Offshoring, Automation, Low-Skilled Immigration, and Labor Market Polarization

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ONLINE APPENDIX

This technical appendix includes:

1. Baseline model equilibrium conditions
2. Alternative model with Hansen-Rogerson lotteries
3. Data sources
4. Sensitivity analysis

1 Model Equilibrium Conditions

We provide the summary of equations for the Home economy. There are similar equations for Foreign, except for those related to labor migration.

1.1 Household Optimization

Labor supply:

$$w_{\mathbf{u},t}/P_t = a_n \left(L_t\right)^{\gamma_n} C_t \tag{1}$$

Law of motion for skilled workers:

$$N_{D,t} = (1-\delta)(N_{D,t-1} + N_{E,t-1}) \tag{2}$$

[1] The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of Atlanta, the Federal Reserve Board, or the Federal Reserve System.

Free entry condition for training:

$$f_{e,t} = \beta (1-\delta) \mathbb{E}_t \left[\frac{P_{t+1}C_{t+1}}{P_t C_t} (f_{e,t+1} + \tilde{\pi}_{t+1}) \right], \text{with } f_{e,t} = w_{\mathbf{u},t} f_e \tag{3}$$

Law of motion for ICT capital:

$$K_t = (1-\delta_{K,t})K_{t-1} + \varepsilon_{K,t} I_t - \frac{\phi^k}{2} \varepsilon_{K,t-1} I_{t-1} \left[\frac{\varepsilon_{K,t} I_t}{\varepsilon_{K,t-1} I_{t-1}} \right]^2 \tag{4}$$

Euler equations for capital and investment:

$$\frac{1}{C_t} = \varepsilon_{K,t} \lambda_t (1-\phi_K \Omega_t) + \beta \mathbb{E}_t \left\{ \varepsilon_{K,t+1} \lambda_{t+1} \left[\phi_K \Omega_{t+1} \frac{I_{t+1}}{I_t} - \frac{\phi_K}{2} \frac{\varepsilon_{K,t}}{\varepsilon_{K,t+1}} (\Omega_{t+1})^2 \right] \right\}, \text{ where } \Omega_t = \frac{\varepsilon_{K,t} I_t}{\varepsilon_{K,t-1} I_{t-1}} \tag{5}$$

$$\lambda_t = \beta \mathbb{E}_t \left\{ \frac{r_{K,t+1}}{P_{t+1} C_{t+1}} + \lambda_{t+1} (1-\delta_{K,t}) \right\} \tag{6}$$

where λ_t is the Lagrange multiplier on the capital constraint.

1.2 Aggregate Output

Total output and the relative demand for tradables, non-tradables:

$$Y_t = \left[(\gamma_c)^{\frac{1}{\rho_c}} (Y_{T,t})^{\frac{\rho_c - 1}{\rho_c}} + (1-\gamma_c)^{\frac{1}{\rho_c}} (Y_{N,t})^{\frac{\rho_c - 1}{\rho_c}} \right]^{\frac{\rho_c}{\rho_c - 1}} \tag{7}$$

$$\frac{Y_{T,t}}{Y_{N,t}} = \frac{\gamma_c}{1-\gamma_c} \left(\frac{P_{T,t}}{P_{N,t}} \right)^{-\rho_c} \tag{8}$$

The aggregate price index, with $P_{T,t}$ set as numeraire:

$$P_t = \left[(\gamma_c) (P_{T,t})^{1-\rho_c} + (1-\gamma_c) (P_{N,t})^{1-\rho_c} \right], \text{with numeraire } P_{T,t} = 1. \tag{9}$$

Income-based GDP in units of the numeraire:

$$P_t Y_t = N_{D,t}\widetilde{\pi}_t + w_{\mathbf{u},t} L_t + r_t^k K_{t-1} \tag{10}$$

Resource constraint:

$$Y_t = C_t + C_{\mathrm{Im},t} + I_t \tag{11}$$

Balanced trade:

$$Q_t N_{X,t} \left(\tilde{w}_{XF,t}\right)^{1-\theta} H_t^* = N_{X,t}^* \left(\tilde{w}_{XH,t}^*\right)^{1-\theta} H_t \tag{12}$$

1.3 Middle and High-Skill Workers

Average wage and productivity of middle-skill workers, i.e., those below the cutoff $\mathbf{z}_{X,t}$:

$$\tilde{w}_{M,t} = \frac{\theta}{\theta-1}\frac{w_{\mathbf{u},t}}{\tilde{\mathbf{z}}_{M,t}} \tag{13}$$

$$\tilde{\mathbf{z}}_{M,t} = \nu z_{\min}\mathbf{z}_{X,t}\left[\frac{\left(z_{X,t}\right)^{k-(\theta-1)} - \left(z_{\min}\right)^{k-(\theta-1)}}{\left(z_{X,t}\right)^{k} - \left(z_{\min}\right)^{k}}\right]^{\frac{1}{(\theta-1)}}, \text{ where } \mathbf{z}_{\min} = 1 \text{ and } \nu = \left[\frac{k}{k-(\theta-1)}\right]^{\frac{1}{(\theta-1)}} \tag{14}$$

Average wage and productivity of high-skill workers, i.e., those above the cutoff $\mathbf{z}_{X,t}$:

$$\tilde{w}_{XH,t} = \frac{\theta_h}{\theta_h-1}\frac{w_{\mathbf{u},t}}{\tilde{\mathbf{z}}_{X,t}} \tag{15}$$

$$\tilde{w}_{XF,t} = \frac{\tau_t}{Q_t}\frac{\theta_h}{\theta_h-1}\frac{w_{\mathbf{u},t}}{\tilde{\mathbf{z}}_{X,t}} \tag{16}$$

$$\tilde{\mathbf{z}}_{X,t} = \nu_h z_{X,t}, \text{ where } \nu_h = \left[\frac{k}{k-(\theta_h-1)}\right]^{\frac{1}{(\theta_h-1)}} \tag{17}$$

where θ_h is the elasticity of substitution between high-skill home and foreign tasks. In the baseline calibration, we set $\theta_h = \theta$, but they can differ in robustness checks.

Skill income premiums:

$$\tilde{\pi}_{M,t} = \frac{1}{\theta} \left(\tilde{w}_{M,t}\right)^{1-\theta} Y_{T,t} \tag{18}$$

$$\tilde{\pi}_{XH,t} = \frac{1}{\theta_h} \left(\tilde{w}_{XH,t}\right)^{1-\theta_h} \left(P_{H,t}\right)^{\theta_h-\sigma} \left(P_{KH,t}\right)^{\sigma-\theta} (1-\alpha)^{\sigma} Y_{T,t} \tag{19}$$

$$\tilde{\pi}_{XF,t} = \frac{Q_t}{\theta_h} \left(\tilde{w}_{XF,t}\right)^{1-\theta_h} \left(P^*_{H,t}\right)^{\theta_h-\sigma} \left(P^*_{KH,t}\right)^{\sigma-\theta} (1-\alpha)^{\sigma} Y^*_{T,t} - f_{o,t}, \text{ with } f_{o,t} = f_o w_{\mathbf{u},t} \tag{20}$$

Average skill premium:

$$\tilde{\pi}_t = \frac{\left(N_{D,t} - N_{X,t}\right) \tilde{\pi}_{M,t} + N_{X,t} \left(\tilde{\pi}_{XH,t} + \tilde{\pi}_{XF,t}\right)}{N_{D,t}} \tag{21}$$

Share of high-skill workers in the total number of Home skilled workers:

$$\frac{N_{X,t}}{N_{D,t}} = \left(\frac{z_{\min} v}{\tilde{\mathbf{z}}_{X,t}}\right)^k \tag{22}$$

Zero-profit offshoring cutoff:

$$\tilde{\pi}_{X,t} = f_{o,t} \frac{\theta_h - 1}{k - (\theta_h - 1)} \tag{23}$$

1.4 Tradable Sector

Production of tradables:

$$Y_{T,t} = \left\{ \left(M_t\right)^{\frac{\theta-1}{\theta}} + \left[\alpha \left(K_{t-1}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(H_t\right)^{\frac{\sigma-1}{\sigma}}\right]^{\left(\frac{\sigma}{\sigma-1}\right)\left(\frac{\theta-1}{\theta}\right)} \right\}^{\frac{\theta}{\theta-1}}, \text{ with KSC if } \theta > \sigma. \tag{24}$$

$$H_t = \left[\left(X_{H,t}\right)^{\frac{\theta_h-1}{\theta_h}} + \left(X^*_{H,t}\right)^{\frac{\theta_h-1}{\theta_h}} \right]^{\frac{\theta_h}{\theta_h-1}}, \text{ with baseline } \theta_h = \theta, \text{ but can differ in robustness checks.} \tag{25}$$

The bundles of middle-skill tasks, as well as domestic and imported high-skill tasks are defined as $M_t = \left[\int_{\mathbf{1}}^{\mathbf{z}_{x,t}} n_t(\mathbf{z})^{\frac{\theta-1}{\theta}} dz\right]^{\frac{\theta}{\theta-1}}$, $X_{H,t} = \left[\int_{\mathbf{z}_{x,t}}^{\infty} n_{,t}(\mathbf{z})^{\frac{\theta_h-1}{\theta_h}} dz\right]^{\frac{\theta_h}{\theta_h-1}}$ and $X^*_{H,t} = \left[\int_{\mathbf{z}^*_{x,t}}^{\infty} n^*_t(\mathbf{z})^{\frac{\theta_h-1}{\theta_h}} dz\right]^{\frac{\theta_h}{\theta_h-1}}$.

Demand for middle and high-skill variety bundles, as well as capital:

$$M_t = (P_{M,t})^{-\theta} Y_{T,t} \tag{26}$$

$$X_{H,t} = (P_{XH,t})^{-\theta_h} (P_{H,t})^{\theta_h-\sigma} (P_{KH,t})^{\sigma-\theta} (1-\alpha)^{\sigma} Y_{T,t} \tag{27}$$

$$X_{F,t} = (P_{XF,t})^{-\theta_h} \left(P^*_{H,t}\right)^{\theta_h-\sigma} \left(P^*_{KH,t}\right)^{\sigma-\theta} (1-\alpha)^{\sigma} Y^*_{T,t} \tag{28}$$

$$K_{t-1} = (r_{K,t-1})^{-\sigma} (P_{KH,t})^{\sigma-\theta} \alpha^{\sigma} Y_{T,t} \tag{29}$$

Price indexes:

$$P_{KH,t} = \left[\alpha^{\sigma} (r_{K,t-1})^{1-\sigma} + (1-\alpha)^{\sigma} (P_{H,t})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{30}$$

$$P_{H,t} = \left[(P_{XH,t})^{1-\theta_h} + \left(P^*_{XH,t}\right)^{1-\theta_h}\right]^{\frac{1}{1-\theta_h}} \tag{31}$$

$$P_{M,t} = \left[(N_{D,t} - N_{X,t}) (\tilde{w}_{M,t})^{1-\theta}\right]^{\frac{1}{1-\theta}} \tag{32}$$

$$P_{XH,t} = \left[N_{X,t} (\tilde{w}_{XH,t})^{1-\theta_h}\right]^{\frac{1}{1-\theta_h}} \tag{33}$$

$$P^*_{XH,t} = \left[N^*_{X,t} \left(\tilde{w}^*_{XH,t}\right)^{1-\theta_h}\right]^{\frac{1}{1-\theta_h}} \tag{34}$$

1.5 Non-Tradable Sector

Production and factor choices:

$$Y_{N,t} = \left[\gamma_N (L_{N,t})^{\frac{\sigma_{N-1}}{\sigma_N}} + (1-\gamma_N) (L_{\mathbf{i},t})^{\frac{\sigma_{N-1}}{\sigma_N}}\right]^{\frac{\sigma N}{\sigma_{N-1}}} \tag{35}$$

$$\frac{w_{\mathbf{u},t}}{P_{N,t}} = \gamma_N \left(\frac{Y_{N,t}}{L_{N,t}}\right)^{\frac{1}{\sigma_N}} \tag{36}$$

$$\frac{w_{\mathbf{i},t}}{P_{N,t}} = (1-\gamma_N) \left(\frac{Y_{N,t}}{L_{\mathbf{i},t}}\right)^{\frac{1}{\sigma_N}} \tag{37}$$

Law of motion for low-skill immigrant labor stock:

$$L_{\mathbf{i},t} = (1-\delta_l)(L_{\mathbf{i},t} + L_{\mathbf{e},t-1}) \tag{38}$$

Immigrant consumption:

$$C_{\mathrm{Im},t} = w_{\mathbf{i},t} L_{\mathbf{i},t} \tag{39}$$

1.6 Labor Market Clearing, Income Shares, and Additional Variables

Labor Market Clearing The total units of raw labor embodied in high-skill tasks are given by: $L_{X,t} = N_{X,t}(\widetilde{l}_{XH,t} + \widetilde{l}_{XF,t}) = N_{X,t}\left[(\theta-1)(\frac{\tilde{\pi}_{XH,t}+\tilde{\pi}_{XF,t}}{w_{\mathbf{u},t}}) + \theta f_{o,t}\right]$. The raw labor embodied embodied in the production of middle-skill tasks is obtained as: $L_{M,t} = L_t - L_{X,t} - N_{E,t} f_{e,t} - L_{N,t}$, and can be decomposed into $L_{M,t} = N_{M,t}\widetilde{l}_{M,t}$. The choice of training and the native unskilled labor, $N_{E,t} f_{e,t}$, and $L_{N,t}$ respectively, come from the household's optimization problem defined above.

Income Shares The income share of high-skill workers is:

$$S^H_{h,t} = \frac{N_{X,t}(\tilde{\pi}_{XH,t} + \tilde{\pi}_{XF,t}) + w_{\mathbf{u},t} L_{X,t}}{\widetilde{Y}_t}, \tag{40}$$

where $\tilde{\pi}_{XH,t}$ and $\tilde{\pi}_{XF,t}$ are the skill premiums for the tasks produced by high-skill workers (i.e., those with productivity above the threshold value $\mathbf{z}_{X,t}$) and sold domestically and abroad. $\widetilde{Y}_t = P_t Y_t - f_{e,t} N_{e,t}$ is the income-based GDP net of training costs, which are not used in production. The income shares of ICT capital, low-skill, and middle-skill labor are:

$$S^K_{h,t} = r^k_t K_{t-1}/\widetilde{Y}_t \tag{41}$$

$$S^L_{h,t} = \frac{w_{\mathbf{u},t} L_{N,t} + w_{\mathbf{i},t} L_{\mathbf{i},t}}{\widetilde{Y}_t} \tag{42}$$

$$S^M_{h,t} = 1 - S^H_{h,t} - S^L_{h,t} - S^K_{h,t} \tag{43}$$

The total low-skill employment comprising both native and immigrant workers is:

$$L_{L,t} = L_{N,t} + L_{\mathbf{i},t}. \tag{44}$$

The CPI-based real exchange rate is:

$$RER_t = \frac{P_t^* Q_t}{P_t} \tag{45}$$

2 Hansen-Rogerson Lotteries

In this section, we propose an alternative micro-founded model of risk-sharing, in which individual household members provide indivisible labor to occupations of various skill levels. Following Hansen (1985) and Rogerson (1988), we model the preferences and optimization problem of individual household members, who provide indivisible labor to each skilled occupation subject to lotteries. We show that the indivisible-labor framework is isomorphic to our baseline model calibrated with an infinite Frisch elasticity of labor supply, and it produces similar implications for labor market polarization.

2.1 Model Setup

Following Hansen (1985) and Rogerson (1988), household members provide indivisible labor and face a binary outcome to either work or not in various skill occupations with certain probabilities. If they work, they typically work a fixed amount of $\bar{L}$ hours, which can be interpreted as full-time employment. In each period t, there is a probability that a worker will work in: (a) a high-skill occupation, $\tilde{\tau}_{X,t}$; (b) a middle-skill occupation, $\tilde{\tau}_{M,t}$; (c) generic low-skill, non-tradable services, $\tilde{\tau}_{N,t}$; or alternatively; (d) training new skilled workers, $\tilde{\tau}_{E,t}$. These probabilities are indexed with t because they are choice variables that households make every period.

Mimicking Rogerson (1988), household members jointly determine the probability of working, but not how much to work (if they work), since the quantity of hours they can work is fixed.[2] There is perfect insurance, in the sense that every household member gets paid and consumes the same amount whether they work or not. In expectation, a household member works: $\tilde{\tau}_{X,t}\bar{L} \equiv \tilde{l}_{X,t}$ hours in a given high-skill occupation. Notice that $\tilde{\tau}_{X,t}$ is the probability of an individual working in *one* of the many

[2] In the data, most of the change in aggregate hours is explained by the extensive margin (number of workers) rather than the intensive margin (number of hours supplied by each worker). See Rogerson (1988) for a discussion.

high-skill occupations. In any period t, the number of high-skill occupations is $N_{X,t}$. Therefore, $N_{X,t}\tilde{\tau}_{X,t}$ is the probability of working in *any* high-skill occupation, and $N_{X,t}\tilde{\tau}_{X,t}\bar{L} \equiv N_{X,t}\tilde{l}_{X,t}$ is the expected number of hours a household member will work in *any* of the high-skill occupations available in period t. An analogous argument holds for middle-skill occupations, with $N_{M,t}\tilde{\tau}_{M,t}\bar{L} \equiv N_{M,t}\tilde{l}_{M,t}$ being the probability of working in any of the middle-skill occupations, $N_{M,t}$. Hereafter, we will use the following definitions to ease the notation: $\tau_{X,t} = N_{X,t}\tilde{\tau}_{X,t}$ and $\tau_{X,t} = N_{M,t}\tilde{\tau}_{M,t}$.

All low-skill service occupations are homogeneous in our setup, so $\tilde{\tau}_{N,t} = \tau_{N,t}$. In expectation, household members work $\tilde{\tau}_{N,t}\bar{L} = \tau_{N,t}\bar{L} \equiv L_{N,t}$ in these occupations. Finally, $\tilde{\tau}_{E,t}\bar{L} = \tau_{E,t}\bar{L} \equiv N_{E,t}f_E$ pins down the expected time household members spend on training the new skilled workers $N_{E,t}$ (also homogenous).

We can define now how much an individual is expected to work as follows:

$$L_t = N_{X,t}\tilde{\tau}_{X,t}\bar{L} + N_{M,t}\tilde{\tau}_{M,t}\bar{L} + \tilde{\tau}_{N,t}\bar{L} + \tilde{\tau}_{E,t}\bar{L} = \tau_{X,t}\bar{L} + \tau_{M,t}\bar{L} + \tau_{N,t}\bar{L} + \tau_{E,t}\bar{L} \tag{46}$$

Given the definitions above, this expression can be re-written as:

$$L_t = N_{X,t}\tilde{l}_{X,t} + N_{M,t}\tilde{l}_{M,t} + L_{N,t} + N_{E,t}f_E, \tag{47}$$

This is observationally equivalent to the labor market clearing condition in the main text (after re-defining $\tilde{l}_{X,t} \equiv \widetilde{l}_{XH,t} + \widetilde{l}_{XF,t}$ as the total raw labor used to produce skilled labor tasks sold in Home and Foreign).

2.2 Utility

Following Rogerson (1988), we can write the household's expected utility flow function as:

$$\begin{aligned} u_t(C_t, 1-L_t) = \ln C_t + \tau_{X,t}\tilde{\theta}\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} + \tau_{M,t}\tilde{\theta}\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} + \tau_{N,t}\tilde{\theta}\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} + ... \\ ... + \tau_{E,t}\tilde{\theta}\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} + \left(1-\tau_{X,t}-\tau_{M,t}-\tau_{N,t}-\tau_{E,t}\right)\tilde{\theta}\frac{(1)^{1-\xi}-1}{1-\xi}, \end{aligned} \tag{48}$$

where $\tilde{\theta}\frac{(.)^{1-\xi}-1}{1-\xi}$ is the utility from leisure and $(1-\tau_{X,t}-\tau_{M,t}-\tau_{N,t}-\tau_{E,t})$ is the probability a household member does not work at all. Collecting terms we get:

$$u_t(C_t, 1-L_t) = \ln C_t + \sum_{i=X,M,N,E} \tau_{i,t}\tilde{\theta}\left[\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} - \frac{(1)^{1-\xi}-1}{1-\xi}\right] + \tilde{\theta}\frac{(1)^{1-\xi}-1}{1-\xi} \tag{49}$$

As defined above, we know that in expectations the household members will work $\tau_{\hat{\imath},t}\bar{L} \equiv L_{\hat{\imath},t}$ hours in a given sector $\hat{\imath} : X, M, N, E$. Therefore, we can write:

$$u_t(C_t, 1-L_t) = \ln C_t + \sum_{\hat{\imath}=X,M,N,E} \frac{L_{\hat{\imath},t}}{\bar{L}}\tilde{\theta}\left[\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} - \frac{(1)^{1-\xi}-1}{1-\xi}\right] + \tilde{\theta}\frac{(1)^{1-\xi}-1}{1-\xi} \tag{50}$$

If $\xi > 0$, then $\frac{(1)^{1-\xi}-1}{1-\xi} > \frac{(1-\bar{L})^{1-\xi}-1}{1-\xi}$. Next, we can define two constants:

$$\begin{aligned} a_n &= \frac{\tilde{\theta}}{\bar{L}}\left[\frac{(1-\bar{L})^{1-\xi}-1}{1-\xi} - \frac{(1)^{1-\xi}-1}{1-\xi}\right], \\ a_{\bar{c}} &= \frac{(1)^{1-\xi}-1}{1-\xi}, \end{aligned} \tag{51}$$

so that $u_t(.)$ can be redefined as:

$$u_t(c_t, 1-L_t) = \ln C_t + L_{X,t}a_n + L_{M,t}a_n + L_{N,t}a_n + L_{E,t}a_n + a_{\bar{c}}. \tag{52}$$

By definition, in expectations, any individual is expected to work L_t (in any sector of the economy), such that $L_t = L_{X,t} + L_{M,t} + L_{N,t} + L_{E,t}$. Using this expression, and taking into account that $a_{\bar{c}}$ is a constant that can be dropped from the utility function, we can rewrite household's utility function as:

$$u_t(C_t, 1-L_t) = \ln C_t - a_n L_t. \tag{53}$$

As in Rogerson (1988), the *indivisible-labor* economy behaves exactly like a standard *representative-agent divisible-labor* economy with a *linear* disutility of labor. Notably, the utility function in the main text is identical to the expression above when the Frisch elasticity is infinite $(1/\gamma_n \to \infty)$.

2.3 Model Implications

The linear disutility from labor resulting from the indivisible labor framework with lotteries implies that the aggregate Frisch labor supply elasticity, $1/\gamma_n$, is *infinite*, even if the micro-level labor supply of each household member is inelastic.

The model implications for the historical evolution of income and earnings across the three skill groups are summarized in Fig. APX-1. This figure shows the contributions from offshoring, automation, and low-skill immigration to each of these variables. (Notice that Fig. 6 in the main text does the same for the baseline model.) The results are little changed when the aggregate Frisch elasticity is infinite under the Hansen-Rogerson specification here, rather than 0.75 as in the baseline model.[3] The presence of log utility implies that, in response to permanent shocks, the income and substitution effects of the labor supply exactly cancel each other. Therefore, regardless of the value of the Frisch elasticity, employment remains constant in the new stationary equilibrium. In principle, the value of the Frisch elasticity could affect the model transition dynamics. Nonetheless, these effects would mostly occur through the intertemporal consumption/savings decision of capital accumulation.[4] Since in our model the ICT capital share is rather small, the model predictions are practically the same if the Frisch elasticity is set to be either infinite or very small.

3 Data Sources

3.1 Employment and Income Polarization

Figure 1 Panels A-D in Fig. 1 are constructed following the methodology in Acemoglu and Autor (2011) and Autor and Dorn (2013). We use data from the Census IPUMS data for 1980, 1990, and 2000

[3] Changing the value of $1/\gamma_n$, requires us to adjust the constant in the utility function, a_n, to keep the same initial stationary conditions of the baseline specification.

[4] The Frisch elasticity is irrelevant in a basic RBC model with no capital and log utility in consumption.

(5% of the population) from the U.S. Census Bureau (1985, 1995, 2003) obtained from Acemoglu and Autor (2011), and also data from the American Community Survey for 2010 (which includes 1% of the population, see Ruggles et al., 2010). See our data files for sources, data, and method. Occupations are sorted into 100 percentiles based on the mean occupational wages in 1980.[5] We compute the employment shares for each occupation and aggregate them at the percentile level. In panels A, C, and D, the vertical axis shows the change in employment shares, computed as the simple difference between the shares of employment in 2010 and 1980 for the occupations in each percentile. In panel B, the percent change in real wages is computed as the log-difference of real wages for the occupations in each percentile. The smoothed changes plotted in each figure are obtained using a locally-weighted polynomial regression between the change in employment (or wages) and the corresponding percentile. In panel C, the counterfactual changes in employment are computed under the assumption that employment in each low-skill service occupation remains at its 1980 level. Following the approach in Acemoglu and Autor (2011) and Autor and Dorn (2013), the counterfactual changes are constructed by pooling ACS data from 2010 with Census data from 1980.[6] In panel D, we use the Census IPUMS and ACS variable "citizen" and take all values other than zero to represent foreign-born status (naturalized citizen, not a citizen, not a citizen but has received first papers, foreign born citizenship status not reported, and born abroad of American parents).

Time series employment and income shares by skill group We use several annual data series from 1983 to 2013 to validate the model predictions for polarization, as shown in Fig. 5 in the main paper, panels C and D. The U.S. Census employment data used in Fig. 1 is decennial and thus not available on a high-frequency basis. Therefore, we closely follow Jaimovich and Siu (2020) and use the U.S. Bureau of Labor Statistics (2020a)'s Current Population Survey (CPS) to construct quarterly time series of **employment** by

[5] As discussed in Acemoglu and Autor (2011), the ordering does not change significantly if a different base year is used.

[6] This approach consists of estimating a weighted logit model for the odds, from which an observation is drawn from the 1980 census sample (relative to the actual sampling year), using a service occupation dummy and an intercept as predictors. The weights used are the product of census sampling weights and annual hours of labor supply. The observations for 2010 are re-weighted using the estimated odds multiplied by the hours-weighted census sampling weight, while weighting downward the frequency of service occupations in 2010 to their 1980 level. Given the absence of other covariates in the model, the extra probability mass is implicitly allocated uniformly over the remainder of the distribution.

skill group. The **labor income shares** for each skill group are similarly obtained from the U.S. Bureau of Labor Statistics (2020a,b) data like in Eden and Gaggle (2018). The annual nominal wage bill is divided by nominal GDP to obtain each occupation's share of labor earnings in aggregate income. See our online data files and readme files for the sources and methodology used to construct these series.

We consider three categories of employment based on the skill content of labor tasks in each occupation: Non-Routine Cognitive (high-skill), Routine (middle-skill), and Non-Routine Manual (low-skill).[7] This classification is based on the categorization of occupations in the 2000 Standard Occupational classification system and follows the "consensus aggregation" suggested by Acemoglu and Autor (2011). *Non-routine cognitive* workers are in "management, business, and financial operations occupations" and "professional and related occupations." *Routine cognitive* workers are those in "sales and related occupations" and "office and administrative support occupations." *Routine manual* occupations are "production occupations", "transportation and material moving occupations," and "installation, maintenance, and repair occupations." *Non-routine manual* occupations are "service occupations" and "construction and extraction occupations." As explained in Jaimovich and Siu (2020) and Firpo et al. (2011), this group classification corresponds to rankings in the occupational income distribution: non-routine cognitive occupations tend to be high-skill, whereas non-routine manual occupations tend to be low-skill. Routine occupations in both cognitive and manual categories are middle-skill.

The categorization of occupations in our paper is slightly different than that in Jaimovich and Siu (2020). Specifically, we group construction occupations among those providing low-skill/non-tradable tasks, rather than middle-skill tasks, for several reasons. First, construction jobs are intrinsically non-tradable and thus not exposed to displacement from offshoring. Second, construction jobs are not subject to automation, since they are often taken by low-skill workers who execute menial non-routine manual tasks. Third, construction often hires low-skill immigrant workers, some of which may be undocumented. In addition, the underground economy is pervasive in the sector, as many contractors are unregistered

[7] Jaimovich and Siu (2020) show that their classification in three groups is consistent with the analysis in Autor and Dorn (2013), which provides a more comprehensive definition of six categories based on an occupation's degree of intensity in abstract, routine, and manual tasks, respectively.

workers, and many registered contractors hire hourly low-wage workers without keeping records.[8] However, the pattern of polarization is similar when construction is included in the middle-skill occupations.

3.2 Data to Discipline Deterministic Shocks

To discipline the offshoring shocks, we use **bilateral iceberg trade costs** between the United States and six major trade partners using data from Novy (2013) and the ESCAP-World Bank (2020) database on international trade costs.[9] The iceberg trade costs are estimated from gravity equation models like in Novy (2006), using macroeconomic data on bilateral trade flows and GDP. Thus, the time series of iceberg trade costs reflects not only the evolution of tariffs, which were already low at the beginning of our sample period, but that of numerous other trade barriers that are difficult to measure, such as transportation, communication, and administrative costs (Novy, 2006). Using these bilateral trade cost data, we construct the trade-weighted index of iceberg trade costs shown in Fig. 2A of the main paper. The weights are given by the shares of exports and imports for six major U.S. trade partners–Canada, Mexico, Germany, the United Kingdom, Japan, and South Korea–from the U.S. Bureau of Economic Analysis and U.S. Census Bureau (2020).

To validate the model implications, we use data on the **offshore employment** of U.S. multinationals from the Bureau of Economic Analysis (2020a) as a proxy for the share of foreign labor tasks embedded in Home output (see Fig. 5A). As standard, we consider the employment of non-bank, majority-owned foreign affiliates of U.S. multinationals. Consistent with our analysis, we consider all industries and not just those in manufacturing. (In robustness analysis, we use these data on offshore employment to discipline the offshoring shock, instead of the iceberg trade cost, with similar results; see Fig. APX-11 and APX-12 of this appendix.)

[8] For instance, a FPI report (2007) shows that despite the residential construction boom of the early 2000s in the New York City metropolitan area in which construction permits more than doubled, there was negligible increase in the official count of the New York City residential construction workers (which contradicts the evidence). In a related paper, Hotchkiss et al (2012) find that the construction industry is, proportionally, the largest employer of undocumented immigrants.

[9] The ESCAP-World Bank (2020) trade costs dataset provides estimates of bilateral trade costs in agriculture and manufactured goods. It is built on trade and production data collected in 178 countries. Symmetric bilateral trade costs are computed using an Inverse Gravity Framework which estimates trade costs for each country pair using bilateral trade and gross national output. These trade costs reflect a geometric average accounting for both importing and exporting costs to each of these destinations.

We rely on several data sources on the unauthorized immigrant population as a proxy for the growth in the **stock of low-skill immigrants** in the model, shown in Fig. 2B. These include the Pew Research Center (2019a, 2019b, 2016) estimates for 1990, 1995, 2000, 2001, 2003, and 2005-2013, as well as Warren and Warren (2013) for the years 1991-1999. There is only scant data on the U.S. undocumented immigrant population before 1990. Therefore, we consider a few estimates available for the early 1980s, then use linear interpolation to fill in the gaps. Thus, we use the U.S. Census Bureau (1987) survey on undocumented alien population for 1983 and the estimates from Warren and Passel (1987) computed from the 1980 U.S. decennial census.

Eden and Gaggl (2018) construct comprehensive data series to assess the aggregate effects of investment in information and communication technology (ICT) capital in the U.S. economy, using data from the U.S. Bureau of Economic Analysis (2018)'s Fixed Assets Accounts.[10] From their data, we use the relative price of ICT capital and its depreciation rate to discipline the automation shock over time (Fig. 2D). The **relative price of ICT capital** with respect to output is based on implicit quality-adjusted price deflators for the price of capital based on chain-type price indices from the Fixed Assets Accounts. An asset is considered to be ICT if it is a software or equipment related to computers or telecommunications devices. Furthermore, the authors show that this definition is in line with other available estimates of ICT capital. The U.S. Bureau of Economic Analysis (2018)'s Fixed Assets Accounts is also the source for the **depreciation rate of ICT capital** and the **capital income share**.[11]

For Fig. 2C, we use the method in Eden and Gaggl (2018) and data from the U.S. Bureau of Labor Statistics (2020a,b). We also use the initial income share of the three occupation groups and ICT capital in 1983 to calibrate the initial steady state of the model. The **labor income shares** by occupatiom groups are constructed from the U.S. Bureau of Labor Statistics (2020a,b), with construction included in the low-skill occupations. Since the model does not consider non-ICT capital shares, the income shares of ICT capital

[10]Special thanks to Paul Gaggl for sharing this dataset with us. See Eden and Gaggl (2018) for a detailed explanations of the data sources and computation methods. Also see our online data files for sources and methodology.

[11]Income shares are computed using the dissagregation methods in Hall and Jorgenson (1967) and Christensen and Jorgenson (1969).

and the three labor groups are rescaled to add up to 100%.

3.3 Additional Empirical Evidence on Polarization

For additional insight into the pattern of employment and income polarization, Fig. APX-2 shows the evolution of employment and real wages by skill group (1983=1) following the methodology in Cavenaile (2017).[12] In this case, the classification of tasks is based on the U.S. Department of Labor's Dictionary of Occupational Titles (U.S. Department of Labor, 1977), as used in Autor and Dorn (2013), with construction included in the middle-skill occupations. In contrast, we consider the construction-related occupations to be low-skill (see the discussion above), rather than middle-skill. However, the pattern of polarization is very similar under the two approaches.[13]

Similarly, Fig. APX-3 shows the polarization charts from Böhm (2020), based on an alternative dataset from the U.S. Bureau of Labor Statistics (2020c)'s National Longitudinal Survey of Youth (NLSY). The asymmetric pattern of polarization in the low-skill manual occupations is notable, with the employment shares rising and the real wages falling for low-skill occupations.

4 Model: Robustness Exercises

4.1 Shock to ICT Capital Depreciation Rate

Fig. APX-4 in this appendix displays the transition dynamics arising from a positive shock (an increase) to the depreciation rate of ICT capital. As explained in the main text, these dynamics very much resemble those arising from a negative shock (an increase) to the relative price of ICT capital.

[12]We are grateful to Laurent Cavenaile for helping with the code.

[13]The annual U.S. Bureau of Labor Statistics (2020a)'s CPS data is used, keeping only working-age individuals with known occupations, who are not self-employed, who work at least 250 hours per year, and make at least $100 per year. Hourly wages are winsorized at the 1% level. We use the Autor and Dorn (2013) subfile to categorize occupations into six categories. Then we categorize individuals in those six categories as either: low-skill, middle-skill, or high-skill workers. Wages are the mean of hourly wage (weighted by hours per year), are converted to real wages using the CPI index, and finally normalized to 1975. The employment share is the share of each category's hours worked per year.

4.2 Asymmetric Shocks to Offshoring Costs

The baseline model assumes that the innovations to iceberg offshoring costs are symmetric across countries. For robustness, Fig. APX-5 in this appendix shows the transition dynamics arising from independent shocks to the iceberg cost of offshoring faced by workers from either Home (blue-dashed lines) or Foreign (red-dotted lines), along with those for the baseline scenario with symmetric innovations (black lines). The results are qualitatively similar. However, the responses are more sizeable when the shock lowers the iceberg offshoring cost for workers in Home (i.e., making it easier to sell their tasks to Foreign).

4.3 The Role of Displacement vs. Upskilling

As discussed in the paper, a symmetric decrease in the iceberg offshoring cost reduces middle-skill employment in Home through two channels: displacement and upskilling. First, as the iceberg cost of importing tasks from Foreign decreases, the greater competition from foreign high-skill tasks displaces some of the middle-skill tasks provided by home workers. All else equal, home workers expect a lower skill premium on average, which reduces their incentive to train. This is the *displacement* effect. Second, as the iceberg cost of selling tasks to Foreign decreases, some of the middle-skill workers from Home (the most productive ones) find it profitable to start selling tasks to Foreign as well. As the productivity cutoff for selling tasks to Foreign declines, some of the home middle-skill workers become high-skill, which we call the *upskilling* effect.[14]

To gauge the relative importance of displacement vs. upskilling, Fig. 4A in the main paper compares transition dynamics for the baseline model (reflecting both displacement and upskilling) vs. those from a model with the training margin held fixed (reflecting just upskilling). The transition dynamics for middle-skill jobs show that the contribution of displacement to the total decline in middle-skill employment is more than twice as large as that of upskilling. While not dominant, upskilling has a non-trivial effect.

To further illustrate the relative contributions of displacement vs. upskilling to polarization, Fig. APX-

[14] See Beerli and Peri (2016), for a discussion.

6 in this appendix shows the historical decomposition of employment and income shares for the same two models: the alternative model with the training margin held fixed (panel A) and the baseline model (panel B). For this exercise, we only activate one deterministic shock in the model, i.e., the decline in the iceberg cost of offshoring. Consistent with the transition dynamics in Fig. 4A, the alternative model with just upskilling (no displacement) generates only about one third of the total decline in middle-skill jobs predicted by the full model, which demonstrates the dominant role of displacement.

While upskilling is not the dominant channel of polarization, its contribution to polarization is empirically plausible. Using BEA data on the activities of multinational enterprises and BLS data, Fig. APX-7 shows an almost three-fold increase in the employment of foreign affiliates in the U.S. over the past three decades, relative to just a 1.4 times increase in the U.S. civilian employment. The disproportionately larger increase in the U.S. employment by foreign multinationals relative to the total U.S. employment is consistent with the downward shift in the productivity cutoff in our model, which reflects upskilling.

4.4 High Elasticity of Substitution between Tasks and Pareto Distribution

In what follows, we discuss the sensitivity of model implications to three interrelated parameters that cannot be properly identified with the data available: The elasticity of substitution among tasks, θ; the shape parameter of the Pareto distribution, κ, which characterizes the dispersion of idiosyncratic productivity among skilled workers; and the elasticity of substitution between home and foreign high-skill tasks θ_h, which we allow to differ from the elasticity of substitution among domestic tasks, θ. The calibration of these parameters affects in particular three steady-state targets for 1983: The ratio of high- to middle-skill employment; the ratio between the income shares of these two skill groups; and the share of foreign high-skill workers in the total number of skilled workers (domestic and foreign) employed by Home.

The Elasticity of Substitution between Tasks We first by pick an extremely high value for the elasticity of substitution between tasks, $\theta = 4$. This value is empirically implausible but coincides with the elasticity of substitution for models with trade in *goods* rather than *tasks*. In this case, we must also increase the Pareto parameter to $\kappa = 3.1$, so that the Pareto condition $\kappa > \theta - 1$ is fulfilled. Notice that the higher κ, the more compressed is the distribution of idiosyncratic productivity, i.e., there will be a lot more skilled workers with productivity toward the lower end of the support interval. Taken together, the higher elasticity and the more compressed distribution imply little incentive for skilled workers to sell tasks abroad. Put it differently, given the easy substitution between tasks and the compressed skill distribution, the high-skill workers are not much more productive on average than the middle-skill workers. In this context, only a few domestic workers choose to pay the offshoring costs required to access the foreign market. To obtain an equilibrium, we must lower the fixed cost of offshoring by about 90%. Not surprisingly, this alternative calibration is empirically implausible. Due to the very high substitutability between tasks and the skewed skill distribution, this parameterization results in an unfeasibly low ratio of the high/middle-skill employment of 0.18, in the initial steady state, and an extremely high ratio of the high/middle-skill income shares of 14.43.[15]

Fig. APX-8 depicts the historical decomposition arising from this calibration. Interestingly, even though the initial steady-state ratios are highly counterfactual, the model implications are qualitatively similar to those in the paper. A few differences emerge though. Since the initial steady-state share of high-skill employment is smaller (i.e., 0.18), the predicted increase in high-skill employment is higher in percentages terms than in the paper. For the same reason, the predicted decline in middle-skill employment is smaller. The opposite happens for the income shares by skill group. Given the high initial income share of high-skill workers, the high-skill income share rises by less, while the middle-skill income share falls by more than in the paper.

The Pareto Distribution Parameter Parameter κ measures the dispersion of idiosyncratic productivity among trained workers. A higher κ means lower dispersion, i.e., a more compressed distribution toward the low end of the support interval. In the baseline specification, we choose $\kappa = 1.82$. For robustness, we experiment with increasing this parameter to $\kappa = 2.82$, which lowers dispersion in labor

[15]For example, this calibration implies that one high-skill engineer can easily substitute several middle-skill workers.

productivity. As a result, the steady-state ratio of high/middle skill workers rises to 0.75, while their income ratio falls to 1.57. Alternatively, we lower $\kappa = 1.32$ to increase the dispersion in labor productivity. In this scenario, the ratio of high/middle-skill workers drops to 0.34, but the ratio of income shares remains about the same at 1.46.

Fig. APX-9 shows the historical decomposition for each of the two cases. The main conclusion arising from this robustness exercise is that the model implications for polarization are qualitatively the same as in the paper. Notably, in the case with low dispersion ($\kappa = 2.82$), there are more workers of similar productivity concentrated toward the lower end of the productivity support interval. As a result, the number of high- and middle-skill workers is more sensitive to the downward shift in the productivity cutoff. Thus, the high-skill employment rises relatively by more, and the middle-skill employment falls by more.

On the contrary, high dispersion ($\kappa = 1.32$) means that the number of high and middle-skill workers is less reactive to the downward shift in the productivity cutoff implied by the data-disciplined shocks. As a result, the high-skill employment rises by less, and the middle-skill employment falls by less.

The Elasticity of Substitution between Home and Foreign Tasks The baseline model assumes that the elasticity of substitution between home and foreign high-skill tasks is the same as the elasticity of substitution among domestic tasks. In this robustness exercise, we allow for these elasticities of substitution to be different from each other. As discussed in the main text, the elasticity of substitution between domestic tasks is $\theta = 1.7$. We now allow for the elasticity between the home and foreign high-skill tasks to be either higher or lower ($\theta^h = 2$ or $\theta^h = 1.3$). There is a close relation between this elasticity and the costs of offshoring: If it is relatively easy to substitute foreign with home tasks, skilled workers have little incentive to pay the fixed and iceberg costs of offshoring. This means that even a relatively small increase in the elasticity of substitution can lead to a sizable decline in trade. On the contrary, the lower elasticity translates into high complementarity between home and foreign tasks, and a stronger incentive to sell tasks abroad. To compensate, we adjust the fixed cost of offshoring in each case, so that the initial stationary equilibrium ratio of exports to output remains as in the baseline case.

The model implications are shown in Fig. APX-10. Qualitatively, the results are similar to those in the main paper. Some slight quantitative differences emerge. With $\theta^h = 1.3$, the relatively high complementarity implies that decline in the iceberg trade cost has a greater impact on trade. Put it differently, the relatively high complementarity between domestic and foreign tasks generates more upskilling because the gains from trade are larger. That is, the middle-skill employment declines by more, while the high-skill employment rises by more in response to offshoring. In addition, since the home and foreign high-skill tasks are relative complements not just with each other, but also with ICT capital, the automation shocks also lead to larger declines in middle-skill employment and larger increases in high-skill employment.

The opposite scenario takes place when we set a high elasticity of substitution between the home and foreign high-sill tasks, $\theta^h = 2$. In this case, the changes in high- and middle-skill employment arising from the data-disciplined shocks are relatively smaller.

4.5 Using Foreign MNC Employment vs. Trade Costs as Observable

The model implications for polarization are highly similar to those in the main paper if, to discipline the offshoring innovations, we use the share of foreign employment of U.S. multinationals from the BEA, rather than the trade-weighted index of bilateral trade costs from Novy (2013) and ESCAP-World Bank (2020). The model counterpart for this alternative observable is the share of foreign high-skill labor tasks (occupations) in the total number of labor tasks (occupations) used for tradable production: $N^*_{X,t}/(N_{D,t} + N^*_{X,t})$.

Under this alternative approach, to assess the model fit, we compare the model predictions for the iceberg trade cost with the data, i.e., the iceberg trade costs index.[16] Fig. APX-11, panel A, shows that the model predictions for the iceberg trade cost and the data counterpart track each other closely. Similarly, in panel B, the model prediction for trade openness, measured as (exports+imports)/GDP, similarly tracks

[16]Notice that we do the opposite in the baseline exercise in the paper, i.e. we use the iceberg trade cost index to discipline the offshoring innovations, and compare the model implications for the share of foreign tasks in Home with the corresponding U.S. Bureau of Economic Analysis (2020a) data series, i.e., the share of foreign employment of U.S. multinationals (see section 5.1 in the paper).

the data well. In addition, in panels C and D, the model generates predictions for polarization that are consistent with the data. They are very similar to the ones from the baseline model, although the changes are slightly larger for the middle and high-skill employment and income shares.

For the same alternative approach, Fig. APX-12 shows the historical decompositions. The results are qualitatively similar to those in the baseline case: While automation has a non-trivial role, offshoring is the dominant factor in explaining the rise in employment and income shares in high-skill occupations, as well as the corresponding declines for middle-skill occupations. Like before, low-skill immigration shapes the developments in low-skill occupations.

4.6 High Share of ICT Capital in Income

Fig. APX-13 shows the historical decomposition for employment and wages with an alternative calibration, so that the initial steady-state share of ICT capital in income almost doubles relative to the baseline model. As a result, the ICT capital share becomes counterfactually large at 6.8%, instead of 3.6% in 1983. The model is recalibrated so that the other initial stationary equilibrium targets remain unchanged.

With a higher share of ICT capital in income, the model implications are roughly similar for the total change in high and middle-skill employment, as well as for income shares. However, the relative contributions of offshoring vs. automation shift in favor of the latter. For high and middle-skill employment, the role of offshoring is still more sizeable than that of automation early in the sample period, but their relative contributions even out in the more recent years. In shaping the income shares of high and middle-skill workers, automation has a larger role than offshoring.

To conclude, the model can generate implications where automation plays a greater role than offshoring in shaping polarization, but that requires a counterfactual calibration with a much higher income share of ICT capital in the initial steady state.

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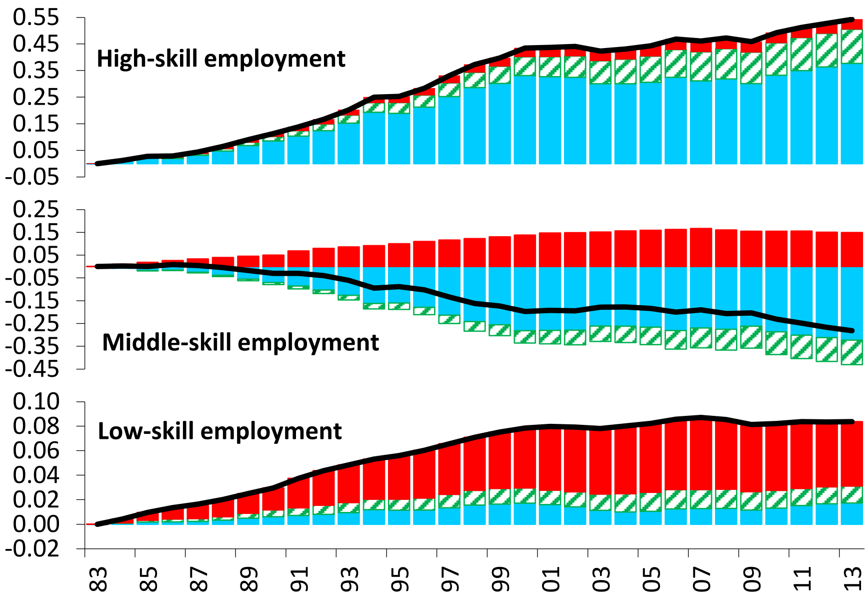
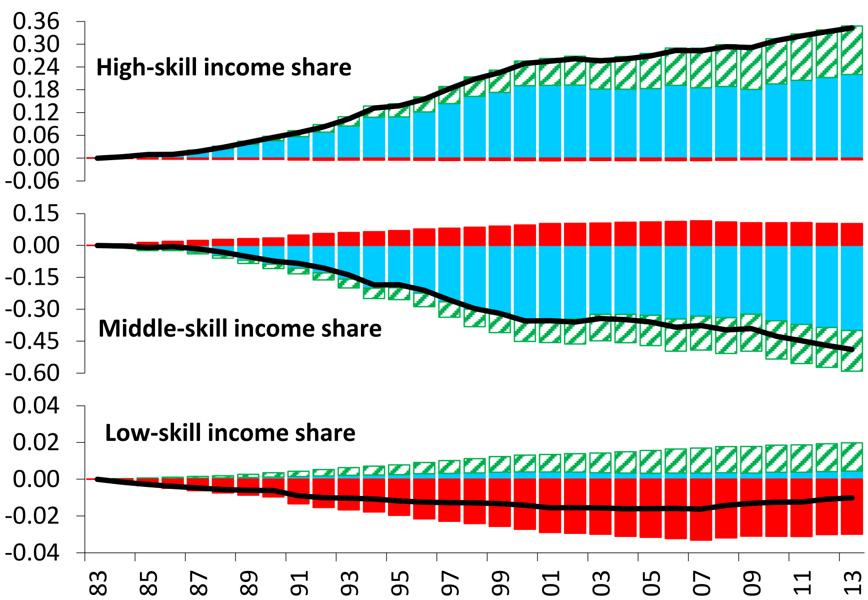
Figure APX-1: Model Implications with Hansen-Rogerson Lotteries

A. Historical decomposition of employment



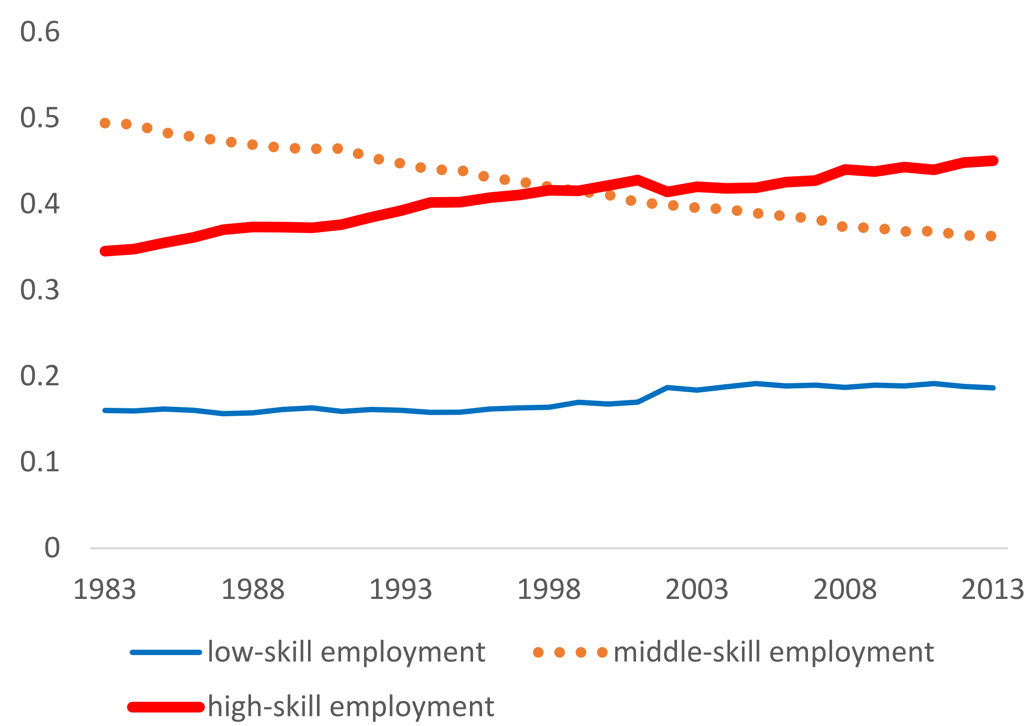
B. Historical decomposition of income shares



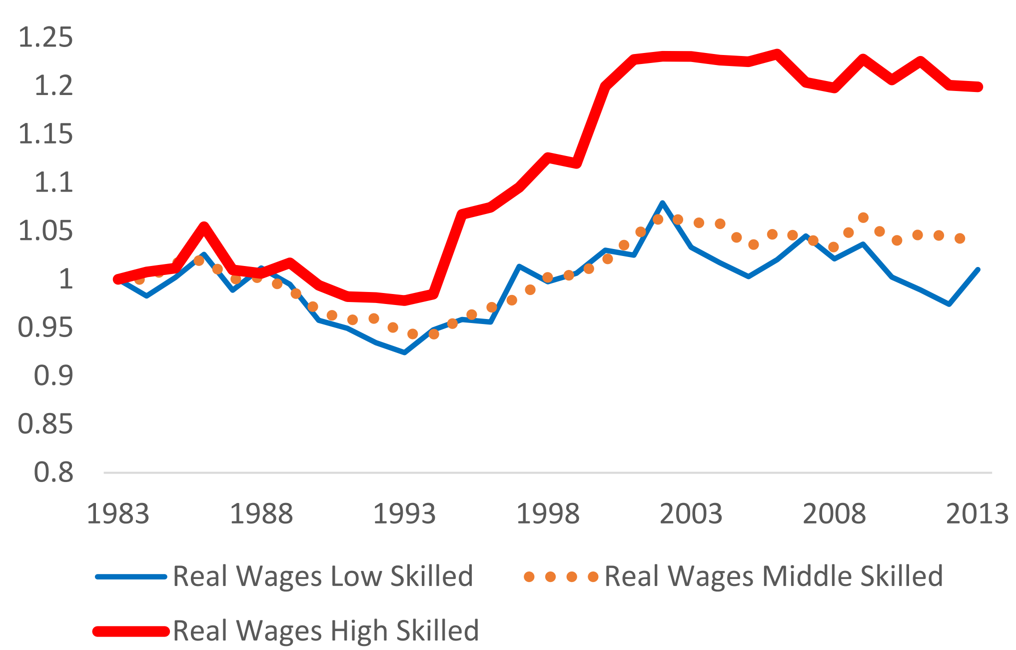
Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. The blue/green/red bars show the contributions of offshoring/automation/low-skill immigration to the total change.

Figure APX-2: Evolution of Employment and Wages, following Cavenaile (2017)

A. Employment

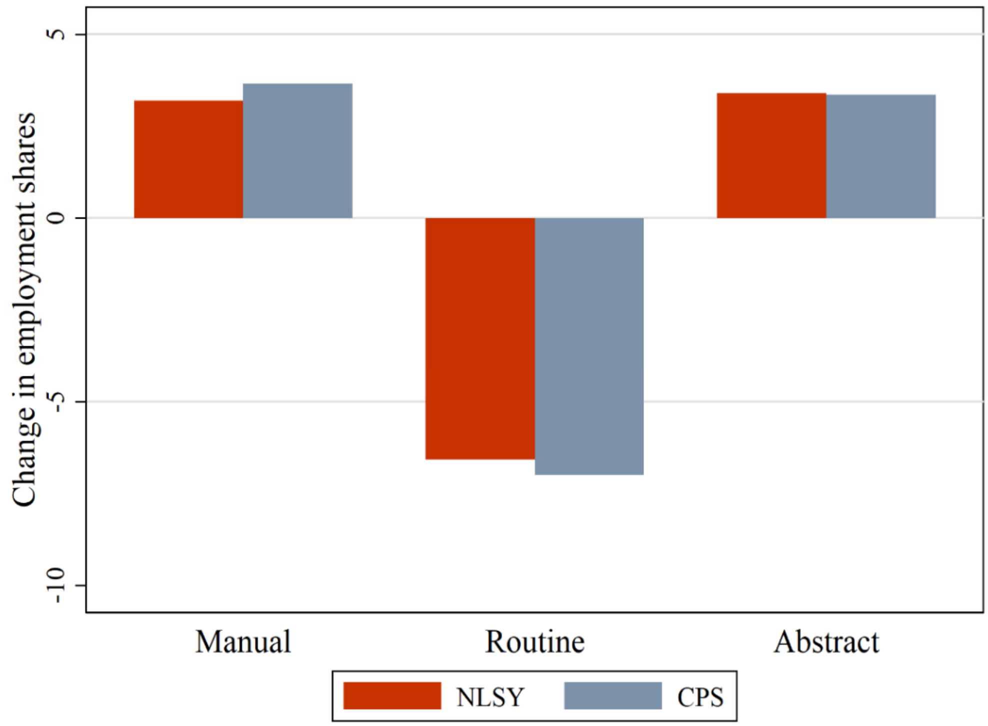


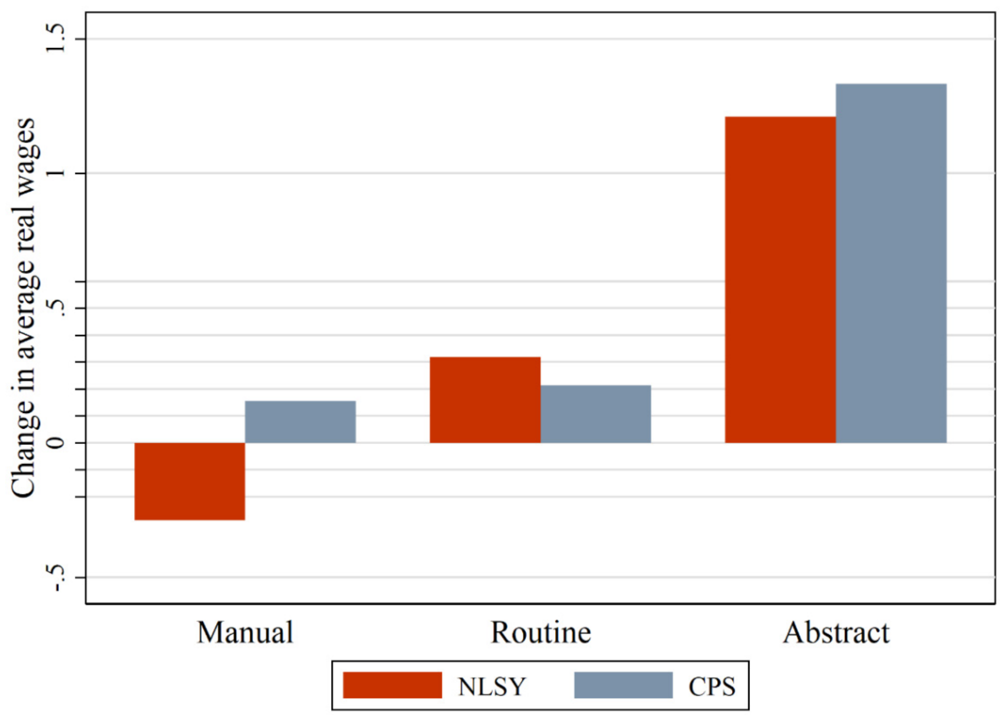
B. Wages



Source: U.S. Bureau of Labor Statistics (2020a) using the methodology in Cavenaile (2017).

Figure APX-3: Evolution of Employment and Wages, from Bohm (2019)





Source: Bohm (2020), using data from U.S. Bureau of Labor Statistics (2020a)'s Current Population Survey (CPS) and U.S. Bureau of Labor Statistics (2020c)'s National Longitudinal Survey of Youth (NLSY). Note: Changes in labor market variables of 27 year old-individuals between 1984-1992 and 2007-2001 for the NLSY 79 and NLSY 97 and the CPS.

Figure APX-4: Transition Dynamics in Response to an Increase in the Depreciation Rate of ICT Capital

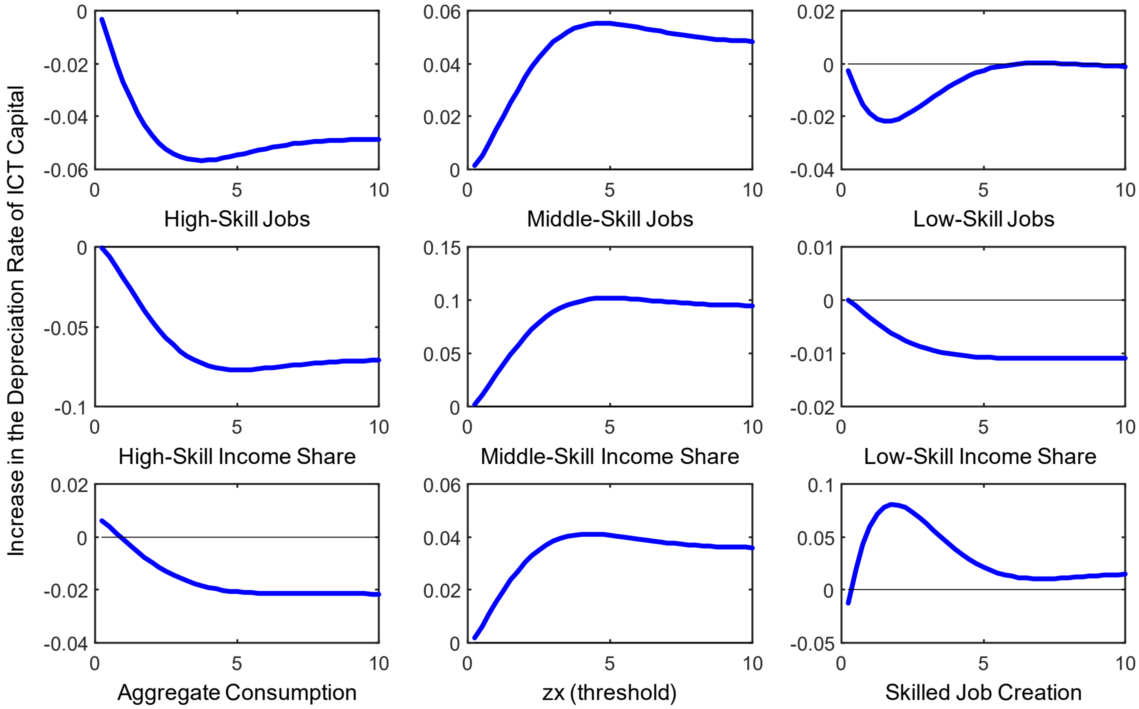
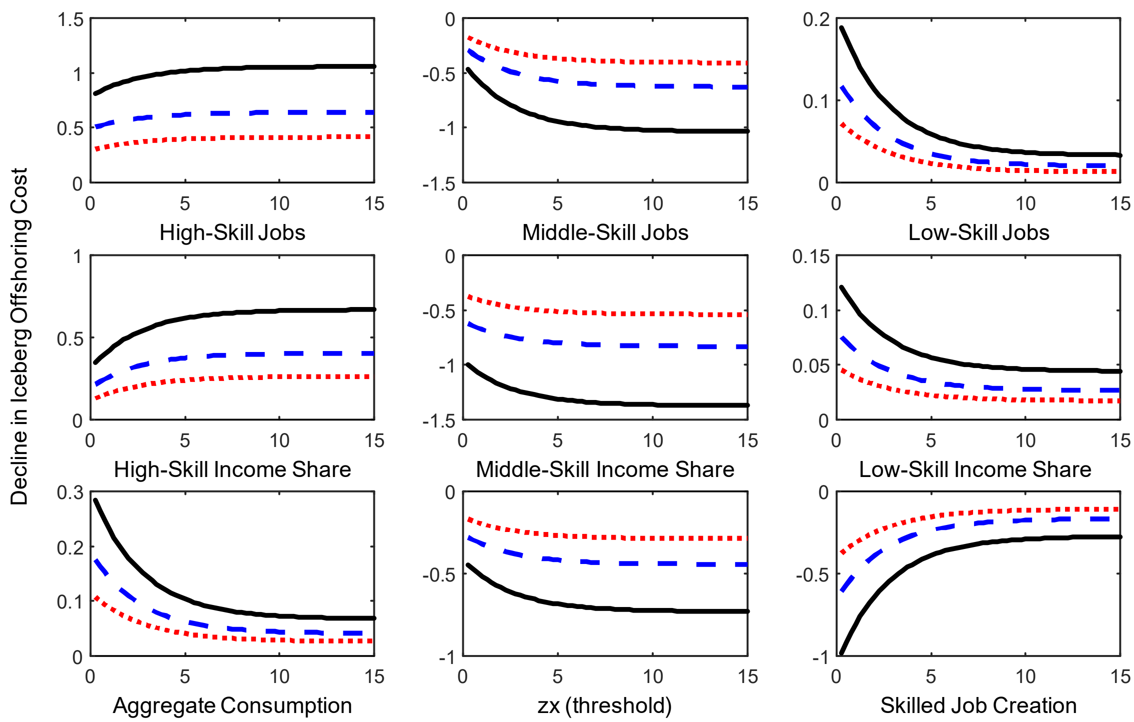


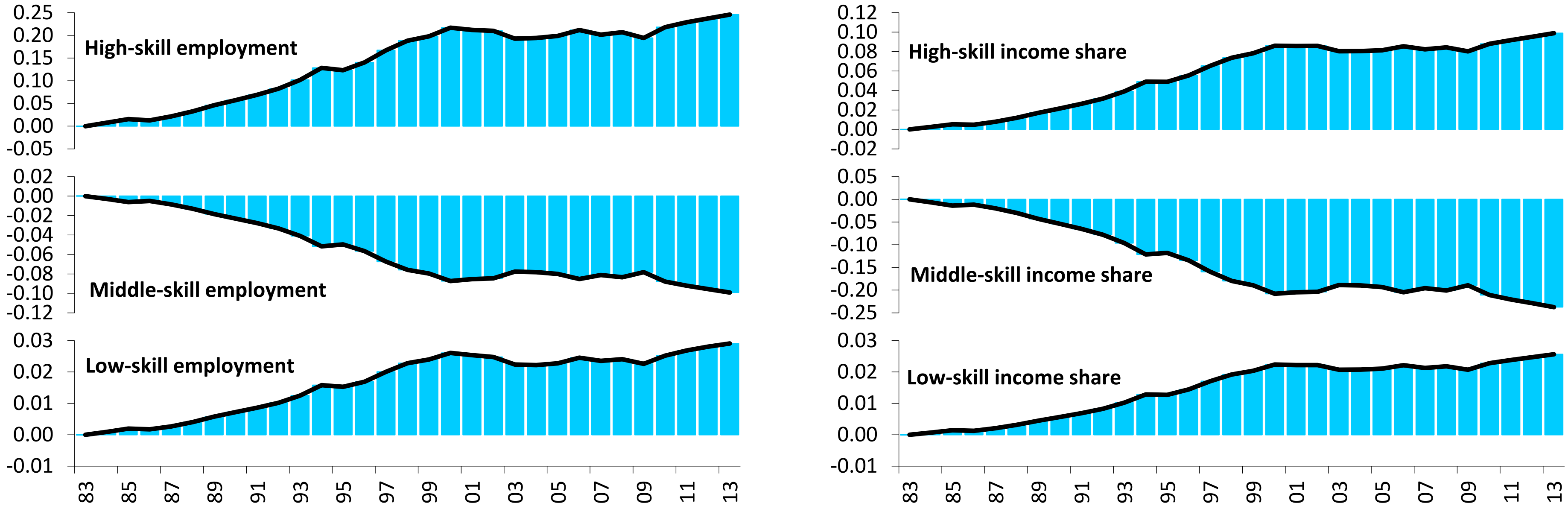
Figure APX-5: Transition Dynamics in Response to Asymmetric Declines in Iceberg Offshoring Costs



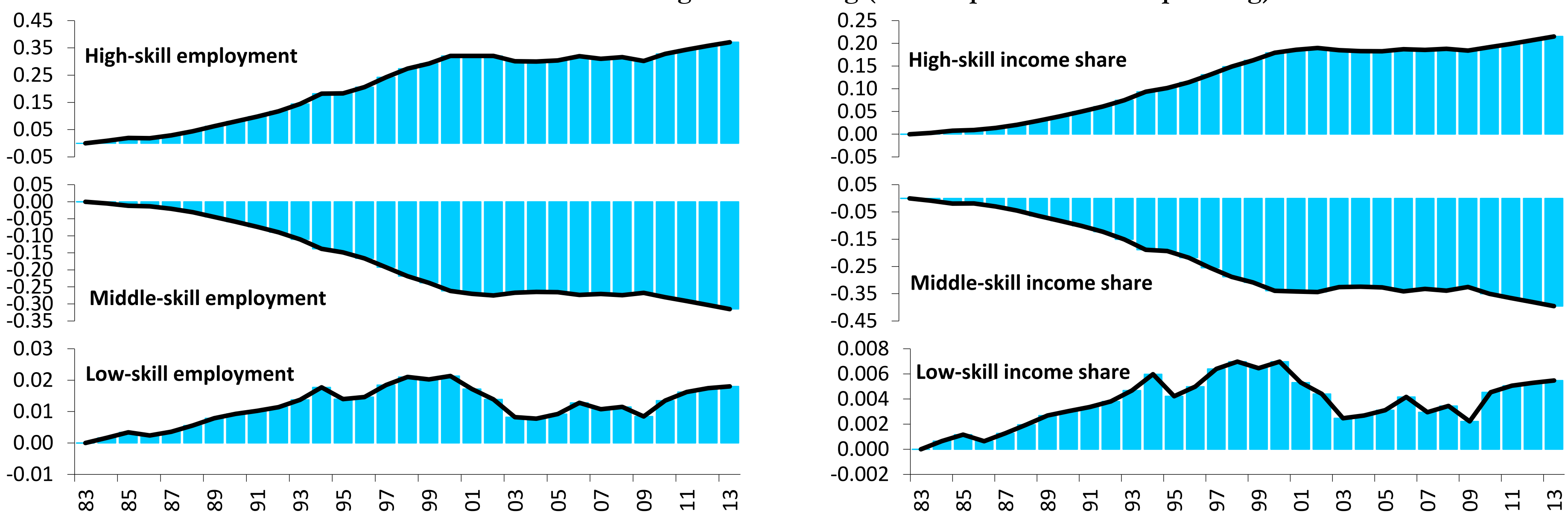
Note: The blue-dashed lines plot responses to a decline in the Home offshoring cost (it becomes easier for home tasks to be delivered to Foreign). The red-dotted lines show responses to a decline in the Foreign cost (it becomes easier for foreign tasks to be delivered to Home). The black solid line combines both shocks.

Figure APX-6: The Role of Displacement vs. Upskilling, with Offshoring Shock Only

A. Alternative model with fixed training margin (no displacement, just upskilling)

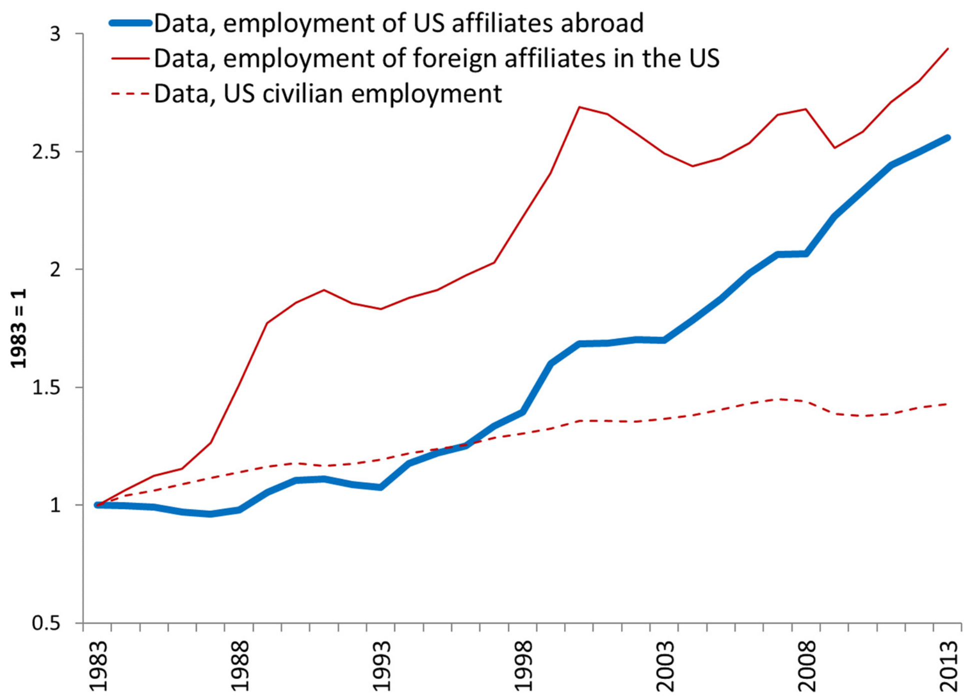


B. Baseline model with endogenous training (both displacement and upskilling)



Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. For the purpose of this exercise, we activate the offshoring shock only, whose contributions are shown by the blue bars.

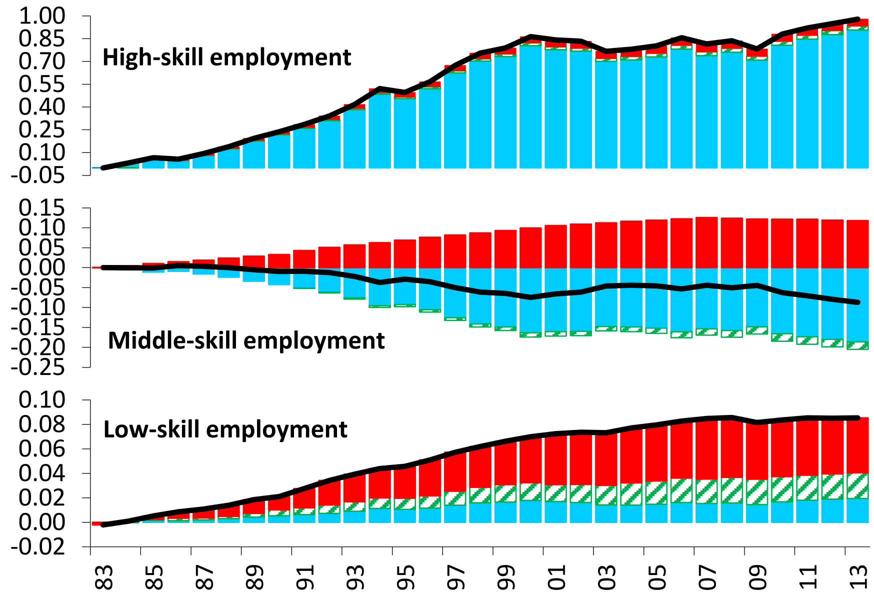
Figure APX-7: Employment of U.S. and Foreign Affiliates of Multinational Enterprises



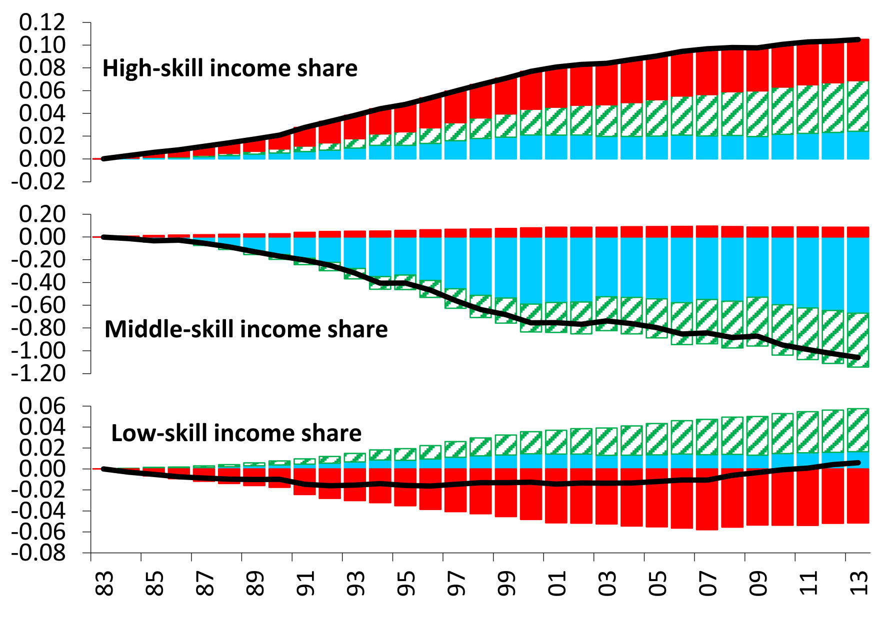
Note: The chart shows the total employment of all majority-owned foreign affiliates in the U.S. and, conversely, U.S. affiliates of foreign multinational enterprises (non-bank affiliates up to 2008), from the U.S. Bureau of Economic Analysis (2020a) data available at https://apps.bea.gov/iTable/index_MNC.cfm and https://www.bea.gov/international/direct-investment-and-multinational-enterprises-comprehensive-data; the U.S. civilian employment, 16 years and over, is from the U.S. Bureau of Labor Statistics (2020a).

Figure APX-8: Robustness for High Elasticity of Substitution between Tasks (*θ=4*)

A. Historical decomposition of employment



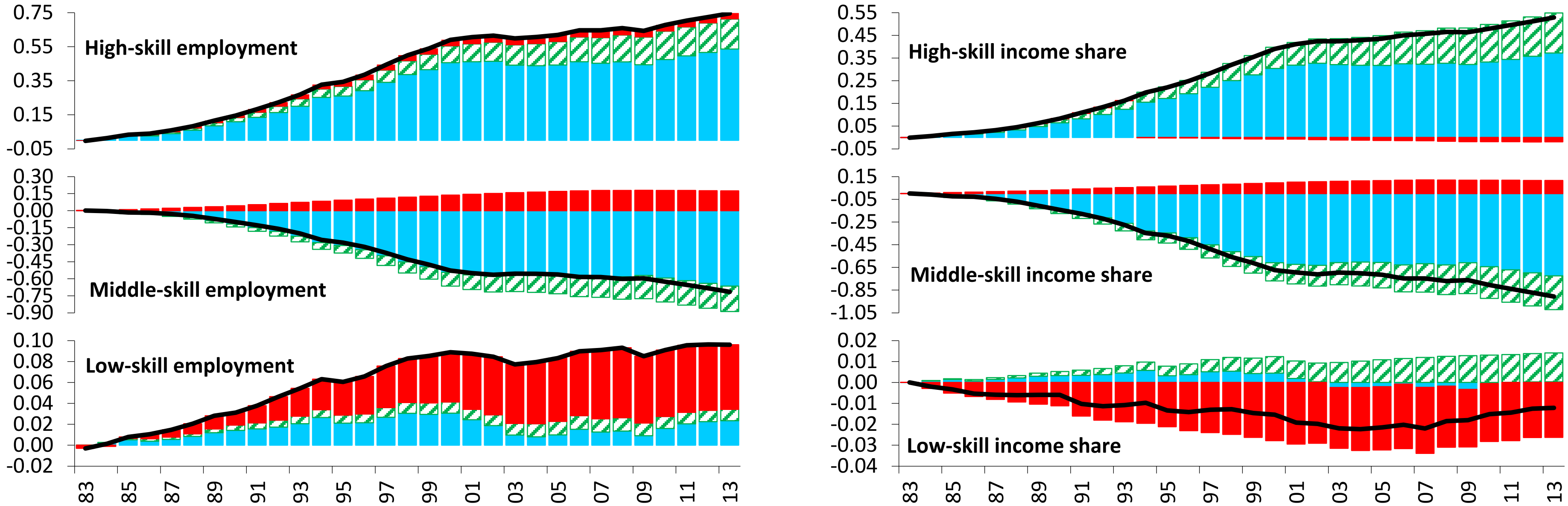
B. Historical decomposition of income shares



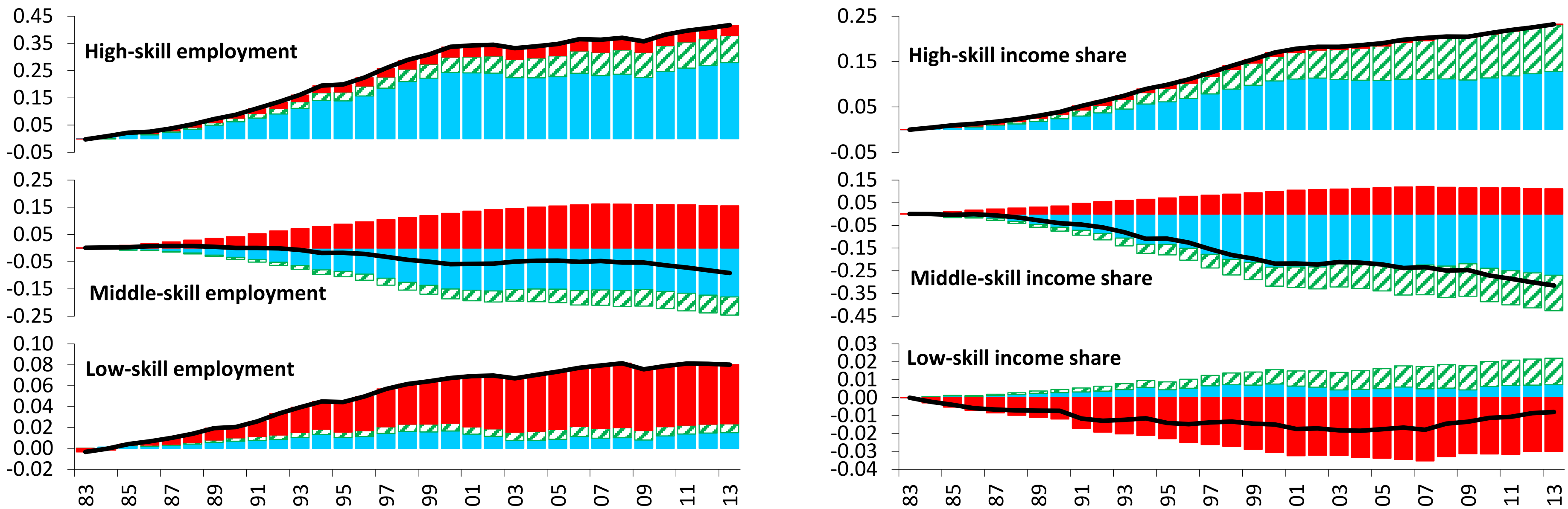
Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. The blue/green/red bars show the contributions of offshoring/automation/low-skill immigration to the total change.

Figure APX-9: Robustness for the Pareto Distribution Dispersion Parameter *k*

A. Low dispersion, $k = 2.82$



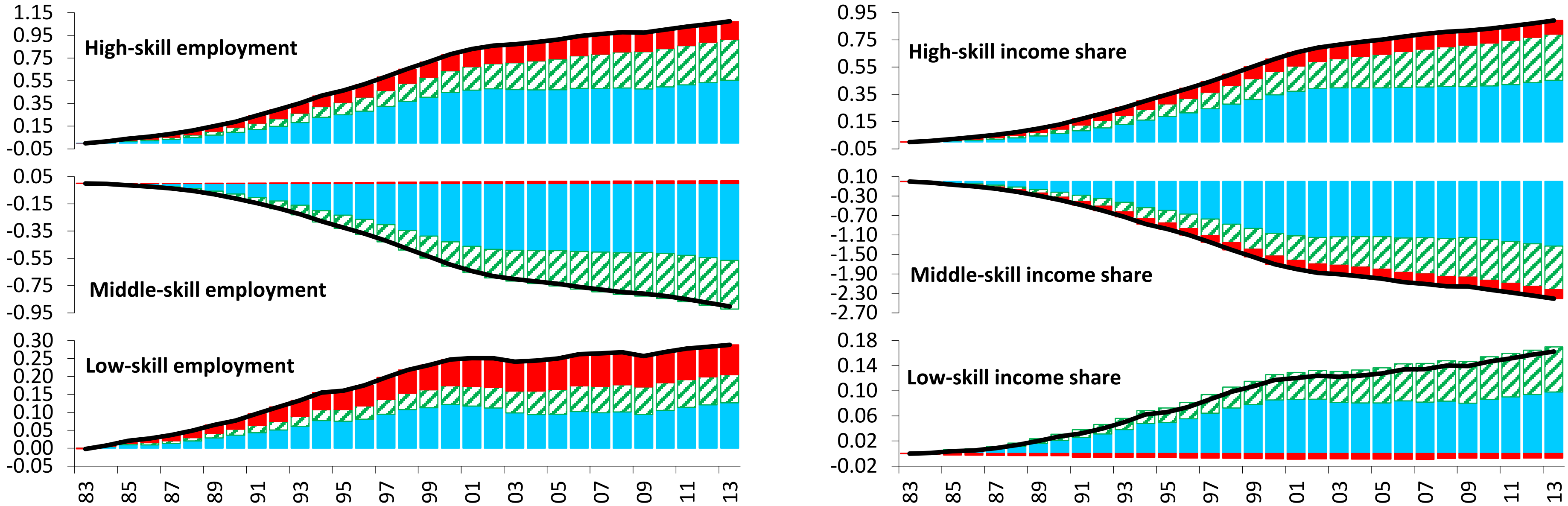
B. High dispersion, $k = 1.32$



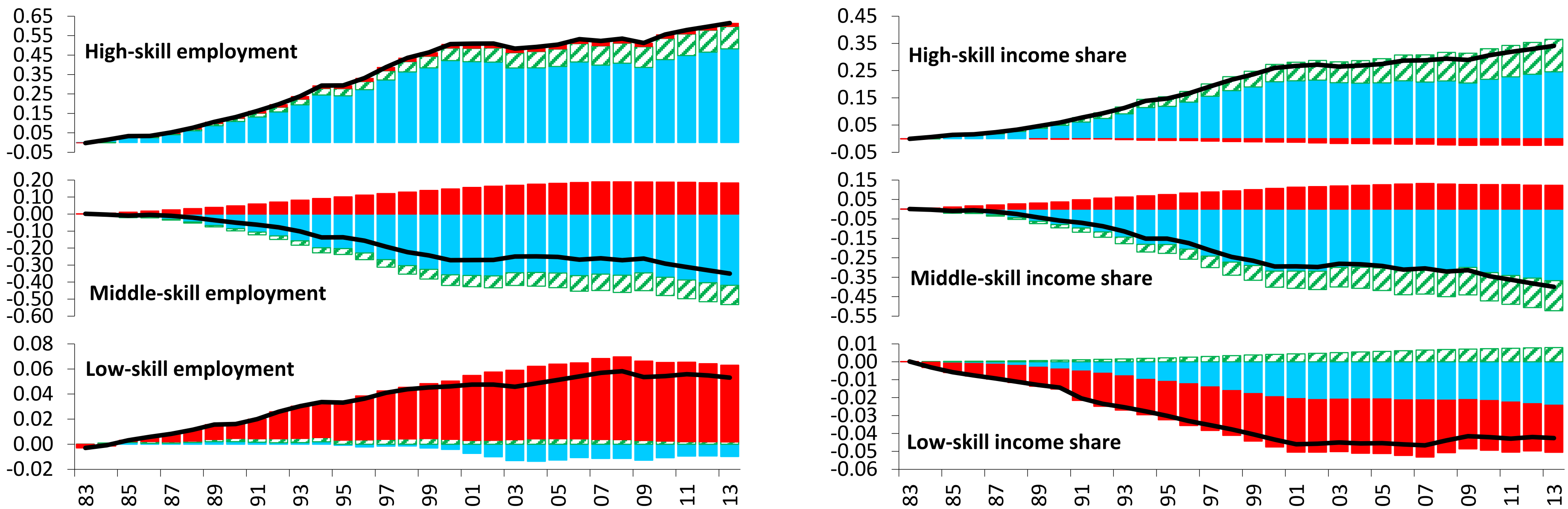
Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. The blue/green/red bars show the contributions of offshoring/automation/low-skill immigration to the total change.

Figure APX-10: Robustness for the Elasticity of Substitution between Home and Foreign High-Skill Tasks

A. Low elasticity, $\theta^H = 1.3$



B. High elasticity, $\theta^H = 2$



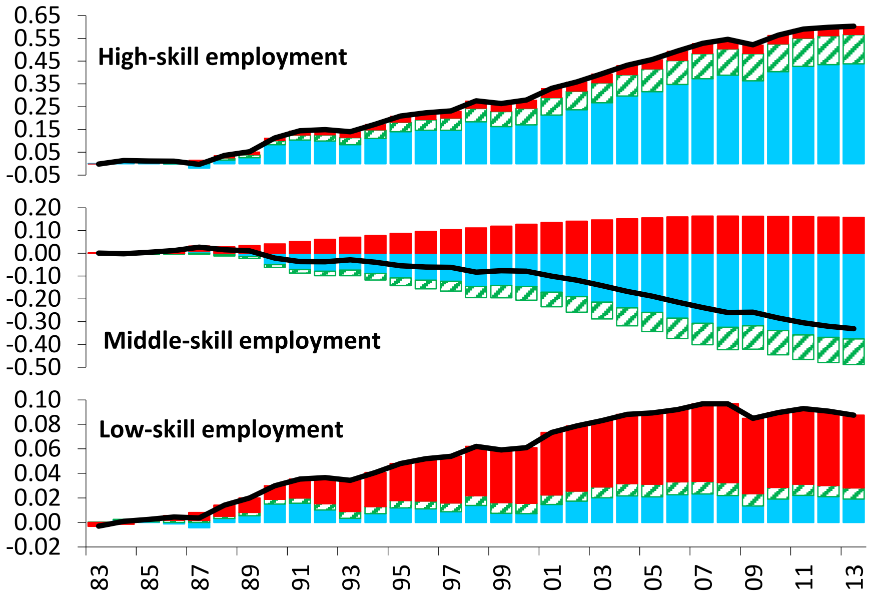
Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. The blue/green/red bars show the contributions of offshoring/automation/low-skill immigration to the total change.

Figure APX-11: Robustness with the Share of Foreign Employment by U.S. Multinationals as Observable: Data vs. Model Implications

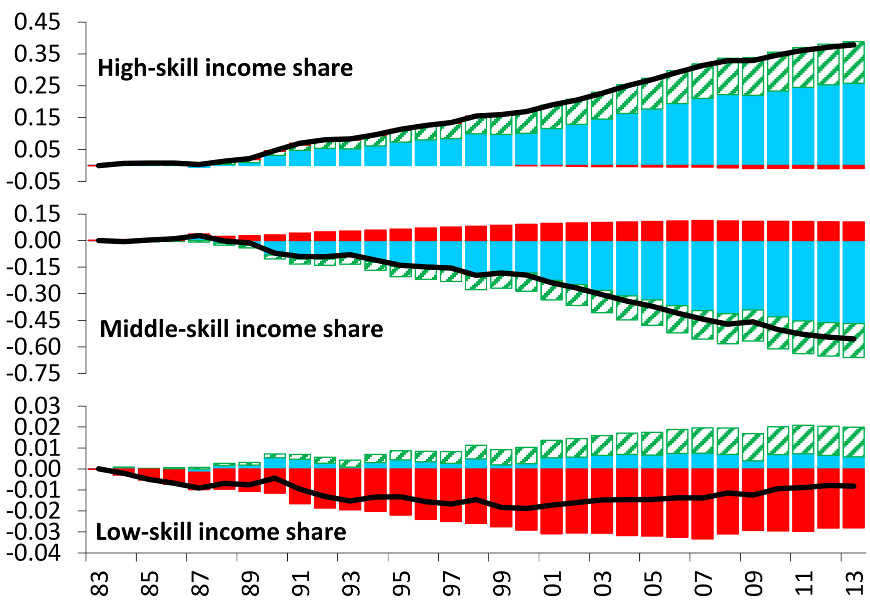
Note: The data are: (A) The trade-weighted index of bilateral iceberg trade costs between the U.S. and six trading partners, with data from Novy (2013) and ESCAP-World Bank (2020). (B) U.S. exports + imports normalized by GDP, from the U.S. Bureau of Economic Analysis (2020b). (C) and (D) The 1983-2013 percentage change in employment and income shares by skill group, using data from the U.S. Bureau of Labor Statistics (2020a,b) like in Eden and Gaggl (2018) and Jaimovich and Siu (2020), with construction in low-skill occupations.

Figure APX-12: Robustness with the Share of Foreign Employment by U.S. Multinationals as Observable

A. Historical decomposition of employment



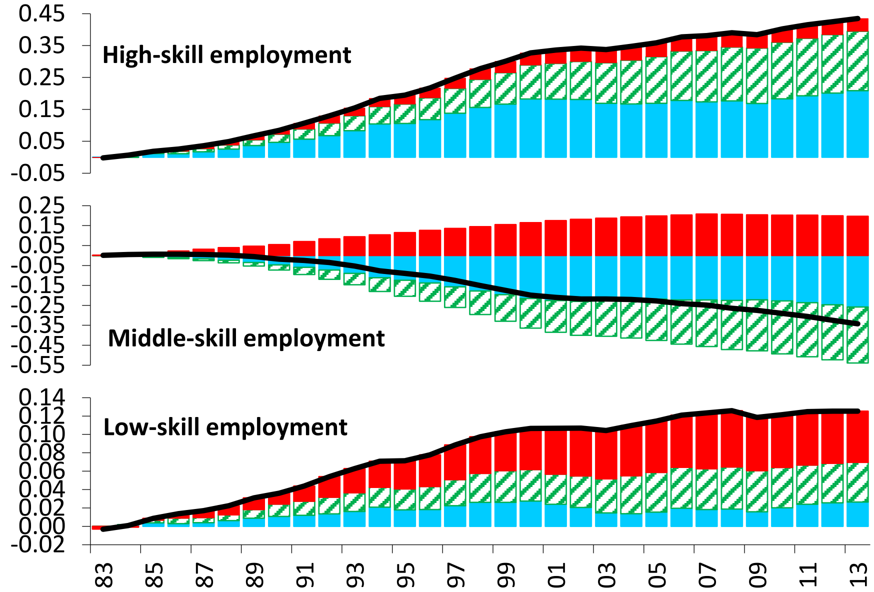
B. Historical decomposition of income shares



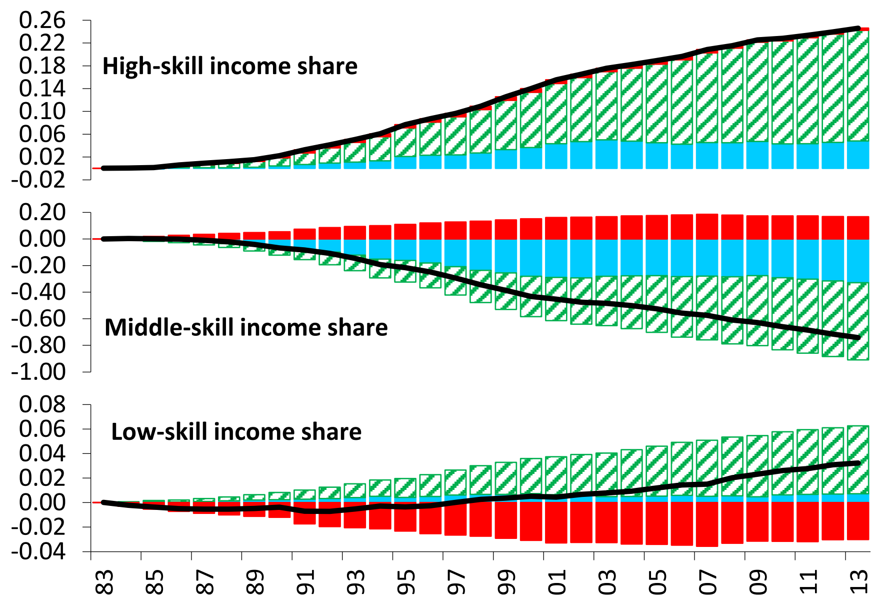
Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. The blue/green/red bars show the contributions of offshoring/automation/low-skill immigration to the total change.

Figure APX-13: Robustness with a High Share of ICT Capital in GDP

A. Historical decomposition of employment



B. Historical decomposition of employment



Note: The black solid lines show the log change since 1983 for each variable, measured on the y-axis. The sample period 1983-2013 is on the x-axis. The blue/green/red bars show the contributions of offshoring/automation/low-skill immigration to the total change.