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Measuring the Bias of Technological Change —Online Appendix—

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The Online Appendix is organized as follows: Section OA1 describes the wage regression that we reference throughout the main paper. The remaining sections contain additional results and technical details pertaining to the indicated sections of the main paper.

OA1 Wage regression

As column (1) of Table OA1 shows, the coefficient of variation for the (level of the) wage W_{jt} ranges from 0.35 to 0.50 across industries.[1] The variance decomposition in columns (2)–(4) shows that around one quarter of the overall variation is within firms across periods. The larger part of this variation is across firms.

To explore the source of this variation, we regress the (log of the) wage w_{jt} on the skill mix of a firm's labor force as given by the share of temporary (as opposed to permanent) labor, the share of white (as opposed to blue) collar workers, and the shares of engineers and technicians (as opposed to unskilled workers), time dummies, region dummies, product submarket dummies, the demand shifter, and an array of other firm characteristics, namely dummies for technological sophistication and identification of ownership and control as well as univariate polynomials of degree 3 in age and firm size.

To motivate this regression, assume that there are Q types of labor with wages W_{1jt}, W_{2jt}, ..., W_{Qjt} and write the wage as

$$W_{jt} = \sum_{q=1}^{Q} W_{qjt} S_{qjt} = W_{1jt} \left(1 + \sum_{q=2}^{Q} \left(\frac{W_{qjt}}{W_{1jt}} - 1 \right) S_{qjt} \right),$$

where S_{qjt} is the share of labor of type q and $\sum_{q=1}^{Q} S_{qjt} = 1$. Because

$$w_{jt} \approx w_{1jt} + \sum_{q=2}^{Q} \left(\frac{W_{qjt}}{W_{1jt}} - 1 \right) S_{qjt},$$

the coefficient on S_{qjt} in the wage regression is an estimate of the wage premium $\left(\frac{W_{qjt}}{W_{1jt}} - 1 \right)$ of labor of type q over type 1. Because we do not have the joint distribution of skills (e.g., temporary white collar technician) in our data, we approximate it by the marginal distributions (e.g., share of temporary labor) and ignore higher-order terms. As columns (5)–(8) of Table OA1 show, the estimated coefficients on the skill mix of a firm's labor force are often significant, have the expected signs, and are quite similar across industries. On average across industries, temporary workers earn 36% less than permanent workers, white collar workers earn 26% more than blue collar workers, engineers earn 85% more than unskilled workers, and technicians earn 23% more than unskilled workers.

The wage regression also shows that some, but by no means all variation in the wage is

[1] The coefficient of variation for the price of materials ranges from 0.12 to 0.19 across industries.

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due to worker quality. To isolate the part of the wage that depends on the skill mix of a firm's labor force, we decompose the predicted wage $\widehat{w}_{jt}$ into a prediction $\widehat{w}_{Qjt}$ based on the skill mix and a prediction $\widehat{w}_{Cjt}$ based on the remaining variables. $\widehat{w}_{Qjt}$ and $\widehat{w}_{Cjt}$ are positively correlated. According to $R^2 = \frac{Var(\widehat{w}_{jt})}{Var(w_{jt})}$ in column (9), depending on the industry, the wage regression explains between 63% and 76% of the variation in the wage, with an average of 70%. The skill mix by itself explains between 2% and 20% of the variation in the wage, with an average of 10% (see $R_Q^2 = \frac{Var(\widehat{w}_{Qjt})}{Var(w_{jt})}$ in column (10)). In contrast, the remaining variables explain between 36% and 64% of the variation in the wage, with an average of 48% (see $R_C^2 = \frac{Var(\widehat{w}_{Cjt})}{Var(w_{jt})}$ in column (11)). The larger part of the variation in the wage therefore appears to be due to temporal and geographic differences in the supply of labor, the fact that firms operate in different product submarkets, and other firm characteristics.

OA2 Additions to Section 3: Data

Table OA2 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.

Outsourcing. Figures OA1 and OA2 illustrate that the fraction of firms that engage in outsourcing as well as the share of outsourcing in the materials bill remain stable over our sample period.

OA3 Additions to Section 4: A dynamic model of the firm

Input usage: Wage ratio. 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. To probe if the wage premium changes over time, we replicate the wage regression in Section OA1 and add an interaction of the share of temporary labor S_{Tjt} and a time trend t (column (2) of Table OA3). 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)) of Table OA3 are similar to those in columns (5)–(8) of Table OA1.

Input usage: 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 adjustment costs, then the Bellman equation becomes

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

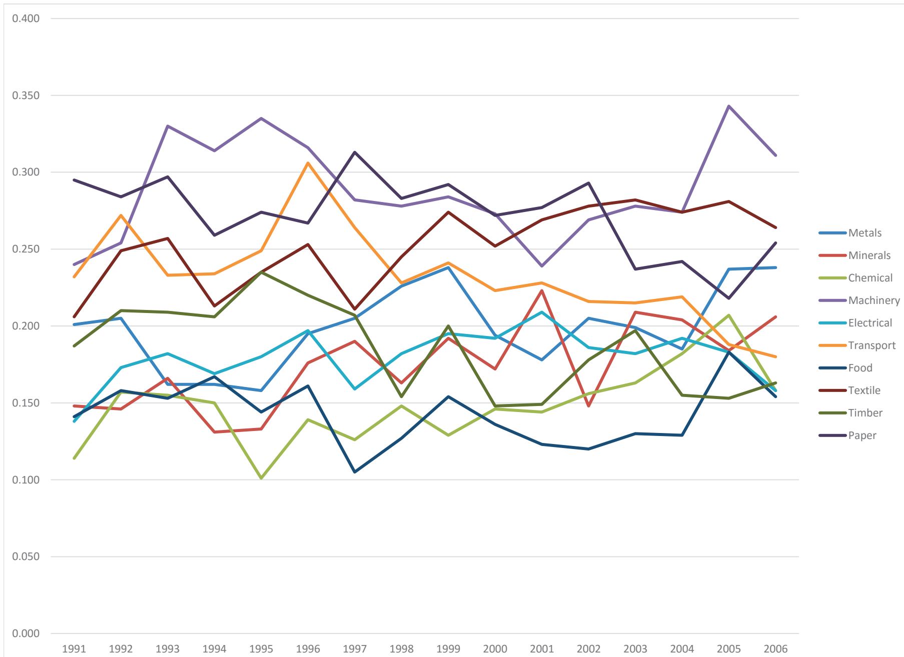

Figure OA1: Fraction of firms that engage in outsourcing.

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

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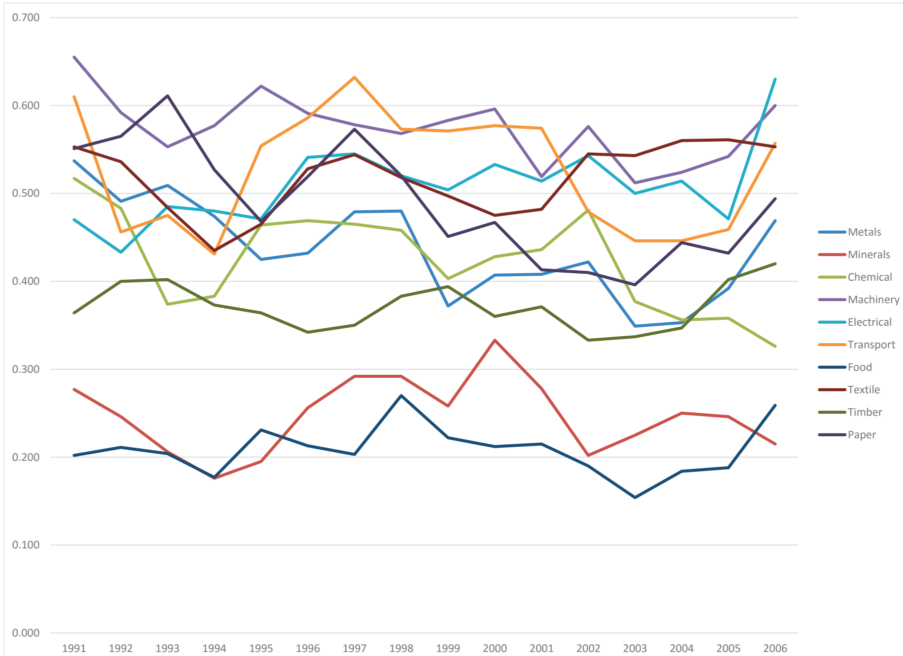

Figure OA2: Share of outsourcing in materials bill.

(OA1) and (OA2) yields

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

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 (25) 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.

OA4 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 eight 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.

The first-order condition for permanent labor of type q is

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

where $\theta_1 = 1$ and the gap between the wage W_{Pqjt} and the shadow wage is

$$\begin{aligned} \Delta_{jt} &= \frac{\partial C_{B_P}(B_{Pjt}, B_{Pjt-1})}{\partial B_{Pjt}} - \frac{1}{W_{Pqjt}} \frac{1}{1+\rho} E_t\left[\frac{\partial V_{t+1}(\Omega_{jt+1})}{\partial L_{Pqjt}} | \Omega_{jt}, R_{jt}\right] \\ &= \frac{\partial C_{B_P}(B_{Pjt}, B_{Pjt-1})}{\partial B_{Pjt}} + \frac{1}{1+\rho} E_t\left[\frac{\partial C_{B_P}(B_{Pjt+1}, B_{Pjt})}{\partial B_{Pjt}} | \Omega_{jt}, R_{jt}\right]. \end{aligned}$$

Equation (OA4) implies that $\theta_q = \frac{W_{Pqjt}}{W_{P1jt}}$ at an interior solution. Multiplying equation (OA4) by the share S_{Pqjt} of permanent workers of type q and summing yields

$$\nu\mu X_{jt}^{-\left(1+\frac{\nu\sigma}{1-\sigma}\right)} \exp\left(\omega_{Hjt}\right) \exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right) \left(L_{jt}^{*}\right)^{-\frac{1}{\sigma}} \frac{\partial L_{jt}^{*}}{\partial L_{Pjt}^{*}} \Theta_{jt} = \frac{W_{Pjt}(1+\Delta_{jt})}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \tag{OA5}$$

where $\Theta_{jt} = S_{P1jt} + \sum_{q=2}^{Q} \theta_q S_{Pqjt} = 1 + \sum_{q=2}^{Q}\left(\frac{W_{Pqjt}}{W_{P1jt}} - 1\right) S_{Pqjt}$ is a quality index and $W_{Pjt} = \sum_{q=1}^{Q} W_{Pqjt} S_{Pqjt}$. Using Euler's theorem to combine equations (22) and (OA5) yields

$$\nu\mu X_{jt}^{-\left(1+\frac{\nu\sigma}{1-\sigma}\right)} \exp\left(\omega_{Hjt}\right) \exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right) L_{jt}^{-\frac{1}{\sigma}} \Lambda((1-S_{Tjt})\Theta_{jt}, S_{Tjt})^{-\frac{1-\sigma}{\sigma}}$$

$$= \frac{W_{jt}\left(1+\frac{\Delta_{jt}}{1+\frac{W_{Tjt}}{W_{Pjt}}\frac{S_{Tjt}}{1-S_{Tjt}}}\right)}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)} = \frac{W_{jt}\left(\frac{\frac{\Lambda_P((1-S_{Tjt})\Theta_{jt},S_{Tjt})\Theta_{jt}}{\Lambda_T((1-S_{Tjt})\Theta_{jt},S_{Tjt})}+\frac{S_{Tjt}}{1-S_{Tjt}}}{\frac{W_{Pjt}}{W_{Tjt}}+\frac{S_{Tjt}}{1-S_{Tjt}}}\right)}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \quad \text{(OA6)}$$

where the second equality follows from dividing equations (22) and (OA5) and solving for Δ_{jt}. We proceed as in the main paper by assuming that $\frac{W_{Pjt}}{W_{Ljt}} = \lambda_0$ is an (unknown) constant and treating $\frac{\frac{\Lambda_P((1-S_{Tjt})\Theta_{jt},S_{Tjt})\Theta_{jt}}{\Lambda_T((1-S_{Tjt})\Theta_{jt},S_{Tjt})}+\frac{S_{Tjt}}{1-S_{Tjt}}}{\lambda_0+\frac{S_{Tjt}}{1-S_{Tjt}}} = \lambda_1(S_{Tjt},\Theta_{jt})$ as an (unknown) function of S_{Tjt} and Θ_{jt} that must be estimated nonparametrically. Replacing $\lambda_2(S_{Tjt}) = \ln\left(\lambda_1(S_{Tjt})\Lambda(1-S_{Tjt},S_{Tjt})^{\frac{1-\sigma}{\sigma}}\right)$ by $\lambda_2(S_{Tjt},\Theta_{jt}) = \ln\left(\lambda_1(S_{Tjt},\Theta_{jt})\Lambda((1-S_{Tjt})\Theta_{jt},S_{Tjt})^{\frac{1-\sigma}{\sigma}}\right)$ in our estimation equation (12) therefore accounts for types of permanent labor that differ in their qualities and wages.

In constructing the quality index Θ_{jt}, we assume that there are Q types of permanent labor. We approximate the wage premium $\left(\frac{W_{Pqjt}}{W_{P1jt}}-1\right)$ of permanent labor of type q over type 1 by the estimated coefficient on S_{qjt} in the wage regression in Section OA1 and the share $S_{Pqjt} = \frac{L_{Pqjt}}{L_{Pjt}} = \frac{L_{Pqjt}}{L_{jt}}\Big/\frac{L_{Pjt}}{L_{jt}}$ of permanent labor of type q by $\frac{S_{qjt}}{1-S_{Tjt}}$.

OA5 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

$$\nu\mu\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)\exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right)\left(L_{jt}^*\right)^{-\frac{1}{\sigma}}\frac{\partial L_{jt}^*}{\partial L_{Pjt}} = \frac{W_{Pjt}(1+\Delta_{jt})}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)} \quad \text{(OA7)}$$

$$\nu\mu\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)\exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right)\left(L_{jt}^*\right)^{-\frac{1}{\sigma}}\frac{\partial L_{jt}^*}{\partial L_{Tjt}} = \frac{W_{Tjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)} \quad \text{(OA8)}$$

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 (OA7) and (OA8) yields

$$\nu\mu\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)\exp\left(-\frac{1-\sigma}{\sigma}\omega_{Ljt}\right)L_{jt}^{-\frac{1}{\sigma}}\Lambda(1-S_{Tjt},S_{Tjt})^{-\frac{1-\sigma}{\sigma}}$$
$$= \frac{W_{jt}\left(1+\frac{\Delta_{jt}}{1+\frac{W_{Tjt}}{W_{Pjt}}\frac{S_{Tjt}}{1-S_{Tjt}}}\right)}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)} = \frac{W_{jt}\left(\frac{\frac{\Lambda_P(1-S_{Tjt},S_{Tjt})}{\Lambda_T(1-S_{Tjt},S_{Tjt})}+\frac{S_{Tjt}}{1-S_{Tjt}}}{\frac{W_{Pjt}}{W_{Tjt}}+\frac{S_{Tjt}}{1-S_{Tjt}}}\right)}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \qquad \text{(OA9)}$$

where the second equality follows from dividing equations (OA7) and (OA8) and solving for Δ_{jt}.

The first-order condition for in-house materials becomes

$$\nu\mu\beta_M\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)\left(M_{jt}^{*}\right)^{-\frac{1}{\sigma}}\frac{dM_{jt}^{*}}{dM_{Ijt}} = \frac{P_{Ijt}+P_{Ojt}Q_{Mjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}, \qquad \text{(OA10)}$$

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 (OA10) yields

$$\nu\mu\beta_M\left(X_{jt}^{KLM}\right)^{-\left(1+\frac{\nu\tau}{1-\tau}\right)}\left(X_{jt}^{LM}\right)^{\frac{-\sigma}{1-\sigma}\frac{-(1-\tau)}{\tau}-1}\exp\left(\omega_{Hjt}\right)M_{jt}^{-\frac{1}{\sigma}}\Gamma\left(1,\frac{P_{Ijt}}{P_{Ojt}}\frac{S_{Ojt}}{1-S_{Ojt}}\right)^{-\frac{1-\sigma}{\sigma}} = \frac{P_{Mjt}}{P_{jt}\left(1-\frac{1}{\eta(p_{jt},D_{jt})}\right)}. \qquad \text{(OA11)}$$

From the labor and materials decisions in equations (OA9) and (OA11) 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 (12) therefore remains unchanged and our second estimation equation (15) becomes

$$\begin{aligned} y_{jt} &= -\frac{\nu\tau}{1-\tau} x_{jt}^{KLM} \\ &+ g_{Ht-1}(h_H^{KLM}(k_{jt-1}, m_{jt-1}, S_{Mjt-1}, p_{jt-1}, p_{Mjt-1}, D_{jt-1}, S_{Tjt-1}, S_{Ojt-1}), R_{jt-1}) + \xi_{Hjt} + e_{jt}. \end{aligned} \tag{OA12}$$

If $\tau = \sigma$, then equation (OA12) reverts to equation (15). 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.

OA6 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 (12) in the main paper:

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

$\Delta\omega_{Kjt}$ 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.

OA7 Additions to Appendix D: Estimation

Concentrating out. To reduce the number of parameters to search over in the GMM problems corresponding to equations (12) (see also equation (16)) and (15) 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

$$\nu_j(\theta) = y_j(\beta) - w_j(\beta)\gamma, \tag{OA13}$$

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

$$\min_\theta \left[\frac{1}{N}\sum_j A_j(z_j)\nu_j(\theta)\right]' \widehat{W} \left[\frac{1}{N}\sum_j A_j(z_j)\nu_j(\theta)\right] \tag{OA14}$$

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 (OA13) 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 (OA14) 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 (15) and, respectively, equation (12), 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 (15) reappear in equation (12).

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 (16) 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

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

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 $\frac{1}{N}\sum_j \triangledown_{\theta_H} g_H(w_j, \widehat{\theta}_H, \widehat{\theta}_L)$ by its probability limit $G_H = E\left[\triangledown_{\theta_H} g_H(w_j, \theta_{H0}, \theta_{L0})\right]$, replacing $\widehat{W}_H$ by its probability limit W_H, and solving for $\sqrt{N}(\widehat{\theta}_H - \theta_{H0})$ yields

$$\sqrt{N}(\widehat{\theta}_H - \theta_{H0}) = -\left[G_H' W_H G_H\right]^{-1} G_H' W_H \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L) + o_p(1). \quad \text{(OA15)}$$

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

$$\begin{aligned} \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L) &= \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \theta_{L0}) + \left[\frac{1}{N} \sum_j \triangledown_{\theta_L} g_H(w_j, \theta_{H0}, \theta_{L0})\right] \sqrt{N}(\widehat{\theta}_L - \theta_{L0}) \\ &= \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \theta_{L0}) + G_{HL}\sqrt{N}(\widehat{\theta}_L - \theta_{L0}) + o_p(1), \quad \text{(OA16)} \end{aligned}$$

where $G_{HL} = E[\triangledown_{\theta_L} g_H(w_j, \theta_{H0}, \theta_{L0})]$. Because $\widehat{\theta}_L$ is a GMM estimator, it has a similar representation to the one derived for $\widehat{\theta}_H$ in equation (OA15):

$$\sqrt{N}(\widehat{\theta}_L - \theta_{L0}) = -\left[G_L' W_L G_L\right]^{-1} G_L' W_L \frac{1}{\sqrt{N}} \sum_j g_L(w_j, \theta_{L0}) + o_p(1), \quad \text{(OA17)}$$

where $G_L = E\left[\triangledown_{\theta_L} g_L(w_j, \theta_{L0})\right]$. Plugging equation (OA17) into equation (OA16), we have

$$\frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \widehat{\theta}_L) = \frac{1}{\sqrt{N}} \sum_j g_H(w_j, \theta_{H0}, \theta_{L0}) - G_{HL}\left[G_L' W_L G_L\right]^{-1} G_L' W_L \frac{1}{\sqrt{N}} \sum_j g_L(w_j, \theta_{L0}) + o_p(1). \quad \text{(OA18)}$$

Plugging equation (OA18) into equation (OA15), we have

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

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 $g_L(w_j, \widehat{\theta}_L)$.

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Table OA1: Wage regression.

Industry	Wage				Wage regression						
	CV	Var	Within (%)	Betw. (%)	Temp. (s. e.)	White (s. e.)	Engin. (s. e.)	Tech. (s. e.)	R^2	R_Q^2	R_C^2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1. Metals and metal products	0.425	39.025	9.779	29.246	-0.425	0.127	1.106	0.316	0.651	0.094	0.480
			(25.1)	(74.9)	(0.057)	(0.097)	(0.298)	(0.094)			
2. Non-metallic minerals	0.441	36.252	10.072	26.180	-0.098	0.124	0.896	0.246	0.742	0.020	0.643
			(27.8)	(72.2)	(0.065)	(0.159)	(0.280)	(0.181)			
3. Chemical products	0.440	54.332	9.673	44.659	-0.465	0.461	0.592	0.203	0.755	0.197	0.376
			(17.8)	(82.2)	(0.066)	(0.074)	(0.137)	(0.099)			
4. Agric. and ind. machinery	0.354	30.980	11.472	19.508	-0.273	0.285	0.803	-0.028	0.631	0.082	0.484
			(37.0)	(63.0)	(0.067)	(0.105)	(0.226)	(0.125)			
5. Electrical goods	0.383	31.047	8.461	22.586	-0.374	0.219	1.092	0.312	0.661	0.200	0.356
			(27.3)	(72.7)	(0.058)	(0.073)	(0.264)	(0.087)			
6. Transport equipment	0.393	40.666	12.876	27.790	-0.377	0.220	0.402	0.274	0.709	0.066	0.552
			(31.7)	(68.3)	(0.079)	(0.108)	(0.300)	(0.166)			
7. Food, drink and tobacco	0.502	36.590	5.952	30.638	-0.451	0.115	1.292	0.357	0.753	0.097	0.481
			(16.3)	(83.7)	(0.053)	(0.053)	(0.265)	(0.154)			
8. Textile, leather and shoes	0.449	16.565	3.654	12.911	-0.260	0.646	1.584	0.346	0.683	0.140	0.389
			(22.1)	(77.9)	(0.048)	(0.084)	(0.402)	(0.241)			
9. Timber and furniture	0.392	14.646	3.643	11.003	-0.356	0.173	0.288	0.002	0.697	0.061	0.525
			(24.9)	(75.1)	(0.051)	(0.089)	(0.377)	(0.164)			
10. Paper and printing products	0.464	51.667	10.003	41.664	-0.477	0.188	0.444	0.277	0.702	0.070	0.505
			(19.4)	(80.6)	(0.099)	(0.084)	(0.210)	(0.127)			

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Table OA2: 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.

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Table OA3: Wage regression with time trend.

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)	

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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: ω_L R&D-No R&D	$\Delta\omega_L$ R&D	$\Delta\omega_L$ No R&D	Firm turnover, Contributions to $\epsilon_{L,-2}\Delta\omega_L$: Survivors (%)	Entrants (%)	Exitors (%)	Share of eng. and tech. 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
				(90.2)	(7.7)	(2.2)		
2. Non-metallic minerals	1.461	0.089	0.101	0.033	0.000	-0.003	0.053	0.097
				(109.5)	(1.6)	(-11.1)		
3. Chemical products	1.239	0.093	-0.083	0.008	0.007	0.000	0.132	0.214
				(53.5)	(46.7)	(-0.3)		
4. Agric. and ind. machinery	1.537	0.129	0.094	0.027	0.003	0.003	0.083	0.134
				(82.4)	(8.2)	(9.4)		
5. Electrical goods	2.783	0.240	0.054	0.019	0.002	0.001	0.146	0.157
				(86.3)	(9.7)	(4.0)		
6. Transport equipment	0.637	0.287	-0.134	0.029	0.003	0.005	0.066	0.129
				(79.7)	(6.9)	(13.4)		
7. Food, drink and tobacco	-0.064	0.055	0.000	0.006	0.000	0.000	0.050	0.104
				(93.3)	(2.5)	(4.2)		
8. Textile, leather and shoes	0.480	0.026	0.008	0.008	-0.001	0.000	0.032	0.070
				(122.1)	(-16.9)	(-5.2)		
9. Timber and furniture	0.001	0.066[a]	0.063[a]	0.003[a]	-0.002[a]	0.000[a]	0.031	0.066
				(274.1)	(-174.3)	(0.2)		
10. Paper and printing products	0.609	0.006	0.046	0.014	0.000	-0.001	0.071	0.185
				(108.4)	(0.4)	(-8.8)		
All industries		0.148	0.005	0.014	0.002	0.001		
				(85.2)	(9.7)	(5.2)		

[a] We trim values of $\Delta\omega_L$, respectively, $\epsilon_{L,-2}\Delta\omega_L$ below -0.25 and above 0.5.

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
	(76.5)	(14.4)	(9.1)	
2. Non-metallic minerals	0.007	0.001	-0.003	0.408
	(147.1)	(13.9)	(-61.0)	
3. Chemical products	0.018	0.000	0.001	0.302
	(94.3)	(-1.2)	(6.9)	
4. Agric. and ind. machinery	0.036	0.000	0.006	0.171
	(83.9)	(1.1)	(15.0)	
5. Electrical goods	0.030	-0.003	-0.008	0.388
	(156.1)	(-13.9)	(-42.1)	
6. Transport equipment	0.043	0.010	-0.011	0.461
	(100.9)	(23.9)	(-24.7)	
7. Food, drink and tobacco	0.012	-0.012	0.000	0.572
8. Textile, leather and shoes	0.017	-0.006	0.001	0.384
	(144.5)	(-53.0)	(8.5)	
9. Timber and furniture	0.013^b	0.006^b	0.003^b	0.516
	(60.6)	(27.0)	(12.4)	
10. Paper and printing products	0.012	-0.009	-0.003	0.411
All industries	0.019	-0.003	-0.002	
	(140.4)	(-22.8)	(-17.6)	

[a] Without replication and weighting.
[b] We trim values of $\Delta\omega_H$ below -0.25 and above 0.5.

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Table OA7: Capital-augmenting technological change.

Industry	GMM σ (s. e.)	GMM χ^2 (df)	GMM 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	0.987	54.484	0.078	0.052[a]	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				-0.032	

[a] We trim values of $\Delta\omega_K$ below -0.5 and above 0.5.