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Changes in Between-Group Inequality: Computers, Occupations, and International Trade†

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We provide a unifying framework to quantify the impact of several determinants of changes in US between-group inequality. We use an assignment framework with many labor groups, equipment types, and occupations in which changes in inequality are driven by changes in workforce composition, occupation demand, computerization, and labor productivity. We parameterize the model using direct measures of computer usage within labor group-occupation pairs and quantify the impact of each shock for various dimensions of between-group inequality between 1984 and 2003. We find, for example, that computerization and shifts in occupation demand jointly account for roughly 80 percent of the rise in the skill premium, with computerization alone accounting for roughly 60 percent. In an open-economy extension of the model, we show how computerization and changes in occupation demand can be caused by changes in the extent of international trade and perform counterfactual exercises to quantify these effects. (*JEL* D63, J16, J22, J23, J24, J31)

The last few decades have witnessed pronounced changes in relative average wages across groups of workers with different observable characteristics (*between-group inequality*). Most notably, the wages of workers with more education relative to those with less and of women relative to men have increased substantially in the United States.

A large literature has emerged studying how changes in relative supply and demand for labor groups shape their relative wages. Changes in relative demand across labor groups have been linked prominently to computerization (or a reduction in the price of equipment more generally)—see, e.g., Krusell et al. (2000), Autor and Dorn (2013), and Beaudry and Lewis (2014)—and to changes in relative demand across occupations and sectors, driven by structural transformation, offshoring, and international trade—see, e.g., Autor, Levy, and Murnane (2003); Buera, Kaboski,

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Table 1—Computer Use over Time

	1984	1989	1993	1997	2003
Panel A					
All	27.4	39.9	49.4	53.3	58.2
Gender					
Female	32.9	47.6	57.1	61.2	65.3
Male	23.5	34.2	43.4	47.1	52.5
Education					
College degree	46.1	63.1	75.0	80.2	86.1
No college degree	22.1	32.5	40.6	43.1	45.6
Panel B					
Gender					
Difference	9.4	13.5	13.7	14.1	12.9
Contribution within	26.9	18.3	15.5	19.9	33.9
Contribution between	73.1	81.7	84.5	80.1	66.1
Education					
Difference	24.0	30.6	34.4	37.1	40.5
Contribution within	50.7	48.3	48.3	43.4	54.0
Contribution between	49.3	51.7	51.7	56.6	46.0

Notes: Panel A shows the share of hours worked with computers by all workers, and by gender and education groups. Panel B shows the difference across gender and education groups in computer use, and the share of these differences accounted for by between- and within-occupation differences; see the online Appendix for details of the decomposition.

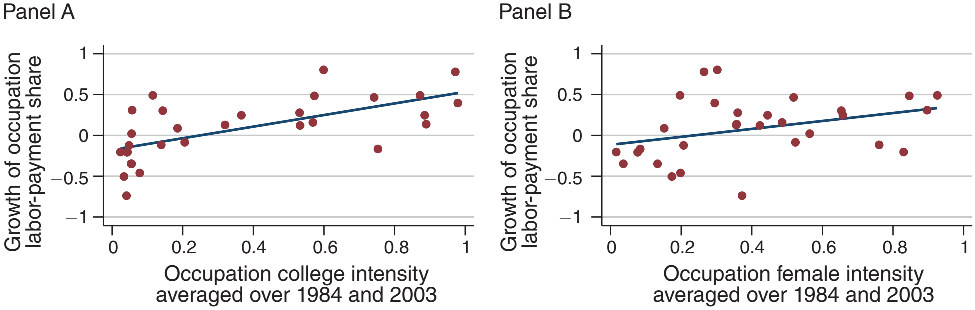

Figure 1. Growth (1984–2003) of the Occupation Share of Labor Payments and the Average (1984 and 2003) of the Share of Workers in the Occupation Who Have a College Degree (Panel A) and Are Female (Panel B)

and Rogerson (2015); and Galle, Rodríguez-Clare, and Yi (2015). Suggestive of the first hypothesis, panel A of Table 1 shows that computer use in the United States rose dramatically between 1984 and 2003 and that computers are used more intensively by educated workers and women. Suggestive of the second hypothesis, Figure 1 shows that education- and female-intensive occupations grew relatively quickly over the same time period.[1]

[1] We describe our data sources in Section IIIA and Appendix B.

In this paper, we provide a model-based quantification of the impacts of various shocks on between-group inequality in the United States. To motivate our approach, consider first the facts presented in panel A of Table 1—that educated and female workers use computers more and that computer usage has risen over time—and what they imply for the college and female bias of computerization. These patterns may be caused by (i) variation in computer usage across worker groups within occupations or (ii) variation in the allocation of worker groups across occupations that differ in computer intensity. In panel B, we decompose the difference in computer usage between women and men and between college and non-college workers into a within-occupation component and a between-occupation component. Women use computers more largely because they are disproportionately employed in computer-intensive occupations whereas more educated workers use computers more both because of the within- and the between-occupation components (roughly in equal parts). Computerization raises the marginal product of worker groups that use computers intensively but reduces the price of output in occupations that are intensive in computers. Since wages equal the value marginal product of labor, the impact of computerization on wage inequality depends crucially both on variation in aggregate computer usage across worker groups—panel A—and on the source of this variation—panel B. Consequently, in order to quantify the impact of computerization on inequality, we must take into consideration the possibility that workers differ in their computer usage both within and across occupations.

Next, consider the facts presented in Figure 1—that college- and female-intensive occupations grew over time—and what they imply for the college and female bias of changes in occupation demand. Occupation growth is shaped not only by changes in relative demand shifters for different occupations, but also by changes in the wages and productivities of different groups of workers and changes in the prices and productivities of different types of capital equipment. For instance, if occupations are gross substitutes, then computerization will tend to shift employment to computer-intensive occupations. Consequently, in order to quantify the impact of occupation demand shifters, we must take into consideration the possibility that computerization and changes in labor supply and productivity shape the size of occupations.

Motivated by these observations, we build a model with many labor groups (to study changes in between-group inequality along various dimensions) that features many occupations and equipment types (to incorporate heterogeneous computer usage within and across occupations as well as shocks to equipment productivity and occupation demand). Given the difficulties in estimating a general production function with a large number of factors by occupation, we parameterize a Roy (1951)-type assignment model that builds on Lagakos and Waugh (2013) and Hsieh et al. (2018), extended to include equipment and international trade. This framework allows for potentially rich patterns of complementarity between labor groups, equipment types, and occupations and, in spite of its high dimensionality, remains tractable enough to perform aggregate counterfactuals in a parsimonious manner. Three-dimensional comparative advantage—between labor groups, equipment types, and occupations—shapes the allocation of workers in each labor group across equipment types and occupations and, thus, also shapes the impact of changes in the economic environment on between-group inequality. Our model's aggregate implications for relative wages nest those of workhorse models of between-group inequality in a closed economy, e.g., Katz and Murphy (1992) and Krusell et al. (2000), and in an open economy, e.g., the Heckscher-Ohlin model.

We use our model to assess the impact of computerization and changes in occupation demand, labor composition, and labor productivity on between-group inequality in the United States. We additionally provide simple counterfactual exercises in which we quantify the extent to which computerization and changes in occupation demand are driven by international trade in equipment goods and occupation output.

In our first exercise, we decompose observed changes in relative wages between labor groups in the United States between 1984 and 2003 into changes in (price-adjusted) equipment productivity, occupation demand, labor supply, and labor productivity in a closed economy. This time period featured large changes in between-group inequality. For instance, the skill premium (i.e., the relative wage of workers with a college degree to those without) rose by 15.1 (log) percent and rose by 7.2 percent more amongst the old than the middle aged, and the gender gap contracted by 13.3 percent; see tables in Section IIID.[2] We infer changes in equipment productivity that result in computerization from changes in the allocation of workers to computers within labor group-occupation pairs; focusing on changes within labor group-occupation pairs is important because aggregate computer usage will rise even in the absence of changes in equipment productivity if labor groups that have a comparative advantage using computers or occupations that have a comparative advantage with computers grow. We infer occupation demand shifters from changes in the allocation of workers to occupations within labor group-equipment type pairs and in labor income shares across occupations. Changes in labor composition are directly observed in the data. We measure labor productivity as a residual to match changes in the average wage of each labor group. Finally, we leverage plausibly exogenous variation and the structure of our model to identify key elasticities.

We find that computerization alone accounts for roughly 60 percent of all shocks that have had a positive impact on the skill premium between 1984 and 2003 and plays a similar role in explaining disaggregated measures of between-education-group inequality (e.g., the wage of workers with graduate training relative to the average wage). Our model's prediction is driven by the following three facts observed in the data. First, there has been a large rise in the share of workers using computers within labor group-occupation pairs, which our model interprets as a large increase in computer productivity (i.e., computerization).[3] Second, more

[2] The relative importance of between- and within-group inequality is an area of active research and is beyond the scope of this paper. On the one hand, based on US data, Autor (2014) writes that "about two-thirds of the overall rise of earnings dispersion between 1980 and 2005 is proximately accounted for by the increased premium associated with schooling in general and postsecondary education in particular," and Lemieux (2006) writes "that residual wage inequality accounts for only a modest share of the growth in overall inequality between 1973 and 2003." On the other hand, based on 1986–1995 Brazilian data, Helpman et al. (2017) concludes that "residual wage inequality is at least as important as worker observables in explaining the overall level and growth of wage inequality."

[3] This observation is consistent with ample direct evidence showing a rapid decline in the price of computers relative to all other equipment types and structures (summarized in footnote 25), which we do not directly use in our estimation.

educated workers use computers within occupations relatively more than less educated workers, which our model interprets as educated workers having a comparative advantage with computers. This pattern of comparative advantage, together with computerization, yields a rise in the relative wages of educated workers according to our model. Third, more educated workers are also disproportionately employed in occupations in which all workers use computers relatively intensively, which our model interprets as educated workers having a comparative advantage in occupations in which computers have a comparative advantage. This pattern of sorting across occupations, together with computerization and an estimated elasticity of substitution between occupations greater than one, also yields a rise in the relative wages of educated workers.

The combination of computerization and changes in occupation demand accounts for roughly 80 percent of the rise in the skill premium, leaving only 20 percent to be explained by labor productivity. This is remarkable, given that we measure changes in labor productivity as a residual that allows our framework to match exactly observed changes in relative wages. We find that computerization, occupation shifters, and labor productivity all play important roles in accounting for the reduction in the gender gap (i.e., the relative wage of male to female workers). Computerization decreases the gender gap because women are disproportionately employed in occupations in which all workers use computers intensively and our estimate of the elasticity of substitution across occupations is larger than one. We show that computerization plays the central role in explaining the distinct evolution of the skill premium across age groups, while labor composition—the focus of previous literature on this issue, e.g., Card and Lemieux (2001)—plays a much smaller role. We obtain this result because computer use among college-educated relative to noncollege-educated workers is substantially higher among young workers than old workers in every year of our sample. More generally, we show that computerization explains over 50 percent of the variance in the change in relative wages (implied by the combination of the 3 demand-side shocks) across the 30 labor groups considered in our analysis.

Whereas in our closed-economy model we treat computerization and occupation demand shifters as primitives; in Sections IV and V, we study the extent to which these changes are a consequence of international trade. Given estimates of the relevant elasticity parameters, we show theoretically that the procedure to quantify the impact on relative wages of moving to autarky in equipment and occupation trade is equivalent to the procedure we follow in our closed-economy model to calculate the impact of domestic shocks on relative wages, with the only difference that the computerization and occupation demand shocks are now measured as functions of import shares of absorption and export shares of output of different equipment types and occupations. For example, if an occupation ω has a high import share relative to another occupation ω', then moving to autarky has an equivalent impact on relative wages in a closed economy as increasing domestic occupation demand for ω relative to ω'. Given the lack of data on the occupation content of exports and imports, measuring occupation trade shares is a challenge; for a full discussion of the difficulties, see Grossman and Rossi-Hansberg (2008). Given these challenges, we consider alternative simple, albeit imperfect, approaches to measure the occupation content of exports and imports. Using our preferred approach, we find that moving from 2003 trade shares to equipment (occupation) autarky would generate a 2.2 (6.3) percent reduction in the skill premium. We also provide a simple procedure to quantify the differential effects on wages in a given country of changes in primitives (i.e., worldwide technologies, labor compositions, and trade costs) between two time periods relative to the effects of the same changes in primitives if that country were a closed economy. Our results indicate that changes in equipment (occupation) trade between 1984 and 2003 accounted for roughly 15 (25) percent of the impact of changes in equipment productivity (occupation shifters) on the skill premium that we obtained in our closed-economy calculations.

Our paper is organized as follows. In Section I, we discuss the related literature. We describe our closed-economy framework, characterize its equilibrium, and discuss its mechanisms in Section II. We parameterize the model and present our closed-economy results in Section III. We extend our model to incorporate international trade in equipment goods and occupation services in Section IV and quantify the impact of international trade in Section V. We conclude in Section VI. Additional details and robustness exercises are relegated to Appendices.

I. Literature

In trying to explain the evolution of between-group inequality as a function of changes in observables, our paper's objective is most similar to Krusell et al. (2000) and Lee and Wolpin (2010). Krusell et al. (2000) estimates an aggregate production function that permits capital-skill complementarity and shows that changes in aggregate stocks of equipment, skilled labor, and unskilled labor can account for much of the variation in the US skill premium. Whereas Krusell et al. (2000) identifies the degree of capital-skill complementarity using aggregate time series data, our approach leverages information on the allocation of workers to computers and occupations and, consequently, yields parameter estimates shaping the degree of equipment-labor group complementarities that are robust to allowing for time trends in the relative productivity of each labor group; see Acemoglu (2002) for a discussion of the relevance of allowing for these time trends in this context. Our decomposition corroborates the findings in Krusell et al. (2000) and extends them by additionally considering the impact of equipment productivity growth on the gender gap and other measures of between-group inequality.

Lee and Wolpin (2010) uses a dynamic model of endogenous human capital accumulation and finds that labor-group productivity (also treated as a residual in their analysis) plays the central role in explaining changes in the skill premium. By considering a greater degree of disaggregation in occupations and labor groups (which would require estimating hundreds of additional elasticities using their aggregate-production-function approach, but which is straightforward in our assignment approach), and by introducing three-dimensional comparative advantage (in order to account for the patterns in panel B of Table 1, which cannot be incorporated into an aggregate production function), our results largely reduce the role of changes in the residual in shaping changes in the skill premium and allow us to study various additional dimensions of between-group inequality. On the other hand, in contrast to Lee and Wolpin (2010), we treat labor composition as exogenous.[4]

In modeling international trade, we operationalize in a quantitative setting the theoretical insights of Costinot and Vogel (2010), Sampson (2014), and Costinot and Vogel (2015) regarding the impact of international trade on inequality in high-dimensional environments. We show that one can use a similar approach to that introduced by Dekle, Eaton, and Kortum (2008) in a single-factor trade model—i.e., replacing a large number of unknown parameters with observable allocations in an initial equilibrium—in a many-factor assignment model. In this respect, our paper is complementary to concurrent work quantifying the impact of international trade on between-group inequality; see, e.g., Adão (2015); Dix-Carneiro and Kovak (2015); Galle, Rodríguez-Clare, and Yi (2015); and Lee (2017). Relative to this concurrent work, we introduce equipment in the framework and quantify the impact of trade both in equipment and in occupations on inequality; however, relative to this work, we only use data for one region: the United States. Whereas a large literature has emerged to argue that trade in occupation (or even task) output is a potentially important force generating changes in inequality—see, e.g., Grossman and Rossi-Hansberg (2008)—there has been much less work conducting model-based counterfactuals to quantify the importance of this phenomenon.[5] Given the crudeness of our measures of occupation trade, our quantification of the impact of trade in occupations on between-group inequality should be viewed as a first step. Our modeling of international trade in equipment extends the quantitative analyses of Burstein, Cravino, and Vogel (2013) and Parro (2013), who study the impact of trade in capital equipment on the skill premium using the model of Krusell et al. (2000).

A large number of papers study the impact of changes in demand across sectors or occupations on relative wages using a shift-share analysis; see, e.g., Katz and Murphy (1992) and Autor, Levy, and Murnane (2003). This approach directly interprets Figure 1 as evidence of the extent to which changes in sector or occupation demand have affected relative wages. We contribute to this literature by estimating the elasticity of substitution across occupations (a necessary condition for a causal interpretation of a shift-share analysis is that this elasticity is one) and incorporating

[4] Extending our model to endogenize education and labor participation—maintaining a static environment—would give rise to the same equilibrium equations determining factor allocations and wages conditional on labor composition. Our measures of shocks—to occupation demand shifters, equipment productivity, and labor productivity—and our estimates of model parameters are therefore robust to extending our model to endogenize the supply of each labor group in a static environment. Through the lens of this model, our counterfactual results would be interpreted as the direct effect of shocks on labor demand and wages, taking labor composition as given. To take into consideration the accumulation of occupation-specific human capital as in, e.g., Kambourov and Manovskii (2009a, b), we would have to include occupational experience as a worker characteristic when defining labor groups in the data (unfortunately, the October CPS does not contain this information) and model the corresponding dynamic optimization problem that workers would solve when deciding which occupation to sort into.

[5] Traiberman (2016) quantifies the impact of import competition on occupation demand and wages. He constructs a measure of import exposure by occupation by allocating observed sectoral imports to occupations according to the share of labor payments going to each occupation in each sector. As we argue later in this paper, this measure is likely to be biased if, within industries, certain occupations are more traded than others. Goos, Manning, and Salomons (2014) measures the impact of offshoring on the growth of occupations imposing a common effect of occupation offshorability on changes in occupation size, independently of whether a country is a net exporter or a net importer in this occupation. Our model however emphasizes the importance of distinguishing whether a country is a net exporter or importer of each occupation when looking at the impact of international trade on occupation growth.

a range of additional possible causes of changes in relative wages and occupation employment and income shares, which becomes necessary to quantify the impact of changes in sector or occupation demand when this elasticity differs from one.[6]

Two related papers use information on regional exposure to computerization to study the differential effect across regions of technical change on the polarization of US employment and wages, Autor and Dorn (2013), and on the gender gap and skill premium, Beaudry and Lewis (2014). Our approach complements these papers, embedding computerization into a general equilibrium model that allows us to quantify at the aggregate level the effect of computerization (as well as other shocks) on changes in between-group inequality (as opposed to the differential effect across regions). By incorporating three-dimensional comparative advantage, our framework introduces heterogeneous treatment effects of computerization across labor groups that use computers at a similar rate.

In exploiting data on workers' computer usage, our paper is related to an earlier literature studying the impact of computer use on wages; see, e.g., Krueger (1993) and Entorf, Gollac, and Kramarz (1999). This literature identifies the impact of computer usage on wages by regressing wages of different workers on a dummy for computer usage, an identification approach that DiNardo and Pischke (1997) criticizes. Our approach to estimate key model parameters does not rely on such a regression.

II. Closed-Economy Model

In this section, we introduce the closed-economy version of our model, characterize its equilibrium, and provide intuition for how different changes in the economic environment affect relative wages.

A. *Environment*

At time t, there is a continuum of workers indexed by $z \in \mathcal{Z}_t$, each of whom inelastically supplies one unit of labor. We divide workers into a finite number of labor groups, indexed by λ. The set of workers in group λ is given by $\mathcal{Z}_t(\lambda) \subseteq \mathcal{Z}_t$, which has mass $L_t(\lambda)$. There is a finite number of equipment types, indexed by κ. Workers and equipment are employed by production units to produce a finite number of occupations, indexed by ω.

A final good is produced combining the services of occupations according to a constant elasticity of substitution (CES) production function

$$(1) \qquad Y_t = \left(\sum_{\omega} \mu_t(\omega)^{1/\rho} Y_t(\omega)^{(\rho-1)/\rho} \right)^{\rho/(\rho-1)},$$

where $\rho > 0$ is the elasticity of substitution across occupations, $Y_t(\omega) \geq 0$ is the output of occupation ω, and $\mu_t(\omega) \geq 0$ is an exogenous demand shifter for

[6] The approach that we use to bring our model to the data does not require mapping occupations into observable characteristics, such as those introduced in Autor, Levy, and Murnane (2003). Instead, we estimate measures of comparative advantage and demand shocks that vary flexibly across occupations, independently of the similarity in the task composition of these occupations.

occupation ω.[7] The final good is used to produce consumption, C_t, and equipment, $Y_t(\kappa)$, according to the resource constraint

$$Y_t = C_t + \sum_{\kappa} \tilde{p}_t(\kappa) Y_t(\kappa), \tag{2}$$

where $\tilde{p}_t(\kappa)$ denotes the cost of a unit of equipment κ in terms of units of the final good.[8]

Occupation services are produced by perfectly competitive production units. A unit hiring k units of equipment type κ and l efficiency units of labor group λ produces $k^{\alpha}\left[T_t(\lambda,\kappa,\omega)\, l\right]^{1-\alpha}$ units of output, where α denotes the output elasticity of equipment and $T_t(\lambda,\kappa,\omega)$ denotes the productivity of an efficiency unit of group λ's labor in occupation ω when using equipment κ.[9] Comparative advantage between labor and equipment is defined as follows: λ' has a comparative advantage (relative to λ) using equipment κ' (relative to κ) in occupation ω if $T_t(\lambda',\kappa',\omega)/T_t(\lambda',\kappa,\omega) \geq T_t(\lambda,\kappa',\omega)/T_t(\lambda,\kappa,\omega)$. Labor-occupation and equipment-occupation comparative advantage are defined analogously.

A worker $z \in \mathcal{Z}_t(\lambda)$ supplies $\epsilon(z)\,\varepsilon(z,\kappa,\omega)$ efficiency units of labor if teamed with equipment κ in occupation ω. Each worker is associated with a unique $\epsilon(z)$, allowing some workers within $\mathcal{Z}_t(\lambda)$ to be more productive than others across all possible (κ,ω); we normalize the average value of $\epsilon(z)$ across workers within each λ to be one, which is without loss of generality (see Appendix A). Each worker is also associated with a vector of $\varepsilon(z,\kappa,\omega)$, one for each (κ,ω) pair, allowing workers within $\mathcal{Z}_t(\lambda)$ to vary in their relative productivities across (κ,ω) pairs. We impose two restrictions. First, the distribution of $\epsilon(z)$ has finite support and is independent of the distribution of $\varepsilon(z,\kappa,\omega)$ for each (κ,ω). Second, each $\varepsilon(z,\kappa,\omega)$ is drawn independently from a Fréchet distribution with cumulative distribution function $G(\varepsilon) = \exp\left(-\varepsilon^{-\theta}\right)$, with $\theta > 1$, where a higher value of θ implies lower within-worker dispersion of efficiency units across (κ,ω) pairs.[10]

[7] We show in Sections IV and V that changes in the extent of international trade in occupation services generate changes in $\mu_t(\omega)$.

[8] We show in Sections IV and V that changes in the extent of international trade in equipment generate changes in equipment prices $\tilde{p}_t(\kappa)$. Our assumption that equipment must be produced every period (five years in our quantitative analysis) is equivalent to assuming that equipment fully depreciates every period. Alternatively, we could have assumed that $Y_t(\kappa)$ denotes investment in capital equipment κ, which depreciates at a given finite rate. All our counterfactual exercises are consistent with this alternative model with capital accumulation: they would correspond to comparisons across balanced growth paths in which the real interest rate and the growth rate of relative productivity across equipment types are constant over time.

[9] We can extend the model to incorporate other inputs such as structures or intermediate inputs s; however, they would not affect any of our results as long as they are produced linearly using the final good and enter the production function multiplicatively as $s^{1-\eta}\left(k^{\alpha}\left[T_t(\lambda,\kappa,\omega)\, l\right]^{1-\alpha}\right)^{\eta}$. Notice that, in either case, α is the share of equipment relative to the combination of equipment and labor. We restrict α to be common across occupations because we do not have the data to estimate $\alpha(\omega)$ by occupation.

[10] The assumption that $\varepsilon(z,\kappa,\omega)$ is distributed Fréchet is made for tractability, as it implies that the average wage and the allocation of workers (in each labor group) across occupations and equipment types are both globally constant elasticity functions of occupation prices and equipment productivities. The wage distribution implied by the Fréchet assumption is a good approximation to the observed distribution of individual wages; see, e.g., Saez (2001) and Figure 3 in Appendix D, Subsection C. In the online Appendix, we show that our results are robust to allowing for variation across labor groups in the dispersion parameter θ, restricting the statistical dependence of $\varepsilon(z,\kappa,\omega)$ across (κ,ω) pairs by using a multivariate Fréchet distribution.

Total output of occupation ω, $Y_t(\omega)$, is the sum of output across all units producing occupation ω. All markets are perfectly competitive, and all factors are freely mobile across occupations and equipment types.

Relation to Alternative Frameworks.—Whereas our framework imposes strong restrictions on occupation production functions, its aggregate implications for wages nest those in Katz and Murphy (1992) and Krusell et al. (2000). Specifically, the aggregate implications of our model for relative wages are equivalent to those in Katz and Murphy (1992) if we assume no equipment (i.e., $\alpha = 0$) and two labor groups, each of which has a positive productivity in only one occupation. Similarly, the aggregate implications of our model for relative wages are equivalent to those in Krusell et al. (2000) if we allow for only two labor groups and one type of equipment, each labor group has positive productivity in only one occupation and the equipment share is positive in only one occupation.

B. *Equilibrium*

We characterize the competitive equilibrium, first taking occupation prices as given and then in general equilibrium. Additional derivations are provided in Appendix A.

Partial Equilibrium.—With perfect competition, equation (2) implies that the price of equipment κ is simply $p_t(\kappa) = \tilde{p}_t(\kappa) P_t$, where P_t is the price of the final good, which we normalize to one so that $p_t(\kappa) = \tilde{p}_t(\kappa)$. An occupation production unit hiring k units of equipment κ and l efficiency units of labor λ earns revenues $p_t(\omega)\, k^{\alpha} \left[T_t(\lambda, \kappa, \omega)\, l\right]^{1-\alpha}$ and incurs costs $p_t(\kappa)\, k + v_t(\lambda, \kappa, \omega)\, l$, where $v_t(\lambda, \kappa, \omega)$ is the wage per efficiency unit of labor λ when teamed with equipment κ in occupation ω and $p_t(\omega)$ is the price of occupation ω output. The profit maximizing choice of equipment quantity and the zero profit condition—due to costless entry of production units—yields

$$v_t(\lambda, \kappa, \omega) = \bar{\alpha}\, p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}} T_t(\lambda, \kappa, \omega)$$

if there is positive entry in $(\lambda, \kappa, \omega)$, where $\bar{\alpha} \equiv (1-\alpha)\, \alpha^{\alpha/(1-\alpha)}$. Facing the wage profile $v_t(\lambda, \kappa, \omega)$, each worker $z \in \mathcal{Z}_t(\lambda)$ chooses the equipment-occupation pair (κ, ω) that maximizes her wage, $\epsilon(z)\, \varepsilon(z, \kappa, \omega) v_t(\lambda, \kappa, \omega)$. The assumption that $\varepsilon(z, \kappa, \omega)$ is distributed Fréchet and independent of $\epsilon(z)$ implies that the probability that a randomly sampled worker, $z \in \mathcal{Z}_t(\lambda)$, uses equipment κ in occupation ω is

$$\pi_t(\lambda, \kappa, \omega) = \frac{\left[T_t(\lambda, \kappa, \omega)\, p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}}\right]^{\theta}}{\sum_{\kappa', \omega'} \left[T_t(\lambda, \kappa', \omega')\, p_t(\kappa')^{\frac{-\alpha}{1-\alpha}} p_t(\omega')^{\frac{1}{1-\alpha}}\right]^{\theta}}. \tag{3}$$

The higher is θ, the more responsive are factor allocations to changes in prices or productivities. According to equation (3), comparative advantage shapes factor allocations. As an example, the assignment of workers across equipment types within any given occupation satisfies

$$\frac{T_t(\lambda', \kappa', \omega)}{T_t(\lambda', \kappa, \omega)} \Big/ \frac{T_t(\lambda, \kappa', \omega)}{T_t(\lambda, \kappa, \omega)} = \left(\frac{\pi_t(\lambda', \kappa', \omega)}{\pi_t(\lambda', \kappa, \omega)} \Big/ \frac{\pi_t(\lambda, \kappa', \omega)}{\pi_t(\lambda, \kappa, \omega)}\right)^{1/\theta},$$

so that, if λ' workers (relative to λ workers) have a comparative advantage using κ' (relative to κ) in occupation ω, then they are relatively more likely to be allocated to κ' in occupation ω.

The wage per efficiency unit of labor λ when teamed with equipment κ in occupation ω, $v_t(\lambda, \kappa, \omega)$, differs from the *average wage* of workers in group λ teamed with equipment κ in occupation ω, denoted by $w_t(\lambda, \kappa, \omega)$, which is the integral of $\epsilon(z)\, \varepsilon(z, \kappa, \omega)\, v_t(\lambda, \kappa, \omega)$ across workers teamed with κ in occupation ω, divided by the mass of these workers. Given our assumptions on $\epsilon(z)$ and $\varepsilon(z, \kappa, \omega)$, we obtain

$$w_t(\lambda, \kappa, \omega) = \bar{\alpha}\gamma T_t(\lambda, \kappa, \omega)\, p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}} \pi_t(\lambda, \kappa, \omega)^{-1/\theta},$$

where $\gamma \equiv \Gamma(1 - 1/\theta)$ and $\Gamma(\cdot)$ is the Gamma function. An increase in productivity or occupation price, $T_t(\lambda, \kappa, \omega)$ or $p_t(\omega)$, or a decrease in equipment price, $p_t(\kappa)$, raises the wages of inframarginal λ workers allocated to (κ, ω). However, the average wage across all λ workers in (κ, ω) increases less than that of inframarginal workers due to self-selection, i.e., $\pi_t(\lambda, \kappa, \omega)$ increases, which lowers the average number of efficiency units of the λ workers who choose to use equipment κ in occupation ω.

Denoting by $w_t(\lambda)$ the average wage of workers in group λ (i.e., total income of the workers in group λ divided by their mass), the previous expression and equation (3) imply $w_t(\lambda) = w_t(\lambda, \kappa, \omega)$ for all (κ, ω), where[11]

$$(4) \qquad w_t(\lambda) = \bar{\alpha}\gamma \left(\sum_{\kappa, \omega} \left(T_t(\lambda, \kappa, \omega)\, p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}}\right)^{\theta}\right)^{1/\theta}.$$

[11] The model implies that changes in wages are common across occupations within a labor group λ. In the online Appendix, we decompose the observed *changes* in average wages for each labor group into a between-occupation component (which is zero in our model) and a within-occupation component. We show that the between component is relatively small in the data (accounting for approximately 15 percent of the variation in wage changes). In the presence of compensating differentials, average wages would vary across (κ, ω) pairs within each labor group λ.

General Equilibrium.—In any period, occupation prices $p_t(\omega)$ must be such that total expenditure in occupation ω is equal to total revenue earned by all factors employed in ω,

$$\mu_t(\omega)\, p_t(\omega)^{1-\rho} E_t \;=\; \frac{1}{1-\alpha}\zeta_t(\omega), \tag{5}$$

where $\zeta_t(\omega) \equiv \sum_{\lambda,\kappa} w_t(\lambda)\, L_t(\lambda)\, \pi_t(\lambda,\kappa,\omega)$ is total labor income in occupation ω, and $E_t \equiv \sum_{\omega} \zeta_t(\omega)$ is total expenditures. The aggregate quantity of the final good is

$$Y_t \;=\; E_t \;=\; (1-\alpha)^{-1} \sum_{\lambda} w_t(\lambda)\, L_t(\lambda),$$

the aggregate quantity of equipment κ is

$$Y_t(\kappa) \;=\; \frac{1}{p_t(\kappa)}\, \frac{\alpha}{1-\alpha} \sum_{\lambda,\omega} \pi_t(\lambda,\kappa,\omega)\, w_t(\lambda)\, L_t(\lambda),$$

and aggregate consumption is given by equation (2).

C. *System in Changes*

To solve for changes in equilibrium wages in response to changes in the economic environment, we express the system of equilibrium equations described in Section IIB in changes, denoting changes in any variable x between any two periods t_0 and t_1 by $\hat{x} \equiv x_{t_1}/x_{t_0}$. Changes in average wages are given by

$$\hat{w}(\lambda) \;=\; \left(\sum_{\kappa,\omega} \left(\hat{T}(\lambda,\kappa,\omega)\, \hat{p}(\kappa)^{\frac{-\alpha}{1-\alpha}} \hat{p}(\omega)^{\frac{1}{1-\alpha}} \right)^{\theta} \pi_{t_0}(\lambda,\kappa,\omega) \right)^{1/\theta}, \tag{6}$$

and changes in occupation prices are determined by the following system of equations:

$$\hat{\pi}(\lambda,\kappa,\omega) \;=\; \frac{\left[\hat{T}(\lambda,\kappa,\omega)\, \hat{p}(\kappa)^{\frac{\alpha}{1-\alpha}}\, \hat{p}(\omega)^{\frac{1}{1-\alpha}} \right]^{\theta}}{\sum_{\kappa',\omega'} \left[\hat{T}(\lambda,\kappa',\omega')\, \hat{p}(\kappa')^{\frac{-\alpha}{1-\alpha}}\, \hat{p}(\omega')^{\frac{1}{1-\alpha}} \right]^{\theta} \pi_{t_0}(\lambda,\kappa',\omega')}, \tag{7}$$

$$\hat{\mu}(\omega)\, \hat{p}(\omega)^{1-\rho} \hat{E} \;=\; \frac{1}{\zeta_{t_0}(\omega)} \sum_{\lambda,\kappa} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa,\omega)\, \hat{w}(\lambda)\, \hat{L}(\lambda)\, \hat{\pi}(\lambda,\kappa,\omega), \tag{8}$$

where $\hat{E} = \sum_{\lambda} \frac{w_{t_0}(\lambda) L_{t_0}(\lambda)}{(1-\alpha) E_{t_0}} \hat{w}(\lambda) \hat{L}(\lambda)$. In this system, the forcing variables are $\hat{L}(\lambda)$, $\hat{T}(\lambda, \kappa, \omega)$, $\hat{\mu}(\omega)$, and $\hat{p}(\kappa)$. Given these variables and a choice of a numeraire, equations (6)–(8) yield the model's implied values of changes in average wages, $\hat{w}(\lambda)$, allocations, $\hat{\pi}(\lambda, \kappa, \omega)$, occupation prices, $\hat{p}(\omega)$, and total expenditure, $\hat{E}$.

D. *Intuition*

The Impact of Shocks on Wages and the Role of ρ.—According to equation (6), changes in productivities $\hat{T}(\lambda, \kappa, \omega)$ and in the price of equipment $\hat{p}(\kappa)$ have a direct effect (i.e., holding occupation prices constant) on wages. In addition, both these shocks as well as changes in occupation shifters and in labor composition affect wages indirectly through their impact on occupation prices $\hat{p}(\omega)$. The importance of changes in productivities, equipment prices, and occupation prices for changes in group λ's average wage depends on factor allocations in the initial period, $\pi_{t_0}(\lambda, \kappa, \omega)$. For example, an increase in occupation ω's price or a reduction in the price of equipment κ between any two periods t_0 and t_1 raises the relative average wage of labor groups that disproportionately work in occupation ω or use equipment κ in period t_0.

We now discuss in more detail the intuition for the impact of each of the shocks (the forcing variables) we consider in our quantitative analysis. Consider an increase in occupation-ω demand, i.e., $\hat{\mu}(\omega) > 1$. This shock raises the price of occupation ω and, therefore, the relative wage of labor groups that are disproportionately employed in ω. Similarly, a decrease in the labor supply of group λ, i.e., $\hat{L}(\lambda) < 1$, raises the relative price of occupations in which group λ is disproportionately employed. This raises the relative wage not only of group λ, but also of other labor groups employed in similar occupations as λ. A proportional increase across all (κ, ω) in labor productivity for group λ —i.e., $\hat{T}(\lambda, \kappa, \omega) = \hat{T}(\lambda) > 1$—directly raises the relative wage of group λ and reduces the relative price of occupations in which this group is disproportionately employed, thus reducing the relative wage of labor groups employed in similar occupations as λ.[12]

Consider the impact of a decrease in the price of equipment κ, i.e., $\hat{p}(\kappa) < 1$, or equivalently a proportional increase in its productivity across all (λ, ω), i.e., $\hat{T}(\lambda, \kappa, \omega) = \hat{T}(\kappa) > 1$. The partial equilibrium impact of this shock is to raise the relative wage of labor groups that use κ intensively at the aggregate level. In general equilibrium, this shock also reduces the relative price of occupations in which κ is used intensively, lowering the relative wage of labor groups that are disproportionately employed in these occupations. Overall, the impact on a group's average wage of changes in equipment price depends on the value of

[12] Costinot and Vogel (2010) provides analytic results on the implications for relative wages of changes in labor composition, $L_t(\lambda)$, and occupation demand, $\mu_t(\omega)$, in a restricted version of our model in which there are no differences in efficiency units across workers in the same labor group (i.e., $\theta = \infty$), there is no capital equipment (i.e., $\alpha = 0$), and $T(\lambda, \omega)$—i.e., our $T(\lambda, \kappa, \omega)$ in the absence of equipment—is log-supermodular.

the elasticity of substitution between occupations, ρ, and the extent to which the group's aggregate computer use is shaped by variation in computer usage within or across occupations.

If the only form of comparative advantage is between workers and equipment—in which case variation in aggregate computer use across labor groups is fully explained by within-occupation variation in computer use—then a decrease in the price of equipment κ does not affect relative occupation prices. Hence, a decrease in the price of κ will increase the relative wages of worker groups that use equipment κ more intensively in the initial period.

On the other hand, if the only forms of comparative advantage are between workers and occupations and between equipment and occupations—in which case variation in aggregate computer use is fully explained by between-occupation allocations—then a decrease in the price of equipment κ has two opposite effects on the relative wages of worker groups that use equipment κ intensively at the aggregate level: a positive effect conditional on occupation prices and a negative effect indirectly through its effect on occupation prices. The relative strength of the direct and indirect channels depends on ρ. The direct effect dominates if and only if $\rho > 1$. Intuitively, a decrease in the price of κ acts like a positive productivity shock to the occupations in which κ has a comparative advantage. If $\rho > 1$, this increases employment in these occupations as well as the relative wages of labor groups disproportionately employed in these occupations. On the other hand, if $\rho < 1$, employment falls in κ-intensive occupations, and relative wages fall disproportionately for labor groups employed in these occupations.

More generally—outside of these two extreme cases—a decrease in the price of computers can simultaneously raise the wage (relative to the average wage) of one labor group (λ_1) that uses computers intensively while reducing the wage (relative to the average wage) of another labor group (λ_2) that also uses computers intensively. This would be the case, for example, if λ_1 has a comparative advantage using computers, λ_2 has a comparative advantage in occupations in which computers have a comparative advantage, and $\rho < 1$. Moreover, our framework is flexible enough that computerization can either contract or expand employment in occupations that are computer intensive.

The Role of θ.—The parameter θ, which governs the degree of within-worker productivity dispersion across occupation-equipment type pairs, determines the extent of worker reallocation in response to changes in occupation prices, equipment prices, and productivities: a higher dispersion of idiosyncratic draws, as given by a lower value of θ, results in less worker reallocation. In order to gain intuition on the role of θ for changes in labor group average wages, we take a first-order approximation of equation (6) at period t_0 allocations:

$$\text{(9)} \quad \log \hat{w}(\lambda) = \sum_{\kappa,\omega} \pi_{t_0}(\lambda,\kappa,\omega)\Big(\log \hat{T}(\lambda,\kappa,\omega) + \frac{1}{1-\alpha}\log \hat{p}(\omega) - \frac{\alpha}{1-\alpha}\log \hat{p}(\kappa)\Big).$$

This expression shows that, given changes in occupation and equipment prices as well as productivities, the change in average wages does not depend on θ up to a first-order approximation.[13] However, a lower value of θ results in less worker reallocation across occupations in response to a shock and, therefore, larger changes in occupation prices. Hence, to a first-order approximation, the value of θ affects the response of average wages to shocks by affecting occupation price changes.

III. Decomposition

In this section, we use our closed-economy model to quantify the impact of computerization, changes in labor composition, changes in occupation demand, and changes in labor-group-specific productivities on observed changes in relative wages in the United States. Throughout this section, we assume that $T_t(\lambda, \kappa, \omega)$ can be expressed as

$$T_t(\lambda, \kappa, \omega) \equiv T_t(\lambda)\, T_t(\kappa)\, T_t(\omega)\, T(\lambda, \kappa, \omega). \tag{10}$$

Accordingly, whereas we allow labor group, $T_t(\lambda)$, equipment type, $T_t(\kappa)$, and occupation, $T_t(\omega)$, productivity to vary over time, we impose that the interaction between labor group, equipment type, and occupation productivity, $T(\lambda, \kappa, \omega)$, is constant over time. We therefore assume that comparative advantage is fixed over time. This restriction allows us to separate cleanly the impact on relative wages of λ-, κ-, and ω-specific productivity shocks.

How restrictive is the assumption in equation (10) in practice? Note that, under this assumption, if we use data generated by our model and regress (i) the log of allocations in 2003 on the log of allocations in 1984 as well as labor-group, equipment-type, and occupation fixed effects or (ii) the log change in allocations between 1984 and 2003 on the same set of fixed effects, we would obtain $R^2 = 1$ in both cases. Using the data described in Section IIIA instead, we run the two regressions described in (i) and (ii), weighing observations by the employment within each $(\lambda, \kappa, \omega)$ cell in 1984, and we obtain $R^2 = 0.85$ and $R^2 = 0.71$, respectively. In the online Appendix, we show that our main conclusions are robust to a set of decompositions in which we allow two-dimensional comparative advantage to vary over time; each of these specifications is less restrictive than that in equation (10).[14] We drop the restriction in equation (10) when computing the international trade counterfactuals in Section VI.

[13] More generally, given changes in occupation prices, the shape of the distribution of $\varepsilon(z, \kappa, \omega)$—which we have assumed to be Fréchet—does not matter for the first-order effect of any shock on average wage changes. The reason is that, for any worker group λ, the marginal worker's wage is equal across occupations and equipment types.

[14] In the most general case, if we let $T_t(\lambda, \kappa, \omega)$ vary freely over time in the closed economy, we would only be able to report the joint effect of the combination of all λ-, κ-, and ω-specific shocks on relative wages (while the impact of labor composition would be exactly the same as in our baseline specification).

Given the restriction in equation (10), the system in equations (6)–(8) simplifies to

$$\hat{w}(\lambda) = \hat{T}(\lambda)\Big[\sum_{\kappa,\omega}\big(\hat{q}(\omega)\,\hat{q}(\kappa)\big)^{\theta}\pi_{t_0}(\lambda,\kappa,\omega)\Big]^{1/\theta}, \tag{11}$$

$$\pi(\lambda,\kappa,\omega) = \frac{\big(\hat{q}(\omega)\hat{q}(\kappa)\big)^{\theta}}{\sum_{\kappa',\omega'}\big(\hat{q}(\omega')\hat{q}(\kappa')\big)^{\theta}\pi_{t_0}(\lambda,\kappa',\omega')}, \tag{12}$$

$$\hat{a}(\omega)\,\hat{q}(\omega)^{(1-\alpha)(1-\rho)}\hat{E} = \frac{\sum_{\lambda,\kappa} w_{t_0}(\lambda)\,L_{t_0}(\lambda)\pi_{t_0}(\lambda,\kappa,\omega)\hat{w}(\lambda)\hat{L}(\lambda)\,\hat{\pi}(\lambda,\kappa,\omega)}{\zeta_{t_0}(\omega)}. \tag{13}$$

In this simplified system, we have combined equipment productivity, $T_t(\kappa)$, with equipment prices, $p_t(\kappa)$, to form a composite equipment productivity measure: $q_t(\kappa) \equiv p_t(\kappa)^{-\alpha/(1-\alpha)}T_t(\kappa)$. Similarly, we have combined occupation productivity, $T_t(\omega)$, with occupation demand, $\mu_t(\omega)$, to form a composite occupation shifter: $a_t(\omega) \equiv \mu_t(\omega)\,T_t(\omega)^{(1-\alpha)(\rho-1)}$. Finally, we have also combined occupation productivity, $T_t(\omega)$, with occupation prices, $p_t(\omega)$, to form transformed occupation prices: $q_t(\omega) \equiv p_t(\omega)^{1/(1-\alpha)}T_t(\omega)$. Thus, the forcing variables (shocks) in this system are (i) $\hat{L}(\lambda)$, which we refer to as *labor composition*; (ii) $\hat{q}(\kappa)$, which we refer to as *equipment productivity*; (iii) $\hat{a}(\omega)$, which we refer to as *occupation shifter*s; and (iv) $\hat{T}(\lambda)$, which we refer to as *labor productivity*. Given these shocks and a choice of a numeraire, equations (11)–(13) yield the model's implied values of changes in average wages, $\hat{w}(\lambda)$, allocations, $\hat{\pi}(\lambda,\kappa,\omega)$, and transformed occupation prices, $\hat{q}(\omega)$.[15]

According to equations (11)–(13), we need the following ingredients to perform our decomposition. First, we require measures of factor allocations, $\pi_{t_0}(\lambda,\kappa,\omega)$, average wages, $w_{t_0}(\lambda)$, labor composition, $L_{t_0}(\lambda)$, and labor payments by occupation, $\zeta_{t_0}(\omega)$, in the initial period. We describe the data we employ to obtain each of these measures in Section IIIA. Second, we require measures of relative shocks to labor composition, $\hat{L}(\lambda)/\hat{L}(\lambda_1)$, occupation shifters, $\hat{a}(\omega)/\hat{a}(\omega_1)$, equipment productivity to the power θ, $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$, and labor productivity, $\hat{T}(\lambda)/\hat{T}(\lambda_1)$. We describe our approach to measure these shocks in Section IIIB. Finally, we require estimates of α, ρ, and θ. We describe our estimation strategy in Section IIIC.

[15] The two components of equipment productivity, $T_t(\kappa)$ and $p_t(\kappa)$, could be measured separately using information on equipment prices, which are subject to known quality-adjustment issues raised by, e.g., Gordon, (1990). Similarly, the two components of the occupation shifter, $T_t(\omega)$ and $\mu_t(\omega)$, could be measured separately using information on occupation prices, which are hard to measure in practice. If the aim of our exercise were not to determine the impact of observed changes in the economic environment on observed wages but rather to predict the impact of hypothetical changes in the economic environment, then it would not be necessary to combine changes in equipment productivity and equipment production costs into a single shock or to combine changes in occupation demand and occupation productivity into a single composite shock.

A. *Data*

We use data from the CPS's Merged Outgoing Rotation Group (MORG CPS) and the October CPS Supplement (October Supplement) for the years 1984, 1989, 1993, 1997, and 2003. We restrict our sample by dropping workers who are younger than 17 or older than 64 years old, do not report positive paid hours worked, or are self-employed. After cleaning, the MORG CPS and October Supplement contain data for roughly 115,000 and 50,000 individuals, respectively, in each year. We provide additional details in Appendix B.

We divide workers into 30 labor groups by gender, education (high school dropouts, high school graduates, some college completed, college completed, and graduate training), and age (17–30, 31–43, and 44–64). We consider two types of equipment: computers and other equipment. We use 30 occupations, which we list, together with summary statistics, in Table 10 in Appendix B.

We use the MORG CPS to construct total hours worked and average hourly wages by labor group by year.[16] We use the October Supplement to construct a measure of the share of total hours worked by labor group λ that is spent using equipment type κ in occupation ω in year t, $\pi_t(\lambda, \kappa, \omega)$. In 1984, 1989, 1993, 1997, and 2003, the October Supplement asked respondents whether they "have direct or hands on use of computers at work," "directly use a computer at work," or "use a computer at/for his/her/your main job." This question defines a computer as a machine with typewriter-like keyboards, whether a personal computer, laptop, minicomputer, or mainframe. Identifying computers with the index κ_c and the non-computer equipment with the index κ_n, we construct $\pi_t(\lambda, \kappa_c, \omega)$ as the hours worked in occupation ω by λ workers who report that they use a computer at work relative to the total hours worked by labor group λ in year t. We construct $\pi_t(\lambda, \kappa_n, \omega)$ as the hours worked in occupation ω by λ workers who report that they do not use a computer at work relative to the total hours worked by labor group λ in year t.[17]

When interpreting our measures of factor allocations, $\pi_t(\lambda, \kappa, \omega)$, one should bear in mind four limitations. First, our measure of computerization is narrow, as it does not capture, e.g., automation of assembly lines. Second, at the individual level, our computer-use variable takes only two values, zero or one, without detailing the share of each worker's time at work spent using computers. Third, we are not using any information on the allocation of non-computer equipment. Finally, the computer-use question was discontinued after 2003.[18]

[16] We measure wages using the MORG CPS rather than the March CPS. Both datasets imply similar changes in average wages for each of our 30 labor groups. However, the March CPS does not directly measure hourly wages of workers paid by the hour and, therefore, introduces substantial measurement error in individual wages (see, e.g., Lemieux 2006). For most of our analysis, we do not use individual wages; however, we do so in sensitivity analyses in Appendix D, Subsection C.

[17] On average, across the five years considered in the analysis, we measure $\pi_t(\lambda, \kappa, \omega) = 0$ for 26.3 percent of the $(\lambda, \kappa, \omega)$ triplets. As a robustness check, in the online Appendix, we drop age as a characteristic defining a labor group and redo our analysis with the resulting ten labor groups. With only 10 labor groups, we measure $\pi_t(\lambda, \kappa, \omega) = 0$ for 11.7 percent of the $(\lambda, \kappa, \omega)$ triplets. Our main decomposition results are largely robust to decreasing the number of labor groups from 30 to 10.

[18] The period 1984–2003, however, accounts for a substantial share of the increase in the skill premium and reduction in the gender gap observed in the United States since the late 1960s. In unreported results, we show that

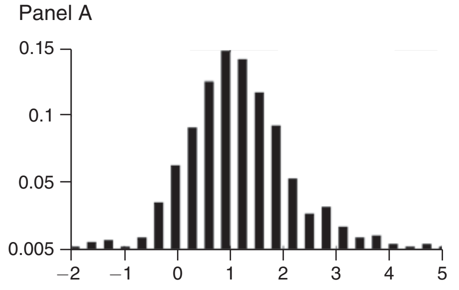

Figure 2. The Distribution of Computer Relative to Non-computer Usage (in logs) for College Degree Relative to High School Degree Workers (Female Relative to Male Workers) across All Gender-Age (Education-Age) Cells in Panel A (Panel B)

Factor Allocation.—Aggregating $\pi_t(\lambda, \kappa, \omega)$ across ω and λ, panel A of Table 1 shows that women and more educated workers use computers more intensively in the aggregate than men and less educated workers, respectively. Panel B shows that this aggregate difference between women and men is largely driven by differences in female and male allocations across occupations whereas this aggregate difference between college- and noncollege-educated workers is driven in equal shares by differences in allocations between occupations and differences in computer usage within occupations. The disaggregated $\pi_t(\lambda, \kappa, \omega)$ data allow us also to identify sorting patterns across equipment types of worker groups differing along a particular dimension of heterogeneity (e.g., education) while holding fixed the other dimensions of heterogeneity (e.g., age, gender, and year) and the occupation. Specifically, to determine the extent to which college-educated workers (λ') compared to workers with high school degrees in the same gender-age group (λ) use computers (κ_c) relatively more than non-computer equipment (κ_n) within occupations (ω), panel A of Figure 2 plots the histogram of

$$\log\frac{\pi_t(\lambda', \kappa_c, \omega)}{\pi_t(\lambda', \kappa_n, \omega)} - \log\frac{\pi_t(\lambda, \kappa_c, \omega)}{\pi_t(\lambda, \kappa_n, \omega)}$$

across all five years, thirty occupations, and six gender-age groups described above. Figure 2 shows that college-educated workers are relatively more likely to use computers within occupations compared to high school-educated workers; hence, according to our model, college-educated workers have a comparative advantage using computers within occupations relative to high school-educated workers. A similar conclusion holds comparing across other education groups: more educated workers systematically have a comparative advantage using computers.

Figure 2, panel B plots a similar histogram, where λ' and λ now denote female and male workers in the same education-age group. This figure shows that there is no clear difference on average in computer usage across genders within occupations

the German *Qualification and Working Conditions* survey, which alleviates some of the limitations of the CPS data, reveals similar patterns of comparative advantage in Germany as what the CPS data reveal for the United States.

(i.e., the histogram is roughly centered around zero). Hence, our model rationalizes the fact that women use computers more than men at the aggregate level—see panel A of Table 1—by concluding that women have a comparative advantage in occupations in which computers have a comparative advantage. For instance, we observe that women are much more likely than men to work in administrative support relative to construction occupations, conditional on the type of equipment used, and that each labor group is much more likely to use computers in administrative support than in construction occupations.

Three-way comparative advantage—between labor groups, equipment types, and occupations, as summarized in the function $T(\lambda, \kappa, \omega)$—is essential for our model to account for the detailed factor allocations that we summarize here and in Table 1.

B. *Measuring Shocks*

Here, we describe our baseline procedure to measure the four shocks into which we decompose the 1984–2003 observed changes in relative average wages: labor composition, $\hat{L}(\lambda)/\hat{L}(\lambda_1)$, equipment productivity (to the power of θ), $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$, occupation shifters, $\hat{a}(\omega)/\hat{a}(\omega_1)$, and labor productivity, $\hat{T}(\lambda)/\hat{T}(\lambda_1)$. We measure changes in labor composition directly from the MORG CPS. We measure changes in equipment productivity using data only on changes in disaggregated factor allocations over time, $\hat{\pi}(\lambda, \kappa, \omega)$. We measure changes in occupation shifters using data on changes in disaggregated factor allocations and labor income shares across occupations as well as model parameters. Finally, we measure changes in labor productivity as a residual to match observed changes in relative wages. We provide details on the baseline procedure described here in Appendix C, Subsection A and alternative procedures in Appendix C, Subsection B and Appendix C, Subsection C. All these procedures yield very similar results.

First, consider the measurement of changes in equipment productivity to the power of θ. Equation (12) implies

$$\frac{\hat{q}(\kappa)^{\theta}}{\hat{q}(\kappa_1)^{\theta}} = \frac{\hat{\pi}(\lambda, \kappa, \omega)}{\hat{\pi}(\lambda, \kappa_1, \omega)} \tag{14}$$

for any (λ, ω) pair. Hence, if computer productivity rises relative to that of other equipment between t_0 and t_1, then the share of labor-group λ hours spent working with computers relative to other equipment in occupation ω will increase. This is true for any (λ, ω) pair. It is important to condition on (λ, ω) pairs when identifying changes in equipment productivity because unconditional growth over time in computer usage, shown in panel A of Table 1, may also reflect growth in the supply of labor groups who have a comparative advantage using computers and/or changes in occupation shifters that are biased toward occupations in which computers have a comparative advantage. Given the possibility of measurement error in $\hat{\pi}(\cdot, \cdot, \cdot)$, we construct an average of these (λ, ω) pair-specific measures to obtain a unique measure of changes in equipment productivity to the power of θ, $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$, as described in Appendix C, Subsection A.

Second, consider the measurement of changes in occupation shifters. Equation (13) implies

$$\frac{\hat{a}(\omega)}{\hat{a}(\omega_1)} = \frac{\hat{\zeta}(\omega)}{\hat{\zeta}(\omega_1)} \left(\frac{\hat{q}(\omega)}{\hat{q}(\omega_1)}\right)^{(1-\alpha)(\rho-1)}. \tag{15}$$

We construct the two components in the right-hand side of equation (15) as follows. First, equation (12) implies

$$\frac{\hat{q}(\omega)^{\theta}}{\hat{q}(\omega_1)^{\theta}} = \frac{\hat{\pi}(\lambda, \kappa, \omega)}{\hat{\pi}(\lambda, \kappa, \omega_1)} \tag{16}$$

for any (λ, κ) pair. For each ω, we construct an average of these (λ, κ) pair-specific measures to obtain a unique measure of changes in transformed occupation prices to the power of θ, $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$, as described in Appendix C, Subsection A.[19] Given values of α, ρ, and θ (which we estimate as described below), we calculate $\left(\hat{q}(\omega)/\hat{q}(\omega_1)\right)^{(1-\alpha)(\rho-1)}$. Second, given values of $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ and $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$, we construct $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$ using the right-hand side of equation (13).

Finally, we measure changes in labor productivity as a residual to match changes in relative wages. Specifically, we rewrite equation (11) as

$$\frac{\hat{w}(\lambda)}{\hat{w}(\lambda_1)} = \frac{\hat{T}(\lambda)}{\hat{T}(\lambda_1)} \left(\frac{\hat{s}(\lambda)}{\hat{s}(\lambda_1)}\right)^{1/\theta}, \tag{17}$$

where $\hat{s}(\lambda)$ is a labor-group-specific weighted average of changes in equipment productivity and transformed occupation prices, both raised to the power of θ,

$$\hat{s}(\lambda) = \sum_{\kappa,\omega} \frac{\hat{q}(\omega)^{\theta}}{\hat{q}(\omega_1)^{\theta}} \frac{\hat{q}(\kappa)^{\theta}}{\hat{q}(\kappa_1)^{\theta}} \pi_{t_0}(\lambda, \kappa, \omega), \tag{18}$$

which we can construct using observed allocations, changes in observed allocations, and equations (14) and (16). Given wage data and a value of θ, we recover $\hat{T}(\lambda)/\hat{T}(\lambda_1)$. Note that only our measures of changes in labor productivities are directly a function of the observed changes in relative wages that we aim to decompose: given parameters α, ρ, and θ, observed changes in wages do not affect our measures of changes in labor composition or equipment productivity to the power of θ, and they only affect our measures of occupation shifters indirectly through their impact on $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$.

[19] We use data on observed allocations to measure these changes in transformed occupation prices. However, in calculating changes in relative wages in response to any subset of shocks in our decomposition, we solve for counterfactual changes in transformed occupation prices and allocations using equations (12) and (13).

C. *Parameter Estimates*

The Cobb-Douglas parameter α, which matters for our results only when ρ is different from one, determines payments to all equipment (computers and non-computer equipment) relative to the sum of payments to equipment and labor. We set $\alpha = 0.24$, consistent with estimates in Burstein, Cravino, and Vogel (2013). Burstein, Cravino, and Vogel (2013) disaggregates total capital payments (i.e., the product of the capital stock and the rental rate) into structures and equipment using US data on the value of capital stocks and—since rental rates are not directly observable—setting the average rate of return over the period 1963–2000 of holding each type of capital (its rental rate plus price appreciation less the depreciation rate) equal to the real interest rate.

As a reminder, the parameter θ determines the within-worker dispersion of productivity across occupation-equipment type pairs, and the parameter ρ is the elasticity of substitution across occupations in the production of the final good. We estimate these two parameters jointly using a method of moments approach. In order to derive the relevant moment conditions, we rewrite equation (17) as

$$\log \hat{w}(\lambda,t) = \varsigma_{\theta}(t) + \frac{1}{\theta}\log \hat{s}(\lambda,t) + \iota_{\theta}(\lambda,t), \tag{19}$$

where $\hat{s}(\lambda,t)$ is defined in equation (18), $\varsigma_{\theta}(t)$ is a time effect, and $\iota_{\theta}(\lambda,t) \equiv \log \hat{T}(\lambda,t)$ captures unobserved changes in labor productivity.[20] Similarly, equation (13) can be expressed as

$$\log \hat{\zeta}(\omega,t) = \varsigma_{\rho}(t) + \frac{1}{\theta}(1-\alpha)(1-\rho)\log \frac{\hat{q}(\omega,t)^{\theta}}{\hat{q}(\omega_1,t)^{\theta}} + \iota_{\rho}(\omega,t), \tag{20}$$

where $\hat{q}(\omega,t)^{\theta}/\hat{q}(\omega_1,t)^{\theta}$ is defined in equation (16), $\varsigma_{\rho}(t)$ is a time effect, and $\iota_{\rho}(\omega,t) \equiv \log \hat{a}(\omega,t)$ captures unobserved changes in occupation shifters.

Equations (19) and (20) may be used to identify θ and ρ jointly. According to our model, however, the observed covariate in equation (19), $\log \hat{s}(\lambda,t)$, is predicted to be correlated with its error term, $\iota_{\theta}(\lambda,t)$, and the observed covariate in equation (20) is predicted to be correlated with its error term, $\iota_{\rho}(\omega,t)$. To address the endogeneity of these covariates, we construct instruments using different averages of observed changes in equipment productivity to the power of θ, $\hat{q}(\kappa,t)^{\theta}/\hat{q}(\kappa_1,t)^{\theta}$. Specifically, we instrument the covariate $\log \hat{s}(\lambda,t)$ using a labor-group-specific average,

$$\log \sum_{\kappa} \frac{\hat{q}(\kappa,t)^{\theta}}{\hat{q}(\kappa_1,t)^{\theta}} \sum_{\omega} \pi_{1984}(\lambda,\kappa,\omega),$$

[20] Since our estimation uses the panel dimension of the data, here, we consider multiple changes (over different time periods) for each variable of interest. Hence, for the purposes of this section and in related appendices, for any variable x, we use $\hat{x}(t)$ to denote the relative change in a variable x between any two consecutive periods t and $t' > t$.

Table 2—Parameter Estimates Based on Joint Estimation

Parameter	Time trend?	Estimate	(SE)
(θ, ρ)	No	(1.81, 1.81)	(0.28, 0.36)
(θ, ρ)	Yes	(1.26, 2.10)	(0.31, 0.75)

and the covariate $\log \hat{q}(\omega, t)^{\theta} / \hat{q}(\omega_1, t)^{\theta}$ using an occupation-specific average,

$$\log \sum_{\kappa} \frac{\hat{q}(\kappa, t)^{\theta}}{\hat{q}(\kappa_1, t)^{\theta}} \sum_{\lambda} \frac{L_{1984}(\lambda)\, \pi_{1984}(\lambda, \kappa, \omega)}{\sum_{\lambda', \kappa'} L_{1984}(\lambda')\, \pi_{1984}(\lambda', \kappa', \omega)}.$$

We use these two instruments and equations (19) and (20) to build moment conditions that identify the parameter vector (θ, ρ).[21]

Our estimates exploit data on four time periods: 1984–1989, 1989–1993, 1993–1997, and 1997–2003. We report the point estimates and standard errors in the top row of Table 2. The resulting estimate of θ is 1.81 with a standard error of 0.28; the estimate of ρ is also 1.81 but with a slightly larger standard error of 0.36.[22]

In reviewing Krusell et al. (2000), Acemoglu (2002) raises a concern that, if valid, will affect the estimates of θ and ρ computed using the expressions in equations (19) and (20) as estimating equations. Specifically, he points out that the presence of common trends in unobserved labor-group-specific productivity, explanatory variables, and instruments may bias the estimates of wage elasticities. In order to address this concern, we follow Katz and Murphy (1992) and Acemoglu (2002) and additionally control for a λ-specific time trend in equation (19). In addition, we also control for an occupation-specific time trend in equation (20). The estimates of θ and ρ that we obtain in this case are, respectively, 1.26 with a standard error of 0.31 and 2.10 with a standard error of 0.75, as displayed in row 2 of Table 2.[23]

When computing the main results of our analysis, we verify in the online Appendix the robustness of our conclusions to the different estimates of θ and ρ reported in this section and in Appendix D.

D. *Results*

In this section, we summarize the results of our decomposition of observed changes in relative wages in the United States between 1984 and 2003. We construct various measures of changes in between-group inequality, each of them aggregating wage changes across our 30 labor groups in a different way. When doing so, both

[21] Additional details on these moment conditions are provided in Appendix D. This appendix also contains a detailed discussion of how, under the assumptions of our model, these two instruments are valid and expected to be correlated with the corresponding endogenous variables.

[22] Estimating θ and ρ without instruments, we find that the direction of the bias in each parameter is consistent with the predictions of our theory (see Appendix D).

[23] In Appendix D, we reestimate θ separately for each labor group using moments of the unconditional distribution of observed wages within each labor group λ. The median value of $\theta(\lambda)$ is 2.62.

Table 3—Decomposing Changes in the log Skill Premium (the Wage of Workers with a College Degree Relative to Those Without)

	Data	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.
1984–1989	0.057	−0.031	0.024	0.052	0.010
1989–1993	0.064	−0.017	−0.004	0.045	0.040
1993–1997	0.037	−0.022	0.041	0.021	−0.002
1997–2003	−0.007	−0.042	−0.012	0.041	0.006
1984–2003	0.151	−0.113	0.049	0.159	0.055

in the model and in the data, we construct *composition-adjusted* wage changes; that is, for each aggregated measure we report, we average disagreggated measures of wage changes across the corresponding labor groups using constant weights over time, as described in detail in Appendix B. For each measure of inequality, we report its cumulative log change between 1984 and 2003, calculated as the sum of the log change over all subperiods in our data.[24] We also report log changes over certain subperiods in our data.

Skill Premium.—The first column in Table 3 reports the change observed in the data, which is also the change predicted by our model when all shocks—in labor composition, occupation shifters, equipment productivity, and labor productivity—are simultaneously considered. The skill premium increased by 15.1 (log) percent between 1984 and 2003. The subsequent four columns summarize the counterfactual percent change in the skill premium predicted by the model if only one of the four shocks is considered (i.e., holding the other exogenous parameters at their t_0 level).

Changes in labor composition decrease the skill premium in each subperiod. Specifically, the increase in hours worked by those with college degrees relative to those without of 47.4 percent between 1984 and 2003 decreases the skill premium by 11.3 percent. Changes in relative demand across labor groups must, therefore, compensate for the impact of changes in labor composition in order to generate the observed rise of the skill premium in the data.

Changes in equipment productivity, i.e., computerization, account for roughly 60 percent of the sum of the demand-side forces pushing the skill premium upward: $0.60 \simeq 0.159/(0.049 + 0.159 + 0.055)$. Furthermore, changes in equipment productivity are particularly important in generating increases in the skill premium in those subperiods in which the skill premium rose most dramatically: 1984–1989 and 1989–1993. These are also precisely the years in which the overall share of workers using computers rose most rapidly; see Table 1. The intuition for why our model predicts that computerization had a large impact on the skill premium is the following. The procedure described in Section IIIC to measure changes in computer productivity implies a large growth in this

[24] We obtain very similar results if we directly compute changes in wages between 1984 and 2003 instead of adding changes in log relative wages over all subperiods.

variable.[25] This growth raises the skill premium for two reasons, as described in detail in Section IID. First, educated workers have a direct comparative advantage using computers within occupations, as shown in panel B of Table 1 and, in more detail, in Figure 2. Second, educated workers have a comparative advantage in occupations in which computers have a comparative advantage, and given our estimate of the elasticity of substitution across occupations, ρ, this implies that computerization raises the wages of labor groups disproportionately employed in computer-intensive occupations.

Changes in occupation shifters account for roughly 19 percent of the sum of the forces pushing the skill premium upward. Skill-intensive occupations grew disproportionately in our sample period, as documented in Figure 1 and in Table 10 in Appendix B. If $\rho = 1$, then our model would attribute this growth fully to occupation shifters, and thus, occupations shifters would have accounted for a larger share of the growth of the skill premium (see the online Appendix). However, because our estimate of ρ is different from one, other shocks also play important roles in shaping income shares across occupations. In the online Appendix, we document the importance of each shock for the growth of occupations with different characteristics (using O*NET constructed task measures) and show that changes in equipment productivity, labor composition, and labor productivity play a significant role in the systematic contraction of occupations that are intensive in routine manual as well as nonroutine manual physical tasks and the systematic expansion of occupations that are intensive in nonroutine cognitive analytical and nonroutine cognitive interpersonal tasks.

Finally, labor productivity, which we estimate as a residual that matches observed changes in relative wages unexplained by the remaining forces included in our model, accounts for roughly 21 percent of the sum of the effects of all three demand-side mechanisms.

In the online Appendix, we demonstrate the importance of accounting for all three forms of comparative advantage by performing similar exercises in versions of our model that omit some of them. For example, if we were to abstract from any comparative advantage at the level of occupations, we would incorrectly conclude that all of the rise in the skill premium has been driven by changes in relative equipment productivities. Similarly, if we were to abstract from any comparative advantage at the level of equipment, we would incorrectly magnify the importance of occupation shifters and labor productivity in explaining the rise of the skill premium.

[25] This is consistent with ample direct evidence showing a rapid decline in the price of computers relative to all other equipment types and structures, which we do not directly use in our estimation. The decline over time in the US price of equipment relative to structures—see, e.g., Greenwood, Hercowitz, and Krusell (1997)—is mostly driven by a decline in computer prices. For example, between 1984 and 2003: (i) the prices of industrial equipment and of transportation equipment relative to the price of computers and peripheral equipment have risen by factors of 32 and 34, respectively (calculated using the BEA's Price Indexes for Private Fixed Investment in Equipment and Software by Type), and (ii) the quantity of computers and peripheral equipment relative to the quantities of industrial equipment and of transportation equipment rose by a factor of 35 and 33, respectively (calculated using the BEA's Chain-Type Quantity Indexes for Net Stock of Private Fixed Assets, Equipment and Software, and Structures by Type).

Table 4—Decomposing Changes in log Relative Wages across Education Groups between 1984 and 2003

	Data	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.
HS dropouts/average	−0.083	0.085	−0.041	−0.181	0.052
HS grad/average	−0.046	0.037	−0.019	−0.055	−0.007
Some college/average	−0.009	−0.009	0.010	0.047	−0.058
College/average	0.091	−0.074	0.024	0.112	0.027
Grad training/average	0.149	−0.101	0.058	0.127	0.064

Table 5—Decomposing the Change in the Skill Premium by Age Group over the Period 1984–2003

Age group	Data	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.
Young	0.154	−0.110	0.040	0.204	0.020
Middle	0.179	−0.108	0.053	0.154	0.078
Old	0.107	−0.117	0.053	0.118	0.051

Five Education Groups.—Table 4 decomposes changes in between-education-group wage inequality at a higher level of disaggregation than what the skill premium captures. The results reported in Table 3 are, however, qualitatively robust: computerization is the central force driving changes in between-education-group inequality, whereas labor productivity plays a relatively minor role.

Skill Premium by Age.—The rise of the skill premium over our time period is substantially larger amongst middle-aged and young workers than among older workers, as shown in column 1 of Table 5. This fact was first identified by Katz and Murphy (1992). In a framework featuring changes in labor composition and labor productivity, Card and Lemieux (2001) shows that differential changes in labor composition can account for this pattern. While we find that changes in labor composition do push the skill premium of older workers below those of younger and middle-aged workers (column 2), changes in equipment productivity explain the vast majority of the lower growth of the skill premium amongst older workers (column 4). This result follows from the fact that, in our data, aggregate computer use of college-educated relative to noncollege-educated workers is higher amongst young and middle-aged workers than amongst old workers.

Gender Gap.—The average wage of men relative to women, the gender gap, declined by 13.3 percent between 1984 and 2003. Table 6 decomposes changes in the gender gap over the full sample and over each subperiod. The increase in hours worked by women relative to men of roughly 12.6 percent between 1984 and 2003 increased the gender gap by 4.1 percent. Changes in relative demand across labor groups must, therefore, compensate for the impact of changes in labor composition in order to generate the observed fall in the gender gap.

Table 6—Decomposing Changes in the log Gender Gap (the Wage of Men Relative to Women)

	Data	Labor comp.	Occ. shifters	Equip. prod.	Labor prod.
1984–1989	−0.056	0.011	−0.012	−0.015	−0.041
1989–1993	−0.052	0.013	−0.036	−0.014	−0.015
1993–1997	−0.003	0.006	0.015	−0.005	−0.020
1997–2003	−0.021	0.011	−0.036	−0.012	0.017
1984–2003	−0.133	0.041	−0.069	−0.046	−0.058

In spite of the fact that comparative advantage using computers does not vary by gender, changes in equipment productivity account for roughly 27 percent of the sum of the impact of the demand-side forces. This is due to women having a comparative advantage in computer-intensive occupations which, together with an estimate of the elasticity of substitution across occupations larger than one, implies that computerization raises the wages of labor groups disproportionately employed in computer-intensive occupations.

Changes in occupation shifters account for roughly 40 percent of the sum of the forces decreasing the gender gap over the full sample. This is reflected in part by the fact that a number of male-intensive occupations—including, for example, mechanics/repairers as well as machine operators/assemblers/inspectors—contracted substantially between 1984 and 2003; see Figure 1 and Table 10 for details. Again, however, with $\rho \neq 1$, all shocks contribute to these changes in occupation size.

Changes in labor productivity account for a sizable share, roughly 34 percent, of the impact of the demand-side forces on the gender gap and play a central role in each subperiod except for 1997–2003. This suggests that factors such as changes in gender discrimination—if they affect labor productivity irrespective of the type of equipment used and the occupation of employment—may have played a substantial role in reducing the gender gap, especially early in our sample (in the 1980s and early 1990s); see, e.g., Hsieh et al. (2018).

Thirty Disaggregated Labor Groups.—One of the advantages of our framework is that we can study the determinants of wage changes across a large number of labor groups. Table 7 presents evidence on the relative importance of the 3 demand-side shocks—occupation shifters, equipment productivity, and labor productivity—in explaining relative changes in wages across the 30 labor groups that we consider in our analysis. More precisely, we show in this table the results from decomposing the variance of the changes in relative wages predicted by our model, when all three demand-side shocks are active, into the covariances of these changes with those that are predicted by our model when only one of the three demand-side shocks is activated. Specifically, we present the 3 OLS estimates of the projection of each of the 30 changes in relative wages predicted by each of the 3 demand-side shocks included in our analysis on the 30 changes in relative wages predicted by our model when all the 3 demand-side shocks are taken into account.

The results show that, in the period 1984 to 2003, equipment productivity explains over 50 percent of the variance in the change in relative wages

Table 7—Variance Decomposition across 30 Labor Groups

	1984–2003	1984–1989	1989–1993	1993–1997	1997–2003
Equipment productivity	53%	48%	33%	27%	50%
Occupation shifter	24%	23%	15%	44%	20%
Labor productivity	24%	29%	52%	28%	30%

Notes: Let $x_i(\lambda)$ denote the change in the average wage of group λ induced by demand-side shock i, and let $y(\lambda) = \sum_{i=1}^{3} x_i(\lambda)$. For each i and time period, we report $\text{cov}(x_i(\lambda), y(\lambda))/\text{var}(y(\lambda))$.

(implied by the combination of the three demand-side shocks) across the 30 labor groups considered in the analysis. In this same time period, occupation shifters and labor productivity each explain slightly less than 25 percent. Whereas equipment productivity is also the most important demand-side contributor in the periods 1984–1989 and 1997–2003, labor productivity is the most important force in 1989–1993, and occupation shifters are the most important force in 1993–1997.

IV. Open-Economy Model

In this section, we extend the model introduced in Section II to allow for international trade in equipment goods and occupation services. Details for this section and Section V are provided in the online Appendix.

A. *Environment*

We assume the final good is non-traded and produced according to the open -economy counterpart of equation (1), with output in country n given by

$$Y_n = \left(\sum_{\omega} \mu_n(\omega)^{1/\rho} D_n(\omega)^{(\rho-1)/\rho}\right)^{\rho/(\rho-1)},$$

where $D_n(\omega)$ denotes absorption of occupation ω in country n and where we omit time subscripts to simplify notation. Absorption of each occupation is itself a CES aggregate of the services of these occupations sourced from all countries in the world,

$$D_n(\omega) = \left(\sum_{i} D_{in}(\omega)^{(\eta(\omega)-1)/\eta(\omega)}\right)^{\eta(\omega)/(\eta(\omega)-1)},$$

where $D_{in}(\omega)$ is absorption in country n of occupation ω sourced from country i, and $\eta(\omega) > 1$ is the elasticity of substitution across source countries for occupation ω.[26] Similarly, absorption of equipment of type κ

[26] The assumption that the final good is non-traded is without loss of generality for our results on relative wages. We assume an Armington trade model only for expositional simplicity. Our results would also hold in a Ricardian model as in Eaton and Kortum (2002).

in country n is a CES aggregate of equipment sourced from all countries in the world,

$$D_n(\kappa) \;=\; \Big(\sum_i D_{in}(\kappa)^{(\eta(\kappa)-1)/\eta(\kappa)}\Big)^{\eta(\kappa)/(\eta(\kappa)-1)}. \tag{21}$$

Trade is subject to iceberg transportation costs, where $d_{ni}(\omega) \geq 1$ and $d_{ni}(\kappa) \geq 1$ denote the units of occupation ω output and equipment κ output, respectively, that must be shipped from origin country n in order for one unit to arrive in destination country i. Output of occupation ω and equipment κ in country n satisfy, respectively,

$$Y_n(\omega) \;=\; \sum_i d_{ni}(\omega)\, D_{ni}(\omega), \tag{22}$$

$$Y_n(\kappa) \;=\; \sum_i d_{ni}(\kappa)\, D_{ni}(\kappa). \tag{23}$$

Since the final good is non-traded, the resource constraint for the final good must satisfy equation (2). As country n's trade costs limit to infinity, $d_{ni}(\omega) \rightarrow \infty$ and $d_{ni}(\kappa) \rightarrow \infty$ for all $n \neq i$, the economy limits to the autarkic version of the model presented in Section II. For the exercises we consider below, we do not need to specify conditions on trade balance in each country.

B. *Equilibrium*

We now describe the differences between the equilibrium conditions of this open-economy model and those of the closed-economy model introduced in Section II. In an open economy, we must distinguish between production prices and absorption prices. We denote by $p_{nn}(\omega)$ the output price of occupation ω in country n and by $p_n(\omega)$ its absorption price. Absorption in country n of occupation ω sourced from country i is given by

$$D_{in}(\omega) \;=\; \left(\frac{p_{in}(\omega)}{p_n(\omega)}\right)^{-\eta(\omega)} D_n(\omega), \tag{24}$$

and the occupation ω absorption price is given by

$$p_n(\omega) \;=\; \Big[\sum_i p_{in}(\omega)^{1-\eta(\omega)}\Big]^{\frac{1}{1-\eta(\omega)}}. \tag{25}$$

Here, $p_{in}(\omega)$ is the price of country i's output of occupation ω in country n (inclusive of trade costs), which is related to the domestic output price by $p_{in}(\omega) \;=\; d_{in}(\omega)\, p_{ii}(\omega)$. Production prices of equipment goods are given by

$p_{nn}(\kappa) = \tilde{p}_n(\kappa) P_n$, as in the closed economy. Absorption in country n of equipment κ sourced from country i is given by

$$D_{in}(\kappa) = \left(\frac{p_{in}(\kappa)}{p_n(\kappa)}\right)^{-\eta(\kappa)} D_n(\kappa), \tag{26}$$

and the equipment κ absorption price is given by

$$p_n(\kappa) = \left[\sum_i p_{in}(\kappa)^{1-\eta(\kappa)}\right]^{\frac{1}{1-\eta(\kappa)}}. \tag{27}$$

As this expression shows, equipment absorption prices in country n depend on equipment output prices in all foreign countries and on trade costs between country n and all of its trading partners.

The relevant prices shaping allocations and average wages—$\pi_n(\lambda, \kappa, \omega)$ and $w_n(\lambda)$ in equations (3) and (4)—are absorption prices for equipment, $p_n(\kappa)$, since equipment is an input in production and domestic production prices for occupations, $p_{nn}(\omega)$, since occupations are produced in each country. Occupation prices must therefore satisfy the open-economy versions of the occupation-market clearing condition in equation (5),

$$\sum_i \mu_i(\omega) p_{ni}(\omega)^{1-\eta(\omega)} p_i(\omega)^{\eta(\omega)-\rho} P_i^{\rho-1} E_i = \frac{1}{1-\alpha} \zeta_n(\omega), \tag{28}$$

where $\zeta_n(\omega)$ is labor income in occupation ω, E_n denotes total expenditure, and P_n is the final good price in country n (which was normalized to one in the closed economy). In general, solving for the level of occupation prices requires solving for prices in the full-world equilibrium; these prices are functions of worldwide technologies, endowments, and trade costs.

V. International Trade Counterfactuals

The aim of this section is twofold. First, we show theoretically how the degree of openness may cause what we have treated in our closed-economy model as primitive shocks to the cost of producing equipment and to the demand for occupations. Second, we present some simple calculations quantifying the impact of equipment and occupation trade on between-group inequality.

In general, calculating counterfactual changes in wages in a given country n in response to changes in trade costs or technologies either in n or in any other country in the world requires detailed data on allocations and trade for all countries, which is unavailable in practice. Instead, with the aim of quantifying the impact of international trade in occupations and equipment on country n, we consider a specific counterfactual exercise that requires neither solving the full-world general equilibrium nor estimating parameters for any country other than n. This counterfactual answers the following question: what are the differential effects on relative wages in country n of changes in primitives (i.e., technologies, labor compositions, and trade costs) in all countries in the world between any two periods t_0 and t_1, relative to the effects of the same changes in primitives if country n were a closed economy?

Formally, define $w_n(\lambda; \Phi_t, \Phi_t^*, d_t)$ to be the average wage of labor group λ in country n if domestic technologies and endowments are given by Φ_t, foreign technologies and endowments are given by Φ_t^*, and the full matrix of world trade costs is d_t. Define $d_{n,t}^A$ to be an alternative matrix of world trade costs in which country n's international trade costs (both for equipment and occupation trade) are infinite ($d_{in,t}(\kappa) = d_{in,t}(\omega) = \infty$ for all $i \neq n$). Our counterfactual calculates

$$\text{(29)} \qquad \frac{w_n\left(\lambda; \Phi_{t_1}, \Phi_{t_1}^*, d_{t_1}\right)}{w_n\left(\lambda; \Phi_{t_0}, \Phi_{t_0}^*, d_{t_0}\right)} \Bigg/ \frac{w_n\left(\lambda; \Phi_{t_1}, \Phi_{t_1}^*, d_{t_1}^A\right)}{w_n\left(\lambda; \Phi_{t_0}, \Phi_{t_0}^*, d_{t_0}^A\right)}.$$

Defining the impact on the wage of group λ of moving country n to autarky at time t as $\hat{w}_{n,t}^A(\lambda) \equiv w_n(\lambda; \Phi_t, \Phi_t^*, d_{n,t}^A)/w_n(\lambda; \Phi_t, \Phi_t^*, d_{n,t})$, notice that our counterfactual can be expressed succinctly as $\hat{w}_{n,t_0}^A(\lambda)/\hat{w}_{n,t_1}^A(\lambda)$. As computing the expression in equation (29) amounts to computing the impact of moving to autarky at two different points in time, we describe here how we calculate the counterfactual change in wages in country n from moving to autarky at a particular point in time t. Moving to autarky affects relative wages through two channels: changing (i) relative absorption prices across equipment types and (ii) relative demand across occupations. We now show that these two channels affect relative wages exactly like changes in (i) equipment productivity and (ii) occupation shifters in the closed economy.

Choosing the final good price in country n as the numeraire, the change in the absorption price of equipment, defined in equation (27), when moving to autarky at time t is

$$\text{(30)} \qquad \hat{p}_n(\kappa) = s_{nn}(\kappa)^{\frac{1}{1-\eta(\kappa)}},$$

where $s_{nn}(\kappa)$ denotes the fraction of expenditures on equipment κ in country n purchased from itself (i.e., one minus the import share) at time t,

$$s_{nn}(\kappa) = \frac{p_{nn}(\kappa)\, D_{nn}(\kappa)}{p_n(\kappa)\, D_n(\kappa)}.$$

In deriving equation (30), we have used equation (26), which implies

$$s_{nn}(\kappa) = \left(p_{nn}(\kappa)/p_n(\kappa)\right)^{1-\eta(\kappa)}.$$

Changes in occupation output prices induced by moving to autarky at time t must satisfy the following occupation clearing condition,

$$\text{(31)} \qquad f_{nn}(\omega)\left(\frac{\hat{p}_{nn}(\omega)}{\hat{p}_n(\omega)}\right)^{\rho-\eta(\omega)} \hat{p}_{nn}(\omega)^{1-\rho}\hat{E}_n = \frac{1}{1-\alpha}\hat{\zeta}_n(\omega),$$

where $f_{nn}(\omega)$ denotes the fraction of total sales of occupation ω in country n purchased from itself (i.e., one minus the export share) at time t,

$$f_{nn}(\omega) = \frac{p_{nn}(\omega)\, D_{nn}(\omega)}{p_{nn}(\omega)\, Y_n(\omega)}.$$

Using equations (24) and (25), we can express equation (31) more simply as

$$f_{nn}(\omega)\, s_{nn}(\omega)^{\frac{\rho-\eta(\omega)}{\eta(\omega)-1}}\, \hat{p}_{nn}(\omega)^{1-\rho}\, \hat{E}_n = \frac{1}{1-\alpha}\hat{\zeta}_n(\omega), \tag{32}$$

where $s_{nn}(\omega)$ is defined analogously to $s_{nn}(\kappa)$ above.

Equations (30) and (32) allow us to calculate changes in relative wages in country n if n were to move to autarky at time t using the closed-economy system of equations in which we imposed no restrictions on $T_t(\lambda, \kappa, \omega)$—(6), (7), and (8)—and the following set of shocks:

$$\hat{T}_n(\lambda, \kappa, \omega) = \hat{L}_n(\lambda) = 1,$$

$$\hat{p}_n(\kappa) = s_{nn}(\kappa)^{\frac{1}{1-\eta(\kappa)}}, \tag{33}$$

$$\hat{\mu}_n(\omega) = f_{nn}(\omega)\, s_{nn}(\omega)^{\frac{\rho-\eta(\omega)}{\eta(\omega)-1}}, \tag{34}$$

where $s_{nn}(\kappa)$, $s_{nn}(\omega)$, and $f_{nn}(\omega)$ correspond to their time t levels.

The mapping between import and export shares at time t and the corresponding closed-economy shocks is intuitive. First, if the import share of equipment type κ is high relative to κ' and trade elasticities are common across equipment goods, then moving to autarky has an equivalent impact on relative wages as increasing the relative price of equipment κ relative to κ' in the closed economy. Second, if occupation ω has a low export share relative to occupation ω', then moving to autarky is equivalent to increasing occupation demand for ω relative to ω' in the closed economy. Third, if occupation ω has a high import share relative to occupation ω', trade elasticities are common across occupations, and $\eta(\omega) \geq \rho$ then moving to autarky has an equivalent impact on relative wages as increasing occupation demand for ω relative to ω' in the closed economy. If $\rho = 1$, then $\hat{\mu}_n(\omega)$ is equal to the ratio of the domestic absorption share to the domestic production share of occupation ω.

In conducting the counterfactual described above, we evaluate separately the impact of changes in trade costs in equipment (assuming that international trade costs in occupations are infinite during the whole sample period) and changes in trade costs in occupations (assuming that international trade costs in equipment are infinite during the whole sample period), imposing the values of θ and ρ that we estimated in Section IIIC.[27]

[27] In an open economy, without additional restrictions, it is possible that the exclusion restrictions underlying the identification of θ and ρ in the procedure described in Section IIIC are violated.

A. *Trade in Equipment*

In order to compute the impact on relative wages in the United States of counterfactual changes in international trade costs in equipment, we need measures of US domestic expenditure shares by equipment type, $s_{nn}(\kappa)$, in 1984 and 2003, and estimates of the elasticity of substitution across countries of origin for each equipment type, $\eta(\kappa)$. For each equipment type κ, we measure $s_{nn}(\kappa)$ as

$$s_{nn,t}(\kappa) \; = \; 1 - \frac{Imports_{n,t}(\kappa)}{GrossOutput_{n,t}(\kappa) - Exports_{n,t}(\kappa) + Imports_{n,t}(\kappa)}.$$

We obtain Production, Export, and Import data from the OECD's Structural Analysis Database (STAN), which is arranged at the two-digit level of the third revision of the International Standard Industrial Classification. We equate computers to industry 30 (Office, Accounting, and Computing Machinery) and non-computer equipment to industries 29, 31, 32, and 33 (Machinery and Equipment less Office, Accounting, and Computing Machinery). We observe that domestic expenditure shares for computers fell from 0.80 in 1984 to 0.26 in 2003, while domestic expenditure shares for non-computer equipment fell from 0.83 in 1984 to 0.59 in 2003; that is, the US import share in computers rose significantly more than in non-computer equipment goods. Because of the lack of existing estimates of computer and non-computer equipment trade elasticities in the literature, we estimate these elasticities using longitudinal data on trade volumes and import tariffs for computer and non-computer equipment manufacturing sectors.[28] Our baseline estimates of the trade elasticities are 3.2 for computers and 3.4 for non-computer equipment sectors.

The high import share of computers relative to non-computer equipment in 2003 (together with the similar estimates of the trade elasticity for computers and non-computer equipment) implies that an increase in the international trade costs of equipment that makes trade in equipment prohibitively costly has an effect equivalent to that of an increase in the price of computers relative to non-computer equipment in the closed-economy model; see equation (33). Column 1 in Table 8 shows that the skill premium would have fallen by roughly 2.2 percent moving from 2003 levels of equipment trade to autarky. On the other hand, given that US import shares in 1984 in computer and non-computer equipment were much more similar, the impact on relative wages of moving to autarky in 1984 would have been much smaller. Column 3 combines the 2 previous trade-to-autarky counterfactuals to quantify how important was

[28] Specifically, for the period 1999–2003, we collect data on trade flows and effective tariffs from WITS by the 2-digit rev. 3 ISIC sector and, in the case of non-computer equipment, aggregate the observations corresponding to industries 29, 31, 32, and 33. Given this data, we use ordinary least squares to estimate $\eta(\kappa)$ from the regression $\ln(X_{nit}(\kappa)) \; = \; f(n,t) + f(i,t) + f(n,i) - (\eta(\kappa) - 1)\ln(1 + d_{nit}(\kappa)) + \varepsilon_{nit}(\kappa)$, where $f(n,t)$, $f(i,t)$, and $f(n,i)$ denote, respectively, exporter-year, importer-year, and exporter-importer fixed effects, $X_{nit}(\kappa)$ denotes the volume of trade from country n to country i at period t, and $d_{nit}(\kappa)$ denotes the effective tariff imposed by country n for imports of good κ from country i. Our point estimate of $\eta(\kappa) - 1$ is equal to 3.2 (0.56 standard error) for computers and 3.4 (0.22) for non-computer equipment.

Table 8—Impact of Moving from 2003 and 1984 to Equipment Autarky as Well as the Impact of Trade in Equipment between 1984 and 2003

	2003 to autarky	1984 to autarky	Impact of trade 1984–2003
Skill premium	−0.022	−0.001	0.021
Gender gap	0.005	0.000	−0.005
HS dropout/average	0.020	0.001	−0.019
HS grad/average	0.007	0.000	−0.007
Some college/average	−0.002	0.000	0.002
College/average	−0.016	0.000	0.015
Grad training/average	−0.017	−0.001	0.016

the rise of trade in equipment in generating relative wage changes between 1984 and 2003. Given changes in worldwide primitives between 1984 and 2003, our model predicts that the rise in the US skill premium between these 2 years was 2.1 percent higher than it would have been had the United States been in autarky over this time period. This 2.1 percentage point increase in the skill premium accounts for roughly 14 percent of the rise in the skill premium between 1984 and 2003 accounted for by changes in equipment productivity according to our closed-economy calculations. The increase in the returns to college and graduate training (relative to the overall average change in wages) accounted for by trade in equipment was roughly 1.5 percent and the decrease in the gender gap was 0.5 percent. These numbers roughly double if we consider a lower trade elasticity of $\eta(\kappa) - 1 = 1.5$.

B. *Trade in Occupations*

In order to compute the impact on relative wages in the United States of counterfactual changes in international trade costs in occupation services, we need both measures of US domestic expenditure shares and domestic output shares by occupation ($s_{nn}(\omega)$ and $f_{nn}(\omega)$, respectively) in 1984 and 2003 and estimates of the elasticity of substitution across countries of origin for each occupation, $\eta(\omega)$. Obtaining these measures is a major challenge given the lack of readily available data on the occupation content of exports and imports; for a full discussion of the difficulties, see Grossman and Rossi-Hansberg (2008).

One possible route to measure the occupation content of exports and imports is to combine readily available information on trade by sector and on the occupation composition of labor payments of each sector, calculating the domestic share of absorption and the domestic share of output of occupation ω in country n as

$$(35) \quad s_{nn,t}(\omega) = 1 - \frac{\sum_{\sigma} \nu_{n,t}(\omega|\sigma)\, Imports_{n,t}(\sigma)}{\sum_{\sigma} \nu_{n,t}(\omega|\sigma)\,(GrossOutput_{n,t}(\sigma) - Exports_{n,t}(\sigma) + Imports_{n,t}(\sigma))},$$

$$(36) \quad f_{nn,t}(\omega) = 1 - \frac{\sum_{\sigma} \nu_{n,t}(\omega|\sigma)\, Exports_{n,t}(\sigma)}{\sum_{\sigma} \nu_{n,t}(\omega|\sigma)\, GrossOutput_{n,t}(\sigma)},$$

where $\nu_{n,t}(\omega|\sigma)$ denotes the share of labor payments to occupation ω in sector σ.[29] This approach is analogous to the basic calculation of the factor content of trade, replacing payments to a factor within each sector with payments to an occupation within each sector. We implement this approach using data for 30 2-digit rev. 3 ISIC manufacturing sectors and one aggregate services sector (obtaining US export and import data from UN Comtrade, gross output data from UNIDO, and labor payments by sector and occupation from the CPS) and imposing a common trade elasticity across occupations of 5. Given that sectors in which the United States has a comparative advantage tend to be intensive in occupations that disproportionately employ high-skill workers, moving from trade to autarky tends to reduce the relative wage of more educated workers. However, the implied wage changes are very small. For example, starting in 2003, moving from trade to autarky reduces the skill premium by only 0.4 percent.

The computation of import and export shares by occupation in equations (35) and (36) assumes that, for each sector, exports and domestic production replaced by imports have the same occupation intensity in labor payments as does gross output. This assumption may be violated in practice. For example, if, within each sector, the US exports tasks that are more intensive in, e.g., abstract occupations than is gross output and imports tasks that are more intensive in, e.g., routine occupations than is gross output, then equation (35) will overstate (understate) the domestic share of absorption for routine (abstract) occupations and equation (36) will understate (overstate) the domestic share of output of routine (abstract) occupations. Hence, domestic absorption and output shares constructed as in equations (35) and (36) are likely to be biased.[30]

We consider an alternative route to measure export and import shares by occupation in 2003 (that does not use information on trade by sector), making strong assumptions to classify occupations as exported, imported, and non-traded. Specifically, we split our set of 30 occupations, Ω, into three groups: the set of abstract occupations (professional, managerial, and technical occupations) denoted by Ω^A, the set of routine occupations (clerical, administrative support, production, and operative occupations) denoted by Ω^R, and the set of non-traded occupations (protective services, food preparation, cleaning, personal services, and sales) denoted by Ω^N.[31] We assume that abstract occupations are the only occupations that are exported

[29] In the online Appendix, we present a version of our model that motivates these measures. In the model, the final good is produced according to a CES aggregator of tradable sectoral goods (allowing for time-varying shifters to the absorption of each sector), where each sectoral good is produced as the final good in our baseline model, i.e., according to a CES aggregator of non-traded occupation services. Occupations are produced exactly as in our baseline specification: a worker's productivity depends only on her occupation, and not on her sector of employment. The system of equations that solves for counterfactual wage changes caused by moving to autarky corresponds to the system of equations described for the closed-economy version in which sectoral shifters are functions of sectoral export and import shares similarly to the expression for $\hat{\mu}_n(\omega)$ in equation (34). Moreover, if both elasticities of substitution across sectors and occupations are equal to one, then changes in relative wages in the autarky counterfactual in the model with trade in sectoral goods are identical to that in the model with trade in occupation services in which $s_{nn,t}(\omega)$ and $f_{nn,t}(\omega)$ are calculated using sectoral trade data as described above.

[30] Closely related, Burstein and Vogel (2017) argues that measures of the factor content of trade constructed under the assumption that sectoral factor intensities are equal across destinations understate the impact of trade on the skill premium.

[31] This is the grouping used in Acemoglu and Autor (2011), except that we include sales in the group of non-traded occupations.

and that all occupations within this set have the same export share, that routine occupations are the only occupations that are imported and that all occupations within this set have the same import share, and that non-traded occupations have a domestic share of absorption and output equal to one. For abstract occupations, $\omega \in \Omega^A$, we set

$$f_{nn,t}(\omega) = 1 - \frac{Exports_{n,t}}{\nu_{n,t}(A)\, GrossOuput_{n,t}}$$

and $s_{nn,t}(\omega) = 1$, where $\nu_{n,t}(A)$ denotes labor payments across all abstract occupations relative to total labor payments. For routine occupations, $\omega \in \Omega^R$, we set $f_{nn,t}(\omega) = 1$ and

$$s_{nn,t}(\omega) = 1 - \frac{Imports_{n,t}}{\nu_{n,t}(R)\, GrossOuput_{n,t} + Imports_{n,t}}.$$

For non-traded occupations, $\omega \in \Omega^N$, we set $s_{nn,t}(\omega) = f_{nn,t}(\omega) = 1$. We calculate the share of labor payments in abstract and routine occupations from the CPS and total gross output, exports and imports from the BEA.[32]

The results from this counterfactual are reported in Table 9. Recall from equation (34) that making trade in occupations prohibitively costly operates in our model exactly like a decline in occupation demand in the closed economy for those occupations with relatively high export shares and/or low import shares. Since abstract occupations (assumed to be only exported) tend to employ relatively more skilled workers than routine occupations (assumed to be only imported), the skill premium would have fallen by 6.3 percent if the United States had moved to autarky in 2003, as reported in column 1 of Table 9. The returns to graduate training (relative to the average change in wages) would have fallen by 6.4 percent, and the gender gap would have increased by 1 percent. These numbers are an order of magnitude larger than those reported above using measures of occupation trade constructed from sectoral trade flows. If the United States had moved to autarky in 1984, the skill premium would have fallen by 5.1 percent. Column 3 combines these two trade-to-autarky counterfactuals to quantify how important was the rise of trade in occupations in generating relative wage changes between 1984 and 2003. Given changes in worldwide primitives between 1984 and 2003, our model predicts that the rise in the US skill premium between these two years was 1.3 percentage points higher than it would have been had the United States been in autarky during this time period. This 1.3 percent increase in the skill premium accounts for roughly 26 percent of the rise in the skill premium between 1984 and 2003 accounted for by occupation shifters in our closed-economy calculations. Given the crudeness of our measures of occupation trade, these calculations should be viewed as a first step to

[32] Since the extent of offshoring of routine tasks was much less prevalent in the 1980s than in the 2000s (see, e.g., Grossman and Rossi-Hansberg 2008), we believe that the strong assumptions that we use to construct occupation trade shares disproportionately increase the impact of moving to autarky in 1984.

Table 9—Impact of Moving from 2003 and 1984 to Occupation Autarky as Well as the Impact of Trade in Occupations between 1984 and 2003

	2003 to autarky	1984 to autarky	Impact of trade 1984–2003
Skill premium	−0.063	−0.051	0.013
Gender gap	0.010	0.003	−0.006
HS dropout/average	0.025	0.023	−0.001
HS grad/average	0.022	0.018	−0.004
Some college/average	0.005	0.002	−0.004
College/average	−0.037	−0.030	0.007
Grad training/average	−0.064	−0.051	0.014

Note: Here, we combine occupations into three groups—abstract (which we assume are exported), routine (which we assume are imported), and non-traded—and assume that all occupations within each group have the same import and export shares.

evaluate the role that occupation trade has had on the evolution of between-group inequality.

VI. Conclusions

We provide an assignment model of the labor market extended to incorporate equipment types as another key dimension along which workers sort and international trade as a determinant of the equilibrium assignment of workers. We thus study within a unified framework the impact of changes in occupation demand shifters, computer productivity, labor productivity, labor composition, and international trade on changes in the relative average wages of multiple groups of workers.

We parameterize our model using detailed measures of computer usage within labor group-occupation pairs in the United States between 1984 and 2003 as well as international trade data. Using the closed-economy version of our model, we conclude that computerization alone accounts for the majority of the observed rise in between-education-group inequality over this period and the differential growth of the skill premium between old and younger workers. The combination of computerization and occupation shifters explains roughly 80 percent of the rise in the skill premium, almost all of the rise in inequality across more disaggregated education groups, and the majority of the fall in the gender gap. We show how computerization and changes in occupation demand in our model can be caused by changes in the extent of international trade and perform counterfactual exercises to quantify these effects.

The focus of this paper has been on the distribution of labor income between groups of workers with different observable characteristics. A fruitful avenue for future research is to extend our framework to address the changing distribution of income accruing to labor and capital, as analyzed in, e.g., Karabarbounis and Neiman (2014) and Oberfield and Raval (2014), as well as the changing distribution of income across workers within groups, as analyzed in, e.g., Huggett, Ventura, and Yaron (2011); Hornstein, Krusell, and Violante (2011); and Helpman et al. (2017).

Appendix A. Additional Model Details

Here, we derive the equations in Section IIB for (i) the wage per efficiency unit of labor λ when teamed with equipment κ in occupation ω, $v_t(\lambda, \kappa, \omega)$; (ii) the probability that a randomly sampled worker, $z \in \mathcal{Z}_t(\lambda)$, uses equipment κ in occupation ω, $\pi_t(\lambda, \kappa, \omega)$; and (iii) the average wage of workers in group λ teamed with equipment κ in occupation ω, $w_t(\lambda, \kappa, \omega)$. We also show that $w_t(\lambda) = w_t(\lambda, \kappa, \omega)$ for all (κ, ω).

Wage per Efficiency Unit of Labor λ: $v_t(\lambda, \kappa, \omega)$.—An occupation production unit hiring k units of equipment κ and l efficiency units of labor λ earns revenues $p_t(\omega)\, k^{\alpha} \left[T_t(\lambda, \kappa, \omega)\, l\right]^{1-\alpha}$ and incurs costs $p_t(\kappa)\, k + v_t(\lambda, \kappa, \omega)\, l$. The first-order condition for the optimal choice of k per unit of l for a given $(\lambda, \kappa, \omega)$ yields

$$k_t(l; \lambda, \kappa, \omega) = \left(\alpha \frac{p_t(\omega)}{p_t(\kappa)}\right)^{\frac{1}{1-\alpha}} T_t(\lambda, \kappa, \omega)\, l,$$

where the second-order condition is satisfied for any $\alpha < 1$. This implies that the production unit's revenue can be expressed as $p_t(\omega)^{\frac{1}{1-\alpha}} \left(\alpha p_t(\kappa)^{-1}\right)^{\frac{\alpha}{1-\alpha}} T_t(\lambda, \kappa, \omega)\, l$ and its cost as $\left[p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} \left(\alpha p_t(\omega)\right)^{\frac{1}{1-\alpha}} T_t(\lambda, \kappa, \omega) + v_t(\lambda, \kappa, \omega)\right] l$. Hence, the zero profit condition requires that

$$v_t(\lambda, \kappa, \omega) = (1-\alpha)\, \alpha^{\frac{\alpha}{1-\alpha}} p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}} T_t(\lambda, \kappa, \omega),$$

which is equivalent to the value in Section IIB given the definition of $\bar{\alpha} \equiv (1-\alpha)\, \alpha^{\frac{\alpha}{1-\alpha}}$.

Labor Allocation: $\pi_t(\lambda, \kappa, \omega)$.—In what follows, denote by $\varphi \equiv (\kappa, \omega)$. A worker $z \in \mathcal{Z}_t(\lambda)$ chooses equipment-occupation pair φ if

$$v_t(\lambda, \varphi)\, \varepsilon(z, \varphi) > \max_{\varphi' \neq \varphi} \left\{ v_t(\lambda, \varphi')\, \varepsilon(z, \varphi') \right\},$$

which is independent of $\epsilon(z)$. The probability that a randomly sampled worker in group λ chooses φ is

$$\pi_t(\lambda, \varphi) = \int_0^{\infty} \Pr\left[\varepsilon > \max_{\varphi' \neq \varphi} \left\{ \frac{\varepsilon(z, \varphi')\, v_t(\lambda, \varphi')}{v_t(\lambda, \varphi)} \right\}\right] dG(\varepsilon)$$

$$= \int_0^{\infty} \exp\left[-\varepsilon^{-\theta(\lambda)} \left(\sum_{\varphi'} \left(\frac{v_t(\lambda, \varphi)}{v_t(\lambda, \varphi')}\right)^{-\theta(\lambda)}\right)\right] \theta(\lambda)\, \varepsilon^{-1-\theta(\lambda)}\, d\varepsilon.$$

Defining $n_t(\lambda,\varphi) \equiv \sum_{\varphi'}\left(\frac{v_t(\lambda,\varphi)}{v_t(\lambda,\varphi')}\right)^{-\theta(\lambda)}$, we have

$$\pi_t(\lambda,\varphi) = -\int_0^\infty \exp\left(-\varepsilon^{-\theta(\lambda)} n_t(\lambda,\varphi)\right)\left(-\theta(\lambda)\right)\varepsilon^{-1-\theta(\lambda)}\,d\varepsilon$$

$$= \frac{1}{n_t(\lambda,\varphi)}.$$

Substituting back in for $n_t(\lambda,\varphi)$, we have

$$\pi_t(\lambda,\varphi) = \frac{v_t(\lambda,\varphi)^{\theta(\lambda)}}{\sum_{\varphi'} v_t(\lambda,\varphi')^{\theta(\lambda)}}. \tag{37}$$

Finally, substituting back for φ and for $v_t(\lambda,\kappa,\omega)$ and setting $\theta(\lambda) = \theta$ for all λ, we obtain equation (3) in Section IIB.

Average Wages: $w_t(\lambda,\kappa,\omega)$ and $w_t(\lambda)$.—As in the previous derivation, denote by $\varphi \equiv (\kappa,\omega)$. The average efficiency units of each worker in $\mathcal{Z}_t(\lambda,\varphi)$, which denotes the set of workers $z \in \mathcal{Z}_t(\lambda)$ who choose φ, is

$$\mathbb{E}\left[\epsilon(z)\,\varepsilon(z,\varphi)|z \in \mathcal{Z}_t(\lambda,\varphi)\right] = \mathbb{E}\left[\epsilon(z)|z \in \mathcal{Z}_t(\lambda,\varphi)\right] \times \mathbb{E}\left[\varepsilon(z,\varphi)|z \in \mathcal{Z}_t(\lambda,\varphi)\right]$$

$$= \mathbb{E}\left[\epsilon(z)|z \in \mathcal{Z}_t(\lambda)\right] \times \mathbb{E}\left[\varepsilon(z,\varphi)|z \in \mathcal{Z}_t(\lambda,\varphi)\right]$$

$$= \mathbb{E}\left[\epsilon(z,\varphi)|z \in \mathcal{Z}_t(\lambda,\varphi)\right],$$

where the first two equalities follow from both the assumption that $\epsilon(z)$ is independent of $\varepsilon(z,\varphi)$ and the result above that the choice φ of each individual z does not depend on the value of $\epsilon(z)$, and the third equality follows from normalizing $\mathbb{E}\left[\epsilon(z)|z \in \mathcal{Z}_t(\lambda)\right]$ to be equal to one.[33] In what follows, let $\bar{\varepsilon}_t(\lambda,\varphi) \equiv \mathbb{E}\left[\varepsilon(z,\varphi)|z \in \mathcal{Z}_t(\lambda,\varphi)\right]$. We have

$$\bar{\varepsilon}_t(\lambda,\varphi) = \frac{1}{\pi_t(\lambda,\varphi)}\int_0^\infty \varepsilon \times \Pr\left[\varepsilon \geq \max_{\varphi'\neq\varphi}\left\{\frac{\varepsilon(z,\varphi')\,v_t(\lambda,\varphi')}{v_t(\lambda,\varphi)}\right\}\right] dG(\varepsilon).$$

Hence, we have

$$\bar{\varepsilon}_t(\lambda,\varphi) = \frac{1}{\pi_t(\lambda,\varphi)}\int_0^\infty \exp\left[-\varepsilon^{-\theta(\lambda)} v_t(\lambda,\varphi)^{-\theta(\lambda)}\sum_{\varphi'} v_t(\lambda,\varphi')^{\theta(\lambda)}\right]\theta(\lambda)\,\varepsilon^{-\theta(\lambda)}\,d\varepsilon.$$

[33] This is a normalization because, for any value of $T_t'(\lambda)$ and $\mathbb{E}\left[\epsilon_t'(z)|z \in \mathcal{Z}_t(\lambda)\right] \neq 1$, we can always define an alternative $T_t(\lambda)$ and $\epsilon(z)$, such that $T_t(\lambda) = T_t'(\lambda)\,\mathbb{E}\left[\epsilon_t'(z)|z \in \mathcal{Z}_t(\lambda)\right]$ and $\mathbb{E}\left[\epsilon(z)|z \in \mathcal{Z}_t(\lambda)\right] = 1$.

Let $j = \varepsilon^{-\theta}$ and, as in the previous derivation, let $n_t(\lambda,\varphi) \equiv \sum_{\varphi'} \left(\frac{v_t(\lambda,\varphi)}{v_t(\lambda,\varphi')}\right)^{-\theta(\lambda)}$. Hence, we have

$$\bar{\varepsilon}_t(\lambda,\varphi) = \frac{1}{\pi_t(\lambda,\varphi)} \int_{-\infty}^{0} \exp(-jz)\, j^{-1/\theta(\lambda)} (-dj) = \frac{1}{\pi_t(\lambda,\varphi)} \int_0^{\infty} j^{-1/\theta(\lambda)} \exp(-jz)\, dj.$$

Let $y_t(\lambda,\varphi) = n_t(\lambda,\varphi)\, j$. Hence, we have

$$\begin{aligned}\bar{\varepsilon}_t(\lambda,\varphi) &= \frac{1}{\pi_t(\lambda,\varphi)} \int_0^{\infty} \left(\frac{y_t(\lambda,\varphi)}{n_t(\lambda,\varphi)}\right)^{-1/\theta(\lambda)} \exp\big(-y_t(\lambda,\varphi)\big) \frac{d y_t(\lambda,\varphi)}{n_t(\lambda,\varphi)} \\ &= \frac{1}{\pi_t(\lambda,\varphi)} n_t(\lambda,\varphi)^{\frac{1-\theta(\lambda)}{\theta(\lambda)}} \times \gamma(\lambda),\end{aligned}$$

where $\gamma(\lambda) \equiv \Gamma\Big(1 - \frac{1}{\theta(\lambda)}\Big)$ and $\Gamma(\cdot)$ is the Gamma function

$$\Gamma(x) \equiv \int_0^{\infty} t^{x-1} \exp(-t)\, dt.$$

Substituting in for $n_t(\lambda,\varphi)$, we obtain

$$\bar{\varepsilon}_t(\lambda,\varphi) = \gamma(\lambda)\, \pi_t(\lambda,\varphi)^{\frac{-1}{\theta(\lambda)}}.$$

Hence, the total income of workers in $\mathcal{Z}_t(\lambda)$ choosing φ, $L_t(\lambda)\, \pi_t(\lambda,\varphi)\, \bar{\varepsilon}_t(\lambda,\varphi)\, v_t(\lambda,\varphi)$, becomes $\gamma(\lambda)\, L_t(\lambda)\, \pi_t(\lambda,\varphi)^{\frac{\theta(\lambda)-1}{\theta(\lambda)}} v_t(\lambda,\varphi)$. Dividing by the mass of these workers, $L_t(\lambda)\, \pi_t(\lambda,\varphi)$, we obtain the wage rate

$$w_t(\lambda,\varphi) = \gamma(\lambda)\, v_t(\lambda,\varphi)\, \pi_t(\lambda,\varphi)^{-1/\theta(\lambda)}. \tag{38}$$

Substituting in for $v_t(\lambda,\varphi)$ and for φ and setting $\theta(\lambda) = \theta$ and $\gamma(\lambda) = \gamma$ for all λ, we obtain the unnumbered equation from Section IIB:

$$w_t(\lambda,\kappa,\omega) = \bar{\alpha}\gamma T_t(\lambda,\kappa,\omega)\, p_t(\kappa)^{\frac{-\alpha}{1-\alpha}} p_t(\omega)^{\frac{1}{1-\alpha}} \pi_t(\lambda,\kappa,\omega)^{-1/\theta}.$$

Finally, substituting in for $\pi_t(\lambda,\varphi)$ from equation (37) into equation (38), we obtain

$$w_t(\lambda) = w_t(\lambda,\varphi) = \gamma(\lambda) \left(\sum_{\varphi'} v_t(\lambda,\varphi')^{\theta(\lambda)}\right)^{1/\theta(\lambda)}.$$

Substituting in for $v_t(\lambda,\varphi)$ and for φ and setting $\theta(\lambda) = \theta$ and $\gamma(\lambda) = \gamma$ for all λ, we obtain equation (4) from Section IIB.

Appendix B. Data Details

Throughout, we restrict our sample by dropping workers who are younger than 17 or older than 64 years old, do not report positive paid hours worked, are self-employed, or are in the military.

MORG.—We use the MORG CPS to form a sample of hours worked and income for each labor group. Specifically, we use the "hour wage sample" from Acemoglu and Autor (2011). Hourly wages are equal to the reported hourly earnings for those paid by the hour and the usual weekly earnings divided by hours worked last week for non-hourly workers. Top-coded earnings are multiplied by 1.5. Workers earning below \$1.675/hour in 1982 dollars are dropped, as are workers whose hourly wages exceed the number arising from multiplying the top-coded value of weekly earnings by 1/35 (i.e., workers paid by the hour whose wages are sufficiently high so that their weekly income would be top coded if they worked at least 35 hours and were not paid by the hour). Observations with allocated earnings are excluded. Our measure of labor composition, $L_t(\lambda)$, is hours worked within each labor group λ (weighted by sample weights).

October Supplement.—In 1984, 1989, 1993, 1997, and 2003, the October Supplement asked respondents whether they "have direct or hands on use of computers at work," "directly use a computer at work," or "use a computer at/for his/her/your main job." Using a computer at work refers only to "direct" or "hands on" use of a computer with typewriter-like keyboards, whether a personal computer, laptop, minicomputer, or mainframe.

Occupations.—The occupations we include are listed in Table 10, where we also list the share of hours worked in each occupation by college-educated workers and by women as well as the occupation share of labor payments in 1984 and in 2003. Our concordance of occupations across time is based on the concordance developed in Autor and Dorn (2013).

Composition-Adjusted Wages.—We construct 30 labor groups defined by the intersection of five education, two gender, and three age categories. When we construct measures of changes in relative wages between broader groups that aggregate across our most disaggregated labor groups—e.g., the group of college-educated workers combines 10 of our 30 labor groups—we composition adjust wages by holding constant the relative employment shares of our 30 labor groups across all years of the sample. Specifically, after calculating mean log wages within each labor group (either from the model or the data), we construct mean wages for broader groups as fixed-weighted averages of the relevant labor group means, using an average share of total hours worked by each labor group over 1984 to 2003 as weights. This adjustment ensures that changes in average wages across broader groups are not driven by shifts in the education $\times$ age $\times$ gender composition within these broader groups.

Table 10—Thirty Occupations, Their College and Female Intensities, and the Occupational Share of Labor Payments

	College intensity		Female intensity		Income share	
Occupations	1984	2003	1984	2003	1984	2003
Executive, administrative, managerial	0.48	0.58	0.32	0.40	0.12	0.16
Management related	0.53	0.61	0.43	0.54	0.05	0.05
Architect	0.86	0.88	0.15	0.24	0.00	0.00
Engineer	0.71	0.79	0.06	0.11	0.03	0.03
Life, physical, and social science	0.65	0.55	0.30	0.30	0.01	0.02
Computer and mathematical	0.86	0.91	0.31	0.41	0.01	0.01
Community and social services	0.76	0.73	0.46	0.58	0.01	0.02
Lawyers	0.98	0.98	0.24	0.35	0.01	0.01
Education, training, etc.[a]	0.90	0.87	0.63	0.68	0.05	0.06
Arts, design, entertainment, sports, media	0.49	0.57	0.39	0.45	0.01	0.01
Health diagnosing	0.96	0.98	0.20	0.33	0.01	0.01
Health assessment and treating	0.51	0.64	0.85	0.84	0.02	0.04
Technicians and related support	0.30	0.43	0.46	0.43	0.04	0.05
Financial sales and related	0.31	0.33	0.31	0.40	0.04	0.05
Retail sales	0.17	0.24	0.54	0.50	0.05	0.05
Administrative support	0.12	0.16	0.78	0.74	0.14	0.12
Housekeeping, cleaning, laundry	0.01	0.03	0.83	0.83	0.01	0.00
Protective service	0.16	0.21	0.11	0.19	0.02	0.02
Food preparation and service	0.05	0.06	0.61	0.51	0.02	0.02
Health service	0.04	0.08	0.90	0.90	0.01	0.01
Building, grounds cleaning, maintenance	0.04	0.05	0.20	0.21	0.02	0.01
Miscellaneous[b]	0.12	0.17	0.67	0.63	0.01	0.01
Child care	0.11	0.12	0.91	0.94	0.00	0.00
Agriculture and mining	0.05	0.06	0.10	0.16	0.01	0.01
Mechanics and repairers	0.04	0.07	0.03	0.04	0.05	0.04
Construction	0.04	0.05	0.01	0.02	0.05	0.04
Precision production	0.07	0.08	0.15	0.25	0.04	0.03
Machine operators, assemblers, inspectors	0.03	0.06	0.40	0.34	0.08	0.04
Transportation and material moving	0.03	0.05	0.06	0.09	0.05	0.04
Handlers, equip. cleaners, helpers, laborers	0.03	0.04	0.17	0.18	0.03	0.02

Notes: College intensity (female intensity) indicates hours worked in the occupation by those with college degrees (females) relative to total hours worked in the occupation. Income share denotes labor payments in the occupation relative to total labor payments. Each is calculated using the MORG CPS.

[a] Education, training, etc., also includes library and legal support/assistants/paralegals.

[b] Miscellaneous includes personal appearance, misc. personal care and service, recreation, and hospitality.

*O*NET*.—We follow Acemoglu and Autor (2011) in our use of O*NET and construct composite measures of O*NET Work Activities and Work Context Importance scales: (i) nonroutine cognitive analytical, (ii) nonroutine cognitive interpersonal, (iii) routine manual, and (iv) nonroutine manual physical. We aggregate their measures up to our 30 occupations and standardize each to have mean 0 and standard deviation 1.

Appendix C. Measurement of Shocks

Equations (11), (12), and (13) can be written so that changes in relative wages, $\hat{w}(\lambda)/\hat{w}(\lambda_1)$, relative transformed occupation price changes, $\hat{q}(\omega)/\hat{q}(\omega_1)$, and allocations, $\hat{\pi}(\lambda, \kappa, \omega)$, depend on relative shocks to labor composition, $\hat{L}(\lambda)/\hat{L}(\lambda_1)$, occupation shifters, $\hat{a}(\omega)/\hat{a}(\omega_1)$, equipment productivity, $\hat{q}(\kappa)/\hat{q}(\kappa_1)$, and labor productivity, $\hat{T}(\lambda)/\hat{T}(\lambda_1)$:

$$\frac{\hat{w}(\lambda)}{\hat{w}(\lambda_1)} = \frac{\hat{T}(\lambda)}{\hat{T}(\lambda_1)} \frac{\left[\sum_{\kappa,\omega}\left(\frac{\hat{q}(\omega)}{\hat{q}(\omega_1)}\frac{\hat{q}(\kappa)}{\hat{q}(\kappa_1)}\right)^{\theta}\pi_{t_0}(\lambda,\kappa,\omega)\right]^{1/\theta}}{\left[\sum_{\kappa',\omega'}\left(\frac{\hat{q}(\omega')}{\hat{q}(\omega_1)}\frac{\hat{q}(\kappa')}{\hat{q}(\kappa_1)}\right)^{\theta}\pi_{t_0}(\lambda,\kappa',\omega')\right]^{1/\theta}},$$

$$\hat{\pi}(\lambda,\kappa,\omega) = \frac{\left(\frac{\hat{q}(\omega)}{\hat{q}(\omega_1)}\frac{\hat{q}(\kappa)}{\hat{q}(\kappa_1)}\right)^{\theta}}{\sum_{\kappa',\omega'}\left(\frac{\hat{q}(\omega')}{\hat{q}(\omega_1)}\frac{\hat{q}(\kappa')}{\hat{q}(\kappa_1)}\right)^{\theta}\pi_{t_0}(\lambda,\kappa',\omega')},$$

and

$$\frac{\hat{a}(\omega)}{\hat{a}(\omega_1)}\left(\frac{\hat{q}(\omega)}{\hat{q}(\omega_1)}\right)^{(1-\alpha)(1-\rho)}$$

$$= \frac{\zeta_{t_0}(\omega_1)}{\zeta_{t_0}(\omega)} \frac{\sum_{\lambda,\kappa} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa,\omega)\frac{\hat{w}(\lambda)}{\hat{w}(\lambda_1)}\frac{\hat{L}(\lambda)}{\hat{L}(\lambda_1)}\hat{\pi}(\lambda,\kappa,\omega)}{\sum_{\lambda',\kappa'} w_{t_0}(\lambda')\, L_{t_0}(\lambda')\, \pi_{t_0}(\lambda',\kappa',\omega)\frac{\hat{w}(\lambda')}{\hat{w}(\lambda_1)}\frac{\hat{L}(\lambda')}{\hat{L}(\lambda_1)}\hat{\pi}(\lambda',\kappa',\omega)}.$$

Note that $\hat{E}$ cancels out of this system of equations.

A. *Baseline*

Here, we describe in detail the steps that we follow to obtain our measures of changes in labor composition, occupation shifters, equipment productivity, and labor productivity.

First, the relative shocks to labor composition $\hat{L}(\lambda)/\hat{L}(\lambda_1)$ are directly observed in the data.

Second, we measure relative changes in equipment productivity (to the power θ) using equation (14) as

$$\frac{\hat{q}(\kappa_2)^{\theta}}{\hat{q}(\kappa_1)^{\theta}} = \exp\left(\frac{1}{N(\kappa_1,\kappa_2)}\sum_{\lambda,\omega}\log\frac{\hat{\pi}(\lambda,\kappa_2,\omega)}{\hat{\pi}(\lambda,\kappa_1,\omega)}\right),$$

dropping all (λ,ω) pairs for which $\pi_t(\lambda,\kappa_1,\omega) = 0$ or $\pi_t(\lambda,\kappa_2,\omega) = 0$ in either period t_0 or t_1. Here, $N(\kappa_1,\kappa_2)$ is the number of (λ,ω) pairs over which we average; in the absence of any zeros in allocations, we have $N(\kappa_1, \kappa_2) = 900$, which is the number of labor groups multiplied by the number of occupations.

Third, we measure changes in transformed occupation prices relative to occupation ω_0 (to the power θ) using equation (16) as

$$\frac{\hat{q}(\omega)^{\theta}}{\hat{q}(\omega_0)^{\theta}} = \exp\left(\frac{1}{N(\omega, \omega_0)} \sum_{\lambda, \kappa} \log \frac{\hat{\pi}(\lambda, \kappa, \omega)}{\hat{\pi}(\lambda, \kappa, \omega_0)}\right),$$

dropping all (λ, κ) pairs for which $\pi_t(\lambda, \kappa, \omega_0) = 0$ or $\pi_t(\lambda, \kappa, \omega) = 0$ in either period t_0 or t_1. Here, $N(\omega, \omega_0)$ is the number of (λ, κ) pairs over which we average; in the absence of any zeros in allocations, we have $N(\omega, \omega_0) = 60$, which is the number of labor groups multiplied by the number of equipment types. In our model, the estimates of the relative occupation shifters for any two occupations ω_A and ω_B should not depend on the choice of the reference category ω_0. However, even if this prediction of the model is right, the fact that some of the values of $\pi_t(\lambda, \kappa, \omega_0)$ are equal to zero in the data implies that the estimates of changes in relative transformed occupation prices (to the power θ) vary with the choice of ω_0. In order to avoid this sensitivity to the choice of ω_0, we compute changes in relative transformed occupation prices using the following geometric average:

$$\frac{\hat{q}(\omega)^{\theta}}{\hat{q}(\omega_1)^{\theta}} = \exp\left(\frac{1}{30} \sum_{\omega_0} \left(\log \frac{\hat{q}(\omega)^{\theta}}{\hat{q}(\omega_0)^{\theta}} - \log \frac{\hat{q}(\omega_1)^{\theta}}{\hat{q}(\omega_0)^{\theta}}\right)\right),$$

where, for each ω and ω_0, $\hat{q}(\omega)^{\theta} / \hat{q}(\omega_0)^{\theta}$ is calculated as described above. This expression yields estimates that do not depend on the choice of ω_1. Furthermore, as we discuss below, this approach yields measures of relative changes in occupation shifters that are very similar to those that arise from projecting changes in allocations on a set of fixed effects.

Third, given our measures of changes in equipment and transformed occupation prices (both to the power θ), we construct $\hat{s}(\lambda)$ using equation (18). Given $\hat{s}(\lambda)$ and using data on changes in payments to occupations, $\hat{\zeta}(\omega)$, the measures of changes in equipment productivity and transformed occupation prices (both to the power θ) in equations (14) and (16), and an estimate of θ, we estimate ρ as described in Section IIIC.

Fourth, given the measures of changes in equipment productivity and transformed occupation prices (both to the power θ) in equations (14) and (16), the estimate of θ, and observed values both of the initial allocation $\pi_{t_0}(\lambda, \kappa, \omega)$ and changes in relative wages $\hat{w}(\lambda)/\hat{w}(\lambda_1)$, we measure changes in labor productivity $\hat{T}(\lambda)/\hat{T}(\lambda_1)$ using equation (17).

Finally, we measure changes in occupation shifters, $\hat{a}(\omega)/\hat{a}(\omega_1)$, using equation (15). A variable in this equation is the relative changes in total payments to occupations ω relative to those in a benchmark occupation ω_1, $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$. We construct this variable as follows. The initial levels,

$\zeta_{t_0}(\omega)/\zeta_{t_0}(\omega_1)$, are calculated directly using the observed values of $\pi_{t_0}(\lambda,\kappa,\omega)$, $w_{t_0}(\lambda)$, and $L_{t_0}(\lambda)$. The terminal levels, $\zeta_{t_1}(\omega)/\zeta_{t_1}(\omega_1)$, are constructed as

$$\frac{\zeta_{t_1}(\omega)}{\zeta_{t_1}(\omega_1)} = \frac{\sum_{\lambda,\kappa} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa,\omega)\, \dfrac{\hat{w}(\lambda)}{\hat{w}(\lambda_1)}\, \hat{L}(\lambda)\, \hat{\pi}(\lambda,\kappa,\omega)}{\sum_{\lambda',\kappa'} w_{t_0}(\lambda')\, L_{t_0}(\lambda')\, \pi_{t_0}(\lambda',\kappa',\omega_1)\, \dfrac{\hat{w}(\lambda')}{\hat{w}(\lambda_1)}\, \hat{L}(\lambda')\, \hat{\pi}(\lambda',\kappa',\omega_1)},$$

where $\hat{\pi}(\lambda,\kappa,\omega)$ are those constructed by the model given the measures of $\hat{q}(\omega)^{\theta}/\hat{q}(\omega)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$. The correlation between $\log\left(\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)\right)$ implied by the model and in the data is 0.77 between 1984 and 2003; the correlation between $\log\left(\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)\right)$ implied by the model using the alternative approach in Appendix C, Subsection C and in the data is 1 and the quantitative results we obtain from these two approaches are very similar.

B. *Alternative Approach 1: Regression Based*

Instead of using the expressions in equations (14) and (16), we can measure $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ using the coefficients of a regression of the observed changes in the log of factor allocations on labor group, occupation, and equipment-type fixed effects. Specifically, we can express equation (12) as

$$\hat{\pi}(\lambda,\kappa,\omega) = \hat{q}(\lambda)\,\hat{q}(\omega)^{\theta}\hat{q}(\kappa)^{\theta},$$

where we define

$$\hat{q}(\lambda) \equiv \left[\sum_{\kappa',\omega'} \hat{q}(\omega')^{\theta}\hat{q}(\kappa')^{\theta}\pi_{t_0}(\lambda,\kappa',\omega')\right]^{-1}.$$

Hence, in the presence of multiplicative measurement error $\iota_t(\lambda,\kappa,\omega)$ in the observed changes in allocations, we have

$$\log\hat{\pi}(\lambda,\kappa,\omega) = \log\hat{q}(\lambda) + \log\hat{q}(\omega)^{\theta} + \log\hat{q}(\kappa)^{\theta} + \iota_t(\lambda,\kappa,\omega).$$

Using this equation, we regress observed values of $\log\hat{\pi}(\lambda,\kappa,\omega)$ on labor group, equipment, and occupation effects. Exponentiating the resulting occupation and equipment fixed effects, we obtain estimates of $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$. Using these estimates instead of those derived from equations (14) and (16), we can recover measures of occupation shifters, $\hat{a}(\omega)/\hat{a}(\omega_1)$, and labor productivity, $\hat{T}(\lambda)/\hat{T}(\lambda_1)$, as well as estimate ρ and θ, following the same steps outlined in Appendix C, Subsection A.

Our alternative and baseline approaches are identical in the absence of zeros in the allocation data. In practice, the correlation between the measures obtained using these 2 approaches is above 0.99 for both equipment productivity and transformed occupation prices (both to the power θ). We use the procedure described in Appendix C, Subsection A as our baseline approach simply because, in our opinion, it more clearly highlights the variation in the data that is being used to identify the changes in occupation prices and equipment productivity (to the power θ).

C. *Alternative Approach 2: Matching Income Shares*

Our baseline approach yields estimate of $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ that do not exactly match observed changes in total labor income by occupation, $\zeta_t(\omega) \equiv \sum_{\lambda,\kappa} w_t(\lambda)\, L_t(\lambda)\, \pi_t(\lambda,\kappa,\omega)$, and by equipment type, $\zeta_t(\kappa) \equiv \sum_{\lambda,\omega} w_t(\lambda)\, L_t(\lambda) \times \pi_t(\lambda,\kappa,\omega)$. In this alternative approach, we calibrate $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ to match $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$ and $\hat{\zeta}(\kappa)/\hat{\zeta}(\kappa_1)$ exactly.

For each time period, we solve simultaneously for $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ to match observed values of $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$ and $\hat{\zeta}(\kappa)/\hat{\zeta}(\kappa_1)$. Specifically, for every t_0, $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ is the solution to the following nonlinear system of equations:

$$\frac{\hat{\zeta}(\omega)}{\hat{\zeta}(\omega_1)} = \frac{\zeta_{t_0}(\omega_1)\sum_{\lambda,\kappa} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa,\omega)\, \hat{w}(\lambda)\, \hat{L}(\lambda)\, \hat{\pi}(\lambda,\kappa,\omega)}{\zeta_{t_0}(\omega)\sum_{\lambda,\kappa} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa,\omega_1)\, \hat{w}(\lambda)\, \hat{L}(\lambda)\, \hat{\pi}(\lambda,\kappa,\omega_1)},$$

$$\frac{\hat{\zeta}(\kappa)}{\hat{\zeta}(\kappa_1)} = \frac{\zeta_{t_0}(\kappa_1)\sum_{\lambda,\omega} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa,\omega)\, \hat{w}(\lambda)\, \hat{L}(\lambda)\, \hat{\pi}(\lambda,\kappa,\omega)}{\zeta_{t_0}(\kappa)\sum_{\lambda,\omega} w_{t_0}(\lambda)\, L_{t_0}(\lambda)\, \pi_{t_0}(\lambda,\kappa_1,\omega)\, \hat{w}(\lambda)\, \hat{L}(\lambda)\, \hat{\pi}(\lambda,\kappa_1,\omega)},$$

where $\hat{w}(\lambda)\,\hat{L}(\lambda)$, $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$ and $\hat{\zeta}(\kappa)/\hat{\zeta}(\kappa_1)$ are observed in the data, and $\hat{\pi}(\lambda,\kappa,\omega) = \frac{\left(\hat{q}(\omega)\,\hat{q}(\kappa)\right)^{\theta}}{\sum_{\kappa',\omega'}\left(\hat{q}(\omega')\,\hat{q}(\kappa')\right)^{\theta}\pi_{t_0}(\lambda,\kappa',\omega')}$ is constructed given $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$. After solving for $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ and $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$, the remaining shocks and parameters are determined exactly as in our baseline procedure. We also consider a variation in which we first measure $\hat{q}(\kappa)^{\theta}/\hat{q}(\kappa_1)^{\theta}$ using our baseline procedure and then $\hat{q}(\omega)^{\theta}/\hat{q}(\omega_1)^{\theta}$ in order to match $\hat{\zeta}(\omega)/\hat{\zeta}(\omega_1)$ in the data. Results using these alternative approaches are very similar to our baseline results.

Appendix D. Estimation of Elasticities

A. *Baseline Estimation of θ and ρ*

This section provides a detailed description of the estimation approach described in Section IIIC. We estimate θ and ρ jointly using a Method of Moments (MM) estimator with two moment conditions.

In order to derive the first moment condition, we express equation (17) as

$$\log \hat{w}(\lambda,t) = \varsigma_{\theta}(t) + \beta_{\theta} \log \hat{s}(\lambda,t) + \iota_{\theta}(\lambda,t). \tag{39}$$

We observe $\log \hat{w}(\lambda, t)$ in our data and construct $\log \hat{s}(\lambda, t)$ as indicated in equation (18). The parameter $\varsigma_\theta(t) \equiv \log \hat{q}(\omega_1, t)\, \hat{q}(\kappa_1, t)$ is a time effect that is common across λ, $\beta_\theta \equiv 1/\theta$, and $\iota_\theta(\lambda, t) \equiv \log \hat{T}(\lambda, t)$ captures unobserved changes in labor group λ productivity. As shown in equation (17), measuring changes in labor productivity requires a value of θ, and therefore, we treat $\iota_\theta(\lambda, t)$ as unobserved when estimating θ.

Our model predicts the observed covariate in equation (39), $\log \hat{s}(\lambda, t)$, to be correlated with its error term, $\iota_\theta(\lambda, t)$. From equation (18), $\log \hat{s}(\lambda, t)$ is a function of changes in transformed occupation prices, $\hat{q}(\omega, t)$, and according to our model, these depend on changes in unobserved labor productivity, $\iota_\theta(\lambda, t)$. Specifically, our model implies that the error term $\iota_\theta(\lambda, t)$ and the covariate $\log \hat{s}(\lambda, t)$ are negatively correlated: the higher the growth in the productivity of a particular labor group, the lower the growth in the price of those occupations that use that type of labor more intensively. Therefore, we expect the Nonlinear Least Squares (NLS) estimate of β_θ to be biased downward and, consequently, the estimate of θ to be biased upward.

To address the endogeneity of the covariate $\log \hat{s}(\lambda, t)$, we construct the following instrument for $\log \hat{s}(\lambda, t)$,

$$\chi_\theta(\lambda, t) \equiv \log \sum_\kappa \frac{\hat{q}(\kappa, t)^\theta}{\hat{q}(\kappa_1, t)^\theta} \sum_\omega \pi_{1984}(\lambda, \kappa, \omega),$$

which is a labor-group-specific average of the observed changes in equipment productivity to the power θ, $\hat{q}(\kappa, t)^\theta / \hat{q}(\kappa_1, t)^\theta$.[34] We use this instrument and equation (39) to build the following moment condition:

$$(40) \qquad \mathbb{E}_{\lambda, t}\left[\left(y_\theta(\lambda, t) - \frac{1}{\theta} x_\theta(\lambda, t)\right) \times z_\theta(\lambda, t)\right] = 0,$$

where (i) $y_\theta(\lambda, t)$ is the (λ, t) OLS residual of a regression that projects the set of dependent variables $\log \hat{w}(\lambda, t)$, for all λ and t, on a set of year fixed effects; (ii) $x_\theta(\lambda, t)$ is the (λ, t) OLS residual of a regression that projects the set of independent variables $\log \hat{s}(\lambda, t)$, for all λ and t, on a set of year fixed effects; (iii) $z_\theta(\lambda, t)$ is the (λ, t) OLS residual of a regression that projects the set of independent variables $\chi_\theta(\lambda, t)$, for all λ and t, on a set of year fixed effects.[35]

In order for the moment condition in equation (40) to correctly identify the parameter θ, after controlling for year fixed effects, the variable $\chi_\theta(\lambda, t)$ must be correlated with $\log \hat{s}(\lambda, t)$ and uncorrelated with $\iota_\theta(\lambda, t)$. Our model predicts that

[34] In constructing the instrument for $\log \hat{s}(\lambda, t)$ between any two periods t_0 and t_1, we could also have used the observed labor allocations at period t_0. However, in order to minimize the correlation between a possibly serially correlated $\iota_\theta(\lambda, t)$ and the instrument, we construct our instrument for $\log \hat{s}(\lambda, t)$ between any two sample periods t_0 and t_1 using allocations in the initial sample year, 1984.

[35] By projecting first on a set of year effects and using the residuals from this projection in the moment condition in equation (40), we simplify significantly the computational burden involved in estimating both the parameter of interest θ and the set of incidental parameters $\{\varsigma_\theta(t)\}_t$. The Frisch-Waugh-Lovell Theorem guarantees that the resulting estimate of θ is consistent and has identical asymptotic variance to the alternative GMM estimator that estimates the year fixed effects $\{\varsigma_\theta(t)\}_t$ and the parameter θ jointly.

the conditioning variable $\chi_\theta(\lambda, t)$ will be correlated with the endogenous covariate $\log \hat{s}(\lambda, t)$, as an increase in the relative productivity of equipment κ between t_0 and t_1 raises the wage of group λ relatively more if a larger share of λ workers use equipment κ in period t_0. Equation (40) implicitly imposes that the shock $\chi_\theta(\lambda, t)$ is mean independent of the labor productivity shock $\log \hat{T}(\lambda, t)$ across labor groups and time periods. A sufficient condition for this mean independence condition to hold is that, between any two periods t_0 and t_1, the change in unobserved labor productivity, $\log \hat{T}(\lambda, t)$, and the weighted changes in equipment productivity are uncorrelated across labor groups.

In order to derive the second moment condition, we express equation (13) as

$$\log \hat{\zeta}(\omega, t) = \varsigma_\rho(t) + \beta_\rho \log \frac{\hat{q}(\omega, t)^\theta}{\hat{q}(\omega_1, t)^\theta} + \iota_\rho(\omega, t). \tag{41}$$

We observe $\log \hat{\zeta}(\omega, t)$ in the MORG CPS and measure $\log \hat{q}(\omega, t)^\theta / \hat{q}(\omega_1, t)^\theta$ following the procedure indicated in Section IIIB. The parameter $\varsigma_\rho(t)$ is a time effect that is common across ω and given by $\varsigma_\rho(t) \equiv \log \hat{E} + (1-\alpha)(1-\rho) \log \hat{q}(\omega_1, t)$, $\beta_\rho \equiv (1-\alpha)(1-\rho)/\theta$, and $\iota_\rho(\omega, t) \equiv \log \hat{a}(\omega, t)$ captures unobserved changes in occupation shifters. As shown in equation (15), measuring changes in occupation shifters requires a value of ρ, and therefore, we treat $\iota_\rho(\omega, t)$ as unobserved when estimating ρ.

Our model predicts that the observed covariate in equation (41), $\log \hat{q}(\omega, t)^\theta / \hat{q}(\omega_1, t)^\theta$, and the error term $\iota_\rho(\omega, t)$ are correlated: according to our model, changes in equilibrium transformed occupation prices, $\hat{q}(\omega, t)$, depend on changes in unobserved occupation shifters, $\iota_\rho(\omega, t)$. Specifically, we expect the error term $\iota_\rho(\omega, t)$ and the covariate $\log \hat{q}(\omega, t)^\theta / \hat{q}(\omega_1, t)^\theta$ to be positively correlated: the higher the growth in the shifter of a particular occupation, the higher the growth in the occupation price. Therefore, given any value of α and θ, we expect the NLS estimate of β_ρ to be biased upward and the resulting estimate of ρ to be biased downward.

To address the endogeneity of the covariate $\log \hat{q}(\omega, t)^\theta / \hat{q}(\omega_1, t)^\theta$, we construct the following Bartik-style instrument for $\log \hat{q}(\omega, t)^\theta / \hat{q}(\omega_1, t)^\theta$,

$$\chi_\rho(\omega, t) \equiv \log \sum_\kappa \frac{\hat{q}(\kappa, t)^\theta}{\hat{q}(\kappa_1, t)^\theta} \sum_\lambda \frac{L_{1984}(\lambda)\, \pi_{1984}(\lambda, \kappa, \omega)}{\sum_{\lambda', \kappa'} L_{1984}(\lambda')\, \pi_{1984}(\lambda', \kappa', \omega)},$$

which is an occupation-specific average of observed changes in equipment productivity to the power θ, $\hat{q}(\kappa, t)^\theta / \hat{q}(\kappa_1, t)^\theta$.[36]

[36] In order to minimize the correlation between a possibly serially correlated $\iota_\rho(\omega, t)$ and the instrument, we construct $\chi_\rho(\omega, t)$ using allocations in 1984: $L_{1984}(\lambda)\, \pi_{1984}(\lambda, \kappa, \omega)$ is the number of λ workers using equipment κ employed in occupation ω in 1984, and the denominator in the expression for $\chi_\rho(\omega, t)$ is total employment in occupation ω in 1984.

We use this instrument and equation (41) to build the following moment condition:

$$(42) \qquad \mathbb{E}_{\omega,t}\Big[\Big(y_\rho(\omega,t) - (1-\alpha)(1-\rho)\frac{1}{\theta}x_\rho(\omega,t)\Big) \times z_\rho(\omega,t)\Big] = 0,$$

where (i) $y_\rho(\omega,t)$ is the (ω,t) OLS residual of a regression that projects the set of dependent variables $\log\hat{\zeta}(\omega,t)$, for all ω and t, on a set of year fixed effects; (ii) $x_\rho(\omega,t)$ is the (ω,t) OLS residual of a regression that projects the set of independent variables $\log\hat{q}(\omega,t)^\theta/\hat{q}(\omega_1,t)^\theta$, for all ω and t, on a set of year fixed effects; and (iii) $z_\rho(\omega,t)$ is the (ω,t) OLS residual of a regression that projects the set of instruments $\chi_\rho(\omega,t)$, for all ω and t, on a set of year fixed effects.

In order for the moment condition in equation (42) to correctly identify the parameter ρ, after controlling for year fixed effects the variable $\chi_\rho(\lambda,t)$ must be correlated with $\log\hat{q}(\omega,t)^\theta/\hat{q}(\omega_1,t)^\theta$ and uncorrelated with $\iota_\rho(\lambda,t)$. Our model predicts that the conditioning variable $\chi_\rho(\omega,t)$ will be correlated with the endogenous covariate $\log\hat{q}(\omega,t)^\theta/\hat{q}(\omega_1,t)^\theta$ as an increase in the relative productivity of κ raises occupation ω's output—and, therefore, reduces its price—relatively more if a larger share of workers employed in occupation ω use equipment κ in period t_0. Equation (42) implicitly imposes that the shock $\chi_\rho(\lambda,t)$ is mean independent across occupations and time periods of the occupation shifter $\log\hat{a}(\omega,t)$. A sufficient condition for this mean independence condition to hold is that, for any given pair of years t_0 and t_1, the change in the (unobserved) occupation shifter and the weighted changes in equipment productivity are uncorrelated across occupations.

We estimate θ and ρ using the sample analogue of the moment conditions in equations (40) and (42). These two moment conditions exactly identify the parameter vector (θ,ρ). In order to build these sample analogues, we use data on four time periods: 1984–1989, 1989–1993, 1993–1997, and 1997–2003. As discussed in Section IIIC, we obtain a point estimate of θ equal to 1.81 (standard error equal to 0.28) and a point estimate of ρ equal to 1.81 (standard error equal to 0.36).

Interestingly, the difference between our baseline estimates and analogous nonlinear least squares NLS estimates—i.e., nonlinear estimation without instruments—is consistent with the bias that, according to our model, should affect these NLS estimates. The fact that the NLS estimate of θ is higher than its baseline counterpart is consistent with the prediction of our model that the error term $\iota_\theta(\lambda,t)$ is negatively correlated with the covariate $\log\hat{s}(\lambda,t)$. The fact that the NLS estimate of ρ is lower than its baseline counterpart is consistent with the prediction of our model that the error term $\iota_\rho(\omega,t)$ is negatively correlated with the covariate $\log\hat{q}(\omega,t)^\theta/\hat{q}(\omega_1,t)^\theta$.

B. *Estimation of θ and ρ Allowing for Time Trends*

Here, we discuss estimates of θ and ρ that result when we add as controls a labor-group-specific time trend in equation (39) and an occupation-specific time trend in equation (41). Allowing for these time trends relaxes the orthogonality restrictions imposed to derive the moment conditions used in our baseline analysis (equations (40) and (42)).

In reviewing Krusell et al. (2000), Acemoglu (2002) raises the concern that the presence of common trends in unobserved labor-group-specific productivity, explanatory variables, and instruments may bias the estimates of wage elasticities. In order to address this concern, we follow Katz and Murphy (1992), Acemoglu (2002), and the estimation of the canonical model more generally. Specifically, we express $\hat{T}(\lambda, t)$ as following a λ-specific time trend with deviations around this trend, $\log\hat{T}(\lambda, t) = \beta_\theta(\lambda) \times (t_1 - t_0) + \iota_{\theta 1}(\lambda, t)$, and build a moment condition that is identical to that in equation (40) except for the fact that each of the variables $y_\theta(\lambda, t)$, $x_\theta(\lambda, t)$, and $z_\theta(\lambda, t)$ is now defined as the (λ, t) OLS residual of a regression that projects $\log\hat{w}(\lambda, t)$, $\log\hat{s}(\lambda, t)$, and $\chi_\theta(\lambda, t)$, respectively, on a set of year fixed effects and on a set of labor-group-specific time trends. The resulting moment condition therefore assumes that, after controlling for year fixed effects, deviations from a labor-group-specific linear time trend in the labor-group-specific productivities $\log\hat{T}(\lambda, t)$ are mean independent of the deviations from a labor-group-specific linear time trend in the labor-group-specific average of equipment shocks $\chi_\theta(\lambda, t)$. This orthogonality restriction is weaker than that imposed in our baseline estimation to derive the moment condition in equation (40). Specifically, explicitly controlling for labor-group-specific time trends in the wage equation guarantees that the resulting estimates of θ will be consistent even if it were to be true that those labor groups whose productivity, $\log\hat{T}(\lambda, t)$, has grown more during the 20 years between 1984 and 2003 also happen to be the labor groups that in 1984 were more intensively using those types of equipment whose productivities, $\hat{q}(\kappa, t)$, have also grown systematically more during the 1984–2003 time period. As an example, if it were to be true that (i) highly educated workers used computers more in 1984, (ii) they experienced a large average growth in their productivities between 1984 and 2003, and (iii) computers also had a relatively large growth in their productivity in the same sample period, then our baseline estimates of θ would be biased but the estimates that control for labor-group-specific time trends would not, unless it were true that those specific years within the period 1984–2003 with higher growth of the productivity of educated workers were precisely also the years in which the productivity of computers also happened to grow above its 1984–2003 trend.

In the same way in which we allow for a labor-group-specific time trend in equation (39), we also additionally control for an occupation-specific time trend in equation (41). Specifically, we express the unobserved changes in occupation shifters, $\log\hat{a}(\omega, t)$, as the sum of a ω-specific time trend and deviations around this trend, $\log\hat{a}(\omega, t) = \beta_\rho(\omega) \times (t_1 - t_0) + \iota_{\rho 1}(\omega, t)$. We then build a moment condition that is analogous to that in equation (42) except for the fact that each of the variables $y_\rho(\omega, t)$, $x_\rho(\omega, t)$, and $z_\rho(\omega, t)$ are now defined as the residuals of a linear projection of each of them on year fixed effects and an occupation-specific time trend. The orthogonality restriction implied by the resulting moment condition is weaker than that in our baseline estimation; specifically, it would not be violated in the hypothetical case in which those occupations whose idiosyncratic productivity grew systematically more during the period 1984–2003 happen to also be the occupations that in 1984 used more intensively the types of equipment whose idiosyncratic productivity also grew more on average during this same period.

The estimates of θ and ρ that result from adding as controls a labor-group-specific time trend in equation (39) and an occupation-specific time trend in equation (41) are, respectively, 1.26 with a standard error of 0.31 and 2.10 with a standard error of 0.75, as discussed in Section IIIC. The fact that the estimate of θ is smaller than that obtained without controlling for labor-group-specific time trends and the estimate of ρ is larger than that obtained without controlling for occupation-group specific time trends is consistent with the hypothesis that our baseline estimates are affected by a weaker version of the same kind of bias affecting the NLS estimates. However, note that allowing for time trends does not have a large quantitative impact in our estimates of θ and ρ: the two estimates of θ are within two standard deviations of each other and the two estimates of ρ are even within one standard deviation of each other. Furthermore, when computing the effects of shocks on relative wages, the estimates that result from controlling for worker-group-specific time trends in equation (39) actually imply a smaller role for changes in labor productivity (the residual), as we show in the online Appendix.

C. *Estimation of θ Using Within-Worker Group Distribution of Wages*

Here, we consider an approach—based on Lagakos and Waugh (2013) and Hsieh et al. (2018)—to estimate θ under a very different set of restrictions than those imposed above. This approach identifies θ from moments of the unconditional distribution of observed wages within each labor group λ and, therefore, trivially allows one to estimate values of θ that vary by labor group.

Recall that in our baseline approach, a worker $z \in \mathcal{Z}_t(\lambda)$ supplies $\epsilon(z)\,\varepsilon(z,\kappa,\omega)$ efficiency units of labor if teamed with equipment κ in occupation ω. Hence, in spite of the fact that each worker $z \in \mathcal{Z}_t(\lambda)$ draws $\varepsilon(z,\kappa,\omega)$ across (κ,ω) pairs from a Fréchet distribution with CDF $G(\varepsilon) = \exp\left(\varepsilon^{-\theta}\right)$, the introduction of $\epsilon(z)$ allows for correlation in efficiency units across (κ,ω) pairs within a given worker in an unrestricted way.

A more typical and restrictive approach to allow for correlation—see, e.g., Ramondo and Rodríguez-Clare (2013) and Hsieh et al. (2018)—assumes away $\epsilon(z)$ (i.e., assumes its distribution across z is degenerate) and instead uses a more parametric assumption: each worker $z \in \mathcal{Z}_t(\lambda)$, draws the vector $\left\{\varepsilon\left(z,\kappa,\omega\right)\right\}_{\kappa,\omega}$ from a multivariate Fréchet distribution,

$$G(\varepsilon(z);\lambda) = \exp\left(-\left(\sum_{\kappa,\omega}\varepsilon\left(z,\kappa,\omega\right)^{-\tilde{\theta}(\lambda)/1-\nu(\lambda)}\right)^{1-\nu(\lambda)}\right).$$

The parameter $\tilde{\theta}(\lambda) > 1$ governs the λ-specific dispersion of efficiency units across (κ,ω) pairs; a higher value of $\tilde{\theta}(\lambda)$ decreases this dispersion. The parameter $0 \leq \nu(\lambda) \leq 1$ governs the λ-specific correlation of each worker's efficiency units across (κ,ω) pairs; a higher value of $\nu(\lambda)$ increases this correlation. We define $\theta(\lambda) \equiv \tilde{\theta}(\lambda)/(1-\nu(\lambda))$. In what follows, we use this generalized distribution.

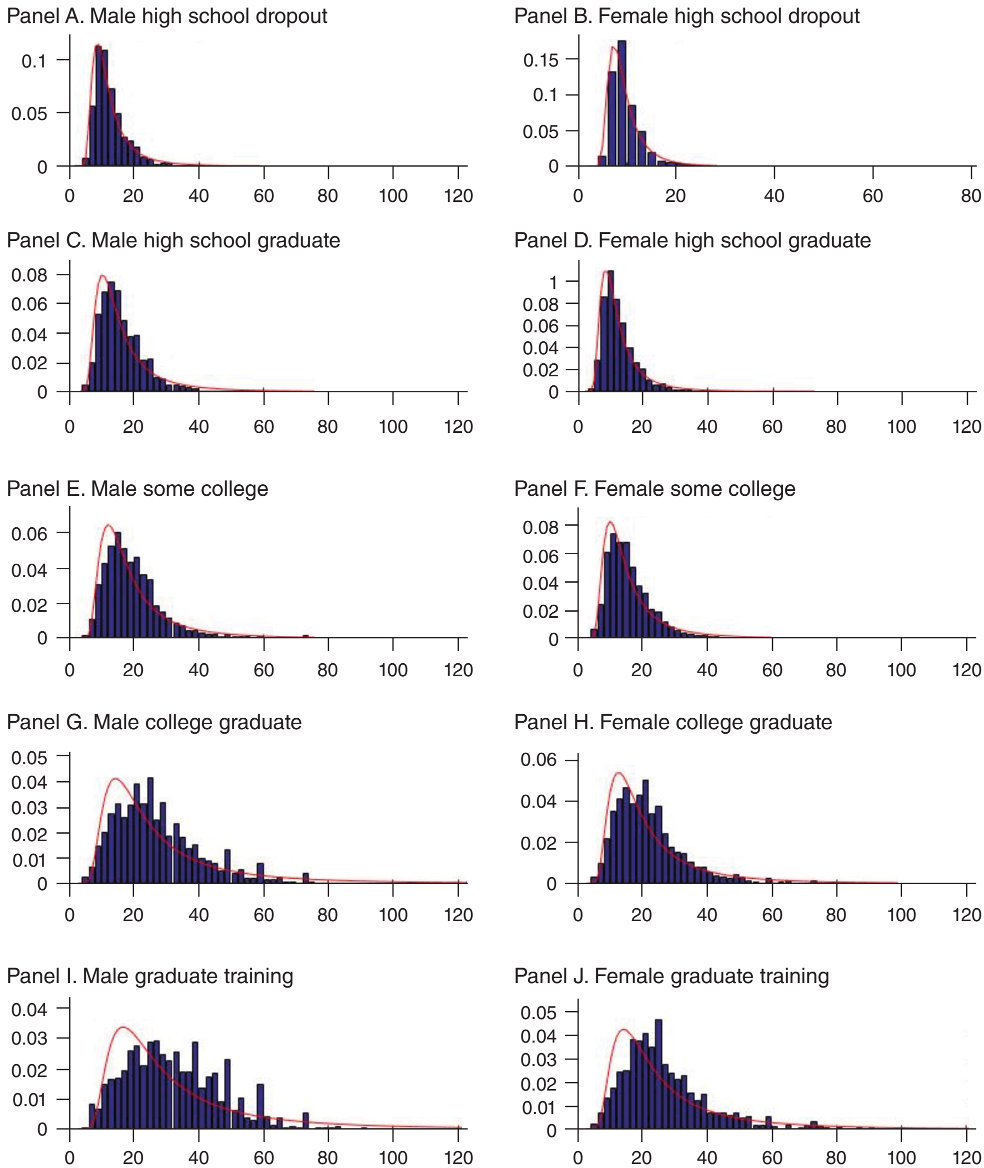

Figure 3. Empirical and Predicted (Fréchet Distribution Estimated Using Maximum Likelihood) Wage Distributions for All Middle-Aged Labor Groups in 2003

Allowing θ to vary by λ, our assumption on the distribution of idiosyncratic productivity implies that the distribution of wages within labor group λ is Fréchet with shape parameter $\tilde{\theta}(\lambda)$, where $\theta(\lambda) \equiv \tilde{\theta}(\lambda)/(1-\nu(\lambda))$. We can therefore use the empirical distribution of wages within each λ to estimate $\tilde{\theta}(\lambda)$, separately for each labor group λ. Specifically, we jointly estimate the shape and scale parameter for each λ in each year t using maximum likelihood. Figure 3 plots the empirical and predicted wage distributions for all middle-aged workers in 2003. We then average across years our estimates of the shape parameter to obtain $\tilde{\theta}(\lambda)$. Finally, we obtain an estimate of $\theta(\lambda)$ from $\tilde{\theta}(\lambda)$ using Hsieh et al.'s (2018) implied estimate of $\nu \equiv \nu(\lambda) \approx 0.1$.

Consistent with the observation that higher earning labor groups have more within-group wage dispersion, see, e.g., Lemieux (2006), we find that $\theta(\lambda)$ is lower (i.e., more within-group wage inequality) for more educated groups than less educated groups—averaging within each of the five education groups across age and gender, we obtain estimates that fall monotonically from 3.46 amongst high school dropouts to 2.03 amongst those with graduate training—for men than women—averaging within each gender across age and education, we obtain an estimate of 2.41 for men and 2.82 for women. The average across λ varies very little over time.

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