6.43</td>
<td>5.17</td>
</tr>
<tr>
<td>Clerks</td>
<td>6.87</td>
<td>8.58</td>
<td>6.96</td>
<td>4.07</td>
<td>6.90</td>
<td>8.86</td>
<td>7.70</td>
<td>9.06</td>
<td>7.30</td>
</tr>
<tr>
<td>Service Workers</td>
<td>5.91</td>
<td>7.66</td>
<td>6.56</td>
<td>4.59</td>
<td>4.89</td>
<td>6.32</td>
<td>6.37</td>
<td>7.32</td>
<td>5.56</td>
</tr>
<tr>
<td>Agriculture</td>
<td>5.26</td>
<td>7.74</td>
<td>6.46</td>
<td>5.00</td>
<td>5.36</td>
<td>4.50</td>
<td>5.24</td>
<td>4.64</td>
<td></td>
</tr>
<tr>
<td>Crafts &amp; Trade</td>
<td>5.97</td>
<td>7.97</td>
<td>6.71</td>
<td>5.14</td>
<td>6.55</td>
<td>5.58</td>
<td>5.24</td>
<td>6.12</td>
<td>5.37</td>
</tr>
<tr>
<td>Machinists</td>
<td>5.14</td>
<td>7.07</td>
<td>5.87</td>
<td>4.41</td>
<td>5.52</td>
<td>4.79</td>
<td>4.45</td>
<td>4.99</td>
<td>4.39</td>
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<tr>
<td>Elementary Labor</td>
<td>5.42</td>
<td>7.57</td>
<td>6.49</td>
<td>4.88</td>
<td>5.49</td>
<td>5.62</td>
<td>5.35</td>
<td>6.06</td>
<td>4.62</td>
</tr>
</tbody>
</table>

Presents average costs by ISCO 1 digit occupations. Costs are not weighted by actual transitions or worker type. So this reflects the baseline costs that workers would pay if they made these transitions, uncorrected for worker’s switching productivity. The diagonal elements reflect the average cost of moving between ISCO 2 digit occupations within a broader category and off-diagonal elements reflect average costs between broader categories.

Table 1.7: Inverse Switching Productivity Parameters

\[ f(\omega) = \exp(\beta f_a \cdot a + \beta f_a^2 \cdot a^2 + \sum_i \beta f_i \times D_i) \]

<table>
<thead>
<tr>
<th>Age Params.</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta _{f_a} )</td>
<td>.0158</td>
</tr>
<tr>
<td>( \beta _{f_a^2} )</td>
<td>( 1.501 \times 10^{-4} )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Type Params.</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta _1 )</td>
<td>.06</td>
</tr>
<tr>
<td>( \beta _2 )</td>
<td>.17</td>
</tr>
<tr>
<td>( \beta _3 )</td>
<td>.20</td>
</tr>
<tr>
<td>( \beta _4 )</td>
<td>.11</td>
</tr>
<tr>
<td>( \beta _5 )</td>
<td>0</td>
</tr>
<tr>
<td>( \beta _6 )</td>
<td>.086</td>
</tr>
</tbody>
</table>

Presents the parameters governing search costs calculated from the structural model. The dum-
 mies refer to types. Types 1 and 2 are high school educated low and high type respectively. Types
3 and 4 are some college educated workers, low and high type respectively. Types 5 and 6 are
low and high type educated workers respectively. Educated low types are the baseline.
### Table 1.8: Mobility Costs by Age Group

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Q25</th>
<th>Q50</th>
<th>Q75</th>
</tr>
</thead>
<tbody>
<tr>
<td>25-29</td>
<td>11.81</td>
<td>7.51</td>
<td>10.45</td>
<td>14.57</td>
</tr>
<tr>
<td>30-39</td>
<td>8.74</td>
<td>5.77</td>
<td>7.74</td>
<td>10.68</td>
</tr>
<tr>
<td>40-49</td>
<td>7.33</td>
<td>4.96</td>
<td>6.51</td>
<td>8.95</td>
</tr>
<tr>
<td>50+</td>
<td>7.05</td>
<td>4.83</td>
<td>6.28</td>
<td>8.47</td>
</tr>
</tbody>
</table>

Presents costs from empirical distribution of workers conditional on age. Costs are displayed relative to the unconditional mean income in the economy (e.g., a value of 4 means 4 years’ income of the average Dane). \(Q_\alpha\) refers to the \(\alpha\) percentile of the distribution. These values do not take into account the idiosyncratic shocks that workers face (compare to figure 1.10).

### Table 1.9: Mobility Costs by Skill and Type

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Q25</th>
<th>Q50</th>
<th>Q75</th>
</tr>
</thead>
<tbody>
<tr>
<td>No College: L</td>
<td>16.76</td>
<td>11.45</td>
<td>16.22</td>
<td>21.07</td>
</tr>
<tr>
<td>No College: H</td>
<td>6.54</td>
<td>4.35</td>
<td>5.78</td>
<td>8.03</td>
</tr>
<tr>
<td>Some Coll: H</td>
<td>6.30</td>
<td>4.38</td>
<td>5.72</td>
<td>7.73</td>
</tr>
<tr>
<td>Some College: L</td>
<td>8.90</td>
<td>6.10</td>
<td>7.99</td>
<td>10.73</td>
</tr>
<tr>
<td>College+ H</td>
<td>5.93</td>
<td>3.59</td>
<td>4.83</td>
<td>7.02</td>
</tr>
<tr>
<td>College+ L</td>
<td>9.15</td>
<td>5.67</td>
<td>7.73</td>
<td>11.09</td>
</tr>
</tbody>
</table>

Presents costs from empirical distribution of workers conditional on a skill and unobservable type. Costs are displayed relative to the unconditional mean income in the economy (e.g., a value of 4 means 4 years’ income of the average Dane). \(Q_\alpha\) refers to the \(\alpha\) percentile of the distribution. These values do not take into account the idiosyncratic shocks that workers face (compare to figure 1.10).

### Table 1.10: Switching Cost Matrix Across Sectors

<table>
<thead>
<tr>
<th>From \ To</th>
<th>Man.</th>
<th>Services</th>
<th>FIRE</th>
<th>Health/Educ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing</td>
<td>5.53</td>
<td>5.86</td>
<td>5.84</td>
<td>6.08</td>
</tr>
<tr>
<td>Services</td>
<td>5.68</td>
<td>5.88</td>
<td>5.69</td>
<td>5.80</td>
</tr>
<tr>
<td>FIRE</td>
<td>6.00</td>
<td>5.96</td>
<td>5.59</td>
<td>5.87</td>
</tr>
<tr>
<td>Health &amp; Educ.</td>
<td>6.41</td>
<td>6.34</td>
<td>6.18</td>
<td>5.55</td>
</tr>
</tbody>
</table>

Presents average costs by broad sector. Costs are not weighted by actual transitions or worker type. So this reflects the baseline costs that workers would pay if they made these transitions, uncorrected for worker’s switching productivity. The diagonal elements reflect the average cost of moving between ISCO 2 digit occupations within a broader category and off-diagonal elements reflect average costs between broader categories.
Table 1.11: Mobility Costs by Transition Type

<table>
<thead>
<tr>
<th>Transition Type</th>
<th>Mean</th>
<th>$Q_{25}$</th>
<th>$Q_{50}$</th>
<th>$Q_{75}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector Only</td>
<td>4.83</td>
<td>4.44</td>
<td>4.78</td>
<td>5.13</td>
</tr>
<tr>
<td>Occ. Only</td>
<td>6.19</td>
<td>4.73</td>
<td>6.12</td>
<td>7.20</td>
</tr>
<tr>
<td>Both</td>
<td>6.65</td>
<td>5.16</td>
<td>6.56</td>
<td>7.90</td>
</tr>
</tbody>
</table>

Presents costs from empirical distribution of workers conditional on a switch type. Costs are displayed relative to the unconditional mean income in the economy (e.g., a value of 4 means 4 years' income of the average Dane). These values do not take into account the idiosyncratic shocks that workers face (compare to figure 1.10).
1.9.2 Appendix B: Figures

Figure 1.2: Patterns of Switching Over Time

A transition at time $t + 1$ is defined as a worker who changes occupation status, sector status or both based on their status in the previous year. Figure based on transitions of all workers over 23 who are employed in both periods $t$ and $t + 1$. This does not include workers who enter unemployment or transition occupations through unemployment. An occupation is defined as an ISCO 2 digit code. Manufacturing includes construction, agriculture and utilities and corresponds to NACE 1 2-digit codes 0-45; FIRE refers to NACE 1 2-digit codes 64-74; Public Services refer to NACE 1 2-digit codes 75, 80, 85-90; Other Services contains all remaining codes.

Figure 1.3: Patterns of Switching by Age

A transition at time $t + 1$ is defined as a worker who changes occupation status, sector status or both based on their status in the previous year. Figure based on transitions of all workers over 23 who are employed in both periods $t$ and $t + 1$. This does not include workers who enter unemployment or transition occupations through unemployment. For ease of visualization, this figure aggregates switching across occupations, sectors and both. Figure 1.2 contains a break down along different kinds of transitions.
Figure 1.4: Growth in the Variance of Earnings

This figure plots the growth of variance of earnings, defined as income in November employment, relative to 1994 earnings variance. The sample only includes those workers who are over 23 years of age, and with data on education. The dashed line includes the following controls: linear and quadratic terms in age, occupation fixed effects, and skill level fixed effects (no college, some college and college graduate).

Figure 1.5: Explanatory Power of Occupations

Figure plots the ratio of the between component of a variance decomposition to the total variance of earnings. i.e., for a variance decomposition of earnings: $\text{Var}(u) = \text{Var}(E(u|g)) + E(\text{Var}(u|g))$ where $g$ is a group (either occupations or firms), the figure plots the ratio of the first term on the right to the term on the left. This is equivalent to an $R^2$ of earnings on group fixed effects.
The Effect of Import Shocks on Occupational Demand

Figure plots the relationship between a measure of import competition and employment growth. Dependent variable is the log change in the share of an occupation-sector code in total employment from 1996 to 2007. Dependent variable is measured as the change in imports per head in a sector-occupation over the same period. Imports (measured in 1000s of DKK) of NACE 1 4-digit industries are allocated to an occupation-sector based on the share of that occupation-sector in the total wage bill of each industry. The plotted line is a best fit line with observations weighted by their initial share in total employment.

Import Shocks and Occupational Switching

This figure plots the log change in transition rates across occupation-sector pairs on the change in an import exposure measure. A transition is defined as a change in an occupation-sector from $t$ to $t+1$, conditioned on continued employment. Dependent variable is the difference in year-on-year changes in imports per head across pairs. For example, if imports per head grow by 500 DKK/head in occupation $A$ and by 300 in occupation $B$ then the dependent variable would be the log change in transition rates from $A$ to $B$ and the independent variable would be 200. I also remove occupation-sector pairwise fixed effect to deal with level differences in movement. I.e., some transitions happen more regularly ceteris paribus so this looks at variation within a pair of occupations over time.
Figure 1.8: Histogram of Switching Costs

This figure plots the empirical density of mean switching costs (i.e., costs exclusive of shocks) across workers in Denmark. It is weighted by the observed switching in Denmark. Costs are calculated from a structural model defined in the text. The plot is conditional on switching as less than 15% of workers switch occupations in a given year. Costs are displayed relative to the unconditional mean income in the economy (e.g., a value of 4 means 4 years’ income of the average Dane). These values do not take into account the idiosyncratic shocks that workers face (compare to figure 1.10).

Figure 1.9: Histogram of Switching Costs Relative to Income

This figure plots the empirical density of mean switching costs (i.e., costs exclusive of shocks) across workers in Denmark. It is weighted by the observed switching in Denmark. Costs are calculated from a structural model defined in the text. The plot is conditional on switching as less than 15% of workers switch occupations in a given year. Costs are displayed relative to the expected income of the switching worker had they not switched. E.g., for a worker moves from $A$ to $B$ at time $t$ to $t + 1$, then costs are displayed relative to $E(w_{A}|t + 1)$ where $w$ is earnings. These values do not take into account the idiosyncratic shocks that workers face (compare to figure 1.10).
This figure plots the empirical density of expected switching costs \textit{conditional} on a switch having taken place. It is weighted by the observed switching in Denmark, and as such reflects an estimate of actual utility costs faced by workers. E.g., if costs are \( c + \epsilon \) then this plots \( c + E(\epsilon |\text{switch}) \) where \( \epsilon \) is GEV distributed and \( c \) is estimated from the structural model defined in the text. The plot is conditional on switching as less than 15% of workers switch occupations in a given year. Costs are displayed relative to the unconditional mean income in the economy (e.g., a value of 4 means 4 years ’ income of the average Dane).

This figure plots the density of exit costs across occupations. It is not weighted by actual observed occupations nor does it take into account that costs vary with workers’ states—so it is an average. Exit costs are defined as the mean cost of entering any other occupation from a base occupation. For example, for occupation \( o \), the exit (or “target”) cost is defined as \( C_{\text{exit}}(o) = \frac{1}{|O|} \sum_{o'} C(o, o') \) where \( C \) is estimated and defined in a structural model. This can be compared to an entry (or “source”) cost that sums up the cost of entering an occupation from any other occupation. I.e., \( \frac{1}{|O|} \sum_{o'} C(o', o) \). I focus on the former to measure the difficulty of moving out of an occupation.
Figure 1.12: Density of Switching Costs by Type of Transition

This figure plots the empirical density of mean switching costs (i.e., costs exclusive of shocks) across workers in Denmark by type of transition (occupations and sectors are defined more precisely in the main text). It is weighted by the observed switching in Denmark. Costs are calculated from a structural model defined in the text. The plot is conditional on switching as less than 15% of workers switch occupations in a given year. Costs are displayed relative to the unconditional mean income of workers in Denmark.

Figure 1.13: Model Fit: Predicted Versus Actual Transitions

Observed transitions (including non-movement and movements into non-employment) from 1996 to 1997 plotted against transitions simulated from my structural model. The 45 degree line implies a perfect fit while the solid line is a best fit line unweighted by transition sizes ($R^2 \approx 0.75$). For the simulation I used only the labor supply model and fed in the time series of wages from 1996 through 2007. For expectations, workers have perfect foresight to 2007 then assume wages are frozen indefinitely.
Figure 1.14: Full Model Fit: Size Distribution of Occupations

This figure plots observed transitions (including non-movement and movements into non-employment) from 1996 to 1997 against transitions simulated from the structural model. The red line is the 45 degree line and implies a perfect fit. This simulation uses both the demand and supply sides of the economy. Simulation uses actual changes in exogenous variables to 2007 and treats them as frozen thereafter. Workers are assumed to have perfect foresight.

Figure 1.15: Full Model Fit: Wages

This figure plots observed skill prices in 1997 against skill prices in 1997 simulated from the structural model. The red line is the 45 degree line and implies a perfect fit. This simulation uses both the demand and supply sides of the economy. Simulation uses actual changes in exogenous variables to 2007 and treats them as frozen thereafter. Workers are assumed to have perfect foresight.
Plot the time series of foreign price indices in NACE 1 two digit industries. Index is normalized to 1 in 1996. Price indices are calculated using a geometric mean of the the average ratio of foreign to domestic prices published by Stats DK, an author-calculated CES index based on COMTRADE data and an author-calculated CES index based on Stats DK provided customs data. For the CES index, HS6-country pairs are treated as varieties. All prices are converted into real terms by the Danish CPI so the indices are relative to the household’s domestic price index.

**Figure 1.17: Import Price Index**

Plots the time series of import-weighted price indices in Denmark across two-digit NACE 1 industries. For each industry an index is calculated (described in the text or in the footer to figure 1.16). These indices are aggregated based on import shares of each industry. The solid black line weights by current import shares so that $P_{t+1}/P_t = \sum_i s_{i,t+1} P_{i,t+1}/P_{i,t}$ while the dotted line weights by initial shares in 1996. All prices are converted into real terms by the Danish CPI so the indices are relative to the household’s domestic price index.
Figure 1.18: Aggregate GDP: Holding 1996 Prices Fixed

Plots the difference in the real value of total output between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. Period 0 corresponds to the year 2005, the last period of observed cost changes. All other exogenous variables are held fixed at 1996 levels.

Figure 1.19: Labor Income: Holding 1996 Prices Fixed

Plots the difference in the real value of total labor income between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. Period 0 corresponds to the year 2005, the last period of observed cost changes. All other exogenous variables are held fixed at 1996 levels.
Figure 1.20: Employment Growth: Holding 1996 Prices Fixed

Plots the log changes in employment shares for each occupation between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. The colors reflect the sectors in the economy, which are defined in the main text. The changes are taken at the steady states of each economy—35 periods after the last changes in trade costs. In the simulations, all exogenous variables besides trade costs are held fixed at 1996 levels.

Figure 1.21: Sectoral Growth: Holding 1996 Prices Fixed

Plots the log changes in employment shares for each economic sector between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. The changes are taken at the steady states of each economy—35 periods after the last changes in trade costs. In the simulations, all exogenous variables besides trade costs are held fixed at 1996 levels.
Figure 1.22: Variance Decomposition of Changes in Outcomes

![Graph](image)

Plots the ratio of the across component of a variance decomposition of differences in income for workers across two equilibria against total variance in income. This variance decomposition is done for three divisions of workers—by occupation, by sector, and by occupation crossed with sector. For calculating differences in income I used the change in income in each period between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. For the weights (of workers) in the variance decomposition I used their weights in the equilibrium with moving trade costs. Period 0 refers to the year 2005—the last year that trade costs change in the model. In the simulations, all exogenous variables besides trade costs are held fixed at 1996 levels.

Figure 1.23: Skill Prices in Manufacturing Over Time

![Graph](image)

Plots the percent difference in skill prices of each occupation in manufacturing between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. Period 0 refers to the year 2005—the last year that trade costs change in the model. In the simulations, all exogenous variables besides trade costs are held fixed at 1996 levels.
Figure 1.24: Net Present Value Effects of Trade, Manufacturing: 1996 Prices

Plots the levels change in value functions for workers in manufacturing between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. Units converted from DKK to USD. The differences are taken in period 1—the first year that trade costs no longer change in the model.

Figure 1.25: Net Present Value Effects of Trade, Non Manufacturing: 1996 Prices

Plots the levels change in value functions for workers in non-manufacturing between a simulated economy facing observed changes in trade costs from 1996 to 2005 and a simulation holding trade costs fixed at their initial levels. Units converted from DKK to USD. The differences are taken in period 1—the first year that trade costs no longer change in the model.
Chapter 2

Offshoring and the Shortening of the Quality Ladder: Evidence from Danish Apparel *

2.1 Introduction

The gains and losses from trade arise through many channels. For example, breaking away from assumptions of perfect competition and homogeneity have allowed economists to study the variety gains and pro-competitive effects of trade liberalization. Recent work has also highlighted cross-country differences in product quality and how access to new markets can effect the quality of consumer goods. This research has mostly been limited to studying cross-country datasets. However, it is also interesting to ask how the distribution of quality within a country changes. For example, if the average quality of a good increases is this because low quality goods left the market or because high quality goods became more available? This matters when consumers themselves are heterogeneous in their preferences. Our paper contributes to filling this gap by estimating how the distribution of apparel quality across firms within Denmark changed in response to Chinese

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*This chapter was co-authored with Valerie Smeets and Frederic Warzynski. Sharon thanks Stephen Redding and Jan De Loecker for substantial guidance on this project. A special thanks to Henning Bunzel for help with the data. We are also thankful to Thomas Chaney, Jonathan Eaton, Oleg Itskhoki, Amit Khandelwal, Thierry Mayer, Mark Roberts, John Romalis and participants at IIOC 2014, the “Aggregate Implications of International Capital Flows and Offshoring” session at the 2015 ASSA, University of Paris Trade Seminar, NOITS 2014, the Toulouse School of Economics, the BBVA Foundation-Ivie Workshop on Trade, Growth and Product Quality and EITI (ASEAN Institute, 2014). Sharon Traiberman received financial support from a Princeton IES Summer Grant, the International Economics Section at Princeton, the Economics Department at Princeton and Aarhus University.
across to the WTO, thus giving firms access to a new set of inputs.

Two recent observations in the literature drive our research question. First, the quality of goods varies substantially across countries.\footnote{See Hallak (2006), Khandelwal (2010), and Hallak and Schott (2011)} Second, a large fraction of trade growth has been in intermediates, offshoring and supply chain disintegration.\footnote{See Yi (2003), Feenstra (2010) and Costinot et al. (2013).} Putting these facts side-by-side offers a mechanism for trade to affect the menu of goods available to consumers within a country. In particular, one can ask whether firms’ importing of cheaper (and thus potentially lower quality) inputs affects their output quality in an appreciable way. This channel is distinct from the effect of trade on output markets, as it is not about the entry and exit of new goods, but also changes to extant goods.

To determine the impact of these new input markets on firms’ domestic output we structurally estimate apparel demand in the Danish economy. We link together and exploit several novel datasets that contain domestic production, trade, and sales of apparel at the firm and product level. Following Khandelwal (2010) and Berry (1994), we estimate a logit demand system that allows us to recover a demand shifter from a regression of prices on market shares. We will interpret this shifter as an estimate, or at least proxy, of output quality. Thus, quality can be interpreted as any force that induces to consumers to buy more of a good than would be predicted given the price of that good.\footnote{In this sense, we take the view of Sutton (2012) who writes that quality “includes not just ‘quality’ in the usual narrow sense (a feature of the product’s physical characteristics), but also a range of characteristics that include, for example: brand advertising... services... and logistics” (Sutton, 2012, p.17).}

The major econometric challenge in demand estimation rests in finding an instrument for price, as it is likely correlated with quality. To get around this challenge we use the peculiarities of our environment and the richness of our dataset to construct exogenous cost shifters that act as instruments. In particular, we exploit the fact that apparel firms make their design and sourcing decisions well in advance of their pricing decision. Thus, we use unanticipated shocks to trade costs as instruments for price that are not correlated with the initial quality and sourcing decisions. Our dataset includes firm-product level information on price and quantity at a fine level: our unit of observation...
are Combined Nomenclature 8 digit goods for each firm, which are a strict refinement of the HS6 classification.

With our estimation in hand we turn to analysis of how the distribution of quality has evolved in Denmark in response to trade shocks. The object we focus on is the distance between the highest and lowest quality goods in the market at a point in time. Following Khandelwal (2010) and others, we refer to this as the length of the quality ladder.\textsuperscript{4} At the aggregate level, we find that as trade costs decrease, the quality ladder shrinks. Moreover, we also find a trend break at the time China joins the WTO. In order to understand these trends more concretely we perform a firm-level analysis. We find that changes in the quality ladder are the result of two forces: a tightening of quality of surviving firms; and the exit of relatively low quality producers, as well as entry of relatively high quality producers.

When we examine how surviving firms respond to new sourcing opportunities we find that, on average, sourcing from abroad is associated with a decrease in quality. We also show that imported input quality, proxied by the per capita GDP of income partners, moderates the downgrading channel: firms sourcing from relatively poorer countries experience larger output quality drops than firms sourcing from elsewhere. However, we also find that this average effect masks a great deal of heterogeneity in firms’ joint sourcing and quality decisions. In particular, we find that lower quality firms that begin to engage in offshoring tend to upgrade their quality relative to other firms’ within the same year, while higher quality firms that increase their offshoring activity tend to downgrade their quality.

In order to understand the forces at play, we build an illustrative model to ground our empirical approach. In our framework, firms endogenously choose their sourcing strategy, their output quality and their price. Firms differ along two dimensions: physical productivity and capability. The first term refers to firms’ productivity at making physical output conditional on a choice of quality—a standard feature of many heterogeneous firm models. The second term refers to firms’ ability to produce higher quality output. Firms leverage their relative advantages in deciding how

\textsuperscript{4}We use this definition in congruency with similar papers, but in our results section we explore other measures of the spread in quality across goods.
much and how high a quality to produce. Thus, our setup is similar in spirit to recent models of quality and quantity choice by firms, such as Hallak and Sivadasan (2013).

In the model, producing a set output quality requires a commensurate input quality. Trade enters the model by allowing firms to access a menu of inputs in different countries. The relative steepness of this menu with respect to quality determines whether a country’s comparative advantage is in quality or quantity. We find that access to new countries can change the quantity and quality tradeoff for firms but that this tradeoff depends on where firms initially are in the quality distribution. For example, if a firm is already producing at a low quality, then cheap inputs abroad may induce little change (or some upgrading) in output quality, with the firm focusing on simply lowering price. However, for a firm producing higher quality output, the ability to lower price and gain market share by using cheaper inputs may induce quality downgrading.

Our work touches on several different strands of the trade literature. First, several recent papers have shown that access to high quality capital or inputs from abroad induces quality upgrading in low and middle income countries. For example, see Fieler et al. (2014) examine how access to new inputs can explain rising skill intensity in Colombia. Our work differs from theirs and others in its focus on a high income country. We also focus on a different tradeoff in this context: the tension between a firm wishing to source cheaper inputs but ceding partial control over the quality of its output in doing so. Moreover, our paper is one of the first to demonstrate that the distribution of quality may contract in response to trade shocks, and we offer a reason why.

In related work, Bloom et al. (2011) and Utar (2014) provide evidence that increased competition from China led to organizational restructuring and increased innovation in the European apparel and textile industry, but do not explicitly focus on product quality. Kugler and Verhoogen (2012) document and model how larger and more efficient firms choose higher quality inputs and produce higher quality output that they sell at a higher price when the scope for differentiation is large enough. Holmes and Stevens (2010) also explore how firms’ quantity and quality choices may diverge. They observe that smaller, more focused and higher quality firms were more resistant to the surge of imports from China, despite their size. Our paper differs from these last two in that
we look more explicitly at heterogeneity in the sourcing decisions of firms, while also allowing for heterogeneity in input and output quality.

Closer to us, Amiti and Khandelwal (2013) extend Khandelwal’s original analysis using product level data from 56 countries to the US and find that lower tariffs are associated with product upgrading for firms close to the world quality frontier, but discourage upgrading for firms distant from the frontier. Roberts et al. (2012) use firm level data on exports by product and destination for Chinese footwear exporters and estimate a firm specific demand component together with a cost and an export market profitability components. They find that both the cost and demand components are related to firms’ success and they also document a reallocation of resources towards more productive and higher demand firms following the removal of EU quotas. Piveteau and Smagghue (2015) use similar French data to study the link between product upgrading and import competition. They find evidence that firms improve the quality of their export products when import competition increases. However, these papers do not focus on how sourcing decisions in advanced economies are related to product quality. Analyzing this relationship is the main contribution of our paper.

The remainder of the paper proceeds as follows. Section 2.2 provides a brief discussion on the Danish apparel industry as well as the MFA and also presents. Section 2.3 describes the various datasets that we use. Section 2.4 presents an illustrative model of offshoring and quality decisions that guides our empirical analysis. Section 2.5 details our empirical methodology. Section 2.6 presents the results of our estimation and a discussion of the results. Finally, Section 2.7 concludes.

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5See also Martin and Mejean (2014) who use a different empirical approach to study the same question. They also find evidence of a positive relationship between upgrading and import competition through a reallocation of market share from low quality firms to high quality firms.
2.2 The Danish Apparel Industry and the End of the Multi Fibre Arrangement

The Danish Apparel Industry

Historically, Danish industries have been famous for the creative and design aspects of their goods. The Danish Design movement in particular, has had a large and lasting influence on modern furniture and architecture. The Danish apparel industry, concentrated predominantly in the medium and high end segment of the fashion industry, continues to be an important part of Denmark’s creative output. The sector represents more than 25% of the so called creative industries that were recently singled out by the Danish government as a major component for future growth.⁶

In Denmark, the majority of apparel firms can be divided into two groups—“Branded Manufacturers” and “Branded Marketers.”⁷ The latter group focus solely on design, distribution and marketing of products, and have grown in recent years with the rise of fast fashion. The former group, in contrast, engage more explicitly with physical input choices. For example, they may produce domestically, and in Denmark there is a small, persistent set of apparel manufacturers.⁸ Even if not producing domestically, they often engage in outward processing whereby they purchase raw materials and send them directly to assembly plants. They may also do some final packaging and assembly locally. Largely, the difference between these two groups is in the definition of the firm’s boundary: whether or not the firm purchases its intermediates directly. Nevertheless, the distinction is important as we only observe branded manufacturers in our data. This is because in Denmark firms who own their own inputs, even if they ultimately do production abroad, are in the production registry.

As our analysis ultimately rests on a single index of quality, it is helpful to understand how the industry normally thinks of this concept. Quality in apparel is normally broken down into two components – the physical quality of the good (e.g., open-end spinning versus ring-spun cotton, ⁶See Danish Ministry of Business and Growth (2013).
⁷See Gereffi (1999) for more on these concepts and other details of the apparel industry.
⁸Utar (2014) calculates that there are 13,000 workers in the combined textile and apparel industries.
thread count, non-bleeding dyes) and the “fashionability” of the item.\(^9\) Branded manufacturers exercise a great deal of control over both of these as they often engage directly with the sourcing partners of assemblers. In our analysis, we identify a demand shifter that combines the firm’s quality along with individual tastes and perceptions. Because of this, we cannot tease apart different aspects of quality. This is an issue insofar as the fashionability of a good is a relative concept, and also can substitute with physical quality.\(^10\) But while we cannot separately out these concepts, it also highlights the idea that quality is partially a feature of a particular firm and its capabilities at making likable designs, and partially an outcome of a sourcing decision. Our results ultimately corroborate the idea that firms exercise some control over our estimated demand shifters, even if imperfectly.

**The MFA and Trade Patterns**

Starting in 1974, the majority of apparel and textile trade was governed by a series of quotas outlined in the Multi-Fibre Arrangement (MFA), and later the Agreement on Textiles and Clothing (ATC). These quotas were set up to allow developed countries to adjust slowly to competitive pressure from abroad. There was an understanding that the quotas would ultimately be lifted. To that end, the MFA was phased out in several stages beginning in 1995 and ending in 2005. In 2005, the majority of apparel quotas were phased out with some countries maintaining the option to reinstitute short-term restrictions on trade if they saw fit.\(^11\)

In this section we briefly detail how the phase out of the MFA made itself felt in the Danish apparel industry. It is worth noting that as China was not in the WTO until late 2001, quotas on Chinese apparel and textile production remained in effect even after the first two rounds of

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\(^9\)We are thankful to Avinash Vora for walking us through the daily goings-on of an Indian textile and clothing factory. Also, to Line Lyngholm at Bestseller for helping us understand the Danish apparel industry. For an attempt at formally modeling the distinctions noted above, see Paul R. Liegey (1993).

\(^10\)This substitution is at the heart of the strategy of many “fast fashion” retailers, such as Zara and H&M.

\(^11\)Some additional quota restrictions were placed on China for a short period, leading to extended negotiations between China and the EU. See “EU and China in ‘bra wars’ deal,” published in The Guardian newspaper on September 5, 2005. Also, see Brambilla et al. (2010) for a history of the MFA as well as how the end of the MFA affected numerous countries.
restriction easing had passed. However, in January 2002 many restrictions on Chinese textile and apparel trade were lifted. Thus, China’s accession to the WTO provided a large, new sourcing opportunity for Danish firms. While China’s entry into the WTO is the largest one-time shock to the Danish fashion industry, the phase out of the MFA/ATC also led to more trade with other Asian and Eastern European countries, such as Turkey and Poland.

Turning to general patterns, from 1997 to 2010, imports of apparel in Denmark grew by 26.5% in real terms. This rise is driven disproportionately by two factors: (1) increased quantities (as prices actually fell in this period) and (2) more re-exporting activity. Figure 2.1 makes this clear by plotting the nominal value of net imports and the weight of net imports. The nominal value is falling. This reflects high re-export activity: total imports have increased while the imports that remain in Denmark has decreased. On the other hand, the weight is increasing. This suggests that the actual quantity of apparel entering Denmark has increased. These two patterns are driven by changes in the structure of the apparel industry in Denmark at this time. In particular, importing by Branded Marketers (those that only engage in importing and re-exporting) grew by 43% while importing activity actually decreased for Branded Manufacturers (who nevertheless maintain around 40% of domestic market share—albeit decreasing over time).

The removal of trade quotas not only increased trade volumes, it also drastically changed the composition of imports. In particular, there is a rapid increase in sourcing from Asian countries and in particular China. Figure 2.2 documents the rise of China in Danish apparel, and figure 2.3 breaks this down by type of firm. While movement to China was steadily growing, starting with its entry to the WTO, trade with China began to rise rapidly and constitutes 45% of Danish apparel imports by the end of the sample. For manufacturers, China is responsible for 16% of imports. In this group we also see a substantial decline in importing from Eastern Europe, as work is supplanted by China and Turkey.

While we exploit and study these changes in sourcing patterns, we have no direct evidence that countries like China offer different quality inputs at different prices than Eastern European countries. That is, we cannot observe, directly, input quality. However, others have studied the
effect of the end of the quotas on the exports of poor countries. For example, Amiti and Khandelwal (2013) find that China upgraded the quality of many of its products after the fall of the MFA, but this upgrading was heterogeneous and highly dependent on firms’ initial quality. Moreover, as documented in Brambilla et al. (2010), Chinese apparel product quality may have risen but decreased relative to the rest of the world. In a similar vein, Manova and Zhang (2012) find evidence that Chinese exporters “use higher quality inputs to produce higher quality goods.” This latter point suggests that apparel firms may actually make demands of their sourcing partners. The overall picture suggest that the dismantling of the MFA led China to engage in some quality upgrading, but nevertheless they focus on production of lower quality goods.

2.3 Data

In order to carry out our analysis we rely on several datasets maintained by Statistics Denmark. All of our datasets can be linked through firm identifiers and ultimately allow us to construct a panel of Danish apparel firms running from 1997 to 2011.

First, we use a dataset that contains annual longitudinal production data for all manufacturing firms employing at least 10 individuals or who meet a minimum revenue threshold. The data contains price and quantity data on sales at the Combined Nomenclature 8 (CN8) digit product level for each firm.\textsuperscript{12} If firms own their materials (i.e., if they source them and route them to producers on their own), they will appear in this dataset even if production is not physically taking place in Denmark. Hence we observe both those firms that produce domestically and engage actively in sourcing materials. We do not observe domestic sales and price data for firms with their headquarters in Denmark, but who do not either manage their own inputs or produce in Denmark. That is to say, we do not observe the firms we described in section 2.2 as Branded Marketers.

To identify our firms, we focus on those firms producing at least one type of apparel product

\textsuperscript{12}The Combined Nomenclature is the EU’s classification system for recording customs transactions. The first 6 digits are the same as HS6 classifications and the last 2 digits are defined by the EU’s documentation. In the case of apparel, the last 2 digits distinguish weight and material used in construction of apparel.
and who make at least 90% of their revenues in the apparel industry.\textsuperscript{13} Table 2.1 shows the most common products made by our sample of firms. While basic these products can still incorporate a large design component.

As the data contains quantity and sales data, we are able to construct unit values. It is well known that unit values can be a noisy proxy for prices, and we cut data that are likely to be outliers and erroneous. In particular, we remove observations based on the following criteria:

1. We remove the top and bottom 5\% of unit values (many of which are in the pennies or the tens of thousands of DKK).

2. We remove products without at least 45000 DKK in sales. This is because sales are rounded to the nearest 1000, so this avoids large swings due to rounding errors.

3. If a variety (firm-product pair) exits and reappears, we keep only the longest contiguous period. This is because sometimes exit and re-entry is met with large price swings, which we believe may be due to aggregation bias. That is, the product may have changed even within a narrow code.

4. We remove firm-product-years where the unit value jumps above twice the within-firm-product median price.

We can link our production data at the firm-product level to firm level data on capital, labor and materials use. More importantly, we link our data to customs data. This dataset contains all import and export transactions at the product level (also CN8) for each firm in a given year. From here we can see how many textiles and apparel products each of our firms imports and exports. The dataset is comprehensive and contains information on the trade partner, quantity, price and unit of the good. This last variable matters because customs data and production data are not often identically scaled (e.g., counts in 1000s versus 10s). Thus, this dataset tells us the sourcing strategy of firms.

\textsuperscript{13}The distribution if heavily bimodal—with most firms making more than 90\% or less than 5\% of their profits in apparel. Upon examination, most of the firms with a small revenue share of apparel are producing niche products (e.g., industrial wear). Thus, while we cannot know for sure, we think it reasonable to assume they are not competing with the majority of apparel firms, who focus on household consumers.
As a final point, we bring in several other data sources. Data on quotas comes from the EU’s SIGL database. This database includes product-level data on quota utilization, quota fill rates and license volume for the entire length of our panel. For data on exchange rates we used data published by the IMF’s International Financial Statistics and the Federal Reserve’s FRED Database.

2.4 Illustrative Model

Before turning to the empirical analysis, we present a model that illustrates the main forces that we test in the data. As we neither calibrate the model nor run any counterfactuals, we do not specify the full general equilibrium model. Instead we focus on a firm in partial equilibrium making a decision about its quality and production. In our setting, production requires two decisions: at what quality to produce output, and how much output to ultimately sell. Similarly, firms differ in two dimensions: first, in their ability to produce output at a given quality (what we call productivity); and second, in the ease with which they can increase the quality of their good (what we call “capability”\textsuperscript{14}). We show how this simple setup can generate a shortening of the quality ladder in response to changes in the cost of imports. Our approach is similar in spirit to recent models with firms both differing in two-dimensions and making quality choices. For example, our model is closely related to that of Hallak and Sivadasan (2013). To this existing literature we build in, explicitly, an extensive sourcing decision. As a final point, in most of the subsequent discussion we focus only on the importing decisions of a firm, and not on the rest of the trade environment. This is for clarity, as our focus is on sourcing, however we discuss import competition and exports in the context of our model at the end of this section.

Consumer Preferences and Demand

In our empirical section, we will estimate a model based on the random utility framework common in the IO literature. In particular, we assume that workers face a choice over a finite and discrete

\textsuperscript{14}This term is borrowed from Sutton (2012) who develops many models of firms making quality choices.
set of goods and each choose one. While this set up is very useful empirically, working with it theoretically can be difficult.\textsuperscript{15} However, in order to maintain some connection to the empirical section that follows we posit that firms face a demand curve that is “approximately” derived from a standard logit model of discrete choice. In particular, we assume that firms face the following demand curve:

$$x(v, p) = A \exp\{\log v - \sigma p\}$$

where $A$ is an aggregate demand shifter, $v$ is quality, $p$ is the price and $\sigma$ is the semi-elasticity of price. This functional form is similar to the logit demand curve which, indexing the firm momentarily by $j$, is given by:

$$x_j(v, p) = \frac{1}{A_0 + \sum_{f \in \mathcal{F}} \exp\{\log v_f - \sigma p_f\}} \exp\{\log v - \sigma p\}$$

where $A_0$ is the value of some outside option and $\mathcal{F}$ indexes all firms including $j$. Given the demand curves above, the setup is reminiscent of monopolistic competition whereby no firm internalizes their impact on the aggregate shifter. In fact, if we had written $\log(p)$ above then this would be a standard CES demand curve and we could make the limiting argument more formally.\textsuperscript{16} The benefit of this approximation is that we can avoid modeling the strategic interactions of firms, which keeps the analysis tractable. When we derive the solution to the firm’s problem we will draw out more of the connections to the traditional logit demand system.

Quality Production and the Cost Function

Firms maximize profits given the consumers’ demand curve choosing both the quality $v$ and price $p$ of their output. Firms in our economy are characterized by two objects: their “capability,” $\omega$ and

\textsuperscript{15}For example, Caplin and Nalebuff (1991) show that even in a simple price setting game where consumers are characterized by a discrete choice, there may be no interior equilibrium where firms’ actions solve the first order conditions of profit maximization. In most of the IO literature (e.g., Berry et al. (1995)) one assumes that such an equilibrium is the one observed.

\textsuperscript{16}It is further true that our model predictions are robust to a CES specification of preferences, although the particular closed form solutions are not identical.
their “productivity,” $\lambda$. The first term will describe how well firms can produce quality, while the latter term describes how well firms can scale production, given a choice of quality. We assume these are drawn from some joint distribution $F$ over $\Omega \times \Lambda$. Moreover, we assume that $\omega$ is bounded below by a strictly positive number. In the remainder of this subsection we will describe how these two terms enter the firms’ cost and production function.

First, physical output is created by combining a homogeneous factor and a differentiated factor in a Leontief fashion. Thus, production is given by,

$$x(v) = \min\{m_1, m_2(\psi \omega)\}$$

where $x(v)$ is output and $m_1$ and $m_2$ are two factors of production. $\psi$ describes input quality. The term $\omega$ captures the capability of the firm—for higher values of $\omega$, the firm can purchase a lower quality input and still achieve the same output quality. Thus $\omega$ may reflect the firm’s ability to design or brand itself. The mapping from input quality to output quality is given by a simple decreasing returns to scale quality production function:

$$v = (\psi \omega)^\alpha$$

We think of the homogeneous factor as a machine and the differentiated factor as either materials, the skill of workers or both.\footnote{We have chosen this production structure for analytic convenience, however our results extend to a setting in which there is constant marginal cost of production and fixed costs of design. What will ultimately matter for our results is that the marginal cost of production is increasing in quality \textit{and} that the slope of the marginal cost curve with respect to quality is increasing in trade costs. In such a setting, reductions in trade costs will induce firms \textit{already} sourcing from abroad to upgrade their quality and any firms \textit{induced} to source will downgrade their quality. Our functional form assumptions in this section let us demonstrate these forces in a closed form. Fixed costs of design or communication costs (as we use in our model) are necessary to create an extensive margin of sourcing. A generalized version with costs of design, which also features more standard CES preferences, is available upon request.} We assume that the homogeneous good is paid a factor price $a$ and that the schedule for the differentiated good is linear in input quality so that $\tilde{c}(\psi) = b\psi$. With these prices, the Leontief structure leads to the following unit cost of production a quality $\psi$:

$$c(\psi) = a + \tilde{c}(\psi)$$
We introduce trade by allowing $a$ and $\bar{c}(\psi)$ to vary across countries. When firms import, they face a communication cost that makes it difficult to transmit their capability. For an importer the quality production function is given by,

$$v = (\psi \omega)^{\alpha}$$

where $z$ reflects the communication cost. We focus on two countries and normalize $z_H = 1$, in order to treat this as the only quality production function. An exponent of $z < 1$ means that sourcing from abroad makes vertical differentiation more difficult, and guarantees that firms will either produce at home or abroad. With multiplicative costs, it would turn out that all firms would make the same decisions about sourcing. Thus, this firm guarantees that not all firms make the same decision. We include the exponent for the sake of generality but at an extreme it has a very intuitive flavor: If $z_F = 0$ then this implies that once sourcing from abroad the firm cannot exploit its own design capabilities. We discuss the role of this exponent in the next subsection, after demonstrating its role in the firms’ optimal sourcing decision.

We introduce productivity in the standard, unit-cost augmenting way. In particular, a firm’s final unit cost is given by $c(\psi)/\lambda$. Combining the above, the firm’s profit function conditional on whether or not they import is given by,

$$\pi(\psi, p) = A \exp \{\alpha \log(\psi \omega^z) - \sigma p\} (p - c(\psi)/\lambda) - a_H f$$

where $f$ is a fixed cost or production, paid in units of the homogeneous good at home. From the first order conditions one can derive the following expression for optimal quality given the firm’s sourcing strategy:

$$\psi^* = (\omega z_s \lambda)^{\alpha} \frac{\alpha}{\sigma b_s}$$

(2.1)
Similarly, one can derive the following expression for optimal price:

\[ p^* = c(\psi^*)/\lambda + \frac{1}{\sigma} \]  

(2.2)

This states that quality choices are increasing both in capability and productivity and that the price is decreasing in productivity. The optimal pricing equation demonstrates the connection between the typical logit demand system and our model. In particular, recall that for the standard logit model the optimal pricing rule would be given by,

\[ p = \frac{c}{\lambda} + \frac{1}{\sigma(1 - s)} \]

where \( s \) is the market share of the firm and \( c \) is marginal cost. Thus in the logit setting, markups are heterogeneous and larger firms charge higher markups. Our setting is the limit case where \( s \to 0 \).

The benefit of our simplification is that we can solve not only the pricing decision, but the quality decision of the firm, in closed form.

Plugging the optimal quantities back into the profit function leads to the following profit conditional on a sourcing strategy:

\[ \pi = \kappa \exp \left\{ -\alpha \log \left( \frac{b_s}{(\lambda \omega^z s)} \right) - \sigma a_s/\lambda \right\} - f \]

where \( \kappa \) is a constant that is independent of productivity and sourcing strategy. The profit function has an intuitive interpretation as it says that profits are determined by a weighted sum of the two components of costs—the unit cost, \( a_s \) of the homogeneous good moderated by price sensitivity, and the cost of the differentiated factor, \( b_s/\omega^z s \), moderated by tastes for quality.

**Trade and the Distribution of Quality**

To discuss trade more concretely we focus on two countries, home and foreign. Furthermore, we assume that \( a_H > a_F \) but \( b_F > b_H \). These restrictions imply that the home country has an absolute
advantage in high quality input production, but the foreign country has an absolute advantage in low quality input production. With this in mind, a firm will source from abroad if

\[
\exp \left\{ \alpha \left[ z \log \omega + \log \lambda - \log b_F \right] - \sigma a_F / \lambda \right\} > \exp \left\{ \alpha \left[ \log \omega + \log \lambda - \log b_H \right] - \sigma a_H / \lambda \right\}
\]

This inequality highlights the role of the exponent in our communication cost. If we had a multiplicative communication cost, for example, it would be the case that the \( \omega \) terms would cancel and all firms would behave symmetrically—either producing abroad or at home depending on parameters.\(^{18}\) By taking logarithms and rearranging, we arrive at the following cutoff for sourcing from abroad:

\[
\omega \leq \exp \left\{ \frac{\alpha (a_H - a_F) - \alpha \log \left( \frac{b_F}{b_H} \right)}{\alpha (1 - z)} \right\}
\]

(2.3)

This cutoff is a function of both productivity and capability—so that sourcing patterns depend on both the joint distribution of these two terms. In particular, the cutoff value is decreasing in productivity. This suggests that conditional on quality, size may be a predictor of sourcing activity. Our general finding that productivity and capability jointly determine firm size and quality echoes the same point made recently by Holmes and Stevens (2010), Hallak and Sivadasan (2013) and Eckel et al. (2015): large firms may not be the highest quality firms and vice versa.

In order to discuss how changes in import costs map into the choices of firms, we break up the discussion into looking at the cost of the homogeneous factor, \( a_s \) and then at the cost of the differentiated factor, \( b_s \). Notice that (2.3) shows that lowering trade costs will lower the cutoff rule for firms, so we also break up our analysis by looking separately at firms who were already sourcing abroad and firms who switch their sourcing strategy.

Turning to the homogeneous factor, if \( a_F \) decreases then firms that were already sourcing from

\(^{18}\)More generally, if the cost of sourcing abroad is given by \( a + b/\tau(\omega) \) where \( \tau \) captures communication costs, we need that \( \tau(\omega)/\omega \) is strictly decreasing. That is, the elasticity of \( \tau \) with respect to \( \omega \) would have to be negative, so that it is more difficult to communicate higher capability than lower capability.
abroad will not change their quality choice. This can be seen in (2.1), which shows that optimal quality choice only depends on the cost of the differentiated factor. On the other hand, it will induce switching by some middle-quality firms, as it moves the threshold for sourcing decisions. Switchers will decrease their quality. This can be seen by dividing the optimal quality decision of firms holding fixed their capability but not their sourcing strategy:

\[ \frac{\psi^* H}{\psi^* F} = \omega^{1-z} \frac{b^F}{b^H} \]

which will be greater than 1 so long as \( b^F \) is sufficiently high. Finally, there will be no response of high quality firms.

Next looking at the differentiated factor, if \( b_F \) decreases then firms that were already sourcing will upgrade their quality. This can be seen in (2.1), where quality choice, conditional on sourcing, is a decreasing function of \( b \). On the other hand, switchers will once again downgrade their quality (as long as it is still the case that \( b_F \) remains sufficiently larger than \( b_H \)).

Finally, we briefly discuss the aggregate demand shifter and entry and exit. Thus far the model has been primarily concerned with import costs and quality choice. However, it is an empirical fact that firms may enter and exit in response to changes in import costs. Moreover, changes in import costs are often concurrent with changes in export costs as well as import competition. This is true of our dataset. And, since we only have data on branded manufacturers, we will treat the combined demand of branded marketers (which includes wholesalers and retailers that do not appear in our production data) as an outside good. Thus, lowering import costs, which acts as a positive shock to all firms, can lead to a negative demand shock to manufacturing firms facing stiffer import competition. On the other hand, removing apparel quotas also lowered export costs for firms. In the model above, \( A \) is a common demand shock facing all firms, and so it can be a useful proxy for thinking about net changes in import competition and export costs. In particular, we think of increased import competition as a decrease in \( A \) and new export opportunities as an increase in \( A \). From equations (2.1) and (2.2), one can see that this aggregate shifter does not affect optimal
prices or quality choices. However, given our assumption that fixed costs of production are strictly positive for all firms, decreases in $A$ will result in the net exit of low profitability firms—which can be either low capability, low productivity or both, depending on the joint distribution of these two firm attributes.

We summarize the above discussion in the following concrete set of observations that guide our empirical analysis:

**Observation 1 (Quality).** *Conditional on productivity, if $b_F$ decreases but $b_H < b_F$ then,*

1. Firms that were already offshoring will increase their output quality.
2. Some firms will begin to offshore and decrease their quality.
3. Firms of sufficiently high quality will not respond.

*Conditional on productivity, if $a_F$ decreases then*

1. Firms that were already sourcing from abroad will not respond.
2. Some firms will begin to offshore and their quality will decrease.
3. Firms of sufficiently high quality will not respond.

**Observation 2 (Entry/Exit).** *If $A$ remains constant and $a_s$ and/or $b_s$ decrease then low quality firms enter. However, if $A$ decreases then exit patterns depend on the joint distribution of $\lambda$ and $\omega.$*

Because the model is highly stylized, these observations are particularly sharp. In the data there are obviously more than two countries and all firms engage in some sourcing activity. Hence one should think of this model as largely descriptive. To operationalize our ideas in the data we will focus on looking at how the distribution of quality changes and how firms of different qualities respond to new importing opportunities. In particular, we modify our predictions about heterogeneity to suggest that lower quality ought to increase their quality relative to other firms,
while middle quality firms and high quality firms ought to decrease their quality or have a more muted response.

It is important to highlight the crucial role of vertical differentiation in this context. In this model, vertical differentiation is not simply a productivity shifter or demand shifter as in the standard set up—rather two sources of heterogeneity separate physical productivity and quality capability. More importantly, this quality capability is affected by the firms' sourcing decisions. Without these separate aspects of the firm, we would predict a strictly monotonic relationship between size, quality and productivity.

2.5 Econometric Model

This section outlines our econometric model, including consumer demand, timing assumptions and decision making by firms, as well as the details of mapping our model to data and instrumenting strategy. The strategy follows closely the recent work of Khandelwal (2010) and Amiti and Khandelwal (2013) in that we use the discrete choice framework common in IO to estimate consumer demand.

2.5.1 Consumer Demand

In this section we will derive a logit style demand curve for each product, similar to the demand curve in the section 2.4. However, things will differ now in two dimensions: we will no longer rely on an approximation to the demand curve and instead assume firms do internalize their impact on aggregate shifters; we will also depart slightly from the logit framework and instead use a nested logit framework. The nested logit setup is almost identical to the standard framework except that goods are grouped together into nests, and substitution patterns are different between and across nests. This modification allows for more realistic substitution patterns as one can imagine that not all apparel is equally substitutable (for example, men’s and women’s clothing). In section 2.5.3 we define the full nesting structure. In the remainder of this subsection, we derive the demand curve
for each firm-product pair, which leads to our estimating equation.

In order to derive a demand curve for a product, we model consumers as making a discrete choice over goods in each period. To make things precise, assume that consumer $i$ has indirect utility for good $(j, t)$ given by,

$$V_{ijt} = \nu_{jt} - \alpha p_{jt} + \epsilon_{ijt}$$

where $\delta_{jt}$ is a common taste for product $j$ at time $t$, $p$ is price and $\epsilon$ is a consumer specific taste shock for product $jt$. We assume that $\epsilon$ is distributed as generalized extreme value (GEV), which allows for the shock to be correlated across some goods and not others. Consumer $i$ picks good $j$ iff $V_{ijt} \geq V_{ikt} \forall (k)$ at time $t$. Berry (1994) shows that if a large number of consumers have preferences as above, then the market share for product $j$ at time $t$ is given by,

$$s_{jt} = \frac{e^{(\delta_{jt} - \alpha p_{jt})/(1-\sigma)}}{\sum_{k \in J_g} e^{(\delta_{kt} - \alpha p_{kt})/(1-\sigma)}} \frac{\left(\sum_{k \in J_g} e^{(\delta_{kt} - \alpha p_{kt})/(1-\sigma)}\right)^{1-\sigma}}{\sum_{g} \left[\left(\sum_{k \in J_g} e^{(\delta_{kt} - \alpha p_{kt})/(1-\sigma)}\right)^{1-\sigma}\right]}$$

where $\sigma$ is a parameter that governs nest substitution, $g$ indexes nests (groups of goods with correlated shocks) and $J_g$ is the set of products in nest $g$. Given this decomposition, one can actually interpret the nested logit structure as one in which a consumer first decides on a type of good he or she wishes to purchase (e.g., “men’s formal wear”) and then chooses a variety from within the nest (e.g., “men’s suit from firm $j$”). The first term in the above decomposition is the probability of buying the variety conditional on choosing from within some nest, while the second term is the probability of choosing a particular nest.

The equation above may appear complicated, but Berry (1994) also demonstrates the following transformation of the data that allows for estimation of model parameters in a linear setting:

$$\log s_{jt} - \log s_{0t} = \delta_{jt} - \alpha p_{jt} - \delta_{0t} + \sigma \log s_{jt/g}$$

where $s_{0t}$ is the market share of some outside good and $s_{jt/g}$ is the within group share of product.
The equation above is not identified as there are more parameters than data points. To this end, we follow the literature and treat quality as a residual in an estimation of $\alpha$ via regression. More concretely, we split the quality parameter into a time fixed effect, a firm-product “average quality” fixed effect, and a residual:

$$
\delta_{jt} = \delta^1_j + \delta^2_t + \delta^3_{jt}
$$

Plugging in yields the following estimating equation:

$$
\log s_{jt} - \log s_{0t} = \delta^1_j + \lambda_t - \alpha p_{jt} + \sigma \log s_{j/g} + \delta^3_{jt}
$$

where $\lambda_t = \delta^2_t - \delta^2_{0t}$ is growth in quality relative to the outside good—which we highlight here as it will be important later on. In general, $\delta^3_{jt}$ is correlated both with price and the nest share. This motivates an IV approach, and we pick up the discussion of constructing instruments in subsection 5.4.

### 2.5.2 Firms’ Decisions and Timing

Since our estimation only relies on consumer choices, we do not need to fully specify firms’ production. However, our instrumenting strategy relies crucially on the timing of firms’ decisions. To that end, we outline the firms’ decision making in this subsection. For the remainder of this section, we also drop all time subscripts as we will assume that firms solve the same problem anew in every period.

We assume that each period can be broken into three stages. In the first stage, firms decide on their quality and production plan given expectations about costs and demand. In the second stage, a vector of costs shocks is realized and the firm produces. Finally, in the third stage, they set prices and compete. The timing here is typical in quality models and is similar to that found in Sutton (2001, 2012). We think this timing assumption is particularly reasonable in the apparel industry, given its institutional features. For example, Frederick and Staritz (2012) walk through the production process for a typical apparel firm and argue that the design and planning process
happens before production takes place while marketing and selling logistics occur after. We also assume that firms can solve their problem statically in each period—so that there are no adjustment costs for price or quality.

To formalize the above, we work backwards. And so, in the final stage of the period, after all cost shocks are realized, firms set their prices and compete. Suppose as in Berry et al. (1995) (henceforth BLP) that there are $F$ firms active on the market producing differentiated products. Each firm produces a subset $\Gamma_f$ of the $J$ products available on the market. Consider first the short run profit function of firm $f$:

$$
\Pi_f = \sum_{j \in \Gamma_f} (p_j - mc_j) q_j
$$

$$
= \sum_{j \in \Gamma_f} (p_j - mc_j) M s_j (p, \delta; \vartheta)
$$

where $q_j$ is the quantity of good $j$ produced by the firm, $p_j$ is the price of the product, $mc_j$ is the marginal cost, $M$ is the size of the market and $s$ is market share, that depends on the price vector, as well as the unobserved quality of the good, $\delta_j$.

Maximizing profits with respect to price, we get the following FOC:

$$
s_j (p, \delta; \vartheta) + \sum_{j \in \Gamma_f} (p_j - mc_j) \frac{\partial s_j (p, \delta)}{\partial p_j} = 0
$$

Given the pricing strategy, in the first stage the firm’s expected profit is given by,

$$
E \left( \sum_{j \in \Gamma_f} (p_j (\delta, \epsilon) - mc(\delta, \epsilon)) M s_j (p, \delta; \vartheta) \right)
$$

where bold denotes the whole vector of quality across firms. The key to our instrumenting strategy is the presence of the cost shocks, $\epsilon$. We assume that firms set prices after these have been observed but choose quality based on expected profits. This assumption will allow us to exploit
the orthogonality between cost shocks and unobserved quality in estimating the demand model’s parameters. This strategy parallels the proxy method of estimating production functions where one uses assumptions about timing of investment and hiring decisions relative to realization of productivity innovations to identify certain parameters.

2.5.3 Nest Structure, Trade and Market Size

In this subsection we give some detail on how apparel products are defined in the Combined Nomenclature, and how we use this to construct nests. Our nests are based on combining CN 4 digits codes. Our nests were chosen so that they approximately group clothing by its purpose (formal wear, undergarments, etc.) and by the gender of the intended consumer (male or female). Within each nest, we observe products at the 8 digit level. These are highly disaggregated and normally include more detail on the type of garment, the material and sometimes other characteristics or weight. For example, some products are “Men’s suits, of wool or fine animal hair, knitted or crocheted” and “Women’s knee-length stockings, measuring per single yarn less than 67 decitex, of synthetic fiber.” In total there are 16 nests listed in Table 2.2.

We will define a variety as a CN8 code at a particular firm. Thus, if 2 firms both make men’s wool suits, then they are counted as two separate varieties. This structure leaves us with around 3,000 varieties in the sample. For each of these varieties, we know sales to the nearest 1000 DKK and the quantity (usually measured as a count of goods sold).

Before discussing our instrumenting strategy, some discussion of the outside good is in order. In our setting, because we use time-fixed effects, the choice of outside good does not effect our estimates of any parameters or elasticities. However, the outside good will largely determine the shape of the time-fixed effects which determine aggregate changes in quality over time. For the outside good, we use the total quantity of imports into Denmark.\(^19\) This means that after quotas

\(^{19}\) At this time, our estimation ignores the distinction between domestic sales and foreign sales by firms. This is because without more data on processing trade, we cannot disentangle between imports for final sale an re-exports. Unfortunately, the extent to which this might bias our results relies on covariance between domestic market shares and the share of sales going to exports. In follow up work we hope to more carefully distinguish these two sources of sales.
fall and imports into Denmark dramatically increase, the outside good grows and this influences our quality estimates. We will discuss interpreting this more in the results section. But, in effect, this fact implies that we can identify changes in the spread of quality, but cannot easily identify changes in the overall average quality of goods across time.

2.5.4 Instrumenting Strategy

Our regression equation runs into the standard endogeneity present in demand estimation: price and the nest share will be correlated with a firm’s quality. To circumvent this issue, we employ an IV strategy. However, finding exogenous instruments in our situation is still difficult as quality and price are both decision variables. Thus, many cost shifters that could be used to instrument for price—e.g., wages—also reflect input quality. However, as outlined in the timing section we use unanticipated cost shocks as instruments. This strategy is the same as that followed by Foster et al. (2008) who used structural estimates of innovations to firm’s productivity as instruments for demand shifters. However, as estimating production functions in a differentiated market is difficult, we construct directly observable cost shocks.

Denmark’s size and location within the EU leads to an economy where the vast majority of firms engage in some trade. Our instrumenting strategy relies on the idea that trade carries the risk of unanticipated cost shocks to the firm. In particular, we will use forecast errors on exchange rates as instruments. The source of variation arises from cross-sectional heterogeneity in import mixes across firms.

More explicitly, we model log exchange rates as an AR(1) process:

\[ \epsilon_{ct} = \mu_c + \rho_c \epsilon_{ct-1} + \sigma_c z_{ct} \]

where \( c \) indexes countries, \( z_{ct} \sim \mathcal{N}(0, 1) \), \( \sigma_c \) is the error variance and \((\mu_c, \rho_c)\) govern the AR process.\footnote{We experimented with different specifications of this process but the best fit is typically a simple random walk with \( \rho = 1 \).} After estimation we use forecast errors, \( \hat{\eta}_{ct} \), defined as, \( \epsilon_{ct} - \hat{E}(\epsilon_{ct}) \), to construct our
instrument as follows:

\[ \zeta_{ft}^{1} = \sum_{c} \hat{\eta}_{ct} s_{ft,c}^{imps} \]

where \( f \) indexes firms and \( s_{ft,c}^{imps} \) is the share of firm \( f \)'s apparel and textile imports that are from country \( c \).\(^{21}\) In our sample, 97\% of firms import apparel or textiles from outside the Eurozone. For the remaining 3\% we set the value of their shock to zero, as they experience no exchange rate uncertainty. Notice that this instrument is measured annually at the firm level, while the demand equation is at the product level. Hence, we cluster all errors at the firm-year level. Even with this conservative clustering strategy, we show in the results section that this is a powerful instrument for price. We construct an analogous measure using exports and include this as a control. This is an important control because the extent to which exchange rates are cost shocks are implicitly hedged by the fact they are positive shocks to export profitability. This mechanism is highlighted by Amiti et al. (2014).

To instrument for the nest share parameters, we use sales weighted averages of the cost shocks across a firm’s competitors within a nest. This is similar in spirit to the approach used by BLP, who use own product characteristics as instruments for price and average characteristics of firms’ competing products as instruments for the nest share. The instrument is constructed as follows:

\[ \zeta_{ft}^{2} = \sum_{f' \neq f} s_{f't}^{sales} \zeta_{f't}^{1} \]

In the estimation, we then interact \( \zeta_{f't}^{2} \) with a dummy for each nest. With or without these interaction terms, the nest instrument is strong, with a very low first stage \( p \) value. However, we found that fitting a linear function given the large differences in nest sizes leads to weak identification in the second stage. Allowing for the interactions yields strong instruments and precision in the second stage. When we present results we present \( p \)-values for both the second stage and the first stage.

\(^{21}\)For those countries that are part of the European Exchange Rate Mechanism (ERM 2), we set the shock equal to 0. This is because the Danish Kroner is pegged to the Euro (and varies less than 1\% around the peg).
As a final point on our instruments, since sourcing strategies are endogenously determined alongside quality, one may think our instrument invalid. However, even if there is a systematic relationship between quality and the exchange rate risk posed by different countries, this does not mean that unanticipated exchange rate errors and unobservable quality are correlated. That is, it should always be the case that $E(\delta_t \zeta^1_{ft}) = 0$ given our timing assumption and given that forecast errors are mean 0.

To conclude this section, we briefly discuss the clustering strategy and particular choice of estimation method. Our instruments are firm level while the unit of observation is a product. It is also plausible that unobservable quality decisions may be autocorrelated for a particular product. To address both of these concerns, we employ a two-way clustering strategy. In particular, we allow for arbitrary correlation of demand across products within a firm each period, and across time within each product.

2.6 Results

In this section we analyze the results of our estimation. In the first subsection, we comment on the parameter estimates and compare them to other estimates in the literature. We find our measures of price elasticity are well within the literature’s bounds, giving us confidence in our measures of quality. Then we turn to analyzing aggregate trends in the shape of the distribution—and demonstrate a break in aggregate trends that occurs when China enters the WTO. In particular, we find that the dispersion in quality across firms, measured as the distance between the lowest and highest quality firms, decreases rapidly after China enters the WTO. With this in mind, we turn to a firm-level analysis, highlighting the heterogeneous response of firms that induce this reduction in the dispersion of quality.
2.6.1 Parameter and Quality Estimates Overview

In this subsection we review our parameter estimates. We also analyze how our quality estimates correlate with various dimensions of the firms—such as size, the price of goods, and input prices. Turning to the parameter estimates, for the sake of comparison, we run an OLS regression, a logit model (That is, no nesting) and the full nested logit. Table 2.3 contains our estimates. As expected, the OLS estimates are biased upwards, and the price coefficient is not significantly different from zero. In the logit specification, the price coefficient is larger and of the correct sign but imprecisely measured. In the complete model all coefficients are significant and of the expected sign.

Our estimated price coefficient of $-0.0077$ falls comfortably in the range of parameters estimated by Khandelwal (2010). Khandelwal used HS 2 headings to define a market (whereas we combine headings 61 and 62). He also defined a nest an HS 6 digit code and the unit of analysis was a country-good pair. Despite the differences in aggregation, we believe it is a useful benchmark. He found a median coefficient on price of $-0.001$ and an IQR for of $0.070$, which places our coefficient close to this range.

Before turning to the main analysis, we explore the plausibility of our results by seeing how our quality estimates compare to observable firm characteristics. We focus on three features of the data: the price elasticities implied by the model, the size-price premium, and wages. The first is useful as there are other studies on what reasonable elasticities of substitution ought to be. The second feature of the data, the size-price premium, is a stylized fact explored by other authors. We show that their findings are corroborated by our estimates, lending credibility to our interpretation of our demand shifters as quality. Finally, we use the mean wages as way to check whether higher output quality is associated with higher input quality. This implicitly assumes that higher wages reflect higher input quality. While all of these checks are imperfect, combined they give credibility to the idea that our estimates of quality reflect meaningful differences in firms outputs and inputs.

To this end, first we calculate the price elasticities implied by the nested logit model according
to the following formula:

\[
\frac{d \log s_j}{d \log p_j} = \varepsilon = \alpha p_j \left[ \frac{1}{1 - \sigma} - s_j - \frac{\sigma}{1 - \sigma} s_{j/g} \right]
\]

where \( \alpha \) is the price coefficient and \( \sigma \) the substitution parameter. Figure 2.4 contains the density of elasticities implied by our estimates. The mean elasticity is 1.90, while the median is 1.66. These are in line estimates of price elasticities in the IO literature using similar demand techniques. There is substantial heterogeneity within nests, and table 2.4 contains summary statistics by nest for the 5 largest nests. In this table we see that cross-nest heterogeneity in elasticities can be very high. Indeed, the elasticities may seem implausibly high for some nests (e.g., women’s coats). This likely reflects the model’s rigidity in having a single price parameter. However, we think this is a reasonable cost to pay for the simple and straightforward estimation. Crucially, there is a tight correlation between the implied price elasticities and quality (which is not imposed by the model). This lines up with intuition that purchasers of higher quality goods tend to be more price inelastic. Nevertheless, formally capturing this kind of heterogeneity in our model is difficult without data on the identity of consumers.

Next, we explore how our estimates of quality compare to prices and firm size. Table 2.5 below summarizes the correlation between price, quality, elasticity and size. As one can see, quality and price are highly correlated. To see the relationship further, figure 2.5 plots this relationship with nest and year means removed. While substantial residual heterogeneity remains, a glance at the red curve (a lowess fit) shows the strong positive relationship between price and quality. Turning to size, measured by employment, the price-size correlation is tighter than the quality-size correlation. Kugler and Verhoogen (2012) suggests that quality may account for the correlation between size and price. This is because larger firms may be able to access higher quality inputs and thus produce higher quality outputs. We assess the validity of our quality estimates by testing this relationship in our data. To that end, we run the following regression:

\[
\log P_{jft} = \alpha_j + \alpha_t + \beta \log Emp_{ft} + \gamma \delta_{jft} + \epsilon_{jft}
\]
where $\delta_{jft}$ is our estimate of quality, and $\alpha_j$ and $\alpha_t$ are product and time fixed effects. We also run a regression with firm-product pair fixed effects to see if changes within a firm-product align with Kugler and Verhoogen’s observation. The results of this set of regressions are in table 2.6. These regressions confirm that on average, larger firms supply a higher quality and charge a higher price. Nevertheless, there appears to be a residual relationship—suggesting that other forces (e.g., market power) are likely still important.

Finally, we turn to a comparison of our quality estimates and wages in the firm—which we think may proxy for input quality. Recall that our concept of quality is multifaceted and captures the whole range of firm decisions that increase the attractiveness of a good—for example, design, marketing, and materials. However, we still assume that the firm has control over these decisions and that quality does not merely reflect taste shocks. To be clear, we are not estimating a quality production function here; rather we are demonstrating that a relationship between input and output quality exists.

In order to perform this exercise, we first aggregate quality to a firm-level measure. This is necessary because we do not observe product-specific inputs, but is difficult because we do not want to conflate product composition across firms with the quality of a firm. Part of this difficulty arises because of the difficulty in defining a “good” precisely, and the desire to separate certain goods in our analysis. For example, we may want to treat women’s pantyhose as separate from women’s bras as one may have different market shares than the other because of tastes not related to quality. On the other hand, we may not want to separate men’s coats of fur from men’s coats of wool, as these sorts of difference may reflect actual differences in the physical quality of a good. The compromise we adopt is removing fixed effects at the 5 digit level from goods.\(^{22}\) Let $\tilde{\delta}_{jft}$ be the quality of product $j$ at firm $f$ with fixed effects removed. Then define

$$
\tilde{\delta}_{ft} = \sum_{j \in J_f} \frac{s_{jft}}{S_{jft}} \delta_{jft}
$$

\(^{22}\)In the apparel industry, the 5 digit level almost exactly corresponds to the 6 digit level. We did not use HS 6 fixed effects because for a handful of products these 6 digit codes are not consistent over time. Nevertheless, this is almost like removing an HS6 fixed effect.
to be the firm-level quality where $s_{fjt}$ represents the sales of product $j$ by firm $f$ at time $t$, and $S_{ft}$ is the total sales of firm $f$ at time $t$. With firm level quality defined, we examine the relationship between firm’s average wage ($\log \bar{w}_{ft}$) and average quality through the following regression:

$$\log \bar{w}_{ft} = \beta_t + \beta_1 \delta_{ft} + \beta_2 X_{ft} + \epsilon_{ft}$$

where $\beta_1$ is our object of interest and $X$ collects control variables such as size (to proxy for productivity). The results of these regressions are in Table 2.7. As can be seen from the first two columns, firm quality and average wages are strongly positively correlated. When we include a measure of the skill share in the firms (defined as the ratio of workers with college or post-college credentials over all workers), the coefficient on quality becomes insignificant. This suggests that much of the “quality premium” may be a composition effect—higher quality firms seem to be paying more because they are employing better workers. This is reinforced in the final two columns of the table. We regress separately wages for high-skilled (those with 4+ years of education) and low-skilled (other) workers. We find that among high-skilled workers there is a quality premium, but not among low skilled workers. The collective evidence demonstrates that our quality measures reflect a feature of products that is both meaningful to consumers (in that they are willing to pay a higher price) and to firms (in that they pay higher input prices). Having established the validity of our quality measure, we turn to an analysis of quality and trade in the next two subsections.

### 2.6.2 Quality Evolution and Quality Ladders

Now we turn to looking at how the distribution of quality shifts over time. Keep in mind that we cannot credibly identify growth in the level of quality over time without strong assumptions on the behavior of the outside good. However, our model makes strong predictions about how the shape of the quality ladder evolves in response to new sourcing opportunities. In particular, it suggests that dispersion in quality across firms should decrease. Moreover, we know that import

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23Our results are robust to quantity based weighting.
competition should have implications for entry and exit of firms. To understand the dynamics at play, we perform two exercises in this section. First, we decompose changes in aggregate quality in order to highlight the problems with looking at means over time as well examine entry and exit patterns. In the second part of this section, we turn to looking at the length of the quality ladder, which we define as the distance between lowest and highest quality goods in a market. With this definition in hand, we examine how this length changes in response to Chinese entry to the WTO.

In order to decompose how quality evolves over time, we first define an aggregate measure of quality by using a sales weighted mean across firm-product pairs:

$$Qual_t = \sum_j \delta_{jt} \frac{sales_{jt}}{\sum_i sales_{it}}$$

We can decompose the above measure in a way similar to that used in the productivity literature. In particular, we break changes in aggregate quality into an average growth term, as well as within-firm-product, across-firm-product and a covariance term as follows:

$$\Delta Qual_t = \delta_t - \delta_{t-1} + \frac{N_{Ent.}}{N_t} \delta^Ent. + \frac{N_{Exit}}{N_{t-1}} \delta^Exit - \Delta \delta^{Stay} + \left[ Cov(\delta_{jt}, s_{jt}) - Cov(\delta_{jt-1}, s_{jt-1}) \right]$$

where $s_{jt}$ is the sales share of product $j$ at time $t$. The first term measures the secular change in quality, contaminated by changes to the outside good. The second captures the effect of entry and exit. The third captures the changes to firms that are present in both periods (Notice that within this effect are two smaller effects: the actual idiosyncratic changes to quality of surviving firms as well as the shifts in weight that these firms receive in the aggregate calculation). The last term captures the covariance between market share and quality. Figure 2.7 plots the evolution of our aggregate measure of quality and its erraticism suggests care needs to be taken in interpretation.

First, we explain the problem with analyzing the time trend. Figure 2.8 plots the time fixed
effects and shows that they drive the majority of aggregate changes in quality. Ideally this term would reflect secular growth in quality and we could look at quality changes relative to this trend to determine if goods are downgrading or upgrading in absolute terms. The issue is that our method can only identify $\delta_{it} - \delta_{0t}$ where $\delta_{0t}$ is the outside good’s quality. So if $\delta_{0t}$ is changing then we cannot estimate the trend of $\delta_{it}$. In particular, a positive supply shock to the outside good (which the MFA would be) will look like a negative demand shock to the inside good. However, there is still much to be learned from the other terms, which we turn to now.

Now looking at entry and exit, figure 2.9 plot their respective contributions to changes in aggregate quality. There is a sharp upward trend in this graph and the sign reverses when China enters the WTO. This means that after the WTO shock, new entrants tend to produce higher quality goods relative to incumbents. Our model predicted that entry and exit patterns ought to depend on the joint distribution of productivity and quality. While we cannot directly observe productivity, the findings on exit and entry are certainly plausible to the extent that for marginal firms, quality and profitability are positively correlated. However, we cannot directly corroborate this. Regardless of its connection to the model, the analysis of the time fixed effects and entry/exit patterns both suggest that the end of the MFA not only opened up new sourcing opportunities, but also led to substantial import competition.

To conclude the discussion of the decomposition, we now turn to the covariance terms. Figure 2.10 plots the evolution of this term. This term is flat for some time before beginning a downward trend in 2003. Two forces my drive this decrease in the covariance. First, it could be that there is less dispersion in quality. To see why, notice that in the extreme if the distribution of quality was degenerate, then this covariance would trivially be zero. On the other hand, this could be driven by changes in other drivers of consumer behavior, such as price. Thus, we avoid drawing strong conclusions from this term; instead, in the remainder of this section, we define our quality ladder concept and demonstrate directly how the dispersion in quality has declined.

To formally explore our predictions, we first define the quality ladder concretely. To this end,
first define good j’s position in the quality ladder at time t as:

\[ l_{jt} = (\delta_{jt}) - \frac{1}{n_t} \sum_{i=1}^{n} (\delta_{it}) \]

Thus, it is the product’s quality relative to the mean quality of all other products present in that year. Clearly this definition removes the aggregate time component from each year, thus we cannot explore changes to average quality over time. This also means that our definition of the quality ladder is insensitive to the choice of the outside option. With this definition, the quality ladder is cardinal: the magnitude in difference between positions is a measure of the quality difference between products. This is clear from the estimation strategy since a larger magnitude of quality, holding price fixed, maps one-for-one into higher market share. Thus, the changing shape of the quality ladder gives insight into aggregate changes.

To understand how the quality ladder looks, figure 2.6 plots the density of the ladder measure at the beginning and the end of our sample. There is less dispersion over time—so that the quality ladder tightens. To make this clearer, figure 2.11 plots the evolution of ladder length over time, where length is measured by subtracting the max and min quality. To analyze the possible impact of China’s accession to the WTO and the MFA, we run a structural break test for 2001, the results of which are in table 2.8. The trend coefficient nearly doubles in magnitude after 2001. With such a short panel, it is hard to determine statistical significance, so in the next section we use firm level variation to explore how firms respond to new import opportunities. Nevertheless, this evidence is suggestive that the end of the MFA played an important role in aggregate trends.

The tightening of the quality ladder is consistent with two forces at play: import competition driving out lower quality firms and offshoring opportunities inducing compression of the ladder as some firms upgrade and other firms downgrades. We have already established that the first force—entry and exit—is important. In the next section, we will use firm-level variation to show evidence of heterogeneity in firms’ response to new offshoring opportunities.

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24 We also used standard deviations and the distance between 95th and 5th percentiles as measures of length. The general trends are robust to these differences, but not all regressions remain statistically significant. In table 2.8 we report results for different measures of length.
2.6.3 Firms’ Quality and Sourcing Decisions

In this final subsection we use firm-level variation, as well as the fall of quotas with the end of the MFA, to analyze the relationship between firms’ sourcing and quality decisions. In our model we had a sharp distinction between sourcing destinations. In reality, there is a mixture of home production and foreign production. In this section we refer to this mixture of domestic and foreign production as offshoring and we also define a measure of this activity. With this measure, the key predictions of our model we explore are (1) the negative relationship between offshoring activity and quality, (2) heterogeneity in firms’ quality upgrading and downgrading decisions in response to new offshoring opportunities and (3) the relationship between a firms’ quality and whether or not they should respond to new offshoring opportunities (in particular, the extent to which quality predicts purchases of Chinese textile and apparel goods).

In order to discuss the sourcing decisions of firms we focus on imports of finished or nearly finished apparel goods. This corresponds to what Hummels et al. (2014) call “narrow offshoring.” The idea is to reflect the part of the supply chain that would most likely be performed by manufacturing plants in apparel that performed all production domestically. For example, it is highly unlikely that apparel firms would manufacture their own textiles from raw cotton, but could presumably make shirts at home or abroad. We focus on this concept because it represents the imports that are closest to the product that firms ultimately sell. Following Hummels and coauthors, as well as Autor et al. (2013), we define offshoring to be imports of apparel divided by the number of domestic employees. Thus, while we use the term offshoring here for convenience, it is shorthand simply for apparel imports per head at each apparel firm. With this measure we hope to capture the idea that the less employees per import volume one has at home, the less these employees are directly involved in production—whether it be actual manufacturing work or even quality control, distribution or other activities.\(^\text{25}\) Figure 2.12 plots the time series of average offshoring by firms.

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\(^{25}\)Discussions with people in the industry as well as the literature on fashion suggests that outsourcing abroad is normally done at arms length. After production, goods are often shipped back to their home country for quality control, inspection and distribution. This is especially true of branded manufacturers in Europe. This suggests a vital role for domestic employees at these firms, even if not directly involved in production. Moreover, by lowering overhead without a concurrent decrease in output, firms may be spending less time on quality control, managing their
While there is some volatility in the measure, there is a broad upward trend in offshoring over the sample period. Figure 2.13 focuses on offshoring to China. Overall, there is a .8 log point increase in overall offshoring activity in our sample and a 1 log point increase in offshoring to China. Thus, offshoring to China doubled and, in general, imports per head increased substantially for the apparel industry.

Before moving on, we address two potential concerns with our measure of offshoring. First, more productive firms may require less workers to generate the same amount of final output, suggesting a positive bias between offshoring and productivity. To deal with this fact, we include export values and the value of intermediates as controls for productivity and size. Many papers in the trade literature suggest that exports and intermediates should be highly correlated with productivity (for example, see Melitz (2003) and Halpern et al. (2015)).

Second, the value of imports contains price information and will be correlated with quality. To address this source of bias we do two things: first, we scale by the wage bill at a firm instead of the headcount of employees, and all of our results are robust to this; second, we use the import share weighted per capita GDP of import partners as a proxy for input quality. We think this is a good proxy as recent work in the trade literature, such as Manova and Zhang (2012) and Khandelwal (2010), suggest that per capita GDP is highly correlated with the quality of a country’s exports.

With our definition of offshoring in hand, we turn to testing our model predictions. First we explore the relationship between offshoring and quality by running regressions of the form:

\[ l_{jt} = \alpha_g + \beta \times \text{Offshoring}_{ft} + X_{ft} \gamma' + \epsilon_{jt} \]

where \( l_{jt} \) is the relative ladder position of good \( j \) at time \( t \), \( \alpha_g \) is a product fixed effect, and \( X \) is a set of controls and year fixed effects. Since our measure of offshoring is constant within a firm, we follow the same clustering strategy as in our structural estimation. Table 2.9 displays the results of our regressions for several choices of controls. In the first column, the coefficient on offshoring sourcing decisions or design. We test and verify this empirically by showing the relationship between our measures of quality and offshoring.
is positive, which may partially reflect productivity as an omitted variable. After we control for productivity, using exports and intermediates as proxies, the coefficient on offshoring is negative. In column (3) we allow for the effect of offshoring to depend on input quality, which makes the negative relationship stronger. The relationship outlined in this section suggests that, on average, firms that intensively source production from abroad will produce lower quality goods than other firms.

While the preceding paragraph discussed the relationship between offshoring and quality in a cross-section of firms, we now turn to the heterogeneous response of firms to new offshoring opportunities. To assess how cheaper inputs induce changes in firms’ relative position in the quality ladder we run regressions of the form:

\[ \Delta l_{jt} = \beta_1 \times \Delta Offshoring_{ft} + \beta_2 \times \Delta Offshoring_{ft} \times l_{t-1} + X_{ft}\gamma' + \epsilon_{jt} \]

where once again \( X \) is a set of controls that includes year fixed effects. We also include lagged offshoring as a control variable. We find this is important as it appears that there may be diminishing returns to offshoring, or that firms find it more difficult to increase offshoring beyond a base amount. Our objects of interest are \( \beta_1 \) and \( \beta_2 \). In particular, \( \beta_2 \) allows movement along the quality ladder to one’s initial position. Our model predicts that \( \beta_1 > 0 \) and \( \beta_2 < 0 \).

Table 2.10 contains the results of this regression. In the next two paragraphs we discuss \( \beta_1 \) and \( \beta_2 \) in turn.

Notice that the coefficient on growth in offshoring, \( \beta_1 \), is positive in all specifications. Thus, firms experiencing an increase in offshoring activity also experience an increase the quality of their output. This fact, along with the fact that offshoring firms tend to have lower quality output, suggests precisely that increasing offshoring is associated with a tightening of the quality ladder. In particular, lower quality firms are more likely to engage in offshoring and also upgrade their quality relative to other firms.

We explore heterogeneity in offshoring and quality, measured by \( \beta_2 \), in column 4. We find that,

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26Technically, it suggests a more complex relationship with difference between middle and high skilled firms. We attempted to include a quadratic term, and while an \( F \) test found all coefficients jointly significant they were not well identified separately.
controlling for productivity and input quality, the response of quality to offshoring is negative for middle and higher quality firms while remaining strongly positive for lower quality firms. This need not be the case and our model demonstrates how the marginal cost of increasing quality in different countries determines firms’ response to new sourcing opportunities. As a caveat, remember that these regressions are about relative movement over time, not absolute changes. So, it could be that all firms upgrade their output quality but some firms engage in more or less than others.

In the last part of this section, we turn our focus to China. China is a useful test case both because of its rapid global rise but also because we can exploit that China’s access to the WTO led to lower quotas under the MFA. However, these quotas were not applied to all products—hence, we can use quota fill rates as a measure of whether the China shock actually mattered to a particular product. The first thing we do is rerun our first set of regressions with a focus on offshoring to China:

\[ l_{jt} = \alpha_g + \beta \times ChinaOffshoring_{ft} + X_{ft}' \gamma' + \epsilon_{jt} \]

The first two columns of table 2.11 present the results of these regressions. Once we control for confounders, we find a significant negative relationship between offshoring intensity to China and output quality. Next we turn to our predictions regarding firms’ heterogeneous responses along the quality ladder. Here, a regression that ignores the possibility of heterogeneity finds that, even with a full set of controls present, there is no relationship between increasing offshoring and changes in quality. However, when the response is allowed to vary along the quality ladder the coefficients become significant and mirror previous findings.

Next, we use China’s entry to the WTO and the dismantling of the MFA to assess how firms respond to an exogenous change in offshoring opportunity. While typical models predict a positive relationship between import intensity and productivity, our model suggests a negative correlation between entry into offshoring to low quality countries and initial quality. To explore this effect quantitatively, we use the sharp drop in quotas that China experienced upon accession to the WTO, first in 2001, then again in 2005 as the MFA came to a close. Our source of variation comes from
the fact that these quotas did not affect all goods, as the quotas were only occasionally binding. We use a continuous measure (quota fill rates) but one may think of this as a treatment on certain products and not others. Our measure of quota fill rates refers to the quantity of apparel imports from China over the total quota allotted to China. Note that this is set at the EU level.\textsuperscript{27} With this discussion in mind, we run the following probit regression:

\[
Y_{\text{Source from CN}}^* = \beta_0 + \beta_1 \times \text{Quality}_{jt} + \beta_2 \times \text{Quota Fill Rate}_{jt} \\
+ \beta_3 \times \text{Quality}_{jt} \times \text{Quota Fill Rate}_{jt} + X'_j \gamma + \epsilon_{jt}
\]

where \( Y^* \) is the latent propensity to offshore, quality refers to our quality ladder measure and the quota fill rate was described above. Table 2.12 contains the regression results for various choices of controls. In all specifications, the coefficient on the ladder position is negative, and is significant when one controls for productivity. Interestingly our final specification shows that size is also an important determinant of offshoring activity. This suggests that ultimately both productivity and capability determine one’s offshoring choices, and understanding which firms and how firms respond to trading opportunities depends on the quality of their outputs.

\section*{2.7 Conclusion}

In this paper, we developed a model of offshoring and quality decisions by firms. In particular, we showed that when firms can outsource production, whether they choose to downgrade or upgrade their product quality will hinge on whether they are a low-capability or high-capability firm. We use detailed information on Danish apparel, including products level data on production, imports and exports to estimate a demand model and recover unobserved product quality. Our demand estimates are found to be in line with the previous literature. For example, we find that our estimated quality differences between firms explain the size-price relationship documented by Kugler and Verhoogen (2012). Moreover, we use our demand estimates and our trade data to demonstrate

\textsuperscript{27}All quota information comes from the EU’s SIGL database.
a heterogeneous response of firms. We find that firms producing at an initially medium or high quality downgraded their quality relative to low quality firms, who upgraded theirs.

To make more headway on the role of trade we use the dismantling of apparel quotas as a source of exogenous variation to the Danish apparel industry’s access to foreign input markets. We use two facts: first that China’s entry to the WTO immediately lowered quotas on Chinese goods; second these quotas fell unevenly across different products. We find that firms’ product quality is strongly affected by the change in the competitive environment and offshoring opportunities. In particular, we find strong evidence that the distribution of quality not only tightens, but patterns of entry into new import markets are driven by quality. The importance of this dimension in firms’ decision making holds even when we control for size and other proxies of productivity.

This tightening of the quality ladder, and the heterogeneous response causing it, complicate previous analyses of firms, especially those in vertically differentiated industries where quality plays a major role. In particular, our model and our results demonstrate that two separate attributes of a firm determine how they respond to trade liberalization: their productivity as well as their capability, the ability to produce high quality goods. How different industries respond to shocks will depend, ultimately, on the joint distribution of these two firm attributes. This suggests that the response of other variables, such as prices and wages, to a trade shock may depend on whether the industry affected by a shock is more vertically or horizontally differentiated.

Our work leaves open several avenues for future research. In particular, while we have documented how offshoring impacts the quality ladder, we have said nothing about the actual welfare changes induced by such a cost shock. While exact welfare calculations are sensitive to the demand system considered, as well as how one defines consumers’ outside options, it would still be interest to determine the extent to which the cost savings induced by offshoring are passed through into quality-adjusted prices. This would require modeling more carefully the quality and physical production function of firms—which requires product-level input data or a model of how inputs are allocated across products. Future work should also bring in wholesale firms and foreign competitors at a more granular level. This would allow researchers to analyze how offshoring opportunities
change the entire industrial structure in vertically differentiated markets, and not just the menu of quality offered by domestic firms. Finally, our estimation procedure relies on income-independent tastes for price and quality. However, if one also had information on the consumers at various firms, future work could attempt to estimate richer demand systems that allow for more precise estimates of quality and richer interactions between price, income heterogeneity and quality.

2.8 Appendices

2.8.1 Appendix A: Tables

Table 2.1: Most Popular Products

<table>
<thead>
<tr>
<th>Top 5 Products (by # of Producers)</th>
<th>1997-2002</th>
<th>2002-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cotton tee shirts</td>
<td>Cotton tee shirts</td>
<td></td>
</tr>
<tr>
<td>Cotton women’s jerseys</td>
<td>Cotton women’s jerseys</td>
<td></td>
</tr>
<tr>
<td>Syn. fiber women’s blouses</td>
<td>Syn. fiber women’s jerseys</td>
<td></td>
</tr>
<tr>
<td>Syn. fiber women’s trousers</td>
<td>Syn. fiber tee shirts</td>
<td></td>
</tr>
<tr>
<td>Syn. fiber women’s skirts</td>
<td>Cotton women’s blouses</td>
<td></td>
</tr>
</tbody>
</table>

Table reports most popular products by number of producers in Denmark. Products are defined at the Combined Nomenclature 8 digit level.
<table>
<thead>
<tr>
<th></th>
<th>Men’s</th>
<th>Women’s</th>
<th>Gender Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coats and jackets</td>
<td>Coats and jackets</td>
<td>Sweaters, jerseys, cardigans</td>
<td></td>
</tr>
<tr>
<td>Suits, jackets, blazers, trousers</td>
<td>Suits, jackets, dresses, skirts, trousers</td>
<td>t-shirts</td>
<td></td>
</tr>
<tr>
<td>Shirts</td>
<td>Shirts, blouses</td>
<td>Miscellaneous</td>
<td></td>
</tr>
<tr>
<td>Underwear, pajamas, gowns</td>
<td>Underwear, lingerie, gowns</td>
<td>Accessories</td>
<td></td>
</tr>
<tr>
<td>Sweaters, jerseys, cardigans</td>
<td>Sweaters, Jerseys, Cardigans</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>Miscellaneous</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Apparel products defined as products in CN categories 61 (Articles of Apparel, Knitted or Crocheted) and 62 (Articles of Apparel, Not Knitted or Crocheted). Nests are based on the first four digits, but ignore the distinction between knitted/crocheted wear and non-knitted/crocheted wear.*
Table 2.3: Demand Estimation for Domestic Apparel

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV: Logit</th>
<th>IV: Nested Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dep Var:</strong></td>
<td>log($s_{jft}/s_{0t}$)</td>
<td>log($s_{jft}/s_{0t}$)</td>
<td>log($s_{jft}/s_{0t}$)</td>
</tr>
<tr>
<td>$p_{fjt}$</td>
<td>-.00013</td>
<td>-.02129*</td>
<td>-.00768*</td>
</tr>
<tr>
<td></td>
<td>(-1.16)</td>
<td>(-1.82)</td>
<td>(-1.89)</td>
</tr>
<tr>
<td>log $s_{jgft}$</td>
<td>.901***</td>
<td>.321***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(95.32)</td>
<td>(3.43)</td>
<td></td>
</tr>
<tr>
<td><strong>Fixed Effects:</strong></td>
<td>Firm-Product, Year</td>
<td>Firm-Product, Year</td>
<td>Firm-Product, Year</td>
</tr>
<tr>
<td><strong>Clusters:</strong></td>
<td>Firm</td>
<td>Product, Firm-Year</td>
<td>Product, Firm-Year</td>
</tr>
<tr>
<td>$n$</td>
<td>7,586</td>
<td>7,586</td>
<td>7,586</td>
</tr>
<tr>
<td>1st Stage p-value - Price</td>
<td>–</td>
<td>.0928</td>
<td>.0369</td>
</tr>
<tr>
<td>1st Stage p-value - Nest</td>
<td>–</td>
<td>–</td>
<td>.0000</td>
</tr>
<tr>
<td>2nd Stage p-value</td>
<td>.0000</td>
<td>.0000</td>
<td>.0000</td>
</tr>
</tbody>
</table>

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.
Dependent variable is the market share of firm-product pair $f,j$ at time $t$ relative to the outside good. $p$ refers to the price measured in 2000 DKK. All specifications include firm-product and year fixed effects. Every specification drops 792 firm-products that are only observable in one period. Column (1) reports an OLS regression. Column (2) reports the results from the regression implied by a logit demand using import share weighted exchange rate shocks as an instrument for price. Column (3) reports the results from a regression based on nested logit system. There are 12 nests today, constructed based on CN 4 digit headings of goods in apparel (CN headings 61 and 62). Included instruments are imported share weighted exchange rate shocks for each firm, and, for each firm-product, the average exchange rate shock across competing firms. This latter variable is also interacted with a dummy for each nest.
Table 2.4: Distribution of Elasticity Estimates

<table>
<thead>
<tr>
<th>Nest</th>
<th>Mean</th>
<th>Q25</th>
<th>Q50</th>
<th>Q75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women’s Dresses</td>
<td>2.17</td>
<td>1.15</td>
<td>2.06</td>
<td>2.88</td>
</tr>
<tr>
<td>Women’s Shirts</td>
<td>1.65</td>
<td>.911</td>
<td>1.61</td>
<td>2.16</td>
</tr>
<tr>
<td>Men’s Suits</td>
<td>2.53</td>
<td>1.39</td>
<td>2.27</td>
<td>3.36</td>
</tr>
<tr>
<td>Women’s Sweaters</td>
<td>1.45</td>
<td>.690</td>
<td>1.24</td>
<td>1.99</td>
</tr>
<tr>
<td>Women’s Coats</td>
<td>3.43</td>
<td>2.07</td>
<td>3.33</td>
<td>4.82</td>
</tr>
</tbody>
</table>

Absolute values of elasticities reported. Elasticities are calculated for each firm-product-year triple according to the equation \[ \left| \frac{d \log s}{d \log p} \right| = \alpha p \left[ \frac{1}{1 - \sigma} - s - \frac{\sigma}{1 - \sigma} s_g \right] \] where \( s \) is total market share and \( s_g \) refers to within-nest market share. Reported means and quantiles are unweighted across all varieties within a nest.

Table 2.5: Correlation between Price, Size and Quality

<table>
<thead>
<tr>
<th>Quality</th>
<th>log(Price)</th>
<th>log(Employment)</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality</td>
<td>1</td>
<td>.1408</td>
<td>1</td>
</tr>
<tr>
<td>log(Price)</td>
<td>.1408</td>
<td>1</td>
<td>.0978</td>
</tr>
<tr>
<td>log(Employment)</td>
<td>.0978</td>
<td>.1785</td>
<td>.2234</td>
</tr>
<tr>
<td>Elasticity</td>
<td>.2234</td>
<td>.9210</td>
<td>.1749</td>
</tr>
</tbody>
</table>

All values are unweighted correlations across firm-product-year triples. Absolute values of elasticities reported. Elasticities are calculated for each firm-product-year triple according to the equation \[ \left| \frac{d \log s}{d \log p} \right| = \alpha p \left[ \frac{1}{1 - \sigma} - s - \frac{\sigma}{1 - \sigma} s_g \right] \] where \( s \) is total market share and \( s_g \) refers to within-nest market share. Quality is estimated from a nested logit demand system, price is in 2000 DKK and employment is measured in number of employees at the firm.
Table 2.6: Estimating the Size-Price Correlation

<table>
<thead>
<tr>
<th></th>
<th>(KV)</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep Var: log $P_{jft}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Employment)</td>
<td>.1130***</td>
<td>.0989***</td>
<td>.0123</td>
</tr>
<tr>
<td></td>
<td>(2.92)</td>
<td>(2.72)</td>
<td>(.44)</td>
</tr>
<tr>
<td>Quality ($\delta_{fjt}$)</td>
<td></td>
<td>.0509***</td>
<td>.1189***</td>
</tr>
<tr>
<td></td>
<td>(12.92)</td>
<td>(5.83)</td>
<td></td>
</tr>
<tr>
<td>Fixed Effects:</td>
<td>Year, CN8</td>
<td>Year, CN8</td>
<td>Year, Firm-CN8</td>
</tr>
<tr>
<td>Cluster:</td>
<td>Firm</td>
<td>Firm</td>
<td>Firm</td>
</tr>
<tr>
<td></td>
<td>177</td>
<td>177</td>
<td>177</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.5709</td>
<td>.5760</td>
<td>.6462</td>
</tr>
<tr>
<td>$N$</td>
<td>8,132</td>
<td>8,132</td>
<td>8,132</td>
</tr>
</tbody>
</table>

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%. Dependent variable in all regressions is log price of a firm-product-year triple, with price measured in 2000 DKK. Employment is calculated as the number of employees at the firm-year level and quality is estimated from a nested logit demand system.
### Table 2.7: Relationship Between Wages and Firm Quality

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>Non-High Only</th>
<th>High Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep Var: log $w_{ft}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quality ($\delta_{fjt}$)</td>
<td>.0245**</td>
<td>.0224*</td>
<td>.0155</td>
<td>.0149</td>
<td>.028**</td>
</tr>
<tr>
<td></td>
<td>(2.20)</td>
<td>(1.73)</td>
<td>(1.25)</td>
<td>(.92)</td>
<td>(2.26)</td>
</tr>
<tr>
<td>log(Employment)</td>
<td>.0055</td>
<td>.0053</td>
<td>.0076</td>
<td>.0079</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td>(0.33)</td>
<td>(.35)</td>
<td>(.61)</td>
<td></td>
</tr>
<tr>
<td>Skill Share</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.3947***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(6.87)</td>
</tr>
<tr>
<td>Cluster:</td>
<td>Firm</td>
<td>Firm</td>
<td>Firm</td>
<td>Firm</td>
<td>Firm</td>
</tr>
<tr>
<td></td>
<td>(160)</td>
<td>(160)</td>
<td>(160)</td>
<td>(157)</td>
<td>(159)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.1775</td>
<td>.1782</td>
<td>.3324</td>
<td>.0917</td>
<td>.1324</td>
</tr>
<tr>
<td>$N$</td>
<td>811</td>
<td>811</td>
<td>811</td>
<td>804</td>
<td>803</td>
</tr>
</tbody>
</table>

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%. Dependent variable is mean wage across workers in 2000 DKK for each firm-year. High-skilled workers are defined as those with at least 4 years of college. Employment and skill shares are based on head counts of employees, while quality is calculated from a nested logit model.
Table 2.8: Aggregate Changes in Ladder Length over Time

<table>
<thead>
<tr>
<th>Length Measures</th>
<th>$l_{max} - l_{min}$</th>
<th>$l_{p95} - l_{p5}$</th>
<th>$\sigma_l$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t$</td>
<td>.269**</td>
<td>.032</td>
<td>.004</td>
</tr>
<tr>
<td></td>
<td>(2.00)</td>
<td>(.57)</td>
<td>(.32)</td>
</tr>
<tr>
<td>$t \times \delta_{MFA}$</td>
<td>-.509***</td>
<td>-.047</td>
<td>-.019</td>
</tr>
<tr>
<td></td>
<td>(.14)</td>
<td>(-.79)</td>
<td>(-1.38)</td>
</tr>
<tr>
<td>$\delta_{MFA}$</td>
<td>1017.78***</td>
<td>95.58</td>
<td>39.74</td>
</tr>
<tr>
<td></td>
<td>(.14)</td>
<td>(.79)</td>
<td>(1.38)</td>
</tr>
<tr>
<td>Constant</td>
<td>-530.20**</td>
<td>-58.92</td>
<td>-7.01</td>
</tr>
<tr>
<td></td>
<td>(1.42)</td>
<td>(-.57)</td>
<td>(-.26)</td>
</tr>
</tbody>
</table>

N 14 14 14

$R^2$

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%. The dependent variable, $l$, refers to the time-demeaned quality of a product-firm-year triple. $\delta_{MFA}$ is a dummy for $t \geq 2002$, for when the penultimate round of quota drops occurred and China was in the WTO for the first full year.
Table 2.9: Offshoring and Quality Ladder Position in the Cross-Section

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Offshoring)</td>
<td>.0599***</td>
<td>-.0298</td>
<td>-.2356***</td>
</tr>
<tr>
<td></td>
<td>(2.55)</td>
<td>(-1.31)</td>
<td>(-4.44)</td>
</tr>
<tr>
<td>$\delta_{ft,\text{input}} \times \log(\text{Offshoring})$</td>
<td>.0213***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.99)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Intermediates)</td>
<td>.0330***</td>
<td>.0358***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.18)</td>
<td>(2.29)</td>
<td></td>
</tr>
<tr>
<td>log(Exports)</td>
<td>.1351***</td>
<td>.1448***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.39)</td>
<td>(5.28)</td>
<td></td>
</tr>
</tbody>
</table>

Fixed Effects: Product, Year Product, Year Product, Year

Cluster: Firm-Year Firm-Year Firm-Year

890  785  785

$R^2$  .3839  .4140  .4159

N  7,905  7,397  6,836

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

Dependent variable is a firm-product-year’s position in the quality ladder, measured as the time-demeaned quality of a product-firm-year triple. Offshoring is measured as the value of imports of apparel products (CN headings 61-62) in 2000 DKK divided by the number of workers in a firm. Exports refer specific to the value of apparel exports (CN headings 61-62) measured at 2000 DKK. Intermediates are reported for each firm-year by Stats DK, and deflated to 2000 DKK. $\delta_{ft,\text{input}}$ is a proxy for input quality at the firm level measured by the import share weighted GDP per capita of all import partners, where imports again refer to goods in CN headings 61-62.
Table 2.10: Offshoring and Ladder Movement - Overall and Heterogeneous Effects

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta l_{jt}$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \log(\text{Offshoring})$</td>
<td>.0596***</td>
<td>.0620*</td>
<td>.0623*</td>
<td>.0885***</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(1.92)</td>
<td>(1.92)</td>
<td>(2.69)</td>
</tr>
<tr>
<td>$\Delta \log(\text{Offshoring}) \times l_{jt-1}$</td>
<td></td>
<td></td>
<td></td>
<td>$-.0827***$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-3.22)</td>
</tr>
<tr>
<td>$\delta_{ft,\text{input}}$</td>
<td>$-.0202$</td>
<td>$-.0103$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-.52)</td>
<td>(-.27)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\log(\text{Intermediates})$</td>
<td>.0069</td>
<td>.0065</td>
<td>.0074</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.83)</td>
<td>(.78)</td>
<td>(.99)</td>
<td></td>
</tr>
<tr>
<td>$\log(\text{Exports})$</td>
<td>.0107</td>
<td>.0099</td>
<td>.0125</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.77)</td>
<td>(.72)</td>
<td>(.95)</td>
<td></td>
</tr>
<tr>
<td>$\log(\text{Offshoring})_{t-1}$</td>
<td>$-.0275$</td>
<td>$-.0269$</td>
<td>$-.0228$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.29)</td>
<td>(-1.26)</td>
<td>(-1.14)</td>
<td></td>
</tr>
</tbody>
</table>

Fixed Effects: CN8, Year  
Cluster: Firm-Year  
<table>
<thead>
<tr>
<th></th>
<th>CN8, Year</th>
<th>CN8, Year</th>
<th>CN8, Year</th>
<th>CN8, Year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>701</td>
<td>631</td>
<td>631</td>
<td>631</td>
</tr>
</tbody>
</table>

$R^2$  
$N$  
|     | .0105     | .0110     | .0112     | .0195     |
|     | 5,199     | 4,923     | 4,923     | 4,923     |

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.
Dependent variable is the change in a firm-product-year’s position in the quality ladder. This position is measured as the time-demeaned quality of a product-firm-year triple. Offshoring is measured as the value of imports of apparel products (CN headings 61-62) in 2000 DKK divided by the number of workers in a firm. Exports refer specific to the value of apparel exports (CN headings 61-62) measured at 2000 DKK. Intermediates are reported for each firm-year by Stats DK, and deflated to 2000 DKK. $\delta_{ft,\text{input}}$ is a proxy for input quality at the firm level measured by the import share weighted GDP per capita of all import partners, where imports again refer to goods in CN headings 61-62. Columns 2-3 only include those firms reporting intermediates to stats DK.
### Table 2.11: Offshoring to China and Ladder Movement

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: $l_{jt}$</th>
<th>Dependent Variable: $\Delta l_{jt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\log(\text{Offshoring}_{CN})$</td>
<td>$-0.230$</td>
<td>$-0.290^*$</td>
</tr>
<tr>
<td></td>
<td>(-1.49)</td>
<td>(-1.90)</td>
</tr>
<tr>
<td>$\Delta \log(\text{Offshoring}_{CN})$</td>
<td>$-0.044$</td>
<td>$-0.113$</td>
</tr>
<tr>
<td></td>
<td>(-0.30)</td>
<td>(-0.70)</td>
</tr>
<tr>
<td>$\Delta \log(\text{Offshoring}<em>{CN}) \times l</em>{jt-1}$</td>
<td></td>
<td>$-0.521^{**}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-3.57)</td>
</tr>
<tr>
<td>$\log(\text{Intermediates})$</td>
<td>$.0246$</td>
<td>$.0053$</td>
</tr>
<tr>
<td></td>
<td>(1.16)</td>
<td>(.30)</td>
</tr>
<tr>
<td>$\log(\text{Exports})$</td>
<td>$.1373^{***}$</td>
<td>$.212$</td>
</tr>
<tr>
<td></td>
<td>(3.03)</td>
<td>(1.27)</td>
</tr>
<tr>
<td>$\log(\text{Offshoring}_{CN,t-1})$</td>
<td>$-0.0141$</td>
<td>$-0.0141$</td>
</tr>
<tr>
<td></td>
<td>(-1.58)</td>
<td>(-1.56)</td>
</tr>
</tbody>
</table>

**Fixed Effects:** CN8, Year

<table>
<thead>
<tr>
<th>Cluster:</th>
<th>CN8, Year</th>
<th>CN8, Year</th>
<th>Year</th>
<th>Year</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Firm-Year</td>
<td>Firm-Year</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>397</td>
<td>366</td>
<td>287</td>
<td>269</td>
<td>269</td>
</tr>
</tbody>
</table>

| $R^2$    | .4563     | .4754     | .0050 | .0059 | .0213 |
| $N$      | 5,173     | 5,006     | 3,159 | 3,107 | 3,107 |

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

In columns (1) and (2), dependent variable is the change in a firm-product-year’s position in the quality ladder. This position is measured as the time-demeaned quality of a product-firm-year triple. In columns (3) - (5), dependent variable is the change in ladder position over time. In all specifications, offshoring is measured as the value of imports of apparel products (CN headings 61-62) in 2000 DKK divided by the number of workers in a firm. Exports refer specific to the value of apparel exports (CN headings 61-62) measured at 2000 DKK. Intermediates are reported for each firm-year by Stats DK, and deflated to 2000 DKK. $\delta_{f,t,\cdot}$ is a proxy for input quality at the firm level measured by the import share weighted GDP per capita of all import partners, where imports again refer to goods in CN headings 61-62. Columns 2-3 only include those firms reporting intermediates to Stats DK.
Table 2.12: Probit Regression: Probability of Offshoring to China Projected on Quality

<table>
<thead>
<tr>
<th>Dep Var: Import from China</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality ( (\delta_{jt}) )</td>
<td>-.0313*</td>
<td>-.0305</td>
<td>-.0233</td>
<td>-.0757***</td>
</tr>
<tr>
<td></td>
<td>(-1.66)</td>
<td>(-1.62)</td>
<td>(-1.22)</td>
<td>(-3.74)</td>
</tr>
<tr>
<td>Quota Fill Rate</td>
<td>-.2189***</td>
<td>-.2016***</td>
<td>-.1765**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.46)</td>
<td>(-3.20)</td>
<td>(-2.36)</td>
<td></td>
</tr>
<tr>
<td>Quality \times Quota Fill Rate</td>
<td>-.1161**</td>
<td>-.0976*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.56)</td>
<td>(-1.84)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Employment)</td>
<td></td>
<td></td>
<td>.5736***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(5.01)</td>
<td></td>
</tr>
<tr>
<td>log(Intermediates)</td>
<td></td>
<td></td>
<td>.1115***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2.61)</td>
<td></td>
</tr>
</tbody>
</table>

Fixed Effects: Year Year Year Year

Cluster: Firm-Year Firm-Year Firm-Year Firm-Year

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pseudo-(R^2)</td>
<td>.1080</td>
<td>.1090</td>
<td>.1096</td>
<td>.2618</td>
</tr>
<tr>
<td>(N)</td>
<td>8071</td>
<td>8071</td>
<td>8235</td>
<td>8057</td>
</tr>
</tbody>
</table>

Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

All specifications are coefficients of a probit regression measuring the probability of importing apparel goods (CN headings 61-62) from China. Quality is measured as the demand shifter derived from a nested logit demand system. Quota fill rates refer to the fraction of total European imports from China over the quota on European imports from China. This quota is calculated at the product level from the EU’s SIGL database. The product codes in the SIGL database strictly contain those in the Combined Nomenclature. Thus, more than one good may be bound under the same quota, but there is no ambiguity in which quota applies to which good. Column (4) includes intermediates and exports as proxies for productivity. Intermediates are reported for each firm-year by Stats DK, and deflated to 2000 DKK, while employment is measured as a headcount of employees at time \(t\) at the firm producing good \(j\).
2.8.2 Appendix B: Figures

Figure 2.1: Time Series of Danish Apparel Import

Changes in Net Apparel Imports

Apparel goods are defined as those in CN headings 61 and 62. Net imports are measured as the sum of all imports minus the sum of all exports, including re-importing and re-exporting activity. Nominal apparel imports are recorded in 1000s of DKK. Weight data is in kilograms. Danish customs records include both count measures and weight measures of goods. We use weight as the units are common across goods.

Figure 2.2: Changes in the Danish Apparel Industry

Evolution of Top Partners’ Import Shares

Apparel goods are defined as those in CN headings 61 and 62. We determine the largest import partners by taking the average import share across years.
Apparel goods are defined as those in CN headings 61 and 62. We plot the 5 largest partners as measured by their average share in imports over the sample period.

Elasticities are calculated with the formula $|d \log s/d \log p| = \alpha p \left[ \frac{1}{1 - \sigma} - 1 + \frac{1}{1 - \sigma} \sigma g \right]$, using estimates from a nested logit demand system. This density is pooled across all firm-product-years ($N = 81.32$).
Figure 2.5: Price versus Quality

Unit of observation is a firm-product-year triple \( (N = 8132) \). Price is recorded in 2000 DKK, while quality is derived from a nested logit demand system. We remove nest and year fixed effects.

Figure 2.6: Evolution of Quality Ladders

Unit of observation is a firm-product-year triple. The quality ladder is the demeaned distribution of residuals from a nested logit demand system for a given year. The above pools over all triples.
Aggregate quality is defined as the unweighted mean quality across all product-firm-year triples in a given year. Quality for each firm is calculated from a nested logit demand system.

Aggregate quality shock refers to time fixed effects estimated in a nested logit demand system.
Quality growth is calculated from an Olley-Pakes decomposition of aggregate quality. The entry exit term is calculated as the difference in the mean quality of entering and exiting firm-products weighted by their respective share in total firms:

\[ \frac{N_{\text{entrant}}}{N_{\text{firms}} \cdot \text{Quality}_{\text{entrant}}} - \frac{N_{\text{exits}}}{N_{\text{firms}} \cdot \text{Quality}_{\text{exits}}} \]

The covariance component is calculated from an Olley-Pakes decomposition of aggregate quality. This measures the covariance between the market share of a firm-product (measured in sales) and the firm-product's quality.
Quality for each firm is calculated from a nested logit demand system. The length of the quality ladder is the distance between the maximum and minimum observed quality in a given year.

Narrow imports are measured as the value (in 2000 DKK) of apparel (CN headings 61 and 62) imports. Offshoring is defined as the value of imports divided by the number of employees in an apparel firm. In order to report an aggregate number we reported total imports over total employees. That is, indexing firms by $f$, we report the log of $\sum_f \text{Imports}_f / \sum_f \text{Employees}_f$. 
Narrow imports are measured as the value (in 2000 DKK) of apparel (CN headings 61 and 62) imports. Offshoring is defined as the value of imports divided by the number of employees in an apparel firm. In order to report an aggregate number we reported total imports over total employees. That is, indexing firms by $f$, we report the log of $\sum_f \text{Imports}_f / \sum_f \text{Employees}_f$. 

Values are average offshoring activity across firms.
Chapter 3

Intermediate Input-Skill Complementarity & Importers: A Quantitative Exercise Using Colombian Data *

3.1 Introduction

Over the last few decades, a large number of countries have seen an increase in the skill premium—the relative wages of highly educated workers to other laborers. Simultaneously there has been a steep decline in world wide trade costs, and a concomitant growth in trade flows. This has led many to ask if the two are related. However, classical trade models have struggled to explain the rise in the skill premium in unskilled abundant countries. In order to address this gap, many have studied the extent to which certain inputs—capital or imported intermediates—substitute differentially with different types of labor. Yet, only recently have researchers attempted to properly quantify the extent of these complementarities. This paper aims to estimate the extent, both across industries and firms, to which there is intermediate-skill complementarity using microdata on production.

In order to examine the extent of complementarities between inputs and different kinds of labor, I estimate a production function that allows for intermediate inputs and skilled workers to substi-

*I am grateful to my advisers Stephen Redding and Jan De Loecker for helping me with this work. This paper grew out of my third year paper. I also thank Ana Fernandes for providing me with data on trade frictions. This research was funded by a Princeton IES summer grant.
tute with each other differently than they substitute with unskilled labor. I work with a flexible translog specification. While this specification is useful for estimation and allows me to explore heterogeneity in the production patterns of plants, it lacks a single parameter that captures the role of complementarities. Moreover, translog production function can be unwieldy, which makes modeling with them difficult. To that end, I also exploit a nested CES production function. I show how my estimated production function can be treated as an approximation to a CES production function. With this in hand, the parameter of interest is the parameter governing the elasticity of substitution between skilled workers and intermediates.

Using plant-level data has three distinct advantages over methods that rely on aggregate data, which are more common in the literature. First, identification comes from observing the actual production decisions of firms, rather than changes in factor and skill prices. Thus, my paper brings a new source of variation to bear on these questions. More importantly, this variation does not come from observations of the aggregate moment in the data I want to explain (the skill premium). Second, micro data allows me to estimate this parameter across a wide range of industries. Oberfield and Raval (2014) have highlighted the extent to which aggregate elasticities in the US have shifted as the composition of industries and firms changes. Their work underscores the importance of understanding heterogeneity in production processes across industries in order to understand aggregate phenomena. To the best of my knowledge, this paper is one of the first to explore complementarity across industries. Third, data with firm information allows me to explore how patterns differ between importers and non-importers.

My estimation yields two results. First, there is evidence of complementarities between skill and imported intermediates, but substantial heterogeneity across industries. When the elasticity of substitution between unskilled labor and the skilled-intermediate composite is assumed to be 1\(^1\), I find the median elasticity of substitution between skilled labor and intermediates to be 3.1 across SIC 3 digit manufacturing industries—which pushes back against the idea of intermediate-skill complementarity. However, I find complementarities in 20% of industries. The range of

\(^{1}\)As I will discuss later, it is difficult to identify a fully flexible production function, so I need to impose additional theoretical restriction to identify my model’s parameters.
substitution elasticities across industries is quite large, with a minimum of .16 and a maximum of 13.6. This strongly suggests that these forces will differ across countries with their patterns of specialization. Moreover, it hints that the extent of complementarity forces to influence the skill premium may actually be shaped by trade forces as resources reallocate across industries.

Second, I find there is heterogeneity in the extent of complementarity forces within industries and across firms. In particular, I find that importers tend to be more productive than non-importers and importers are more likely to use a production process displaying intermediate-skill complementarity. These two forces combined imply that lowered trade costs may shift resources (through the productivity effect) to precisely those plants that use intermediate-skill complementary technology. I describe this heterogeneity more concretely in the main text.

The next section offers a comprehensive review of the literature. My work is closely related to the recent work of Lewis (2011), Parro (2013), Burstein et al. (2013) (henceforth BCV), all of whom explore the importance for complementarities and substitution patterns in analyzing wage movements in open economies. I contribute to the literature in two ways. First, as discussed above, I use microdata to identify model parameters. Second, whereas other authors have focused largely on capital-skill complementarity, my focus is on intermediate inputs. The latter more closely reflect changes in the supply chain decision of firms. My paper is also related to recent papers using firm-level data to understand trade patterns (e.g., Pavcnik (2002), De Loecker (2011), De Loecker et al. (2012)). However, these papers have predominantly focused on estimating productivity and not on identifying the substitution patterns of different inputs.

In section 3, I present an illustrative model demonstrating how intermediate-skill complementarity can overturn standard results, such as the Stolper-Samuelson theorem. In particular, I embed input-skill complementarity in a Melitz (2003) framework. The introduction of cheaper foreign intermediates increases demand for skilled labor, even in an unskilled-labor abundant country. This force places upward pressure on the skill premium as in Krusell et al. (2000), and can undo standard Stolper-Samuelson effects. This model is purely illustrative, but highlights the importance of understanding these complementarities.
In sections 4 and 5 I briefly review the data that I use and my empirical methodology. I use a panel of Colombian manufacturers that runs from 1982-1989.\footnote{This data has been extensively used since its introduction. For early work and descriptions of the data see Roberts (1996) and Roberts and Tybout (1997).} I also outline how I map the CES production function into the proxy-method of production function estimation.

I section 6 I present my results, which I have already discussed above. Finally, I conclude in section 7.

### 3.2 Literature Review

A long running question in the trade literature has been what role does globalization play in explaining increases in the skill premium across countries. One puzzle is that liberalization has been met with a rising skill premium even in unskilled labor abundant countries. This has led to theories exploring technology that is, in some way, skill biased. One of the most common stories involves factor-augmenting technological change. In this world, there is a possibly exogenous technology process that may favor skilled or unskilled labor. An example of this is in the work of Autor et al. (1998) which considers a simple production function of the form,

\[
Q_t = \left[ a_t N_c^\rho + b_t N_h^\rho \right]^{1/\rho}
\]

where \( \{a_t, b_t\} \) is a productivity process, \( N_c \) are skilled workers and \( N_h \) unskilled. Their work explored different forces that might impact \( a_t \) and \( b_t \)—for example, changes in the price of computing which may be complementary to skilled workers. This paper explores a similar mechanism for skill-biased technical change: the reduction in the price of potentially complementary inputs.

My analysis is largely informed by two papers: Krusell et al. (2000) (henceforth, KORV) and Lewis (2011). KORV estimate a nested CES production function in order to decompose changes in the skill premium in the US into changes in the supply of skills, the price and supply of different kinds of capital and also changes in the average quality of different types of labor. Lewis (2011)
looks at capital-skill complementarity through wage equations. Exploiting immigration patterns as a source of exogenous variation in a locality’s skill mix, he finds strong evidence that machinery substitutes with unskilled labor. My approach is similar to these authors in that I attempt to recover actual production function parameters and relate them to a model of wages. However, I use a panel data set of firms, which affords some benefits outlined in the introduction.

While the above papers did not explicitly address trade, the interaction between complementarities and trade activity has been extensively studied. My paper touches on two strands of the literature: the literature on the skill premium and trade, and the impact of imported intermediates on wages.

The classic mechanism through which trade impacts the skill premium is the Stolper-Samuelson effect: the idea that lower trade barriers tend to favor the factors abundant in a country. This theorem predicts that the skill premium should decrease in unskilled labor abundant countries as they ease trade restrictions. Goldberg and Pavcnik (2007) catalog the skill premium in numerous developing countries and find that, contrary to the predictions of the Stolper-Samuelson theorem, the skill premium increases more often than not. However, richer models, especially the recent work on heterogeneous firms, have shown a number of additional effects that can potentially undo these forces. For example, I draw largely on the work of Bernard et al. (2007). In this model, the ability for reallocation of resources within as well as across industries allows for the tempering of the Stolper-Samuelson effect. In particular, under the right circumstances real wages for all types of labor may rise. However, this model cannot capture a reversal of the skill premium, as real wages increase more for the abundant factor. I show that introducing complementarities into this model can reverse this result.

Turning to the study of complementarities in trade, one of the first papers that embeds capital-skill complementarity into an open economy model is that of Stokey (1996). She constructs an open economy macroeconomic model that allows for capital inflows and has complementarities. She finds that international integration leads to an initial increase in the skill premium, and eventual decrease as human capital accumulation occurs. More recently, BCV and Parro (2013) calibrate
an Eaton-Kortum model with capital-skill complementarity using aggregate moments of the skill premium and skill supply. They use their models to explore the effects of lower capital prices on wages across countries and workers. A related paper by Burstein and Vogel (2010) explores the skill premium and capital prices, but focus on factor-augmenting technical change alongside capital-skill complementarity. They find that trade explains a large fraction of reallocation of resources to skill-intensive sectors in most countries. My work builds on this tradition, but I turn my attention to imported intermediates rather than capital. Moreover, as previously stated I use microdata to explore heterogeneity across industries.

The above work largely focuses on general equilibrium models across many countries. However, there has been a concurrent strand of the literature that explores heterogeneity across firms without estimating a general equilibrium model for the world. For example, Harrigan and Reshef (2011) estimate a model of factor augmenting technological differences across firms. In their model, firms inherit both a productivity shock and a technology shock that affects the share of skilled labor each firm uses in production. The correlation in these shocks gives rise to complementarities. They estimate a positive correlation. Thus, lower trade costs reallocate production not only to more productive, but also to more skill-biased firms. On the other hand, they find a modest effect of trade barriers on the skill premium. In related work, Bustos (2011b,a) allows for explicit technology upgrading in a heterogeneous firms model. She finds strong evidence of technological differences across firms that engage in trade and those that do not. Moreover, she finds evidence of technological upgrading by exporters, only after they have access to international markets. She ties this upgrading to the skill premium. Finally, Koren and Csillag (2011), using a unique dataset that matches workers to their machines, find strong evidence for capital-skill complementarity in Hungarian firms.

The above papers have largely focused on capital, but recent papers have also explored the role of imported intermediates more directly. A brief overview of many of the general facts can be found in Kugler and Verhoogen (2009) and Goldberg et al. (2010). For example, Halpern et al. (2015) find that importers behave differently than non-importers, even controlling for export sta-
tus. They find large effects of import status on productivity. These results are echoed by Kasahara and Lapham (2013), who build and estimate a dynamic model of importing choice. Focusing on the skill premium in particular, Amiti and Davis (2012) find evidence that firms that import intermediates pay different wages than non-importing firms. In follow-up work, Amiti and Cameron (2012) find that importing intermediates leads to a decrease in the skill premium among firms that import. They argue that the differences arise because of a very small supply of skills in their country of interest, Indonesia. This finding also hints at potential heterogeneity in production processes across countries and, more importantly, that countries may specialize in ways that interact with this heterogeneity.

Finally, I briefly comment on the methodology I employ. I follow a trend in the trade literature that uses proxy methods, introduced by Olley and Pakes (1996), in order to estimate production functions using firm-level data. Important papers in this thread include Pavcnik (2002), Van Biesenbroeck (2005), Fernandes (2007), De Loecker (2011), and De Loecker et al. (2012). These papers have used panel data methods to carefully explore a variety of hypotheses from the new trade literature—including learning by exporting, the impact of trade liberalization on product scope and the effects of trade liberalization on markups across firms. To date, these papers have focused largely on productivity and not looked at differential substitution patterns between different types of labor and inputs. My exact strategy closely follows De Loecker (2011), who demonstrates how one may control both for demand and endogeneity in estimation.

### 3.3 Illustrative Model

In this section I briefly outline a two country model with two sectors and capital-skill complementarity. I include this model only to motivate the forces that I explore in the subsequent estimation. The model is a modified version of that in Bernard et al. (2007) (henceforth BRS) and Amiti and Davis (2012). I will define intermediate-skill complementarity as it applies in this model and also outline the production function and environment in which the firms operate. I also explain the in-
teraction between the Stolper-Samuelson effect and the effect of complementarities. As the focus of this paper is on empirically investigating the production function, I keep the model brief but highlight key equations and mechanisms.

In this model there are two types of labor, skilled and unskilled labor supplied inelastically at levels $\bar{S}$ and $\bar{U}$. I focus on roundabout production, as in Krugman and Venables (1995) to keep things tractable. This means that all firms will import the same bundle of inputs; however, the same forces are present in a model with an extensive margin of importing. In the empirical section I explore differences along the extensive margin more concretely. In the counterfactual, I posit two countries that are symmetric in all ways except their relative endowments of skilled and unskilled labor are the inverse of one another. However, to keep the exposition simple and avoid cumbersome notation, I focus on only one country below, as the other is symmetric.

**Households**

Households consume goods in a two-tiered fashion. In the upper tier they consume a Cobb-Douglas aggregator of final goods and in the lower tier a CES aggregator of varieties from firms. That is to say,

$$U = Q_1^\alpha Q_2^{1-\alpha}$$

$$Q_i = \left(\int_\Omega q_i(\omega)^\theta d\omega\right)^{1/\theta}$$

where $\omega$ indexes goods within a sector, $i$ indexes sectors and $\Omega$ is the measure of available varieties. This leads to a price index and demand system of the form,

$$P_i = \left(\int_\Omega p_i(\omega)^{1-\eta} d\omega\right)^{1/(1-\eta)}$$

$$q_i(\omega) = E_i P_i^{\eta-1} p_i(\omega)^{-\eta}$$

where $\eta = \frac{1}{1-\theta}$ and $E_i$ is household expenditure spent in sector $i$.  

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Firms

Production

The final goods in the economy are produced using unskilled labor, skilled labor and an intermediate good, which is the same composite good that households consume. In this section I describe only one industry—the other is completely symmetric. Firms have a Hicks neutral productivity shock, $\varphi$, drawn from a distribution $G$. Their production function is given by:

$$q(u, s, x, \varphi) = \varphi \left[ \mu \frac{u^\sigma}{\text{Unskilled}} + (1 - \mu) \left( \lambda \frac{x^\rho}{\text{Intermediates}} + (1 - \lambda) \frac{s^\rho}{\text{Skill}} \right) \right]^{\sigma/\rho}$$

where $u$ is unskilled labor, $s$ is skilled labor and $x$ is intermediate inputs. In this model, $\frac{1}{1-\rho}$ is the elasticity of substitution between skilled labor and intermediates, while $\frac{1}{1-\sigma}$ is the elasticity of substitution between unskilled labor and the intermediates-skilled bundle. The remaining parameters, $\lambda$ and $\mu$, are weights on the inputs and govern the share of expenditure of each input (in the limiting Cobb-Douglas case, they are exactly the expenditure shares). As this production function displays constant returns to scale, there exists a unit cost, $c$, and so a firm of productivity $\varphi$ will ultimately face a production cost of $c/\varphi$. In order to produce, firms must also pay a fixed production cost, $f_d$. Furthermore, if firms want to trade then they must pay a fixed cost of exporting given by $f_x$. Moreover, I assume that firms pay an iceberg trade cost, $\tau$, to ship goods. This implies that for an exporting firm, the marginal cost of moving goods abroad is given by $c\tau/\varphi$.

In order to discuss the idea of intermediates-skill complementarity, I first formalize the concept following Fallon and Layard (1975). In particular, I will define intermediates-skill complementarity as:

$$\frac{\partial \log q_s}{\partial \log x} > \frac{\partial \log q_u}{\partial \log x}$$

where $q_j$ refers to the derivative of output with respect to input $j$. Intuitively, this states that $s$ is complementary of $x$ relative to $u$ if a proportional increase in $x$ increases the marginal product of
s more than the marginal product of \( u \). One can show that this is equivalent to

\[
\frac{\partial q/ (\partial s \times \partial x)}{\partial q/ \partial s} > \frac{\partial q/ (\partial u \times \partial x)}{\partial q/ \partial u}
\]

In the CES case above this reduces to the condition that \( \rho < \sigma \). To better understand this concept, suppose that \( \sigma = 1 \) and \( \rho = -\infty \). That is, suppose that unskilled labor substitutes perfectly with the intermediates-skill bundle while intermediates and skill are perfect complements in the production of the bundle. Then the production technology becomes,

\[
q = \varphi [\mu u + (1 - \mu) \min \{x_o, s\}]
\]

Here unskilled labor substitutes perfectly with intermediates/skills while the others are perfect complements. If the price of intermediates decreases substantially, then \textit{ceteris paribus} one will demand more of both intermediates and skills, lowering use of unskilled labor. In such a setting, a reduction in trade costs can have two effects in an unskilled labor abundant country. Standard Heckscher-Ohlin forces effect suggest that a country should specialize in the unskilled intensive sector, thus increasing factor payments to unskilled labor. However, lowering the price of intermediates may also increase demand for skilled workers, as long as every sector displays some degree of complementarity. We explore this intuition with different values of \( \rho \) at the end of this section and then empirically examine these forces with our structural estimation.

**Firm Profits and Exporting**

A firm in industry \( i \) with productivity \( \varphi \) operating in the domestic market seeks to maximize total profits given by,

\[
\pi_{d,i}(\varphi) = \max_p Q_i \left( \frac{p}{P_i} \right)^{-\eta} (p - c_i) - P f_{d,i}
\]

where \( c_i \) is the unit cost of production in industry \( i \) and \( f_{d,i} \) is a fixed cost of production that is paid for in the aggregate consumer bundle across all industries. I will call the portion of profits
not including fixed costs variable profits. The demand curve above is the same as that derived from consumers except that I have replaced $E_i$ with an aggregate quantity index. This is because total expenditure will be a sum of consumer and intermediates expenditure. Here is where the assumption that firms and consumers have the same elasticity of substitution across varieties is useful, as it leads to a simple modification of the standard CES demand curve.

The CES demand structure implies that firms price at a constant markup over marginal cost. Moreover, it can be shown that variable profits are given by revenues scaled by $1/\eta$. Firms will only operate if variable profits are positive. So, plugging the pricing rule into the profit function leads to the following zero profit condition for production:

$$Q_i P^\eta \left( \frac{c_i}{\theta} \right)^{1-\eta} \varphi_{d,i}^{\eta-1} = \eta P f_{d,i}$$

where $\varphi_{d,i}$ is the productivity of the marginal domestic producer. The left-hand side is the revenues to a firm setting prices optimally, while the right hand side reflects fixed costs multiplied by $\eta$. This cutoff rule is analogous to that in Melitz (2003) and BRS, except for the appearance of price indices that arise because costs are paid with intermediates and not pure labor.

There is an analogous profit function for exporters using $\tau c_i$ as the unit cost and paying a fixed cost $f_{x,i}$. The variable profit of exporting firms will be proportional to domestic firms. In particular,

$$\pi_{x,i}^{\text{var}}(\varphi) = \Lambda_i \pi_{d,i}^{\text{var}}(\varphi)$$

where $\pi^{\text{var}}$ refers to variable profits. The term reflects competitive forces abroad relative to those at home and is given by,

$$\Lambda = \tau^{1-\eta} Q_i^* \left( \frac{P^*}{F^*} \right)^\eta$$

where asterisks denote foreign variables. This leads to the following cutoff rule for exporting:

$$\Lambda r_{d,i}(\varphi, c) \geq \eta f_x$$

where $r_{d,i}$ is revenue for the optimally pricing domestic revenue. With these cutoff rules in hand,
one can integrate across all firms to calculate aggregate revenues in each industry, \( R_i \). Notice that this also gives aggregate variable profits as these are revenues scaled by \( 1/\eta \).

In order to close the model, I need to specify what happens with firms’ profits. As in Melitz (2003), I will assume there is free entry in each industry which pushes average profits (net of fixed costs) to zero. To explain further, first I assume that firms are infinitely lived and die with exogenously given probability \( \delta \). Hence, expected profit for a firm with productivity \( \varphi \) in industry \( i \) is given by \( \pi(\varphi)/\delta \). A potential entrant can pay a cost \( f_e \) to enter and learn their productivity. Since productivity is not known \textit{ex-ante} firms will enter based on expected profits. As more firms enter, each firm, conditional on \( \varphi \), makes less profit. Melitz (2003) demonstrates how the zero profit conditions on production and exporting, paired with a free entry condition determines both the ultimate mass of firms in the market as well as the production and export cutoffs.

**Equilibrium**

The conditions for an equilibrium are exactly like those in Melitz (2003) and BRS with an additional clearing condition for intermediates. The key objects of equilibrium are a vector of factor and goods prices, \( \{w^H_u, w^F_u, w^H_s, w^F_s, P^H_i, P^F_i\} \), masses of firms, \( \{M^H_i, M^F_i, M^H_{i,e}, M^F_{i,e}\} \), productivity cutoffs, \( \{\varphi^H_{i,d}, \varphi^F_{i,d}, \varphi^H_{i,x}, \varphi^F_{i,d}\} \), sectoral revenues, \( \{R^H_i, R^F_i\} \) and intermediate goods consumption, \( \{X^H_i, X^F_i\} \) so that firms maximize profits, consumers maximize utility, markets clear and firm masses are consistent with aggregation, exogenous exit and free entry.\(^3\)

In international equilibrium, standard trade forces suggest that an unskilled labor abundant country will specialize in the unskilled labor intensive sector. Normally, this pushes up wages of labor and drives down the wages of skilled labor—seemingly shrinking the skill premium. However, if imports drive down the price of intermediates, then complementarity between skilled labor and intermediates can undo this effect. In equilibrium, for an unskilled labor abundant country, there is a race between the forces reallocating resources to the unskilled labor-intensive sector and the desire to increase skilled labor usage in response to cheaper inputs. This is the same mechanism

\(^3\)An appendix with the exact equilibrium conditions, along with all code for simulations is available upon request.
at work in Parro (2013) and BCV, but I have placed it into the heterogeneous firms framework of Melitz (2003) and BRS.

Analyzing this model analytically is difficult as nearly all forces depend on parameters in non-tractable ways. To that end, I proceed as in BRS and focus on numerical experiments. I specify two countries that are symmetric in their endowments with one exception: the ratio of skilled to unskilled laborers is reversed in the foreign country, so that it is relatively unskilled labor abundant. I focus on two industries—both of which have Cobb-Douglas production functions over unskilled labor and the intermediates-skill bundle (i.e, $\sigma = 0$ in both industries). They differ in their use of unskilled labor so that $\mu_1 > \mu_2$. Without the presence of intermediates, this would mimic the setup in BRS. When I introduce intermediates, I set the $\rho$ parameter to be the same in both industries and I focus on symmetric reductions in trade costs in both industries. I do this in order to focus on the complementarity effect versus the Stolper-Samuelson.

The figure 3.1 summarizes the model’s key prediction: that the skill premium may increase if there are sufficiently high complementarity forces. In this figure the blue line is the skill premium in the unskilled labor abundant country when $\rho$ is close to 0—so that there is very little complementarity. In this setting, the Stolper-Samuelson force completely dominates given the other parameters, and as trade costs fall (reading right to left) the skill premium monotonically declines. The red line, on the other hand, is the skill premium when there are significant complementarities between skilled labor and intermediates. A value of $\rho = -1.5$ implies an elasticity of substitution of .4. In this setting, as trade costs decline the skill premium initially declines but eventually increases substantially. This demonstrates not only that the gradient of the skill premium with respect to trade costs depends on complementarity forces but also suggests that countries liberalizing may initially see a dip in the skill premium followed by a reversal. The remainder of this paper is largely concerned with trying to quantify complementarity forces across industries.

While beyond the scope of this paper, this fact may speak to the finding in Goldberg and Pavcnik (2007) that within the same country, early and later trade liberalization episodes had different effects on the skill premium. However, I do not currently have the data required to formally test this.
3.4 Data

As my identification ultimately relies on variation in input choices, in this section I document the extent to which firms differ in input use and the characteristics of firms that explain these differences. I also examine how firms differ in characteristics relevant to trade—such as import and export status.

Data Description

I use a panel of data from the Colombian Manufacturing Census from 1981-1989. This dataset covers all plants with over 10 employees. I remove plants with missing observations over time, or display unreasonably large swings in input shares. I also only focus on those industries with at least 500 firm-year observations. This leaves me with 21 industries and 40084 observations. The final sample covers 80% of total value added in the original data, and a similar fraction of total wages and sales.

First, I look at the size of firms in various industries. Table 3.1 displays the median firm size, measured by number of employees, and the 95th percentile firm by industry in the sample. It also shows the average skill share. Two facts stand out in this table. First, there is substantial heterogeneity in firm size across industries as well as within industries. Median firm sizes range from around 20 employees to over 40, and some cases over 100. Moreover, the ratio of 95th percentile firm to median firm ranges from 31.2 to 4.5. Second, there is heterogeneity in the intensity of skilled labor both across and within industries. This heterogeneity motivates my industry-level analysis. However, as it is cumbersome to constantly catalog facts by industry, for the remainder of the section I turn to analysis of the manufacturing sector as a whole.

Next I turn to brief overview of the heterogeneity in input use across firms. As previously mentioned, this variation is key to identification. Table 3.2 display summary statistics on market

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5The full panel runs from 1977-1991, but I drop years without data on import and export status, as well as years with breaks in identifiers.

6For example, a handful of firms report spending a single dollar on intermediates or capital in one year. All code is available upon request.
Table 3.2 displays the variation in input use across firms. The median firm in this dataset is small—controlling less than 1% of market share within an industry. There is also substantial variation in skill intensity across firms. In addition to the facts presented in the table, one can look at the raw correlation of the share of skilled workers in the wage bill and the materials share of a firm. I find a strong positive correlation. A simple regression of skill shares in the wage bill on materials share in production (with industry fixed effects) has an $R^2$ of .19. I explore this strong relationship formally in my estimation. However, first I summarize facts about trade in the data.

**Are Importers Different?**

In this subsection, I discuss first the extent of trade activity that takes place, in particular the extent of intermediate importing that occurs. Second, I discuss the extent to which importers differ from non-importers along several dimensions, with a focus on skill intensity. In discussing trade, I break up the discussion into extensive margin and intensive margin patterns. To that end, table 3.3 outlines the extent of participation in trade activity. This table displays the fraction of firms engaging in each activity, so that the four quadrants sum to one. One can see that approximately 12% of firms engage in some exporting behavior. On the other hand, over 25% of firms engage in importing activity. Over time, 2.2% of firms begin importing in the sample. This suggests that importing may be as importing to exporting in understanding how firms respond to lowered trade costs.

In terms of the intensive margin, firms that import are larger than non-importers. Interestingly, the size distributions of firms that engage in only one of importing and exporting are similar. Those firms that engage in both import and export activity are substantially larger than all other firms. Figure 3.3 displays these facts graphically. Notice the substantial overlap, which is common

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7Sales, value added, materials and imported materials are directly reported in the data. I measure skilled workers and unskilled workers as white collar and blue collar employees, respectively. My capital variable is based on the book value of capital as reported by firms in the data. When relevant, I deflate sales and materials by industry level price indices. I construct “efficiency-adjusted” measures of labor by dividing the wage bill by industry averages.
in such datasets. Turning to the intensive margin of importing, the median firm imports 30% of its materials. However, there is variation in import activity across firms. For example, the 25th percentile firm only imports 11% of its materials while at the 75th percentile, 60% of materials are imported.

As a final exercise, I explore whether imported materials behave differently than other materials. In the structural estimation section below, I will discuss the reasons that I have difficulty separately identifying the effects of imported and non-imported inputs. However, we can still provide some evidence on this issue by looking at some reduced form relationships. First, in figure 3.2, I plot the density of skill intensity of importers versus non-importers.

Importers are more skill-intensive on average. One may worry that this may be confounded with size or other variables. However, a regression of the skill share of firms on size (in terms of sales), industry fixed effects and an importer dummy show that importers, on average, have 5% larger skill shares than their counterparts. Interestingly, this effect appears to be driven entirely by the extensive margin. Within importers, increasing intensity in imported intermediates does not appear to have substantially different effects than increasing intensity of domestic intermediates. Regressions of the log of the share of skilled workers in the wage bill on log shares of intermediate inputs broken out by imports and domestic purchases show some evidence of intermediate-skill complementarity, but no difference between the two types of goods. This suggests that the benefits of importing may simply be access to cheaper intermediates.

### 3.5 Empirical Methodology

In this section I detail my estimation strategy. To test for complementarities in the data I will estimate a production function directly. Production function estimation is difficult because firms’ input choices are made with knowledge of productivity, which is unobserved to the econometrician. To estimate my parameters of interest I will follow the proxy method of Olley and Pakes (1996) as refined by Ackerberg et al. (2006) (henceforth OP and ACF, respectively) as well as De Loecker
The major benefit of the proxy method is that it imposes few restrictions on the shape of the production function. This allows me to actually break my analysis into two pieces. First, I show how I can map my estimated parameters into a CES production function. This allows me to discuss a single parameter ($\rho$, as in the model section) that governs complementarity forces in an industry. However, while this is useful as it ties to the model discussion and reduces the analysis to a single number, stringently focusing on a CES production function might miss potential heterogeneity in production processes across firms with an industry—this is something we may especially worry about if importing changes a firms’ production decisions. Thus, in the second part of my analysis, I use the estimated coefficients of my production function to show how these complementarity forces may differ across firms and importers. The cost of this second approach is that there is no closed form for the production function, and so aggregating to the industry level is difficult. Thus, I see these two pieces of the analysis as complementary to each other: one is an approximation for an industry level force, while the other attempts to look how much these forces are heterogeneous within an industry.

### 3.5.1 Estimating Equation

To test for complementarities I need to take a stand on the structure of the production function that is more flexible than simple Cobb-Douglas. Here I briefly outline how I derive a translog production function—which is the easiest form for estimation—from a CES production function. Notice that the translog does not strictly nest the CES structure, and so I will rely on a local approximation. Unfortunately, due to multicollinearity issues in the data, trying to estimate a multiple tiered CES production function with many inputs proved difficult. To this end, I opt for a simplified production function that restricts the outer nest to Cobb-Douglas. I also bring capital into the estimation. The ultimate CES production function is given by,

$$Q_r = e^{\omega_{it} + \epsilon_{it}} K_{it}^{\gamma} L_{it}^{(1-\gamma)\mu} ((1 - \lambda) M_{it}^\rho + \lambda S_{it}^\rho)^{(1-\mu)(1-\gamma)}/\rho$$
where $Q$ is output, $K$ is capital, $L$ is unskilled labor, $S$ is skilled labor and $M$ are intermediates. The two productivity terms are a term that is observable to the firm when decisions are made, denoted by $\omega$ and a productivity shock that is only revealed after decisions are made, $\epsilon$. Denoting logged variables by lower-case variables, the log production function can be written,

$$ q_{it} = \gamma k_{it} + (1 - \gamma) \mu l_{it} + (1 - \gamma)(1 - \mu) \log \left( ((1 - \lambda) M_{it}^\rho + \lambda S_{it}^\rho)^{1/\rho} \right) + \omega_{it} + \epsilon_{it} $$

This is not a translog production function and non-linear least squares estimation of the above can be difficult since I do not observe $M$ and $S$ directly, but rather expenditures. However, one can construct a translog approximation to the above by doing a local approximation around $\rho = 0$, which is the Cobb-Douglas case. In particular, Kmenta (1967) demonstrates how one can approximate a CES production function in the translog form as follows:

$$ \log X_{it} \approx (1 - \lambda) \log M_{it} + \lambda \log S_{it} + \frac{1}{2} \rho \lambda (1 - \lambda) [\log M_{it} - \log S_{it}]^2 $$

where $X_{it}$ is generic notation for the CES aggregate. This leads to a final translog production function of the form:

$$ q_{it} = \tilde{\alpha}_K k_{it} + \tilde{\alpha}_S s_{it} + \tilde{\alpha}_L l_{it} + \tilde{\alpha}_M m_{it} + \tilde{\alpha}_{MS} (m_{it} - s_{it})^2 + \omega_{it} + \epsilon_{it} \quad (3.1) $$

The above is a translog quantity production function. For capital and unskilled labor, the coefficients correspond to output elasticities, but this is not the case for skilled labor and materials due to higher order terms. In particular, the relationship between output elasticities, which I denote by $\alpha$, and the production function coefficients, $\tilde{\alpha}$, is given as follows:

$$ \alpha_K = \tilde{\alpha}_K \alpha_L = \tilde{\alpha}_L \alpha_M = \tilde{\alpha}_M + 2 \tilde{\alpha}_{MS} (m - s) \alpha_S = \tilde{\alpha}_S - 2 \tilde{\alpha}_{MS} (m - s) $$
Moreover, the cross derivative of log output with respect to log skills and log materials is given by $\alpha_{MS} = -2\tilde{\alpha}_{MS}$. From the above equations one can see that returns to scale is the sum of the coefficients on capital, labor, materials and skill, but excluding the cross term.

While the above is a quantity production function, I only observe sales. To get around this issue, I assume that there is a CES demand system (as in the Melitz framework). With this assumption, De Loecker (2011) shows that one must augment the regression in (3.1) with a total quantity measure\(^8\) leading to the following final estimating equation:

$$r_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_s s_{it} + \beta_{ms}(m_{it} - s_{it})^2 + \beta_q q_{it} + \omega_{it} + \epsilon_{it}$$  \hspace{1cm} (3.2)

where here $\omega$ is now a convex combination of productivity and demand shocks and $\beta_q = 1/|\eta|$ is a Lerner index for each industry. The coefficients between (3.1) and (3.2) are related by the expression $\alpha_i = \beta_i \times \eta / (\eta + 1)$ where $i$ indexes inputs and $\eta$ comes from $\beta_q$. In the next subsection I explain how I estimate (3.2). With these estimates in hand I can recover $\alpha$ from the quantity production function and also the approximate parameters of the nested CES function.

### 3.5.2 Methodological Overview

In this section I briefly discuss how I identify the translog production function outlined above. Later in the results section I will also discuss the CES parameters implied by my estimation, using the approximate relationship between the translog and CES parameters. To estimate the production function, I use the proxy methods of ACF and De Loecker (2011), which I review below. These papers provide identification proofs for general translog production functions, of which mine is a special case. The problem with estimating (3.2) directly is that static inputs (i.e., those chosen at time $t$ for production observed at time $t$) will be correlated with unobservable productivity. The proxy method makes the following observation regarding static inputs: if static input demand is increasing in productivity conditioned on other inputs, then this demand function can be inverted.

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\(^8\)I use total sales deflated by a SIC 3 price index.
to solve for productivity. For example, if \( m_{it} = m(k_{it}, l_{it}, s_{it}, \omega_{it})\) and \( \partial m/\partial \omega > 0 \) then, \( \omega_{it} = m^{-1}(k_{it}, l_{it}, s_{it}, m_{it})\).

This motivates a two-stage procedure. In the first stage, one non-parametrically controls for productivity using the above relationship between materials and output. This allows one to estimate expected output. In particular I estimate,

\[
\tilde{r}_{it} = \Phi(k_{it}, m_{it}, s_{it}, l_{it}, q_{it}) + \epsilon_{it}
\]

where \( \Phi \) is a quadratic in all inputs and all interaction terms. Notice that,

\[
\Phi = f(X; \beta) + \omega
\]

where \( f \) is the production function and \( X \) is a vector collecting the inputs. By plugging in \( f \) and \( \hat{\Phi} \) we have,

\[
\omega_{it} = \hat{\Phi}_{it} - (\beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_s s_{it} + \beta_{ms}(m_{it} - s_{it})^2 + \beta_q q_{it})
\]

Now one uses the orthogonality condition that any dynamic inputs chosen in period \( t - 1 \) cannot be correlated with the unanticipated shock to productivity. More concretely, first define \( \xi_{it} = \omega_{it} - E(\omega_{it} | \mathcal{I}_{it-1}) \) where \( \mathcal{I} \) is the firm’s information set. Then one can form the following moment condition:

\[
E\left( \begin{pmatrix}
  k_{it} \\
  l_{it} \\
  s_{it} \\
  m_{it-1} \\
  (s_{it-1} - m_{it-1})^2 \\
  q_{t-1}
\end{pmatrix} \xi_{it}(\beta) \right) = 0
\]
where everything above is observed. This is a non-linear GMM problem and can readily be minimized. Notice that the system is just identified.

3.6 Results

In this section, I discuss the results of my estimation. First, I present the parameters from the translog production function, which I will call the raw estimations. Then I present the parameters of the nested CES production function that I derive from the coefficients. When I focus on the CES parameters, I find mixed evidence of complementarities across industries—some industries display strong intermediates-skill complementarity while others suggest substitution. In the second subsection I turn to a look at importers, and present suggestive evidence of differences between this group and non-importers. This second section does not use the strict CES set up and instead relies on looking at raw coefficients of the estimated production functions.

3.6.1 Complementarities and Elasticities

Turning first to the estimated parameters of the translog production function, table 3.4 displays the output elasticities implied by the translog production function. The results are rescaled by the elasticity of demand, $\eta$, as described in De Loecker (2011). Hence, these capture the output elasticities from the parameters of the quantity production function described in (3.1). Since the elasticities for materials and skilled workers differ across firms, I report $\alpha_S$, $\alpha_M$ and $\alpha_{MS}$ for the unweighted, median firm.

Before turning to the main analysis, a few words about the estimation are in order. First, many of the parameters look reasonable—but not all. Returns to scale are between .85 and 1.15 in 11 out of 21 industries, albeit the median is high. As a basis for comparison, Gandhi et al. (2011) use the same dataset with slightly different methods to estimate a similar production function. We differ in

\footnote{As usual in this literature, I approximate $E(\omega_{it}|I_{it-1})$ by regression $\hat{\omega}$ on a polynomial of lags. I also include interactions with export and import status. De Loecker (2013) and Fernandes (2007) point out that this is necessary if one assumes that import and export activity may affect productivity.}
that they aggregate labor, estimate a Cobb-Douglas production function, and ignore the aggregate
sales term. Nevertheless, this is a useful baseline by which to compare estimates. Pooling across
industries, they find that there are essentially constant returns to scale in manufacturing. However,
at the median I find returns to scale of 1.4. One reason for the discrepancy is that the demand
shock is poorly estimated in many industries. In fact, for many industries, the estimate of the
inverse elasticity is at its lower bound, zero, suggesting that after controlling for inputs there is
insufficient variation to credibly identify this parameter.\textsuperscript{10} Looking at the actual parameters, my
estimates and theirs are qualitatively similar, but with some differences. Estimating a production
function across all manufacturing, they find a capital elasticity of .14, a labor elasticity of .35
and an elasticity of .54 (they also find constant returns to scale). Correcting for demand and
allowing for a richer specification of labor and intermediates leads to the same qualitative results
and numbers of similar magnitude. But I find, for example, a much lower capital coefficient across
most industries. Nevertheless, despite the noise in the aggregate quantity measure, the production
function parameters themselves appear reasonable to similar estimates using different approaches.

Having looked at the raw estimates, I turn to the CES parameters implied by my estimation. For
this section, I only focus on those industries with estimated returns to scale between .85 and 1.15,
since the CES production function is constant returns. The translog function I have estimated is
a first order approximation to the CES function. To back out the CES parameters, I use a least
squares fitting procedure. While there is no formal way to test the quality of the first order ap-
proximation, the RMSE on this procedure is small for most industries. Table 3.5 contains these
estimates for each industry. From the table, one can see that the estimates are reasonable. The cap-
ital share is .041 at the median, with a range of close to 0 and up to .15. While the extremely small
case is suspect, the majority of cases compare favorably with other work estimating gross output
production functions. This lends some credibility to the estimates, in light of the introduction of
the new parameter, $\rho$.

\textsuperscript{10}If I estimate the model without the correction for aggregate quantity, I find decreasing returns to scale in most
industries, as in De Loecker (2011). But I also find stronger evidence of complementarities across industries. I present
the version with the quantity correction as my output is measured in revenue, however the results without correcting
for aggregate quantity are available upon request.
Turning to the analysis, recall that for intermediates-skill complementarity to exist, it must be that $\rho < \sigma$, where $\sigma$ is the CES parameter on unskilled labor and the intermediates-skill bundle. In the restricted case taken to the data, $\sigma = 0$ so intermediates-skill complementarity requires that $\rho < 0$. Here we find mixed results. The elasticity of substitution implied by the $\rho$ ranges from .4 to 13—suggesting both a high degree of complementarity and a high degree of substitutability between intermediates and skills depending on the industry. There is evidence of intermediates-skill complementarity in 2 out of 11 industries. In the next section I look at these complementarity forces directly across firms.

In those industries displaying intermediates-skill complementarity, the elasticity of substitution is below .52 for both. While there is no baseline to determine when the complementarity forces are large, in the numerical exercises one can see that even for moderate values of the complementarity parameter, there will be some range of trade costs where the complementarity effect can dominate the Stolper-Samuelson effect. The lens of the CES model is useful as it reduces complementarity to one parameter, however it is clear from the point estimates that this may not be an accurate measure of production technology for all industries and firms. To that end, in the next section I turn to analyzing the translog production function more directly in order to unpack these layers of heterogeneity.

### 3.6.2 Import Status and Input Mix

In this section I turn from the structurally estimated CES production function and focus on the translog production function. Working directly with the translog production function allows me to explore heterogeneity in how firms actually use inputs, and whether these differences translate to firms operating at points where there are high complementarities between inputs. It also allows me to explore whether or not there is a connection between import status and complementarities. At

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11 The returns to scale for the industries in which $\rho < 0$ are 1.02 and .96. Thus, the choice to focus on industries with returns to scale between .85 and 1.15 does not influence which industries display complementarities. In most industries away from the specified bounds on return to scale, the fitting procedure behaves poorly and puts most parameters at corner solutions.
the end of this section I also examine productivity differences across importers and non-importers and discuss how this may interact with complementarity forces.

Before moving to complementarity forces across firms, recall that intermediates-skill complementarity requires,

$$\frac{\partial Q}{\partial M \times \partial S} \frac{\partial Q}{\partial S} - \frac{\partial Q}{\partial M \times \partial L} \frac{\partial Q}{\partial L} > 0$$

which is equivalent to saying that a proportional increase in $M$ holding all else constant raises the marginal output of $S$ more than that of $L$. The above is for the production function, whereas I have estimated the log. However, it can be shown that,

$$\left[ \frac{\partial \log Q}{\partial \log S \times \partial \log M} - \frac{\partial \log Q}{\partial \log L \times \partial \log M} \right] e^{\log Q - \log M}$$

where I have also scaled by output as in the original Fallon and Layard paper. Denoting the left hand term by $\theta$, I calculate this complementarity measure for each firm and report results pooling across all years and industries. The estimated production function implies a substantial spread in the distribution of $\theta$. For example, the median across firms is -0.65 with an IQR of 1.4. Table 3.6 displays the median, 25th and 75th quantiles for the parameter $\theta$, while figure 3.4 displays the full distribution. In both cases I have reported importers and non-importers separately, but pooled across industries. As one can see, $\theta$ is often negative which is in line with the results from the CES parameter fitting. Nevertheless, for over 25% of firms this number is positive, suggesting complementarities exist in many firms.

Turning to importers in particular, the table above suggests that importers may actually be less likely to be using inputs in a way such that there is intermediates-skill complementarity. However, at least part of this can be explained by compositional effects. To show this, table 3.7 contains a series of regressions of import status on $\theta$. In the first specification I present the regression of import status on the complementarity measure. The second specification includes industry fixed
effects, while the third looks at changes in import status across firms. These regressions suggest that import status is associated with an increase in $\theta$. The regressions cannot and need not be interpreted causally; rather, the point is simply that there is evidence that some firms are using inputs in a way such that skilled workers and intermediates are relative complements. Moreover, importing firms may be using inputs in this way more often than firms that do not import.

As a final exercise, I explore the extent to which import behavior is related to productivity. This is important because many models of firms and international trade, including the model presented in section 3, suggest that an outcome of lower trade prices should be a reallocation of resources to more productive firms. Moreover, while my illustrative model ignored the extensive margin decision of firms to import, in reality this is a major channel by which trade can affect a nation's economy. If importers are both more productive and more likely to use technology that displays complementarities then importing can actually shift the aggregate elasticities of substitution between intermediates and different kinds of labor. This may magnify the original complementarity effect.\footnote{Notice that the effect is only magnified when the extensive margin “has bite.” If all firms import then this effect is irrelevant. However, the empirically important case is precisely that in which not all firms import.}

From my estimates, I can construct estimates of revenue productivity for each firm. Revenue productivity is a mixture of a firm’s demand shock and their physical productivity, and is a useful proxy for the true productivity of the firm. Unfortunately, true productivity cannot be separately identified from this composite. With these estimates in hand, figure 3.5 plots the densities of estimated revenue productivity, with industry fixed effects removed. As one can see, importers are more productive, albeit there is substantial overlap between the two sets of firms. To test this relationship further, I can actually use the structural model to determine if importing and productivity are related. In particular, I assumed the following form for firms’ forecasts of future productivity,

\[
\omega_{it} = \beta_0 + \beta_1 \omega_{i,t-1} + \beta_2 \omega_{i,t-1}^2 + \beta_3 \mathbb{1}\{\text{Importer}\}_{i,t-1} + \beta_4 \mathbb{1}\{\text{Exporter}\}_{i,t-1} + \xi_{it}.
\]
Thus, the coefficients on import status are informative about whether importing is actually associated with a higher productivity. Table 3.8 shows the terms in this regression for all industries. Results on the importance of importing are mixed. In many industries the effect is 0 or negligible. On the other hand, in other industries the effect of importing on productivity are very high with importers being 2-3% more productive than their counterparts. For the median industry, importing is associated with a 1.3% increase in productivity. This number is small, but is nevertheless in the same range as the relationship between productivity and export status, which is 1.8% for the median industry. This suggests a small but real relationship between importing and productivity. Thus, lowering import costs may have a two-fold effect: it may move resources to more productive firms and may also be associated with a technology that is more intermediates-skilled complementary.

3.7 Conclusion

This paper has three contributions. First, I demonstrate the heterogeneity in the elasticity of substitution between intermediates and skilled labor across industries. Second, I have presented suggestive evidence that importing firms are operating at a point on the production frontier where there are stronger intermediates-skill complementary forces than the point at which non-importers operate. Finally, I have shown that importers tend to be more productive that non-importers. Taken together these forces suggest a role for imported intermediates in explaining the increased skill premium in countries as they open up to trade, even if they are abundant in unskilled labor.

The heterogeneity in the elasticity of substitution between intermediates and skilled labor is particularly important in a trade context. This is because countries’ comparative advantage may actually be influenced by this parameter and so the aggregate elasticity may change as countries reallocate production across industries. Fully exploring this adjustment process, as well as how these micro measures of complementarity map into aggregates, is useful future research.

I also find evidence that importing firms are more productive. Future research should try to
understand the direction of causality in this relationship. If importing increases productivity then it may increase the size of those firms displaying intermediate-skill complementarity. Thus importing can potentially exacerbate the effect of complementarity on the skill premium. Future research should pin down more quantitatively how these channels may interact.

Finally, I used proxy methods to estimate my production function. While these methods yield insights the limitations of my dataset leave ample room for future work. In particular, a more complete study of these forces would attempt to separately identify the importance of imports versus domestic outsourcing. One could also more flexibly specify the substitution patterns between unskilled labor and other inputs into production.
### 3.8 Appendices

#### 3.8.1 Appendix A: Tables

Table 3.1: Firm Size and Skill Shares Across Industries

<table>
<thead>
<tr>
<th>Industry</th>
<th># Firms</th>
<th>Labor Force</th>
<th>Skill Share</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Median</td>
<td>Median</td>
</tr>
<tr>
<td>Food Processing</td>
<td>775</td>
<td>25</td>
<td>322</td>
</tr>
<tr>
<td>Clothing</td>
<td>735.5</td>
<td>29</td>
<td>149.5</td>
</tr>
<tr>
<td>Metal Products</td>
<td>422.5</td>
<td>25.25</td>
<td>210.5</td>
</tr>
<tr>
<td>Textiles</td>
<td>348.5</td>
<td>41.5</td>
<td>572.5</td>
</tr>
<tr>
<td>Printing</td>
<td>285</td>
<td>21</td>
<td>228.5</td>
</tr>
<tr>
<td>Chemicals (Other)</td>
<td>251</td>
<td>37.5</td>
<td>314.5</td>
</tr>
<tr>
<td>Machinery (excl. Electric)</td>
<td>244</td>
<td>25.5</td>
<td>141</td>
</tr>
<tr>
<td>Plastic</td>
<td>231.5</td>
<td>34</td>
<td>185</td>
</tr>
<tr>
<td>Nonmetal Products</td>
<td>212</td>
<td>33.75</td>
<td>370</td>
</tr>
<tr>
<td>Transportation Equipment</td>
<td>171</td>
<td>29.5</td>
<td>302</td>
</tr>
<tr>
<td>Leather Shoes</td>
<td>166</td>
<td>25</td>
<td>171</td>
</tr>
<tr>
<td>Electronic Machinery</td>
<td>163</td>
<td>35.5</td>
<td>377.5</td>
</tr>
<tr>
<td>Other Food Processing</td>
<td>151.5</td>
<td>25.75</td>
<td>201.5</td>
</tr>
<tr>
<td>Furniture</td>
<td>142.5</td>
<td>26.25</td>
<td>126</td>
</tr>
<tr>
<td>Lumber</td>
<td>140</td>
<td>19.5</td>
<td>122.5</td>
</tr>
<tr>
<td>Beverages</td>
<td>116</td>
<td>125</td>
<td>752</td>
</tr>
<tr>
<td>Paper</td>
<td>116</td>
<td>40</td>
<td>270</td>
</tr>
<tr>
<td>Misc. Manufacturing</td>
<td>112</td>
<td>30</td>
<td>201.5</td>
</tr>
<tr>
<td>Industries</td>
<td>96.5</td>
<td>45.25</td>
<td>638</td>
</tr>
<tr>
<td>Chemicals (Industrial)</td>
<td>71</td>
<td>35</td>
<td>350.5</td>
</tr>
<tr>
<td>Rubber Products</td>
<td>67.5</td>
<td>27</td>
<td>797.5</td>
</tr>
</tbody>
</table>

Industries are SIC 5 digit industries. All quantiles are calculated by first looking within years and then across years. The labor force and the skill share are both measured in numbers of employees.
### Table 3.2: Summary Statistics for Manufacturing Firms

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>IQR</th>
<th>Q99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Share</td>
<td>0.08</td>
<td>0.23</td>
<td>5.58</td>
</tr>
<tr>
<td>Skilled Labor Share</td>
<td>5.90</td>
<td>6.59</td>
<td>29.14</td>
</tr>
<tr>
<td>Unskilled Labor Share</td>
<td>13.57</td>
<td>15.10</td>
<td>60.38</td>
</tr>
<tr>
<td>Materials Share</td>
<td>51.94</td>
<td>25.90</td>
<td>91.14</td>
</tr>
<tr>
<td>Capital Share</td>
<td>12.06</td>
<td>18.22</td>
<td>99.44</td>
</tr>
</tbody>
</table>

Reported values are unweighted statistics pooling firms across all industries and years. All shares refer to payments over sales and are scaled by 100 for readability. Market share is calculated as sales of a firm over total sales in an SIC 3 digit industry. Skilled labor is defined as owners, managers, skilled workers and technicians. Unskilled labor refers to all others. Materials are the sum of domestic and imported raw materials. Capital is the reported book value of fixed assets.

### Table 3.3: Matrix of Trade Activity

<table>
<thead>
<tr>
<th></th>
<th>Non-Exporter</th>
<th>Exporter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Importer</td>
<td>0.685</td>
<td>0.043</td>
</tr>
<tr>
<td>Importer</td>
<td>0.194</td>
<td>0.078</td>
</tr>
</tbody>
</table>

Each cell is the fraction of total firms with a given trade status; hence, the sum of all four cells is one. Reported values are unweighted by sales and pool firms across all years and industries.
Table 3.4: Translog Production Function Results

<table>
<thead>
<tr>
<th>Industry</th>
<th>Parameter</th>
<th>α_K</th>
<th>α_L</th>
<th>α_S</th>
<th>α_M</th>
<th>α_MS</th>
<th>1/</th>
<th>μ</th>
<th></th>
<th>RoS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Processing</td>
<td></td>
<td>0.063</td>
<td>0.177</td>
<td>0.129</td>
<td>1.075</td>
<td>-0.346</td>
<td>0.292</td>
<td>1.444</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other Food Processing</td>
<td></td>
<td>0.043</td>
<td>0.151</td>
<td>0.137</td>
<td>0.856</td>
<td>-0.207</td>
<td>0.132</td>
<td>1.187</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beverages</td>
<td></td>
<td>0.002</td>
<td>0.136</td>
<td>0.160</td>
<td>0.805</td>
<td>-0.125</td>
<td>0.013</td>
<td>1.103</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Textiles</td>
<td></td>
<td>0.048</td>
<td>0.143</td>
<td>0.194</td>
<td>0.623</td>
<td>-0.164</td>
<td>0.000</td>
<td>1.008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clothing</td>
<td></td>
<td>0.075</td>
<td>0.547</td>
<td>0.276</td>
<td>1.228</td>
<td>-0.309</td>
<td>0.533</td>
<td>2.126</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leather Products (excl. Shoes)</td>
<td></td>
<td>0.189</td>
<td>0.386</td>
<td>0.249</td>
<td>1.398</td>
<td>-0.251</td>
<td>0.560</td>
<td>2.221</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leather Shoes</td>
<td></td>
<td>0.016</td>
<td>0.164</td>
<td>0.066</td>
<td>0.748</td>
<td>-0.146</td>
<td>0.000</td>
<td>0.994</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lumber</td>
<td></td>
<td>0.065</td>
<td>0.326</td>
<td>0.206</td>
<td>0.839</td>
<td>-0.134</td>
<td>0.302</td>
<td>1.436</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Furniture</td>
<td></td>
<td>0.027</td>
<td>0.183</td>
<td>0.175</td>
<td>0.572</td>
<td>0.160</td>
<td>0.001</td>
<td>0.957</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paper</td>
<td></td>
<td>0.038</td>
<td>0.067</td>
<td>0.100</td>
<td>0.780</td>
<td>-0.034</td>
<td>0.000</td>
<td>0.985</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Printing</td>
<td></td>
<td>0.041</td>
<td>0.128</td>
<td>0.161</td>
<td>0.671</td>
<td>-0.174</td>
<td>0.017</td>
<td>1.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chemicals (Industrial)</td>
<td></td>
<td>0.101</td>
<td>0.101</td>
<td>0.226</td>
<td>0.550</td>
<td>-0.133</td>
<td>0.000</td>
<td>0.978</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chemicals (Other)</td>
<td></td>
<td>0.030</td>
<td>0.079</td>
<td>0.213</td>
<td>0.679</td>
<td>-0.020</td>
<td>0.000</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rubber Products</td>
<td></td>
<td>0.000</td>
<td>0.147</td>
<td>0.351</td>
<td>0.810</td>
<td>-0.254</td>
<td>0.226</td>
<td>1.307</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plastic</td>
<td></td>
<td>0.235</td>
<td>0.321</td>
<td>0.431</td>
<td>1.635</td>
<td>-0.686</td>
<td>0.623</td>
<td>2.622</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonmetal Products</td>
<td></td>
<td>0.163</td>
<td>0.352</td>
<td>0.353</td>
<td>0.161</td>
<td>0.110</td>
<td>0.000</td>
<td>1.029</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metal Products</td>
<td></td>
<td>0.665</td>
<td>2.020</td>
<td>2.692</td>
<td>5.964</td>
<td>-2.104</td>
<td>0.912</td>
<td>11.342</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Machinery (excl. Electric)</td>
<td></td>
<td>0.339</td>
<td>1.039</td>
<td>0.847</td>
<td>3.243</td>
<td>-0.658</td>
<td>0.819</td>
<td>5.468</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronic Machinery</td>
<td></td>
<td>0.050</td>
<td>0.141</td>
<td>0.207</td>
<td>0.634</td>
<td>-0.137</td>
<td>0.000</td>
<td>1.031</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transportation Equipment</td>
<td></td>
<td>0.155</td>
<td>0.213</td>
<td>0.202</td>
<td>1.367</td>
<td>-0.386</td>
<td>0.498</td>
<td>1.937</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Misc. Manufacturing Industries</td>
<td></td>
<td>0.016</td>
<td>0.111</td>
<td>0.224</td>
<td>0.660</td>
<td>-0.093</td>
<td>0.000</td>
<td>1.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>0.063</td>
<td>0.177</td>
<td>0.225</td>
<td>0.872</td>
<td>-0.309</td>
<td>0.292</td>
<td>1.444</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The first 5 columns are the output elasticities of a rescaled translog production function, estimated separately for each industry, given by \( q_{ft} = \beta_K k_{ft} + \beta_L l_{ft} + \beta_S s_{ft} + \beta_M m_{ft} + \beta_{MS} (m_{ft} - s_{ft})^2 - 1/\eta \times q_t + \omega_{ft} \) where \( q_t \) is the log total sales in a given industry in a given year. For capital and labor, reported parameters are given by \( \alpha_j = (\eta + 1) / \eta \beta_j \) and correspond to a quantity production function. The output elasticity with respect to materials is \( \beta_M + 2 \beta_{MS} (m_{ft} - s_{ft}) \) rescaled by the factor \( (\eta + 1) / \eta \). For this term, the median across firms within an industry are reported, and similarly for the output elasticity of skilled labor. The cross elasticity is given by \( -2 \beta_{MS} \) rescaled. In the last column, RoS refers to Returns to Scale, which are given by \( \alpha_K + \alpha_M + \alpha_L + \alpha_S \). The last row, Total, presents the unweighted median value across all industries. Standard errors for the original parameters (\( \beta \)) are calculated by block bootstrapping at the firm level. For the sake of clarity the full results and standard errors are in the appendix.
Table 3.5: CES Production Function Results

<table>
<thead>
<tr>
<th>Industry</th>
<th>γ</th>
<th>μ</th>
<th>λ</th>
<th>ρ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beverages</td>
<td>0.000</td>
<td>0.105</td>
<td>0.779</td>
<td>0.806</td>
</tr>
<tr>
<td>Textiles</td>
<td>0.046</td>
<td>0.148</td>
<td>0.487</td>
<td>0.810</td>
</tr>
<tr>
<td>Leather Shoes</td>
<td>0.017</td>
<td>0.169</td>
<td>0.609</td>
<td>0.752</td>
</tr>
<tr>
<td>Furniture</td>
<td>0.038</td>
<td>0.202</td>
<td>0.958</td>
<td>-5.208</td>
</tr>
<tr>
<td>Paper</td>
<td>0.042</td>
<td>0.073</td>
<td>0.822</td>
<td>0.259</td>
</tr>
<tr>
<td>Printing</td>
<td>0.041</td>
<td>0.133</td>
<td>0.658</td>
<td>0.927</td>
</tr>
<tr>
<td>Chemicals (Industrial)</td>
<td>0.107</td>
<td>0.120</td>
<td>0.497</td>
<td>0.678</td>
</tr>
<tr>
<td>Chemicals (Other)</td>
<td>0.030</td>
<td>0.081</td>
<td>0.743</td>
<td>0.117</td>
</tr>
<tr>
<td>Nonmetal Products</td>
<td>0.156</td>
<td>0.408</td>
<td>0.420</td>
<td>-0.900</td>
</tr>
<tr>
<td>Electronic Machinery</td>
<td>0.042</td>
<td>0.139</td>
<td>0.597</td>
<td>0.691</td>
</tr>
<tr>
<td>Misc. Manufacturing Indus.</td>
<td>0.013</td>
<td>0.109</td>
<td>0.670</td>
<td>0.478</td>
</tr>
<tr>
<td>Total</td>
<td>0.041</td>
<td>0.133</td>
<td>0.658</td>
<td>0.678</td>
</tr>
</tbody>
</table>

Each industry is a 3 digit SIC industry in Colombia. These parameters are imputed from a translog approximation. Of 21 total industries, only industries with return to scale between .85 and 1.15 are shown. The estimated parameters refer to the following CES production function:

\[ Q = K^{\gamma} L^\mu (\lambda M^\rho + (1 - \lambda) S^\rho)^{(1 - \gamma - \mu)/\rho} \]

where \( K \) is capital (measured as the book value of fixed assets), \( L \) is unskilled labor, \( M \) is materials (including raw materials and goods in process) and \( S \) is skilled labor (the sum of managers, skilled workers and technicians). The last row, Total, presents the unweighted median value across all industries.

Table 3.6: Complementarities in Importers and Non-Importers

<table>
<thead>
<tr>
<th></th>
<th>( Q_{25} )</th>
<th>( Q_{50} )</th>
<th>( Q_{75} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Importer</td>
<td>-1.205</td>
<td>-0.559</td>
<td>0.385</td>
</tr>
<tr>
<td>Importer</td>
<td>-1.193</td>
<td>-0.661</td>
<td>-0.100</td>
</tr>
<tr>
<td>Total</td>
<td>-1.194</td>
<td>-0.649</td>
<td>0.184</td>
</tr>
</tbody>
</table>

The complementarity measure is defined as the ratio of the cross-derivative of production with respect to intermediates and skilled labor to the marginal product of skilled labor: \( Q_{MS}/Q_S \). This is calculated from production function estimates done for each 3 digit industry with at least 500 firm-year observations. Reported quantiles are sales-weighted and calculated by pooling firms across all years and industries.
Table 3.7: Relationship Between Importing and Complementarities

<table>
<thead>
<tr>
<th>Dep Var: $\theta$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importer</td>
<td>3.299**</td>
<td>2.518*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td>(1.18)</td>
<td></td>
</tr>
<tr>
<td>Importer (Diffs)</td>
<td>1.698</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.023***</td>
<td>-3.811***</td>
<td>0.503***</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td>(0.32)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Industry FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>R-sqr</td>
<td>0.000</td>
<td>0.003</td>
<td>0.000</td>
</tr>
<tr>
<td>N</td>
<td>40084</td>
<td>40084</td>
<td>32533</td>
</tr>
</tbody>
</table>

*-10%, **-5%, ***-1%. All standard errors are clustered at the plant level.
The dependent variable is a measure of complementarity between intermediate inputs and skilled workers
defined as the ratio of the cross derivative of output with respect to intermediates and skills to the
derivative of output with respect to skills. In each specification, firms in all SIC 3 digit industries with at
least 500 total firm-year observations are used, and there is no weighting applied. In columns (1) and (2)
the independent variable is a dummy for whether imports are positive, while in column (3) the independent
variable is changes in this dummy over time. In column (3) the entire initial year and firms only present
for one year do not enter the estimation sample.
Table 3.8: Conditional Expectation Parameters

<table>
<thead>
<tr>
<th>Industry</th>
<th>Parameter</th>
<th>( \beta_0 )</th>
<th>( \beta_{\omega t-1} )</th>
<th>( \beta_{\omega^2 t-1} )</th>
<th>( \beta_{Imp} )</th>
<th>( \beta_{Exp} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Processing</td>
<td></td>
<td>-2.166</td>
<td>0.392</td>
<td>-0.029</td>
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<tr>
<td>Other Food Processing</td>
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<td>-2.149</td>
<td>-0.193</td>
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<td>-0.016</td>
<td>0.008</td>
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<td>0.025</td>
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<td>0.006</td>
<td>0.025</td>
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<tr>
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<td>-0.049</td>
<td>0.035</td>
<td>0.008</td>
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<td>-0.060</td>
<td>0.016</td>
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<td>1.238</td>
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<td>-0.007</td>
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<td>0.020</td>
<td>-0.037</td>
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<td>Total</td>
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<td>0.594</td>
<td>0.019</td>
<td>0.013</td>
<td>0.018</td>
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In the ACF procedure for estimating production functions, firms forecast their productivity at \( t \) given their productivity at \( t-1 \). The coefficients above are the coefficients from the forecasting specification which I used that allowed for a polynomial in lagged productivity as well importer and exported fixed effects. The last row, Total, presents the unweighted median value across all industries.
### Table 3.9: Production Function Parameters

<table>
<thead>
<tr>
<th>Industry</th>
<th>Capital</th>
<th>Unskilled Labor</th>
<th>Skilled Labor</th>
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<tr>
<td></td>
<td>$\beta_K$</td>
<td>$Q_5$</td>
<td>$Q_{95}$</td>
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<tr>
<td>Food Processing</td>
<td>0.045</td>
<td>0.034</td>
<td>0.056</td>
</tr>
<tr>
<td>Other Food Processing</td>
<td>0.037</td>
<td>0.014</td>
<td>0.061</td>
</tr>
<tr>
<td>Beverages</td>
<td>0.002</td>
<td>-0.032</td>
<td>0.003</td>
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<tr>
<td>Textiles</td>
<td>0.048</td>
<td>0.029</td>
<td>0.092</td>
</tr>
<tr>
<td>Clothing</td>
<td>0.035</td>
<td>0.015</td>
<td>0.046</td>
</tr>
<tr>
<td>Leather (excl. Shoes)</td>
<td>0.083</td>
<td>0.025</td>
<td>0.122</td>
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<tr>
<td>Leather Shoes</td>
<td>0.016</td>
<td>-0.012</td>
<td>0.031</td>
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<tr>
<td>Lumber</td>
<td>0.045</td>
<td>0.033</td>
<td>0.060</td>
</tr>
<tr>
<td>Furniture</td>
<td>0.027</td>
<td>0.005</td>
<td>0.042</td>
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<tr>
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<td>0.002</td>
<td>0.071</td>
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<td>0.000</td>
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<td>0.138</td>
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<td>Nonmetal Products</td>
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<td>0.098</td>
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<tr>
<td>Electronic Machinery</td>
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<td>0.094</td>
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<td>Misc. Manufacturing</td>
<td>0.016</td>
<td>-0.065</td>
<td>0.032</td>
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</table>

This reports the capital coefficient from a revenue production function given by $q_{ft} = \beta_K k_{ft} + \beta_L l_{ft} + \beta_S s_{ft} + \beta_M m_{ft} + \beta_{MS} (m_{ft} - s_{ft})^2 - 1/n \times q_t + \omega_{ft}$. Standard errors are calculated by block bootstrapping at the firm level. I report 90% basic bootstrapped confidence intervals. For a parameter $\hat{\theta}$, the basic bootstrap confidence interval is defined as $2 \times \hat{\theta} - \theta_{0.025}^*, 2 \times \hat{\theta} - \theta_{0.975}^*$, where $\theta_{\alpha}^*$ refer to the $\alpha$ quantiles of the bootstrapped distribution. Notice that even if $\theta$ is assumed to be bounded, if quantiles are sufficiently far from $\hat{\theta}$ then the reported confidence intervals can be outside of feasible range of values. For each industry I performed 50 bootstrap repetitions.
Table 3.10: Production Function Parameters

<table>
<thead>
<tr>
<th>Industry</th>
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<th></th>
<th></th>
<th>Industry</th>
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<th>Materials-Skill</th>
<th>Industry</th>
<th>Aggregate Quantity</th>
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<td>$Q_{95}$</td>
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<td>Beverages</td>
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<td>Leather (excl. Shoes)</td>
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<td>-0.105</td>
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<td>Misc. Manufacturing</td>
<td>0.046</td>
<td>-0.147</td>
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</table>

This reports the capital coefficient from a revenue production function given by $q_{ft} = \beta_K k_{ft} + \beta_L l_{ft} + \beta_S s_{ft} + \beta_M m_{ft} + \beta_{MS} (m_{ft} - s_{ft})^2 - 1/\eta \times q_t + \omega_{ft}$. Standard errors are calculated by block bootstrapping at the firm level. I report 90% basic bootstrapped confidence intervals. For a parameter $\hat{\theta}$, the basic bootstrap confidence interval is defined as $2 \times \hat{\theta} - \theta_{0.025}^*$, $2 \times \hat{\theta} - \theta_{0.975}^*$, where $\theta_{\alpha}^*$ refer to the $\alpha$ quantiles of the bootstrapped distribution.

Notice that even if $\theta$ is assumed to be bounded, if quantiles are sufficiently far from $\hat{\theta}$ then the reported confidence intervals can be outside of feasible range of values. For each industry I performed 50 bootstrap repetitions.
3.8.2 Appendix B: Figures

Figure 3.1: Comparing the Stolper-Samuelson Effects and Complementarity Effects

![Graph showing the comparison of Skill Premium in Unskilled Labor Abundant Country with different levels of trade costs and complementarity effects.]

Figure 3.2: Skill Shares Across Trade Activity

![Graph showing the unweighted density of the share of skilled workers in the wage bill across firms. Firms are pooled across years and manufacturing industries. Skilled workers are defined as workers classified as owners, managers, skilled workers and technicians. All other workers are classified as unskilled.]

Figure presents the unweighted density of the share of skilled workers in the wage bill across firms. Firms are pooled across years and manufacturing industries. Skilled workers are defined as workers classified as owners, managers, skilled workers and technicians. All other workers are classified as unskilled.
Figure 3.3: Size Distribution of Firms

Figure presents the unweighted kernel density of firm size, pooled across all industries and years.

Figure 3.4: Examining Complementarity Across Firms

This plots the unweighted density of a complementarity measure across firms, pooling across years and industries. The complementarity measure is defined as the ratio of the cross derivative of production with respect to intermediates and skilled labor to the marginal product of skilled labor: $Q_{MS}/Q_{S}$. The derivatives and marginal products are based on a production function estimation run separately for each 3-digit manufacturing industry in Colombia with at least 500 firm-year observations.
Figure 3.5: Comparing Productivity by Import Status

Figure presents the unweighted density of log productivity with industry fixed effects removed. Log productivity is calculated as the residual from a production function estimated separately for each 3-digit industry in Colombia with at least 500 firm-year observations.
Bibliography


Brambilla, Irene, Amit Khandelwal, and Peter Schott, “China’s Experience under the Multi-Fiber Arrangement (MFA) and the Agreement on Textiles and Clothing (ATC),” in R. Feenstra


