Training, Offshoring and the Job Ladder*

Preliminary. Comments Welcome.

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Abstract

Over the past 30 years, skill premiums have grown, jobs in the middle of the skill distribution have become relatively scarce, and job and worker turnover rates have declined. At the same time, the fraction of the population attending college has grown, much of the manufacturing work force has shifted into services, and employers' investments in on-the-job training have increasingly favored high-skilled workers. This paper interprets these patterns through the lens of a dynamic structural model that explains workers' human capital accumulation, unemployment spells, and earnings trajectories over their life cycles. Offshoring and import competition shift job creation away from trade-exposed occupations, thereby changing job offer arrival rates for each worker type, increasing incentives to invest in college degrees, and shifting patterns of employers' investments in on-the-job training. A quantitative version of the model explains observed changes in U.S. labor markets as consequences of a globalization shock and technological progress, isolating the relative importance of each.

Keywords: Offshoring, job turnover, on-the-job training, job ladders, labor market frictions, inequality
JEL Codes: F12, F16, E24, J64, L11

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1 Introduction

1.1 Overview

Over the past 30 years, labor market conditions in the United States and elsewhere have rapidly evolved. Skill premia have grown (Acemoglu and Autor, 2011), jobs in the middle of the skill distribution have become relatively scarce (Acemoglu and Autor, 2011), and job and worker turnover rates have declined (Davis and Haltiwanger, 2014, Decker et al., 2014). At the same time, the fraction of the population attending college has grown (Acemoglu and Autor, 2011), much of the manufacturing work force has shifted into services (Lee and Wolpin, 2006, 2010; Eberstein et al., 2014), and on average, jobs have involved increasing amounts of on-the-job training (Cairo, 2013).

Behind these aggregate trends, there is great heterogeneity in the earnings trajectories and career paths of different types of workers. We use U.S. data from the Survey and Income and Program Participation (SIPP) and the Occupational Information Network (O'NET) to document how job-to-job and employment-to-non employment transitions have changed during recent decades. We find that the decline in the job-to-job transitions has been much greater for workers who are employed in low-skilled occupations, while there has been no decline and even an increase for workers who work in high-skilled occupations. There has also been an increase in movements from employment to non-employment for workers in low-skilled occupations. Hence, some have moved more easily up the job ladder, while others have increasingly languished in dead-end occupations. Similarly, some have enjoyed more job security and more frequent job offers, while others have more become more likely to experience unemployment spells. We also show that on-the-job training rates have increased for workers in high-skilled occupations, while they have remained flat or fallen for low-skilled ones. At the same time, returns to training have increased significantly. Finally, the age-earning profiles in trade-exposed occupations have flattened relative to others.

We develop an open economy search model that predicts these changing patterns of career development, and we show that, qualitatively, they can be viewed as closely interrelated consequences of import competition and offshoring. Then, after calibrating our model to data, we quantify the extent to which globalization–as opposed to skill-biased technological change–accounts for the changing career paths and earnings trajectories of U.S. workers.

The basic idea is as follows. Before entering the labor market, high school graduates of differing initial ability decide whether to attend college. Thereafter they seek jobs as either skilled (college educated) or unskilled (high school only) workers, eventually matching with heterogeneous employers and performing particular tasks.

Once matched, workers build human capital through experience and—when it benefits

their employers—through on-the-job training. These accumulation processes contribute to wage growth over their life cycles. But workers also generate wage increases through on-the-job search, which leads to job offers from poaching firms. And they suffer earnings reductions when shocks throw them into unemployment, interrupting their human capital accumulation and reducing their bargaining power with potential new employers.

In this environment, offshoring and import competition affect workers' life cycle earnings by changing the relative demand for different tasks. In particular, globalization reduces domestic demand for "trade-exposed" tasks, thereby changing job offer arrival rates for the associated worker types. With lower arrival rates, these workers have fewer opportunities to move to better-paying jobs or generate counter-offers. They also tend to end up in unemployment more frequently, as their employers eventually draw negative shocks and shed their labor. Further, given their skills and occupations, those that *do* move tend to end up in low- to mid-skill service sector jobs, for which on-the-job training is relatively unprofitable. Finally, these labor market conditions induce marginally-talented high school graduates to pursue college degrees in order to leapfrog the missing rungs in the middle of the job ladder.

Some of these mechanisms are also in play when a technology shock occurs. So to distinguish the effects of offshoring from those of skill-biased technological change, we rely on a simple identification strategy. As we define them, the labor market effects of offshoring trace to falling trade costs, holding production technologies fixed. In contrast, the effects of skill-biased technological progress manifest themselves through changes in production function parameters and have no effect on trade costs.

Aside from our literature review, we organize the remainder of the paper into three main sections. Section 2 documents the changes in labor market conditions we mentioned above, using the Survey of Income and Program Participation (SIPP) and other data sets. Some of the patterns we summarize are well known, but some have not been previously noted, to our knowledge. Specifically, despite the overall increase in on-the-job training rates, training rates have declined among workers in low-skill, trade-exposed occupations. Also, even as worker turnover rates have declined, rates of transition into unemployment have risen among the low-skill occupations. Finally, life-cycle wage profiles have flattened relatively dramatically for those tradable sectors jobs that have been subject to foreign competition and offshoring.

Section 3 then develops our model. To characterize labor markets, we take key building blocks from the recent on-the-job search literature and the literature on endogenous investments in training. We also incorporate the device of "task-producing firms," which resemble employment agencies. Each hires workers in a frictional labor market in order to produce a particular service—secretarial, assembly, construction, banking, and so on. It then sells

its output to goods-producing firms in a competitive service market. This formulation allows us to divorce the bargaining game between employers and workers from the decisions of goods producers regarding the mix of labor services that they purchase. To characterize goods markets, we generalize Caliendo and Parro's (2015) model of the global economy by introducing inter-sectoral factor intensity differences for the various types of labor services. This effectively links the offshoring of intermediate goods to labor market outcomes, and it provides the basis for our experiments involving technological change.

In section 4, we explore our model's empirical properties. Calibrating our model to match various base-year features of U.S. markets and bilateral trade flows, we first demonstrate that a generic reduction in the relative price of moderately skill-intensive goods is sufficient to qualitatively replicate the changes in U.S. labor markets mentioned above. Then, to isolate the role of globalization, we perform counterfactual simulations in which we reduce trade frictions, shift production function parameters, or both. (This final exercise is still in progress.)

1.2 Relation to the Literature

Our model combines features from a number of recent contributions to the labor literature. First, following Bagger et al. (2014), Lise et al. (2016), and Lise and Robin (2017), we allow for long-term contracts, on-the-job search, and counter-offers, all in a context with *ex ante* heterogeneous workers and firms. Second, as in Cairo (2013) and Cairo and Kajner (forthcoming), we allow job and worker turnover decisions to depend upon training investments. And, as in Flinn, et al. (2017), we treat on-the-job training decisions as the result of a bargaining game between workers and their employers. Third, like Lee and Wolpin (2006, 2010), we allow workers to respond to skill-biased technical change, both by adjusting their investments in college education and by moving toward service sector jobs. Finally, as in Bagger et al. (2014) and Kong et al. (2016), our model links workers' life-cycle earnings profiles to their education choices and the skill premium.

We also draw from and contribute to several strands of the trade literature. First, in the spirit of Grossman and Rossi-Hansberg (2008) and Eaton et al. (2017), we posit a production technology that bundles specific tasks, some of which can be accomplished offshore and embodied in intermediate goods trade. Second, as in Caliendo and Parro (2015), we allow for input-output linkages that transmit product market shocks through intermediate input markets. Third, like Cosar (2013), Davidson and Sly (2014), and Blanchard and Willmann (2016), we allow globalization to affect the skill distribution by changing the returns to human capital investment for different types of workers. Fourth, we contribute to the growing literature that empirically characterizes barriers to worker mobility across sectors and/or

occupations (Lee and Wolpin, 2006 and 2010; Cosar, 2013; Artuc et al., 2014 and 2016; Dix-Carneiro, 2014; Caliendo et al., 2016; Lee, 2016; Traiberman, 2017). Fifth, our model provides a dynamic structural interpretation for the effects of Chinese import competition on wage trajectories and unemployment spells that have been documented by Autor et. al (2014, 2015) and Acemoglu et al. (2016). Sixth, like Cosar, et al., (2016), Helpman et al. (2017), Grossman et al (2017) and Fajgelbaum (2017), we invoke random search processes to link openness with job turnover and unemployment. And seventh, like Fajgelbaum (2017) and Davidson et al. (2017 and 2018), we allow globalization to affect the nature of the job ladder faced by different types of workers.

Finally, though it is not the main focus of our analysis, this paper connects to the large literature on the labor market effects of skill-biased technological progress. The contributions therein that most directly relate to our work are Acemoglu and Restrepo (2018), which provides the basis for our characterization of production technologies, and Autor et al. (2015), who also provide estimates of the relative importance of trade and technology shocks in driving labor market outcomes, albeit using a reduced-form approach.

2 Stylized facts

Before describing the specific structure of our model, it is useful to review the patterns in the data it is designed to capture. We do so using variables constructed from three data sets, each of which is discussed in more detail in Appendix A. In all calculations, we focus on workers between ages 25 and 60.

2.1 Data

2.1.1 Survey of Income and Program Participation (SIPP)

The data set we exploit most extensively for this exercise is the Survey of Income and Program Participation (SIPP). This is a nationally representative household survey conduced by the U.S. Census Bureau. It is collected as a series of panels, each lasting approximately four years. Households in each panel are interviewed in waves, which typically take place every three months, and are asked for retrospective information on their employment status (employed, unemployed, or out of labor force) and earnings. Each panel also provides a monthly a job identifier and a code indicating workers' Standard Occupational Categories (SOC). The SOC codes can be 4 digit (99 occupations), 2 digit (22 occupation) or 1 digit (5 occupations). We use this information to track workers' transitions across jobs and employers, as well as

their movements into and out of unemployment.[1]

In Wave 2 of each SIPP panel, we also observe which respondents received job training. And for those who did, we observe information on training duration, purpose, and funding source. However, the specifics of these questions have varied across panels, so we can only consistently recover the fraction of the employed sample that reports "receiving training to improve job skills during the past 10 years".

In the analysis below we use three SIPP panels: the 1990 panel, which covers 1989-1991 period, the 1996 panel, which covers 1996-2000 period, and the 2008 panel, which covers 2008-2011. For several outcomes, e.g. fraction of workers with training or job-to-job transitions, we report both average outcomes from the first and the third panels, which we refer as 1990 and 2010, and changes between them. We refer to the second panel as 2000.

Panel Study of Income Dynamics (PSID) Because the SIPP does not allow us to keep track of individuals for more than a panel (about 4 years), we also exploit data collected for the Panel Study of Income Dynamics (PSID). This is a longitudinal nationally representative household survey conducted by the Survey Research Center at the University of Michigan, and extensively used in the literature.[2] It is collected as a series of annual waves between 1968 and 1997 and biennial waves thereafter, through to the most recent wave in 2011. In each wave, PSID respondents provide information about current employment status, and, if employed, tenure in their current job, current occupation and industry of employment, and labor earnings in the previous wave. For the purpose of this analysis, we focus on the period between 1990 and 2011, keeping track of different cohorts of individuals born between 1960 to 1980.

2.1.2 Occupation Network Database (O*Net)

For each occupation, we construct measures of cognitive (brain) and manual (brawn) skill content using selected descriptors of abilities provided by the Occupation Network Database (O*NET).[3] This data set, sponsored by the U.S. Department of Labor, classifies roughly 1,000 occupations on the basis of worker attributes and job characteristics. The classifications are

[1] We identify job to job transitions as those transitions where the worker works in two consecutive months without reporting unemployment in between, and either the worker's employer identification number or his four-digit occupational identifier changes. We construct our measure of job-to-job transition rates for workers in each of the four-digit occupations by computing the ratio between total movers between jobs in two consecutive months and total employment in the previous month in the original occupation.

[2] See, among many others, Kambourov and Manovskii (2009) and Kambourov, Manovskii and Plesca (2018)

[3] The O*NET database is a US source of occupational information. It provides a taxonomy of 947 occupational titles covering the entire U.S. economy, and it contains hundreds of standardized and occupation-specific descriptors of skill, experience and ability requirements. For an application of this dataset, see, among the others, Goos and Manning (2007).

based on questionnaires distributed to workers. We use principal component analysis (PCA) to construct our "brain" and "brawn" indices from the large set of occupational descriptors, and we aggregate to the four-digit occupational level, thereby distinguishing 99 occupations.[4] Finally, we merge these indices with the Standard Occupational Categories (SOC) reported in the SIPP using a crosswalk provided by the U.S. Census Bureau.

2.1.3 World Input-Output Database

For our descriptive analysis of trade and labor market outcomes, we need a measure of the exposure of each occupation to import competition. For this we exploit trade flow information from the World Input-Output Database (WIOD). This is a public database containing time-series on input-output tables for 27 EU countries and 13 other major countries in the world covering the period from 1995 to 2011.[5]

Our occupation-specific index of import exposure is a share-weighted import penetration rate,

$$IMP_{j,t} = \sum_{k=1}^{K} \frac{L_{k,j,t}}{L_{j,t}} \frac{imports_{k,t}}{output_{k,t} + imports_{k,t} - exports_{k,t}},$$

where $k = 1, ..., K$ denotes sector and $\frac{L_{k,j,t}}{L_{j,t}}$ is the employment share of sector k in occupation j at time t. Of course, this measure is endogenous, and it does not account for cross-industry linkages through intermediate input markets, so it serves as a crude approximation to the effects of globalization. We will deal with both issues in the context of our structural model.

2.2 Employment Shares

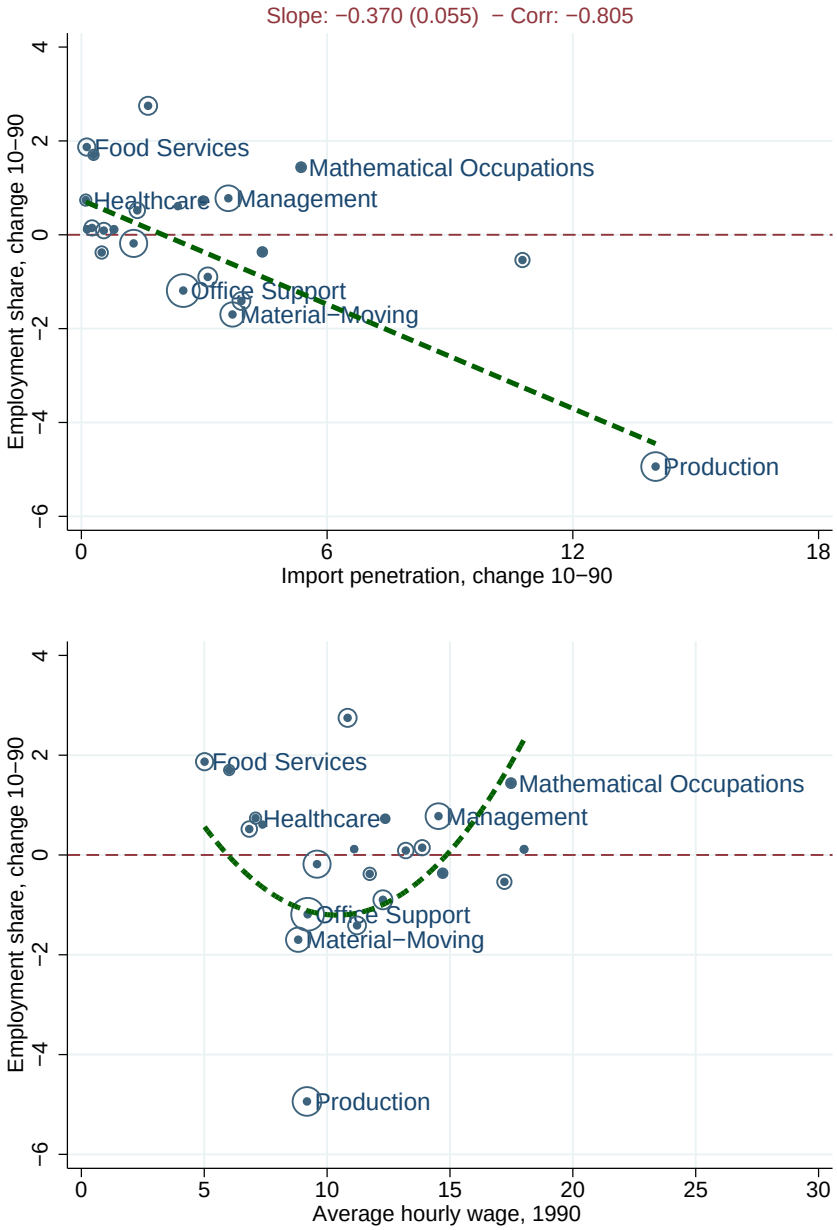
We begin by using the SIPP to review some well-known relationships between employment shares, import penetration rates, and wages. Comparing 1990 to 2010, the upper panel of Figure 1 plots changes in the employment shares of each 2-digit occupation against changes in their import exposure, with bubble sizes reflecting occupation-specific employment levels. The lower panel plots these same changes in the employment shares against occupation-specific real hourly wage in 1990.

Note that between 1990 and 2010, jobs relocated from more import-exposed, moderate wage occupations to less import-exposed occupations, placed either at the bottom or at the

[4]Our brain measure is based on the first principal component of the O*NET vector of brain-related occupational characteristics, and our brawn measure is based on the first principal component of the O*NET vector of brawn-related occupational characteristics. The former explains 60% of the variation among the cognitive ability descriptors, and the latter explains 74.5% of the variation among the psycho-motor and physical ability descriptors. Appendix A provides further details.

[5]The same dataset has been used in Costinot and Rodriguez-Clare (2014), Caliendo and Parro (2015) and Fajgelbaum and Khandelwal (2016), among others.

Figure 1: Change in employment shares, by occupations



top of the wage distribution. Overall, import-exposed occupations lost 9.42 percentage points of employment share, being replaced by low-paid non-tradable services (+7.81 percentage points) and, to lesser extent, by higher-paid occupations (+1.61 percentage points).

Related patterns can be found in earlier studies. For example, Acemoglu and Autor (2011) use the Current Population Survey (CPS), the Census of Population (Census) and the American Community Survey (ACS) to document that employment growth has been concentrated in the lowest three deciles of the wage ladder from the 1990s onward, offset by

a negative change in employment shares of middle-paid occupations, including *sales*, *office and administrative support*, *production*, *craft and repair*, *operator*, *fabricator,* and *laborers*. Similarly, sorting occupations by their 1980 wages, Autor and Dorn (2013) document the "hollowing out" of the U.S. labor market over the period 1980-2005. Specifically, they show that employment shares grew over this period at both the low-end and the high-end of the wage distribution, while they shrank in the middle. They further show that the non-monotonicity of the shift largely reflects the growth of low-skill service sector jobs and the demise of low-skill, non-service sector jobs. Lee and Wolpin (2006) likewise document the long run shift of workers toward service sector jobs. Finally, the negative association between import penetration and employment growth has been extensively documented, perhaps most famously by Autor, et al. (2013).

2.3 Job and worker flows

Next we examine occupation-specific worker turnover patterns in the SIPP and relate them to four occupational characteristics: average hourly wages, college education rates, brain-skill content, and brawn-skill content. As mentioned above, we observe wages and college education rates directly in the SIPP dataset, but we map "brain" and "brawn" indices based on O*NET occupations onto the SIPP occupational categories using a crosswalk.

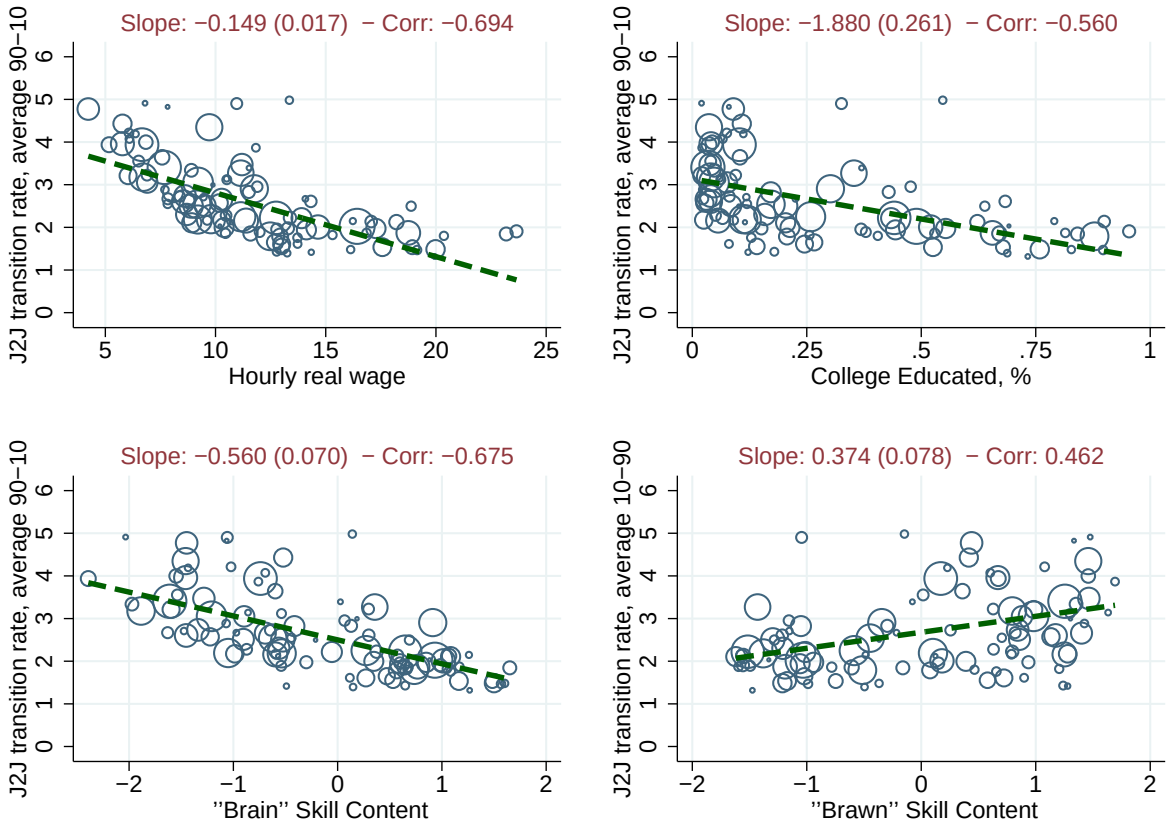
Figure 2 shows employment-weighted average monthly job-to-job flows, treating each 4-digit 2002 Standard Occupational Code (SOC) as an observation. Each panel graphs these flows against one of the four job characteristics mentioned above. These panels confirm Davis and Haltiwanger's (2014) finding that average job-to-job flows decrease with the brain-skill/wage/education content of occupations.

Figure 3 redoes Figure 2, replacing the rate of job-to-job flows on the vertical axis with the *change* in this rate between 1990 and 2010. The fact that most bubbles are below zero reflects a general slowdown in job turnover that has been extensively documented.[6] More interestingly, the drop in transition rates is relatively large among low-skill workers. Although this pattern has received less attention in the literature, it appears in Cairo et al. (2015), who find that declines in job-to-job transitions have been greater for jobs that are at the lower end of the pay distribution, whether that is measured by education, occupation, industry, or firm wage. It is also consonant with Davis and Haltiwanger's (2014) Chart 7, which shows relatively rapid declines in job turnover for high school dropouts.

Figures 4 and 5 report the average and the change in monthly employment-to-nonemployment

[6]Examples of papers that document this trend include Hyatt and Spletzer (2012), Decker et al. (2014), and Davis and Haltiwanger (2014). The datasets involved include the Longitudinal Employer-Household Dynamics (LEHD), the Business Employment Dynamics (BED), the Job Openings and Labor Turnover Survey (JOLTS), the Current Population Survey (CPS), and the Longitudinal Business Database (LBD).

Figure 2: Average Monthly Job-to-Job Transition

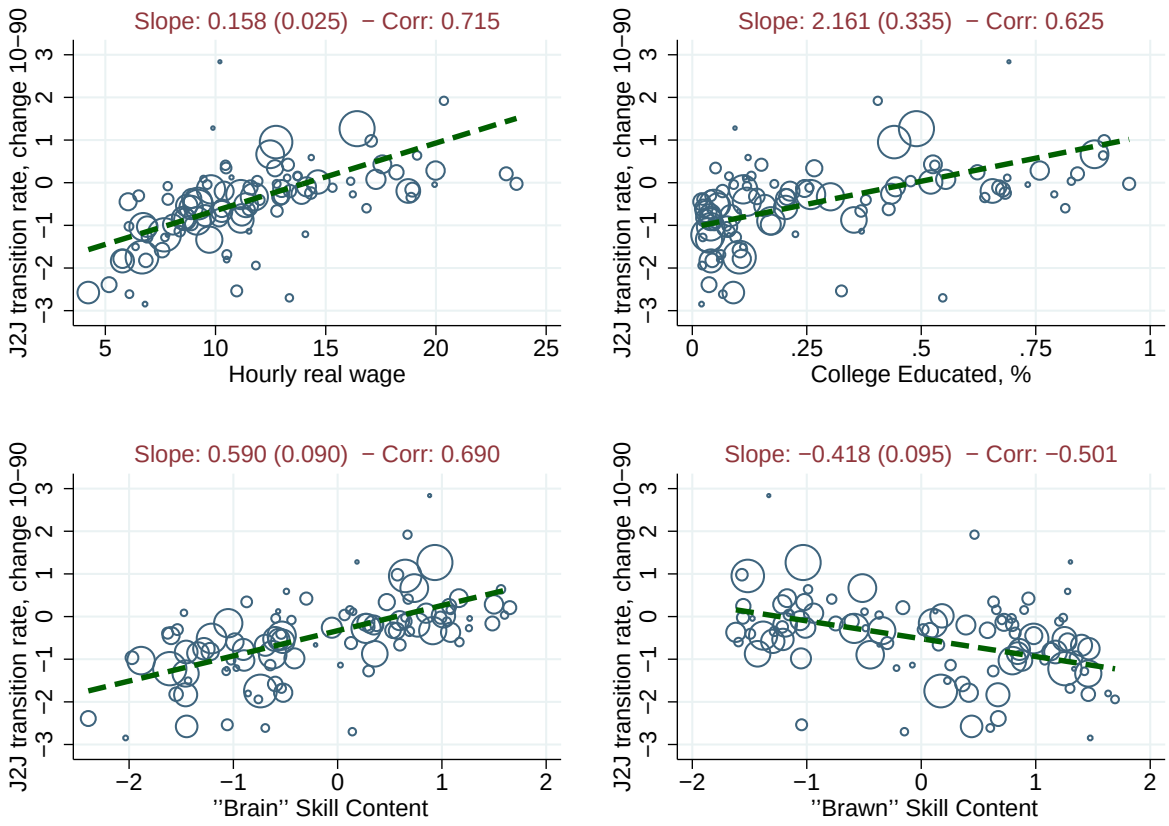


(E-NE) rates between 1990 and 2010. Once again, each bubble corresponds to a 4-digit Standard Occupational Code and the changes are plotted against our various measures of worker skills. The first message is that the E-NE transition rate is significantly larger in low-skill and low-paid occupations. The second message is that, despite the overall reduction in job turnover, flows into non-employment have increased. This aligns with Davis et al. (2006 and 2010), who find that flows into non-employment rose after the mid 1990s. Finally, and more importantly for our purposes, these figures show that the change in average E-NE transition rates was significantly higher among less skilled workers. Hence when these workers leave their jobs, they are increasingly unlikely to be headed for more attractive employment elsewhere.

2.4 Job Training

We next use the SIPP to investigate the relationship between training patterns, workers' skills, and the tradability of their occupations. For this exercise we rely on the job-related-

Figure 3: Change in Monthly Job-to-Job Transition

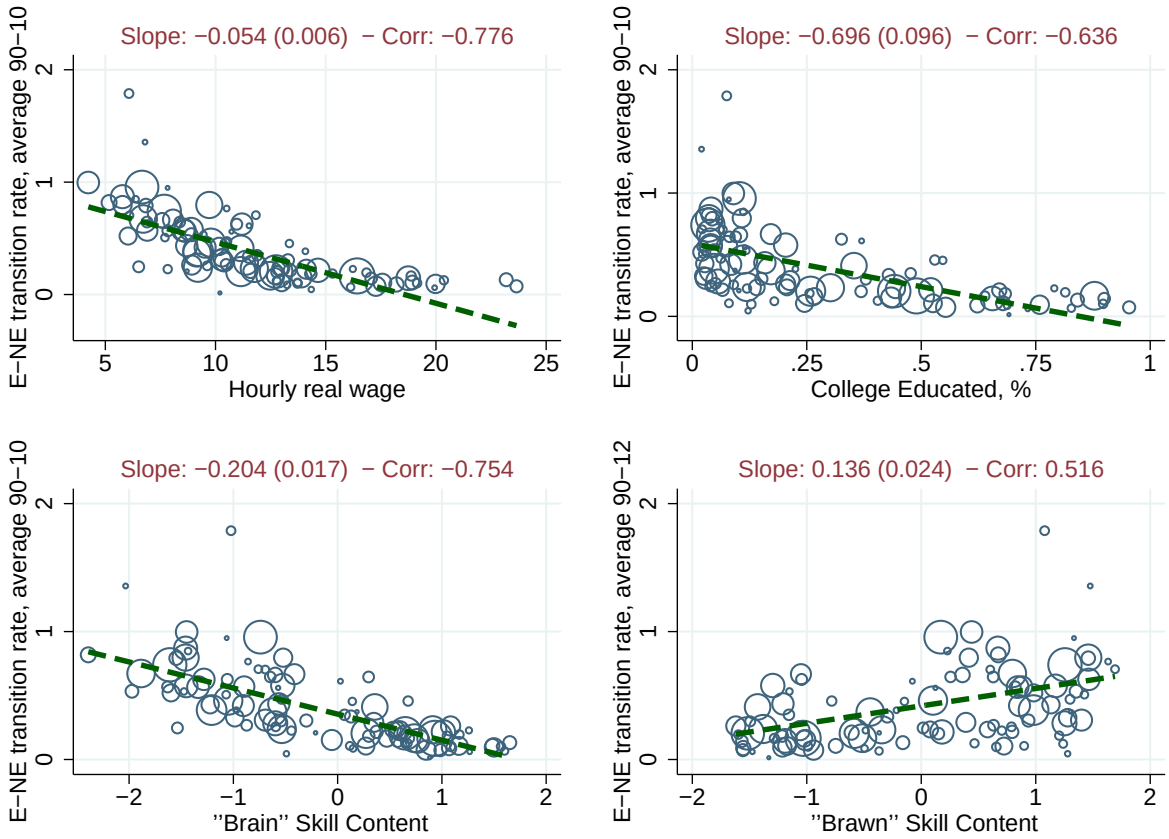


training questions in the SIPP, which allow us to recover occupation-specific shares of workers who received on-the-job training during the previous decade.

The four panels of Figure 6 plot average fraction of workers who receive training in each occupation against various measures of job characteristics: average initial (1990) hourly wages, the share of college-educated workers, brain-skill and our brawn-skill contents. Unsurprisingly, average training rates correlate positively with brain-skill content, initial wage and education level, whereas they correlate negatively with brawn-skill intensity of occupation.

Figure 7 redoes figure 6, replacing average training rates with *changes* in training rates between 1990 and 2010. Training increased relatively more among occupations with high brain-skill content, high starting wages, high education requirements, and/or low brawn-skill intensity. These findings refine the results reported by Cairo (2013) who documents a general rise in worker training but does not explore different rates of increase for different

Figure 4: Average Monthly Job-to-Non-Employment Rates



occupations.[7]

2.5 Wages

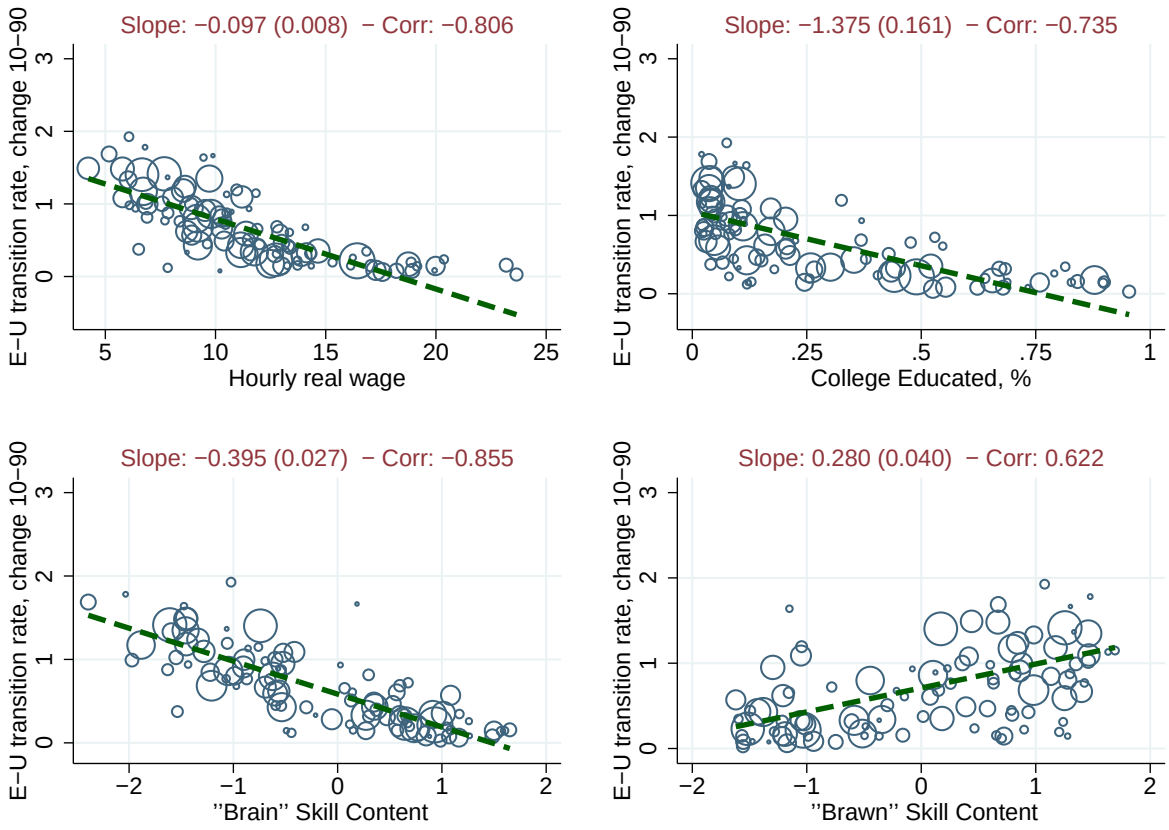
Finally, we examine age-earnings profiles for workers.[8] Using the SIPP, we break these down by training status (Figure 8) and by broad sectoral/skill categories (Figure 9). These graphs simply compare workers of different ages at a given point in time, so their shapes reflect a combination of cohort effects and individual worker ages. Nonetheless, to the extent that cohort effects are common to all cohort members, they are informative about the relative earnings trajectories of different types of workers.

Each set of figures is done twice—once for 1990 (1989-1991 period), and once for 2010

[7]Cairo's (2013) findings are based on the Business Employment Dynamics (BED) database. Cairo and Kajner (forthcoming) use the same data set to show that highly educated workers experience much lower and less volatile separation rates than their less educated peers. They link this finding with differences in on-the-job training, reporting that the average duration of training received on the job is larger for high educated workers.

[8]See Appendix A for description of our measure of labor earnings.

Figure 5: Changes in Job-to-Non-Employment Rates

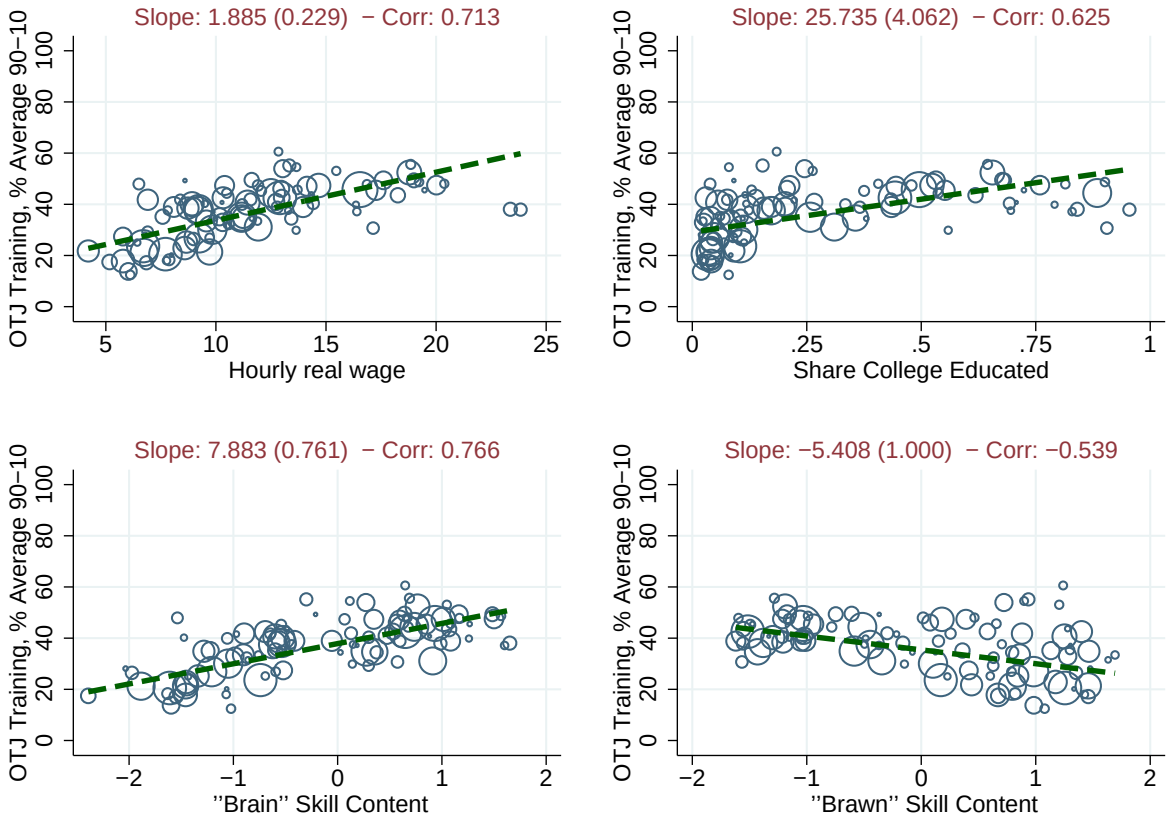


(2008-2011 period). Not surprisingly, in both periods, those who received training tended to show steeper earnings profiles over their first 20 years of labor market participation. (Compare the two curve in either panel of Figure 8.) But compared to untrained workers, trained workers tend to gain more with age during the later subperiod. (Compare the first and second panel.)

Similar comments apply regarding high-skill workers versus low-skill workers. (Compare the two panels in Figure 9.) During the more recent period, the age gradient continues to be positive for a larger share of the working life of the former while it flattens out more rapidly for the latter. This is especially true for those low-skill workers in the non-tradable sectors, which as noted earlier, are the sectors that have been absorbing workers displaced by import competition.

These patterns are consistent with Autor and Dorn's (2013) findings regarding changes in wages by skill level for U.S. workers. Comparing 1980 to 2005 they show that the lowest rates of growth occurred in the middle of the skill distribution, while the highest rates occurred at the top. Our findings are also consistent with the literature on life cycle earnings profiles,

Figure 6: Average fraction of trained workers



though most studies therein do not focus on profile shifts over time.[9]

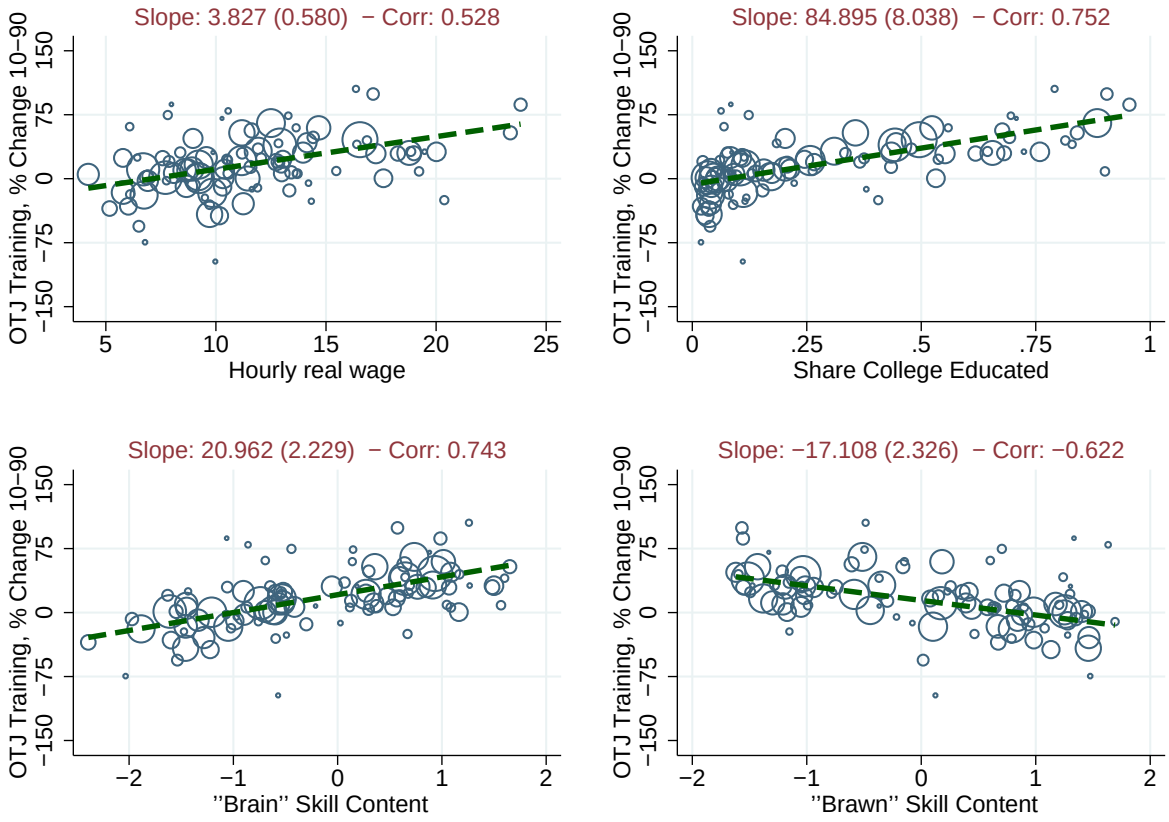
A limitation of figures 8 and 9 is that they are constructed from cross-sectional variation in the data at a point in time. By switching to the PSID, we gain the ability to follow cohorts over substantial portions of their life cycle but we sacrifice the ability to study training rates.

To this end, the top three panels of Figure 10 report life-cycle earnings profiles over the period 1980-1991 for individuals born between 1950 and 1960. The bottom three panels repeat this exercise for individuals born between 1970 and 1980 and observed during the period 2001-2011. As we did for the SIPP, we distinguish between workers employed in tradable and non-tradable occupations and between high and low brain-content occupations.

Figure 10 conveys a message similar to that of Figure 9. Workers in trade-exposed

[9]Bagger et al. (2014) estimate life-cycle earnings profiles for workers with differing amounts of education. They find that early- through mid-career wage growth is more rapid and prolonged for workers with more than 15 years of schooling. They also find a larger accumulated return from experience over the life-cycle for these workers. Their findings are based on Danish matched Employer-Employee data spanning the period 1985-2003. Lagakos et al. (2018) report extensive cross-country comparisons, noting flatter profiles in the poorer countries. They also provide a useful literature review.

Figure 7: Change in the fraction of trained workers



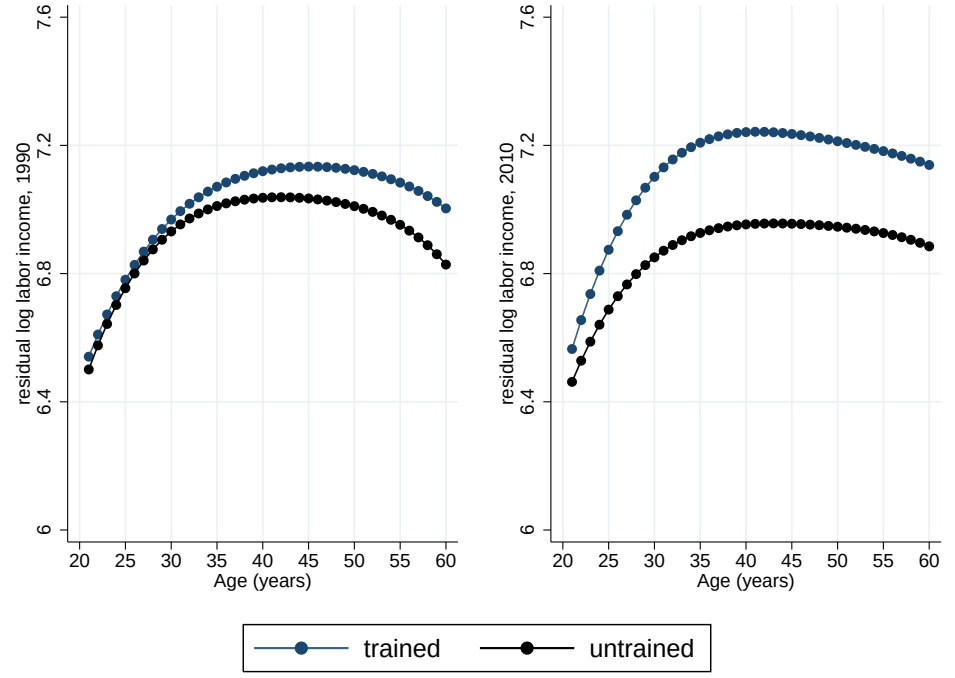
occupations who entered the labor market in 2001 followed a flatter earning trajectory than that of their predecessors. But this was not the case for younger cohorts employed in high-skill non-tradable occupations.

3 The Model

3.1 Agents

We now develop a dynamic model designed to capture the patterns discussed above. Figure (11) displays a schematic summary. The model involves three types of agents: worker/consumers, task-producing firms, and goods producing firms. Task-producing firms essentially serve as employment agencies. They acquire their workers through costly search processes in a frictional labor market and they use them to produce a particular service, or occupations/tasks. Cleaning services, assembly services, and managerial services are examples.

Figure 8: Labor income over the cycle, by training



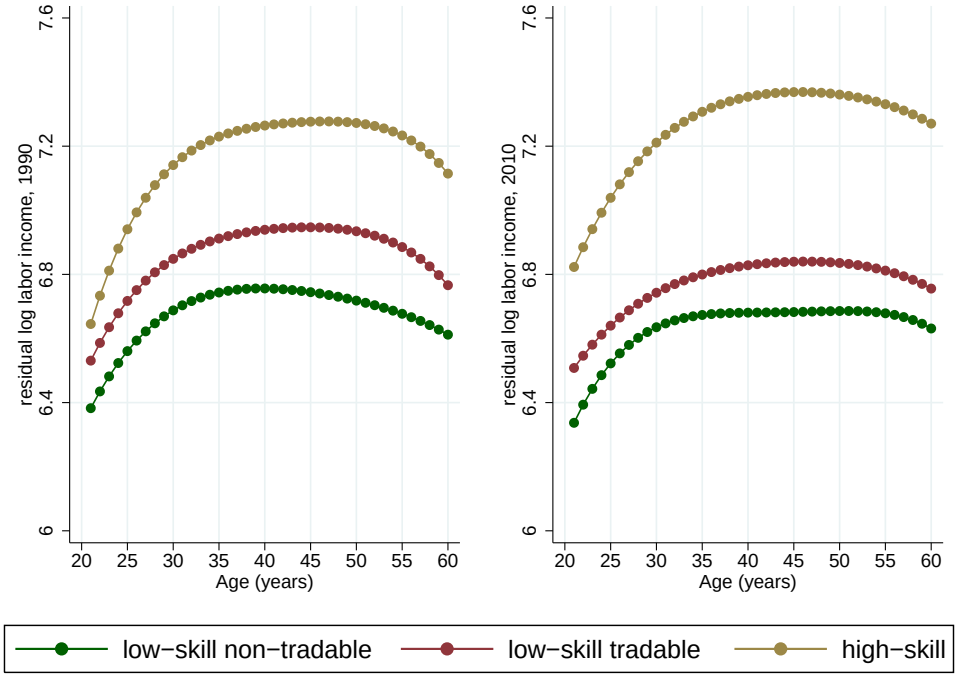
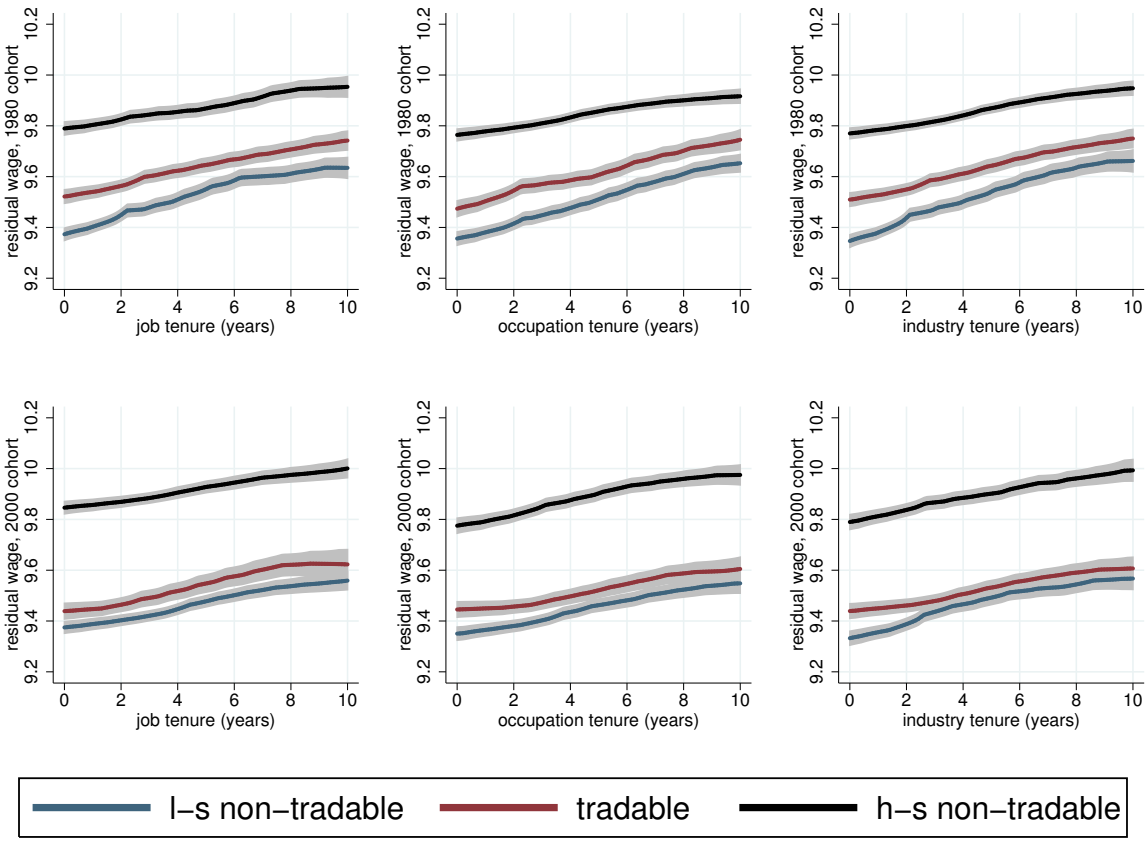


Figure 9: Labor income over the cycle, by occupation

Goods producing firms purchase the services supplied by task producers and combine

Figure 10: Labor income over tenure, by occupation

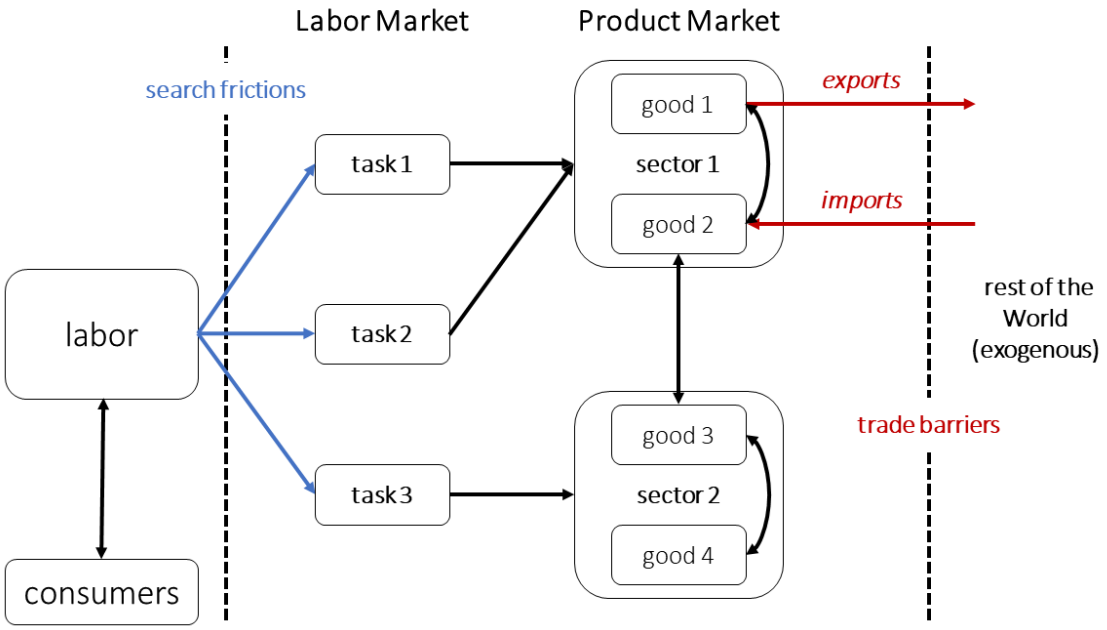


them with intermediate inputs to produce output. Each supplies a particular variety that can be used as either a consumption good or an intermediate input. And those goods producers whose output is tradable compete in global markets, shipping their products to all destinations where their good is cheapest, inclusive of trade costs. Similarly, these goods producers can also obtain their intermediate inputs from a global market.

Finally, worker/consumers supply labor to task producers, accumulating human capital over their life cycles through experience and/or training, improving their wages through on-the-job search, and periodically falling into unemployment.

We begin our description of model specifics with our characterization of workers' life cycles and the task producers who help to shape them. We then link the experiences of these agents to global product markets and explain how they are affected by changes in trade frictions.

Figure 11: Model summary



3.2 Life Cycles and Task Production

Workers are eligible to work upon completion of their schooling, and they participate in the labor force until they experience a retirement shock, which arrives with constant hazard $\delta_\ell > 0$.[10] Each worker is born with an initial ability level $a^0 \in \mathcal{A} = \{a_1, ..., a_I\}$ with $a_{i+1} > a_i$ that is randomly drawn from the cumulative distribution $F_a(\cdot)$. Newly-born workers can invest in a college degree and become highly educated (H) or skip college and enter the labor market immediately as low-skilled (L) workers. Those who go to college incur a utility cost of κ/a^0, so it is less costly for more able individuals to obtain a college degree.

Once chosen, a worker's education type is fixed for the duration of her working career. However, over the course of her working life she stochastically improves her ability level, a, moving though the discrete set $\mathcal{A}$. All workers do so through on-the-job experience, but those whose employers give them on-the-job training tend to enjoy faster rates of improvement. These human capital improvements enhance a worker's productivity in *all* occupations, regardless of which occupation she held when they were made.

Wages also evolve with the arrival of job offers and job separations. Upon entering the labor market, each new worker eventually matches with a firm offering a vacancy for one of the J tasks in the set $\mathcal{S} \equiv \{1, ..., J\}$. If this worker-firm match generates rents, she takes the job and negotiates a starting wage; otherwise she continues searching.

[10] Retirees enjoy no utility and consume no goods, so they could less euphemistically be described as dead.

Once employed, a worker may receive job offers from other firms seeking to fill vacancies, not necessarily of the same type. She may also be separated from her employer by exogenous shocks that destroy her job. The arrival of a job offer constitutes a new opportunity, so it can only improve her expected earning stream. But an unemployment shock does the opposite because it creates gaps in her earnings stream, it interrupts her accumulation of experience, it forestalls any on-the-job training, and it reduces her bargaining power with potential new employers.

The frequency and nature of these changes in occupation, employment status, and expected earnings respond to product market conditions. These in turn reflect the forces of globalization and technological progress. But for now, in order to focus on workers and task-producing firms, we will take product market prices and technologies as given.

3.2.1 Task Production and Training

Together, all the j-type task-producing firms generate the economy-wide supply of task j services for goods producers. Each offers a single job and shares a common, time-invariant productivity factor, s_j. But these task producers are heterogeneous in terms of their idiosyncratic productivity draws, $z \in \mathcal{Z}$, which evolve over time according to a stationary jump process with jump hazard φ and transition probabilities, conditioned on a jump, given by the matrix $\Lambda(z'|z)$.

Task-j producers are also heterogenous in terms of their current employment status: At any point in time, some are matched with workers while others have vacancies they seek to fill. Vacant firms generate flow revenue $-(c^v + c^o)$ where c^v is the cost of remaining visible to job-seekers and c^o is the fixed flow cost of the capital stock all firms acquire upon entry. Producing firms also pay fixed costs c^o, but as will be seen shortly, they generate an output flow that depends on their own productivity, zs_j, and the ability of their employee, a.

While matched to a type-j firm, type-a workers acquire experience, and this causes their ability to jump one step in the sequence $\{a_1, ..., a_I\}$ with hazard γ^1_{Ej}. Further, these workers bargain with their employers over whether they will receive training, which increases their jump hazards by γ^2_{Ej}. Accordingly, the total jump hazard for a type-a worker with education level $E \in \{L, H\}$ at a type-j firm is:

$$\gamma_E(a, j, z) = \gamma^1_{Ej} + \gamma^2_{Ej} \mathbf{1}^t_E(a, j, z), \tag{1}$$

where $\mathbf{1}^t_E(a, j, z)$ is an indicator function characterizing firms' training policies.

The net flow production in a match between a type-j firm with productivity z and a

type-a worker is given by

$$y_E(a, j, z) = z s_j a^{\zeta_{Ej}} - c^o - c^t/a, \tag{2}$$

where ζ_{Ej} is a parameter that governs the return to human capital, c^o is a fixed cost of production and c^t/a is the training-related productivity loss. Hence, workers with higher skills have lower effective cost of training, which helps us to generate a training-premium that is close to one we obsreve in the data.

Aggregating across task producers, the total domestic supply of type-j labor services is

$$N_j \sum_{E\in\{L,H\}} \sum_{\mathrm{a}_i\in\mathcal{H}} \sum_{z\in\mathcal{Z}} y_E(a_i, j, z) f(a_i, z, E|j),$$

where N_j is the (endogenous) measure of type-j employers, and $f_E(\mathrm{a}_i, z, E|j)$ is the (endogenous) distribution of these employers over productivity levels and worker types, (a, z, E).

3.2.2 The matching process

Denote the total measure of vacant jobs in occupation j as V_j and the total measure of workers seeking jobs in occupation j, expressed in units of search intensity, as

$$K_j = \lambda_0^L U_L + \lambda_0^H U_H + \sum_{\tilde{j}\in\Omega_J} \lambda_{\tilde{j},j} N_{\tilde{j}},$$

where $U = U_H + U_L$ is the mass of unemployed workers, $N_{\tilde{j}}$ is the mass of employed workers in occupation $\tilde{j}$. The parameter λ_0^E denotes the visibility of type-E unemployed workers to j-type employers, and $\lambda_{\tilde{j},j}$ measures the visibility of workers employed in occupation $\tilde{j}$ to j-type employers. By letting λ vary with $\tilde{j}$ and j, we allow certain types of workers to be highly visible to certain types of employers, and nearly invisible to others. That is, the $\lambda_{\tilde{j},j}$'s help to control the occupational paths that different types of workers follow as they climb the job ladder.

Aggregate vacancies and searching workers are matched through a standard constant returns matching function,

$$m(V_j, K_j) = \frac{K_j V_j}{(K_j^\chi + V_j^\chi)^{\frac{1}{\chi}}}, \tag{3}$$

where $\chi > 0$ govern the elasticity of matches between open vacancies and the pool of searchers. Thus, letting $\phi_j = m(V_j, K_j)/V_j K_j$, a task-producing firm with a type-j vacancy meets an unemployed worker with hazard

$$\phi_{0,j}^f = \left(\lambda_0^L U_L + \lambda_0^H U_H\right) \phi_j, \tag{4}$$

and it meets a worker currently employed in occupation $\tilde{j}$ with hazard

$$\phi^{f}_{\tilde{j},j} = \lambda_{\tilde{j},j} N_{\tilde{j}} \phi_j. \tag{5}$$

Similarly, an unemployed type-E worker meets a type-j hiring firm with hazard

$$\phi^{E,\ell}_{0,j} = \lambda^{E}_{0} V_j \phi_j, \tag{6}$$

and a worker currently employed in occupation $\tilde{j}$, meets a type-j hiring firm with hazard

$$\phi^{\ell}_{\tilde{j},j} = \lambda_{\tilde{j},j} V_j \phi_j \ . \tag{7}$$

3.2.3 Wage Schedules

Wages are negotiated using a generalized-Nash bargaining protocol, extended to account for changes in the relative bargaining position of workers and firms after productivity jumps or human capital updates.

Negotiation with an unemployed worker. Consider first an unemployed worker with education E and current ability a who meets a type-j task-producing firm with productivity z. Let $S_E(a, j, z)$ be the surplus associated with this match. If $S_E(a, j, z) \leq 0$, the worker and the firm decline to form a relationship. If $S_E(a, j, z) > 0$, the firm hires the worker and engages in Nash bargaining with her to determine her wage. Thus, with worker's bargaining parameter equal to $\beta \in (0, 1)$, the worker's wage w_u is the implicit solution to:

$$J^{e}_{E}(w_u, a, j, z) - J^{u}_{E}(a) = \beta S_E(a, j, z), \tag{8}$$

where $J^{e}_{E}(w_u, a, j, z)$ and $J^{u}_{E}(a)$ are, respectively, the values the worker assigns to the employment and to unemployment.

Bargaining after meeting a potential poacher. We follow Mortensen (2010) and assume that an employed worker leaves his current job if he encounters another job opening with a larger surplus. Consider next a worker with the same education and abilities (E, a) who is currently earning wage w at a type-(j, z) firm. If this worker learns of a vacancy at another firm of type $(\tilde{j}, \tilde{z})$, the effect on her wages depends upon whether the surplus she could generate with the newly encountered firm is larger than the surplus she generates with her current employer: $S_E(a, \tilde{j}, \tilde{z}) > S_E(a, j, z)$. When this condition is satisfied, she abandons her current job to fill the new vacancy, thereby obtaining a share β of the larger surplus. When this condition is not satisfied, the newly encountered firm understands that it will not win a bidding war with the worker's current employer, so it does not make her an

offer and no re-negotiation takes place. More precisely, the worker's post-encounter wage w_o in the two cases can be summarized as follows:

- (Case 1 – Worker moves) $\forall \tilde{z} \in \mathcal{A}_E(a,j,z|\tilde{j}) := \{\tilde{z} \in \mathcal{Z} : S_E(a,\tilde{j},\tilde{z}) > S_E(a,j,z)\}$, w_o is set such that
$$J_E^e(w_o,a,\tilde{j},\tilde{z}) - J_E^u(a) = \beta S_E(a,\tilde{j},\tilde{z}) \tag{9}$$
- (Case 2 – Worker stays) $\forall \tilde{z} \notin \mathcal{A}_E(a,j,z|\tilde{j})$,
$$w_o = w.$$

Renegotiation after productivity shocks. Now consider a type-(a,E) worker employed at type-(j,z) firm when the employer undergoes an idiosyncratic productivity shock, resulting in a new $\tilde{z} \neq z$. If $S(a,j,\tilde{z}) < 0$, the match is endogenously destroyed, the worker becomes unemployed, and the firm posts a new vacancy or exits. If $S(a,j,\tilde{z}) \geq 0$, the firm and the worker engage in Nash bargaining to determine her wage, w_φ. Productivity shocks therefore determine employment and wages according to:

- (Case 1 – Worker becomes unemployed) $\forall z \in \mathcal{B}_E(a,j) := \{z \in \mathcal{Z} : S_E(a,j,z) < 0\}$, $w_\varphi = b_E$
- (Case 2 – Worker renegotiates) $\forall z \notin \mathcal{B}_E(a,j)$, w_φ is set such that
$$J_E^e(w_\varphi,a,j,\tilde{z}) - J_E^u(a) = \beta S_E(a,j,\tilde{z}) \tag{10}$$

Renegotiation after ability shocks. Finally, consider an ability improvement from a to $a' > a$, due either to on-the-job learning or training.[11] It is possible that such a shock improves a worker's outside options sufficiently that she quits her job in order to search for an employer who values her skills more. Then $S(a',j,z) < 0$, the match is endogenously destroyed, and the employer either shuts down or posts a new vacancy. Otherwise, $S(a',j,z) \geq 0$, and the worker engages in Nash bargaining with her employer to determine her new wage, w_γ. These cases can be summarized as follows:

- (Case 1 – Worker becomes unemployed) $\forall z \in \mathcal{C}_E(a,j) := \{z \in \mathcal{Z} : S_E(a',j,z) < 0\}$,
$$w_\gamma = b_E$$

[11] Bagger et al. (2014) consider a simpler version of this scenario with exogenous human capital accumulation.

- (Case 2 – Worker renegotiates) $\forall z \notin \mathcal{C}_E(a,j)$, w_γ is set such that

$$J_E^e(w_\gamma, a', j, z) - J_E^u(a') = \beta S_E(a', j, z) \tag{11}$$

3.2.4 Workers' Problem

High school graduates choose their education levels $E \in \{L, H\}$ before entering the labor market; thereafter the only decisions they make are whether to accept or reject the job offers they receive through a random matching process. However, these decisions are nontrivial for several reasons. First, the rates at which task-specific job offers arrive depend upon workers' current states through the visibility parameters, $\lambda_{\tilde{j},j}$. Second, the wages workers are able to negotiate depend upon their current ability levels, which in turn reflect their employment histories and the training they have received. In this section we summarize their strategies, starting with unemployed workers.

Value of Unemployment. For a worker with education E and ability a, the flow value of being unemployed is:

$$[\rho + \delta_\ell] J_E^u(a) = b_E + \beta \sum_{j \in \mathcal{S}} \phi_{0,j}^\ell \sum_{z \in \mathcal{Z}} \max\{S_E(a,j,z), 0\} v_j(z). \tag{12}$$

Recall that $\rho > 0$ is the discount rate and $\delta_\ell \in (0,1)$ is the exogenous hazard of worker retirement. An unemployed worker enjoys the flow value of unemployment $b_E > 0$ and matches with a type-j task producing firm with hazard $\phi_{0,j}^\ell$. If she has ability a and education level E, the expected surplus she gains from a match with a type-j employer in state z is $\beta \max\{S_E(a,j,z), 0\}$. (Refer to equation 8.) And since we are assuming random matching, we calculate the value of finding a job as the expectation of this object over both the type of job (j) and the productivity of the employer (z). The latter is a random draw from $v_j(z)$.

Value of Employment. For a worker with education E and human capital level a, the flow value of being employed at wage w in a type-j firm with productivity z, $J_E^e(w,a,j,z)$, is:

$$
\begin{aligned}
[\rho+\delta_\ell]J_E^e(w,a,j,z) &= w+\delta_f[J_E^u(a)-J_E^e(w,a,j,z)] \\
&+\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{J_E^e(w_\varphi,a,j,\tilde{z})-J_E^e(w,a,j,z),J_E^u(a)-J_E^e(w,a,j,z)\}\Lambda(\tilde{z}|z) \\
&+\gamma_E(a,j,z)\max\{J_E^e(w_\gamma,a',j,z)-J_E^e(w,a,j,z),J_E^u(a')-J_E^e(w,a,j,z)\} \\
&+\sum_{\tilde{j}\in\mathcal{J}}\phi_{j,\tilde{j}}^\ell\sum_{\tilde{z}\in\mathcal{A}_E(h_i,j,z|\tilde{j})}[J_E^e(w_o,a,\tilde{j},\tilde{z})-J_E^e(w,a,j,z)]v_{\tilde{j}}(\tilde{z})
\end{aligned}
\tag{13}
$$

As noted earlier, δ_f is an exogenous firm destruction rate, φ is the hazard of a firm-specific productivity jump, and $\gamma_E(a,j,z)$ is the hazard of a one-step jump in ability (defined in equation 1). Also, w_φ, w_γ and w_0 are the renegotiated wages associated with productivity shocks, human capital shocks, and outside offers, respectively (refer back to Section 3.2.3). Finally, the set $\mathcal{A}_E(a,j,z|\tilde{j})$ includes all productivity levels for type-$\tilde{j}$ firms that allow them to successfully poach workers with education E and ability a from type$-j$ firms with productivity z.

The intuition behind equation (13) is straightforward. The right-hand side term on the first line is the flow wage associated with the current job, plus the expected capital loss associated with death of the firm. The second line gives the expected capital gains or losses associated with a productivity jump, recognizing that the worker's best option after a bad shock might be to quit her job. The third line gives the expected capital gains associated with human capital accumulation, again recognizing that it may be in the interest of the worker to quit after such a shock. Finally, the fourth line represents the expected capital gain associated with an outside offer that the worker accepts.

The education decision As noted earlier, high school graduates must decide whether to attend college before entering the labor market. Each is born with an initial ability level a^0, which is a random draw from the cumulative distribution $F_a(\cdot)$. Given this beginning state, a graduate optimally chooses to pursue higher education if her initial capital satisfies

$$\frac{\kappa}{a^0}\leq J_H^u(a^0)-J_L^u(a^0),$$

where $\frac{\kappa}{a^0}$ is the utility cost of doing so. Since $J_H^u(a^0)-J_L^u(a^0)$ is monotonic in a^0, this inequality implies a threshold level for initial ability, a^*, below which high school graduates do not invest in higher education. Of course, a^* is an equilibrium object that responds to changes in labor market conditions.

3.2.5 Task-producing Firms' Problem

Value of a Vacant Job. The value of a vacant job for a type-j firm in state z is:

$$\begin{aligned}(\rho+\delta_f)\Pi^v(j,z) &= -c^v+(1-\beta)\phi^f_{0,j}\sum_{E\in\{L,H\}}\sum_{\mathrm{a}_i\in\mathcal{H}}\max\{S_E(\mathrm{a}_i,j,z),0\}g_E(\mathrm{a}_i) \\ &\quad +(1-\beta)\sum_{E\in\{L,H\}}\sum_{\mathrm{a}_i\in\mathcal{H}}\sum_{\tilde{j}\in\mathcal{S}}\phi^f_{\tilde{j},j}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}S_E(\mathrm{a}_i,j,z)f(\mathrm{a}_i,\tilde{z},E|\tilde{j})\end{aligned} \tag{14}$$

Here c^v is the flow cost of keeping a job vacant, $g_E(a)$ is the distribution of unemployed workers with education E over their ability levels, and $f(a,z,E|j)$ is the joint distribution of type-j active matches over firm and worker states. The double summation gives the expected capital gain from matching with an unemployed worker and the quadruple summation gives the expected capital gain from poaching an employed worker.

Entry. Potential firms enter the industry until the expected value of posting a vacancies is no longer positive. In equilibrium with a positive mass of firms, firm will enter if

$$\sum_{z\in\mathcal{Z}}\Pi^v(j,z)\Gamma_z(z)\geq 0 \qquad \forall j\in\Omega \tag{15}$$

Value of an Active Job. For a type-j firm in state z, the value of employing a type (E,a) worker at wage w is:

$$\begin{aligned}&[\rho+\delta_f]\Pi^e_E(w,a,j,z) \\ &= r_j y_E(a,j,z)-c^o-w+\delta_\ell[\Pi^v(j,z)-\Pi^e_E(w,a,j,z)] \\ &\quad +\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{\Pi^e_E(w_\varphi,a,j,\tilde{z})-\Pi^e_E(w,a,j,z),\Pi^v(j,\tilde{z})-\Pi^e_E(w,a,j,z)\}\Lambda(\tilde{z}|z) \\ &\quad +\gamma_E(a,j,z)\max\{\Pi^e_E(w_\gamma a',j,z)-\Pi^e_E(w,a,j,z),\Pi^v(j,z)-\Pi^e_E(w,a,j,z)\} \\ &\quad +\sum_{\tilde{j}\in\mathcal{S}}\phi^\ell_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(h_i,j,z|\tilde{j})}[\Pi^v(j,z)-\Pi^e_E(w,a,j,z)]v_{\tilde{j}}(\tilde{z})\end{aligned} \tag{16}$$

where, as discussed earlier, $y_E(a,j,z)$ is the output flow defined in equation (2) and r_j is the market price for task j. The first line gives the net revenue, adjusted for the expected capital loss associated with exogenous worker separations. The second line gives the expected capital gain or loss associated with a productivity shock, with $w_{\tilde{z}}$ defined to be the renegotiated wage discussed in Section 3.2.3. The third line gives the capital gain or loss associated with an improvement in the worker's human capital, again recognizing wage renegotiation. And

the last line gives the expected capital losses associated with the loss of the worker to a poaching firm. The latter leads to a new wage w_0 as discussed in section Implicit in the max operators on the second and third lines are optimal choices concerning worker retention.

Training decision. Finally, firms train their workers whenever doing so increases the total match surplus. Recognizing that both $y_E(a,j,z)$ and $\gamma_E(a,j,z)$ depend on training, this decision rule implies the policy function:

$$\mathbf{1}_E^t(a,j,z) = \begin{cases} 1 & \text{if} \quad S_E(a,j,z;\mathbf{1}_E^t(a,j,z)=1) \geq S_E(a,j,z;\mathbf{1}_E^t(a,j,z)=0) \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

3.3 Goods Markets and Demand for Tasks

We now turn to our characterization of the goods market, which is based on Caliendo and Parro (2015). The menu of available goods is fixed in the global economy. We group these goods into K general categories (sectors), and we denote the set of available varieties within category k by Ω_k. If category k is tradable, foreign and domestic versions of each variety $\omega \in \Omega_k$ are available to consumers in each country. These are identical up to their price.

All individuals have identical preferences over goods, which are characterized by the nested flow utility function:

$$c(t) = \prod_{k=1}^{K} \left[\bar{c}_k(t)\right]^{\nu_k}, \tag{18}$$

where

$$\bar{c}(t)^k = \left(\int_{\omega \in \Omega_k} \left[c_{k,\omega}(t)\right]^{\frac{\eta_k - 1}{\eta_k}} d\omega \right)^{\frac{\eta_k}{\eta_k - 1}}.$$

Here η_k is the elasticity of substitution between varieties, $\nu_k \in [0,1)$, $(\sum_{k=1}^{K} \nu_k = 1)$, and we have suppressed country subscripts.

Worker-consumers maximize the expected present value of their utility stream,

$$\mathcal{U} = \int_0^\infty c(t) \exp^{-(\rho + \delta_\ell)t} \, dt,$$

where $\rho > 0$ is a subjective discount rate of workers. There is no saving technology, so at each point in time, consumers' spending on type-k goods is given by

$$\bar{p}_k(t)\bar{c}_k(t) = \nu_k I(t),$$

where $I(t)$ is household income and the exact price index for k-type bundles is

$$\bar{p}_k(t) = \left(\int_{\omega \in \Omega_k} \left[p_{k,\omega}(t) \right]^{1-\eta_k} d\omega \right)^{\frac{1}{1-\eta_k}} \tag{19}$$

3.3.1 Goods production

To characterize production, we generalize Caliendo and Parro (2015) to allow for multiple types of labor inputs. Specifically, suppressing time and country subscripts, we assume that within sector k, firms that supply quantity $q_{k,\omega}$ of variety $\omega \in \Omega_k$ do so using the following technology:

$$q_{k,\omega} = e_{k,\omega} \left(\frac{\bar{y}_{k,\omega}}{\alpha_k} \right)^{\alpha_k} \prod_{\tilde{k}=1}^{K} \left(\frac{x_{k,\omega}^{\tilde{k}}}{(1-\alpha_k)\vartheta_{k\tilde{k}}} \right)^{(1-\alpha_k)\vartheta_{k\tilde{k}}}, \tag{20}$$

Here $e_{k,\omega} > 0$ is a productivity draw from a Fréchet distribution, $\bar{y}_{k,\omega}$ is an index of labor service (task) usage, and $x_{k,\omega}^{\tilde{k}}$ is an index of type $\tilde{k}$ intermediate input usage.[12] More precisely, we assume these latter two variables can be expressed as:

$$x_{k,\omega}^{\tilde{k}} = \left[\int_{\tilde{\omega} \in \Omega_{\tilde{k}}} \left(x_{k,\omega}^{\tilde{k},\tilde{\omega}} \right)^{\frac{\eta_k - 1}{\eta_k}} d\tilde{\omega} \right]^{\frac{\eta_k}{\eta_k - 1}}, \tag{21}$$

$$\bar{y}_{k,\omega} = \prod_{j=1}^{J} \left(\frac{y_{k,\omega}^{j}}{\mu_k^j} \right)^{\mu_k^j}, \quad \mu_k^j \geq 0, \sum_j \mu_k^j = 1, \tag{22}$$

where $y_{k,\omega}^{j}$ is the quantity of type-j labor services purchased, and $x_{k,\omega}^{\tilde{k},\tilde{\omega}}$ is the amount of variety $\tilde{\omega} \in \Omega_{\tilde{k}}$ used as an intermediate input.[13] Variation in the task weights $\left\{ \mu_k^j \right\}_{j=1,J;\ k=1,K}$ across sectors (k) creates the link between openness and relative labor demands that will drive our counterfactual experiments. Similarly, *temporal* variation in the task weights $\left\{ \mu_k^j \right\}_{j=1,J;\ k=1,K}$and intermediate shares $\{\alpha_k\}_{k=1,K}$ will allow us to link technological progress to changes in demand for different types of workers.[14]

[12] Provided that we limit our attention to steady state, introducing capital into the production technology does not affect the form of equation (20). Input purchases simply include the replacement of depreciated capital.

[13] Here we are making the standard assumption that producers' variety nest function (21) mimics consumers' sub-utility function (18), thus imposing that consumers and producers who face the same product prices bundle the varieties within a sector in the same way.

[14] The microfoundations for interpreting changes in these coefficients as a consequence of automation can be found in Acemoglu and Restrepo (2018).

3.3.2 Factor markets

To discuss factor markets, it is necessary to distinguish goods by source. Accordingly, we now introduce country superscripts $n \in \{1, ..., N\}$ and apply them as needed.

Bundlers. Also, to keep the accounting tractable, it is convenient to imagine that a measure-zero group of firms bundles the individual varieties from each sector on behalf of producers demanding intermediate inputs and consumers demanding final goods. These agents compose their bundles by maximizing the value of (18), or equivalently, (21) for each dollar they spend. The resulting price index for k-type bundles in country n is

$$\bar{p}_k^n = \left[\int_{\omega \in \Omega_k} \left(p_{k,\omega}^n \right)^{1-\eta_k} d\omega \right]^{\frac{1}{1-\eta_k}}, \tag{23}$$

where $p_{k,\omega}^n$ is the lowest available price for variety $\omega \in \Omega_k$ in country n. Denoting the total value of the k-type bundles they supply X_k^n, the associated quantity index is $Q_k^n = X_k^n / P_k^n$.

Factor prices. The prices for the individual varieties are determined as in Eaton and Kortum (2002). Assuming competitive task and goods markets, equations (20), (21) and (22) imply that the marginal cost of producing variety $\omega \in \Omega_k$ in country n is $u_k^n / e_{k,\omega}^m$, where

$$u_k^n = (\bar{r}_k^n)^{\alpha_k} \prod_{\tilde{k}=1}^{K} \left(\bar{p}_{\tilde{k}}^n \right)^{(1-\alpha_k)\vartheta_{k\tilde{k}}}, \tag{24}$$

$$\bar{r}_k^n = \prod_{j=1}^{J} \left(r_j^n \right)^{\mu_{kj}}, \tag{25}$$

and r_j^n is the market price for task j in country n.

Together with productivity draws $(e_{k,\omega}^n)$ and trade costs, u_k^n values determine the variety prices $p_{k,\omega}^n$ that appear in equation (23). Specifically, taking stock of the prices for each variety in all possible source countries, bundlers choose the cheapest supplier for each variety they purchase. So with perfect competition, the price they pay for type-k, variety ω goods is

$$p_{k,\omega}^n = \min_{\tilde{n}} \frac{d_k^{n,\tilde{n}} u_k^{\tilde{n}}}{e_{k,\omega}^{\tilde{n}}},$$

where $d_k^{n,\tilde{n}} = \kappa_k^{n,\tilde{n}}(1 + \tau_k^{n,\tilde{n}}) \geq 1$ adjusts the f.o.b. prices of imported type-k goods for iceberg trade costs, $\kappa_k^{n,\tilde{n}}$, and tariffs, $\tau_k^{n,\tilde{n}}$. (Neither applies for goods obtained from domestic producers, so $d_k^{n,\tilde{n}} = 1$ for all $\tilde{n}$). As in Caliendo and Parro (2015), we model non-tradable sectors in the same way as tradable sectors but imposing $d_k^{n,\tilde{n}} = \infty, \forall \tilde{n} \neq n$. It follows that in some sectors goods are not traded because it is always cheaper to buy goods from local

suppliers. Thus,

$$p_{k,\omega}^{n} = \frac{u_k^n}{e_{k,\omega}^{n}}.$$

Assuming that the productivity draws $e_{k,\omega}^{\tilde{n}}$ are distributed Fréchet with location parameter $T_k^{\tilde{n}}$ and dispersion parameter θ_k, the share of type-k goods (in value terms *and* in terms of number of varieties) that country n sources from country $\tilde{n}$ is (Eaton and Kortum, 2002):

$$\pi_k^{n,\tilde{n}} = \frac{T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}} \right)^{-\theta_k}}{\sum_{\tilde{n}=1}^{N} T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}} \right)^{-\theta_k}} \tag{26}$$

Also, the associated price of the composite intermediate can be re-stated as:

$$\bar{p}_k^n = A_k \left[\sum_{\tilde{n}=1}^{N} T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}} \right)^{-\theta_k} \right]^{-\frac{1}{\theta_k}} \tag{27}$$

where A_k is a constant.[15] For nontradable goods, (27) simplifies to:

$$\bar{p}_k^n = A_k \left[T_k^n \left(u_k^n \right)^{-\theta_k} \right]^{-\frac{1}{\theta_k}} \tag{28}$$

Finally, the consumer price index in country n is $P^n = \prod_{k=1}^{K} \left(\frac{\bar{p}_k^n}{\nu_k} \right)^{\nu_k}$.

The task market. The demand for tasks in each country is implied by the characterization of variety sourcing summarized above (equations 21 and 22). Each type-k domestic goods producer devotes the share α_k of her revenue to purchasing task bundles, which cost $\bar{r}_k^n$ per unit. Accordingly, in country n, total demand for task bundles by producers of k-type varieties can be written as:

$$\bar{y}_k^n = \frac{\alpha_k}{\bar{r}_k^n} X_k^n \tag{29}$$

Finally, since each task bundle is a Cobb-Douglas aggregation of individual tasks, the demand for task j in country n can be written:

$$y^{n,j} = \sum_{k=1}^{K} \mu_k^j \frac{\bar{r}_k^n}{r_j^n} \bar{y}_k^n \tag{30}$$

Note that this characterization of the task market does not preclude direct trade in tasks (service offshoring). To see how this possibility is accommodated, consider some sector k' that uses no intermediate goods ($\alpha_{k'} = 1$) and only uses type-j tasks ($\mu_{k'}^j = 1$ and $\mu_{k'}^{j'} = 0$ $\forall j' \neq j$). Trade in type-k' varieties is then equivalent to trade in task j.

[15] $A_k = \Gamma(1 + \frac{1-\eta_k}{\theta_k})^{1/(1-\eta_k)}$ where $\Gamma()$ is the gamma function.

Market clearing. To complete our discussion of the generalized Parro and Caliendo (2015) model, we reproduce the market clearing condition for bundles. Total spending by all bundlers in the world on domestically-produced type-$\tilde{k}$ goods is $\sum_{\tilde{n}=1}^{N} \frac{\pi_{\tilde{k}}^{\tilde{n},n} X_{\tilde{k}}^{\tilde{n}}}{1+\tau_{\tilde{k}}^{\tilde{n},n}}$. This induces domestic suppliers of type-$\tilde{k}$ goods in country $\tilde{n}$ to spend $(1-\alpha_{\tilde{k}})\vartheta_{\tilde{k}k} \sum_{\tilde{n}=1}^{N} \frac{\pi_{\tilde{k}}^{\tilde{n},n} X_{\tilde{k}}^{\tilde{n}}}{1+\tau_{\tilde{k}}^{\tilde{n},n}}$ on type-k input varieties from country n. Summing these intermediate demands across countries and sectors, then adding the bundle demands of domestic consumers, yields total type-k bundle demand, which must match supply:

$$X_n^k = \sum_{\tilde{k}=1}^{K} (1-\alpha_{\tilde{k}})\vartheta_{\tilde{k}k} \sum_{\tilde{n}=1}^{N} \frac{\pi_{\tilde{k}}^{\tilde{n},n} X_{\tilde{k}}^{\tilde{n}}}{1+\tau_{\tilde{k}}^{\tilde{n},n}} + \nu_k I_n \tag{31}$$

Here I^n is household income plus government tariff revenue (T^n) plus the current account deficit (D^n), which we will take as exogenous:

$$I^n = Y^n + T^n + D^n, \tag{32}$$

where

$$T^n = \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{n,\tilde{n}}}{1+\tau_k^{n,\tilde{n}}} \tau_k^{n,\tilde{n}} X_k^n, \tag{33}$$

and

$$D^n = \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{n,\tilde{n}}}{1+\tau_k^{n,\tilde{n}}} X_k^n - \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{n,\tilde{n}}}{1+\tau_k^{n,\tilde{n}}} X_k^{\tilde{n}}.$$

3.4 Solving the model

Our model consists of a dynamic block and a static block. The former, developed in Section 3.2, characterizes workers' and task producers' policy functions and thereby determines the steady state supply of tasks as a function of task prices. The latter, developed in Section 3.3, characterizes spot market equilibria in global product markets and thereby determines demand for tasks at any set of task prices. We find the global steady state equilibrium by iterating between these two blocks until the vector of task prices clears all task markets. In doing so, we treat labor markets in countries *other* than the U.S. as competitive in order to keep the speed of the solution algorithm managable. We also shut down intra-national worker heterogeneity in these countries, effectively fixing their task supplies. This is necessary because data are unavailable on the composition of some countries' work forces.

To perform counterfactual analyses we first impute base year task prices from data and solve the dynamic block, thereby imputing base year task supplies.[16] Once we have our base

[16]Details concerning the construction of task prices appear in Appendices C and D.

year solution, we perform counterfactual analyses using standard "hat algebra" techniques. Beginning from an exogenously given shock to trade costs, $\hat{d}_k^{n,\tilde{n}}$, and/or technology, $\mu'_{kj} - \mu_{kj}$, $\alpha'_k - \alpha_k$, we guess an associated vector of changes in task prices $(\hat{\mathbf{r}}_{US}, \hat{\mathbf{r}}_{ROW})$. These task prices imply a new vector of task supplies through the dynamic block, as discussed above, and a new vector of task demands based on the static block. If these task demands match the task supplies $\mathbf{y}$, the equilbrium has been identified; if not, we update the vector of task prices and repeat the calculations. A full description of our algorithm for counterfactual analysis appears in Appendix B.

4 Calibration

We turn next to a calibration that links changes in global market conditions to changes in individuals' career trajectories. This exercise involves calibrating the parameters that determine prices in the global economy at each vector of task prices, and it involves a more detailed characterization of U.S. labor markets. We use as the numeraire US average per capita income in 2005.

Calibrating the spot market for goods and tasks We treat the world economy as composed of 30 countries, plus a constructed rest of the world.[17] We consider $K = 30$ ISIC Rev.3.1 sectors, reported in Appendix D, Table 11, the first $K_1 = 15$ of which are defined as tradable. We set the number of occupations to 5 following the 1-digit SOC classification, and corresponding to Management, Business, Science, and Arts Occupations (SOC $11-29$), Service Occupations (SOC $31-39$), Sales and Office Occupations (SOC $41-43$), Natural Resources, Construction, and Maintenance Occupations (SOC $45-49$) and Production, Transportation, and Material Moving Occupations (SOC $51-53$).

Parameters from other sources. Table 1 reports the parameters we need in order to characterize the spot markets for goods and tasks.[18] Some of these are available from other sources. In particular, we take the elasticities of substitution between varieties, $\{\eta_k\}$, from Broda and Weinstein (2006), and (for now) we take both the productivity dispersion parameters $\{\theta_k\}$ and tariff rates $\{\tau_k^{n\tilde{n}}\}$ from Caliendo and Parro (2015). The latter are based in turn on the UNCTAD TRAINS dataset.

[17]The countries are Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, UK, and USA.

[18]Note that, because wages are determined by a bargaining protocol rather than a zero-profit condition, we are unable to use the "hat algebra" approach due to Deckle et al. (2008) for counterfactual analysis. Thus, in addition to production function parameters and tariff rates, we need estimates of iceberg transport costs $\{\kappa_k^{n,\tilde{n}}\}_{k,\tilde{k}=1,..,K}^{n,\tilde{n}=1,..,N}$ and sectoral efficiency parameters $\{T_k^n\}_{k,\tilde{k}=1,..,K}^{n=1,..,N}$.

Table 1: Markets for goods - Parameters

Parameters	Description	Data Source
	Estimated	
ν_k	Consumption elasticity of product k	WIOD-IOT (2013)
$\vartheta_{k\tilde{k}}$	Sector k output elasticity of sector $\tilde{k}$ intermediates	WIOD-IOT (2013)
α_k	Sector k output elasticity of labor tasks	KLEMS (2017)
μ_{kj}	Industry k labor tasks elasticity of task j	OES (2017)
$\kappa^k_{n\tilde{n}}$	Bilateral iceberg costs (countries n and $\tilde{n}$, sector k)	WIOD-IOT (2013)
T^k_n	Location Frechet (country n, sector k)	WIOD-IOT (2013)
	Taken from the literature	
η_k	Elasticity of substitution between varieties (sector k)	Broda and Weinstein (2006)
$\tau^k_{n\tilde{n}}$	Bilateral tariffs (countries n and $\tilde{n}$, sector k)	Caliendo and Parro (2015)
θ_k	Dispersion Frechet (sector k)	Caliendo and Parro (2015)

Estimated share parameters. The country-specific production function parameters $\{\alpha^n_k, \mu^n_k, \vartheta^n_{k,\tilde{k}}\}$ govern elasticities of output with respect to task bundles, individual tasks, and intermediate inputs. (Refer to equation 20.) Given our assumption of Cobb-Douglas technologies, we base these on the cost shares implied by the World Input-Output Tables (WIOD-IOT) and by the U.S. Bureau of Economic Analysis's Integrated Indsutry-Level Production Accounts (KLEMS). Appendix D, section 8.1 provides details.

Estimated trade parameters. Taking trade shares $\pi^{n,\widetilde{n}}_k$ from the 2005 WIOD, task prices ($\bar{r}^n_k$) from 2005 SIPP data, and θ_k values from Caliendo and Parro (2015). Because we use standard "hat algebra" techniques to perform counterfactual analyses, we do not need to estimate location parameters ($T^{\tilde{n}}_k$) or iceberg trade costs ($d^{n,\widetilde{n}}_k$).

Calibrating the labor market. In order calibrate parameters that relate to the labor market, we first assign values to several parameters based on their data counterparts or choose them based on available estimates from the literature. These parameters are listed in Table 2. We set the model period to a month and set the discount factor ρ to correspond to a 4% annual interest rate. As we detail below, when we calibrate several parameters to match a set of labor market moments, we focus on workers who are between 25 and 60. As a result, the probability of retirement, δ_w, is chosen so that on average workers stay in the model for 35 years. We chose δ_f to match the rate of employment loss due to firm closing.[19]

For the matching function, we set χ, the elasticity of matches between open vacancies and the pool of searchers, to 0.45, a value estimated by Den Haan et al (2006) for the US economy. Following Pissarides (2009), we assume that workers and firms have the same

[19]We use information from Business Employment Dynamics dataset reported in the BLS website. See https://data.bls.gov/cgi-bin/dsrv?bd .

Table 2: Labor Market - External Parameters

Parameter	**Description**	**Value**	**Source**
ρ	Discount factor	0.0033	4% yearly
δ_w	Retirement rate	0.0023	ages 25-60
δ_f	Firm exit rate	0.0045	BLS 2005
β	Bargaining power	0.50	Pissarides (2009)
χ	Matching function	0.45	Den Haan et al (2006)
(b_L, b_H)	Home production	(0.31, 0.52)	ACS 2005
c_v	Cost of vacancy	0.29	Abowd and Kramarz (2003)
c_t	Cost of training	0.16	Abowd and Kramarz (2003)
$(\alpha_{a_0}, \beta_{a_0})$	Distribution of a_0	(2.11, 2.45)	AFQT test distribution
(φ, Δ_z)	Productivity shock	(1.57, 0.24)	Lee and Mukoyama (2015)

bargaining power, i.e. $\beta = 0.5$. For value of home production, b_E, we simply compute average non-wage income for unemployed workers as a fraction of average monntly income from the 2005 American Community Survey (ACS). As in Hagedorn and Manovskii (2008), we take value of cost of vacancy (c^v) and cost of training (c^t) from Abowd and Kramarz, who compute these values for France.[20] The initial distribution of worker abilities, $F_a(\cdot)$, is assume to be a beta distribution with parameters $(\alpha_{a_0}, \beta_{a_0})$. We chose these parameters replicate the The Armed Forces Qualification Test (AFQT) percentiles from the National Longitudinal Survey of Youth 1997 (NLSY97).

Finally, we treat z as a Poisson jump process with hazard φ and realizations

$$\ln z' = \begin{cases} \ln z + \Delta_z \\ \ln z - \Delta_z \\ \text{other} \end{cases} \text{ with probability } \begin{cases} \frac{1}{2}\left(1 - \frac{\ln z}{n\triangle}\right) \\ \frac{1}{2}\left(1 + \frac{\ln z}{n\triangle}\right) \\ 0 \end{cases},$$

where $2g+1$ is the number of discrete points in the support of $\ln z$, $\ln Z \equiv \{-n\Delta_z, -(n-1)\Delta_z, ..., 0, ..., n\Delta_z\}$. Shimer (2005) shows that this process is approximated by the differential equation $dy = -\gamma_y y dt + \sigma_y d\epsilon$, which can be estimated using discrete data as an AR(1) to obtain approximations to γ_y and σ_y. The jump hazard can then be retrieved as $\varphi = n\gamma_y$ and the step size parameter can be retrieved as $\Delta_z = \sigma_y/\sqrt{\varphi}$. Using Lee and Mukoyama's (2015) estimates of an AR(1) productivity process for U.S. establishments ($\gamma_y = 0.157$, $\sigma_y = 0.301$) and choosing $n = 10$, we obtain $\varphi = 1.57$ and $\Delta_z = 0.24$.

[20] Abowd and Kramarz (2003) estimate a per-working hiring cost of 5560 FF in 1992, which is 772\$ in 1992. We convert this to 2005 US\$, 1073\$ (using CPI). In terms of our numeraire (monthly GDP per capita), this is 0.29. They also estimate a cost per worker of 3025 FF in 1992, which is 584.01\$ in 2005, which is in terms of our numeraire 0.158.

We then make several parametric assumptions to reduce the number of parameters to be able to match them to a set of moments from the data. Recall that the production function for tasks is given by

$$y_E(a, j, z) = z s_j a^{\zeta_{Ej}} - c^o - c^t/a.$$

For s_j values, we assume that

$$s_j = (1 + \Delta_s)^j.$$

Parameter Δ_s captures how much on average hourly wage rates (as a proxy for productivity) grow in different occupations, with occupation $j + 1$ having a higher productivity than occupation j.

We also assume that $\zeta_{Ej} = \zeta_E$ for all j. Similarly, for the on-the-job-learning and training hazards,

$$\gamma_E(j, z, i) = \gamma^1_{Ej} + \gamma^2_{Ej} \mathbf{1}^t_E(j, z, i),$$

we also set $\gamma^1_{Ej} = \gamma^1_E$ and $\gamma^2_{Ej} = \gamma^2_E$ for all j.

Finally, for labor market visibility parameters, we set

$$\lambda_{0,j} = \lambda_0,$$

i.e. all unemployed workers have the same visibility to all occupations, and assume that visibility of worker who are currently employed in occupation j to firms in occupations $\widetilde{j}$ is given by

$$\lambda_{\tilde{j},j} = \frac{\lambda_1}{\left[1 + d(j, \tilde{j})\right]^{\xi}},$$

where $d(j, \tilde{j})$ is a measure of the distance between task j and task $\tilde{j}$ based on their brain and brawn content. The functional form for $d(j, \tilde{j})$ is taken from Traiberman (2017), who expresses the task content of each occupation j as a vector of loadings $\boldsymbol{\upsilon}^j$ on O*NET job characteristics and writes the distance between occupations j and $\tilde{j}$ as $d(j, \tilde{j}) = \sqrt{\left(\boldsymbol{\upsilon}^j - \boldsymbol{\upsilon}^{\tilde{j}}\right)' \sum^{-1} \left(\boldsymbol{\upsilon}^j - \boldsymbol{\upsilon}^{\tilde{j}}\right)}$ where $\sum = var(\boldsymbol{\upsilon})$. (Note that $d(j, \tilde{j})$ is unit-free and parameter-free.)

Given all these assumptions, and that the fixed cost of production, c^0, is determined by the free entry condition, we have 11 parameters to calibrate:

$$\boldsymbol{\theta} = \{ \underbrace{\kappa}_{\text{education}} , \underbrace{\Delta_s, \zeta^E, c^o}_{\text{production (4)}} , \underbrace{\gamma^1_E, \gamma^2_E}_{\text{training (4)}} , \underbrace{\lambda_0, \lambda_1, \xi}_{\text{visibility (3)}} \}.$$

We select these parameters to match a set of labor market moments. Let $\mathbf{M}$ represent a vector of these moments. A vector of the analogous moments can be obtained from the steady state equilibrium of the model. The moments for the model are a function of the

Table 3: Tasks Market - Calibrated Parameters

Parameter	Description	Value
κ	Cost of college education	181.02
c^o	Cost of operating	1.18
Δ_s	Permanent productivity	0.64
λ_0	Visibility, unemployed	0.032
(λ_1, ξ)	Visibility, employed	(0.038, 0.02)
(ζ^L, ζ^H)	Return from human capital	(0.09, 0.24)
(γ_L^0, γ_H^0)	Experience, hazard rate	(0.03, 0.05)
(γ_L^1, γ_H^1)	Training, hazard rate	(0.06, 0.15)

parameters to be estimated. Let $\mathcal{M}(\boldsymbol{\theta})$ represent this vector of moments, where $\boldsymbol{\theta}$ denotes the vector of 12 parameters to be estimated. Define the vector of deviations between the data and the model by $\mathbf{G}(\boldsymbol{\theta}) \equiv \mathbf{M} - \mathcal{M}(\boldsymbol{\theta})$. Minimum distance estimation picks the parameter vector, $\boldsymbol{\theta}$, to minimize a weighted sum of the squared deviations between the data and the model, i.e.,

$$\widehat{\boldsymbol{\theta}} = \arg\min \mathbf{G}(\boldsymbol{\theta})' \mathbf{W} \mathbf{G}(\boldsymbol{\theta}).$$

The estimated parameters $\widehat{\boldsymbol{\theta}}$ is consistent for any semi-definite matrix $\mathbf{W}$. We set $\mathbf{W}$ equal to the identity matrix. Table 3 shows the estimated parameter values.

As discussed in Section 3.4, for a given set of task prices $\mathbf{r} = [\mathbf{r}_{US}, \mathbf{r}_{ROW}]$ the model economy generates demand and supply of tasks.[21] Iteration on $\mathbf{r}$ equates the two. For the base year calibration, we take $\mathbf{r}$ from data and find parameters such that model-based moments are matched with data counterparts. (Details appear in Section 4 below.)

Measuring task prices in the U.S. is challenging, since these include both the labor income received by workers and income received by task-producing firms. The former can be easily measured using data on wages across occupations, but the latter are unobservable. Conceptually, task producers' incomes cover the costs of filling a vacancy and the discounted flow operating costs. So although they are a modeling device with no exact correspondence in the real world, we approximate their total income using the cost of firms' human resource departments. Task prices in other countries are simply wages, since we treat labor markets as competitive there. Further details appear in Appendix E.

Model Fit. Table 4 shows chosen moments from the data and their model counterparts. Appendix A details the construction of data moments. We target 3 different sets of moments

[21] In countries other than the U.S., we treat labor markets as competitive, we shut down intra-national worker heterogeneity, and we take the labor supply as exogenous.

Table 4: Estimation moments

Moments	**Data** (2005)	**Model**
Labor income		
College premium	0.557	0.491
St.Dev., non-college	0.605	0.375
St.Dev., college	0.735	0.641
45-25 y.o. premium, non-college	0.261	0.144
45-25 y.o. premium, college	0.482	0.376
Training premium	0.376	0.103
Brain-skill premium	0.337	0.199
Labor market flows		
NE-E rate	0.023	0.016
E-NE rate	0.022	0.025
J-J rate	0.015	0.022
Shares		
College share	0.281	0.310
Training share	0.392	0.304

for 2005. The first set pertains to inequality among workers. In particular, we target standard deviation of log residual earnings among college and non-college workers, and the college premium (see Table 9 in Appendix A). Both in the data and the model, there is more inequality among college-educated than non-college educated workers. In the model economy, this happens as college educated workers are more likely to receive training. The inequality gap between college and non-college educated workers is, however, larger in the data than it is in the model economy.

We also compute life-cycle earnings growth for college and non-college educated worker, captured by wage growth between ages 45 and 25 (see Figure 12 in Appendix A) Again both in the data and the model, college educated worker have steeper age-earnings profiles. Finally, we force the model to generate training premium (earnings of workers with training relative to earnings of workers without training) as in Figure 8 of Section 2 and brain skill premium, i.e. earning gaps between occupation with the highest skill, s_j, relative to occupations in lowest skill (see Table 10 in Appendix A). These inequality targets allow us to discipline production parameters (Δ_s and ζ^E) and parameters for the learning-by-doing and training hazards (γ_E^1 and γ_E^2).

The second set of moments are on monthly labor market flows: the transitions between employment and non-employment and between jobs (see table 7 in Appendix A). These

Table 5: Imputed task price changes

tasks j	1	2	3	4	5
1-digit SOC	31-39	51-53	41-43	45-49	11-29
Brain-content	0	0.056	0.134	0.236	1
Δr_j, %	+3.55	- 4.14	-1.62	-2.43	+10.12

target are mainly determined by parameters that affect the visibility of workers in the labor market, (λ_0, λ, and ξ). The last set of moment are the fraction of workers that receive college education (which determines κ) and training.

Generic counterfactual. In this section we present a simple counterfactual exercise to highlight how labor market in the model economy react to changes in task prices. As a proxy for changes in prices of tasks, we simply use changes in average wages in each occupations and reconstruct the price of each task as we describe above. Recall that the benchmark economy is calibrated to 2005. Hence, the exercise goes back to 1990, before the large increase in the US imports, and studies the effects of changes in task prices on inequality, training, and labor market flows. The exercise abstracts from trade equilibrium, by shutting down link between product markets and task markets. A full-fledged counterfactual would study how changes in tariffs and iceberg costs would affects task prices and feed to labor market outcomes in general equilibrium.

Table 5 shows changes in task prices. The task prices (or average wages) for occupations in the middle of the skill distribution declined between 1990 and 2005, while task prices for occupations at the bottom and the top have increased. How would workers and firms react to these changes in the model economy? Table 6 compares the counterfactual economy with the benchmark economy.

There is a lower number of vacancies posted by the task-producing firms that are in the middle of the job ladder, while task producers firms at the top and the bottom will increase their demand for workers. The employment shares in each occupation simply mimic changes in task prices. Changes in task prices are also reflected in how much average earnings change in different occupations. As the surplus from matches in middle of the job ladder decline, these firms will be less willing to provide training to the workers. At the same time, workers in these firms also see less benefit from training since probability of going up in the ladder is lower. While surplus of the firms at the very bottom of the job ladder increase, the training in these firms also decline for the exact same reason. In contrast, the training at the top of the ladder increases. These workers have strong incentives to train and not to fall in the

Table 6: Counterfactual outcomes

tasks j	1	2	3	4	5
1-digit SOC	31-39	51-53	41-43	45-49	11-29
Brain-content	0	0.056	0.134	0.236	1
Employment share, $\Delta\%$	+0.9	-1.5	-0.8	-0.7	+2.1
J-J rate , $\Delta\%$	-1.06	-0.57	-0.43	-0.48	0.02
E-NE rate, $\Delta\%$	+0.01	+0.60	+0.40	+0.07	-0.05
Training share, $\Delta\%$	-1.03	-27.23	-15.39	-11.20	+12.54
Labor income, avg. %	+2.61	-4.12	-3.12	-1.04	+6.01
Labor income growth, 45-25 y.o. %	+0.02	-5.32	-3.45	-0.95	+7.32

job ladder. With a gap in the middle of the job ladder, there is also a decline in the job-to-job transitions and an increase in employment to non-employment transitions for low-skill occupations. All these forces make wages more stagnant along the life-cycle for workers who are again in the middle of the job ladder. These changes are broadly consistent with the set of facts documented in Section 2.

Trade shock counterfactual

(in progress)

Technology shock counterfactual

(in progress)

Composite counterfactual

(in progress)

5 Conclusion

In this paper, we study the effect of offshoring and import competition on workers' careers, employment reallocation and earning trajectories. To do so, we develop an open-economy search model that connects trade exposure to the career development of workers. In this framework, globalization destroys low-skill jobs in the trade exposed occupations - thereby changing incentives to invest in college degrees and on-the-job training - whereas improving the relative demand for high-skill occupations. After calibrating our model to data, we show that the changes in career paths and earning trajectories observed in the US economy in the last 30 years they can be viewed as closely interrelated consequences of import competition and offshoring. More generally, this paper contributes to the literature on trade and labor market providing a structural micro-foundation of a number of reduced form evidence linking trade openness to labor market performance and inequality.

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APPENDIX A - Data

The Survey of Income and Participation Program (SIPP) data. The Survey of Income and Participation Program (SIPP) is a household-based survey designed as a continuous series of national panels. Each panel features a nationally representative sample interviewed over a multi-year period lasting approximately four years. The SIPP is a source of data for a variety of topics and provides for the integration of information for separate topics to form a single, unified database. This allows for the examination of the interaction between tax, transfer, and other government and private policies. Government policy analysts depend heavily upon the SIPP for information on the distribution of income and the success of government assistance programs. The SIPP collects information for assistance received either directly as money or indirectly as in-kind benefits. The SIPP data provide the most extensive information available on how the nation's economic well-being changes over time, which has been the SIPP's defining characteristic since its inception in 1983. The sample size ranges from approximately 14000 to 52000 interviewed households.

There are in total 14 Panels of the SIPP (1984-1993, 1996, 2001, 2004, 2008). Panels do not have uniform starting and ending dates: as a result some Panels overlap. However, each individual in the SIPP belongs to only one Panel. In each Panel, individuals are interviewed every month (these interviews are called waves), and asked retrospective monthly labor market questions. A set of core questions are asked in every wave. Some additional questions, including those concerning training, are asked only in particular waves. In the main text, we make use mainly of three Panels: 1990, 2008 and 2012 Panels.

The survey provides information about an individual's work history from the beginning of the reference year through the interview month. In particular, the topics covered in the survey include weeks of employment, amount and type(s) of earnings, and business characteristics. For respondents with a period time not working, SIPP collects data on the reasons why the respondent did not hold a job, and whether the respondent looked for work. Basic information about the job such as beginning and ending dates, the type of work arrangement, and reason for the job ending (when applicable) are collected as well. Respondents are asked whether the jobs currently held are with the same employer as in the previous month or not, and a job identifier is recorded. While it is not possible to assess whether two individuals held a job with the same employer (SIPP is not a matched employer-employee dataset), the data allow one to keep track of the identity of a job for each individual. Together with information about employment status in each week of the current month, the SIPP therefore allows to identify the monthly employer-to-employer transition of workers. Information about the type of occupation allows to recover occupation-to-occupation transition of workers, both between employers and within the same employer.

Information on hourly wages workers paid by the hour is collected in SIPP at every interview for up to two jobs held during the survey′s four month reference period.

The data we used are based on the original files available for download at *http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html*. In the main analysis, we use observations from individuals aged 25-60, for whom we require complete information on the individual′s employment status, age and employer id. We only consider an individual's primary job, defined as the employment position where the largest share of hours worked is spent, and we drop workers who are recalled by former employers or have missing reporting months during a job spell. We also drop workers who report theyare enrolled in school, self-employed, family-workers, members of the armed forces, workers at non profit companies and anyone whose wage information was imputed by the SIPP.

The Occupation Information Network (O*NET) Database. The Occupational Information Network (O*NET henceforth) database is source of occupational information in the U.S. labor market developed by the U.S.Department of Labor, containing information on hundreds of occupations, classified using the 8-digit 2010 Standard Occupation Classification. This database is a replacement for the Dictionary of Occupational Titles (DOT) which was extensively used in earlier research.[22] The O*NET database describes the key features of an occupation using a standardized and measurable set of variables called "descriptors". A subset of these descriptors are related to worker skills and measures cognitive abilities, psycho-motor abilities and physical abilities required to perform at each occupations.

Occupational Codes: recoding the SIPP and O*NET. The Standardized Occupation Classification (SOC henceforth) structure is summarized in a 6-digit coding system, in which the first two digits indicate the major group, the third digit represents the minor group, the fourth and fifth digits correspond to the broad occupation and the sixth digit signals the detailed occupation (SOCPC, 2010). For instance, sales managers (11-2022) is a detailed occupation contained inside a broad occupation called *"Advertising and Promotions Managers"* (11-2010), which is part of a minor group called *"Advertising, Marketing, Promotions, Public Relations, and Sales Managers"* (11-2000). This minor group belongs to a major group called *"Management Occupations"* (11-0000). In the main text, we refer to 4-digit 2002 SOC occupation classifications. To homogenize the occupation structure across different data sources, we had to perform a number of re-classifications.

Occupation classifications in the SIPP differ by Panels. In the 2008, 2004 and 2001 Panels, occupations are coded using the 4-digit 2000 Census Occupations Classification, while

[22]See for instance Autor, Levy and Murnane (2003), Goos and Manning (2007), Bacolod and Blum (2010).

in Panels before 1996, occupations are coded using the 4-digit 1990 Census Occupations Classification. Both classification are reclassified into the 6-digit 2002 SOC equivalents. Conversion is made possible through the crosswalks provided by the U.S. Census Bureau, available at *census.gov/people/io/methodology/*, and by the National Longitudinal Survey of Youth (NLSY79), available at
nlsinfo.org/site/nlsy97/nlsdocs/nlsy97/codesup/Round7CS/matt1codes90.htm
Technical paper No. 65 (Scopp 2003) describes the relation between the 1990 and 2000 Census Occupation System. It can be downloaded at *census.gov/people/io/files/techpaper2000.pdf*

The 15^{th} edition of the O*NET classifies occupations using an 8-digit code. The first 6 digits correspond to the equivalent 6-digit SOC 2010 detailed occupation, while the seventh and eighth digit further disaggregate occupations. If no refinement is made, then the seventh and eighth digits are equal to "00". In the overwhelming majority of the occupation, there is a perfect match between an 8-digit O*NET SOC code and a 6-digit SOC 2010 occupation. In the remaining cases, when the last two digits are different than "00", the refined (8-digit) occupations are grouped within the relative detailed (6-digit) definition, and the average observation is assigned. Starting from 964 8-digit 2010-SOC different occupations, we end up with 763 6-digit 2010 SOC different equivalents, which are further converted into 6-digit 2002 SOC occupations using crosswalks provided by the Bureau of Labor Statistics (BLS), and available at *bls.gov/soc/soccrosswalks.htm*.

For the majority of occupations, there is a one-to-one correspondence between most detailed occupations from both systems. In some cases though, two or more 2012 SOC detailed occupations were grouped into a unique title in the 2002 classification. For instance, the 2012 SOC codes for *"Computer and Information Research Scientist"* (15-1111), *"Computer Systems Analysts"* (15-1121) and *"Computer Occupations, All Other"* (15-1199) are recoded into a unique 2002 title, 15-10XX, *"Computer Scientists and Systems Analysts"*. Same happens with the 2012 SOC codes for *"Registered Nurses"* (29-1141), *"Nurse Anesthetists"* (29-1151), *"Nurse Midwives"* (29-1161) and *"Nurse Practitioners"* (29-1171), that were grouped into *"Registered Nurses"*, coded as 29-1111 under the 2002 SOC.

To ensure representativeness in the empirical analysis, we further aggregate the 6-digit SOC from both the SIPP and the O*NET into a 4-digit SOC structure, by grouping detailed definitions of occupations into minor groups (up to third digit) and keeping the fourth digit to describe the broad occupation. Eventually, we are left with 105 different 2002 SOC occupations, of which 5 belong to *"Management Occupations"* (major code: 11), 3 to *"Business and Financial Operations Occupations"* (major code: 13), 2 to *"Computer and Mathemati-*

cal Occupations" (major code: 15), 4 to *"Architecture and Engineering Occupations"* (major code: 17), 4 to *"Life, Physical, and Social Science Occupations"* (major code: 19), 2 to *"Community and Social Service Occupations"* (major code: 21), 2 to *"Legal Occupations"* (major code: 23), 6 to *"Education, Training, and Library Occupations"* (major code: 25), 4 to *"Arts, Design, Entertainment, Sports, and Media Occupations"* (major code: 27), 4 to *"Healthcare Practitioners and Technical Occupations"* (major code: 29), 3 to *"Healthcare Support Occupations"* (major code: 31), 4 to *"Protective Service Occupations"* (major code: 33), 4 to *"Food Preparation and Serving Related Occupations"* (major code: 35), 3 *"Building and Grounds Cleaning and Maintenance Occupations"* to (major code: 37), 7 to *"Personal Care and Service Occupations"* (major code: 39), 5 to *"Sales and Related Occupations"* (major code: 41), 10 to *"Office and Administrative Support Occupations"* (major code: 43), 4 to *"Farming, Fishing, and Forestry Occupations"* (major code: 45), 7 to *"Construction and Extraction Occupations"* (major code: 47) 4 to *"Installation, Maintenance, and Repair Occupations"* (major code: 49), 11 to *"Production Occupations"* (major code: 51), 8 to *"Transportation and Material Moving Occupations"* (major code: 53) and the last one to *"Military-related Occupations"* (major code: 55).

The graphs in Section 2 of the text are based on the 105 codes described above. But to solve and estimate of the model, we employ occupational data at higher levels of aggregation than the SOC major groups. To maintain consistency and representativeness, we use the data tabulation proposed by the U.S. Bureau of Labor Statistics, reported in Table 3 of the 2002 SOC User Guide. This aggregation results into 22 final major occupational categories (*major codes*, reported above), plus *"Military-related Occupations"* which is excluded.

Skill-Intensity Measures. For each occupation available in the O*NET, we construct measures of cognitive (brain) and manual (brawn) skill content using the Principle Component Analysis (PCA) based on the correlation matrix between descriptors.[23] Following the literature, we perform two separate PCAs (one for brain skills, one for brawn skills) on two different sets of selected descriptors of abilities. Since O∗Net rates these abilities using two scales, *"importance"* and *"level"*, we follow Blinder (2007) and combine the two scales in a Cobb-Douglas fashion, giving weights of two third to *"importance"* and one third to *"level"*. Letting I_{ij} and l_{ij} represent respectively the values for the importance and the level of a given descriptor i, the final attribute i of occupation j will be equal to $s_{ij} = I_{ij}^{\frac{2}{3}} l_{ij}^{\frac{1}{3}}$.

In the analysis, we use twenty one different measures of cognitive ability intensity to identify brain skills. Similarly, we use ten measures of psycho-motor ability intensity, $s_{ij}^{cognitive}$,

[23]For similar applications of PCA to construct task or skill measures from the DOT or O*NET data, see for instance Autor, Levy and Murnane 2003.

and nine measures of physical ability intensity to identify brawn skills, s_{ij}^{manual}. Tables [**include table**] and [**include table**] report the list of cognitive- and manual-skill descriptors used in the two PCAs. One PCA is performed among the former group of descriptors and the other using only the second group of descriptors. Figure [**include figure**] reports the values of the first 10 principal components, in both PCAs. With a value of 11.16, the first principal component of the first PCA explain almost 60% of the variation among the cognitive ability descriptors, whereas the first principal component of the second PCA explain around 74.5% of the variation among the psycho-motor and physical ability descriptors. Because of this reason, we rely only on the first principal component of each PCA to construct our two measures of skill-content.

To assess the role of each descriptor, table [**include table**] reports the loadings of each attribute i involved in the two PCAs. Sign and magnitude of the loadings are useful to assess how each attribute contributes to the selected principal components. Notice that the principal components based on transformation of correlation matrix to eigenbasis coordinates are unit free, thus if the loadings of all descriptors related to the same skill in the corresponding component is positive, then a higher component score implies a higher intensity in that skill. The opposite happens if the corresponding component is negative. In our analysis, except for *"Spatial Orientation"*, all the cognitive ability descriptors have positive weights on the first principle component of the first PCA. Similarly, all the psycho-motor and manual ability descriptors have positive loadings on the first principal component of the second PCA. Therefore, we define the first component of the the first and second PCA as, respectively, *brain-skill intensity* and *brawn-skill intensity*.

The PCAs are performed on the original 964 8-digit 2010-SOC different occupations provided in O*NET. After having brain and brawn skill intensities of each of them, we averaged out those values so to obtain a 6-digit 2010-SOC structure, composed by 763 occupations (see section above). We convert them to a 6-digit 2002-SOC definition, and we standardize each value with respect to the average occupations. Table [**include table**] reports values for standardized brain and brawn skill intensities for a sample of selected of 6-digit 2002-SOC occupations, ordered by their brain skill content.

Brain- and brawn-skill content indexes are ultimately grouped into 105 4-digit 2002-SOC occupations, so to obtain concordance with the classification structure used for the SIPP data (see section above). This aggregation is done by taking averages of non-standardized 6-digit values within each 4-digit occupation and after that by standardizing each value with respect to the average occupations. Tables in the main text report data aggregated to the 4-digit level. In the main text we refer to LOW skill occupations as those values for brain

skill intensity below zero (the median) and to HIGH skill occupations as those with brain skill intensity above zero.

Wages and Education Measures. The SIPP data contains information on monthly labor force participation, employment, and earnings. Results reported in the main text are based on the hourly wage rate (variable *wage*). To construct this variable, the SIPP combines information on wage and salary income in the reference month and hours worked per month, which is smoothed over four- and five-week months (assuming that individuals are not varying their response to the question based on whether the month is four-or five-weeks long). For more details on how wage rates and hours worked are constructed and homogenized across Panels, see *http://ceprdata.org/wp-content/sipp/set-d-memo.pdf* and *ceprdata.org/wp-content/sipp/recode/clean-d-employment.do*. We trim the wage distribution at the top and bottom 1 percent to take care of outliers and top-coding and we deflated it to 1990 dollars using the monthly consumer price index.

Set B of each Panel in the SIPP contains data on demographics, including educational attainment. For more details on how educational attainment is constructed and homogenized across Panels, see *ceprdata.org/wp-content/sipp/set-b-memo.pdf* and *ceprdata.org/wp-content/sipp/recode/clean-b-demographics.do*. Our two final measures of education are based on information recorded in the variable *educ*, which classifies educational attainment into four categories, namely *"less than high school*, *"high school graduate"*, *"some college"* and *"college degree"*. The first measure used in the main text is the share of workers with college degree or more. To construct it, we simply record workers with at least a college degree and take weighted average within each occupation considered. To construct the second measure we use the values assigned to each category of education attainments, going from 1 for the least attaintment to 4 for the highest one, and we average them out within each occupation, using the share of workers in each category as weights.

Training Measures. The wave 2 topical module of each Panel in the SIPP provides details on the education, training, qualifications, and skill development of the adult population. In this module job-related-training questions address training designed to help and or develop skills for a new job as well as to improve skills at the current or most recent job. Due to availability of data across Panels, we can only construct a measure of training along the extensive margin, i.e. we can only recover the share of workers who had received on-the-job training by occupation. People are asked whether they have received job training, and if they have, they are asked about the duration of the training, how it was used, how it was paid for, and if it was federally sponsored.

In particular, in the 2008 Panel we compute the share of workers who received training

in the previous 10 years by counting for each occupation the number of individuals who are employed during the reference month and a value one is assigned to the variable ERCVTR10. The variable ERCVTR10 corresponds to answers of the following question: *"Received training to improve job skills in the past ten years?"*, and a value equal to one corresponds to *"YES"*. Since the same question was not asked in topical modules of panels before 1996, for 1990 we can only compute the share of workers who ever received training to upgrade their skills in their entire working history. To do so, we count the number of respondents who are employed at the time of the interview and reported YES to the following questions: *Has ever received training designed to help nd a job, improve skills or learn a new job?* The answers to this question are recorded in the variable TM8446. Among those who reported YES, we keep only those who undertook one of the following types of training: *"Classroom Training - Job Skills"*, recorded in variable TM8460, *"On the job training"*, recorded in variable TM8462, *"Classroom Training - Basic Education"*, recorded in variable TM8464, *"Work Experience"*, recorded in variable TM8468, and *"Other training"*, recorded in variable TM8670. These restrictions allow us to remove the share of respondent who received training through *"Job Search Assistance"*, recorded in variable TM8466, from our final measure.

Worker Flows. Each panel in SIPP provides information on worker′s employment status (employed, unemployed and out of labor force) together with a job identifier (variable *jobid*) and the 4-digit code for occupations at a monthly frequency. We use this information to identify whether a worker moves between different employers and different occupations between two consecutive months in panels 1990 and 2008, and whether a worker moves between employment status and non-employment status. We identify job to job transitions as those transitions where the worker works in two consecutive months without reporting unemployment in between, and either the worker's employer identification number or his four-digit occupational identifier changes. We construct a measure of the average job-to-job transition rate for workers in each of the 4-digit occupations by computing the ratio between total movers between jobs in two consecutive months and total employment in the previous month in the original occupation. Index 4-digit occupations by $o \in O$, workers by $i \in I$, and employers by $d \in D$. Further, let $E_{i,t}^{o,d}$ be a worker-specific dummy that indicates employment in occupation o by employer d and time t:

$$E_{i,t}^{o,d} = \begin{cases} 1 & \text{if individual } i \text{ is employed in occupation } o \text{ by employer } d \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

The job to job transition rate is computed as

$$\text{J-J}_t^o = \frac{\sum_{i\in I}\sum_{d\in D}\sum_{k\in O}\sum_{s\in D, s\neq d} E_{i,t}^{o,d} E_{i,t+1}^{k,s}}{\sum_{i\in I}\sum_{d\in D} E_{i,t}^{o,d}}$$

We identify employment to non-employment transition as those transition where the workers report to be employed in a month and being non-employed (unemployed or out of labor force) in the next month. We construct a measure of average employment-to-non employment rate in each of the 4-digit occupations by computing the ratio between total movers between employment status in two consecutive months and total employment in the previous month in the original occupation. The employment to non-employment transition rate is computed as

$$\text{E-NE}_t^o = \frac{\sum_{i\in I}\sum_{d\in D} E_{i,t}^{o,d}(\text{NE}_{i,t+1})}{\sum_{i\in I}\sum_{d\in D} E_{i,t}^{o,d}}$$

Finally, we construct non-employment to employment transition rate tracking workers who report to be in a month and being non-employed (unemployed or out of labor force) in the previous month We construct a measure of average non-employment-to employment rate in each of the 4-digit occupations by computing the ratio between total movers between employment status in two consecutive months and total non-employment in the previous month The non-employment to employment transition rate is computed as

$$\text{NE-E}_t^o = \frac{\sum_{i\in I}\sum_{d\in D}(\text{NE}_{i,t-1}) E_{i,t}^{o,d}}{\sum_{i\in I}\text{NE}_{i,t-1}}$$

Table 7 reports descriptive statistics for E-NE$_t$, NE-E$_t$ and J-J$_t$ flows for the entire sample of workers, and separately for college and non-college educated workers.

Labor Income. To compute residual labor income profiles, we first orthogonalize our measures of labor income from individual observable characteristics not accounted for within the model. Therefore, we first run the following two regressions,

$$\begin{aligned}\log y_{it} = {} & \alpha_1 \text{female}_{it} + \alpha_2 \text{white}_{it} + \alpha_3 \text{married}_{it} + \alpha_4 \text{metro}_{it} + \alpha_5 \#\text{kids}_{it} \\ & + \alpha_6 \text{multi-job}_{it} + \alpha_7 \text{worker-union}_{it} + \alpha_8 \text{disability}_{it} + \delta_t + \delta_{s(i)} + \epsilon_{it}\end{aligned} \tag{34}$$

where $\log y_{it}$ is the log real monthly labor income in the main job for individual i at time t. The variable female$_{it}$ is a dummy for gender, white$_{it}$ is a dummy for white individuals, married$_{it}$ is a dummy for marital status, metro$_{it}$ is a dummy for metropolitan residence, multi job$_{it}$ is a dummy for multiple job holding, # kids$_{it}$ is a set of dummies for 1, 2, 3 and 4+ number of kids, worker-union is a dummy for worker union belonging, and δ_t and $\delta_{s(i)}$

Table 7: Labor Market Flows

	Full-sample Data	Non-College Data	College Data
	Job-to-job transition		
Overall	1.527	1.594	1.361
Age			
21-30 y.o.	2.286	2.347	2.089
31-40 y.o.	1.511	1.579	1.371
41-50 y.o.	1.322	1.398	1.145
51-60 y.o.	1.069	1.061	1.049
	Employment-Non Employment transition		
Overall	2.258	2.536	1.610
Age			
21-30 y.o.	3.177	3.620	1.834
31-40 y.o.	2.217	2.505	1.519
41-50 y.o.	1.873	2.092	1.560
51-60 y.o.	1.911	1.965	1.783
	Non-Employment-Employment transition		
Overall	2.276	2.273	2.285
Age			
21-30 y.o.	4.712	4.417	6.979
31-40 y.o.	2.520	2.551	2.415
41-50 y.o.	1.915	1.935	1.846
51-60 y.o.	1.182	1.113	1.408

are time and state fixed effects. Table 8 reports the OLS estimates[24]

Our measure of residual labor income, $\hat{\epsilon}_{it}$ is constructed as follows,

$$\hat{\epsilon}_{it} = \log y_{it} - \hat{\log} y_{it}$$

[24]The reference group in the estimation is made of single black male individuals with no kids, a single job, no union belonging, no-disability and living out of metropolitan areas.

Table 8: First-stage Regression

	$\log y_{it}$ Labor income
female_{it}	-0.299
	[0.001]***
white_{it}	0.079
	[0.002]***
married_{it}	0.287
	[0.001]***
metro_{it}	0.201
	[0.002]***
1 kid_{it}	-0.071
	[0.002]***
2 kids_{it}	-0.058
	[0.002]***
3 kids_{it}	-0.181
	[0.003]***
4+ kids_{it}	-0.255
	[0.004]***
multi job_{it}	-0.237
	[0.003]***
worker-union_{it}	0.205
	[0.003]***
disability_{it}	-0.460
	[0.003]***
constant	7.403
	[0.009]***
N.Obs.	1,350,839
R-squared	0.140
State FE	yes
Time FE	yes

Table 9 reports selected descriptive statistics for the residual labor income, overall in the sample and separately for college and non-college educated workers.

Figure 12 display the residual income profile across different ages, for college and non-college educated workers.

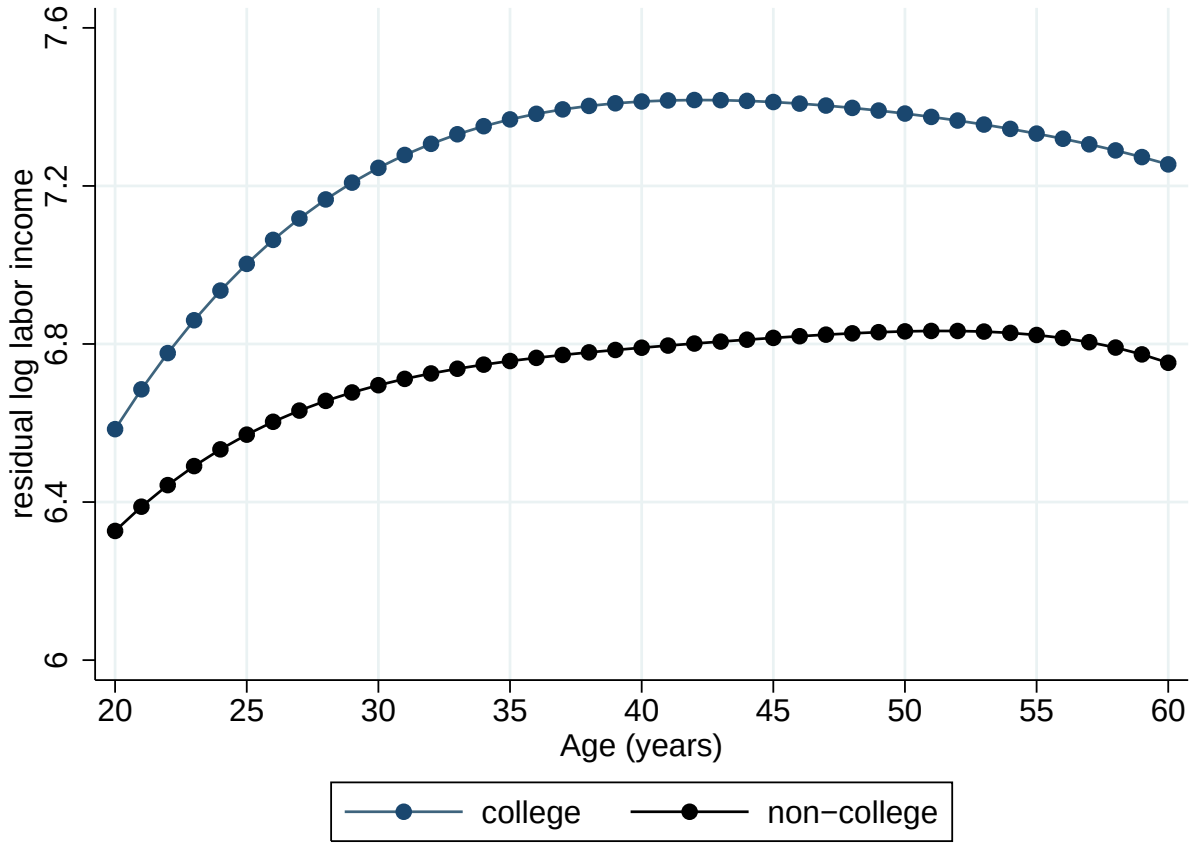
Finally, to describe how residual labor income vary across occupation, we estimate

$$\bar{\hat{\epsilon}}_j = \alpha + \beta \text{brain-skill}_j + \nu_j \tag{35}$$

Table 9: Residual labor income

	$\hat{\epsilon}_{it}$		
	Full-sample Data	Non-College Data	College Data
Overall			
Mean	6.897	6.748	7.305
St.Dev.	0.653	0.605	0.735
Distribution			
$10^{th}-$pctile	6.061	5.998	6.450
$25^{th}-$pctile	6.489	6.382	6.925
Median	6.929	6.782	7.360
$75^{th}-$pctile	7.348	7.156	7.698
$90^{th}-$pctile	7.719	7.483	7.981

Figure 12: Age income profiles, by education



where $\bar{\hat{\epsilon}}_j$ is the average residual labor income for workers in occupation j, while brain-skill$_j$ is a measure of brain-skill content of occupation j. Table 10 reports the result.

Table 10: Average residual income, by occupation

	Data (*1-digit SOC*)
α	6.984
	[0.024]***
β	0.337
	[0.045]***
R^2	0.942

Note: This table reports the OLS estimates of equation 35.

The World Input-Output Database (WIOD). The World Input-Output Database (WIOD) contains annual time-series of world input-output tables and factor requirements covering the period from 1995 to 2011. It provides values of domestic and cross-border transactions among 35 ISIC Rev.3.1 industries in 40 countries plus the "Rest of the World" (RoW) and from these industries to households, governments and users of capital goods in the same set of countries.

In the quantitative analysis, we aggregate industries into 30 major groups, *Agriculture, forestry and fishing* (code: AtB), *Mining and Quarrying* (code: C), *Food, Beverages and Tobacco* (code: 15t16), *Textiles, Textile Products, Leather and Footwear* (code: 17t19), *Wood and Product of Wood and Cork* (code: 20), *Pulp, Paper, Printing and Publishing* (code: 21t22), *Coke, Refined Petroleum and Nuclear Fuel* (code: 23), *Chemicals and Chemical Products* (code: 24), *Rubber and Plastics* (code: 25), *Other Non-Metallic Minerals* (code: 26), *Basic Metals and Fabricated Metals* (code: 27t28), *Machinery, Nec* (code: 29), *Electrical and Optical Equipment* (code: 30t33), *Transport Equipment* (code: 34t35), *Manufacturing, Nec; Recycling* (code: 36t37), *Electricity, Gas and Water Supply* (code: E), *Construction* (code: F), *Sale, Maintenance and Repair of Motor Vehicles* (code: 50), *Wholesale Trade, Except of Motor Vehicles* (code: 51), *Retail Trade, Except of Motor Vehicles* (code: 52), *Hotels and Restaurants* (code: H), *Transportation* (code: 60t63), *Post and Telecommunications* (code: 64), *Financial Intermediation* (code: J), *Real Estate Activities* (code: 70), *Renting and Other Business Activities* (code: 71t74),*Public Admin and Defence; Compulsory Social Security* (code: L),*Education* (code: M),*Health and Social Work* (code: N), *Other Community, Social, Personal Services* (code: OtP)

Moreover, we consider only the following 29 countries, Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, In-

dia, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, UK and USA. The remaining countries are aggregate to the RoW.

The Occupational Employment Statistics (OES) data. The Occupational Employment Statistics (OES) database collects data on wage and salary workers in non-farm establishments in order to produce employment and wage estimates for about 800 occupations at annual frequency. These estimates are available for the nation as a whole, and broken across occupation and industries. The OES definition of occupation reflects the 2002-SOC classification of *major* occupations provided above, whereas the OES definition of industry follows the 6-digit industry-levels 2002 NAICS classification. Therefore, it is converted into the ISIC Rev.3.1 classification using the crosswalk available here *https://www.census.gov/eos/www/naics/concordances/concordances.html*

We use information on employment to calibrate the elasticity of output with respect to each task category in each industry.

APPENDIX B - Solution algorithm

The task supply function. As in Lise et al. (2016), the key to solving for labor market equilibrium in our model is finding the match surplus function. Once this has been found it is straightforward to calculate the remaining objects of interest.

Employment values. To this end, we first use the bargaining protocol described in Section 3.2.3 to express the value of employment (13) in terms of the match surplus and the value of unemployment:

$$\begin{aligned}
& [\rho+\delta_\ell+\delta_f+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{J}}\phi^\ell_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z,|\tilde{j})}v_{\tilde{j}}(\tilde{z})]J^e_E(w,a,j,z) \qquad (36)\\
= \;& w+[\delta_f+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{J}}\phi^\ell_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}v_{\tilde{j}}(\tilde{z})]J^u_E(a)\\
& +\gamma_E(a,j,z)(J^u_E(a')-J^u_E(a))+\beta\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{S_E(a,j,\tilde{z}),0\}\Lambda(\tilde{z}|z)\\
& +\beta\gamma_E(a,j,z)\max\{S_E(a,j,z),0\}+\beta\sum_{\tilde{j}\in\mathcal{J}}\phi^\ell_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z,|\tilde{j})}S_E(a,\tilde{j},\tilde{z})v_{\tilde{j}}(\tilde{z})
\end{aligned}$$

Next we eliminate $J^e_E(w,a,j,z)$ using $J^e_E(w,a,j,z)-J^u_E(a)=\beta S_E(a,j,z)$:

$$\begin{aligned}
& [\rho+\delta_\ell+\delta_f+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{J}}\phi^\ell_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(j,z,i|\tilde{j})}v_{\tilde{j}}(\tilde{z})]\beta S_E(a,j,z) \qquad (37)\\
= \;& w-[\rho+\delta_\ell]J^u_E(a)+\gamma_E(a,j,z)\,[J^u_E(a')-J^u_E(a)]+\beta\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{S_E(a,j,\tilde{z}),0\}\Lambda(\tilde{z}|z)\\
& +\beta\gamma_E(a,j,z)\max\{S_E(a',j,z),0\}+\beta\sum_{\tilde{j}\in\mathcal{J}}\phi^\ell_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z,|\tilde{j})}S_E(a,\tilde{j},\tilde{z})v_{\tilde{j}}(\tilde{z})
\end{aligned}$$

Job values. Analogously, we use the bargaining protocol to express the value of a filled vacancy (16) in terms of the value of an unfilled vacancy and the match surplus function:

$$
\begin{aligned}
&[\rho+\delta_f+\delta_\ell+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{S}}\phi^{\ell}_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}v_{\tilde{j}}(\tilde{z})]\Pi^e_E(w,a,j,z)\\
&=r_j y_E(a,j,z)-c^o-w+[\delta_\ell+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{S}}\phi^{\ell}_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}v_{\tilde{j}}(\tilde{z})]\Pi^v(j,z)\\
&+\varphi\sum_{\tilde{z}\in\mathcal{Z}}[\Pi^v(j,\tilde{z})-\Pi^v(j,z)]\Lambda(\tilde{z}|z)+(1-\beta)\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{S_E(a,j,\tilde{z}),0\}\Lambda(\tilde{z}|z)\\
&+(1-\beta)\gamma_E(a,j,z)\max\{S_E(a',j,z),0\}
\end{aligned}
\tag{38}
$$

And we eliminate $\Pi^e_E(w,a,j,z)$ using $\Pi^e_E(w,a,j,z)-\Pi^v(j,z)=(1-\beta)S_E(a,j,z)$:

$$
\begin{aligned}
&[\rho+\delta_f+\delta_\ell+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{S}}\phi^{\ell}_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}v_{\tilde{j}}(\tilde{z})](1-\beta)S_E(a,j,z)\\
&=r_j y_E(a,j,z)-c^o-w-[\rho+\delta_f]\Pi^v(j,z)+\varphi\sum_{\tilde{z}\in\mathcal{Z}}[\Pi^v(j,\tilde{z})-\Pi^v(j,z)]\Lambda(\tilde{z}|z)\\
&+(1-\beta)\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{S_E(a,j,\tilde{z}),0\}\Lambda(\tilde{z}|z)+(1-\beta)\gamma_E(a,j,z)\max\{S_E(a',j,z),0\}
\end{aligned}
\tag{39}
$$

The surplus function. Finally, adding equations (37) and (39), we obtain an expression in the surplus function $S_E(a,j,z)$, the jump hazard $\gamma_E(a,j,z)$, the value of unemployment $J^u_E(a)$, and the value of a vacancy $\Pi^v(j,z)$:

$$
\begin{aligned}
&[\rho+\delta_f+\delta_\ell+\varphi+\gamma_E(a,j,z)+\sum_{\tilde{j}\in\mathcal{S}}\phi^{\ell}_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}v_{\tilde{j}}(\tilde{z})]S_E(a,j,z)=\underbrace{r_j y_E(a,j,z)-c^o}_{\text{net flow value}}\\
&+\underbrace{\varphi\sum_{\tilde{z}\in\mathcal{Z}}\max\{S_E(a,j,\tilde{z}),0\}\Lambda(\tilde{z}|z)}_{\text{surplus gain from productivity jump}}+\underbrace{\gamma_E(a,j,z)\max\{S_E(a',j,z),0\}}_{\text{surplus gain from human capital jump}}+\underbrace{\sum_{\tilde{j}\in\mathcal{J}}\phi^{\ell}_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{A}_E(a,j,z|\tilde{j})}S_E(a,\tilde{j},\tilde{z})v_{\tilde{j}}(\tilde{z})}_{\text{surplus gain from j2j transition}}\\
&+\underbrace{\varphi\left[\sum_{\tilde{z}\in\mathcal{Z}}[\Pi^v(j,\tilde{z})-\Pi^v(j,z)]\Lambda(\tilde{z}|z)\right]}_{\text{outside option gain from productivity jump}}+\underbrace{\gamma_E(a,j,z)\left[J^u_E(a')-J^u_E(a)\right]}_{\text{outside option gain from human capital jump}}\\
&-\underbrace{[\rho+\delta_\ell]J^u_E(a)}_{\text{worker's outside option}}-\underbrace{[\rho+\delta_f]\Pi^v(j,z)}_{\text{firm's outside option}}
\end{aligned}
$$

By equations (1), (17), (12) and (14), the objects $\gamma_E(a,j,z)$, $J^u_E(a)$, and $\Pi^v(j,z)$ depend only on the surplus function. Accordingly, $S_E(\cdot)$ is the fixed point of the functional equation

above, and can be written as:

$$S_E = T\left(S_E|\ \boldsymbol{\phi}, \mathbf{f}, \mathbf{y}, \boldsymbol{\upsilon}; \mathbf{r}_{US}\right). \tag{40}$$

Here $\boldsymbol{\phi} = \{\phi^m_{\tilde{j},j}\}$ is the set of match hazards defined in Section 3.2.2, $\mathbf{f} = \{f_E(a,j,z)\}$ gives the distribution of workers across states, $\mathbf{y} = \{y_E(a,j,z)\}$ is the task production function, $\boldsymbol{\upsilon} = \{\upsilon(j,z)\}$ is the task-specific measure of firms in each productivity state, and $\mathbf{r}_{US} = \{r_{US,,j}\}$ is the vector of task prices in the U.S.

The task supply function. Starting from candidate values for $[\boldsymbol{\phi}, \mathbf{f}, \mathbf{y}, \boldsymbol{\upsilon}]$, we calculate the associated surplus function S_E using (40). This surplus function implies associated candidate policy functions, which we use to update our guess for $[\boldsymbol{\phi}, \mathbf{f}, \mathbf{y}, \boldsymbol{\upsilon}]$. Repeating this iteration on S_E and $[\boldsymbol{\phi}, \mathbf{f}, \mathbf{y}, \boldsymbol{\upsilon}]$ until convergence, we infer the base year supply of tasks in the US and base year labor force estimates in all other countries:

$$\mathbf{y}^S_{US} = y\left(\mathbf{r}_{US}\right) \tag{41}$$

Base year task equilibrium. After estimating base year values for $\mathbf{r}^S_{US,0}$, we impute base year task supplies in the U.S. by evaluating equation (41) at $\mathbf{r}^S_{US,0}$. For other countries we take labor supplies $\mathbf{y}^S_{ROW,0} = \{y^S_{n,0}\}_{n=1,n\neq US}$ and task prices, $\mathbf{r}_{ROW,0} = \{r_{n,0}\}_{n=1,n\neq US}$, directly from data. (Our base year measurements are discussed in Appendices C and D.) Since each country except the U.S. is treated as having a single type of labor, and labor markets outside the U.S. are assumed to be competitive, the task price vector $\mathbf{r}_{ROW}$ amounts to a vector of foreign wage rates.

Counterfactuals. Once we have our base year solution, we perform counterfactual analyses using standard "hat algebra" techniques. Denote the complete vector of task prices by $\mathbf{r} = [\mathbf{r}_{US}, \mathbf{r}_{ROW}]$ and define the relative change in this vector between period 0 and 1 to be $\hat{\mathbf{r}} = \left\{\frac{r_{n,1}}{r_{n,0}}\right\}_{n=1,N}$. That is, for an exogenous set of shocks to trade costs, $\hat{d} = \left\{\frac{d^{n,\tilde{n}}_{k,1}}{d^{n,\tilde{n}}_{k,0}}\right\}$, and/or technology, $\mu'_{kj} - \mu_{kj}$, $\alpha'_k - \alpha_k$, we calculated the associated market-clearing chages in task prices $\hat{\mathbf{r}}$. In turn, these imply associated changes in features of the steady state labor market.

These task prices imply a vector of relative changes in task supplies through the dynamic block, as discussed above, and a vector of relative changes in task demands based on the static block in Section (3.3). If these vectors match eachother the equilbrium has been identified; if not, we update the vector of task prices and repeat the calculations.

Hat algebra details. To summarize our approach to finding the changes in task de-

mands after a trade or technology shock, it is helpful to break the static block of our model into two sub-blocks.

Sub-block 1: The first block expresses equations (23) through (26), in relative changes:

$$\widehat{\widetilde{p}}_k^n = \frac{A_k \left[\sum_{\tilde{n}=1}^N T_k^{\tilde{n}} \left(u_k^{\tilde{n}\prime} d_k^{n,\tilde{n}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}}{A_k \left[\sum_{\tilde{n}=1}^N T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}} = \frac{\left[\sum_{\tilde{n}=1}^N T_k^{\tilde{n}} \left(\hat{u}_k^{\tilde{n}} \hat{d}_k^{n,\tilde{n}}\right)^{-\theta_k} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}}{\left[\sum_{\tilde{n}=1}^N T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}}$$

$$= \left[\sum_{\tilde{n}=1}^N \left(\hat{u}_k^{\tilde{n}} \hat{d}_k^{n,\tilde{n}}\right)^{-\theta_k} \frac{T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}}\right)^{-\theta_k}}{\left[\sum_{\tilde{n}=1}^N T_k^{\tilde{n}} \left(u_k^{\tilde{n}} d_k^{n,\tilde{n}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}}\right]^{-\frac{1}{\theta_k}} = \left[\sum_{\tilde{n}=1}^N \left(\hat{u}_k^{\tilde{n}} \hat{d}_k^{n,\tilde{n}}\right)^{-\theta_k} \pi_k^{n,\tilde{n}}\right]^{-\frac{1}{\theta_k}} \quad (42)$$

$$\hat{u}_k^n = \left(\widehat{\widetilde{r}}_k^n\right)^{\alpha_k} \prod_{\tilde{k}=1}^K \left(\widehat{\widetilde{p}}_{\tilde{k}}^n\right)^{(1-\alpha_k)\vartheta_{k\tilde{k}}} \quad (43)$$

$$\widehat{\widetilde{r}}_k^n = \prod_{j=1}^J \left(\hat{r}_j^n\right)^{\mu_{kj}} \quad (44)$$

For any set of initial trade shares ($\pi_k^{n,\tilde{n}}$), and any set of proposed changes in trade costs ($\hat{d}_k^{n,\tilde{n}}$) and task prices ($\hat{r}_j^n$), the system implies an associated set of changes in unit input costs ($\hat{u}_k^n$) and output prices ($\widehat{\widetilde{p}}_k^n$). Also, given the rates of change in unit costs, the rates of change in trade shares can be calculated using the standard expressions:

$$\hat{\pi}_k^{n,\tilde{n}} = \left(\frac{\hat{u}_k^{\tilde{n}} \hat{d}_k^{n,\tilde{n}}}{\widehat{\widetilde{p}}_k^n}\right)^{-\theta_k}$$

Equations (43) and (44) can be generalized to accomodate counter-factual changes in technology that take the form of changes in production function parameters, as in Acemoglu and Restrepo (2018). Suppose the exponents on tasks versus intermediate inputs are adjusted ($\alpha_k \to \alpha_k'$) , as are the exponential weights on the specific tasks ($\mu_{kj} \to \mu_{kj}'$). This adds the terms in brackets {} to equations (43) and (44); otherwise the calculations proceed as before:

$$\hat{u}_k^n = \left\{ (\bar{r}_k^n)^{\alpha'_k - \alpha_k} \left[\prod_{\tilde{k}=1}^{K} \left(\bar{p}_{\tilde{k}}^n\right)^{\vartheta_{k\tilde{k}}} \right]^{(\alpha_k - \alpha'_k)} \right\} \left(\widehat{\bar{r}}_k^n\right)^{\alpha'_k} \left[\prod_{\tilde{k}=1}^{K} \left(\widehat{\bar{p}}_{\tilde{k}}^n\right)^{\vartheta_{k\tilde{k}}} \right]^{(1-\alpha'_k)} \tag{45}$$

$$\widehat{\bar{r}}_k^n = \left\{ \prod_{j=1}^{J} \left(r_j^n\right)^{\mu'_{kj} - \mu_{kj}} \right\} \prod_{j=1}^{J} \left(\hat{r}_j^n\right)^{\mu'_{kj}} \tag{46}$$

These bracketed terms capture the effects of technology shifts on prices. Technological changes that affect labor's share (α_k) cannot be analyzed unless output prices $\bar{p}_{\tilde{k}}^n$ can be calculated in levels for the base period.

Sub-block 2: Given the changes in trade shares and task prices from the pricing sub-block, the new output and employment levels can be calculated using (31) through (33), (29), and (30):

$$\begin{aligned}
X_n^{k\prime} &= \sum_{\tilde{k}=1}^{K} (1 - \alpha_{\tilde{k}}) \vartheta_{\tilde{k}k} \sum_{\tilde{n}=1}^{N} \frac{\hat{\pi}_{\tilde{k}}^{\tilde{n},n} \pi_{\tilde{k}}^{\tilde{n},n} X_{\tilde{k}}^{\tilde{n}\prime}}{1 + \tau_{\tilde{k}}^{\tilde{n},n}} + \nu_k I'_n \\
I^{n\prime} &= \sum_{k=1}^{K} \alpha_k X_n^{k\prime} + \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\hat{\pi}_k^{n,\tilde{n}} \pi_k^{n,\tilde{n}}}{1 + \tau_k^{n,\tilde{n}}} \tau_k^{n,\tilde{n}} X_k^{n\prime} + D^{n\prime} \\
y^{n,j\prime} &= \sum_{k=1}^{K} \mu_k^{j\prime} \frac{\alpha'_k}{\hat{r}_j^n r_j^n} X_k^{n\prime}
\end{aligned}$$

APPENDIX C - Equilibrium Conditions in the Labor Market

Worker Distribution. Each instant a unitary measure of workers enter the labor market and sort into high- and low-educated. The measures of new entrants with low- and high-education are respectively equal to

$$L_E^e = \begin{cases} 1 - F_a\left(a^*\right) \geq 0 & \text{if} \quad E = H \\ F_a\left(a^*\right) \geq 0 & \text{if} \quad E = L \end{cases}, \tag{47}$$

where a^* solves $\frac{\kappa}{a^*} = J_H^u(a^*) - J_L^u(a^*)$. Using equation (47) and the higher education cut-off a^* we can write the measure of workers entering the labor market by skill level as follow

$$L_{Li}^e = \begin{cases} L_L^e f_a(\mathrm{a}_i) & \text{if} \quad \mathrm{a}_i \leq a^* \\ 0 & \text{if} \quad \mathrm{a}_i > a^* \end{cases} \tag{48}$$

and

$$L_{Hi}^e = \begin{cases} 0 & \text{if} \quad \mathrm{a}_i \leq a^* \\ L_H^e f_a(\mathrm{a}_i) & \text{if} \quad \mathrm{a}_i > a^* \end{cases}$$

where $f_a(\cdot)$ is the probability density function associated to $F_a(\cdot)$. In stationary equilibrium, the measure of workers with education E, $L_E = \sum_{i \in \mathcal{H}} L_{Ei}$ is constant at every instant. This implies that the entry rate in the labor market is equal to rate of retirement, i.e.

$$\mu_E^{w^e} \equiv \underbrace{\frac{L_E^e}{\sum_{i \in \mathcal{H}} L_{Ei}}}_{\text{worker entry rate}} = \underbrace{\frac{\sum_{i \in \mathcal{H}} \delta_w L_{Ei}}{\sum_{i \in \mathcal{H}} L_{Ei}}}_{\text{retirement rate}} \equiv \delta_w$$

which implies the following aggregate measures of workers with education E

$$L_E = \sum_{i \in \mathcal{H}} L_{Ei} = \frac{L_E^e}{\delta_w}$$

In steady state the flows of workers between different level of human capital are fixed, i.e.

$$\begin{aligned} L_{E1} &= \frac{L^e_{E1}}{\delta_w + \sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}\gamma_E(\mathrm{a}_1,j,z)f_E(a_1,j,z)} \\ L_{Ei} &= \frac{L_{Ei-1}\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}\gamma_E()f_E(\mathrm{a}_{i-1},j,z) + L^e_{Ei}}{\delta_w + \sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}\gamma_E(j,z,i)f_E(\mathrm{a}_i,j,z)} \quad \text{if} \quad i\in\{2,3,...,I-1\} \\ L_{EI} &= \frac{L_{EI-1}\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}\gamma_E(\mathrm{a}_{I-1},j,z)f_E(\mathrm{a}_{I-1},j,z) + L^e_{EI}}{\delta_w} \end{aligned} \tag{49}$$

Let the distribution of E-educated workers over ability levels a_i be

$$\ell_E(i) = \frac{L_{Ei}}{\sum_{i\in\mathcal{H}} L_{Ei}} = \frac{\delta_w}{L^e_E} L_{Ei} \tag{50}$$

In stationary equilibrium, $\dot{\ell}_E(i) = \dot{L}_{Ei} = 0, \quad \forall i \in \mathcal{H}$.

Firm Distribution. In steady state the measure of total firms in occupation $j \in \mathcal{S}$ and productivity $z \in \mathcal{Z}$ is fixed at each instant. Potential entrant firms decide to set up a type-j business if

$$c^p \leq \sum_{z\in\mathcal{Z}} \Pi^v(z_0,j)\Phi_\Lambda(z)$$

where $\Phi_\Lambda(z)$ is the probability a new firm draws productivity z_0, based on the ergodic z distribution implied by Λ. Let $F^e_{jz} = \Phi_\Lambda(z)F^e_j$ be the measure of firms entering in occupation j so that $F^e_{jz} = \Phi_\Lambda(z)F^e_j$ be measure of new entrant firms in occupation j with productivity z. In steady state, the total measure of firms exiting the industry is replaced by the same measure of new firms, i.e.

$$\mu^{f^e}_j \equiv \underbrace{\frac{F^e_j}{\sum_{z\in\mathcal{Z}} F_{jz}}}_{\text{firm entry rate}} = \underbrace{\frac{\sum_{z\in\mathcal{Z}}\delta_f F_{jz}}{\sum_{z\in\mathcal{Z}} F_{jz}}}_{\text{firm exit}} \equiv \delta_f \tag{51}$$

which implies the following aggregate measures of workers in occupation j

$$F_j = \sum_{z\in\mathcal{Z}} F_{jz} = \frac{F^e_j}{\delta_f} \tag{52}$$

Finally, in steady state the flows of firms between different productivity levels has to be

stationary, i.e.

$$F_{jz}\left[\delta_f+\varphi\sum_{\tilde{z}\in\mathcal{Z}/z}\Lambda(\tilde{z}|z)\right]=\varphi\sum_{\tilde{z}\in\mathcal{Z}}\Lambda(z|\tilde{z})F_{j\tilde{z}}+\Phi_\Lambda(z)F_j^e\quad\forall z\in\mathcal{Z}$$

where $\varphi\Lambda(z|\tilde{z})$ is the hazard of transiting from $\tilde{z}$ to z. This implies the following measure of firms in occupation j with productivity z,

$$F_{jz}=\frac{\varphi\sum_{\tilde{z}\in\mathcal{Z}}\Lambda(z|\tilde{z})F_{j\tilde{z}}+\Phi_\Lambda(z)F_j^e}{\left[\delta_f+\varphi\sum_{\tilde{z}\in\mathcal{Z}/z}\Lambda(\tilde{z}|z)\right]}\quad\forall z\in\mathcal{Z}\tag{53}$$

Let the distribution of firms in occupation j over productivity z be

$$f_j(z)=\frac{F_{jz}}{\sum_{z\in\mathcal{Z}}F_{jz}}=\frac{\delta_f}{F_j^e}F_{jz}\tag{54}$$

In stationary equilibrium, $\dot{f}_j(z)=\dot{F}_{jz}=0,\quad\forall z\in\mathcal{Z},\forall j\in\mathcal{S}$.

Distribution of matches, unemployment and vacancies. Let $u_E(i)$ be human capital density of workers who are unemployed. In steady state, a measure U_E of E-educated workers is unemployed and a measure $U_{Ei}=u_E(i)U_E$ of unemployed workers unemployed with human capital h_i. Let $n_{Ej}(z,i)$ be the density of matches across firm and worker′s types, and let $n_{Ejz}(i)$ be the density of matches across workers′ types. A measure N_E of $E-$educated workers is employed, a measure N_{Ej} of workers is employed in occupation j, and a measure $N_{Ejzi}=n_{Ej}(z,i)N_{Ej}$ of workers with skills i is employed in a (z,j)-type firm. Let $v_{Ej}(z)$ be the density of job vacancy in occupation j across productivity. In steady state, V_{Ej} is the measure of open vacancy in occupation j, and $V_{Ejz}=v_{Ej}(z)V_{Ej}$ is the measure of open vacancy in occupation j with productivity z. In stationary equilibrium, for each human capital level $h_i\in\mathcal{H}$ unemployed and matched workers adds up to the total measure of workers, while in each occupation $j\in\mathcal{S}$ vacant and active jobs sum up to the total mass of firms. Thus, the measure of matches in the labor market is equal to

$$\sum_{E\in\{L,H\}}\sum_{i\in\mathcal{H}}\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}N_{Ejzi}=\sum_{E\in\{L,H\}}\sum_{i\in\mathcal{H}}L_{Ei}-\sum_{E\in\{L,H\}}\sum_{i\in\mathcal{H}}U_{Ei}=\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}F_{jz}-\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}V_{jz}\tag{55}$$

which simplifies into

$$\begin{aligned}\sum_{E\in\{L,H\}}\sum_{j\in\mathcal{S}} N_{Ej}\underbrace{\sum_{i\in\mathcal{H}}\sum_{z\in\mathcal{Z}} n_{Ej}(z,i)}_{=1} &= \sum_{E\in\{L,H\}} L_E \underbrace{\sum_{i\in\mathcal{H}}\ell_E(i)}_{=1} - \sum_{E\in\{L,H\}} U_E \underbrace{\sum_{i\in\mathcal{H}} u_E(i)}_{=1} \\ &= \sum_{j\in\mathcal{S}} F_j \underbrace{\sum_{z\in\mathcal{Z}} f_j(z)}_{=1} - \sum_{j\in\mathcal{S}} V_j \underbrace{\sum_{z\in\mathcal{Z}} v_j(z)}_{=1}\end{aligned} \tag{56}$$

$$\begin{aligned}&\implies \sum_{E\in\{L,H\}}\sum_{j\in\mathcal{S}} N_{Ej} = \sum_{E\in\{L,H\}} L_E - \sum_{E\in\{L,H\}} U_E = \sum_{j\in\mathcal{S}} F_j - \sum_{j\in\mathcal{S}} V_j \\ &\implies \sum_{E\in\{L,H\}} N_E = \sum_{E\in\{L,H\}} L_E - \sum_{E\in\{L,H\}} U_E = F - V\end{aligned} \tag{57}$$

In a steady state the match distribution should stay unchanged. A match can be destroyed because of several reasons. First, there is an exogenous destruction rate, δ_f; second, workers retire and exit the labor market with a hazard rate δ_w; third, at a rate φ firms receive a productivity shock that can lead to endogenous match destruction; fourth, as a result of learning on-the job and on-the-job training, ability a jumps up with a hazard rate $\gamma_E(a,j,z)$ and this can push the surplus below zero for some value of z and j; finally a worker may receive an outside offer and quit to a higher surplus. On the other hand, a new match in occupation j, with productivity z and worker ability a can be created because of human capital update of lower ability employed workers, productivity change at rate $\varphi\Lambda(z'|z)$, or because of new hirings. It follows that, $\forall(a,j,z)$ such that a match is feasible (i.e. such that $S_E(a,j,z)\geq 0$), the stationary distribution of active matches should be time-invariant, implying the equality between inflows and outflows of each type of match pairs,

$$\begin{aligned}&\underbrace{\gamma_E(\mathrm{a}_{j-1},j,z)N_{Ej}f_E(\mathrm{a}_{i-1},j,z)}_{\text{inflows due to training updates}} + \underbrace{\varphi\sum_{\tilde{z}\in\mathcal{Z}}\Lambda(z|\tilde{z})N_{Ej}f_E(\mathrm{a}_i,j,\tilde{z})}_{\text{inflows due to productivity change}} \\ &+ \underbrace{\left[\tilde{\phi}_{0,j}U_E u_E(\mathrm{a}_i) + \sum_{\tilde{j}\in\mathcal{S}}\tilde{\phi}_{\tilde{j},j}N_{E\tilde{j}}\sum_{\tilde{z}\in\mathcal{C}_1(\mathrm{a}_i,\tilde{j},z|j)} n_E(\mathrm{a}_i,\tilde{j},\tilde{z})\right] v_{Ej}(z)}_{\text{inflows due to new hirings}} \\ &= \underbrace{\left[\delta_w+\delta_f+\varphi\sum_{\tilde{z}\in\mathcal{Z}/z}\Lambda(\tilde{z}|z)+\gamma_E(\mathrm{a}_i,j,z)+\sum_{\tilde{j}\in\mathcal{S}}\phi^w_{j,\tilde{j}}\sum_{\tilde{z}\in\mathcal{C}_2(\mathrm{a}_i,j,z|\tilde{j})} v_{E\tilde{j}}(\tilde{z})\right] N_{Ej}f_E(\mathrm{a}_i,j,z)}_{\text{outflows}}\end{aligned} \tag{58}$$

where the sets $\mathcal{C}_1$ and $\mathcal{C}_2$ are defined as

$$\mathcal{C}_1(a,\tilde{j},z|j) := \{\tilde{z}\in\mathcal{Z} : S_E(a,j,z) \geq S_E(a,\tilde{j},\tilde{z})\}$$
$$\mathcal{C}_2(a,j,z|\tilde{j}) := \{\tilde{z}\in\mathcal{Z} : 0 < S_E(a,j,z) < S_E(a,\tilde{j},\tilde{z})\}$$

Stationarity also requires equality between inflows and outflows from unemployment,

$$\begin{aligned}&\underbrace{U_{Ei}[\delta_w + \sum_{j\in\mathcal{S}}\phi^w_{0,j}\sum_{z\in\mathcal{Z}}\mathbf{1}_{\{S_E(\mathrm{a}_i,j,z)\geq 0\}}v_{Ej}(z)]}_{\text{outflows from unemployment}}\\ &= \underbrace{\delta_f\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}N_{E\mathrm{a}_i,j,z} + \varphi\sum_{j\in\mathcal{S}}\sum_{z\in\mathcal{Z}}N_{E,\mathrm{a}_i,j,z}\sum_{\tilde{z}\in\mathcal{Z}}\mathbf{1}_{\{S_E(\mathrm{a}_i,j,\tilde{z})<0\}}\Lambda(\tilde{z}|z)}_{\text{inflows to unemployment}} + \underbrace{L^e_{Ei}}_{\text{new entrants}}\end{aligned} \tag{59}$$

Define the distribution of unemployed workers across skills as

$$u_E(i) = \frac{U_{Ei}}{\sum_{i\in\mathcal{H}}U_{Ei}} \tag{60}$$

the distribution of open vacancies across occupations and productivity as

$$v_j(z) = \frac{V_{jz}}{\sum_{\tilde{z}\in\mathcal{Z}}V_{j\tilde{z}}} \tag{61}$$

and the distribution of active matches across states as

$$f_E(\mathrm{a}_i,j,z) = \frac{N_{E,\mathrm{a}_i,j,z}}{\sum_{i'\in\mathcal{H}}\sum_{\tilde{z}\in\mathcal{Z}}N_{E,\mathrm{a}_{i'},j,\tilde{z}}}. \tag{62}$$

In stationary equilibrium, $\dot{f}_E(\mathrm{a}_i,j,z) = \dot{N}_{E,\mathrm{a}_i,j,z} = 0, \forall j\in\mathcal{S}, z\in\mathcal{Z}, \forall i\in\mathcal{H}$, $\dot{u}_E(\mathrm{a}_i) = \dot{U}_{Ei} = 0, \forall i\in\mathcal{H}$ and $\dot{v}_j(z) = \dot{V}_{jz} = 0, \forall j\in\mathcal{S}, z\in\mathcal{Z}$.

APPENDIX D - Numerical Algorithm

We obtain an equilibrium in the trade market with 30 countries, i.e. Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, UK, USA, plus a constructed rest of the world, and 30 ISIC Rev.3.1 sectors, reported in Table 11. We solve the equilibrium in the labor market with $J = 5$ occupations, resembling the 1-digit ranking in the 2002 standard occupation classification (SOC). We discretize the space for human capital, $\mathcal{H}$, using 200 equi-distant points and the space for (log) productivity $\mathcal{Z}$ using 100 equi-distant points. We set aggregate domestic income per capita, I_n, as the numeraire of the economy.

Equilibrium in task markets. Guess a price for each task in each US market for tasks, $\{r_j\}_{j\in\mathcal{J}}$. Compute the demand of tasks after clearing the market for goods. Compute the supply of tasks after clearing the market for labor. Update the price of tasks, r_j, till demand equals supply. In particular, increase r_j if demand in occupation j is larger than supply, decrease it otherwise. Use the new set of prices for tasks to solve for the equilibrium in the goods and labor markets. Iterate until convergence.

For foreign countries, we have insufficient data to characterize a separate market for each task. As a result, in order to implement this algorithm, we take $\mathbf{r}_{-US}$ as given, and measure it at the sectoral level, using equation (25) in the main text, as the aggregate cost of labor (the wage bill) in sector k in country n.

Equilibrium in goods market. For a set of prices for tasks in the US economy, $\{r_j\}_{j\in\mathcal{J}}$, the solution algorithm goes as follows:

- Use equations (24), (27) and (28) to solve for the unit costs, u_n^k, and the prices of intermediates, $\bar{p}_n^k$.
- Construct the import shares, $\pi_{n\tilde{n}}^k$, using equation (26)
- Use the market-clearing conditions (31) evaluated at $\pi_{n\tilde{n}}^k$ to solve for gross revenues in each sector. This involves stacking the conditions (31) by sector and country; then inverting the matrix of $N \cdot K$ equations in $N \cdot K$ sectoral revenues, X_n^k.
- Use X_n^k to construct the domestic demand for each tasks, equal to

$$\sum_{k=1}^{K} \mu_{kj} \frac{\alpha^k}{r_j} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{\tilde{n}n} X_k^{\tilde{n}}}{1+\tau_k^{\tilde{n}n}}$$

Equilibrium in labor market. For a set of prices for tasks, $\{r_j\}_{j\in\mathcal{J}}$, the solution algorithm goes as follows.

- Guess the following objects

    1. human capital threshold for high-education choice, h_i^*
    2. market tightness in each occupation, $\{\phi_j\}_{j\in\mathcal{J}}$
    3. measure of entrant firms, $\{F_j^e\}_{j\in\mathcal{J}}$
    4. measure of firms in each occupation j and productivity level z, $\{F_{jz}\}_{j\in\mathcal{J},z\in\mathcal{Z}}$
    5. measure of vacancies in each occupation j and productivity level z , $\{V_{jz}\}_{j\in\mathcal{J},z\in\mathcal{Z}}$
    6. measure of matches in each occupation j, productivity level z, human capital h_i and education level E, $\{N_{Ejzi}\}_{E\in\{L,H\},j\in\mathcal{J},z\in\mathcal{Z},i\in\mathcal{H}}$
    7. measure of unemployed workers over abilities h_i and education E, $\{U_{Ei}\}_{E\in\{L,H\},i\in\mathcal{H}}$
    8. surplus function and training decision, $S_E(j,z,i)$ and $\mathbf{1}_E^t j,z,i$

- Use h_i^* to back out the share of entrant workers by education level. Construct the measure of entrants over education E and abilities h_i.

- Use $\{\phi_j\}_{j\in\mathcal{J}}$ and $\{V_{jz}\}_{j\in\mathcal{S},z\in\mathcal{Z}}$ to construct job finding rates for unemployed and unemployed workers, ϕ_{0j}^w and $\phi_{j\tilde{j}}^w$ using equations for contact rates of unemployed and employed workers

- Use $\{\phi_j\}_{j\in\mathcal{J}}$ and $\{U_{Ei}\}_{E\in\{L,H\},i\in\mathcal{H}}$ to construct the firm job filling rates with unemployed workers

- Use $\{\phi_j\}_{j\in\mathcal{J}}$ and $\{N_{Ejzi}\}_{E\in\{L,H\},j\in\mathcal{S},z\in\mathcal{Z},i\in\mathcal{H}}$ to construct the firm job filling rates with employed workers

- Compute the measure and the distribution of workers over abilities h_i.

- Update the measure of entrant firms F_j^e in each occupations and overall measure of firms $F_j z$ in each occupations and productivity and the definition of matching function. Construct the distribution of firms in each occupation over productivity

- Update the measure of vacancies in each occupation and productivity and construct its distribution

- Update the measure of unemployed workers for each abilities and construct its distribution

- Update the measure of active matches in each occupation and over productivity and abilities and construct its distribution

- Apply value function iteration to update the surplus function
- Use the value of unemployment to update the ability threshold for high-education
- Use the value of vacant job to construct the expected value of entering the market for a firm in each occupation. Update the value for market tightness using the free-entry condition
- Iterate until convergence of each of the guessed objects.
- Once convergence is achieved, construct the supply of each tasks, i.e.

$$N_j \sum_{E\in\{L,H\}} \sum_{z\in\mathcal{Z}} \sum_{i\in\mathcal{H}} y_E(j,z,i) n_{Ej}(z,i)$$

APPENDIX E - Spot Markets for Goods and Tasks

We treat the world economy as composed of 30 countries, plus a constructed rest of the world.[25] We consider $K = 30$ ISIC Rev.3.1 sectors, reported in Table 11, $K_1 = 15$ of which are defined as non-tradable.

Elasticity parameters. Table 1 in the main text reports the parameters that characterise the spot markets for goods and tasks. The elasticities of substitution between varieties, η_k, are taken from Broda and Weinstein (2006), who report an estimate of 8.2 for the case of 14,549 goods categories during the period 1990-2001. We set $\eta_k = 8.2$, for each $k = 1, .., K$.[26] Estimates for the dispersion of productivity in tradable sectors, θ_k are taken from Caliendo and Parro (2015).

Share parameters. To identify the parameters $\{\alpha_k\}_{\forall k \in \{1..K\}}$ we construct the ratio between domestic sector$-k$ expenditure in intermediate bundles and in task bundles, i.e.

$$\begin{aligned} \frac{\sum_{\tilde{k}=1}^{K} \bar{p}_{\tilde{k}}^{n} x_{\tilde{k}}^{n}}{\sum_{\tilde{k}=1}^{K} \bar{p} x_{\tilde{k}}^{k} + \bar{r}_{k}^{n} \bar{y}_{k}} &= \frac{(1-\alpha_k) \sum_{\tilde{k}=1}^{K} \vartheta_{k\tilde{k}} \sum_{\tilde{n}=1}^{N} \frac{\pi_{k}^{\tilde{n}n} X_{k}^{\tilde{n}}}{1+\tau_{\tilde{n}n}^{k}}}{\alpha_k \sum_{\tilde{n}=1}^{N} \frac{\pi_{k}^{\tilde{n}n} X_{k}^{\tilde{n}}}{1+\tau_{k}^{\tilde{n}n}} + (1-\alpha_k) \sum_{\tilde{k}=1}^{K} \vartheta_{k\tilde{k}} \sum_{\tilde{n}=1}^{N} \frac{\pi_{k}^{\tilde{n}n} X_{k}^{\tilde{n}}}{1+\tau_{k}^{\tilde{n}n}}} \\ &= \frac{(1-\alpha_k) \sum_{\tilde{k}=1}^{K} \vartheta_{k\tilde{k}}}{\alpha_k + (1-\alpha_k) \sum_{\tilde{k}=1}^{K} \vartheta_{k\tilde{k}}} = 1 - \alpha_k \end{aligned} \tag{63}$$

To identify the parameters $\{\vartheta_{k\tilde{k}}\}_{\forall k,\tilde{k} \in \{1,...,K\}}$, we use the share of sector$-k$ expenditure in intermediate good $\tilde{k}$ out of total expenditure in materials,

$$\frac{(1-\alpha_k)\vartheta_{k\tilde{k}} \sum_{\tilde{n}=1}^{N} \frac{\pi_{k}^{\tilde{n}n} X_{k}^{\tilde{n}}}{1+\tau_{k}^{\tilde{n}n}}}{(1-\alpha_k) \sum_{\tilde{k}=1}^{K} \vartheta_{k\tilde{k}} \sum_{\tilde{n}=1}^{N} \frac{\pi_{k}^{\tilde{n}n} X_{k}^{\tilde{n}}}{1+\tau_{k}^{\tilde{n}n}}} = \frac{\vartheta_{k\tilde{k}}}{\sum_{\tilde{k}=1}^{K} \vartheta_{k\tilde{k}}} = \vartheta_{k\tilde{k}} \tag{64}$$

To identify the parameters $\{v_k\}_{\forall k=1..K}$ we construct the share of sector$-k$ consumption expenditure in final goods k, i.e.

$$\frac{\bar{c}_{k}^{n}}{\bar{c}^{n}} = \frac{\nu_k I^n}{I^n} = \nu_k \tag{65}$$

To identify $\{\mu_{kj}\}_{\forall k=1..K, \forall j=1..J}$, we construct the share of tasks $j = 1..J$ demanded in sector $k = 1..K$ (measured by the employment share of occupation j for industry k) out of

[25] The countries are Argentina, Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, UK, and USA.

[26] Broda and Weinstein (2006) report three average estimates for the period 1990-2001: 3.9 for the case of 255 goods categories, 5.6 for the case of 2,731 categories, and 8.2, for the case of 14,549 categories. We choose the last estimate because... [**AR: mention reasons to choose such estimate**].

Table 11: ISIC Rev.3.1. Sectors

Code	ISIC Rev.3.1	Description	Import Penetration	Tradable
1	AtB	Agriculture, forestry and fishing	11.421	yes
2	C	Mining and Quarrying	51.757	yes
3	15t16	Food, Beverages and Tobacco	7.366	yes
4	17t19	Textiles, Textile Products, Leather and Footwear	138.992	yes
5	20	Wood and Product of Wood and Cork	18.645	yes
6	21t22	Pulp, Paper, Printing and Publishing	7.814	yes
7	23	Coke, Refined Petroleum and Nuclear Fuel	12.067	yes
8	24	Chemicals and Chemical Products	27.391	yes
9	25	Rubber and Plastics	17.987	yes
10	26	Other Non-Metallic Minerals	18.199	yes
11	27t28	Basic Metals and Fabricated Metals	22.139	yes
12	29	Machinery, Nec	44.211	yes
13	30t33	Electrical and Optical Equipment	81.201	yes
14	34t35	Transport Equipment	41.497	yes
15	36t37	Manufacturing, Nec; Recycling	59.991	yes
16	E	Electricity, Gas and Water Supply	0.942	no
17	F	Construction	0.102	no
18	50	Sale, Maintenance and Repair of Motor Vehicles	0.189	no
19	51	Wholesale Trade, Except of Motor Vehicles	1.092	no
20	52	Retail Trade, Except of Motor Vehicles	0.458	no
21	H	Hotels and Restaurants	0.182	no
22	60t63	Transportation	5.907	no
23	64	Post and Telecommunications	0.208	no
24	J	Financial Intermediation	1.501	no
25	70	Real Estate Activities	0.077	no
26	71t74	Renting and Other Business Activities	5.472	no
27	L	Public Admin and Defence; Compulsory Social Security	0.065	no
28	M	Education	0.601	no
29	N	Health and Social Work	0.048	no
30	OtP	Other Community, Social, Personal Services	0.907	no

industry-k demand for task bundles,

$$\frac{r_{nj}y_k^{nj}}{\bar{r}_k^n\bar{y}_k^n} = \frac{\mu_{kj}\alpha_k\sum_{\tilde{n}=1}^N \frac{\pi_k^{\tilde{n}n}X_k^{\tilde{n}}}{1+\tau_k^{\tilde{n}n}}}{\alpha_k\sum_{\tilde{n}=1}^N \frac{\pi_k^{\tilde{n}n}X_k^{\tilde{n}}}{1+\tau_k^{\tilde{n}n}}} = \mu_{kj}$$

Notice that the μ_{kj} are identified up to $r^{n,j}/\bar{r}_k^n$ and $y_k^{n,j}$, which are not directly observable from the data. However, we can approximate the ratio of the price for task j ($r^{n,j}$) to the sector-k price for task bundles ($\bar{r}_k^n$) using employment levels, $\ell_k^{n,j}$, to approximate task levels, $y_k^{n,j}$. Sectoral wages and employment are observable, and the μ_{kj} are then pinned down as follows

$$\frac{r^{n,j}y_k^{n,j}}{\bar{r}_k^n\bar{y}_k^n} \approx \frac{w^{n,j}\ell_k^{n,j}}{\bar{w}_k^n\bar{\ell}_k^n} = \mu_{kj} \tag{66}$$

Our model implies that task prices include a return to task-producing firms. We approximate the total earnings of these firms using total earnings of workers employed in human

resource occupations. Then we apportion these earnings across tasks in proportion to the number of workers employed. Given this strategy, the ratio (66) is unaffected by unaffected by task producers' earnings.

Trade parameters. As discussed in the text, our approach to estimating the bilateral trade costs ($d_k^{n,\tilde{n}}$) and the sector-specific productivity location parameters (T_k^n) involves equation (**??**). This expression can be found in Bolatto (2015), and can be derived as follows.

By equation (26), the share of type-k goods sourced from country n by country $\tilde{n}$ is:

$$\frac{X_k^{\tilde{n},n}}{X_k^{\tilde{n}}} = \frac{T_k^n (u_k^n d_k^{\tilde{n},n})^{-\theta_k}}{\sum_{m=1}^N T_k^m (u_k^m d_k^{\tilde{n},m})^{-\theta_k}}.$$

Hence we can write $X_k^{\tilde{n},n}/X_k^{\tilde{n},\tilde{n}}$ as:

$$\begin{aligned}
\frac{X_k^{\tilde{n},n}}{X_k^{\tilde{n},\tilde{n}}} &= \frac{T_k^n}{T_k^{\tilde{n}}} \left(\frac{u_k^n}{u_k^{\tilde{n}}}\right)^{-\theta_k} (d_k^{\tilde{n},n})^{-\theta_k}, \text{ or re-arranging,} \\
\ln \frac{T_k^{\tilde{n}}}{T_k^n} &= -\theta_k \left[\ln\left(\frac{u_k^n}{u_k^{\tilde{n}}}\right) + \ln d_k^{\tilde{n},n}\right] + \ln \frac{X_k^{\tilde{n},\tilde{n}}}{X_k^{\tilde{n},n}}
\end{aligned}$$

Finally, using equation (24) to state unit costs u_k^n and $u_k^{\tilde{n}}$ in terms of factor prices, we obtain equation (**??**) of the text:

$$\begin{aligned}
\log \frac{T_k^{\tilde{n}}}{T_k^n} &= \log \frac{X_k^{\tilde{n},\tilde{n}}}{X_k^{\tilde{n},n}} - \theta_k \log d_k^{\tilde{n},n} + \theta_k \left[\alpha_k^{\tilde{n}} \log \bar{r}_k^{\tilde{n}} - \alpha_k^n \log \bar{r}_k^n\right] \\
&\quad + \theta_k \left[(1-\alpha_k^{\tilde{n}}) \sum_{\tilde{k}=1}^K \vartheta_{k\tilde{k}}^{\tilde{n}} \log p_{\tilde{k}}^{\tilde{n}} - (1-\alpha_k^n) \sum_{\tilde{k}=1}^K \vartheta_{k\tilde{k}}^n \log p_{\tilde{k}}^n\right]
\end{aligned}$$

Task prices. In the estimation algorithm, we treat the price of tasks, $\{r_j\}_{j=1}^J$, as exogenous parameters. Measuring these prices pose a challenge, since there is no empirical counterparts to them. In fact, the model-implied prices of tasks account for both payments to employees and payments to job employers. While payments to employees corresponds to the labor income received by workers and can be easily measured using data on wages across occupations, payments to the task-producing firms who employ them are not observable. To quantify this payment, we will interpret it as the profit margin from an active job needed by a job employer to cover the initial cost of posting the vacancy and the discounted sum of per-period operating costs. Since the model does not allow for an explicit notion of firm (thus of profits), we will use the cost of human resources as a proxy for that. Denote the

empirical prices of tasks as $\{\hat{r}_j\}_{j=1}^J$. They are constructed as the sum of two components,

$$\hat{r}_j = \hat{w}_j + \hat{c}_j$$

where $\hat{w}_j$ denotes the wage payment received by an employee in occupation j while $\hat{c}_j$ is the average profits accruing to the employer of a job in the same occupation. Therefore, we proxy $\hat{c}_j$ using the relative costs of human resources in each occupation j, i.e.

$$\hat{c}_j = \frac{\#\text{emp}_j}{\#\text{emp}} \hat{w}_{HR}$$

where $\hat{w}_{HR}$ is the average labor income received by employees in human resource while $\frac{\#\text{emp}_j}{\#\text{emp}}$ is the share of employees in occupation j out of total employment. Fixing the price of tasks to those constructed from the data during the estimation algorithm will not necessarily ensure that, at the estimated parameters, an equilibrium in each market for tasks is obtained. To make sure an equilibrium is satisfied at the selected parameters, we include a list of clearing conditions for each market of tasks into the set of moment conditions to be matched. Remember though that, while these prices are fixed during the estimation, they will be allowed to react in general equilibrium. [**JT: need to add discussion of r measurement outside the U.S.**]