

Occupations and Import Competition

Evidence from Danish Matched Employee-Employer Data

Current Version

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December 1, 2016

Abstract

There is a growing concern that many workers do not share in the gains from trade. In this paper, I argue that occupational reallocation plays a crucial role in determining the winners and losers from trade liberalization: what specific workers do *within* an industry or a firm matters. Adjustment to trade liberalization can be protracted and costly, especially when workers need to switch occupations. To quantify these effects, I build and estimate a dynamic model of the Danish labor market. The model features nearly forty occupations, complicating estimation. To reduce dimensionality I project occupations onto a lower-dimensional task space. This parameter reduction coupled with conditional choice probability techniques yields a tractable nonlinear least squares problem. I find that for the median worker, a 1% decrease in income, holding the income in other occupations fixed, raises the probability of switching occupations by .3%. However, adjustment frictions can be large—on the order of five years of income—so that workers tend to move in a narrow band of similar occupations. To quantify the importance of these forces for understanding import competition, I simulate the economy with and without observed changes in import prices. In the short-run, import competition can cost workers up to one half percent of lifetime earnings. Moreover, the variance in earnings outcomes is twice the size of the total gains from trade.

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.,](#)

*This paper is a continuation and revised version of the first chapter of my PhD thesis. I thank my advisors Stephen Redding and Jan De Loecker for their support and guidance in this project. I also thank Erhan Artuç, Max Dvorkin, 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 at various 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, Aarhus University, and the Cowles Foundation.

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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 liberalization. Yet, extant literature has focused 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 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—albeit costs are sub-additive. These costs also vary with the worker’s state. 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 lifetime earnings, the interquartile range of effects *across* occupations is nearly as large as the *total* gains from trade. In the long run, aggregate effects on labor income are sensitive to assumptions about capital. Nevertheless, I still find substantial heterogeneity within workers, but negative effects are tempered as workers fully adjust.

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. Taking these complications into account can alleviate two sources of bias in estimates of switching costs. 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. I.e., income differentials are not a sufficient statistic for the relative value of occupations. To overcome the first issue, I use an empirical likelihood method to separate workers into a finite set of types. To overcome the second issue, 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—implying the existence of 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 occupations 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 or needing to construct instruments for prices. 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. I briefly summarize the Danish labor market and the connections to import competition in Section 2. In Sections 3 and 4 I outline my econometric model and the estimation strategy used to recover key parameters. In these sections I also position my methodology in the literature. In Section 5 describes how I map my highly granular data to aggregates widely enough for estimation. I turn to my results and counterfactual experiments in Section 6. The final section concludes.

2 Stylized Facts on Occupational Switching and Trade¹

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 (Manufacturing, FIRE Services, Public Services and Other Services). In the data section and data appendix I discuss the data in more detail.

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.²

The vibrancy of the Danish labor market can be seen in the rates of occupational switching in Denmark over time. Table 1 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).³ 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.⁴ Figure 2 breaks out switching by age and skill and demonstrates the substantial heterogeneity in switching patterns by demographics.

Finally, in this subsection I demonstrate the importance of occupations to understanding income dynamics in Denmark. In particular, I look at a variance decomposition of log income. While there

¹This section is more preliminary than other parts of the paper.

²For example, the OECD 2013 Employment Outlook ? 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.

³My number here is actually a lower bound because of some aggregation issues (see data appendix).

⁴Kambourov 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.

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 φ are fixed effects for occupation and firm. I include firm fixed effects because firms are generally collinear for industry, so this removes both the fact that the composition of occupations may reflect industry differentials. Moreover, this allows me to contrast the importance of occupations with recent work on firms. Figures 3 and 4 plot the time series of variance in earnings and the ratio of the variance in fixed effects over the variance in earnings over time. Two things stand out. First, much like in other developed countries, there has been a rise in income inequality in Denmark. Second, even at a coarse 2-digit level, occupations are nearly as informative as firm fixed effects in explaining variation in income. While not shown here, the relationship is strengthened when I allow for occupation-specific returns to worker characteristics which are proven to be important after estimation.

2.2 Occupational Reallocation and Trade

In this subsection,⁵ 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

⁵Note: Some of the figures and tables in this section need to be updated to reflect a consistent notion of occupations.

exposure. Mathematically,

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

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

Figure 5 presents the regression of changes in imports per head on changes in occupational shares in total employment, focusing on the time span of 1995-2006. 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.⁶

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:

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

where π 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 6 plots this relationship. The slope is negative and statistically significant⁷. That β 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

⁶At 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.

⁷I have not yet written this up, but the results are robust to the use of instruments for import competition shocks, such as world demand and lagged shocks.

dynamics in Denmark, as well as the connection between import competition and occupational reallocation, I turn to my structural model and counterfactual analysis in order to more precisely explain the relationship between occupations and trade.

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 $o \in \mathcal{O}$, 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, ω) , 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 $o \in \mathcal{O}$, 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 worker 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 and introduce the stochastic components of the model.

Information and Shocks

meanThere 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:

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

where C are switching costs, η are the non-pecuniary benefits of occupations, common to all workers, w_{ot} 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, ϵ_{oit} are the moving cost shocks while ς_{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.⁸

Despite the heavy notation, the problem is straightforward. The first two terms represents the cost 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 η . 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. Hence, in aiming to estimate the parameters of a particular model, I shut down well-documented

⁸[Keane et al. \(2011\)](#) refer to this as the EMAX function and offer a complete, rigorous introduction to the DCDP framework.

aspects of workers' career paths. Instead, I focus on those features of the labor market that matter most when considering the impacts of trade shocks.

State Variables and Human Capital

The worker's state ω 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 θ . 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 θ across occupations for two different workers. If $\theta_{io}/\theta_{io'} > \theta_{jo}/\theta_{jo'}$ 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

$$h_o(\omega_{it}, \vartheta_{it}) = \exp \{ \beta_1^o \times age_{it} + \beta_2^o \times age_{it}^2 + \beta_3^o \times ten_{it} + \beta_4^o \times \mathbf{1}\{skill_i = med\} + \beta_5^o \times \mathbf{1}\{skill_i = high\} + \theta_{oi} + \sigma_o \varsigma_{iot} \}$$

where ς_{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, θ captures unobservable absolute and comparative advantage. I treat θ as constant over the lifecycle.⁹

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.

⁹In an appendix I describe how one could allow for a Markov chain on the unobservable state. While possible in principle, it is difficult to identify this underlying process given my panel length.

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. 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 o to o' :

$$\mathbf{Costs}(o, o', \omega) = C(o, o', \omega) + \rho \epsilon_{oo'}$$

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 ρ 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 ρ plays in governing worker movement. This second parameter is particularly important as it ultimately governs the elasticity of worker flows with respect to wage differentials. This connection is important later, as it maps directly into my identification.

Turning to the first component, I posit 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 estimated 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 θ . 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:

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

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 in the absence of additional instruments.

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. Suppose that each occupation is associated with a vector, $v^o \in \Upsilon \subset \mathbb{R}_+^{|\Upsilon|}$. 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 v 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. For example to become a baker, economists must learn to operate an oven or 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:

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

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 Γ terms are the coefficients on linear distance in each component of the characteristics vector.¹⁰ That Γ 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, ρ 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 ρ . In the case that $\rho = 0$, switching is entirely deterministic, implying a transition matrix across occupations consisting entirely of 1s and 0s. Thus in this scenario, movement is entirely determined by the value of C and in any equilibrium with full employment in occupations, there ought to be zero transitions. In the case where $\rho \rightarrow \infty$, costs play no role, and one's future occupation is a draw from a uniform distribution.

As a result of its role as the variance of shocks, ρ governs the 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 ultimately 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

¹⁰In practice I allow the coefficients to differ depending on whether the movement in characteristics is positive or negative, reflecting that costs may differ if a worker needs to gain skills or shed them. Thus there are actually two Γ terms per characteristic. I also experimented with quadratic terms, but found they added little explanatory power.

is given by,

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

Hence, a larger ρ implies that workers are *less* responsive to changes in wages. Measuring this responsive not only helps identify ρ , but describes how ρ determines the extensive margin response to changes in economic environment.

Non-Employment

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

$$w^N(\omega, o) = \beta_{skill} + \beta_\theta + \beta_a \times a + \beta_{a2} \times a^2$$

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. 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., early retirement).

Shocks

Finally, I describe the distribution of worker shocks. I mostly follow the extant literature and specify the following distributions:

$$\epsilon \sim Logistic(0, \rho)$$

$$\vartheta \sim \mathcal{N}(0, 1)$$

$$\theta \sim (q_1, q_2, \dots, q_K)$$

The logistic assumption on shocks is standard as it yields a closed form for the value function conditional on θ . 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 θ is free to vary across occupations. Thus, the estimation of types adds $(\mathcal{O} + 1) \times (K - 1)$ parameters to the estimation.

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 comparative advantage across works, as well as the wage parameters and transition matrices across states; then in a second stage, I use a series of non-linear least squares regressions to extract remaining 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 precisely 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 transparently estimate models like mine. In the second stage, I recover the cost matrix of moving across occupations conditional on observables. This is a high dimensional object and I describe how I use task space to get around this problem.

For the sake of clarity I present the estimation procedure in several steps: first, I outline the second stage procedure *as if* the transition probabilities conditional on the worker's state were fully observable; second, I describe the first stage that recovers the distribution of unobservable heterogeneity *and* the full set of conditional choice probabilities; finally, I describe more precisely the exact estimating equation I use and the variation in the data that identifies the parameters of interest.

4.1 Occupational Flows and Selection

In order to understand the selection problem at the heart of my estimating strategy, consider a simplified 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 of ϵ . The logistic is particularly attractive for such problems as it leads to the following simple estimating equation:

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

where π 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,

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

where C is the cost and V are continuation values that arise whenever $C_{switch} > C_{stay}$. 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.

4.2 Estimating Structural Parameters with Renewal Actions

Given the problem above, identification proceeds by leveraging the structure of the model to remove the unobserved continuation values. In particular, I combine the properties of the logistic distribution explored with 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:

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

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.

With this notation in place I can write probability of observing a career path from time t to τ 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 (Hotz and Miller (1993)).¹¹ The particular equation is given by,

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

where ζ_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 τ . 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 observing two different career trajectories for workers, i and j :

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

Notice that if workers have the same initial inclusive values and the same terminal continuation

¹¹In the technical appendix I review these steps in more depth, especially as they pertain to my particular problem.

values, then the unobservable terms disappear. The left hand side of the above equation are the choice probabilities across occupations and can be estimated directly from data, and the right hand side is a non-linear function of observables with an additive error term. In the next subsection I outline how this observation yields an intuitive identification strategy.

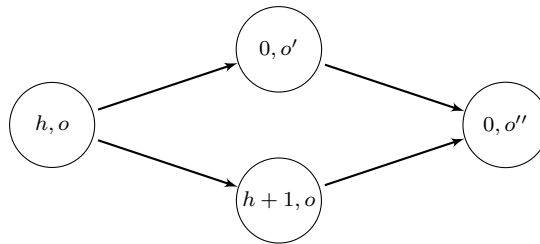
4.3 Identification

To make use of the AM insight, I exploit 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 *ex-post* income shock
2. Occupational switching is a *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 substantially 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. These two assumptions imply that occupational switching is a *renewal action*. They move initially identical workers who have diverged back to an identical state.

In order to generate a regression equation, I focus on career trajectories that I call one-shot deviations:



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:

$$\begin{aligned} \log \frac{\pi_t(\omega, o, o')}{\pi_t(\omega, o, o)} + \beta \log \frac{\pi_{t+1}(\omega', o', o'')}{\pi_{t+1}(\omega'', o, o'')} = & -C(\omega, \omega', \omega'', o, o', o'') + \frac{1}{\rho} (w_{o't} h_{o'}(\omega) - w_{ot} h_o(\omega)) \\ & + \frac{1}{\rho} (\eta_{o'} - \eta_o) + \tilde{\zeta}_{ot} + m_{too'o''} \end{aligned}$$

where the ζ 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. First, sensitivity to wage differentials, both over time and cross-sectionally across workers of different tenure profiles, identifies the inverse variance of the costs shock, which is the semi-elasticity of switching. Second, conditional on wage differentials and the variance of the shock, differences in worker's occupational choices determine the actual costs of moving. Notice that the number of possible choice probabilities is $|\mathcal{O}|^3 \times |\mathcal{S}|$ where $|\mathcal{S}|$ denotes the number of states. This number is on the order of 75 million so I pick up a subsample of moments. In the next subsection I describe how I construct these choice probabilities while in the final subsection I return to the regression equation and provide details on which subsets of the state space I focus on, as well as more details of the final regression.

4.4 Estimating Mincer Regressions and Unobserved Heterogeneity

In order to model unobserved heterogeneity I suppose that workers' comparative advantage is a vector θ drawn from a finite distribution $\mathbf{Q}_\Theta$. 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.¹² The particular estimation strategy I use is the Expectation-Maximization and CCP hybrid approach

¹²Heckman 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.

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:

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

where q_k is the probability of being type k , f is the Gaussian pdf on wages and π is the probability of being in state ω_{it}, o_{it} conditional on the initial state summarized by $\mathcal{H}_{t-1}$. If one could easily solve the model, then they could maximize this likelihood function to solve for unobserved states. To see how, notice that the model provides a formula for both f and π , 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.¹³ Thus, if one could solve the model explicitly, they could use standard likelihood techniques to back out all structural parameters including the distribution of unobserved heterogeneity.

AM's insight is that if the model can be factored into separate pieces where one piece contains some subset of model parameters and the other piece 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:

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

where the only difference between the true likelihood is the hat on the transition rates, implying that I estimate the transition rates from the data rather than using the model. The actual algorithm, details of which are in the appendix, now proceeds as in the standard EM algorithm. An important detail of this procedure is precisely how one estimates $\hat{\pi}$.

Ultimately, I specify $\hat{\pi}$ by running a truncated linear probability model for each origin-destination-year-skill-type pentuple. The regressors in the LPM are age, tenure and previous unemployment

¹³As 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.

status. I do this in order to smooth out across ages and tenure profiles as there is simply insufficient data for a bin estimator along the state. While most details I leave to the data appendix, I specify the exact LPM here because of its importance in the second stage. In particular, I use the following model:

$$\hat{\pi}(o'_{t+1}|o_t, e_t, \omega_t) = \max(.9999, \min(1 \times 10^{-5}, \beta_X X_t + \beta_{\tilde{X}} e_t \tilde{X}_t))$$

where X_t is a constant, a cubic polynomial in age, a cubic polynomial in tenure and a cross-term in age and tenure, and $\tilde{X}_t$ is a dummy for last period employment, and a cubic in age interacted with the employment dummy. The LPM framework can lead to corners for a subset of individuals, which is a problem that other estimators such as multinomial logit or probit models do not have. However, the flexible LPM framework can be estimated by ordinary least squares and then truncated. This has the benefit of being fast whereas methods that rely on large integrations can be prohibitively costly from a computational perspective. In the technical appendix, I explain how I deal with particularly small bins as well as initial conditions.

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, 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.

4.5 Combining the First and Second Stage

With the first stage estimates in one hand, one can construct the conditional choice probability regressions for the second stage. As discussed, there are tens of millions of possibilities and it would be infeasible to calculate them all. Instead, I use a grid approach to construct the set of movements. I proceed in the following steps:

1. I use all observed pairs of occupational moves to construct counterfactual one-shot deviation transitions. For example, if I observe transitions from occupation A to B, from A to C and from B to C then I construct the counterfactual probabilities of going from A to B to C and then from A to A to C.
2. Step 1 only defines the possible paths, in step 2 I define a grid across individual states by specifying: (1) a subset of ages starting at 28 and moving up by 5s until 53; (2) repeating

this for all possible skill groups and types ; and (3) a subset of possible initial tenures, 1, 3, 5.

This grid approach yields a substantially more manageable number of possible histories. One drawback of the grid approach is that many of the counterfactual histories constructed (especially for older workers) lead to corners in the estimated choice probability. [Artuc and McLaren \(2012\)](#) discuss the importance of *including* corners in the estimation of the parameter of such models. Hence, including all estimated transitions from the pre-specified grid is the preferred specification.¹⁴ However, in the results I also include results dropping any transitions with estimated corners as well as results that keep some corners but drop observations in the bottom and top 1% of the left hand side variables.

Finally, the forecast error on future continuation values is uncorrelated with contemporaneous wages, so I estimate the regressions in levels. However, estimation in levels relies on cross-sectional variation as well as time variation since I assume that non-pecuniary benefits and costs are (up to observables) constant across different groups. In order to isolate pure time-series variation within-groups I use a differences estimator that identifies only $1/\rho$. I find that the differences estimator can be sensitive to pooling across transitions through employment with those through non-employment, so I choose as instruments for changes in wage differentials, a constant, a dummy for transitions through non-employment and lagged wage differentials.

5 Data Description

The Danish 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 the data appendix.

¹⁴The only exception being dropping situations where $\pi_{oo} + \pi_{oo'} > 1$, which can arise in the LPM framework

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 24 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 also crossing these codes 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, 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 natural bridge between highly disaggregated codes and less disaggregated codes. Second, including sectors allows me to benchmark my results against the literature. Most of the literature has focused on movement across broad sectors. 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).

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. 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 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.¹⁵ I standardize these values to quantiles and then treat them as cardinal.¹⁶ 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.¹⁷ Table 1 lists the survey questions with the highest loadings for each task.

¹⁵The 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.

¹⁶In 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.

¹⁷PCA 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 appendix, I review this strategy as it applies to my problem.

6 Results

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 2 presents all income parameters, including the value of the comparative advantage for each skill group and unobserved type (high or low). Tables 4 and 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 1.28%. At the other extreme, there is a surprisingly steep tenure profile for laborers and personal workers in the services sector, with an additional year of occupational tenure yielding gains of 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 estimates the returns to general experience for 30 years, then the returns to occupational specific human capital are on average 2.4 times as large. This highlights an important channel by which switching occupations can carry large costs. 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: disruption hits those in traditionally lower-skilled occupations more severely.

A key technical contribution of this work is allowing for persistent unobserved comparative advantage across workers. Table 2 contains the estimated comparative advantage term for each of the six types of workers. One can see from the last row that there are clear differences in absolute advantage across workers with a clear “low” and “high” productivity type within each skill group. However, by looking across occupations one can see that there is a great deal of variation in worker productivity across occupations. In fact, in some occupations the overall low type workers actually have an absolute advantage over the high types.

The fact that workers differ in their ability helps explain variation in income across workers within broad skill groups. However, it remains to be shown that these differences in productivity across occupations are large enough to induce meaningful sorting of workers. To that end, figure 7 plots the share of each worker type across occupations. There is clear evidence of sorting across occupations, with some occupations being comprised almost entirely of one type of worker while others are evenly split. The large degree of sorting should give pause to researchers studying worker reallocation. First of all, because ignoring this dimension may bias estimates of pairwise moving costs in ambiguous ways. Second of all, because predicting the effects of import competition on workers will depend on the distribution of workers’ comparative advantage within affected sectors, as this determines the value of workers’ alternatives and not observed average wages across sectors.

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 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 η can be interpreted relative to this number. Thus the value of merely being employed is worth on the order of two years of income. These numbers can also be contrasted with those in Table 5, which describe 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.

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 8 presents the histogram of costs of observed switches relative to unconditional mean income, while Figure 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:

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

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

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

Discussing costs clearly requires discussing both C and ρ . 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, ρ 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) as the realized cost of switching. Figure 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. As I will discuss when I break switching up into inter and intra sectoral movement, the large median costs are actually a feature of my model. 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 10, realized costs are closer to a quarter years of income with substantial spread¹⁸ Second, many switchers are young, implying that their incomes are low. This makes the costs relative to income seem high when they reflect a worker’s investment decision. Table 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 run 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 heterogeneity 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 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 cheapest and the most expensive occupation differ by a factor of 2.11. The implication isn’t that workers in these occupations face

¹⁸Interpreting negative moving costs can be difficult, however one may think of them as a disemployment shock. Losing one’s occupation makes switching “easier.”

costly transitions—as we have seen workers often times pay low moving costs conditional on their shocks. Instead, this heterogeneity 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 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—i.e., low wage occupations.

Turning to the second component of realized costs, recall that ρ governs the importance of observable benefits in determining flows relative to shocks. In particular, ρ 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 ρ 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 ρ in between 2 and 3 using a similar specification. However, one expects ρ to fall as choice sets become more granular since wage differentials become more informative. Thus, we can say that the value of ρ is close but understandably smaller than extant estimates of the importance of wage differentials in describing worker movement.

Moving on to heterogeneity across workers’ states, Table 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 8. Moreover, they simply switch less than younger workers: workers in their 50s switch at half the rate of younger workers.

Workers’ skill and unobserved type matter as much as age. Looking again at the point estimates

in Table 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. For example, the mobility costs for high type medium skilled workers are 23% higher than for low type high skilled workers. In general, high skilled workers face lower mobility costs for the same occupational transitions. Table 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.

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. One of the major contributions of my work is arguing that this lack of focus is misplaced and that trade economists have missed out on substantial heterogeneity in moving costs as well as completely failing to take into account substantial intrasectoral adjustment. 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 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 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% 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 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 across occupations within sectors as well. Thus the diagonals 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. This tells us three things: (1) that observed switching costs are higher within sectors reflects a composition effect; (2) even without controlling for worker composition, switching occupations within a sector is as costly as switching sectors; (3) as the costs of between and within sector movement are similar, it is occupational heterogeneity and *not* sectoral heterogeneity, which matters for worker adjustment.

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 fitting procedure to determine the in-sample fit. The centered and uncentered¹⁹ 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, its magnitude is large and reassures us that a relatively parsimonious model can explain a substantial amount of variation.

The second, and more telling, model assessment comes from looking at over-identifying restrictions. A natural choice of restrictions are 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 13 plots actual unconditional transition rates against the log of predicted unconditional transition rates. The dotted line is the 45 degree line while the black line is the best fit line. There are three takeaways. First, the overall fit of the empirical distribution is very good, with a regression of actual on predicted having an R^2 .8557 and a coefficient of .747. Second,

¹⁹I report the uncentered R^2 because a non-linear model lacks a natural interpretation for the R^2 .

the fit is dramatically improved when weighting observations by their empirical likelihood—the R^2 increases and a slope coefficient of .889. The fit is imperfect, and the error is systematic with a regression coefficient of less than 1. However, this does not reflect a shortcoming of this model in particular. Rather, this is a consequence of the multinomial logit approach that tends to equalize transition rates. Hence, multinomial logit models will under predict the diagonal and imply overly uniform transitions across choices. This is particularly problematic when there are larger choice sets since the multinomial logit approach precludes zero transitions, even though these are observed empirically. 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 wage 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.

7 Counterfactuals

In this section I summarize my procedure for performing counterfactuals and perform several such exercises. To close the model, I specify a labor demand system based on a model of industry spillovers. Modeling narrow 2-digit industries within sectors 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 perform three counterfactuals. First, I simulate the Danish economy as if foreign prices were constant at their 1996 levels — before China’s entry to the WTO and the inclusion of Eastern European countries in the EU. Second, I simulate the effects of a direct subsidy to switching costs for workers in occupations affected by trade shocks. In the third counterfactual I consider how early retirement programs can help smooth consumption losses to affected and displaced workers.

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, $1, \dots, T$. 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:

$$U = \prod_{i \in \mathcal{I}} C_i^{\alpha_i}$$

where $i \in \mathcal{I}$ indexes industries or goods and C is consumption of industrial aggregate i . The second tier is an Armington aggregator over domestic and foreign varieties:

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

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,

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

Lastly, I assume that export demand is exogenous and given by, $A_i^F (P_i^D)^{-\sigma}$ where A_i is a de-

mand shifter. Putting these pieces together yields the demand curve for domestic final production:

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

where 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 standard models, the focus is on broad sectors (e.g., manufacturing and services) or on aggregate output, whereas I focus on highly disaggregated industries. This disaggregation 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.²⁰ With this in mind, I posit “roundabout” production as in [Foerster et al. \(2011\)](#):

$$Y_i = z_i K^{\beta_i^K} \prod_{o \in \mathcal{O}} H_o^{\beta_{oi}^H} \prod_{j \in \mathcal{I}} M_i^{\beta_{ij}^M}$$

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 β 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 assume that world markets determine a perfectly elastic price of capital, r_i . This characterization leads to the following demand for industry output:

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

²⁰[Baqae \(2015\)](#) discusses a macro model describing how an IO matrix can lead to non-trivial labor supply aggregate elasticities. He also provides conditions under which an interconnected economy cannot be collapsed into a composite commodity economy.

To illustrate the flexibility of this approach, consider the market demand for occupations. The Cobb-Douglas system implies the following market expenditure on occupation o :

$$w_o H_o = \sum_{i \in \mathcal{I}} \beta_{oi}^H E_i^D$$

where E_i^D is domestic expenditure in industry i . 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:

$$w_o dH_o = \underbrace{\beta_{ok}^H (\sigma - 1) \times \left[\left(\alpha_i^D W + \sum_{j \in \mathcal{I}} \beta_{kj}^M R_j \right) \frac{(P_k^D)^{1-\sigma}}{P_k} \times \frac{(P_k^F)^{-\sigma}}{P_k} \right] dP_k^F}_{\text{Import Competition Effect}} + \underbrace{\sum_{i \in \mathcal{I}} \beta_{oi}^H \left(\alpha_i^D dW + \sum_{j \in \mathcal{I}} \beta_{ij}^M dR_j \right) \frac{(P_i^D)^{1-\sigma}}{(P_i^D)^{1-\sigma} + (P_i^F)^{1-\sigma}}}_{\text{Input Price Effect}}$$

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, $\{P_i^D\}_{i \in \mathcal{I}}$, wages $\{w_o\}_{o \in \mathcal{O}}$, labor stocks, $\{H_o\}_{o \in \mathcal{O}}$ and revenues, $\{R_i\}_{i \in \mathcal{I}}$ such that:

1. Representative firms choose intermediates, labor and capital optimally
2. Workers act optimally
3. Goods Market Clearing (for each $i \in \mathcal{I}$):

$$\underbrace{R_i}_{\text{Revenue}} = \underbrace{\left(\alpha_i^D W + \sum_{j \in \mathcal{I}} \beta_{ij}^M R_j \right)}_{\text{Domestic Exp. in } i} \underbrace{\frac{(P_i^D)^{1-\sigma}}{(P_i^D)^{1-\sigma} + (P_i^F)^{1-\sigma}}}_{\text{Domestic Share}} + \underbrace{A_i^F (P_i^D)^{1-\sigma}}_{\text{Foreign Exp.}}$$

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

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

5. Capital Market Clearing:

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

6. Balanced Trade:

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

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 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 first calculate a labor coefficient from the Danish IO tables as above.²¹ Then I use relative wage bills within industries to calculate β_{io}^H . Finally, I calculate β_i^K using gross surplus in the IO tables. This actually completes the estimation of the production parameters.

To estimate foreign prices, I use Danish customs data and a slightly modified version of the procedure of [Broda and Weinstein \(2006\)](#).²² This method allows one to construct a CES price index

²¹The reason I do not use wage bills for the aggregate components is because of missing and imputed data. An implicit assumption is that missing and imputed data is random.

²²More precisely, I use a geometric mean of the naive estimator arising from a change in industry prices over time, the CES estimator from customs data and the CES estimator from 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 aim to smooth out these noisy years. Full details, along with figures illustrating the price swings, can be found in the data appendix.

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:

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

An important parameter is the Armington elasticity, σ_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.

7.3 Procedure for Counterfactuals

Before turning to results, in this section I briefly describe the algorithm which I use to perform counterfactuals. This section is necessarily terse, but there are complete details in the technical appendix. 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 demonstrate the following formula for changes in production side variables:

$$\Delta \begin{bmatrix} \log r_{ti} \\ \dots \\ \log P_{ti} \end{bmatrix} = \left(I_{N \times N} - \begin{bmatrix} B_{\mathcal{T},\mathcal{T}}^M \circ \frac{r_t^{1-\sigma}}{1+r_t^{1-\sigma}} & B_{\mathcal{T},\mathcal{NT}}^M \\ \dots & \dots \\ B_{\mathcal{NT},\mathcal{T}}^M \circ \frac{r_t^{1-\sigma}}{1+r_t^{1-\sigma}} & B_{\mathcal{NT},\mathcal{NT}}^M \end{bmatrix} \right)^{-1} \left(\underbrace{\begin{bmatrix} B_{\mathcal{T},\mathcal{T}}^M - I_{|\mathcal{T}|} \\ \dots \\ B_{\mathcal{NT},\mathcal{T}}^M \end{bmatrix}}_{\text{Exogenous}} \Delta \log P_i^F + B^K \Delta \log p_k + B^L \underbrace{\Delta \log w}_{\text{Wages}} \right) \quad (2)$$

$$\begin{bmatrix} E_{\mathcal{T}} \\ \dots \\ E_{\mathcal{NT}} \end{bmatrix} = \left(I_{N \times N} - \begin{bmatrix} (B_{\mathcal{T},\mathcal{T}}^M)' \circ \frac{r_t^{1-\sigma}}{1+r_t^{1-\sigma}} & (B_{\mathcal{NT},\mathcal{T}}^M)' \circ \frac{r_t^{1-\sigma}}{1+r_t^{1-\sigma}} \\ \dots & \dots \\ (B_{\mathcal{T},\mathcal{NT}}^M)' & (B_{\mathcal{NT},\mathcal{NT}}^M)' \end{bmatrix} \right)^{-1} \left(\begin{bmatrix} \alpha_{\mathcal{T}} \circ \frac{r_t^{1-\sigma}}{1+r_t^{1-\sigma}} \\ \dots \\ \alpha_{\mathcal{NT}} \end{bmatrix} (W + p_K K) + \begin{bmatrix} X \circ r_t^{1-\sigma} \\ \dots \\ 0 \end{bmatrix} \right) \quad (3)$$

where $\circ$ refers to appropriate element-wise multiplication, $\mathcal{T}$ collects tradable industries while $\mathcal{NT}$ collects those that are not. Looking first at 2, 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.²³ 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 relative price information across industries—only between domestic and foreign goods. This is important because in the data one rarely observes long time series of relative prices across goods but the price of imports to domestic goods is estimable. To conclude I summarize the algorithm in more detail below:

²³This 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 is on the order of 1e-6.

Algorithm: Given information on initial wages and initial relative price and wage *levels*, $\{r_{t-1}, w_{t-1}\}$, as well as information on *changes* in exogenous variables $\{\Delta P^F, \Delta z\}$, and a current guess of $w_t^{(j)}, p_{K,t}$ equilibrium factor prices:

1. Solve the agent's dynamic problem given $w_t^{(j)}$ in order to construct labor demand $\{H_o^D\}$ and

$$W_t = \sum_i w_{o(i)} h_{o(i)}(\omega_i)$$

2. Solve for new levels of relative prices, r_t using (2)

3. Update the export demand shifter with $X_{it} = \frac{D_{it}^F}{A} (P_{it}^F)^{1-\sigma}$

4. Solve for new levels of expenditure using (3)

5. Construct labor demand from the expenditure system:

$$H_{ot}^D = \frac{\sum_i \beta_{iL} \gamma_{io} E_{it}}{w_{ot}}$$

- 6a. If $\left\| \frac{H_o^D - H_o^S}{H_o^D} \right\| < \varepsilon^{tol}$ STOP

- 6b. If $\left\| \frac{H_o^D - H_o^S}{H_o^D} \right\| > \varepsilon^{tol}$ update wages to $w_t^{(j+1)} = \chi w_t^{(j)} + (1 - \chi) \kappa \left(\frac{H_o^D - H_o^S}{H_o^D} \right)$ where κ 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 [14](#) and [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. *In current work, I am also adding in the path of changes to export demand in order to extract the full consequences of globalization.* 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 has a multiplied influence on 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.

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 16 plots the time series of all foreign price changes while 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 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 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 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 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,

$$\sum_{i=1}^n s_i (\Delta w_i - \overline{\Delta w})^2 = \underbrace{\sum_{o \in \mathcal{O}} s_o (\Delta w_o - \overline{\Delta w})^2}_{\text{Across Variation}} + \underbrace{\sum_{i=1}^n s_i (\Delta w_i - \overline{\Delta w}_{o(i)})^2}_{\text{Between Variation}} \quad (4)$$

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 22, which plots, for each year, the fraction of total variance explained by the across component of equation (4). 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 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 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 affected workers can lose several thousand dollars. Young workers in particular lose, largely because they are further from retirement. Figure 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.

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 re-

searchers 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

example, 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 progress

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9 Appendices

9.1 Appendix: Tables

Table 1: Examples of Tasks

Com. 1: Communicative Activities	Com. 2: Monitoring
Written Expression	Far Vision
Written Comprehension	Operation Monitoring
Writing	Perceptual Speed

Com. 3: Facetime Tasks	Com. 8: Routine Maintenance
Performing for or Working Directly with the Public	Installation
Assisting and Caring for Others	Repairing
Resolving Conflicts and Negotiating with Others	Equipment Maintenance

Table 2: Income Regression Coefficients

		Age	Age ²	Tenure	High School L	H	Some Coll. L	H	College+ H
MANU.	Managers	5.74	-0.06	3.85	-58.16	42.44	48.18	-26.84	53.12
	Science Professional	6.46	-0.07	7.42	0.00	0.00	15.79	-23.48	17.97
	Science Assc. Professional	6.18	-0.06	4.60	-22.86	35.23	38.42	-0.34	48.08
	Other Assc. Professional	6.47	-0.07	6.54	-24.93	28.12	32.90	-4.89	37.91
	Clerks	7.40	-0.08	6.74	-21.41	43.78	50.07	9.11	52.62
	Agriculture	3.83	-0.04	1.59	-2.95	105.43	115.12	13.86	100.42
	Building Trades	5.04	-0.05	4.70	-3.93	59.40	65.45	0.00	0.00
	Metal Trades	4.23	-0.05	4.85	39.80	91.07	98.57	52.40	85.28
	Other Crafts	5.11	-0.05	6.45	-18.42	40.29	56.98	0.00	0.00
	Plant Operator	6.69	-0.07	6.55	45.58	79.34	89.90	47.34	66.86
	Machine Operator	4.14	-0.04	5.98	-22.99	33.55	44.35	0.00	0.00
	Drivers	4.10	-0.04	6.96	-3.50	29.63	32.97	0.00	0.00
	Laborers	3.85	-0.04	6.90	-35.64	46.11	52.22	0.00	0.00
	Mean	5.33	-0.06	5.62	-9.95	48.80	5.17	56.99	35.56
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	-4.54	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	88.09	-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

Notes: Coefficients presented $\times 100\%$. Mean is unweighted average across occupations. College educated high type is reference group. Blanks imply occupation is not part of the relevant group's choice set.

Table 3: Type Distribution

Type	Unconditional Share
No College: L	2.36
No College: H	23.55
Some Coll: H	5.63
Some College: L	39.69
College+ H	3.11
College+ L	25.65

Table 4: Occupation Fixed Effects

MANUFACTURING	Managers	2.06
	Science Professional	2.02
	Science Assc. Professional	1.93
	Other Assc. Professional	1.97
	Clerks	1.93
	Agriculture	1.98
	Building Trades	1.90
	Metal Trades	2.19
	Other Crafts	1.19
	Plant Operator	0.84
	Machine Operator	1.89
	Drivers	2.10
	Laborers	2.31
	Mean	1.87
SERVICES	Managers	2.33
	Science Professional	2.53
	Other Professional	2.44
	Science Assc. Professional	1.94
	Other Assc. Professional	2.29
	Clerks	2.51
	Personal Workers	2.56
	Retail Workers	1.87
	Metal Trades	2.71
	Drivers	2.42
	Elementary Occupations	2.29
	Laborers	2.16
	Mean	2.34
FIRE	Managers	2.57
	Science Professional	2.46
	Other Professional	2.43
	Science Assc. Professional	2.15
	Other Assc. Professional	2.09
	Clerks	2.29
	Customer Service	1.45
	Mean	2.21
HEALTH & EDUC.	Health Professional	1.98
	Teachers	2.26
	Health Assc. Professional	2.06
	Teaching Assc. Professional	2.44
	Clerks	2.40
	Personal Workers	3.22
	Mean	2.39

Table 5: Non-Employment Virtual Wage

$w^N(\omega) = \beta_a^f * a + \beta_{a^2}^f a^2 + \sum_i \beta_i^f \times D_i$	
Age Params.	
β_a^f	.004
$\beta_{a^2}^f$	-3.59×10^{-4}
Type Params.	
β_1^f	.645
β_2^f	.557
β_3^f	.602
β_4^f	.280
β_5^f	.300
β_6^f	0

Table 6: Switching Cost Matrix Across Occupations

From\To	Mgmt.	Prof.	Tech.	Clerks	Services	Agri.	Crafts	Mach.	Elem.
Managers	3.17	5.49	5.08	3.86	4.90	5.09	4.75	5.81	4.47
Professionals	3.95	4.56	4.35	3.41	4.42	5.35	4.35	5.35	4.21
Technicians	4.32	5.09	4.28	3.24	4.55	5.25	4.52	5.65	4.49
Clerks	5.70	6.90	5.63	3.38	5.71	7.26	6.25	7.66	6.07
Service Workers	4.87	6.23	5.34	3.85	3.73	5.24	5.20	6.15	4.63
Agricultures	4.33	6.29	5.25	4.18	4.48	3.02	3.68	4.43	3.89
Crafts & Trade	5.05	6.80	5.58	4.41	5.57	4.70	4.02	5.27	4.58
Machinists	4.26	5.75	4.79	3.72	4.56	3.93	3.61	3.88	3.68
Elementary Labor	4.50	6.20	5.32	4.12	4.58	4.66	4.38	5.13	3.60

Table 7: Inverse Switching Productivity Parameters

$f(\omega) = \exp \left(\beta_a^f * a + \beta_{a^2}^f a^2 + \sum_i \beta_i^f \times D_i \right)$	
Age Params.	
β_a^f	.0158
$\beta_{a^2}^f$	1.501×10^{-4}
Type Params.	
β_1^f	-0.089
β_2^f	0.076
β_3^f	-0.021
β_4^f	0.105
β_5^f	-0.106
β_6^f	0

Table 8: Mobility Costs by Age Group

	Mean	Q_{25}	Q_{50}	Q_{75}
25-29	11.81	7.51	10.45	14.57
30-39	8.74	5.77	7.74	10.68
40-49	7.33	4.96	6.51	8.95
50+	7.05	4.83	6.28	8.47

Table 9: Mobility Costs by Skill and Type

	Mean	Q_{25}	Q_{50}	Q_{75}
No College: L	16.76	11.45	16.22	21.07
No College: H	6.54	4.35	5.78	8.03
Some Coll: H	6.30	4.38	5.72	7.73
Some College: L	8.90	6.10	7.99	10.73
College+ H	5.93	3.59	4.83	7.02
College+ L	9.15	5.67	7.73	11.09

Table 10: Switching Cost Matrix Across Sectors

From\To	Man.	Services	FIRE	Health & Educ.
Manufacturing	5.53	5.86	5.84	6.08
Services	5.68	5.88	5.69	5.80
FIRE	6.00	5.96	5.59	5.87
Health & Educ.	6.41	6.34	6.18	5.55

Table 11: Mobility Costs by Transition Type

Transition Type	Mean	Q_{25}	Q_{50}	Q_{75}
Sector Only	4.10	3.81	4.09	4.38
Occ. Only	5.32	4.20	5.26	6.15
Both	5.72	4.61	5.67	6.68

Table 12: Real Difference in Wages Along Transition Path: 1996 Prices

		Periods				
		-5	0	10	20	40
MANUFACTURING	Managers	0.24	-0.69	-0.60	-0.59	-0.61
	Science Professional	0.04	-0.49	-0.43	-0.44	-0.42
	Science Assc. Professional	0.18	-0.53	-0.48	-0.47	-0.49
	Other Assc. Professional	0.22	-0.81	-0.68	-0.67	-0.69
	Clerks	0.25	-0.84	-0.71	-0.71	-0.75
	Agriculture	0.32	-1.40	-1.10	-1.07	-1.16
	Building Trades	0.08	-0.12	-0.13	-0.13	-0.12
	Metal Trades	0.76	-0.25	-0.29	-0.27	-0.28
	Other Crafts	0.10	-1.17	-0.97	-0.96	-1.04
	Plant Operator	-0.27	0.87	0.70	0.72	0.75
	Machine Operator	0.32	-0.95	-0.70	-0.68	-0.75
	Drivers	0.04	-0.55	-0.44	-0.41	-0.45
	Laborers	0.19	-0.57	-0.44	-0.42	-0.45
	Mean	0.19	-0.58	-0.48	-0.47	-0.50
	SD	0.23	0.56	0.44	0.44	0.47
SERVICES	Managers	0.06	-0.26	-0.24	-0.23	-0.23
	Science Professional	0.06	-0.32	-0.30	-0.28	-0.28
	Other Professional	0.08	-0.33	-0.28	-0.26	-0.26
	Science Assc. Professional	0.06	-0.22	-0.17	-0.16	-0.17
	Other Assc. Professional	0.06	-0.20	-0.17	-0.16	-0.16
	Clerks	0.04	-0.23	-0.22	-0.22	-0.21
	Personal Workers	0.05	-0.25	-0.29	-0.30	-0.29
	Retail Workers	0.04	-0.16	-0.16	-0.17	-0.16
	Metal Trades	0.07	-0.36	-0.33	-0.33	-0.31
	Drivers	0.02	-0.21	-0.17	-0.15	-0.15
	Elementary Occupations	0.06	-0.28	-0.25	-0.26	-0.26
	Laborers	0.07	-0.33	-0.26	-0.25	-0.26
	Mean	0.06	-0.26	-0.24	-0.23	-0.23
	SD	0.02	0.06	0.06	0.06	0.06
FIRE	Managers	0.05	-0.30	-0.29	-0.27	-0.27
	Science Professional	0.06	-0.28	-0.22	-0.20	-0.21
	Other Professional	0.07	-0.29	-0.23	-0.21	-0.21
	Science Assc. Professional	0.06	-0.23	-0.18	-0.17	-0.17
	Other Assc. Professional	0.06	-0.21	-0.16	-0.15	-0.15
	Clerks	0.07	-0.29	-0.25	-0.24	-0.24
	Customer Service	0.06	-0.22	-0.19	-0.20	-0.20
	Mean	0.06	-0.26	-0.22	-0.21	-0.21
	SD	0.01	0.04	0.04	0.04	0.04
HEALTH & EDUC.	Health Professional	0.03	-0.10	-0.09	-0.08	-0.08
	Teachers	0.02	-0.12	-0.17	-0.17	-0.16
	Health Assc. Professional	0.03	-0.14	-0.14	-0.14	-0.14
	Teaching Assc. Professional	0.02	-0.11	-0.15	-0.16	-0.15
	Clerks	0.03	-0.11	-0.12	-0.13	-0.10
	Personal Workers	0.00	-0.17	-0.46	-0.52	-0.49
	Mean	0.02	-0.13	-0.19	-0.20	-0.19
	SD	0.01	0.03	0.14	0.16	0.15
GRAND MEAN		0.10	-0.35	-0.31	-0.30	-0.31
GRAND SD		0.15	0.36	0.29	0.29	0.31

Table 13: Real Difference in Total Income Along Transition Path: 1996 Prices

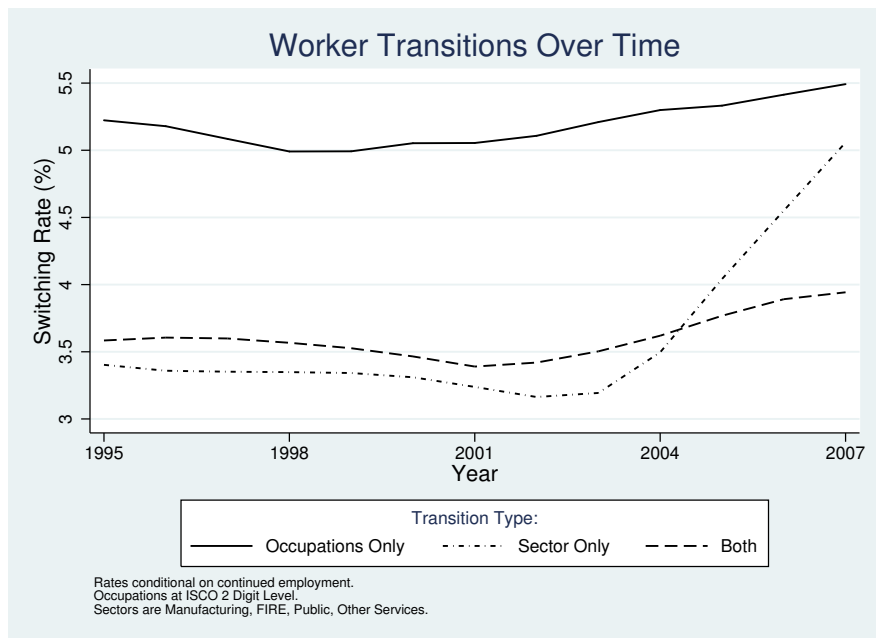
		Periods				
		-5	0	10	20	40
MANUFACTURING	Managers	14.38	-9.84	-5.62	-5.78	-5.72
	Science Professional	-0.06	5.67	8.25	5.95	8.91
	Science Assc. Professional	10.08	-0.71	1.15	0.41	1.00
	Other Assc. Professional	11.91	-11.28	-4.88	-5.06	-5.16
	Clerks	11.80	-3.16	1.05	0.47	0.86
	Agriculture	18.96	-55.07	-37.57	-36.05	-40.02
	Building Trades	3.94	23.00	20.21	18.80	21.86
	Metal Trades	48.83	26.90	21.89	20.56	22.51
	Other Crafts	5.42	-57.67	-45.62	-45.91	-48.31
	Plant Operator	-23.71	96.47	80.94	82.31	85.49
	Machine Operator	20.90	-33.42	-18.03	-17.76	-20.60
	Drivers	-0.13	3.06	9.15	9.74	8.66
	Laborers	9.36	5.97	12.49	12.50	12.30
	Mean	10.13	-0.77	3.34	3.09	3.21
	SD	16.15	39.09	30.93	30.95	32.77
SERVICES	Managers	0.93	26.88	25.97	25.81	27.24
	Science Professional	-0.89	36.02	34.34	34.50	36.35
	Other Professional	2.73	15.09	17.12	17.68	18.66
	Science Assc. Professional	1.91	20.66	22.05	21.96	23.28
	Other Assc. Professional	0.82	30.40	30.36	30.11	31.72
	Clerks	-2.23	48.39	45.22	43.30	46.91
	Personal Workers	-1.84	43.56	38.04	36.04	38.75
	Retail Workers	-0.18	28.37	24.88	22.50	26.76
	Metal Trades	-1.85	53.13	50.81	48.25	52.33
	Drivers	-1.65	29.45	30.60	30.13	31.74
	Elementary Occupations	0.01	32.07	29.87	28.12	31.06
	Laborers	1.24	26.21	27.35	26.42	28.51
	Mean	-0.08	32.52	31.38	30.40	32.78
	SD	1.64	11.11	9.55	8.90	9.58
FIRE	Managers	-1.03	36.62	34.38	34.41	35.93
	Science Professional	-0.27	31.90	33.20	33.13	34.40
	Other Professional	1.06	28.84	30.20	30.25	31.67
	Science Assc. Professional	0.15	31.49	32.74	32.33	34.00
	Other Assc. Professional	1.18	25.91	27.45	27.37	28.66
	Clerks	-0.89	45.63	44.02	43.21	45.92
	Customer Service	1.96	18.01	17.66	16.42	18.42
	Mean	0.31	31.20	31.38	31.02	32.71
	SD	1.13	8.62	7.95	8.10	8.28
HEALTH & EDUC.	Health Professional	-0.39	24.87	24.00	23.95	24.72
	Teachers	-0.69	23.87	18.19	17.48	19.81
	Health Assc. Professional	-0.35	27.09	24.91	23.45	25.80
	Teaching Assc. Professional	-2.43	39.86	34.36	32.85	35.16
	Clerks	-4.20	67.92	63.33	61.24	65.51
	Personal Workers	-7.87	98.22	86.73	82.68	85.96
	Mean	-2.65	46.97	41.92	40.27	42.83
	SD	2.96	30.11	27.19	25.93	26.76
	GRAND MEAN	3.08	23.17	23.45	22.73	24.24
GRAND SD		10.69	31.64	26.02	25.56	27.06

Table 14: Real Difference in Skill Prices Along Transition Path: 1996 Prices

		Periods		
		0	10	30
MANUFACTURING	Managers	-0.57	-0.42	-0.43
	Science Professional	-0.44	-0.32	-0.32
	Science Assc. Professional	-0.46	-0.37	-0.38
	Other Assc. Professional	-0.72	-0.54	-0.56
	Clerks	-0.76	-0.58	-0.62
	Agriculture	-1.04	-0.63	-0.67
	Building Trades	-0.15	-0.18	-0.17
	Metal Trades	-0.25	-0.30	-0.30
	Other Crafts	-0.86	-0.42	-0.46
	Plant Operator	0.64	0.07	0.10
	Machine Operator	-0.84	-0.50	-0.53
	Drivers	-0.51	-0.39	-0.40
	Laborers	-0.55	-0.40	-0.41
SERVICES	Managers	-0.28	-0.27	-0.26
	Science Professional	-0.32	-0.33	-0.31
	Other Professional	-0.32	-0.27	-0.26
	Science Assc. Professional	-0.24	-0.22	-0.21
	Other Assc. Professional	-0.23	-0.24	-0.22
	Clerks	-0.26	-0.28	-0.27
	Personal Workers	-0.25	-0.31	-0.31
	Retail Workers	-0.18	-0.20	-0.19
	Metal Trades	-0.39	-0.39	-0.38
	Drivers	-0.25	-0.25	-0.24
	Elementary Occupations	-0.29	-0.28	-0.28
	Laborers	-0.33	-0.29	-0.28
FIRE	Managers	-0.32	-0.33	-0.31
	Science Professional	-0.30	-0.26	-0.25
	Other Professional	-0.30	-0.27	-0.25
	Science Assc. Professional	-0.27	-0.23	-0.23
	Other Assc. Professional	-0.25	-0.22	-0.21
	Clerks	-0.32	-0.30	-0.29
	Customer Service	-0.23	-0.20	-0.20
HEALTH & EDUC.	Health Professional	-0.12	-0.15	-0.15
	Teachers	-0.13	-0.21	-0.19
	Health Assc. Professional	-0.17	-0.19	-0.18
	Teaching Assc. Professional	-0.13	-0.23	-0.22
	Clerks	-0.16	-0.19	-0.17
	Personal Workers	-0.16	-0.49	-0.53

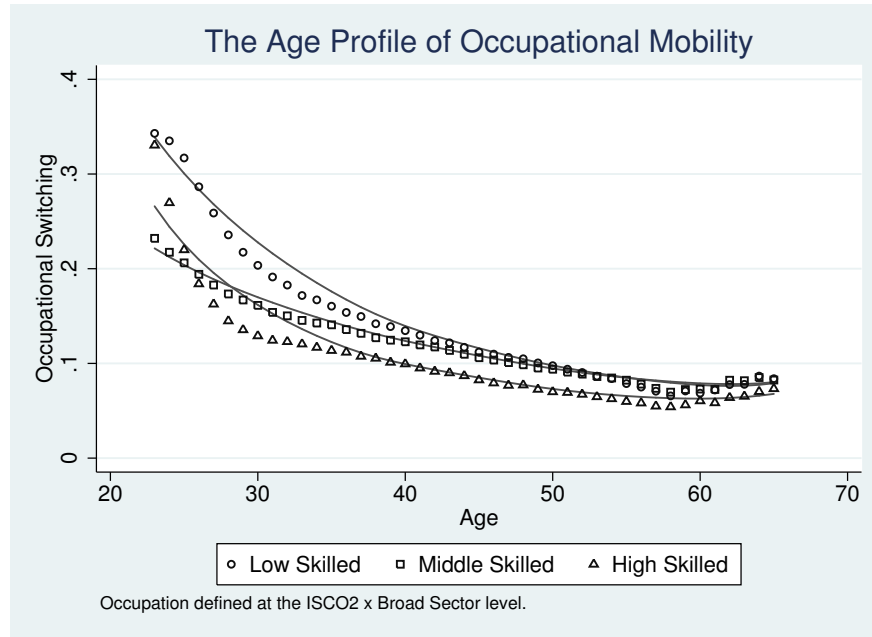
9.2 Appendix: Figures

Figure 1: Patterns of Switching Over Time



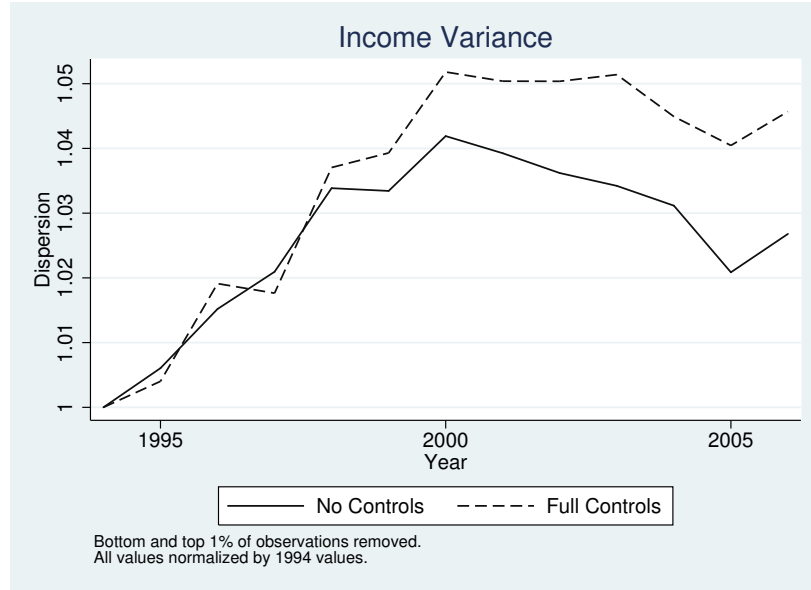
A transition at time $t + 1$ is defined as a worker who changes occupation status, sector status or both based on their status in the previous year. Figure based on transitions of all workers over 23 who are employed in both periods t and $t + 1$. This does not include workers who enter unemployment 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 2: 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 contains a break down along different kinds of transitions.

Figure 3: 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 4: 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: $Var(w) = Var(E(w|g)) + E(Var(w|g))$ 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.

Figure 5: Correlation Between Import Competition and Occupational Demand

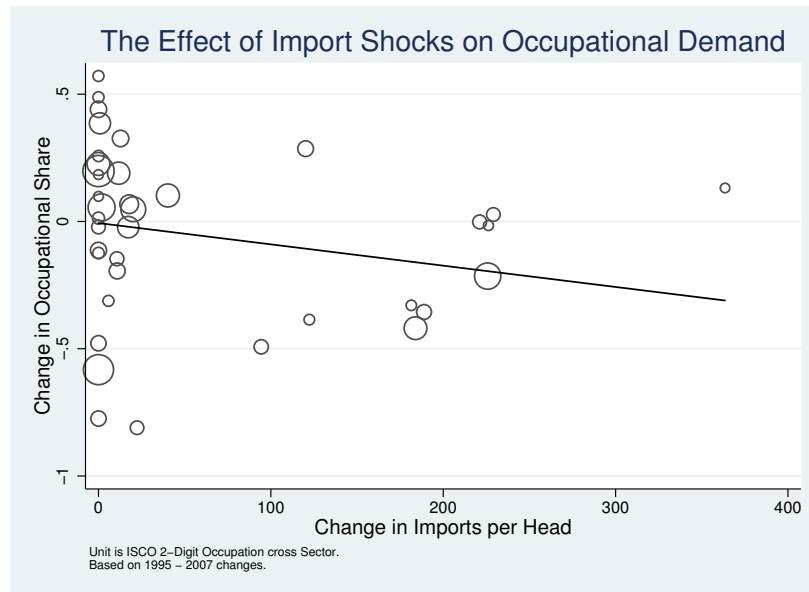


Figure 6: Correlation Between Import Competition and Movement

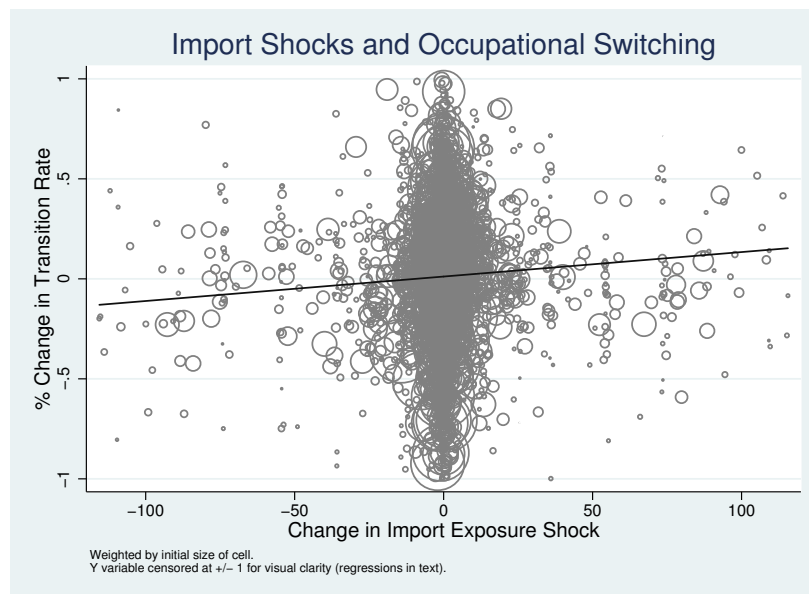


Figure 7: Histogram of Switching Costs

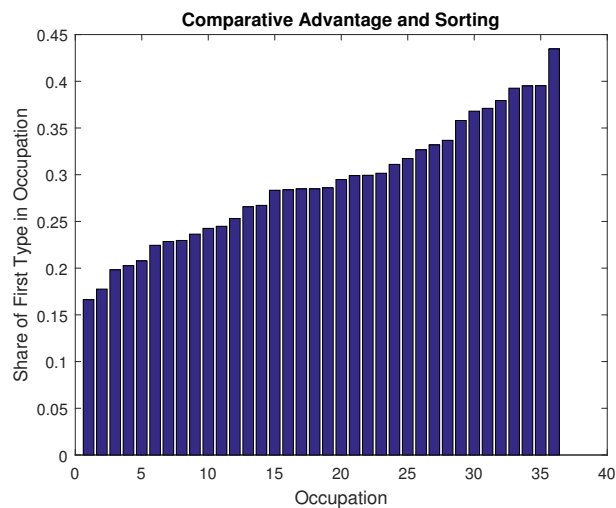


Figure 8: Histogram of Switching Costs

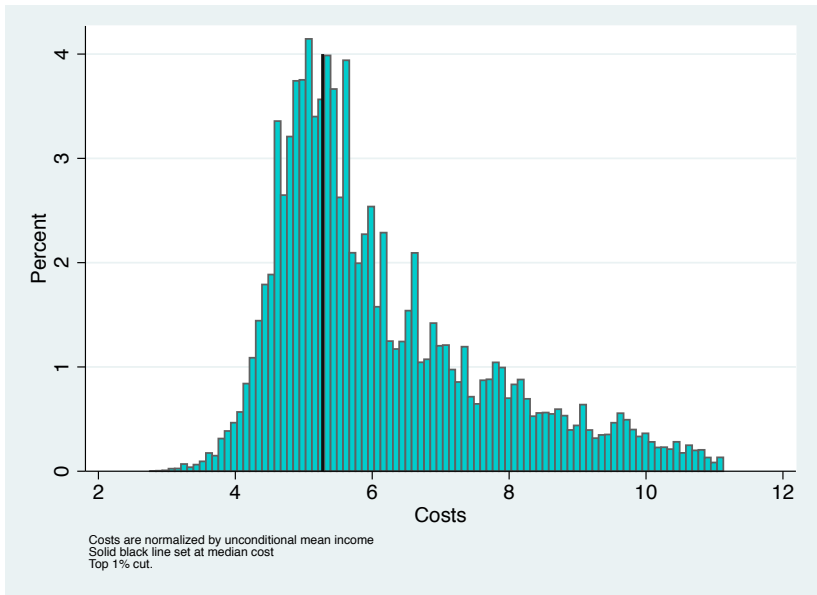


Figure 9: Histogram of Switching Costs Relative to Income

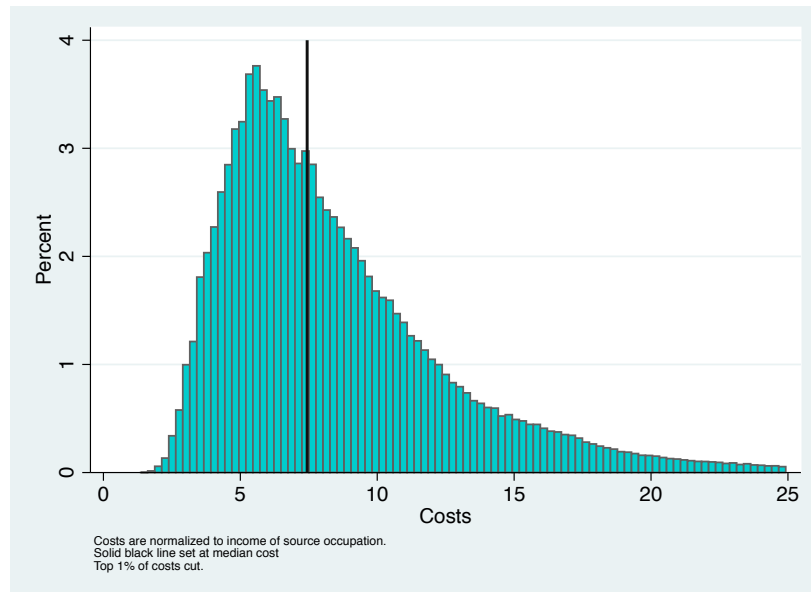


Figure 10: Histogram of Realized Switching Costs

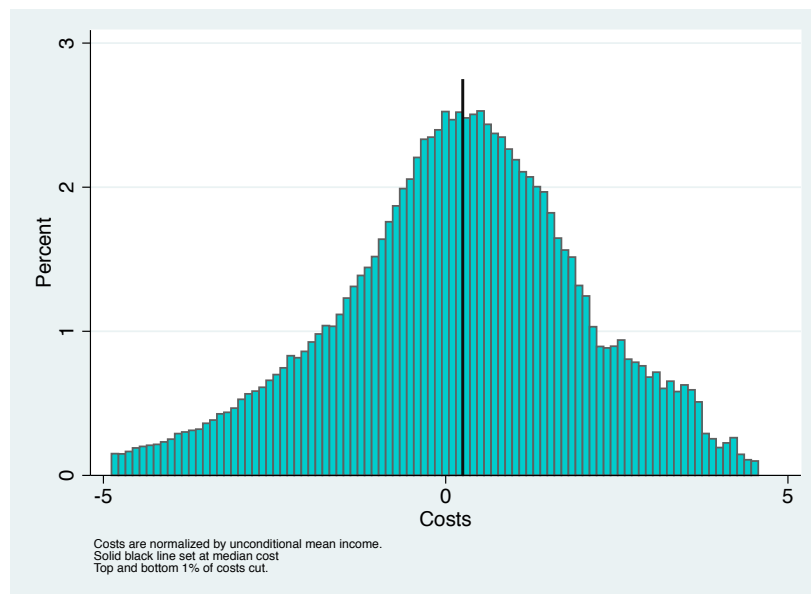


Figure 11: Density of Mean Costs Out of Source Occupation

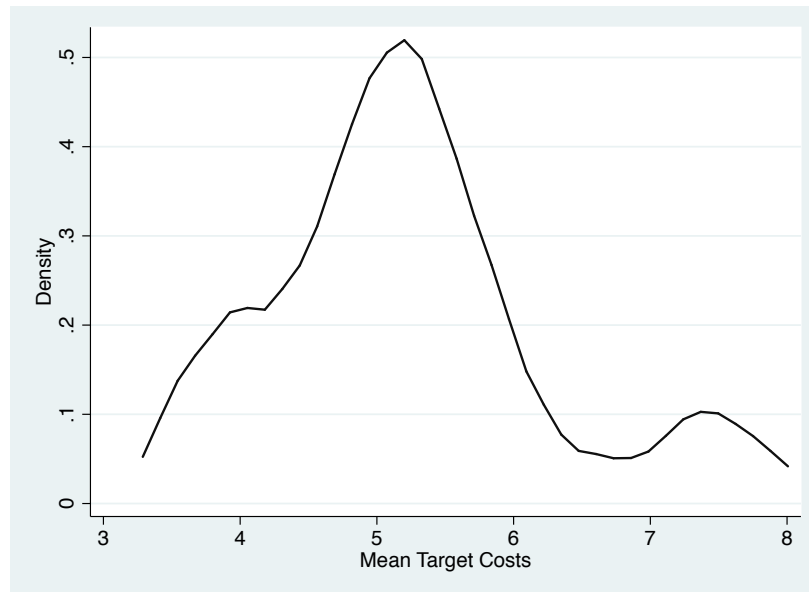


Figure 12: Density of Switching Costs by Type of Transition

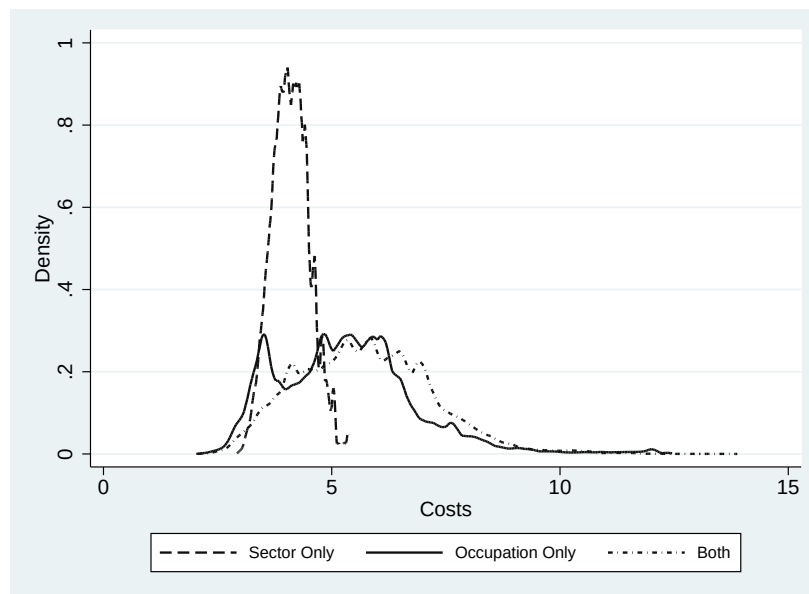


Figure 13: Model Fit: Predicted Versus Actual Transitions

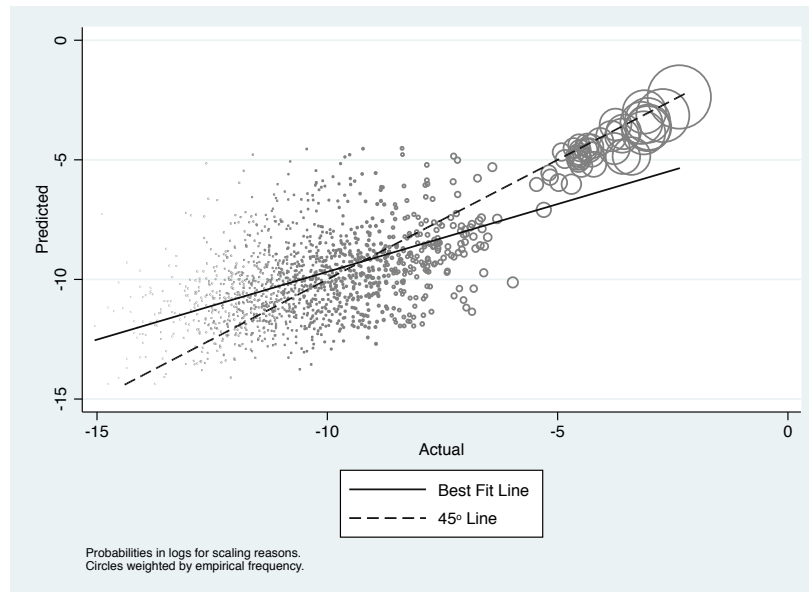


Figure 14: Full Model Fit: Size Distribution of Occupations

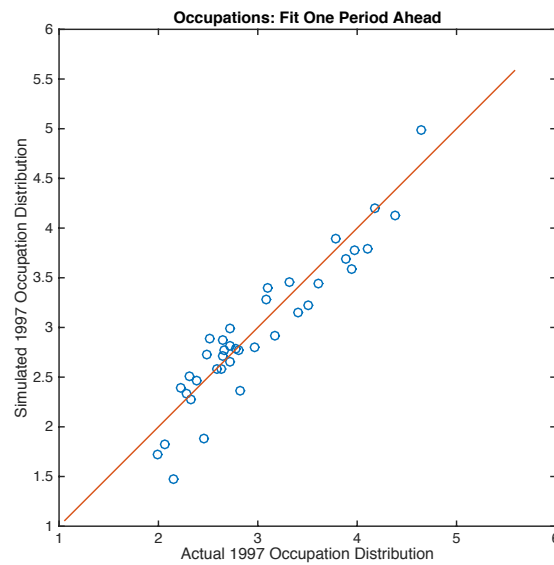


Figure 15: Full Model Fit: Wages



Figure 16: Import Price Indices by Industry

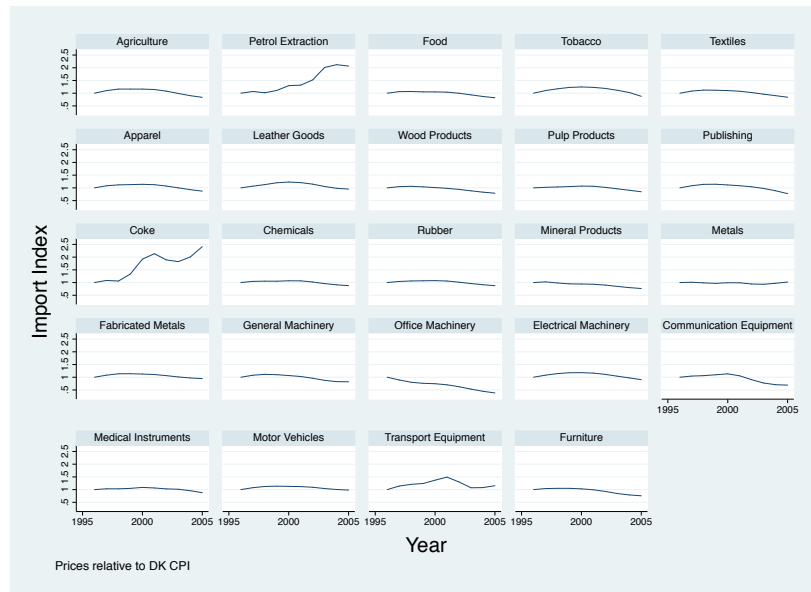


Figure 17: Import Price Index

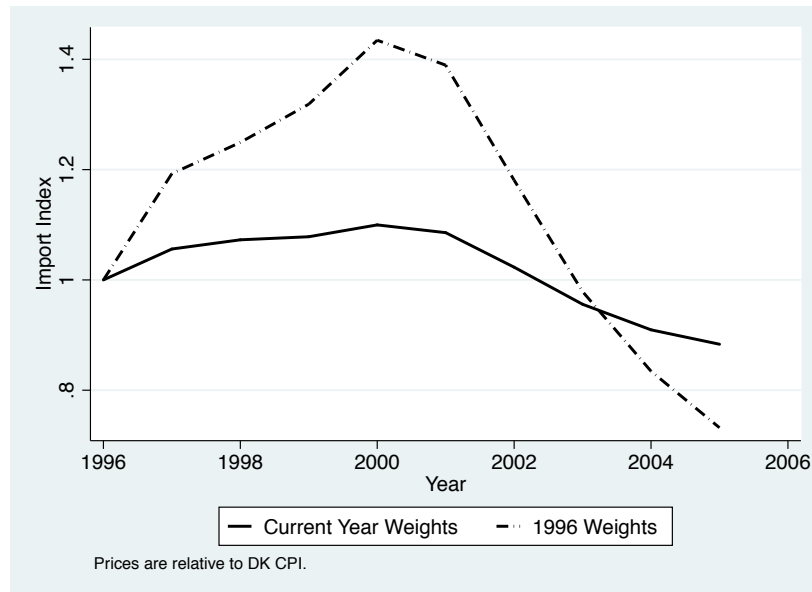


Figure 18: Aggregate GDP: 1996 Prices

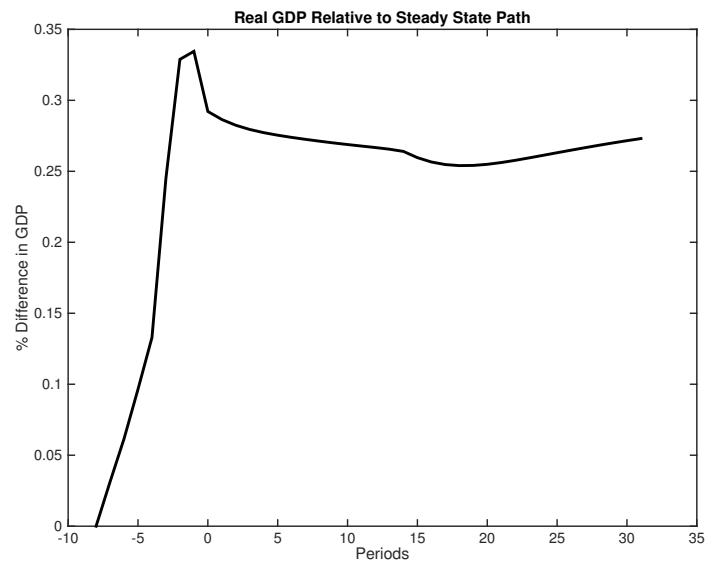


Figure 19: Labor Income: 1996 Prices

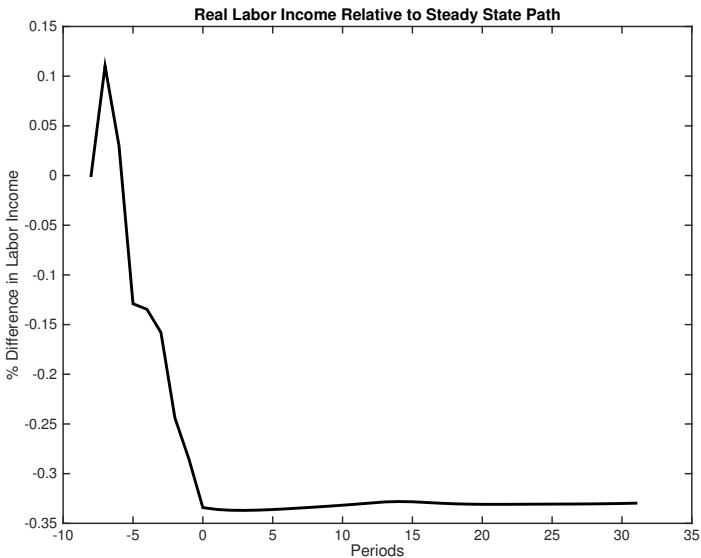


Figure 20: Employment Growth: 1996 Prices

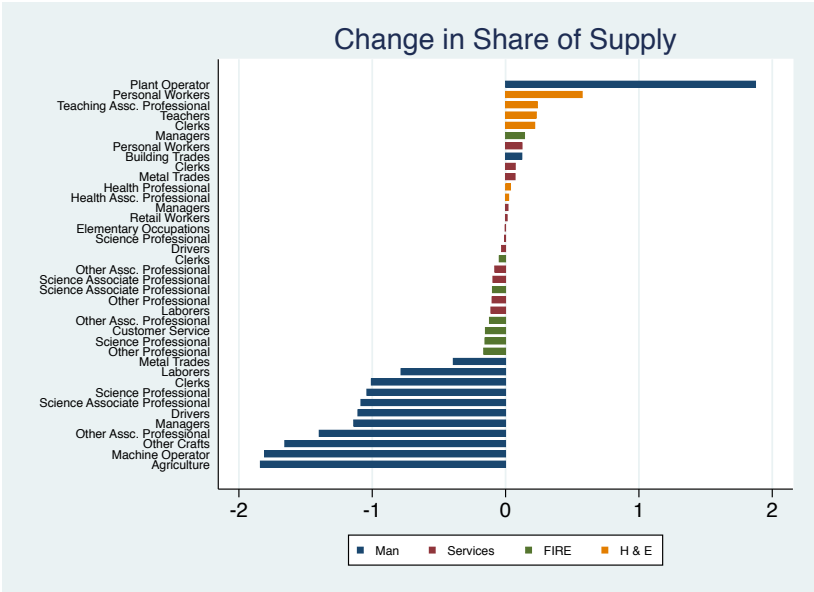


Figure 21: Sectoral Growth: 1996 Prices

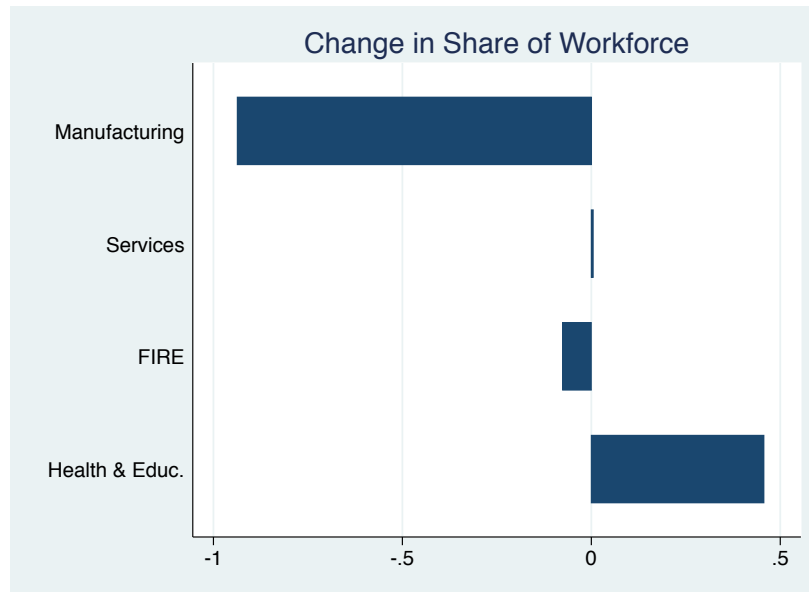


Figure 22: Variance Decomposition of Changes in Outcomes

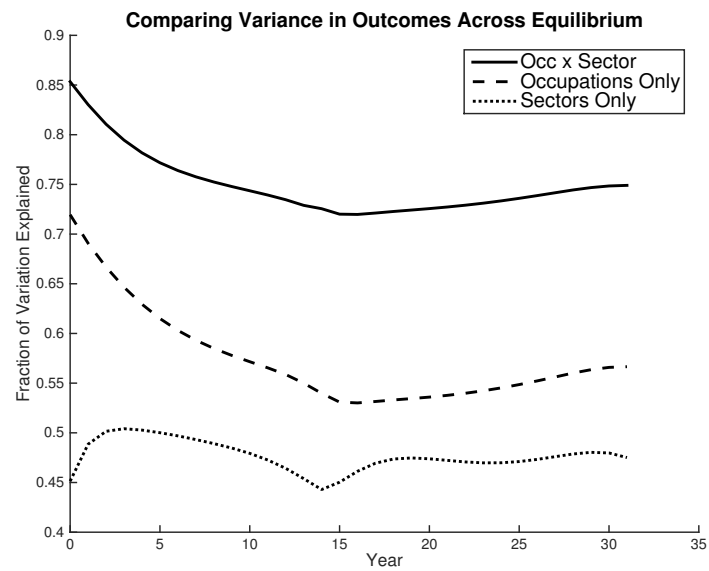


Figure 23: Skill Prices in Manufacturing Over Time

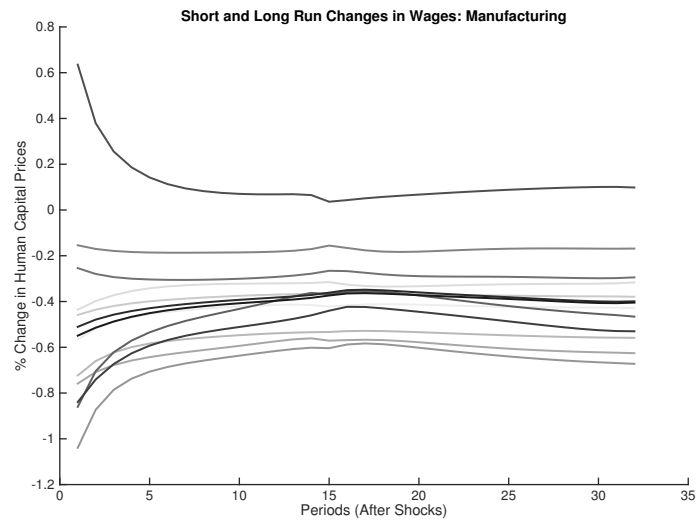


Figure 24: Net Present Value Effects of Trade, Manufacturing: 1996 Prices

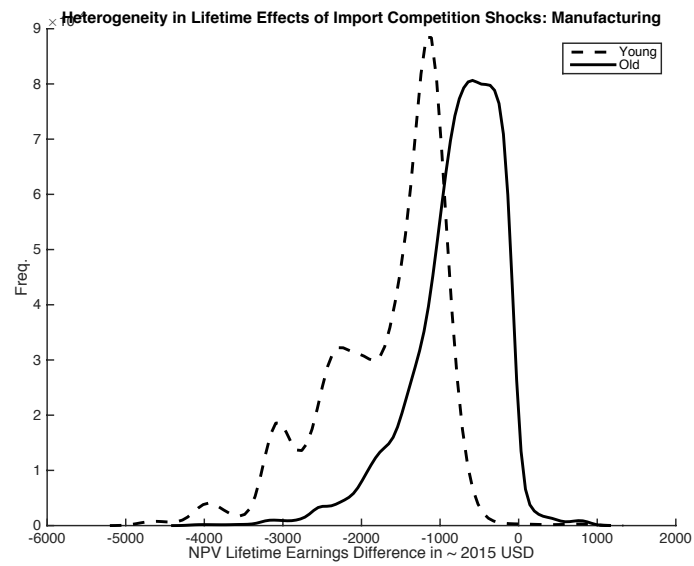


Figure 25: Net Present Value Effects of Trade, Non Manufacturing: 1996 Prices

