Measuring the Bias of Technological Change
—Online Appendix—

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OA1 Additions to Section 3: Data

Table OA1 complements Table 1 in the main paper. Columns (1) and (2) document the extent of entry and, respectively, exit. Column (3) describes the demand shifter. Columns (4)–(6) document the rate of growth of the prices of the various inputs.

OA2 Additions to Section 4: A dynamic model of the firm

Correction terms. In developing the correction term $\lambda_1(S_{Tjt})$ in the main paper we assume that the ratio $\frac{W_{Pjt}}{W_{Tjt}} = \lambda_0$ is an (unknown) constant. Table OA2 replicates the wage regression in Appendix E. To probe if the wage premium changes over time, we add an interaction of the share of temporary labor S_{Tjt} and a time trend t (column (2)). In line with our assumption, this interaction is borderline significant in just two industries and insignificant in the remaining industries. The remaining estimates (columns (1) and (3)–(5)) are similar to those in columns (5)–(8) of Table A2.

In developing the correction term $\gamma_1(S_{Ojt})$ we assume that the ratio $\frac{P_{Ijt}}{P_{Ojt}} = \gamma_0$ is an (unknown) constant. Alternatively, we assume that $\frac{P_{Ijt}}{P_{Ojt}} = \gamma_0(t)$ is an (unknown) function of time t and treat $\ln \Gamma\left(1, \gamma_0(t)\frac{S_{Ojt}}{1-S_{Ojt}}\right) = \gamma_1\left(\gamma_0(t)\frac{S_{Ojt}}{1-S_{Ojt}}\right)$ as an (unknown) function of $\gamma_0(t)S_{Ojt}$.[1] In the simplest case, we set $\gamma(t) = \gamma_0 + \gamma_1 t$ with the normalization $\gamma_0 = 1$. As can be seen from column (2) of Table OA3, γ_1 is significantly different from zero in three industries but very imprecisely estimated. Equation (17) yields lower estimates of σ (column (1)) in five industries compared to our leading estimates in column (3) of Table 4; the estimates of σ are essentially unchanged in three industries. In the remaining two industries, the estimates of σ are either implausibly low (industry 4) or high (industry 8). Equation (20) becomes substantially more difficult to estimate. Compared to our leading estimates in columns (1) and (2) of Table 7 the estimates of β_K (column (6)) are lower in six industries and essentially unchanged in two industries. The estimates of ν (column (7)) are lower in one industry and essentially unchanged in seven industries. Comparing columns (5) and (10) of Table OA3 to column (1) of Table 5 and, respectively, column (1) of Table 8 shows that, on average, the growth of labor-augmenting productivity is higher in one industry, essentially unchanged in five industries, and lower in four industries. The growth of Hicks-neutral productivity is higher in two industries, essentially the same in four industries, and lower in two industries. Overall, our conclusions about technological change remain the same.

An alternative model of outsourcing. If both in-house and outsourced materials are static inputs that the firm may combine in arbitrary proportions without incurring adjust-

[1] Treating it as an unknown function of $\gamma_0(t)\frac{S_{Ojt}}{1-S_{Ojt}}$ instead of $\gamma_0(t)S_{Ojt}$ introduces additional nonlinearities and considerably complicates estimation.

ment costs, then the Bellman equation becomes

$$\begin{aligned} V_t(\Omega_{jt}) &= \max_{K_{jt+1},L_{Pjt},L_{Tjt},M_{Ijt},M_{Ojt},R_{jt}} P\left(X_{jt}^{-\frac{\nu\sigma}{1-\sigma}}\exp(\omega_{Hjt}),D_{jt}\right)X_{jt}^{-\frac{\nu\sigma}{1-\sigma}}\exp(\omega_{Hjt})\mu \\ &\quad -C_I(K_{jt+1}-(1-\delta)K_{jt})-W_{Pjt}L_{Pjt}-C_{L_P}(L_{Pjt},L_{Pjt-1})-W_{Tjt}L_{Tjt} \\ &\quad -P_{Ijt}M_{Ijt}-P_{Ojt}M_{Ojt}-C_R(R_{jt})+\frac{1}{1+\rho}E_t\left[V_{t+1}(\Omega_{jt+1})|\Omega_{jt},R_{jt}\right], \end{aligned}$$

where $\Omega_{jt}=(K_{jt},L_{Pjt-1},\omega_{Ljt},\omega_{Hjt},W_{Pjt},W_{Tjt},P_{Ijt},P_{Ojt},D_{jt})$ is the vector of state variables. The corresponding first-order conditions for in-house and outsourced materials are

$$\nu\beta_M\mu X_{jt}^{-\left(1+\frac{\nu\sigma}{1-\sigma}\right)}\exp\left(\omega_{Hjt}\right)\left(M_{jt}^*\right)^{-\frac{1}{\sigma}}\frac{\partial M_{jt}^*}{\partial M_{Ijt}} = \frac{P_{Ijt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \tag{OA1}$$

$$\nu\beta_M\mu X_{jt}^{-\left(1+\frac{\nu\sigma}{1-\sigma}\right)}\exp\left(\omega_{Hjt}\right)\left(M_{jt}^*\right)^{-\frac{1}{\sigma}}\frac{\partial M_{jt}^*}{\partial M_{Ojt}} = \frac{P_{Ojt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}. \tag{OA2}$$

Equations (OA1) and (OA2) imply that the mix of in-house and outsourced materials depends on their prices.

We assume that $P_{Mjt}=P_{Ijt}(1-S_{Ojt})+P_{Ojt}S_{Ojt}$ so that the price of materials is an appropriately weighted average of the prices of in-house and outsourced materials. We continue to assume that $\Gamma(M_{Ijt},M_{Ojt})$ is linearly homogenous and normalize $\Gamma(M_{Ijt},0)=M_{Ijt}$. This implies $M_{jt}^*=M_{jt}\frac{P_{Mjt}}{P_{Ijt}}\Gamma\left(1-S_{Ojt},\frac{P_{Ijt}}{P_{Ojt}}S_{Ojt}\right)$. Using Euler's theorem to combine equations (OA1) and (OA2) yields

$$\begin{aligned} &\nu\beta_M\mu X_{jt}^{-\left(1+\frac{\nu\sigma}{1-\sigma}\right)}\exp\left(\omega_{Hjt}\right)M_{jt}^{-\frac{1}{\sigma}}\left(\frac{P_{Mjt}}{P_{Ijt}}\Gamma\left(1-S_{Ojt},\frac{P_{Ijt}}{P_{Ojt}}S_{Ojt}\right)\right)^{-\frac{1-\sigma}{\sigma}} \\ &\qquad = \frac{P_{Mjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}. \end{aligned} \tag{OA3}$$

If $\frac{P_{Ijt}}{P_{Ojt}}=\gamma_0$ is an (unknown) constant, then $\frac{P_{Mjt}}{P_{Ijt}}=1-S_{Ojt}+\frac{S_{Ojt}}{\gamma_0}$ and $\ln\left(\frac{P_{Mjt}}{P_{Ijt}}\Gamma\left(1-S_{Ojt},\frac{P_{Ijt}}{P_{Ojt}}S_{Ojt}\right)\right)=\gamma_2(S_{Ojt})$ is an (unknown) function of S_{Ojt}. Equation (OA3) is thus indistinguishable from equation (14) in the main paper. Note that if $S_{Ojt}=0$ and thus $P_{Mjt}=P_{Ijt}$ and $M_{jt}=M_{Ijt}$, then equation (OA3) reduces to the first-order condition in a model without outsourcing.

OA3 Additions to Section 6: Labor-augmenting technological change

Additional checks: Lagged input prices. Table OA4 complements Table 4 in the main paper. Columns (1)–(3) show that our estimates of the elasticity of substitution are robust to purging the variation due to differences in the quality of labor from the lagged wage w_{jt-1}. In contrast to the main paper, $\widehat{w}_{Qjt}$ is the part of the wage that depends on the available data on the skill mix of a firm's labor force as well as on firm size.

Firms' R&D activities. Table OA5 complements Table 5 in the main paper. Column (1) shows that firms that perform R&D have, on average, higher levels of labor-augmenting productivity than firms that do not perform R&D in nine industries. Columns (2) and (3) show that firms that perform R&D have, on average, higher rates of growth of labor-augmenting productivity than firms that do not perform R&D in seven industries.

Firm turnover. Columns (4)–(6) of Table OA5 show that survivors account for most of the output effect of labor-augmenting technological change.

Skill upgrading. Columns (7) and (8) of Table OA5 document the increase in the share of engineers and technicians in the labor force between 1991 and 2006.

OA4 Additions to Section 8: Hicks-neutral technological change

Elasticity of substitution: Lagrange-multiplier test. We replace the CES production function in equation (6) by the nested CES production function (with $\beta_0 = \beta_L = 1$)

$$Y_{jt} = \left[\beta_K K_{jt}^{\frac{-(1-\tau)}{\tau}} + \left[\left(\exp(\omega_{Ljt})L_{jt}^*\right)^{\frac{-(1-\sigma)}{\sigma}} + \beta_M \left(M_{jt}^*\right)^{\frac{-(1-\sigma)}{\sigma}}\right]^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}}\right]^{\frac{-\nu\tau}{1-\tau}} \exp(\omega_{Hjt}) \exp(e_{jt}),$$

where the additional parameter τ is the elasticity of substitution between capital and labor, respectively, materials.

The first-order conditions for permanent and temporary labor become

$$\nu\mu \left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)} \left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1} \exp\left(\omega_{Hjt}\right) \exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right) \left(L_{jt}^*\right)^{-\frac{1}{\sigma}} \frac{\partial L_{jt}^*}{\partial L_{Pjt}} = \frac{W_{Pjt}(1+\Delta_{jt})}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)} \quad \text{(OA4)}$$

$$\nu\mu \left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)} \left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1} \exp\left(\omega_{Hjt}\right) \exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right) \left(L_{jt}^*\right)^{-\frac{1}{\sigma}} \frac{\partial L_{jt}^*}{\partial L_{Tjt}} = \frac{W_{Tjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)} \quad \text{(OA5)}$$

where

$$X_{jt}^{LM} = \left(\exp(\omega_{Ljt})L_{jt}^*\right)^{\frac{-(1-\sigma)}{\sigma}} + \beta_M \left(M_{jt}^*\right)^{\frac{-(1-\sigma)}{\sigma}},$$

$$X_{jt}^{KLM} = \beta_K K_{jt}^{\frac{-(1-\tau)}{\tau}} + \left[\left(\exp(\omega_{Ljt})L_{jt}^*\right)^{\frac{-(1-\sigma)}{\sigma}} + \beta_M \left(M_{jt}^*\right)^{\frac{-(1-\sigma)}{\sigma}}\right]^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}}.$$

Proceeding as in the main paper and using Euler's theorem to combine equations (OA4) and (OA5) yields

$$\nu\mu\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)\exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right)L_{jt}^{-\frac{1}{\sigma}}\Lambda(1-S_{Tjt},S_{Tjt})^{-\frac{1-\sigma}{\sigma}}$$
$$=\frac{W_{jt}\left(1+\frac{\Delta_{jt}}{1+\frac{W_{Tjt}}{W_{Pjt}}\frac{S_{Tjt}}{1-S_{Tjt}}}\right)}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}=\frac{W_{jt}\left(\frac{\frac{\Lambda_P(1-S_{Tjt},S_{Tjt})}{\Lambda_T(1-S_{Tjt},S_{Tjt})}+\frac{S_{Tjt}}{1-S_{Tjt}}}{\frac{W_{Pjt}}{W_{Tjt}}+\frac{S_{Tjt}}{1-S_{Tjt}}}\right)}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \tag{OA6}$$

where the second equality follows from dividing equations (OA4) and (OA5) and solving for Δ_{jt}.

The first-order condition for in-house materials becomes

$$\nu\mu\beta_M\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)\left(M_{jt}^*\right)^{-\frac{1}{\sigma}}\frac{dM_{jt}^*}{dM_{Ijt}}=\frac{P_{Ijt}+P_{Ojt}Q_{Mjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \tag{OA7}$$

where $P_{Ijt}+P_{Ojt}Q_{Mjt}$ is the effective cost of an additional unit of in-house materials. Proceeding as in the main paper and rewriting equation (OA7) yields

$$\nu\mu\beta_M\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)M_{jt}^{-\frac{1}{\sigma}}\Gamma\left(1,\frac{P_{Ijt}}{P_{Ojt}}\frac{S_{Ojt}}{1-S_{Ojt}}\right)^{-\frac{1-\sigma}{\sigma}}=\frac{P_{Mjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}. \tag{OA8}$$

From the labor and materials decisions in equations (OA6) and (OA8) we recover (conveniently rescaled) labor-augmenting productivity $\widetilde{\omega}_{Ljt}=(1-\sigma)\omega_{Ljt}$ and Hicks-neutral productivity ω_{Hjt} as

$$\begin{aligned}\widetilde{\omega}_{Ljt} &= \widetilde{\gamma}_L+m_{jt}-l_{jt}+\sigma(p_{Mjt}-w_{jt})-\sigma\lambda_2(S_{Tjt})+(1-\sigma)\gamma_1(S_{Ojt})\\ &\equiv \widetilde{h}_L(m_{jt}-l_{jt},p_{Mjt}-w_{jt},S_{Tjt},S_{Ojt}),\\ \omega_{Hjt} &= \gamma_H+\frac{1}{\sigma}m_{jt}+p_{Mjt}-p_{jt}-\ln\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)\\ &\quad+\left(1+\frac{\nu\tau}{1-\tau}\right)x_{jt}^{KLM}+\left(1-\frac{\sigma}{1-\sigma}\frac{1-\tau}{\tau}\right)x_{jt}^{LM}+\frac{1-\sigma}{\sigma}\gamma_1(S_{Ojt})\\ &\equiv h_H^{KLM}(k_{jt},m_{jt},S_{Mjt},p_{jt},p_{Mjt},D_{jt},S_{Tjt},S_{Ojt}),\end{aligned}$$

where

$$X_{jt}^{LM}=\beta_M\left(M_{jt}\exp\left(\gamma_1(S_{Ojt})\right)\right)^{-\frac{1-\sigma}{\sigma}}\left(\frac{1-S_{Mjt}}{S_{Mjt}}\lambda_1(S_{Tjt})+1\right),$$
$$X_{jt}^{KLM}=\beta_K K_{jt}^{\frac{-(1-\tau)}{\tau}}+\left[\beta_M\left(\frac{1-S_{Mjt}}{S_{Mjt}}\lambda_1(S_{Tjt})+1\right)\right]^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}}\left(M_{jt}\exp\left(\gamma_1(S_{Ojt})\right)\right)^{\frac{-(1-\tau)}{\tau}}.$$

Our first estimation equation (17) therefore remains unchanged and our second estimation equation (20) becomes

$$y_{jt} = -\frac{\nu\tau}{1-\tau} x_{jt}^{KLM}$$
$$+g_{Ht-1}(h_H^{KLM}(k_{jt-1}, m_{jt-1}, S_{Mjt-1}, p_{jt-1}, p_{Mjt-1}, D_{jt-1}, S_{Tjt-1}, S_{Ojt-1}), R_{jt-1}) + \xi_{Hjt} + e_{jt}. \qquad \text{(OA9)}$$

If $\tau = \sigma$, then equation (OA9) reverts to equation (20). This allows us to conduct a Lagrange-multiplier test for $\tau = \sigma$, with σ fixed at our leading estimates in column (3) of Table 4.

Firm turnover. Table OA6 complements Table 8 in the main paper. Columns (1)–(3) show that survivors account for most of Hicks-neutral technological change.

Total technological change and its components. Column (4) of Table OA6 shows that the correlation between labor-augmenting productivity in output terms $\epsilon_{Ljt-2}\omega_{Ljt}$ and Hicks-neutral productivity ω_{Hjt} is positive in all industries.

OA5 Additions to Section 10: Capital-augmenting technological change

Table OA7 complements Table 10 in the main paper. Columns (1)–(3) present the results from estimating the analog to our first estimation equation (17) in the main paper:

$$m_{jt} - k_{jt} = -\sigma(p_{Mjt} - p_{Kjt}) - (1-\sigma)\gamma_1(S_{Ojt})$$
$$+\widetilde{g}_{Kt-1}(\widetilde{h}_K(m_{jt-1} - k_{jt-1}, p_{Mjt-1} - p_{Kjt-1}, S_{Ojt-1}), R_{jt-1}) + \widetilde{\xi}_{Kjt}.$$

$\Delta\omega_{Kjt}$ in column (4) presents the implied rate of growth of a firm's effective capital stock $\exp(\omega_{Kjt-1})K_{jt-1}$.

Column (5) of Table OA7 documents the implausibly low elasticity of output with respect to the firm's effective capital stock that drives the output effect to zero when we plug our leading estimates from Section 5 into equation (24) in the main paper.

OA6 Additions to Appendix C: Estimation

Concentrating out. To reduce the number of parameters to search over in the GMM problems corresponding to equations (17) (see also equation (21)) and (20) in the main paper, we "concentrate out" the parameters that enter it linearly (Wooldridge 2010, p. 435). To simplify the notation, in what follows we omit the subscripts L and H that distinguish these equations.

We exploit that the $T_j \times 1$ vector of residuals $\nu_j(\theta)$ as a function of the $P \times 1$ vector of parameters to be estimated θ can be written as

$$\nu_j(\theta) = y_j(\beta) - w_j(\beta)\gamma, \tag{OA10}$$

where β is a $P_1 \times 1$ vector of "nonlinear" parameters and γ is $P_2 \times 1$ vector of "linear" parameters with $\theta = (\beta', \gamma')'$ and $P = P_1 + P_2$. $y_j(\beta)$ is a $T_j \times 1$ vector and $w_j(\beta)$ is a $T_j \times P_2$ matrix of "composite" variables whose values depend on the nonlinear parameters β.

The first-order conditions for the GMM problem

$$\min_{\theta} \left[\frac{1}{N}\sum_j A_j(z_j)\nu_j(\theta)\right]' \widehat{W} \left[\frac{1}{N}\sum_j A_j(z_j)\nu_j(\theta)\right] \tag{OA11}$$

are

$$\left[\sum_j \frac{\partial(A_j(z_j)\nu_j(\theta))}{\partial\beta}, \sum_j \frac{\partial(A_j(z_j)\nu_j(\theta))}{\partial\gamma}\right]' \widehat{W} \left[\sum_j A_j(z_j)\nu_j(\theta)\right] = 0.$$

This is a system of P equations. Equation (OA10) implies $\sum_j \frac{\partial(A_j(z_j)\nu_j(\theta))}{\partial\gamma} = -\sum_j A_j(z_j)w_j(\beta)$. Hence, the lower P_2 equations can be rewritten as

$$\left[\sum_j A_j(z_j)w_j(\beta)\right]' \widehat{W} \left[\sum_j A_j(z_j)y_j(\beta) - \sum_j A_j(z_j)w_j(\beta)\gamma\right] = 0.$$

Solving yields the linear parameters as a function of the nonlinear parameters:

$$\gamma(\beta) = \left[\left(\sum_j A_j(z_j)w_j(\beta)\right)' \widehat{W} \sum_j A_j(z_j)w_j(\beta)\right]^{-1} \left(\sum_j A_j(z_j)w_j(\beta)\right)' \widehat{W} \sum_j A_j(z_j)y_j(\beta).$$

Plugging this back into the GMM problem in equation (OA11) concentrates out the linear parameters and reduces the GMM problem to a search over the nonlinear parameters.

We estimate the asymptotic variance of $\widehat{\theta} = (\widehat{\beta}', \gamma(\widehat{\beta})')'$ as

$$Avar(\widehat{\theta}) = \left[\widehat{G}'\widehat{W}\widehat{G}\right]^{-1} \widehat{G}'\widehat{W} \left[\sum_j A_j(z_j)\nu_j(\widehat{\theta})\nu_j(\widehat{\theta})'A_j(z_j)'\right] \widehat{W}\widehat{G} \left[\widehat{G}'\widehat{W}\widehat{G}\right]^{-1}$$

if $\widehat{W}$ is an arbitrary weighting matrix and as

$$Avar(\widehat{\theta}) = \left[\widehat{G}' \left[\sum_j A_j(z_j)\nu_j(\widehat{\theta})\nu_j(\widehat{\theta})'A_j(z_j)'\right]^{-1} \widehat{G}\right]^{-1}$$

if $\widehat{W}$ is the optimal weighting matrix. Both expressions depend on $\widehat{G} = \sum_j \frac{\partial(A_j(z_j)\nu_j(\widehat{\theta}))}{\partial\theta}$. Using the fact that $\frac{d(A_j(z_j)\nu_j(\theta))}{d\beta} = \frac{\partial(A_j(z_j)\nu_j(\theta))}{\partial\beta} - A_j(z_j)w_j(\beta)\frac{\partial\gamma(\beta)}{\partial\beta}$, we compute

$$\widehat{G} = \left[\sum_j \frac{d(A_j(z_j)\nu_j(\widehat{\theta}))}{d\beta} + \left(\sum_j A_j(z_j)w_j(\widehat{\beta})\right)\frac{\partial\gamma(\widehat{\beta})}{\partial\beta}, -\sum_j A_j(z_j)w_j(\widehat{\beta})\right].$$

Correcting standard errors. We proceed as follows. Let w_j be a $T_j \times 1$ vector of i.i.d. random variables and consider the functions $g_L(w_j, \theta_L)$ and $g_H(w_j, \theta_H, \theta_L)$ corresponding to equation (20) and, respectively, equation (17), where $E[g_L(w_j, \theta_{L0})] = 0$ and $E[g_H(w_{ji}, \theta_{H0}, \theta_{L0})] = 0$ at the true values θ_{L0} and θ_{H0}. Note that our notation differs from that in the main paper to make explicit that some of the parameters in equation (20) reappear in equation (17).

To estimate the parameters θ_L and θ_H we set up the GMM problems

$$\min_{\theta_L} \left[\frac{1}{N}\sum_j g_L(w_j, \theta_L)\right]' \widehat{W}_L \left[\frac{1}{N}\sum_j g_L(w_j, \theta_L)\right]$$

(see also equation (21) in the main paper) and

$$\min_{\theta_H} \left[\frac{1}{N}\sum_j g_H(w_j, \theta_H, \widehat{\theta}_L)\right]' \widehat{W}_H \left[\frac{1}{N}\sum_j g_H(w_j, \theta_H, \widehat{\theta}_L)\right].$$

If $E[\bigtriangledown_{\theta_L} g_H(w_j, \theta_{H0}, \theta_{L0})] \neq 0$, then we have to correct the standard errors of $\widehat{\theta}_H$ to ensure their consistency (Newey & McFadden 1994, Wooldridge 2010).

The first-order condition for $\widehat{\theta}_H$ is

$$\left[\sum_j \bigtriangledown_{\theta_H} g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)\right]' \widehat{W}_H \left[\sum_j g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)\right] = 0.$$

Expanding $\sum_j g_H(w_i, \widehat{\theta}_H, \widehat{\theta}_L)$ around θ_{H0} and substituting back into the first-order condition we have

$$\begin{aligned} 0 = &\left[\sum_j \bigtriangledown_{\theta_H} g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)\right]' \widehat{W}_H \left[\sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L)\right] \\ &+ \left[\sum_j \bigtriangledown_{\theta_H} g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)\right]' \widehat{W}_H \left[\sum_j \bigtriangledown_{\theta_H} g_H(w_j, \overline{\theta}_H, \widehat{\theta}_L)\right](\widehat{\theta}_H - \theta_{H0}), \end{aligned}$$

where $\overline{\theta}_H$ is the value that makes the expression exact according to the mean value theorem. Appropriately dividing and multiplying by N and replacing $\frac{1}{N}\sum_j \bigtriangledown_{\theta_H} g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)$ by its probability limit $G_H = E\left[\bigtriangledown_{\theta_H} g_H(w_j, \theta_{H0}, \theta_{L0})\right]$, replacing $\widehat{W}_H$ by its probability limit W_H, and solving for $\sqrt{N}(\widehat{\theta}_H - \theta_{H0})$ yields

$$\sqrt{N}(\widehat{\theta}_H - \theta_{H0}) = -\left[G_H' W_H G_H\right]^{-1} G_H' W_H \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L) + o_p(1). \qquad \text{(OA12)}$$

Expanding $\sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L)$ around θ_{L0} we have

$$\begin{aligned} \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L) &= \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \theta_{L0}) + \left[\frac{1}{N} \sum_j \bigtriangledown_{\theta_L} g_H(w_j, \theta_{H0}, \theta_{L0})\right] \sqrt{N}(\widehat{\theta}_L - \theta_{L0}) \\ &= \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \theta_{L0}) + G_{HL} \sqrt{N}(\widehat{\theta}_L - \theta_{L0}) + o_p(1), \qquad \text{(OA13)} \end{aligned}$$

where $G_{HL} = E[\bigtriangledown_{\theta_L} g_H(w_j, \theta_{H0}, \theta_{L0})]$. Because $\widehat{\theta}_L$ is a GMM estimator, it has a similar representation to the one derived for $\widehat{\theta}_H$ in equation (OA12):

$$\sqrt{N}(\widehat{\theta}_L - \theta_{L0}) = -\left[G_L' W_L G_L\right]^{-1} G_L' W_L \frac{1}{\sqrt{N}} \sum_j g_L(w_j, \theta_{L0}) + o_p(1), \qquad \text{(OA14)}$$

where $G_L = E\left[\bigtriangledown_{\theta_L} g_L(w_j, \theta_{L0})\right]$. Plugging equation (OA14) into equation (OA13), we have

$$\begin{aligned} &\frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L) \\ &= \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \theta_{L0}) - G_{HL} \left[G_L' W_L G_L\right]^{-1} G_L' W_L \frac{1}{\sqrt{N}} \sum_j g_L(w_j, \theta_{L0}) + o_p(1). \end{aligned} \qquad \text{(OA15)}$$

Plugging equation (OA15) into equation (OA12), we have

$$\begin{aligned} &\sqrt{N}(\widehat{\theta}_H - \theta_{H0}) \\ &= -\left[G_H' W_H G_H\right]^{-1} G_H' W_H \frac{1}{\sqrt{N}} \sum_j \left[g_H(w_j, \theta_{H0}, \theta_{L0}) - G_{HL} \left[G_L' W_L G_L\right]^{-1} G_L' W_L g_L(w_j, \theta_{L0})\right] + o_p(1). \end{aligned}$$

Defining

$$\widetilde{g}_H(w_j, \theta_{H0}, \theta_{L0}) = g_H(w_j, \theta_{H0}, \theta_{L0}) - G_{HL} \left[G_L' W_L G_L\right]^{-1} G_L' W_L g_L(w_j, \theta_{L0})$$

and

$$D = E[\widetilde{g}_H(w_j, \theta_{H0}, \theta_{L0}) \widetilde{g}_H(w_j, \theta_{H0}, \theta_{L0})'],$$

we finally have

$$Avar(\widehat{\theta}_H) = \frac{\left[G'_H W_H G_H\right]^{-1} G'_H W_H D W_H G_H \left[G'_H W_H G_H\right]^{-1}}{N}.$$

The asymptotic variance can be estimated by replacing the probability limits by estimates and the matrix D by an estimate based on $g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)$ and $g_L(w_j, \widehat{\theta}_L)$.

References

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Table OA1: Descriptive statistics.

Industry	Entry (%)	Exit (%)	Demand shifter (s. d.)	Rates of growth[a] P_K (s. d.)	W (s. d.)	P_M (s. d.)
	(1)	(2)	(3)	(4)	(5)	(6)
1. Metals and metal products	142	18	0.600	-0.007	0.049	0.041
	(45.4)	(5.8)	(0.344)	(0.073)	(0.163)	(0.067)
2. Non-metallic minerals	42	23	0.581	-0.012	0.043	0.031
	(25.8)	(14.1)	(0.337)	(0.100)	(0.144)	(0.034)
3. Chemical products	93	28	0.589	-0.013	0.047	0.032
	(31.1)	(9.4)	(0.330)	(0.122)	(0.138)	(0.065)
4. Agric. and ind. machinery	49	16	0.569	-0.011	0.045	0.030
	(27.6)	(9.0)	(0.352)	(0.091)	(0.150)	(0.038)
5. Electrical goods	56	31	0.557	-0.015	0.051	0.030
	(26.8)	(14.8)	(0.353)	(0.086)	(0.168)	(0.044)
6. Transport equipment	57	19	0.569	-0.005	0.047	0.028
	(35.4)	(11.8)	(0.372)	(0.082)	(0.162)	(0.048)
7. Food, drink and tobacco	81	31	0.540	-0.016	0.052	0.033
	(24.8)	(9.5)	(0.313)	(0.104)	(0.170)	(0.058)
8. Textile, leather and shoes	115	83	0.436	-0.009	0.052	0.031
	(34.3)	(24.8)	(0.343)	(0.092)	(0.178)	(0.044)
9. Timber and furniture	101	26	0.530	-0.032	0.054	0.035
	(48.8)	(12.6)	(0.338)	(0.118)	(0.166)	(0.039)
10. Paper and printing products	73	16	0.533	-0.011	0.052	0.035
	(39.9)	(8.7)	(0.324)	(0.092)	(0.139)	(0.076)

[a] Computed for 1991 to 2006.

Table OA2: Wage regression.

Industry	Temp. (s. e.)	Time trend ×temp. (s. e.)	White (s. e.)	Engin. (s. e.)	Tech. (s. e.)	R^2
	(1)	(2)	(3)	(4)	(5)	(6)
1. Metals and metal products	-0.378	-0.005	0.125	1.114	0.315	0.651
	(0.115)	(0.010)	(0.096)	(0.297)	(0.094)	
2. Non-metallic minerals	-0.257	0.017	0.131	0.881	0.240	0.743
	(0.131)	(0.011)	(0.158)	(0.281)	(0.180)	
3. Chemical products	-0.461	0.000	0.461	0.592	0.203	0.755
	(0.120)	(0.015)	(0.074)	(0.137)	(0.099)	
4. Agric. and ind. machinery	-0.072	-0.024	0.284	0.806	-0.038	0.633
	(0.120)	(0.012)	(0.105)	(0.227)	(0.124)	
5. Electrical goods	-0.339	-0.004	0.218	1.093	0.310	0.661
	(0.113)	(0.012)	(0.073)	(0.264)	(0.087)	
6. Transport equipment	-0.389	0.001	0.220	0.403	0.275	0.709
	(0.117)	(0.014)	(0.107)	(0.300)	(0.169)	
7. Food, drink and tobacco	-0.413	-0.004	0.115	1.286	0.355	0.753
	(0.089)	(0.008)	(0.053)	(0.264)	(0.154)	
8. Textile, leather and shoes	-0.281	0.003	0.646	1.589	0.349	0.683
	(0.080)	(0.008)	(0.083)	(0.406)	(0.243)	
9. Timber and furniture	-0.443	0.009	0.175	0.276	0.003	0.698
	(0.114)	(0.010)	(0.089)	(0.381)	(0.164)	
10. Paper and printing products	-0.209	-0.036	0.185	0.450	0.255	0.704
	(0.182)	(0.018)	(0.083)	(0.202)	(0.126)	

Table OA3: Elasticity of substitution, distributional parameters, and elasticity of scale.

Industry	GMM					GMM				
	σ (s. e.)	γ_1	χ^2 (*df*)	*p* val.	$\Delta\omega_L$	β_K (s. e.)	ν (s. e.)	χ^2 (*df*)	*p* val.	$\Delta\omega_H$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Metals and metal products	0.446	1.011	48.760	0.093	0.082	0.205	0.960	5.369	0.718	0.054
	(0.117)	(7.592)	(38)			(0.071)	(0.028)	(8)		
2. Non-metallic minerals	0.619	-0.079	39.079	0.377	0.096	0.013	0.853	6.928	0.544	0.027
	(0.091)	(0.009)	(38)			(0.042)	(0.087)	(8)		
3. Chemical products	0.608	-0.081	45.432	0.161	0.055	0.076	0.955	0.497	1.000	0.018
	(0.114)	(0.041)	(38)			(0.047)	(0.048)	(8)		
4. Agric. and ind. machinery[a]	0.254	5.798	42.376	0.251	0.119					
	(0.203)	(190.555)	(38)							
5. Electrical goods	0.511	-0.039	42.182	0.257	0.171	0.055	0.813	3.090	0.979	0.021
	(0.118)	(0.030)	(38)			(0.026)	(0.035)	(10)		
6. Transport equipment[b]	0.797	-0.007	45.867	0.150	0.144	0.720	0.829			0.025
	(0.089)	(6.262)	(38)			(0.580)	(0.101)			
7. Food, drink and tobacco	0.624	0.110	53.030	0.043	0.021	0.372	0.898	0.608	1.000	0.002
	(0.079)	(0.054)	(38)			(0.357)	(0.108)	(8)		
8. Textile, leather and shoes[a]	1.187	0.651	47.937	0.107	-0.028					
	(0.274)	(2.897)	(38)							
9. Timber and furniture	0.449	2.570	40.257	0.328	-0.010	0.078	0.936	5.740	0.676	0.001[c]
	(0.095)	(56.118)	(38)			(0.545)	(0.592)	(8)		
10. Paper and printing products	0.409	-1.869	51.890	0.053	0.022	0.128	0.947	0.020	1.000	0.011
	(0.100)	(12.217)	(38)			(0.518)	(0.589)	(8)		
All industries					0.067					0.021

[a] We have been unable to compute the first-step GMM estimate for equation (20).
[b] We have been unable to compute the second-step GMM estimate for equation (20).
[c] We trim values of $\Delta\omega_H$ below -0.25 and above 0.5. This amounts to trimming around one third of observations.

Table OA4: Elasticity of substitution.

Industry	GMM with quality-corrected wage as instr.[a]		
	σ (s. e.)	χ^2 (df)	p val.
	(1)	(2)	(3)
1. Metals and metal products	0.418 (0.112)	52.492 (38)	0.059
2. Non-metallic minerals	0.833 (0.099)	49.028 (38)	0.108
3. Chemical products	0.694 (0.085)	42.154 (38)	0.296
4. Agric. and ind. machinery	0.600 (0.197)	46.655 (38)	0.158
5. Electrical goods	0.618 (0.119)	45.458 (38)	0.189
6. Transport equipment	0.666 (0.096)	43.834 (38)	0.238
7. Food, drink and tobacco	0.796 (0.082)	37.644 (38)	0.486
8. Textile, leather and shoes	0.928 (0.208)	56.628 (38)	0.026
9. Timber and furniture	0.556 (0.089)	37.422 (38)	0.496
10. Paper and printing products	0.475 (0.083)	44.470 (38)	0.218

[a] $\widehat{w}_{Qjt-1}$ based on firm size in addition to skill mix.

Table OA5: Labor-augmenting technological change.

Industry	Firms' R&D activities			Firm turnover Contributions to $\epsilon_{L,-2}\Delta\omega_L$			Share of eng. and tech.	
	ω_L	$\Delta\omega_L$						
	R&D-No R&D	R&D	No R&D	Survivors (%)	Entrants (%)	Exitors (%)	1991	2006
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Metals and metal products	0.885	0.105	0.077	0.019	0.002	0.000	0.068	0.107
				(90.5)	(9.5)	(0.0)		
2. Non-metallic minerals	1.534	0.095	0.107	0.033	0.001	-0.003	0.053	0.097
				(106.5)	(3.2)	(-9.7)		
3. Chemical products	1.325	0.103	-0.063	0.008	0.008	0.000	0.132	0.214
				(50.0)	(50.0)	(0.0)		
4. Agric. and ind. machinery	1.525	0.127	0.093	0.027	0.002	0.003	0.083	0.134
				(84.0)	(6.3)	(9.4)		
5. Electrical goods	2.737	0.235	0.045	0.019	0.002	0.001	0.146	0.157
				(90.5)	(9.5)	(4.8)		
6. Transport equipment	0.636	0.252	-0.161	0.024	0.002	0.004	0.066	0.129
				(80.0)	(6.7)	(13.3)		
7. Food, drink and tobacco	-0.037	0.058	-0.004	0.006	0.000	0.000	0.050	0.104
				(100.0)	(0.0)	(0.0)		
8. Textile, leather and shoes	0.656	0.062	0.032	0.009	0.000	0.000	0.032	0.070
				(100.0)	(0.0)	(0.0)		
9. Timber and furniture	0.001	0.059	0.070	0.003	-0.001	0.000	0.031	0.066
				(150.0)	(-50.0)	(0.0)		
10. Paper and printing products	0.502	0.001	0.026	0.013	-0.001	0.000	0.071	0.185
				(108.3)	(-8.3)	(0.0)		
All industries				0.014	0.002	0.001		
				(87.5)	(0.125)	(0.063)		

Table OA6: Hicks-neutral technological change.

Industry	Firm turnover Contributions to $\Delta\omega_H$			
	Survivors (%)	Entrants (%)	Exitors (%)	$corr(\epsilon_{L,-2}\omega_L, \omega_H)^a$
	(1)	(2)	(3)	(4)
1. Metals and metal products	0.035	0.007	0.004	0.057
	(79.5)	(15.9)	(9.1)	
2. Non-metallic minerals	0.007	0.001	-0.003	0.422
	(140.0)	(20.0)	(-60.0)	
3. Chemical products	0.018	0.000	0.001	0.302
	(94.7)	(0.0)	(5.3)	
4. Agric. and ind. machinery	0.036	0.000	0.006	0.162
	(87.8)	(0.0)	(14.6)	
5. Electrical goods	0.030	-0.003	-0.008	0.386
	(150.0)	(-15.0)	(-40.0)	
6. Transport equipment	0.043	0.010	-0.011	0.456
	(102.4)	(23.8)	(-26.2)	
7. Food, drink and tobacco	0.012	-0.012	0.000	0.573
8. Textile, leather and shoes	0.017	-0.006	0.001	0.380
	(141.7)	(-50.0)	(8.3)	
9. Timber and furniture	0.013[b]	0.006[b]	0.003[b]	0.506
	(61.9)	(28.6)	(14.3)	
10. Paper and printing products	0.012	-0.009	-0.003	0.426
All industries	0.019	-0.003	-0.002	
	(135.7)	(-21.4)	(-14.3)	

[a] Without replication and weighting.

[b] We trim values of $\Delta\omega_H$ below -0.25 and above 0.5. This amounts to trimming around one third of observations.

Table OA7: Capital-augmenting technological change.

Industry	GMM				
	σ (s. e.)	χ^2 (df)	p val.	$\Delta\omega_K$	$\epsilon_{K,-2}$
	(1)	(2)	(3)	(4)	(5)
1. Metals and metal products	0.504	52.421	0.109	0.050	0.036
	(0.240)	(38)			
2. Non-metallic minerals	0.135	40.637	0.487	-0.028	0.043
	(0.219)	(38)			
3. Chemical products	0.154	53.445	0.092	-0.028	0.031
	(0.141)	(38)			
4. Agric. and ind. machinery	0.391	43.039	0.384	-0.017	0.024
	(0.289)	(38)			
5. Electrical goods	-0.315	42.579	0.403	-0.046	0.018
	(0.253)	(38)			
6. Transport equipment	-0.298	54.967	0.071	-0.024	0.039
	(0.152)	(38)			
7. Food, drink and tobacco	0.214	58.864	0.035	-0.039	0.032
	(0.105)	(38)			
8. Textile, leather and shoes	-0.051	61.566	0.020	-0.064	0.031
	(0.176)	(38)			
9. Timber and furniture	1.006	54.734	0.074	-2.377	0.029
	(0.220)	(38)			
10. Paper and printing products	0.299	39.358	0.544	-0.029	0.050
	(0.091)	(38)			
All industries				-0.187	