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Occupations and Import Competition: Evidence from Denmark†

By Sharon Traiberman*

I argue that the winners and losers from trade are decided primarily by occupation. In addition to fixed adjustment costs, workers build up specific human capital over time that is destroyed when they must change occupations. I show that ignoring human capital biases estimates of adjustment costs upward by a factor of 3. Estimating an occupational choice model of the Danish labor market, I show that 57 percent of the dispersion in worker outcomes is accounted for by occupations, and only 16 percent by sectors. Finally, the model suggests that rising import competition from 1995–2005 reduced lifetime earnings for 5 percent of workers. (*JEL* F14, F16, J24, J31)

Free trade creates winners and losers, both in the short and long term. These differences arise not only from shifting economic activity, but also from differences in workers' abilities to adjust to import competition. Economists have known since at least Shaw (1987) that a key margin of adjustment for workers is occupational reallocation. Yet, empirical trade economists have focused primarily on sectoral or firm reallocation, and largely ignored the impacts of destroyed occupational human capital. Nevertheless, accurately quantifying the short-run costs of globalization is critical to policymakers seeking to assist displaced workers. To address this need, I estimate a structural model of occupational choice that quantifies the distributional consequences and dynamic costs of trade shocks.

The core of this model is a recurring occupational choice: in each period, workers select into an occupation by weighing their menu of incomes against the costs of switching occupations. On top of fixed costs à la Artuç, Chaudhuri, and McLaren (2010), switching entails destruction of human capital. Workers are thus forward looking, taking the implications of their choices on future earnings into account. Factoring in human capital leads to new dynamic implications for the short- and

*Department of Economics, New York University, 19 W. 4th Street, 8th Floor, New York, NY 10012 (email: sharon.traiberman@nyu.edu). Penny Goldberg was the coeditor for this article. I thank Stephen Redding and Jan De Loecker for their support and guidance in this project. I thank Kirill Evdokimov, Chris Flinn, Bo Honoré, Elena Manresa, Ricardo Reyes-Heroles, and participants at numerous workshops, and five anonymous referees for helpful discussions and comments. I am particularly indebted to Frederic Warzynski, Henning Bunzel, and the Labor Market Dynamics Group at Aarhus University. I have received support from the Princeton International Economics Section and the Cowles Foundation. I declare that I have no relevant or material financial interests that relate to the research described in this paper.

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long-run effects of import competition. For example, workers with accumulated human capital will be less willing to move than workers with none.

On the production side, each sector comprises many industries that use different mixes of occupations. Moreover, through an input-output structure à la Caliendo and Parro (2015), the model features industry spillovers that allow foreign price shocks to have uneven effects across occupations. For example, a reduction in the foreign price of trucks may squeeze occupations used in domestic truck production, but can *spur* demand for occupations in industries that use trucks as inputs. I use the model to study the effect of the precipitous decline in import prices in Denmark from 1995 to 2005. Over this time period, the rise of China and Eastern Europe led to a 17 percent decline in the aggregate import price index. However, this rise was uneven across industries: for example, office equipment prices declined 60 percent, while transport equipment prices were unchanged.

Estimating the parameters of the worker's decision problem is complicated by three features of the model: first, workers make decisions based on unobservable comparative advantage and dynamically evolving human capital; second, there is a large number of occupations; and third, workers must forecast future wages. A methodological contribution of this paper is to show that incorporating these features into a model of labor and trade can be done tractably, without requiring a full solution to the model until counterfactual analysis. Indeed, as the study of transition dynamics spreads, there is a growing need to capture realistic margins for workers (e.g., occupations, neighborhoods, or commuting zones) *and* model the full dynamic concerns of workers, such as human capital accumulation.

The method I develop can handle choice sets of arbitrary size, circumvent the issue of expectations, and still capture the fact that workers differ in experience. The method borrows from the structural labor literature on conditional choice probabilities (CCPs), specifically the recent work of Arcidiacono and Miller (2011). The basic idea is to exploit the log-linear relationship between observed transition probabilities across occupations and workers' payoffs, including costs, income, and continuation values. Through a linear regression, the elasticity of switching occupations is identified from the responsiveness of occupational and sectoral transitions to income changes. With this elasticity in hand, fixed switching costs are identified from the patterns of movement conditional on a switch.

The regression is complicated by two factors: workers' unobserved continuation value of being in an occupation is on the right-hand side, and transition rates may differ based on unobserved comparative advantage. In a first stage, I use the two-step approach of Arcidiacono and Miller (2011) to recover unobservable comparative advantage and the returns to accumulated human capital. Then, to difference out continuation values, I compare workers with identical characteristics, who begin and end in the same occupation and sector, but make different decisions along their career arcs. Using administrative panel data on the universe of Danish workers allows me to precisely estimate transition rates for narrowly defined groups of workers, and therefore estimate the labor supply model.

Controlling for human capital accumulation is crucial for accurately estimating the model's key parameter, the elasticity of switching occupations and sectors in response to an income shock. My model predicts that a 1 percent decline in income leads to a 4.4 percentage point increase in exit from an occupation. Models that omit

human capital only predict one-third of this effect, and compensate with excessively large estimates of fixed switching costs. In other words, omitting tenure leads to the mistaken impression that one-time switching costs, which can reflect policy-relevant objects like retraining, are very large. In reality, switching costs are more manageable, but workers take time to recover foregone human capital.

In order to quantify the occupational margin's importance for workers, I simulate an economy where import prices fall as they do in the data, and compare this to a counterfactual scenario where import prices are fixed at base levels. The exercise has three takeaways. First, the majority of the distributional impacts, especially in the short run, are across occupations. Specifically, occupations explain nearly 60 percent of variation in lifetime earnings changes, while sectors only account for 16 percent. Second, the impact of import competition is largest for occupations within the tradable sector. For example, both the largest gains and losses in income are within manufacturing. Finally, while adjustment is costly and protracted, most workers still benefit from trade due to lower prices; only 5 percent of workers see a decline in lifetime earnings. Unsurprisingly, losses are concentrated amongst workers with comparative advantage in exposed occupations.

This paper relates to and builds on several literatures. First, there is a long history of reduced-form studies of workers and trade. These authors have primarily focused on comparisons of workers in import-competing sectors, locations, firms, or occupations.[1] Second, a growing literature builds labor market adjustment into trade models. For example, Helpman et al. (2017) and Coşar, Guner, and Tybout (2016) have added labor market frictions to Melitz's (2003) model. Others, in particular, Dix-Carneiro (2014); Artuç, Chaudhuri, and McLaren (2010); Artuç and McLaren (2015); and Caliendo, Dvorkin, and Parro (2019), have used dynamic discrete choice models to study worker dynamics, often in a general equilibrium trade model. This literature has spilled over into more general spatial equilibrium models studying the dynamics of immigration (Caliendo et al. 2017), educational opportunities (Eckert and Kleineberg 2019), and infrastructure (Balboni 2019). My contribution to this literature is twofold. I add an occupational margin to a fully dynamic, open economy, general equilibrium model; and, I introduce techniques to capture unobserved comparative advantage and human capital accumulation. The latter is particularly important as combining high dimensional choice sets for workers, with realistic dynamics in human capital, is crucial, but has been absent from this literature.

I also contribute to the resurgent literature on occupational reallocation in labor markets. For example, Kambourov and Manovskii (2009a) and Huckfeldt (2016) discuss the importance of occupational transitions for understanding inequality and worker responses to recessions. Papageorgiou (2014) and James (2012) have reexamined the importance of learning about occupational comparative advantage for career trajectories. In contrast, I focus on the connection between occupations and increasing import competition.

The rest of the paper proceeds as follows. Section I describes the Danish employee-employer data, and presents key facts about the Danish labor market

[1] For example, Revenga (1992); Autor, Dorn, and Hanson (2013); Autor et al. (2014); Hummels et al. (2014); Ebenstein et al. (2014); Harrigan, Reshef, and Toubal (2016); and Keller and Utar (2016).

and import competition. Sections II and III present the labor supply model, and the estimation strategy. Sections IV and V present model estimates and counterfactual experiments. The final section concludes.

I. Data and Stylized Facts

A. *Data Sources*

I rely on three administrative datasets for analysis. For data on workers, I use the *Integrated Database for Labour Market Research* (IDA), a panel dataset that assigns a unique identifier to each Danish resident at age 15. It provides information on workers' highest completed education, socioeconomic characteristics, employment status, occupation, and income. Moreover, it links employed workers to a unique employer identifier. I group workers into three skill groups based on their education: high school completion or less, short cycle education (which corresponds to two years of vocational training), or a professional bachelor's (medium cycle) or more. The last group correspond to categories 5 and 6 in the International Standard Classification of Education (ISCED), and so this split is similar to Hummels et al. (2014). Workers with purely vocational training are separated as they may be particularly sensitive to trade shocks.[2] Income and employment are measured each November. More detail on data construction, and comparisons between sample aggregates (e.g., employment and skill distribution) and published national accounts, can be found in online Appendix D.1.

Data on firms come from the *Firm Accounting Statistics Register* (FIRE), which contains information on firms' wage bill, capital expenditures, and their NACE 1.1 industry code. I link this to IDA to construct occupation-sector histories for each worker. The match rate between employed workers and firms is nearly perfect, allowing me to construct these histories for the universe of Danish residents. Finally, data on international trade come from the *Discretionary Foreign Trade Database* (UHDI). This dataset contains annual quantities and values of imports and exports by firms at the product-country level. UHDI and FIRE can be linked, allowing me to construct import penetration measures at both the industry and occupation level. Price and quantity data allow for construction of industry-level import price indices, which I discuss in more detail in Section V.

The International Standard Classification of Occupations (ISCO) was substantially updated to reflect modern occupations in 1988, and was slowly adopted in Denmark. High-quality occupational codes become available starting in 1991. To this end, I restrict the data to follow workers older than 23 and below 65 from 1996 through 2008. I avoid the first few years of the sample in order to construct occupational histories for workers, and due to a series of labor market reforms in 1994 that led to large changes in the occupational and industrial structure. In the next subsection, I detail how I aggregate industries and occupations into occupation-sector pairs. Occasionally, a worker's occupation is imputed by a worker's education, industry, and income. Statistics Denmark flags such imputations and I drop them

[2] The Professional Bachelor's in Denmark is often vocational as well, but also contains more majors such as business or communication.

to avoid circularity in regressing income on occupations. I drop observations with income at the bottom and top 2.5 percent in order to remove outliers. At the bottom end, these numbers are small and such workers are likely to have spent substantial time unemployed in that year; at the top end, these incomes are unlikely well modeled by a competitive labor market model, and distort estimated skill prices. The final dataset contains 18.2 million worker-year observations from an underlying sample of 32 million. Dropping imputed and missing data does not substantially change the composition of workers; summary statistics for both the sample frame and raw data, and trends in demographics such as labor force participation and education, are provided in online Appendix Table A.7.[3]

B. *Defining Occupations*, *Sectors*, *and Tasks*

I define occupations at the ISCO two-digit level.[4] The ISCO was developed by the ILO and classifies occupations by their tasks and work activity.[5] The two-digit aggregation is useful for two reasons. First, this level of aggregation avoids estimating many zero transitions. Second, most workers can be attached to a two-digit code, while finer gradations are often noisy. Nevertheless, the stylized facts in Section ID are shown for various levels of disaggregation.

In addition to occupations, workers are grouped into four sectors based on the worker's industry: manufacturing (including utilities and construction); FIRE[6] and R&D; health and education; and other services. This aggregation serves two purposes. First, it allows for the possibility that occupations are nominally similar but substantively different across sectors. Second, it allows for comparisons with previous work in assessing the relative importance of occupations versus sectors.[7] After cleaning the data, there are 38 occupation-sector pairs. Online Appendix Tables A.10 and A.11 contain a detailed breakdown of the shares of the most disaggregated occupational codes in each constructed occupation-sector pair, as well as the industrial composition of each sector.

Each occupation is attached to a vector of occupational characteristics I call *tasks*; the loadings on each vector reflect the importance of a task in a particular occupation. Tasks are constructed from the O*NET database's survey of working activities. In this survey, the US Department of Labor presents workers with a list of predetermined work activities and asks them to rank the importance of each on a scale of 1 to 5. Examples include "active learning," "writing," "equipment maintenance," "assisting and caring for others," and "handling and moving objects." As there are nearly 130 survey questions, covering over 800 highly disaggregated occupations, I

[3] Unfortunately, IDAS contains limited information on immigrants and Danes commuting abroad. I do not treat immigrants differently from Danes. However, their education is often missing and so they are more likely to be dropped from the sample.

[4] There are 27 ISCO two-digit codes. However, I drop the army (code 01), legislators (code 11), and combine managerial occupations (codes 12 and 13).

[5] The system is set up on "the basis [that] 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." Source: http://www.ilo.org/public/english/bureau/stat/isco/intro2.htm.

[6] This acronym stands for finance, insurance and real estate, and is a typical grouping of highly skilled services. It is defined as the H grouping in the SIC system, and headings 52 and 53 in NAICS.

[7] Unlike in some previous work, including Dix-Carneiro (2014), I group together manufacturing, agriculture and construction. This is because in Denmark, the shares of workers in the latter two are small.

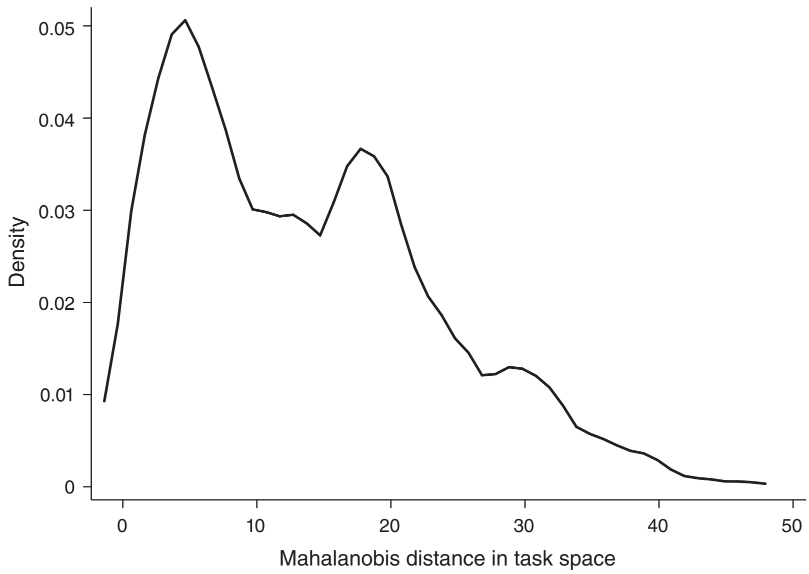

Figure 1. Distribution of Task Distance for Switchers

Note: Transition defined as changing occupation-sector status from last employed occupation-sector.

use principal components analysis (PCA) for data reduction.[8] PCA constructs tasks from weighted averages of survey questions. The first ten combinations explain over 80 percent of the variation in survey responses, and are the "tasks" in the empirical analysis. Online Appendix Table A.12 contains the survey questions with the highest and lowest loadings in each task. Online Appendix D contains details on the procedure, and a mapping from the US's 6-digit SOC occupations to the 38 occupations in the data.

Occupational tasks play an important role in the cost of switching occupations and sectors. To illustrate this, Figure 1 plots the density of the Mahalanobis Distance between occupation and sectoral transitions in Denmark.[9] The mode of this distribution is near zero, implying most switching workers do not travel far in task space. Moreover, the density is right-skewed and almost monotonically decreasing in distance. Hence, workers are less likely to switch to occupations far away. Having defined the variables of interest, the next two subsections provide some details on the Danish labor market and analyze in between occupational demand and import competition.

[8] PCA uses the spectral decomposition of the correlation matrix between survey responses to construct linear combinations of responses with the properties that (i) components are orthogonal and (ii) components can be ranked by fraction of variance explained. Bai and Ng (2002) contains discussion on how to estimate the components and decide on the optimal number of components.

[9] The Mahalanobis distance between two vectors in a space, $\mathcal{V}$, is the Euclidean distance shifted by the inverse of the covariance matrix, Σ, of vectors in $\mathcal{V}$. Mathematically, if occupation-sector pair, (o,s), and occupation-sector pair, (o',s') have tasks, $v_{o,s}$ and $v_{o',s'}$ then the distance between them is given by

$$d\big((o,s),(o',s')\big) = \sqrt{\big(v_{o,s} - v_{o',s'}\big)'\Sigma^{-1}\big(v_{o,s} - v_{o',s'}\big)}.$$

C. *Overview of the Danish Labor Market*

Denmark has several features which make it a good environment for studying occupational reallocation and trade. First, the Danish labor market is one of the most flexible in Europe, albeit more rigid than the United States, Canada, or the United Kingdom.[10] This is due to a series of reforms beginning in the 1990s aimed at reducing high unemployment. Danish labor market policy encourages worker churn, while providing ample social insurance, a system termed "flexicurity." Second, despite heavy unionization, Denmark encourages retraining and reallocation through several programs geared toward the unemployed, collectively dubbed Active Labor Market Policy. Thus, there is a good deal of movement in the Danish labor market. Finally, as a small open economy in the EU, Denmark experienced significant, plausibly exogenous, changes in import competition in the 1990s and 2000s, especially from China and Eastern European countries. Foreign prices will be further discussed in Section V, while the next subsection presents key facts on occupations and import competition.

D. *Facts about Occupations and Trade*

To illustrate the churn in the Danish labor market, Figure 2 plots the time series of occupational transition rates. Workers move across occupations at a rate of over 10 percent per year. This is in line with Kambourov and Manovskii (2009a) in the United States, using a similar disaggregation. There is a noticeable uptick in 2007 and 2008, partially driven by the financial crisis,[11] but switching is high in all years.

Table 1 presents a series of summary statistics on worker switching, across various levels of aggregation of occupations, as well as across firms. Mechanically, the rate of switching across occupation-sector pairs is higher than across two-digit occupations. And the rate is higher still across the most disaggregated occupations. The second row of Table 1 shows that over the 12-year time span, an average worker has 1.7 occupations. This number is small in light of the high mobility,[12] and reflects that workers move in a narrow band of occupations and sectors, often returning to a previous job. This can be explained by a mix of persistent heterogeneity in workers' talent and the presence of high reallocation costs.

The aggregate numbers above obscure substantial heterogeneity in switching across workers, especially differences in workers of different ages and human capital. Figure 3 plots the hazard rate of switching with respect to both age and occupational tenure. There is a sharp drop along both margins. For example, workers with 6 years of tenure are 20 percent less likely to move compared to those with none.[13]

[10] For more on the Danish labor market and how it compares to other European countries, see either Hendeliowitz (2008), OECD (2013), or Botero et al. (2004). Dahl, le Maire, and Munch (2013) contains a fuller discussion of changes in the Danish labor market and the effects of reforms on wages over time.

[11] In 2005, there was also a change in coding from NACE 1.1 to NACE 2. I have concorded industries across time, but recoding may lead to some spurious reallocation. This only occurs in a handful of occupations, and mostly in the public sector. The rise in mobility also occurred across occupations, which were unaffected by the code change, suggesting the uptick is genuine.

[12] Given the average probability of switching, if the probability of entering any particular occupation from another were uniform, then the average worker should take on 2.4 distinct occupations.

[13] The numbers are very close to Groes, Kircher, and Manovskii (2015), which uses the same dataset.

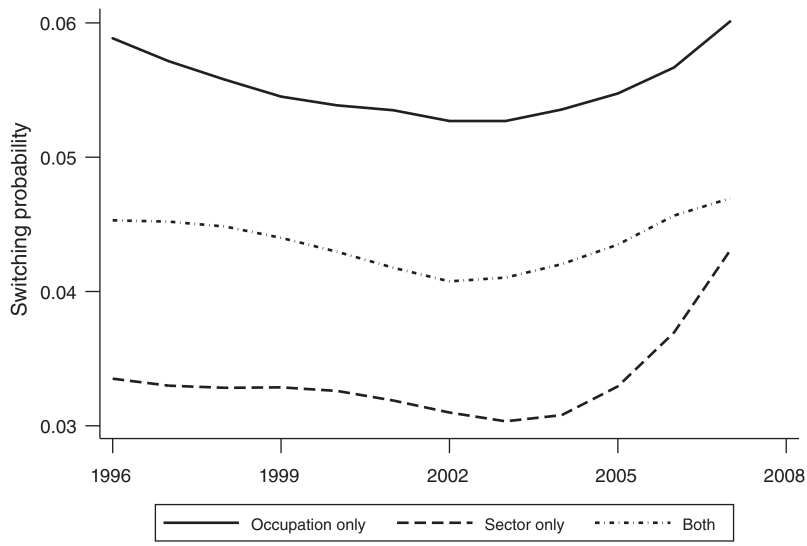

FIGURE 2. SWITCHING PATTERNS OVER TIME

Notes: Transition defined as changing occupation status from occupation when last employed, and does not include transitions into non-employment. Data from sample frame, as discussed in the online Appendix. 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.

TABLE 1—SUMMARY STATISTICS ON WORKER TRANSITIONS

	Author def.	ISCO-2	ISCO-3	Firms
Average switching rate	13.2	9.9	18.1	21.8
Average positions held	1.7	1.6	2.0	2.4
Total number	38	22	145	169,406

Notes: Transition defined as a change from position when last employed, and does not include transitions into non-employment. Switching rate is defined as the mean unconditional probability of switching across workers; number held is the number of positions held by a worker; total number refers to the number of possible positions. Sample frame discussed in the online Appendix. All averages across workers are weighted by number of periods of employment. At the two-digit level, managerial and agricultural occupations are aggregated (discussed in the data Appendix); raw figures available upon request.

These hazard rates play an important role in subsequent estimation. In particular, they imply that workers switching occupations are unlikely to have the same characteristics as incumbent workers.

Turning to income, Table 2 presents results from a series of variance decompositions. Following Kambourov and Manovskii (2009a) and Helpman et al. (2017), each entry in the table is the fraction of the variance in incomes explained by the between component across different aggregations of occupations, as well as across firms. I include firms as a benchmark, given how extensively they have been studied in the literature. Each column contains a different income concept: the first uses raw data, with no individual controls; the second uses the residuals from a Mincer

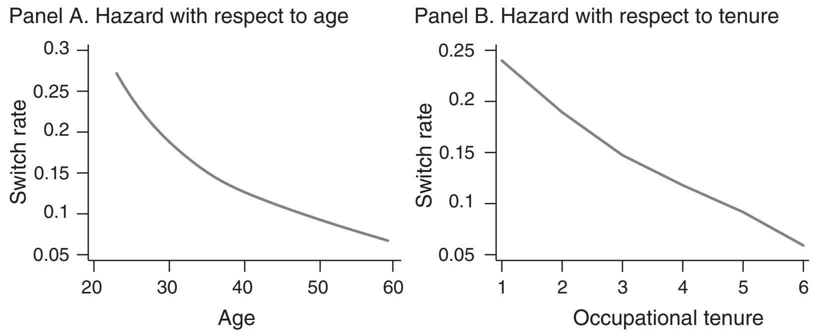

Figure 3. Rates of Occupational Switching

Notes: Occupations defined by author as described in text. This includes data on all individuals included in the sample frame, polling across years.

Table 2—Variance Decomposition of Income

	(1)	(2)	(3)
ISCO-2 Dig.	11.52	9.14	10.85
ISCO-3 Dig.	14.62	12.09	14.16
Author defined	11.84	9.73	11.87
Firm	17.98	18.32	13.55

Notes: Variance decomposition uses sample frame. Column 1 uses raw income with no controls; column 2 based on residuals from a regression of income on age (quadratic), skill and time fixed effects; column 3 based on residual from a full set of controls, limited to firms with at least 5 employees in every year. ISCO-2 and ISCO-3 codes based on ILO classifications. Firms defined by tax ID, pooling plants. Data details in online Appendix.

regression with standard covariates;[14] the third includes the controls from specification 2 and conditions on firms with at least 5 employees.

In all specifications, occupations explain a sizable percentage of variance in incomes. At the two-digit level, occupations account for 9–11.5 percent of income. By way of comparison, firms account for 13.5–18 percent of variation in outcomes. Thus, firms and occupations account for a similar fraction of the variance in income. Moreover, the omission of tenure effects likely biases down the importance of occupations. Table 3 reports the same decomposition, but includes firm and occupation fixed effects. Regardless of controls, including occupation fixed effects alongside firm fixed effects reduces the contribution of each. Nevertheless, the large covariance term implies that occupational mixes tend to differ, systematically, along firms paying different mean wages. Summing the variance and covariance terms implies that occupations account for up to one-fifth of the variation in wages.

Finally turning to trade, Figure 4 plots both the rapid increase in trade activity and its relationship with changing occupational demand. Panel A plots the rise in the real value of imports, which far exceeds GDP growth. Rising imports have

[14] In particular, I look at the residual from a regression of log income on a quadratic in age, with year and skill fixed effects.

TABLE 3—OCCUPATIONS, FIRMS, AND SORTING IN INCOME VARIANCE

	(1)	(2)	(3)
var(occ. fixed effects)	9.51	6.03	6.76
var(firm fixed effects)	14.69	13.07	8.55
cov(firm, occ.)	1.21	13.86	14.29
Residual	74.60	67.04	70.40

Notes: Variance decomposition uses sample frame. All three specifications contain firm and occupation (author defined) fixed effects. Column 1 includes no controls. Column 2 includes as controls a quadratic in age, and skill and time fixed effects. Column 3 includes controls and conditions the sample on firms with at least 5 workers in all years. Residual includes contribution from controls.

been driven primarily by a rise in the share of imports from developing and middle income countries such as China, Turkey, and those in Eastern Europe. Panel B plots the relationship between the growth of occupations in the economy and exposure to import competition from 1995 to 2007. I measure exposure similarly to Ebenstein et al. (2014). First, industry-level exposure measures are calculated as the change in imports per worker. Second, an occupation-exposure measure is calculated by weighting income exposure by that industry's employment share in each occupation. Mathematically,

$$exposure_o = \sum_{j \in Inds} \frac{L_{ojt-1}}{L_{ot-1}} \times \frac{\Delta Imps_j}{L_{jt-1}}, \tag{1}$$

where o,j, and t index occupations, industries, and time, respectively. There is a clear negative correlation between import exposure and occupational demand,[15] echoing the firm-level findings in Hummels et al. (2014) and Keller and Utar (2016). While this is suggestive of a role for occupations in understanding globalization, the subsequent structural model acts as a lens to understand these reduced-form facts, and how they operate in general equilibrium.

II. An Econometric Model of Labor Supply

This section describes workers' labor supply, with labor demand left to Section V. Consider an economy populated by a mass L continuum of workers, that unfolds in discrete time indexed by t. Workers are finitely lived, and new workers are born every period to replace retirees. Each period, a worker, i, chooses labor supply in order to maximize expected discounted real income. Specifically, they choose whether to be employed, a sector of employment, and an occupation within that sector. I refer to workers choices, indexed by $o \in \mathcal{O}$, as "occupation-triples." Let d_{oit} be an indicator variable for a worker choosing triple o. The following subsections lay out payoffs and information sets for workers, the econometric specification for income, the evolution of human capital, the costs of moving across states, and details on non-employment.

[15] This relationship is significant and robust to controlling for measures of worker productivity (exports), using world export supply of Danish trading partners as an instrument for imports, including zeros in the regression, and using more disaggregated occupations. Details are available upon request.

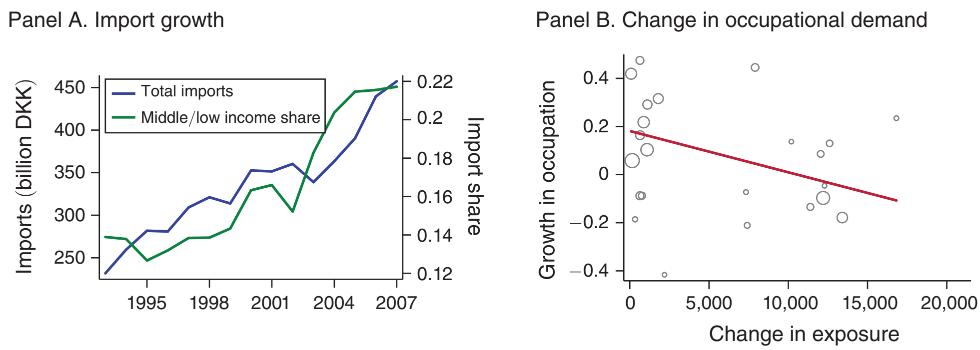

Figure 4. Import Growth and Occupational Demand

Notes: Import values normalized by 2000 Danish CPI. Details of occupation definition in main text. Exposure is calculated as the share weighted mean changes in imports per head in each NACE 4-digit industry by occupation (i.e., $exposure_o = \sum_{i \in Inds} \Delta M_i / L_i \times L_{io} / L_o$). All weights calculated in base year. Growth defined as the log change in supply. Only observations with nonzero exposure plotted.

A. *Income, Information, and Timing*

At the beginning of each period, workers are described by a vector of characteristics, ω_{it}, their previous occupation-triple, $o_{i,t-1}$, and a vector of shocks, ϵ_{iot}, that shift the costs of moving across different occupation-triples. The aggregate state, observed at the beginning of the period, is the vector of skill prices across occupations, $\mathbf{w}_{ot}$. Workers' real income is a product of skill prices at time t and their human capital supply. The latter, denoted $H_o(\omega_{it}, \varsigma_{iot})$, is a function of their characteristics and an idiosyncratic productivity shock ς_{iot} that is revealed *after* decisions are made.[16] Mathematically,

$$w_{o_{it}it} = w_{ot} H_o(\omega_{it}, \varsigma_{iot}).$$

The human capital function only depends on one's current state, choice of occupation-triple, and idiosyncratic shock. Skill prices changes over time for two reasons: (i) new entrants to the economy change the demographic mix of the labor market, and (ii) productivity shocks to industries heterogeneously impact occupational demand. The next assumption details workers' information set at the beginning of the period.

ASSUMPTION 1 (Information Sets): *The worker's information set at the time of choosing d_{oit} contains the full set of skill prices at time t, $\mathbf{w}_{ot}$, and idiosyncratic switching cost shocks, ϵ_{oit}. Idiosyncratic shocks to productivity, ς_{oit}, are unknown at the time decisions are made and are only revealed upon employment.*

[16]This shock plays a minimal role in the analysis, but absorbs residual income inequality in the data.

In addition to income and ϵ, workers' payoffs include a linear function of occupation-specific non-pecuniary benefits, η_o, and switching costs, $\tilde{C}(o_{it-1}, o_{it}, \omega_{it})$. Hence, workers' nonrandom flow payoff can be written as

$$(2) \qquad U(w_{it}, \omega_{it}, o_{it-1}, o_{it}) = \tilde{C}(o_{it-1}, o_{it}, \omega_{it}) + \eta_{o_{it}} + w_{o_{it}it}.$$

The additively separable ϵ shocks assume the common logit form.

ASSUMPTION 2 (Conditional Independence and GEV(1) Errors): *Conditional on the state* (ω_{it}, o_{it-1}), *the* ϵ *shocks are independently and identically distributed across occupation-triples*, o_{it}, *individuals*, i, *and time* t, *according to a Generalized Extreme Value Type 1* (*Gumbel*) *distribution.*[17] *That is*,

$$F(\epsilon_{oit}) = e^{-e^{-\epsilon_{oit}}}.$$

Under Assumptions 1 and 2, and denoting current age by a and retirement age by $\bar{A}$, the value function for a worker at time t can be expressed as

$$(3) \quad v(\omega_{it}, o_{it-1}, \epsilon_{iot}) = \max_{\{d_{ois}\}_{o\in\mathcal{O},s}} E_t \int_\epsilon \sum_{s=0}^{\bar{A}-a} \beta^s \sum_{o'\in\mathcal{O}} d_{o'it}\left[U(w_{it}, \omega_{it}, o_{it-1}, o'_{it}) + \rho\,\epsilon_{o'it}\right] dG(\epsilon),$$

where the integral refers to integration over the ϵ shocks while E_t refers to the expectation over future realizations of skill prices. Cost shocks, ϵ, have mean $\rho\gamma$, where γ is the Euler constant, and variance $\rho^2\pi^2/6$. I return to the economic significance of ρ in Section IIC.

A convenient feature of the GEV(1) distribution is that the integral over the switching cost shocks has a closed form. To this end, define $V_t(o,\omega) = \int v_t(o,\omega,\epsilon)\, dG(\epsilon)$ to be the *integrated* value function,[18] replace $\mathbf{w}_{ot}$ with time subscripts. Define $E_t V_{t+1}$ to be the expected value of the integrated value function at time t. Finally, let T be the transition function on ω. With this notation, the worker's problem can be written recursively as

$$(4) \quad v_t(o_{i,t-1}, \omega_{it}, \boldsymbol{\epsilon}_{it}) = \max_{o'\in\mathcal{O}} \Big\{ \tilde{C}(o_{it-1}, o', \omega) + \rho\,\epsilon_{o'it} + \eta_{o'} + w_{o't} E_\varsigma H_{o'}(\omega_{it}, \varsigma_{iot}) + \beta E_t V_{t+1}\big(o', T(\omega_{it}, o')\big) \Big\}.$$

Here, I have also substituted the assumed structure on income into (2), while the expectation in front of H reflects the timing implicit in Assumption 1. If one defines $\tilde{v}_t(o, o', \omega)$ as the value of v_t conditional on choosing o', net of the idiosyncratic cost shock, then the worker's problem can be written as

$$(5) \qquad v_t(o_{i,t-1}, \omega_{it}, \boldsymbol{\epsilon}_{it}) = \max_{o'\in\mathcal{O}} \tilde{v}_t(o_{i,t-1}, o', \omega) + \rho\epsilon_{o'it}.$$

[17] The difference between two GEV(1) distributions is a logistic distribution. Hence, in the binomial choice case, this collapses to a logit model.

[18] Keane, Todd, and Wolpin (2011) calls this the EMAX function and provide a thorough introduction to discrete choice dynamic programming (DCDP) models.

This formulation highlights the connection between the worker's problem in each period and a standard multinomial choice model: the $\tilde{v}$ terms are the unconditional mean values of choice o' to a worker in state (o, ω).

B. *State Variables and Human Capital*

From the econometrician's perspective, ω, can be partitioned into an *observable* and an *unobservable* component. The observable state consists of a worker's age, her current occupational tenure, and her skill level. Workers enter at 23 and retire at 60, and skill is assumed to be time-invariant. I discuss human capital accumulation after introducing workers' unobservable state, their comparative advantage.

Worker's unobservable comparative advantage is a vector of time-invariant, occupation-triple-specific productivity shifters denoted by $\boldsymbol{\theta}$.[19] These shifters multiply the efficiency units supplied by a worker so that otherwise-identical workers can be better at different occupations. For example, some workers may be more well suited to office or clerical jobs, while others to hands-on work in research laboratories or manufacturing. Combined with workers' skill and age, human capital takes the following log-linear form:

$$\begin{aligned} \log\big(H_o(\omega_{it}, \varsigma_{it})\big) \; = \; & \beta_1^o \times age_{it} + \beta_2^o \times age_{it}^2 + \beta_3^o \times ten_{it} \\ & + \beta_4^o \times \mathbf{1}\{skill_i \; = \; med\} + \beta_5^o \times \mathbf{1}\{skill_i \; = \; high) \\ & + \log(\theta_{oi}) + \sigma_o \varsigma_{iot}. \end{aligned} \tag{6}$$

In addition, I assume that the productivity shocks are independent and Gaussian.

ASSUMPTION 3 (Independent Normal Errors on Human Capital): *Idiosyncratic productivity shocks for workers*, ς_{oit}, *are independent across occupations*, o, *individuals*, i, *and time* t. *Moreover, they are independent and jointly Gaussian so that*

$$\varsigma \sim \mathcal{N}\big(0, I_{|\mathcal{O}|}\big).$$

Despite ς being unobserved at the time decisions are made, workers select into occupations on several dimensions. Clearly, there is selection on observable differences. More importantly, there is selection on unobserved comparative advantage. To see why this would induce selection, consider the value of $\boldsymbol{\theta}$ across occupations for two different workers. If $\theta_{io}/\theta_{io'} > \theta_{jo}/\theta_{jo'}$ then worker i has comparative advantage in occupation-triple o and subsequently makes relatively more in that occupation for the same skill prices. Indeed, for any two types and any two occupation-triples one can define a comparative advantage index:

$$CA_{jj'}^{oo'} \; = \; \frac{\theta_{jo}\theta_{j'o'}}{\theta_{jo'}\theta_{j'o}}. \tag{7}$$

[19] Online Appendix B describes how to put a Markov chain on the unobservable state. While possible in principle, this requires a long panel in practice.

Absolute advantage is also governed by $\boldsymbol{\theta}$. This is clear in the extreme case that for some pair of workers, i and j, $\theta_{io} > \theta_{jo}$ for all o. In this situation, regardless of comparative advantage, i has an absolute advantage over j. More generally, define worker i to have absolute advantage relative to j if $(1/\mathcal{O})\sum_o(\theta_{io} - \theta_{jo}) > 0$. That is, if i is more productive on average.

The next assumption summarizes the evolution of human capital.

ASSUMPTION 4 (Human Capital Accumulation): *Human capital is nontransferable across occupation-triples. For workers going from any state to an employed state, human capital evolves according to*

$$ten_{it+1} = \begin{cases} ten_{it} + 1 & \textit{if } o_{it-1} = o_{it} \\ 0 & \textit{if } o_{it-1} \neq o_{it} \end{cases}.$$

For workers going to a non-employed state, human capital evolves according to

$$ten_{it+1} = \begin{cases} ten_{it} & \textit{if } o_{it-1} \neq o_{it} \\ 0 & \textit{if } o_{it-1} = o_{it} \end{cases}.$$

The second equation states that upon entry to non-employment workers keep their tenure for one period, but lose it if non-employed any longer. This assumption helps fit the data, as few workers who are unemployed for longer than one period reenter the labor force.

While at first glance Assumption 4 seems to shut down spillovers between current and future occupations, the model allows for experience in previous occupations and sectors to matter in three important ways. First, general experience is fully transferable across occupations. Second, unobservable comparative advantage substitutes for transferability of human capital. This is because comparative advantage, and thus human capital, can be arbitrarily correlated across occupations. The limit of this approach is that experience carries no *additional* gains for workers of the same comparative advantage, nor does idleness depreciate a worker's endowed comparative advantage. Third, since $\tilde{C}(o, o', \omega)$ is pair-specific, workers may still find it easier to enter occupations similar to their own. However, these costs enter as a fixed utility payment, instead of through income. Section III describes the role that Assumption 4 plays in identification, how one could relax this assumption, and discusses further threats to identification that arise if human capital is transferable.

Besides specific human capital, experience in the model is captured by workers' age, regardless of unemployment spells. This is a limitation of the model, as only specific human capital ever depreciates. Not separately tracking experience and age is ultimately a data constraint: estimation relies on precisely measuring conditional transition rates for different workers, limiting the number of possible continuous state variables. However, there are three reasons that age is a reliable proxy for experience. First, skill dummies capture the trade-off between time in school and labor market experience. Second, specific human capital, which is quantitatively important, captures some human capital depreciation. Third, unemployment spells are short-lived at annual frequencies.

C. *Switching Costs*

Combining the fixed and stochastic parts of switching costs from (4), the total cost of moving from occupation o to o', for a worker of type ω, is given by

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

Intuitively, ρ governs workers' responsiveness to costs and income differentials between occupations. This can be seen by analyzing the probability of choosing o', given o and ω:

$$\pi(o'|o,\omega) \;=\; \frac{\exp\big(\tilde{v}(o',o,\omega)/\rho\big)}{\sum_{o''}\exp\big(\tilde{v}(o',o,\omega)/\rho\big)}. \tag{8}$$

Two limiting cases of the equation above illustrate the role of ρ. First, as ρ approaches 0, the choice probabilities converge to 0 or 1, with one occurring if $\tilde{v}(o',o,\omega) \;=\; \max_{o''} v(o'',o,\omega)$. Hence, if ρ is small, transitions will be almost deterministically governed by fundamentals (e.g., income differentials). On the other hand, as ρ approaches infinity, (8) collapses to $1/|\mathcal{O}|$. In this situation, one's choice of occupation-triple would be drawn independently from a discrete uniform distribution.

In addition to shocks, there is the deterministic portion of the costs, which I subsequently call the moving cost function. The moving cost function is assumed to decompose as follows:

$$\tilde{C}(o,o',\omega) \;=\; f(\omega)C(o,o').$$

The first function, $f(\omega)$, is an occupation-invariant shifter of moving costs which I specify with the following log-linear form:

$$\begin{aligned} f(\omega_{it}) \;=\; \exp\big\{&\alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2 \\ &+ \alpha_3 \times \mathbf{1}\{skill_i \;=\; med\} + \alpha_4 \times \mathbf{1}\{skill_i \;=\; high\} + \theta_{fi}\big\}. \end{aligned} \tag{9}$$

This functional form allows for workers of different ages and education levels to face different frictions, such as the costs of acquiring new skills. In light of the differences in switching across age shown in Figure 3, the inclusion of these terms seems important for accurately estimating switching costs. The second function, $C(o,o')$, represents the individual-invariant costs of moving across occupation-triples. In order to parametrize the cost function, I first project occupation-triples onto task space, $\mathcal{V}$, by associating with each triple a vector, $v_o \in \mathcal{V} \subset \mathbb{R}_{+}^{|\mathcal{V}|}$, as detailed in Section I. The cost function is

$$\log C(o,o') = \Gamma^M + \Gamma^S\delta_{sec} + \Gamma^O\delta_{occ} + \sum_{i=1}^{|\mathcal{V}|}\big(|v_i^{o'} - v_i^{o}|_{+}\Gamma_i^{+} + |vi^{o'} - vi^{o}|_{-}\Gamma_i^{-}\big). \tag{10}$$

The first term in (10) is the common cost of moving across both occupations and sectors. The next two terms pick up the change in costs associated to moving *only* across sectors and *only* within sectors, respectively. Specifically, the base cost of switching only sectors is $\Gamma^M + \Gamma^S$, while the cost of switching only occupations within a sector is $\Gamma^M + \Gamma^O$. The remaining Γ terms are the coefficients on linear distance in each component of the characteristics vector. I allow for the coefficients to depend on the sign of the change, reflecting that "up-tasking" and "down-tasking" may have different costs.

D. *Non-Employment*

The occupation-triple for non-employed workers is denoted by $(N, \tilde{o})$, where $\tilde{o}$ is the occupation-triple of previous employment. This previous triple determines the cost of reentry, so that $C((N,\tilde{o}), o') = C(\tilde{o}, o')$. The flow value of non-employment is given by

$$w^N(\omega) = \beta_{skill} + \beta_\theta + \beta_a \times a + \beta_{a2} \times a^2. \tag{11}$$

While the cost of entering non-employment is set to zero, $C(o,(N,o)) = 0$, workers entering non-employment still receive an idiosyncratic shock, $\epsilon_{(N,o)}$.[20] As non-employment is a voluntarily elected state, caution should be exercised in interpreting ϵ, especially in welfare calculations. To see why, note that since utility is only defined up to affine transformations, the model could be equivalently written by subtracting ϵ_N from each choice. In this case, the cost of entering non-employment would be zero. While observationally equivalent models, ϵ plays different roles: in the first formulation, workers choose non-employment whenever receiving a "positive" shock to that state; in the second formulation workers choose non-employment whenever receiving a sufficiently "negative" shock to all other occupation-triples.

III. Estimation

Estimation occurs in two stages: in the first stage, I use the EM algorithm to estimate the distribution of comparative advantage across workers, as well as the income parameters and transition matrices across states; in the second stage, I exploit finite dependence in the model to estimate the remaining structural parameters. The second stage relies on differencing across individuals with the same initial and final state, but different intermediating choices. This section largely follows recent papers in the industrial organization and structural labor literatures, notably Arcidiacono and Miller (2011) and Scott (2014).

To organize thinking, an observation in the data is a vector for an individual, $i \in 1, \ldots, N$ at time $t \in 1, \ldots, T$ that contains $\{w_{it}, o_{it}, \omega_{it}^{observed}, o_{it-1}, \omega_{it-1}^{observed}\}$,

[20]Equation (11) allows for heterogeneity in the responsiveness to skill prices along the age distribution. However, a limitation of the model is that heterogeneity in *reasons* for entering non-employment is not modeled and assumed not to interact with aggregate shocks. This deficiency, which should be kept in mind for future work, casts aside some undoubtedly interesting and important phenomena, such as the interaction between fertility and skill price shocks. Moreover, if ϵ is seen as a way of capturing contact and separation rates, then future work could make this connection explicit and allow ρ to respond to shocks.

where $\omega^{observed}$ refers to the observed components of ω: age, skills, and tenure. The parameters to be estimated, which I collect into the vector Ξ, can be partitioned into three subsets: the income parameters, $\{\beta^W, \theta, w_{ot}, \sigma\}$; the cost function parameters, $\{\rho, \Gamma, \alpha, \theta\}$; and, the unobserved benefits to each occupation and the value of non-employment, $\{\eta, \beta^N\}$. The discount factor is only tenuously identified in dynamic discrete choice models. Hence, I fix its value at $\beta = 0.96$.

A. *First Stage: Unobserved Heterogeneity and Income Parameters*

In the first stage, I estimate the income parameters, and the distribution over θ. I assume that at the beginning of a worker's career, θ is drawn from a distribution with finite support, $\mathbf{Q}_\Theta$. There are K types in the economy, indexed by k. This approach is common in the structural literature (e.g., Miller 1984 or Dix-Carneiro 2014) and, to the best of my knowledge, was first suggested by Heckman and Singer (1984). Given an observation for individual i, of type k, at time t, their likelihood contribution, $L_{it|k}$, is given by

$$L_{it|k} = L\left(w_{it}, o_{it}, o_{it-1}, \omega_{it-1}^{observed} \,|\, t, k\right). \tag{12}$$

By Assumption 1, ς is independent of o_{it-1} conditional on calendar time and the choice of o_{it}. Thus, one can factor the likelihood into a portion from income conditional on occupational choice, and the occupational choice itself. Income is conditionally log-normally, while the likelihood of observing o_{it} is given by the conditional choice probabilities in equation (8). Finally, conditional on k, ω is fully observed, so one can drop the superscript. Augmenting (12) in light of these observations yields

$$L_{it|k} = f\left(\log w_{it} \,|\, o_{it}, \omega_{it}, t, k\right)\pi\left(o_{it}, \omega_{it} \,|\, o_{it-1}, \omega_{it-1}, t, k\right),$$

where f is the Gaussian PDF, and π is the probability of being in state (ω_{it}, o_{it}) conditional on the previous state. Integrating out k and combining the likelihood contributions of all observations yields the following data likelihood function:

$$L(\Xi) = \prod_{i=1}^{N}\left(\sum_{k=1}^{K} q_k\left[\prod_{t=1}^{T} f\left(w_{it}|o_{it}, \omega_{it}, k; \Xi\right)\pi\left(o_{it}, \omega_{it}|o_{it-1}, \omega_{it-1}, t, k; \Xi\right)\right] \times \pi_0\left(o_{i0}, 0, \omega_{i0}, k; \Xi\right)\right), \tag{13}$$

where q_k is the probability of being type k and $\pi_0(o_{i0}, 0, \omega_{i0}, k; \Xi)$ is the probability of one's initial occupation being o and type being k. If one could solve for π, then one could estimate the parameters by maximum likelihood via the expectation-maximization algorithm (EM), described below. However, a full solution is infeasible for two reasons: first, I have not specified beliefs over aggregate shocks; second, solving the model for every parameter update is computationally infeasible. To circumvent these issues, I use the pseudo-EM approach described in Arcidiacono and Miller (2011)—henceforth, AM.

AM's insight is that one can use the empirical distribution of transitions in lieu of the model-implied probabilities. This is useful if the model can factor out the term

governing unobserved heterogeneity, from the transition rates. By Assumption 1 income shocks are independent of moving cost shocks, leading to such a factorization. To implement AM's approach, let $\hat{\pi}$ refer to nonparametrically estimated transition probabilities and consider the modified likelihood given by

$$\tilde{L} = \prod_{i=1}^{N}\left(\sum_{k=1}^{K} q_k \left[\prod_{t=1}^{T} f(w_{it}|o_{it},\omega_{it},k;\Xi)\hat{\pi}(o_{it},\omega_{it}|o_{it-1},\omega_{it-1},t,k;\Xi)\right] \times \pi_0(o_{i0},0,\omega_{i0},k;\Xi)\right). \tag{14}$$

Maximizing this function proceeds as in the standard EM algorithm, iterating on two steps. In the first step, given a guess of the distribution of types, and the conditional probability that each worker i is of a given type, estimate $\hat{\pi}$ (for example, through a q_{ik}-weighted regression of d_{oikt} on ω_{it}). Then, with $\hat{\pi}$ in hand, estimate the wage parameters via maximum likelihood. In the second step, update the type probabilities using Bayes' rule:

$$\Pr(k|\omega,o)^{Update} = \frac{\Pr(\omega,o|k)^{Guess}\Pr(k)^{Guess}}{\Pr(\omega,o)}.$$

One iterates on this procedure until $\tilde{L}$ converges within some tolerance.[21]

Identification relies on Assumption 1 paired with the fact that there are finite types. The timing assumption implies that an income regression with worker-occupation-triple fixed effects is consistent for β, σ, and w_{ot} (up to a normalization). Identification in the EM algorithm and FE estimator have the same intuition: unexplained persistence in income in a particular occupation identifies the productivity of a worker in that occupation-triple. The finite types assumption means that a combination of workers whose collective transitions span the set of occupations can identify the full vector of productivity shifters. For example, if two workers are both, persistently, in the ninetieth percentile of the wage distribution for occupation o, then the EM algorithm will allocate them to a type with a high productivity in o. Then, if one worker moves to occupation o', and operates lower in the income distribution, the EM algorithm will determine that the worker has comparative advantage in o. This can also be imputed as the comparative advantage of the worker who never moved.

In sum, the first stage recovers the distribution over types, Q_Θ, transition probabilities *conditional on unobservables*, $\pi(o'|o,\omega)$, and the first partition of Ξ, $\{\beta^W,\theta,w_{ot},\sigma\}$. As a final point, I assume two unobserved types for each skill level. The next subsection describes how the first-stage estimates can be used to estimate the remaining structural parameters.

B. *Second Stage: Estimating Cost Function Parameters*

The second stage uses first-stage estimates of transition rates and human capital parameters in a regression equation. Since the first stage uncovers all parameters

[21] Online Appendix B contains practical details on estimating $\hat{\pi}$, a discussion of initial conditions, and describes computational details. This is omitted from the main text as it mostly rehashes AM.

governing unobservable comparative advantage, the worker's state is effectively observed in the second stage. This fact allows me to exploit methods developed in Hotz and Miller (1993), Arcidiacono and Miller (2011), and Scott (2014) to estimate the remaining model parameters.

The first step to building a regression equation is exploiting the structure on ϵ to construct a log-linear relationship between the workers' dynamic problem and the transition probabilities. Specifically, under Assumptions 1, 2, and 3, the solution to (4) for a worker in occupation-triple o, with state ω, and for *any* occupation-triple, o', can be written as

$$\frac{V_t(o,\omega)}{\rho} = \gamma + \frac{-f(\omega)C(o,o') + \eta_{o'} + w_{o't}E_\varsigma H_{o'}(\omega,\varsigma_{o't})}{\rho} + \frac{\beta}{\rho}E_t V_{t+1}\big(T(\omega,o,o'),o'\big) - \log \pi_t(\omega,o,o'). \tag{15}$$

A detailed derivation of this result, first exploited in the dynamic discrete choice literature by Rust (1987), and subsequent equations can be found in online Appendix B.1. To exploit (15) for estimation, iterate forward once more, move all transition rates to the left-hand side, and all value functions to the right-hand side. Then for any set of choices o,o',o'', one has

$$\begin{aligned}\log \pi_t(\omega,o,o') + \beta E_t \log \pi_{t+1}(\omega',o',o'') &= \kappa_0 + \frac{-f(\omega)C(o,o') + \beta f(\omega')C(o',o'')}{\rho} + \frac{\eta_{o'} + \beta\eta_{o''}}{\rho} \\ &+ \frac{w_{o't}E_\varsigma H_{o'}(\omega_t,\varsigma_{o't}) + \beta E_t E_\varsigma w_{o''t+1} H_{o''}(\omega',\varsigma_{o't+1})}{\rho} \\ &+ \frac{\beta^2}{\rho}E_t V_{t+2}\big(T(\omega',o',o''),o''\big) - \frac{V_t(\omega,o)}{\rho},\end{aligned} \tag{16}$$

where $\omega' = T(\omega,o,o')$ and κ_0 is a constant. Equation (16) illustrates how finite dependence can be used in this model. The first stage provides estimates of all terms *except* for the last two: the initial value of occupation o, and the final expected value of being in o''. To this end, consider two workers who begin in state (o,ω) at time $t-1$ and end in $o'' \neq o$ at $t+1$. However, suppose the first worker stays in o at time t while the other goes to o', which is distinct from both o and o''. Since o'' is new to both workers, by Assumption 4, $T\big(T(\omega,o,o),o,o'\big) = T\big(T(\omega,o,o'),o',o''\big)$. In words, if two workers are identical at $t-1$ and both switch into a new occupation at $t+1$, then they will again be identical, *regardless* of any intervening career decisions.[22]

[22] Arcidiacono and Miller (2011) refers to actions that move agents to the same state as *renewal actions*. They are an example of the more general concept of finite dependence.

Differencing equation (16) between the worker who goes to o' at t and the worker who stays in o leads to the following equation:

$$\log\frac{\pi_t(\omega,o,o')}{\pi_t(\omega,o,o)}+\beta E_t\log\frac{\pi_{t+1}(\omega',o',o'')}{\pi_{t+1}(\omega'',o,o'')}$$
$$= -\frac{f(\omega)C(o,o')+\beta\big[f(\omega')C(o',o'')-f(\omega)C(o,o')\big]}{\rho}$$
$$+\frac{\eta_{o'}-\eta_o}{\rho}+\frac{1}{\rho}\big(w_{o't}E_\varsigma H_{o'}(\omega,\varsigma)-w_{ot}E_\varsigma H_o(\omega,\varsigma)\big).$$

Comparing this equation to (16), the final continuation value, and the initial continuation value are differenced out. This can almost be operationalized as a regression, except for the presence of the expectation in front of the π_{t+1} terms. To arrive at an estimating equation, I follow Altuğ and Miller (1998) and Scott (2014) and replace forecasted terms by their realization and a forecast error, ζ. This yields the estimating equation:

$$\log\frac{\pi_t(\omega,o,o')}{\pi_t(\omega,o,o)}+\beta\log\frac{\pi_{t+1}(\omega',o',o'')}{\pi_{t+1}(\omega'',o,o'')}\tag{17}$$
$$= -\frac{f(\omega)C(o,o')}{\rho}+\frac{\eta_{o'}-\eta_o}{\rho}-\frac{\beta\big[f(\omega')C(o',o'')-f(\omega)C(o,o')\big]}{\rho}$$
$$+\frac{1}{\rho}\big(w_{o't}E_\varsigma H_{o'}(\omega,\varsigma)-w_{ot}E_\varsigma H_o(\omega,\varsigma)\big)+\zeta_{oo'o''t}+m_{oo'o''t}.$$

Here, ζ is the aforementioned expectational error,[23] and m is measurement error that arises from first-stage error in estimating transition rates. To write down the final objective function, collect the left-hand-side terms into $Y_{t,o,o',o'',\omega,\omega',\omega''}$. Similarly, collect the right-hand-side terms into $g\big(o,o',o'',\omega,\omega',\omega'';t,\Xi^{SS}\big)$, where Ξ^{SS} denotes the remaining subset of Ξ to be estimated. I construct (17) for all admissible series of occupation-triples, for all skill levels and types, and for a grid over age and tenure. There are more details, especially on computational concerns, in online Appendix B. The final nonlinear least squares object can be written as

$$\min_{\Xi^{SS}}\sum_{t=1}^{T-1}\sum_{\omega\in\Omega^{Grid}}\sum_{j=1}^{\mathcal{O}}\sum_{j'\neq j}\sum_{j''\neq j,j'}\Big(Y_{t,o,o',o'',\omega,\omega',\omega''}-g\big(o,o',o'',\omega,\omega',\omega'';t,\Xi^{SS}\big)\Big)^2.\tag{18}$$

The key identifying assumption is that $t+1$ forecast errors are uncorrelated over time and with contemporaneous variables at time t. Equation (17) closely resembles the estimating equation of Artuç, Chaudhuri, and McLaren (2010)—hence-

[23] I treat these as forecast errors as they reflect serially uncorrelated deviations between workers' expected and realized continuation values. However, ζ may also reflect shocks to η_o. I must assume any such shocks are unanticipated and i.i.d. over time. The presence of serially correlated unobservable aggregate preference shocks is an important area for future research. However, as Kalouptsidi, Scott, and Souza-Rodrigues (2018) points out, identification is difficult in this situation. Their work outlines the potential value of IV methods for solving the issue. Nevertheless, they point out good instruments will be hard to find in practice.

forth, ACM.[24] However, there are two important differences. First, because workers can accumulate human capital, I use switching into a third occupation as a renewal action, rather than focus on workers switching into the same occupation at different times. Second, under Assumption 1, workers *know* skill prices when choosing their occupation. This is a strong assumption; it rules out, for example, trade shocks having contemporaneous effects on workers. ACM's timing assumption is almost the polar opposite: workers can only adjust to contemporaneous shocks with a lag and must forecast the skill prices for the occupation into which they switch. In this situation, ζ_t and w_t are correlated. They employ an IV strategy to circumvent this issue. In online Appendix H, I show that estimates are not very sensitive to either timing assumption. Highlighting these connections is useful as ACM has become a standard model for reallocation in the trade literature, and will serve as a benchmark for understanding quantitative results.

There are two outstanding econometric issues. The first is how to calculate standard errors. The residuals in (17) reflect (i) measurement error in the transition probabilities (m) and (ii) workers' forecast errors (ζ). The first source of error is from the first stage, and dies as the number of *individuals* in a given bin grows. The second source of error is complicated because forecast errors are correlated within *years*. Putting this together, one should ideally cluster over both individuals and time. However, two-way clustering, even with bootstrapping, is difficult in this setting.[25] Lacking an ideal solution, I present two sets of standard errors. The first, reported in parentheses, bootstraps over individual histories, and reestimates both the first and second stage. The second, reported in brackets, ignores first-stage measurement error while bootstrapping over time periods and reestimating (18).

The second outstanding issue is the panel length $\left(T = 12\right)$. The short panel means that the time bootstrapped errors have flew clusters, and also could lead to small sample bias. In order to deal with the small number of clusters, in online Appendix G, I reestimate the model using a $\sqrt{N}$ consistent estimator based on Altuğ and Miller (1998). This changes point-estimates slightly, but $1/\rho$ and the parameters governing costs all remain significant. To deal with short sample bias, I implement the split-sample correction procedure proposed by Dhaene and Jochmans (2015). The bias is small, but not insignificant.[26] Online Appendix B.9 contains a more complete discussion of the procedure, along with the full set of results.

Finally, there are two possible threats to identification. First, if workers have more or less information than assumed, the use of equilibrium *observed* skill prices in (17) will be a noisy measure of the worker's *forecasted* skill prices. As discussed in Dickstein and Morales (2018), measurement error can lead to large and ambiguously signed biases in nonlinear models. To this end, in online Appendix H, I consider two modifications to Assumption 1: the case that wage shocks, ς, are observed, as in Dix-Carneiro (2014), and the case that neither wage shocks *nor* skill prices, w_{ot} are observed at the time of decision making. Neither assumption significantly changes my estimates.

[24] This model is reviewed in online Appendix E. The estimating equation is the same if workers do not accumulate human capital, and if the only career arcs entering (18) are o, o', o' and o, o, o'.

[25] For example, if one bootstraps an individual and histories for that individual, it is unclear which initial condition to use for the worker.

[26] This is in line with Monte Carlo simulations on a simplified version of the model, available upon request.

Second, if human capital is partially transferable, then equation (17) is misspecified. In particular, workers will be more likely to switch into occupations where capital can be transferred and their starting incomes will be higher in those occupations. This leads to nonclassical measurement error in both the right- and left-hand-side variables. In online Appendix F, I show how one can allow for *known* patterns of human capital transferability, and estimate an alternative model with sector- as well as occupation-specific human capital. Nevertheless, I present the occupation-sector specific capital model in the results to keep the focus on occupations and within-sector heterogeneity.

IV. Results

In this section I discuss the results from the estimation. Due the large number of occupations, the full set of parameter estimates can be found in online Appendix A.

A. *Income Regression Parameters*

Human Capital Accumulation Parameters.—Returns to tenure can be found in the first column of online Appendix Tables A.2a–A.2d. Returns are large, ranging from 3 to 5 percent. By way of comparison, for 2-digit occupations in the United States, Kambourov and Manovskii (2009b) finds annual returns of 2.7 percent, while Gathmann and Schönberg (2010) finds returns close to 1 percent in Germany. Returns vary across occupations, with tests of equality of coefficients being rejected. In online Appendix F, I show the magnitudes on returns to occupational tenure are robust to extending the model to allow for sector-specific capital.

These estimates should be interpreted with some caution. While tenure effects can reflect human capital accumulation, they can also reflect learning (as I treat comparative advantage as known), or within-occupation firm upgrading that generates tenure effects.[27] While completely ruling out a learning or firms story requires a much richer model, many authors suggest the bulk of experimentation happens in youth; for example, James (2012) focuses on workers younger than 28. I focus on workers who are at least 23, and nearly 80 percent of occupational switching occurs after age 28. Moreover, incorporating unobserved heterogeneity partially addresses differences across workers, and can help explain why some workers exit occupations without building up tenure. Indeed, omitting unobserved comparative advantage raises the estimated returns to occupational tenure by 57 percent on average.

Returns to experience, proxied by age, are in the second and third columns of online Appendix Tables A.2a–A.2d. The linear coefficients are smaller than those on occupational tenure, and the negative quadratic coefficients imply diminishing returns to experience. Interestingly, coefficients on specific and general human capital are positively correlated across occupations ($\rho = 0.336$), suggesting that specific and general human capital are complements. Foreshadowing subsequent discussion, the positive correlation raises the costs of exiting occupations with steep tenure profiles relative to others.

[27] See Miller (1984) for a classic treatment of this idea in an empirical setting, or James (2012) and Papageorgiou (2014) for recent examples.

Table 4—Absolute Advantage across Types

Type	Classification	Mean θ	Mean income (relative)	$\operatorname{corr}(CA, w_o)$
1	HS, L	0.405	0.330	−0.302
2	HS, H	0.932	0.823	−0.239
3	Voc, L	0.555	0.539	−0.206
4	Voc, H	1.005	0.921	−0.496
5	Col, L	0.631	0.576	0.216
6	Col, H	1.000	1.000	0.000

Note: Comparative advantage of type k in occupation o relative to type 6 (high absolute advantage and college educated) in occupation 1 (manufacturing managers).

Comparative Advantage and Sorting.—Columns 4–8 of online Appendix Tables A.2a–A.2d display the $\log(\theta)$ terms for each type in each occupation. There are two types in each skill group: workers with some high school or less are either type 1 or type 2; workers with vocational training are of type 3 or 4; and workers with a college degree or more are of type 5 or 6. Coefficients are normalized so that $\log(\theta)$ for type 6 workers is 0 in every occupation. By defining absolute advantage of type k as the mean value of θ across occupations, I classify types within each skill group as "high" or "low." Table 4 displays the absolute advantage and average income for each type. Differences in absolute advantage are large, with the largest gaps *within* skill groups. Specifically, the low type in each group is substantially less productive than the high type, while high types have similar levels of productivity regardless of education. Unsurprisingly, within education groups, pairwise tests of θ_{ok} across types are rejected.

For each type k, θ_{ok} varies significantly across occupations, capturing large differences in comparative advantage across groups.[28] But how can one know if these differences matter economically? The third column of Table 4 answers this question: differences in income are *larger* than differences in productivity. That is to say, income differences depend on both the skill prices of occupations workers sort into and their productivity in those occupations.

An important corollary of this fact is that conditional on absolute advantage, the more correlated one's comparative advantage is with skill prices, the higher one's income. To analyze this further, the last column of Table 4 displays the correlation between skill prices and the comparative advantage index from equation (7), setting management ability of high type, high education individuals as the base case. The correlation between comparative advantage and skill prices is generally negative, so that high type, highly educated individuals have comparative advantage in high-paying careers. Figure 5 plots the CA index against the rank of skill prices, with 1 corresponding to the highest-paying occupation.[29] Workers have comparative advantage in occupations with an index above 1. Three patterns emerge: low type individuals, in all three education groups, display much higher variance in their comparative advantage; low type workers with high school or vocational training

[28] One can test if comparative advantage is present by testing if $\theta_{ko} = \theta_k \; \forall o$. To do so, form a test statistic from $\left(\hat{\theta}_k - \bar{\theta}_k\right)' \Sigma^{-1}_{\left(\hat{\theta}_k - \bar{\theta}_k\right)} \left(\hat{\theta}_k - \bar{\theta}_k\right)$ where $\bar{\theta}_k$ is the average value of θ across occupations for type k. Alternatively, one can use $\hat{\theta}_{ko} - \hat{\theta}_{k1}$. F-tests performed for each type strongly reject constancy of θ_o.

[29] Online Appendix Table A.13 displays the *comparative* advantage for every occupations and type.

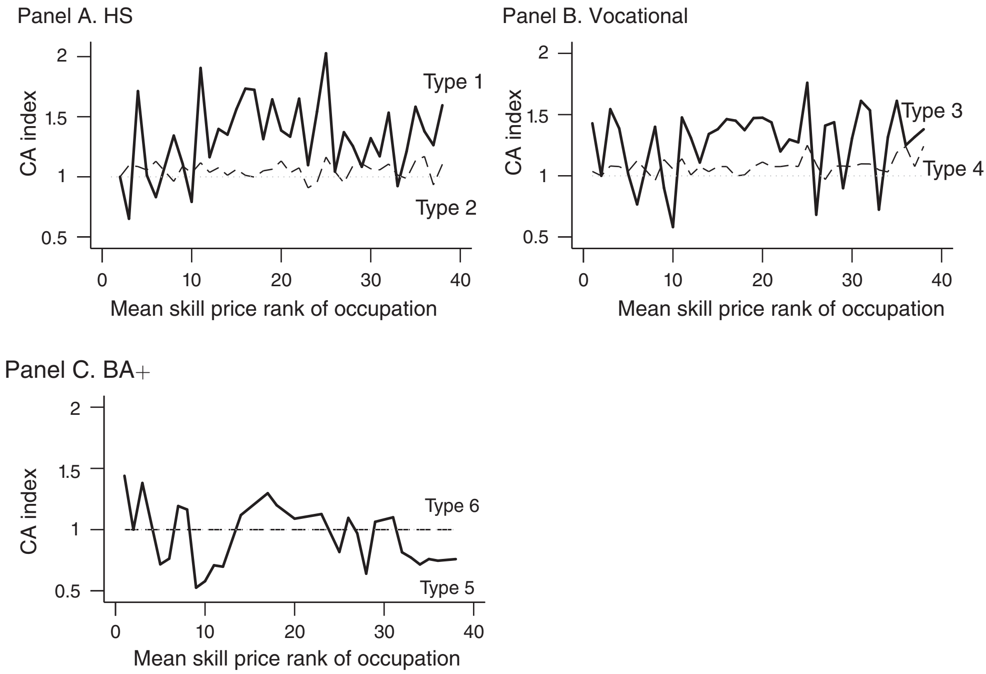

FIGURE 5. COMPARATIVE ADVANTAGE AND SKILL PRICES

Notes: Plots the comparative advantage of type k in occupation o relative to type 6 (high absolute advantage + college educated) in occupation 1 (manufacturing managers). Skill prices averaged over time and ranked highest to lowest.

have a clear comparative advantage in middle-paying occupations, from rank 10–25; and college-educated individuals have comparative advantage in a narrow band of high-paying occupations, since the lines are most often above 1 for other types.

B. *Cost Function Parameters*

The cost of switching occupations, sectors, or both consists of two components: the mean value of switching, $f(\omega)C(o,o')$, and the idiosyncratic component, $\rho\epsilon_{o'}$. The first column of Table 5 displays the baseline estimate of $1/\rho$, corresponding to the slope on wages in (17), and the value of C/ρ averaged across possible o,o' pairs.

The estimated value of $1/\rho$ is 1.43. This parameter is one of the most important in the model, as it governs the elasticity of switching occupations with respect to income shocks. To see this, differentiate (8) with respect to a transitory shock to w_o:

$$\frac{d\log\big(1-\pi(o\,|\,o,\omega)\big)}{d\log w_o} = -\frac{H_o(\omega)\,w_o}{\rho}\pi(o\,|\,o,\omega). \tag{19}$$

Evaluating (19) for each worker and averaging yields a mean elasticity of -1.33. In words, a temporary 1 percent decrease in the skill price of o will lead to a 1.33 percent increase in the exit rate. Permanent shocks to skill prices will amplify this effect, through their impact on continuation values. As a back-of-the-envelope calculation, a permanent 1 percent decline in the skill price of an occupation-sector

Table 5—Switching Elasticity and Switching Costs

	(1)	(2)	(3)	(4)	(5)
$1/\rho$	1.428	−0.365	0.457	0.529	0.610
	(0.045)				
	[0.104]	[0.714]	[0.361]	[0.046]	[0.201]
Mean C/ρ	4.618	4.072	6.781	4.135	4.830
	(0.038)				
	[0.040]	[0.785]	[0.617]	[0.541]	
Specific human capital	✓				
Occupations	✓		✓	✓	✓
Demographic controls	✓			✓	✓
Zero transitions					✓
Time-varying costs					✓

Notes: Results from regressing transitions rates on wage differentials. Specifications (2)–(4) use the IV strategy of Artuç, Chaudhuri, and McLaren (2010). Specification (5) using the strategy of Artuç and McLaren (2015). Mean C/ρ refers to simple mean across all cells of cost matrix with no adjustment for observed transition rates. Standard errors calculated by block bootstrapping: parentheses is blocks by individual; brackets is over periods in the second stage. For final column, costs are estimated in first stage and treated as known.

pair will decrease the total value of that occupation-sector pair by $1/(1-\beta)$ percent.[30] At the base switching rate of 13.2 percent, a permanent 1 percent decline in skill prices would increase the exit rate to 17.6 percent. Since workers can exit employment, this parameter also governs the labor supply elasticity: hence, it not only controls the speed of adjustment to shocks, but determines the disemployment effects of shocks.

While ρ governs workers' responsiveness to shocks, patterns of mobility are determined by the cost matrix, $C(o,o')$. Table 6 presents the average cost of switching across workers, relative to the income in their *source* occupation. The first column presents the mean unadjusted for the value of ϵ conditional on switching, while the second adjusts for the expected value of the shock.[31] The average switcher faced a cost of 4.3 years of income relative to their initial occupation. Since workers pay this entire cost up front, weighing the cost against a *stream* of income, annualizing costs makes for a cleaner comparison to a year's income. In annualized terms, done by multiplying costs by $(1-\beta)$, the mean cost to workers is 17 percent of their annual income. Conditional on the expected value of ϵ, costs are much lower. Exact numbers are in the second column of Table 6 and are often *negative*. The negative sign implies workers wait for large shocks, even more favorable than the 17 percent cost, before actually switching activities. Hence, as will be shown in the counterfactual analysis, workers accept large changes in income in the short run.

In the last few years, several papers have estimated models of workers' transitions. For example, Artuç, Chaudhuri, and McLaren (2010) and Artuç and McLaren

[30] This ignores spillovers on occupations with workers that switched *into* o. A fuller analysis requires simulating the model as in Section V.

[31] Dubin and McFadden (1984) shows that under the GEV assumption on shocks, the expected shock to a switching worker is given by

$$\rho E(\epsilon_{o'} - \epsilon_o | o \rightarrow o') = \rho\left(\log\pi(o'|o,\omega) + \frac{\pi(o|o,\omega)}{1-\pi(o|o,\omega)}\log\pi(o|o,\omega)\right).$$

Table 6—Mobility Costs by Type of Move

Switch type	Unconditional cost (1)	Conditional cost (2)	Percent of switchers (3)
Occupation only	4.208	−0.316	43.1
Sector only	2.526	−0.983	27.5
Both	5.982	0.130	29.3
Total	4.266	−0.367	100.0

Notes: Moving costs weighted by empirical distribution of switchers and normalized by income of source occupation. Unconditional costs refer to $f(\omega)C(o,o')$. Unconditional costs adjusted by $E(\rho\epsilon_o|\mathbf{1}(o_t = o))$.

(2015) have modeled both occupations and sectors under the assumption that workers are essentially homogeneous. In contrast, Dix-Carneiro (2014) captures rich heterogeneity in worker characteristics, but ignores occupational transitions. My paper improves on the extant literature in three ways. First, workers differ in human capital due to tenure and unobservable comparative advantage. Second, through the use of finite dependence, the model captures very fine margins on which workers can adjust: namely occupations. Third, this richness comes at a minimal computational cost and can flexibly accommodate large state spaces and choice sets for workers. Naturally, one may ask whether capturing both human capital and occupations matters. As I demonstrate below, it does.

To isolate the roles of these two factors, columns 2–5 present estimates of $1/\rho$ and C/ρ under different assumptions on workers' margins of adjustment and their human capital. The first column displays estimates of the model with homogeneous workers[32] and no preference parameters, and ignores occupations, focusing solely on sectors. The estimate of $1/\rho$ is *negative*, albeit insignificant.[33] The second column includes occupations, in addition to sectors, but keeps workers homogeneous. The estimate of $1/\rho$ is now of the correct sign, but the estimated elasticity of worker movement is very small, and costs are very large. In fact, adjusting for ρ, costs are up to 15 years of income, compared to 3.2 in the main specification.

The fourth and fifth specifications offer the cleanest comparison to the full model. Here, workers select on occupations and sectors, and workers' incomes and costs differ with skill and age. The difference between columns 4 and 5 is that the final specification uses Artuç and McLaren's (2015) technique, which allows for zeros in the transition matrix and for time varying switching costs.[34] The estimates of $1/\rho$ ignoring human capital, even accounting for occupations, are around two-fifths of the

[32] Wages are residualized but transitions, costs, and incomes are then calculated pooling skill and age groups. This keeps the sample across specifications, but draws in a wider set of workers than the subpopulation considered by ACM.

[33] My estimation strategy is nearly equivalent ACM if workers have no human capital. To this end, and to make comparison across papers coherent, I use exactly ACM's estimator in each of specifications (2)–(4). Details are in online Appendix E. The estimate of $1/\rho$ in (2) is very sensitive to the instrumenting strategy; for example, the ordinary least squares (OLS) estimate is positive and about 0.5.

[34] Artuç and McLaren (2015) primarily deals with zeros in the transition matrix, and this is a minor issue in aggregated administrative data. This can explain why the estimates are broadly similar across methods. This contrasts with the large differences that Artuç and McLaren (2015) found across methods. Reconciling this comparison is speculative as the United States and Denmark have different institutions, workers, and geography. Without US data, it is impossible to know how human capital changes estimates in the United States, but these discrepancies open up an important question for future researchers.

point estimation in the main specification. This implies a permanent 1 percent decline in income would only increase the exit rate by 1.8 percentage points on impact, compared to the 4.4 percentage points. This smaller exit rate will lead to overestimates of the sluggishness of adjustment in counterfactual analysis. In fact, as pointed out in Caliendo, Dvorkin, and Parro (2019), $1/\rho$ is often the *only* parameter one needs to predict counterfactual labor market outcomes, putting its accurate estimation at the heart of modeling worker dynamics in trade.

Intuitively, human capital accumulation matters if the income of switching workers, who have no experience, is poorly modeled by the average income of incumbents, who have substantial experience. In this case, switching workers will face smaller changes in their income than an econometrician would measure using incumbent wages. The overinflated estimates of income differentials will make workers *appear* less responsive to income differentials. Consequently, the model will inflate moving costs to rationalize small transitions. This intuition is borne out in the results discussed above: ignoring human capital systematically biases down how responsive workers are to wages, and this does not seem to hinge on the inclusion of observable differences in skill, or on any particular econometric technique. The second row of Table 5 demonstrates the inflated estimates of switching costs. Adjusting for ρ and annualizing, the mean cost of switching is 59 percent of income in (2), and still 31 percent of income in (5). These numbers are between two and three times the estimates that account for human capital. In other words, failing to account for tenure significantly overstates the fixed costs of switching. This, consequently, understates workers' abilities to smooth out losses over time, by rebuilding human capital.

Turning to occupations, this ingredient matters if *intra*-sectoral costs are large, meaning *inter*-sectoral costs alone do not capture the primary barriers facing workers. In column 2 of Table 5, the coefficient on wages is not positive when one ignores occupations. However, this specification ignores substantial worker heterogeneity, and pools together large swaths of the population. Moreover, there are other methods, such as the full solution method of Dix-Carneiro (2014), that can capture human capital differences across workers, but cannot allow for large choice sets.[35] Thus, a more robust measure of this model's value would be a direct comparison to a similarly rich, or richer, model of worker heterogeneity and human capital, but with only sectors. To this end, Ashournia (2018) estimates DC's model, using Danish data, and nearly the same *sectoral* aggregation as I use. He estimates $1/\rho$ at 2.2, which is close to my estimate.[36] The similar estimates suggest that capturing experience is crucial to modeling marginal switchers' incomes, but that the precise margins on which workers move may matter less for this parameter.

Nevertheless, I find that modeling occupations is important because of the clear differences in moving costs both across and within sectors. Table 6 shows that switching costs are greater across occupations within sectors than across sectors.

[35] In particular, Dix-Carneiro (2014) relies on fully solving the model and using indirect inference in estimation. The use of auxiliary moments places lighter constraints on the data, but one must be able to solve the model sufficiently many times, and be able to fully specify worker beliefs. This means that for M choices, one would need to integrate an M dimensional integral, T times, *for every parameter guess*. These are the exact issues that Arcidiacono and Miller (2011) circumvents.

[36] In online Appendices F and G, I estimate variants of my model and find $1/\rho \in (1.4, 2.2)$. The counterfactuals are qualitatively, and even quantitatively, robust to this range since $1/\rho = 1.5$ already implies workers are quite sensitive to income differentials.

Moreover, the difference is large: switching across occupations requires 4.2 years of income, while across sectors requires only 2.5. The explanation for this disparity is that workers moving across occupations receive larger shifts in income than those moving across sectors. This would happen, for example, if comparative advantage is correlated across sectors within the same occupation, but not vice versa. This heterogeneity can explain the lower estimated moving costs in Ashournia (2018), which ignores within-sector transitions entirely. The last column of Table 6 presents the distribution of switches. Nearly three-quarters of switching involves an occupational switch, and over 40 percent of reallocation in the data occurs within sector. While this matters for estimating switching costs, whether this matters for understanding globalization hinges on what sort of reallocation trade shocks induce. In Section V, I show that these within- and across-sector differences have bite: nearly all the impacts of trade shocks are across occupations, and largely within the tradable sector. Nevertheless, the tools used by DC cannot adequately model the level of disaggregation I find to be quantitatively important.

C. *Non-Pecuniary Benefits and Non-Employment Parameters*

The non-pecuniary benefits to workers, and the value of non-employment are displayed in online Appendix Tables A.5 and A.6 respectively.[37] I normalize the value of non-employment for 23-year-old, high absolute advantage, college-educated workers to 0. Hence, η can be interpreted as the years of mean income that a young, highly capable worker values employment. Estimates range predominantly from 1 to 2, suggesting a high value on employment. Adjusting the non-pecuniary values by the non-employment parameter for each type allows for calculations of non-pecuniary benefits for each worker. For example, younger workers of low absolute advantage (types 1, 3, and 5) face small, but positive, non-pecuniary benefits. This is in line with these workers also receiving lower income.

The value of non-employment is convex in age, with the linear coefficient being negative, but only marginally different from zero, and the quadratic term being positive. This is in line with older workers eventually retiring from the labor force. The linear term is not large even though young workers tend to have high non-employment. Perhaps surprisingly, this suggests that youth unemployment is well explained by their work opportunities, rather than heterogeneity in the value of non-employment along the life cycle.

V. Counterfactuals

This section first outlines the remaining ingredients of the model, and concludes with an analysis of the Danish labor market response to a sudden decline in import prices. The counterfactual experiment holds technology shocks fixed and compares workers across two simulated economies: one with, and one without, the observed changes in import prices from 1996 to 2005. In what follows: $i,j \in \mathcal{I}$

[37] These parameters are less precisely estimated than others. Indeed, the alternative estimator in online Appendix G estimates a negative η. The imprecision arises from this group's low unemployment rate.

index industries, which comprise sectors; o indexes occupation-sector pairs; and, D and F refer to Denmark and foreign, respectively.

A. *Closing the Model*

Consumer Preferences and Export Demand.—Workers consume all income in the period it is earned, consistent with the labor supply model. They aggregate goods according to a three-tiered, constant elasticity of substitution (CES), consumption aggregator, following Broda and Weinstein (2006). In the bottom tier, for each industry, j, each foreign country, c, produces a unique variety that is imperfectly substitutable across countries. Denoting a foreign aggregate by C_i^F the formula is given by

$$C_i^F = \left(\sum_c b(c)\, q_i(c)^{\frac{\eta_i - 1}{\eta_i}}\right)^{\frac{\eta_i}{\eta_i - 1}}.$$

This aggregator allows for imperfect substitution between countries' outputs, differences in quality, $b(c)$, across countries' outputs, and admits an exact price index. Details of how I construct this price index can be found in online Appendix D. The second tier of the utility function is an Armington aggregator, C_i, over domestic and foreign varieties:

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

Like the lowest tier aggregator, this admits a price index which is a function of the domestic price, P_i^D and the foreign price index, P_i^F. Finally, the top tier is a Cobb-Douglas aggregator over industry-level aggregates:

$$U = \prod_{i \in \mathcal{I}} C_i^{\alpha_i}. \tag{20}$$

Maximizing (20) subject to prices and total expenditure E leads to the following function for expenditure on domestic goods for each industry, E_i^D:

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

The CES demand system is a useful starting point for the analysis given its simplicity and its ubiquity in the trade literature.

In addition to consumer demand at home, there is demand for Danish output abroad. I assume that export demand in industry i is exogenously determined by the following demand curve:

$$X_i = A_i^F \left(P_i^D\right)^{-\sigma_i},$$

where A_i^F is a demand shifter. This is a small open economy approximation to the export demand system that would arise in a gravity model.[38]

Labor Demand: Representative Firm's Problem.—Each sector is comprised of a large number of industries. Each industry is modeled by a representative firm operating a CRS technology and earning zero profits in equilibrium. Firms employ factors at competitively determined spot prices. In light of the facts in Section I, labor demand should be modeled so that occupations respond differentially to import competition. To capture heterogeneity in the elasticity of substitution between imports and occupations, I model spillovers in demand through input-output linkages across industries and sectors. Following Caliendo and Parro (2015), firms aggregate local output and foreign output in each industry using the same aggregator as consumers into a composite intermediate, M_i. Then, firms operate a Cobb-Douglas technology[39] taking as inputs capital, K, human capital in each occupation H_o, and input aggregates from other industries, M_j:

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

This production structure has two features which make it attractive for counterfactual analysis. First, constant expenditure shares remove the need to take a stand on the substitution patterns between different occupations with each other, and with different inputs. As a contrast, a nested CES production function would require knowing the nesting structure *and* estimating multiple elasticities for each industry.[40] Second, in spite of the constant expenditure shares, the input-output spillovers in the economy lead to flexible elasticities of substitution between occupations and imports in the aggregate.

This second feature can be seen by differentiating the demand function facing each local industry. Denoting revenues by R_i and total earnings in the economy (including rents) by W, expenditure on local output from industry i is given by the following formula:

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

The first multiplicative term reflects the expenditure shares on industry i coming from consumers and from each industry j; the second multiplicative term reflects the share of expenditure on i that is spent on local goods; the additive term is export

[38] A formal treatment of such an argument can be found in Demidova and Rodríguez-Clare (2013), while online Appendix C contains a heuristic argument.

[39] In a separate note, available upon request, I show that expenditure shares are mostly stable over time. While there is a decrease in expenditure on some occupations in manufacturing, these appear to be uncorrelated with trade shocks. Nevertheless, I perform a counterfactual with time-varying expenditure shares. This experiment can be found in the same note.

[40] Crinò (2010) attempts to estimate flexible elasticities of substitution between many occupations. However, he must use a translog production function, which cannot be easily aggregated, and counterfactual analysis would require knowledge of wages in each occupation abroad. Expenditure shares are relatively stable over this time period. However, there are some clear trends in the middle income occupations; I leave the analysis of this phenomena to future work.

demand. Holding wages fixed and differentiating with respect to a single foreign price shock, dP_k^F:

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

$$+ \underbrace{\sum_{i\in\mathcal{I}} \beta_{oi}^H\left(\alpha_i^D dW + \sum_{j\in\mathcal{I}} \beta_{ij}^M dR_j\right)\frac{\left(P_i^D\right)^{1-\sigma}}{\left(P_i^D\right)^{1-\sigma} + \left(P_i^F\right)^{1-\sigma}} dP_k^F}_{\text{Input Price Effect}}.$$

The first term on the right is the direct impact on industry k from having to compete with lower prices from abroad; whenever $\sigma > 1$, the direct effect of a drop in the price of k is lower demand for occupation o. The second term reflects the fact that lowering the price of k implies lower input costs for all industries that use k. Hence, the change in P_k^F can lead to changes in revenues in other industries, who will consequently adjust their demand for o.[41] The sum of the direct and indirect effects is ambiguous and determined by the relative sizes of industries, the intensity of o in each industry, and the intensity of k.[42]

Equilibrium.—Two final assumptions are necessary to close the model: (i) the total stock of capital is fixed and perfectly mobile across sectors; (ii) workers have perfect foresight over the path of exogenously given foreign prices. With this in mind, an equilibrium is a set of domestic prices, $\{P_{i,t}^D\}_{i\in\mathcal{I}}$, wages, $\{w_{o,t}\}_{o\in\mathcal{O}}$, labor stocks, $\{H_{o,t}\}_{o\in\mathcal{O}}$, and revenues, $\{R_{i,t}\}_{i\in\mathcal{I}}$, such that

(i) representative firms choose intermediates, labor, and capital optimally in each period;

(ii) workers behave optimally both statically and dynamically by:

- maximizing (20) in each period;
- maximizing (3) conditional on the aggregate price index in each period, period wages, and perfect foresight;

(iii) goods market clear every period (for each $i \in \mathcal{I}$):

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

[41] This force is closely related to the "productivity effect" of offshoring discussed in Grossman and Rossi-Hansberg (2008) and Hummels et al. (2014).

[42] Both input-output linkages and stickiness in labor supply matter for this result: 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. Baqaee (2015) provides a formal treatment.

(iv) labor markets clear every period (for each $o \in \mathcal{O}$):

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

(v) capital markets clear every period:

$$p_K K = \sum_{i\in\mathcal{I}} \beta_i^K R_i; \quad \text{and}$$

(vi) beliefs are consistent: workers' beliefs about V_t accurately reflect the true path of labor supply, output prices, and skill prices.

Since workers are hand-to-mouth and goods markets clear every period, there is no scope for endogenous trade imbalances in this model. Including a deficit exogenously, which is the usual practice for trade models, would appear as a transfer, D, to workers in every period. Over the period of study, Denmark runs an almost constant and small surplus of 0.5 percent of GDP. Since there are no dynamics to this surplus, and since the model has no mechanism for modeling this surplus beyond an exogenous transfer, I ignore it in the counterfactuals.

Demand-Side Calibration and Simulation.—Table 7 summarizes the full set of parameters to be calibrated in order to close the model. All production coefficients are estimated as the time-averaged expenditure shares. Online Appendix D contains details of how price indices are constructed, as well as how productivities and demand shifters are recovered. As a brief outline of data sources and methods: demand coefficients, capital input coefficients and input-output coefficients are estimated from the Danish national accounts, published by Statistics Denmark; total wage bills in occupation-industry pairs identify the input coefficients on human capital; Danish customs data provide price and quantity-level information on goods sold to Denmark by each trading partner, which can be fed into the procedure of Broda and Weinstein (2006) to calculate foreign price indices; I calibrate the trade elasticity, σ_i, from Simonovska and Waugh (2014); I use total "gross surplus" deflated by the LIBOR rate to estimate the capital stock; finally, export demand and TFP in each industry are calculated from the national accounts as residuals, given price indices and utility and production function parameters.

B. *Simulation*

With an exogenous path of foreign prices and TFP terms in hand, simulating the model proceeds in six steps:

(i) Define an initial equilibrium (usually the observed equilibrium in 1996).

(ii) Guess a set of nominal wages for each $t = 1, \ldots, T$.

Table 7—Calibrated Parameters and Prices

Symbol	Size	Meaning	Data sources
Production			
α	$\lvert\mathcal{I}\rvert \times 1$	Consumer demand	Natl. accounts
B_M	$\lvert\mathcal{I}\rvert \times \lvert\mathcal{I}\rvert$	IO matrix	Natl. accounts
B_K	$\lvert\mathcal{I}\rvert \times 1$	Capital input coefficients	Natl. accounts
B_L	$\lvert\mathcal{I}\rvert \times \lvert\mathcal{O}\rvert$	Labor input coefficients	IDAS
$\{\sigma_i\}_{i=1}^{\mathcal{T}}$	$\lvert\mathcal{T}\rvert \times 1$	Substitution elasticities	Simonovska and Waugh (2014)
Prices			
r_0	$\lvert\mathcal{T}\rvert \times 1$	Initial relative prices	
$\left\{\Delta P_t^F\right\}_{t=1}^{T}$	$\lvert\mathcal{T}\rvert \times 1 \times T$	Foreign prices	UHDI, Broda and Weinstein (2006)
$\{\Delta r_{Kt}\}_{t=1}^{T}$	$\lvert\mathcal{I}\rvert \times 1 \times T$	Capital prices	LIBOR
$\{\Delta z_t\}_{t=1}^{T}$	$\lvert\mathcal{I}\rvert \times 1 \times T$	Industry TFP	Natl. accounts
Income			
$\{r_{Kt} K_t\}_{t=1}^{T}$	$T \times 1$	Capital income	Natl. accounts (gross surplus)
$\{A_{it}\}_{t=1}^{T}$	$\lvert\mathcal{T}\rvert \times 1 \times T$	Foreign demand shifter	Natl. accounts

(iii) Use the constant returns to scale production system and perfect competition to calculate the path of real prices and thus real wages.

(iv) Use the path of real wages to construct a path of continuation values.

(v) From the continuation values and initial equilibrium: solve for workers' policy rules, labor market demand, and product demands. Then clear markets period by period, yielding a new set of prices.

(vi) Update the guess of nominal wages using a weighted average[43] of the initial guess and the prices that cleared markets period by period.

In order to do step (iii), I rewrite the market-clearing conditions in changes relative to the initial equilibrium. This is important because there are no data on initial relative prices between nontradable industries, only changes in relative prices is observed. The mathematical details of this system are outlined in online Appendix C. Solving this block of the model in changes is similar to Caliendo, Dvorkin, and Parro (2019), and necessary since some prices are unobserved. However, as I solve for V in levels, the shooting algorithm employed to solve for the final steady state and transition path is most similar to the algorithm employed in Lee (2005). The algorithm converges from different initial points, and is numerically stable.

C. *The Labor Market Impacts of Lower Import Prices*

To understand the change in import competition, Figure 6 plots changes in the foreign prices relative to the Danish CPI.[44] Import prices decline by 17 percent on

[43] I find that such a penalized scheme is important for numerical stability.

[44] I have shut down changes in the price of commodities related to energy (coke and petroleum) to focus attention on the industries more associated with offshoring and import competition.

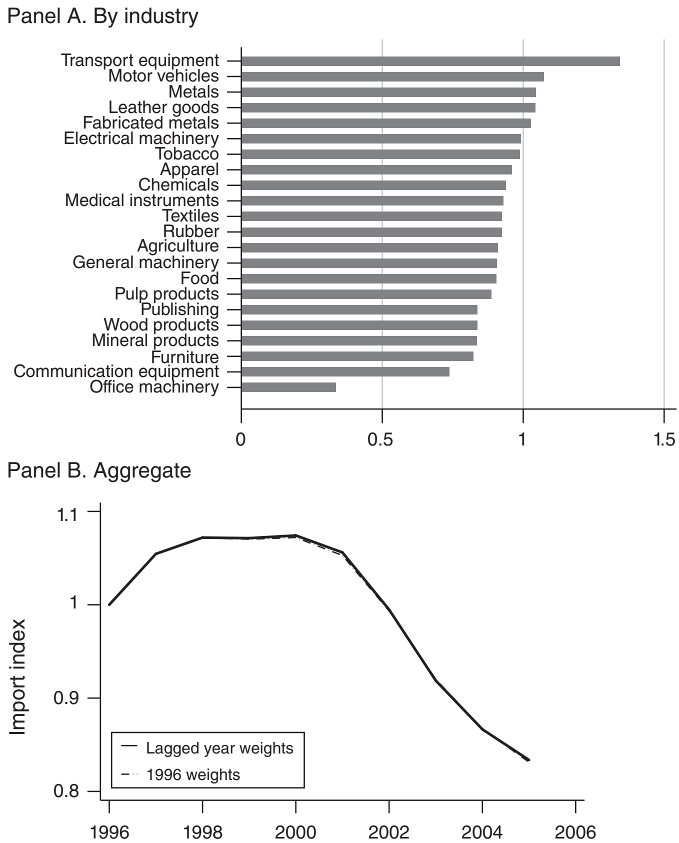

Figure 6. Changes in Foreign Prices, 1995–2005

Notes: Panel A: Calculated by author using Danish customs data and the method of Broda and Weinstein (2006). Danish custom codes mapped to industries using Prodcom. Panel B: Aggregate index calculated from import shares and presented relative to the Danish CPI.

average. However, there is large dispersion: communications equipment prices drop by 25 percent, while the price of transport equipment rises by the same proportion. This dispersion will play a role in how input-output linkages shape labor and wage responses.

To understand the role of occupations and heterogeneity for worker outcomes I focus on five outcomes: (i) the dynamic response to trade shocks, and the difference between long- and short-run outcomes; (ii) the importance of occupations relative to broad sectors in understanding workers' outcomes; (iii) quantifying the welfare losses and income losses to the initial cohort of workers; (iv) the role of skill, both observed and unobserved, in the distribution of outcomes; and (v) the role of age in the distribution of outcomes.

Turning to dynamics, Figure 7 plots the time series of nominal changes in skill prices across occupations and sectors for ten periods after impact. Panel A highlights the substantial dispersion in changes in skill prices. Within manufacturing, some occupations (e.g., plant operators) see as much as a 1.5 percent increase in nominal skill prices, while other occupations see declines up to 3 percent. It takes ten years

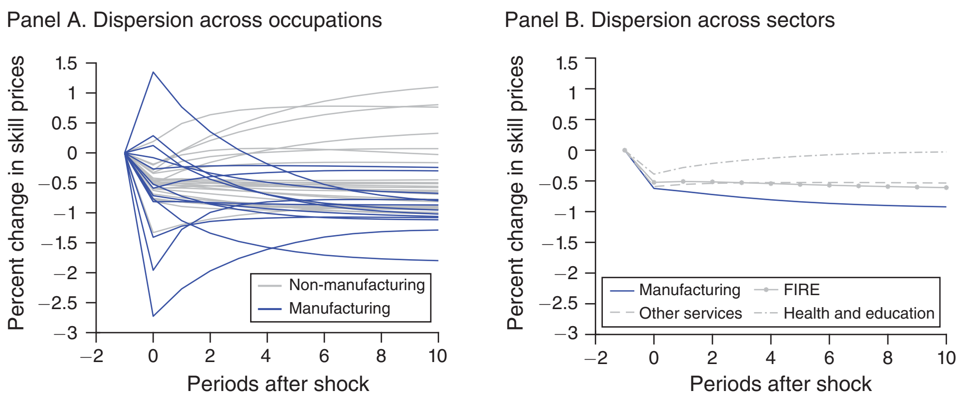

Figure 7. Dynamic Effects of an Import Price Shock on Nominal Skill Prices

for skill prices to settle down at the new steady state; hence, transitions can last up to one-third of a worker's life. Two more patterns emerge. First, in the short run, the dispersion in outcomes is plainly concentrated in manufacturing occupations. This reflects the intuition of a specific-factors model: at impact, many tradable industries face an immediate decline in demand, while a few face an increase (driven by export growth); since in the short run workers are relatively immobile, the changes in labor demand translate into changes in skill prices. The second pattern is that in the long run, the dispersion within manufacturing subsides, and dispersion grows in the nontradable sector. These changes reflect the effect of cheaper intermediate inputs, and the ability of workers to fully reallocate across sectors after enough time passes.

Panel B of Figure 7 plots the average change in skill prices by sector. This panel stands in stark juxtaposition to panel A: sectoral differences are small, and there is little dispersion in both the short and long runs. In steady state, the average skill price in manufacturing declines by less than 1 percent.[45]

Despite the large negative impacts in *nominal* skill prices, real skill prices increase for all occupations.[46] This is because good prices decline by approximately 4 percent, offsetting even the largest nominal losses. Since any worker could, in principle, make the same choices in any equilibrium, higher skill prices imply that workers benefit in welfare terms. However, as welfare includes non-pecuniary benefits and switching costs, workers can still see declines in real income. That all workers benefit in welfare terms would not arise absent the input-output linkages that allow for foreign inputs to lift productivity in *all* sectors. Absent such forces, the labor demand side of the model would closely resemble a standard Heckscher-Ohlin model, where it is known that certain factors tend to lose in real terms in response to import competition.[47] The "productivity enhancing" effect of imports was noted

[45] I present unweighted average changes in each sector; using worker-weighted averages does not change the qualitative point.

[46] Online Appendix Figure 9 contains a plot of the real skill price series, as well as aggregate real income for the economy.

[47] As a crude estimate of the change in nominal prices absent input-output links, one could multiply the weighted average decline in trade prices (17 percent) by the share of imports in final consumption (approximately 10 percent in the 2000 Danish IO tables). Thus, absent the IO structure prices would have only declined by about 1.7 percent, less than one-half of the drop in the model. While not an identical shock, Artuç and McLaren's (2015)

Table 8—Percent of Income Variance Explained

	Levels	Differences	
		Short run	Long run
Occupations and sectors	65.5	66.3	49.0
Occupations only	58.0	57.0	42.6
Sectors only	16.5	16.4	5.7

Notes: Income variance is calculated weighting by the distribution of workers in the equilibrium *with trade*. Residual variance reflects worker demographics within each economic unit. Short run is defined as the period at impact, long run is based on a steady state that is assumed to be reached at 40 periods.

theoretically by Grossman and Rossi-Hansberg (2008), and highlighted empirically in reduced-form work by Hummels et al. (2014). While the net effect of input-output links will generally depend on the constellation of trade shocks across industries, my results demonstrate that, in Denmark, the productivity enhancing impact of foreign price changes dominated the costs of reallocation.

The most important results in this paper are in quantifying the importance of occupational reallocation over sectoral, and for allowing various margins of heterogeneity into the analysis. To properly quantify the importance of sectors and occupations, Table 8 displays the fraction of variance in worker incomes explained at three levels of economic analysis: occupation-sector pairs, occupations alone, and sectors alone. The first column, which I include as a benchmark, displays results for income levels in steady state. For example, occupations explain 58 percent of the variance in incomes in steady state, while sectors explain 17 percent.

The second and third columns of Table 8 display the fraction explained of the variance in *differences* in expected[48] income across equilibria. Concretely, denote the income of a worker in state $\tilde{\omega}$ (where this includes demographics, occupation, etc.) in the shocked equilibrium by $w(\tilde{\omega})$, the income of a worker in the non-shocked equilibrium by $\tilde{w}(\tilde{\omega})$, and the change by $\Delta w(\tilde{\omega})$. Due to reallocation, the share of workers in state $\tilde{\omega}$ will be different across equilibria, so let $s(\tilde{\omega})$ denote the share of workers of type ω in the shocked equilibrium. Then, given a grouping g, each cell of the table displays

$$\frac{\sum_g s(g)\left(\overline{\Delta w(g)} - \overline{\Delta w}\right)^2}{\sum_{\tilde{\omega}} s(\tilde{\omega})\left(\overline{\Delta w(\tilde{\omega})} - \overline{\Delta w}\right)^2}.$$

A large fraction of the variation is explained by occupations and sectors. However, there are important differences between these units of analysis. First, the majority of variation in outcomes is explained by occupations, while a much smaller fraction is explained by a worker's sector. While slightly coarser, my definition of sectors largely follows Dix-Carneiro (2014); Artuç, Chaudhuri, and McLaren (2010); and Artuç and McLaren (2015). The small impact of trade shocks across sectors is in line with previous work. For example, ACM find a 3 percent change in wages from a 30 percent

model, ignoring the possible input-output effects, finds that improvements in foreign productivity devastate local wages, without sufficient offsetting price declines.

[48] The i.i.d. Gaussian innovations to worker's incomes is integrated out in this analysis.

Table 9—Distribution of Lifetime Earnings Differentials

	Mean	Standard deviation	Q5	Q50	Q95	$\% < 0$
Low [L]	5.67	7.97	0.67	4.85	16.60	4.62
Low [H]	4.40	5.30	0.19	4.01	10.88	4.87
Med [L]	5.24	9.10	−3.26	4.50	18.01	6.57
Med [H]	4.22	4.33	1.92	4.02	7.29	3.87
High [L]	5.28	8.36	−1.49	4.24	19.35	5.68
High [H]	4.41	4.51	2.16	3.96	9.29	3.29
Total	4.72	6.31	0.60	4.14	12.05	4.64

Notes: Table reports the $(100\times)$ log difference in discounted total earnings across individuals. Results are based on simulating 100,000 individuals from the initial cohort under both the equilibrium with and without changes in trade prices. The same shocks are used in both simulations. Discounted at $\beta = 0.96$.

reduction in manufacturing prices. However, introducing workers' occupations into the analysis demonstrates that these small impacts missed a crucial margin.

The second important difference is that in the long run sectors explain almost no variation in outcomes, even relative to steady-state income levels. This is visualized in Figure 7, where sectoral variation is swamped by within-sector variation. This result has implications even for nondynamic analyses of trade: the tasks in which workers have sorted themselves reveals more about their exposure to shocks than the outputs to which those tasks are attached. Moreover, the importance of different economic levels of analysis are not constant over time, and can vary as the economy adjusts to a shock. This finding is largely a corollary to the numbers in Table 6. Specifically, as the costs of reallocating across sectors are small, sectoral income differentials will tend to equalize more than across occupations. This is especially true in the long run, where differences in skill prices largely reflect differences in switching costs.

Turning to heterogeneity, controlling for unobserved human capital in workers revealed large differences across workers in both absolute and comparative advantage. To assess whether these differences in ability matter, I follow the lifetime trajectories of the initial cohort of workers[49] both under the shocked and non-shocked equilibrium. Table 9 shows several conditional moments from the distribution of the discounted lifetime earnings across workers. I focus solely on income, as interpreting other parameters in welfare terms is difficult. For example, switching costs reflect a myriad of factors including psychic utility costs of learning new skills, labor market frictions, and standard search costs, an amalgam with scant normative interpretation. Nevertheless, in online Appendix Table A.14, I reproduce these results including the non-pecuniary benefits and the qualitative message remains the same.

The numbers in Table 9 show the highly uneven distribution of outcomes across workers. For example, while the average increase in real lifetime earnings is 4.72 percent, there is a small fraction of the population, slightly under 5 percent, who lose income in real terms. This population itself is represented more by some types of workers than others. Nearly 7 percent of low absolute advantage, medium-skilled

[49] In particular, I simulate the full set of shocks for 100,000 workers drawn from the empirical distribution of workers alive at the incident of the trade shock, corresponding to calendar year 1996.

workers have lower real lifetime earnings after the trade shock, and over 5 percent of these workers lose 3 percent or more in lifetime earnings: almost the exact negative of the average *gains* from trade. This same group also features some of the biggest *winners* from trade, with the top 5 percent of earners in this group seeing increases of 18 percent or more in lifetime earnings. The highly disperse and often negative outcomes of middle skilled types can be contrasted with highly educated workers. For this group, a smaller share of workers lose in real terms and those that do lose face smaller losses, with the fifth percentile worker still seeing gains of 2 percent.

The table also helps highlight the crucial role of *comparative advantage* in understanding worker outcomes. This point is most clear with an example: low absolute advantage, medium type workers make less than their high absolute advantage counterparts, and this would be true no matter import prices. However, it is differences in their comparative advantage that lead to differences in the distribution of losses versus gains between these workers. Recall from Figure 5 that low AA, medium skilled workers are exactly those workers with comparative advantage in the middle income occupations, those susceptible to import competition. Recent commentaries on trade have questioned if the losers from trade tend to be narrow and hard to see. The analysis here confirms this intuition. General equilibrium analyses that ignore differences in human capital will be too blithe about the outcomes facing workers most suited to impacted jobs.

Finally, Figure 8 plots the average change in earnings by age group, across types. A general pattern is that the youngest in the initial cohort gain the most. What may be surprising is that this is *not* driven by lower import prices being felt over time, but by the fact that reallocation is more costly for older workers. To understand why, note that prices actually adjust almost immediately: hence the gains from trade arising from cheaper goods come at impact.[50] However, young workers face lower switching costs and have less accumulated human capital built up at the time of the shock. Hence, they can change their career trajectories without bearing much of a cost. The fact that differences in costs explains the age profile also explains why the slope varies across types. For example, medium skilled, high absolute advantage workers display a flat profile of gains with respect to age. While the young often gain more, the age profiles are surprisingly flat, in light of the importance of human capital. This generally flat profile is partially a result of the suddenness of the import competition. There are no anticipation effects in the model: neither young, nor old workers can react to import competition before it begins. In online Appendix I, import competition is announced ten periods in advance. In this setting, the differences between young and old workers is more pronounced.

In this section, I used the estimated model to quantify the key role of occupations in understanding both the distributional consequences and dynamic path of worker outcomes. Occupations and comparative advantage clearly shape dispersion in outcomes. And while the presence of input-output linkages leads to large gains from trade, cushioning many, the costs of reallocation lead to a small but substantial set of workers who lose, especially in the short run, from rapid increases in import competition.

[50] See online Appendix Figure 9 for the evolution of the price index.

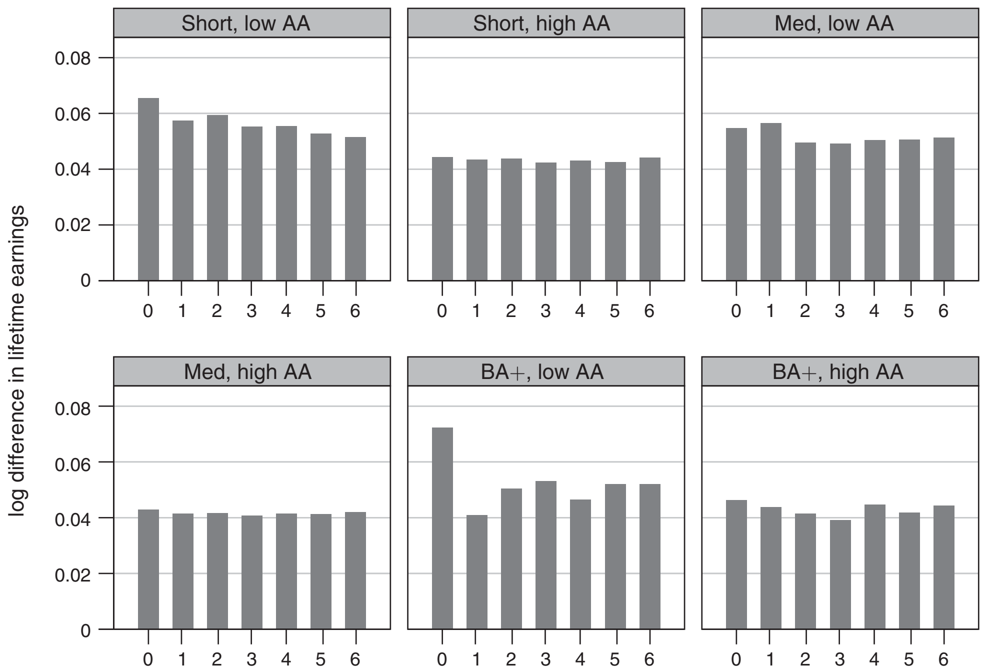

Figure 8. Distributional Impacts across Age Groups

Notes: Figures report the $(100\times)$ log difference in discounted total earnings across individuals. Results are based on simulating 100,000 individuals from the initial cohort under both the equilibrium with and without changes in trade prices. The same shocks are used in both simulations. Discounted at $\beta = 0.96$.

VI. Conclusion

Understanding the margins on which workers adjust, and how these margins shape the consequences of import competition, are classic themes in international trade. As many policymakers begin to hold an increasingly dour view of trade, economists have devoted considerable attention to the labor market consequences of the last few decades of globalization. In this paper, I add to this discussion by highlighting the role that occupations and worker comparative advantage can play in shaping worker experiences.

Exploiting administrative data from Denmark, I developed and estimated a dynamic model of occupational choice featuring switching costs, human capital accumulation, and both observable and unobservable comparative advantage. Methodologically, I show that ignoring occupational tenure leads to biased estimates of key elasticities. The fact that including tenure triples estimates of switching elasticities should give pause to how we interpret the increasing number of dynamic adjustment models ignoring this feature of the data. The methods used in this paper, based on advances in the structural labor literature, show that adding realistic human capital into models of trade and labor market adjustment does not substantially complicate estimation.

After embedding this model in a small open economy, featuring heterogeneous substitution patterns between imports and occupations, I quantified the impact of the

sudden drop in import prices arising from the rise of Eastern Europe and China. In my counterfactual analysis I find that occupations explain three-fifths of the distribution consequences of trade, while sectoral reallocation accounts for only one-sixth. This result implies that the classic dichotomy between import- and export-competing sectors may be misplaced, the key to understanding worker mobility is import- and export-competing occupations, or tasks.

In terms of economic impact, I find that 5 percent of workers face lower lifetime incomes as a result of import competition. These workers tend to be middle or lower skilled, and their comparative advantage is ill suited to reallocating in response to import competition. These differences give credence to the view that a small, but nonnegligible, share of workers may have missed out from the recent growth in trade.

The framework employed here can be readily ported to other datasets and there is ample room for future research. First, geography has been ignored. While this may be reasonable for Denmark, it is likely not the case in countries like Germany or the United States. Second, capital reallocation and trade imbalances are not modeled, which could be important along the transition path for workers. Understanding the interaction between capital adjustment and trade imbalances alongside labor adjustment is a key next step in more fully understanding how globalization has impacted workers, and continues to do so. Finally, while human capital can explain why workers adjust sluggishly, estimated fixed costs remain large. Further unpacking the black box of switching costs is an important step in crafting policies to aid dislocated workers.

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