# A Online Appendix

## A.1 Additional Figures and Tables

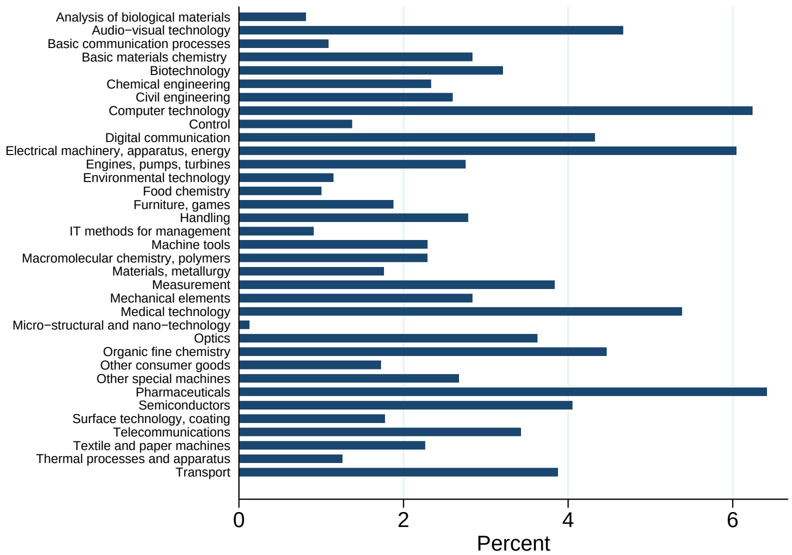
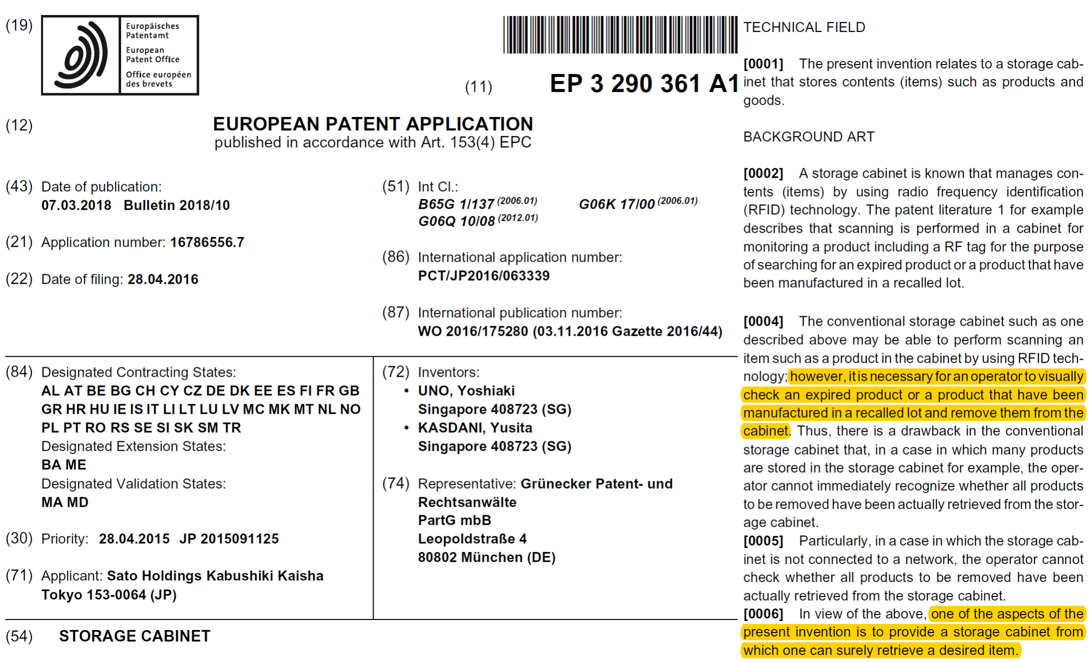



**Figure A.1:** Share of biadic patent applications in the different technical fields in 1997-2011



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(54) STORAGE CABINET

TECHNICAL FIELD

[0001] The present invention relates to a storage cabinet that stores contents (items) such as products and goods.

BACKGROUND ART

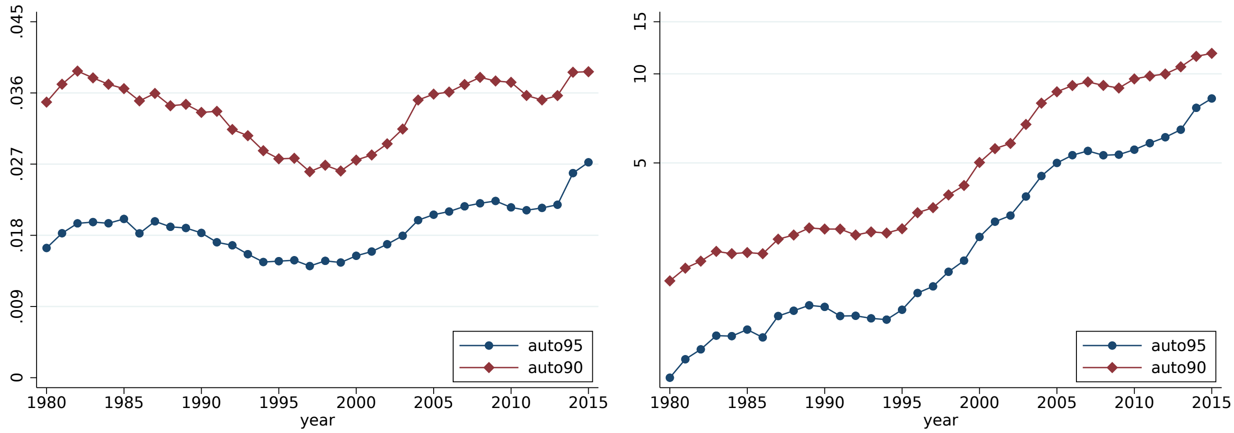
[0002] A storage cabinet is known that manages contents (items) by using radio frequency identification (RFID) technology. The patent literature 1 for example describes that scanning is performed in a cabinet for monitoring a product including a RF tag for the purpose of searching for an expired product or a product that have been manufactured in a recalled lot.

[0004] The conventional storage cabinet such as one described above may be able to perform scanning an item such as a product in the cabinet by using RFID technology; however, it is necessary for an operator to visually check an expired product or a product that have been manufactured in a recalled lot and remove them from the cabinet. Thus, there is a drawback in the conventional storage cabinet that, in a case in which many products are stored in the storage cabinet for example, the operator cannot immediately recognize whether all products to be removed have been actually retrieved from the storage cabinet.

[0005] Particularly, in a case in which the storage cabinet is not connected to a network, the operator cannot check whether all products to be removed have been actually retrieved from the storage cabinet.

[0006] In view of the above, one of the aspects of the present invention is to provide a storage cabinet from which one can surely retrieve a desired item.

**Figure A.2:** Example of an automation patent without keywords




**(a)** Share of automation patents in machinery out of total patents according to the auto90 and auto95 definitions.

**(b)** Number of automation patents worldwide according to the auto90 and auto95 definitions

**Figure A.3:** Trends in automation (for biadic applications)

**Table A.1:** Summary statistics on the prevalence of keywords

| | IPC/CPC 6 digit | | | | | IPC4 + (G05 or G06) | | | | | IPC4 pairs | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Share | all | robot | automat* | CNC | labor | all | robot | automat* | CNC | labor | all | robot | automat* | CNC | labor |
| Mean | 20.9 | 4.3 | 11.2 | 2.4 | 5.9 | 53.2 | 15.4 | 32.4 | 11.2 | 9.5 | 18.5 | 4.5 | 8.8 | 1.8 | 5.4 |
| S. d. | 14.4 | 8.4 | 9.5 | 5.8 | 3.7 | 19.3 | 17.7 | 11 | 16.5 | 3.8 | 16.3 | 10 | 9.9 | 4.7 | 3.8 |
| p25 | 10.5 | 0.8 | 4.2 | 0 | 3.3 | 40 | 6.7 | 26.6 | 0.8 | 2.6 | 7.7 | 0.6 | 2.5 | 0 | 2.6 |
| p50 | 18 | 2 | 8.7 | 0.4 | 5.3 | 54.3 | 10 | 31.9 | 3 | 4.6 | 13.6 | 1.8 | 5.2 | 0.4 | 4.6 |
| p75 | 26.6 | 4.5 | 15.3 | 1.8 | 7.7 | 63.8 | 16 | 40.3 | 15.5 | 7.3 | 23 | 4.2 | 10.7 | 1.4 | 7.3 |
| p90 | 38.7 | 9.1 | 24.3 | 6.1 | 10.4 | 77.9 | 36.4 | 43.3 | 38.2 | 10.4 | 36.8 | 8.9 | 21.7 | 4.4 | 10.4 |
| p95 | 47.7 | 13.7 | 29.4 | 12.7 | 12.7 | 85.6 | 44.3 | 45.2 | 55.3 | 12.3 | 51.8 | 14.5 | 31 | 7.7 | 12.3 |
| p99 | 75 | 35.8 | 43.8 | 33.1 | 17.9 | 90.1 | 82.9 | 59.9 | 56.6 | 17.9 | 84.5 | 60 | 45.3 | 23.1 | 17.9 |

Note: This table computes summary statistics on the share of patents with any automation keywords, robot keywords, automat* keywords, CNC keywords or labor keywords for each type of technological categories (6 digit codes, pairs of 4 digit codes and combinations of ipc4 codes with G05 or G06) within machinery with at least 100 patents.

**Table A.2:** Industry of innovators

| | Industry | Share auto95 (%) | Share firms (%) |
|---|---|---|---|
| 20 | Manufacture of chemicals and chemical products | 2.18 | 3.45 |
| 25 | Manufacture of fabricated metal products, except machinery and equipment | 1.18 | 4.39 |
| 26 | Manufacture of computer, electronic and optical products | 22.83 | 7.42 |
| 27 | Manufacture of electrical equipment | 9.19 | 2.76 |
| 28 | Manufacture of machinery and equipment n.e.c. | 24.52 | 20.97 |
| 29 | Manufacture of motor vehicles, trailers and semi-trailers | 5.31 | 3.48 |
| 30 | Manufacture of other transport equipment | 4.5 | 1.2 |
| 46 | Wholesale trade, except of motor vehicles and motorcycles | 1.34 | 3.3 |
| 64 | Financial service activities, except insurance and pension funding | 1.75 | 0.96 |
| 72 | Scientific research and development | 2.04 | 2.37 |
| | Other industries | 13.23 | 27.15 |
| | No information on industry | 11.94 | 22.5 |

Notes: The table reports the industry of manufacturing of firms included in our baseline regression with industry-year fixed effects at the NACEv2 division level and the share of biadic auto95 families for each industry. Industries representing less than 1% of patents are summed up in the "Other industries" category.

**Table A.3:** Correlation matrix

| | Low-skill wage | Middle-skill wage | High-skill wage | GDP gap | GDP per capita | Labor productivity |
|---|---|---|---|---|---|---|
| Low-skill wage | 1.00 | | | | | |
| Middle-skill wage | 0.94 | 1.00 | | | | |
| High-skill wage | 0.60 | 0.75 | 1.00 | | | |
| GDP gap | -0.06 | -0.05 | -0.03 | 1.00 | | |
| GDP per capita | 0.70 | 0.80 | 0.73 | 0.11 | 1.00 | |
| Labor productivity | 0.67 | 0.73 | 0.77 | 0.04 | 0.66 | 1.00 |

Note: Correlation of residuals for the auto95 sample controlling for firm and year-industry fixed effects.

**Table A.4:** Top 10 auto95 innovators in our sample

| Company | Number of biadic auto95 patents in 1997-2011 |
|---|---|
| Siemens Aktiengesellschaft | 1738 |
| Honda Motor Co., Ltd. | 810 |
| Fanuc Co. | 777 |
| Samsung Electronics Co., Ltd. | 706 |
| Robert Bosch GmbH | 655 |
| Mitsubishi Electric Co. | 652 |
| Tokyo Electron, Ltd. | 578 |
| Murata Machinery, Ltd. | 501 |
| Kabushiki Kaisha Toshiba | 473 |
| General Electric Company | 464 |

**Table A.5:** Baseline regressions for auto95 with country-level clustering

| Dependent variable | Auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | 2.21*** | 2.83*** | 1.80*** | 2.46*** | 2.32*** | 2.54*** | 2.90*** | 2.67*** | 3.59*** |
| | (0.54) | (0.73) | (0.63) | (0.61) | (0.77) | (0.70) | (0.65) | (0.74) | (1.04) |
| | [0.000] | [0.000] | [0.004] | [0.000] | [0.002] | [0.000] | [0.000] | [0.000] | [0.001] |
| | {0.000} | {0.002} | {0.030} | {0.031} | {0.038} | {0.094} | {0.008} | {0.019} | {0.015} |
| High-skill wage | | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| GDP gap | | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Labor productivity | | | | | Yes | | | Yes | |
| GDP per capita | | | | | | Yes | | | Yes |
| Stocks | | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Spillovers | | | | | | | Yes | Yes | Yes |
| Fixed effects | F+Y | F+Y | F+Y | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY |
| Observations | 50115 | 50115 | 50115 | 49174 | 49174 | 49174 | 49174 | 49174 | 49174 |
| Firms | 3341 | 3341 | 3341 | 3329 | 3329 | 3329 | 3329 | 3329 | 3329 |

Note: This table reproduces the baseline table but clusters standard errors at the country-level. [ ] brackets correspond to the p-value associated with estimated standard errors, { } brackets correspond to the p-values associated with the clustered standard errors following Cameron et. (2008). See text for details. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

## Table A.6: Auto90 innovations

| Dependent variable | Auto90 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | 2.19*** | 1.95*** | 3.10*** | 1.57* | 1.57* | 2.61** | 3.02*** | 3.49*** | 3.46** |
| | (0.65) | (0.67) | (0.77) | (0.81) | (0.87) | (1.03) | (1.12) | (1.30) | (1.42) |
| High-skill wage | -1.85*** | -2.27*** | -0.85 | -1.78** | -1.76* | -1.09 | -3.50*** | -2.80** | -3.24*** |
| | (0.59) | (0.65) | (0.65) | (0.80) | (0.91) | (0.85) | (1.14) | (1.30) | (1.22) |
| GDP gap | -3.85* | -4.41** | -1.53 | 4.47 | 4.49 | 6.23 | -0.95 | 0.06 | -0.09 |
| | (2.10) | (2.14) | (2.25) | (5.20) | (5.29) | (5.37) | (3.25) | (3.52) | (3.66) |
| Labor productivity | | 0.95 | | | -0.03 | | | -1.11 | |
| | | (0.73) | | | (1.29) | | | (1.32) | |
| GDP per capita | | | -2.60** | | | -2.55* | | | -0.79 |
| | | | (1.03) | | | (1.45) | | | (1.53) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 72721 | 72721 | 72721 | 72439 | 72439 | 72439 | 72439 | 72439 | 72439 |
| Firms | 4890 | 4890 | 4890 | 4887 | 4887 | 4887 | 4887 | 4887 | 4887 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Stock and spillover variables are calculated with respect to the dependent variable (auto90). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

## Table A.7: Wages weighted by inventor weights

| Dependent variable | Auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | 2.99*** | 2.39*** | 3.39*** | 2.15** | 2.30** | 3.44*** | 5.53*** | 6.39*** | 5.37*** |
| | (0.87) | (0.92) | (1.08) | (1.03) | (1.17) | (1.32) | (1.63) | (1.81) | (2.08) |
| Low-skill wage (iw) | -0.22 | 0.12 | 0.10 | -0.02 | 0.26 | 0.14 | 0.00 | 0.74 | 0.71 |
| | (0.44) | (0.45) | (0.47) | (0.45) | (0.45) | (0.47) | (0.53) | (0.58) | (0.54) |
| High-skill wage | -2.59*** | -3.45*** | -2.04** | -3.02*** | -2.60** | -2.15** | -5.15*** | -4.53*** | -5.66*** |
| | (0.85) | (0.93) | (0.87) | (1.02) | (1.09) | (1.08) | (1.58) | (1.65) | (1.67) |
| High-skill wage (iw) | 0.41 | 0.90** | 0.58 | 0.18 | 0.60 | 0.24 | -0.27 | 1.01* | 0.21 |
| | (0.39) | (0.43) | (0.40) | (0.37) | (0.41) | (0.39) | (0.47) | (0.52) | (0.51) |
| GDP gap | -8.38** | -9.83*** | -6.89* | 1.83 | 1.69 | 4.16 | -2.28 | -1.22 | -3.06 |
| | (3.67) | (3.66) | (3.85) | (6.02) | (5.97) | (6.28) | (4.26) | (4.27) | (4.72) |
| GDP gap (iw) | 3.25 | 3.89 | 3.52 | 1.94 | 2.43 | 2.05 | 2.50 | 3.35* | 3.89 |
| | (2.51) | (2.41) | (2.64) | (2.68) | (2.49) | (2.83) | (2.29) | (1.86) | (2.38) |
| Labor productivity | | 2.10* | | | -0.91 | | | -1.54 | |
| | | (1.12) | | | (1.75) | | | (1.62) | |
| Labor productivity (iw) | | -1.14** | | | -1.02* | | | -2.08*** | |
| | | (0.54) | | | (0.54) | | | (0.65) | |
| GDP per capita | | | -1.27 | | | -3.16* | | | 0.81 |
| | | | (1.43) | | | (1.86) | | | (2.29) |
| GDP per capita (iw) | | | -0.66 | | | -0.29 | | | -1.41** |
| | | | (0.59) | | | (0.63) | | | (0.61) |
| Stock automation | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock other | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 48376 | 48376 | 48376 | 47977 | 47977 | 47977 | 36234 | 36234 | 36234 |
| Firms | 3274 | 3274 | 3274 | 3268 | 3268 | 3268 | 2480 | 2480 | 2480 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson fixed-effects regressions (HHG) in Columns (1), (3), and (5). In Columns (2), (4), and (6), estimation is done by Poisson regressions where the firm fixed effects are replaced by the pre-sample mean, following Blundell, Griffith and Van Reenen (1999, BGVR). All columns include industry-year fixed effects and Columns (3) to (6) include country-year fixed effects. In Columns (5) and (6) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.8:** Predicting weights using subsequent wages

| | | | | | *Panel A* | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Dependent variable | | | | | $\omega_{i,c,1995}$ | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $g_{LSW,2000}$ | -0.14 | -0.14 | -0.27 | -0.14 | -0.14 | -0.27 | -0.12 | -0.12 | -0.13 |
| | (0.12) | (0.12) | (0.28) | (0.12) | (0.12) | (0.28) | (0.12) | (0.12) | (0.29) |
| $g_{HSW,2000}$ | | | 0.13 | | | 0.13 | | | 0.01 |
| | | | (0.24) | | | (0.24) | | | (0.27) |
| Firm fixed effect | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Clustering | C | C | C | F + C | F + C | F + C | C | C | C |
| Observations | 136981 | 136981 | 136981 | 136981 | 136981 | 136981 | 136981 | 136981 | 136981 |
| Firms | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 |
| | | | | | *Panel B* | | | | |
| Dependent variable | | | | | $foreign\_\omega_{i,c,1995}$ | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $g_{LSW,2000}$ | -0.10 | -0.10 | -0.31 | -0.10 | -0.10 | -0.31 | -0.10 | -0.10 | -0.33 |
| | (0.11) | (0.11) | (0.26) | (0.11) | (0.11) | (0.26) | (0.12) | (0.12) | (0.30) |
| $g_{HSW,2000}$ | | | 0.20 | | | 0.20 | | | 0.23 |
| | | | (0.21) | | | (0.21) | | | (0.24) |
| Firm fixed effect | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Clustering | C | C | C | F + C | F + C | F + C | C | C | C |
| Observations | 133640 | 133640 | 133640 | 133640 | 133640 | 133640 | 133640 | 133640 | 133640 |
| Firms | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 | 3341 |

Note: OLS regressions of firm-level weights/foreign weights on country growth rates for low-skill and high-skill wages between 1995 and 2000. Columns (2), (3), (5), (6), (8) and (9) include firm fixed effects. Columns (7)-(9) weigh observations by the number of auto95 patents between 1997 and 2011. Standard errors are clustered at the country-level for columns (1)-(3), (7)-(9)and clustered at both the country and firm levels for (4)-(6). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.9:** Alternative weights

| Dependent variable | Auto95 | | | | | |
|---|---|---|---|---|---|---|
| | 1970–1989 | 1985–1994 | start 2000 | $GDP^0$ | $GDP^1$ | $(w_L \cdot L)^{0.35}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Foreign:* | | | | | | |
| Low-skill wage | 5.07*** | 4.98*** | 6.81*** | 4.12*** | 5.81*** | 5.11*** |
| | (1.88) | (1.48) | (2.10) | (1.37) | (1.68) | (1.50) |
| High-skill wage | -3.41** | -1.51 | -3.56* | -3.74*** | -3.19** | -3.40** |
| | (1.66) | (1.52) | (2.03) | (1.32) | (1.62) | (1.32) |
| GDP gap | 1.70 | 2.19 | -0.47 | -3.44 | -1.83 | -1.19 |
| | (4.13) | (4.72) | (3.78) | (3.56) | (3.85) | (3.66) |
| Labor productivity | -2.03 | -3.53** | -4.38** | -1.29 | -1.59 | -2.03 |
| | (1.75) | (1.58) | (1.74) | (1.42) | (1.57) | (1.55) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 34710 | 44476 | 26577 | 48665 | 48802 | 48679 |
| Firms | 2386 | 3031 | 2695 | 3323 | 3322 | 3325 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm, country-year and industry-year fixed effects. In column (1) firms' country weights for the macroeconomic variables are computed over the period 1970–1989; and over the period 1985–1994 for column (2). Columns (3) to (6) use the baseline pre-sample period of 1970–1994. Column (3) restricts the sample to the years 2000–2009. Column (4) does not adjust for GDP in the computation of the weights; Column (5) uses GDP instead of $GDP^{0.35}$ to adjust for country size and Column (6) replaces GDP with total low-skilled payment $wL$ in the baseline formula. In all columns the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.10:** Excluding one country at the time

| Dependent Variable | Auto95 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Excl. country | None | US | DE | JP | GB | FR | IT | ES |
| Average weight | | 0.21 | 0.20 | 0.17 | 0.09 | 0.09 | 0.03 | 0.03 |
| | (0) | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Foreign*: | | | | | | | | |
| Low-skill wage | 5.08*** | 5.41*** | 3.60*** | 3.43*** | 4.78*** | 3.60** | 5.20*** | 4.84*** |
| | (1.54) | (1.68) | (1.37) | (1.33) | (1.33) | (1.48) | (1.45) | (1.51) |
| High-skill wage | -2.95** | -2.74* | -1.72 | -1.57 | -0.82 | -2.31* | -4.62** | -2.51* |
| | (1.46) | (1.46) | (1.26) | (1.29) | (1.34) | (1.33) | (1.90) | (1.48) |
| GDP gap | 1.29 | 0.73 | 2.62 | 1.59 | 1.99 | 0.97 | 1.19 | 1.05 |
| | (4.84) | (5.14) | (5.58) | (3.88) | (4.85) | (5.02) | (5.13) | (4.90) |
| Labor productivity | -2.15 | -3.39** | -2.26 | -1.43 | -3.24** | -1.49 | -0.73 | -2.35 |
| | (1.58) | (1.67) | (1.39) | (1.48) | (1.58) | (1.48) | (1.63) | (1.56) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+CY+IY | F+CY+IY | F+CY+IY | F+CY+IY | F+CY+IY | F+CY+IY | F+CY+IY | F+CY+IY |
| Control | | $\omega_c * Y$ | $\omega_c * Y$ | $\omega_c * Y$ | $\omega_c * Y$ | $\omega_c * Y$ | $\omega_c * Y$ | $\omega_c * Y$ |
| Observations | 48773 | 47997 | 48319 | 48594 | 48391 | 48713 | 48638 | 48702 |
| Firms | 3324 | 3270 | 3291 | 3312 | 3299 | 3320 | 3315 | 3319 |

Notes: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions effects (HHG). All columns include firm, industry-year and country-year fixed effects. In Column (0), the macroeconomic variables are the normalized foreign variables previously defined. Columns (1) to (7) further exclude the country in the column header in addition to the domestic country when computing the normalized foreign macroeconomic variables. Columns (1) to (7) also control for the weight of the header-country times year dummies. The average weight is the average country weight for firms in the sample of Column (0). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.16:** Addressing Nickell's bias

| Dependent variable | Auto95 | | | | | |
|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | Foreign | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Low-skill wage | 2.64*** | 2.41*** | 2.67** | 2.85*** | 4.71*** | 4.09*** |
| | (0.79) | (0.83) | (1.05) | (1.08) | (1.42) | (1.39) |
| High-skill wage | -2.46*** | -0.81 | -2.30** | -1.26 | -2.78** | -1.55 |
| | (0.77) | (0.79) | (0.99) | (1.00) | (1.39) | (1.50) |
| GDP gap | -4.71* | -2.66 | 4.51 | 8.28 | 0.73 | 1.20 |
| | (2.73) | (3.52) | (7.05) | (7.72) | (4.92) | (5.47) |
| Labor productivity | 0.81 | 0.09 | -1.32 | -1.90 | -1.66 | -1.53 |
| | (0.90) | (1.04) | (1.67) | (1.53) | (1.48) | (1.52) |
| Stock automation | No | Yes | No | Yes | No | Yes |
| Stock other | Yes | Yes | Yes | Yes | Yes | Yes |
| Spillovers | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Estimator | HHG | BGVR | HHG | BGVR | HHG | BGVR |
| Observations | 49174 | 49174 | 48773 | 48787 | 48773 | 48787 |
| Firms | 3329 | 3329 | 3324 | 3326 | 3324 | 3326 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG) in columns (1), (3), and (5). In columns (2), (4), and (6), estimation is done by Poisson regressions where the firm fixed effects are replaced by the pre-sample mean, following Blundell, Griffith and Van Reenen (1999, BGVR). Columns (1) and (2) include year-industry fixed effects and columns (3) to (6) include year-industry and country-year fixed effects. In Columns (5) and (6) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.11:** Lags and leads

| Dependent variable | Auto95 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Lags (Leads) | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Low-skill wage | 2.08*** | 2.53*** | 2.66*** | 2.67*** | 2.34*** | 2.60*** | 2.45*** | 1.48* |
| | (0.76) | (0.78) | (0.81) | (0.84) | (0.83) | (0.82) | (0.84) | (0.82) |
| High-skill wage | -1.23* | -2.16*** | -3.04*** | -2.61*** | -2.75*** | -3.12*** | -2.94*** | -2.80*** |
| | (0.74) | (0.76) | (0.78) | (0.79) | (0.76) | (0.81) | (0.76) | (0.72) |
| Labor productivity | 1.17 | 1.46* | 2.11** | 0.91 | 0.54 | 0.11 | 0.03 | 0.51 |
| | (0.81) | (0.84) | (0.88) | (0.92) | (0.89) | (0.91) | (0.93) | (0.92) |
| Fixed effects | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY |
| Observations | 46783 | 47422 | 48514 | 49174 | 49657 | 50216 | 51262 | 52659 |
| Firms | 3156 | 3202 | 3279 | 3329 | 3368 | 3412 | 3490 | 3587 |
| | Panel B: country-year fixed effects | | | | | | | |
| Low-skill wage | 1.81* | 1.89* | 2.15* | 2.55** | 2.27** | 2.04* | 1.85 | 0.88 |
| | (1.03) | (1.10) | (1.10) | (1.13) | (1.13) | (1.12) | (1.15) | (1.10) |
| High-skill wage | -0.05 | -1.32 | -1.98* | -2.16** | -2.51** | -3.17*** | -2.95*** | -2.19** |
| | (1.20) | (1.12) | (1.03) | (1.05) | (1.15) | (1.15) | (1.06) | (1.07) |
| Labor productivity | -1.91 | -1.03 | -0.70 | -1.68 | -0.92 | -0.17 | 0.13 | -0.13 |
| | (1.65) | (1.58) | (1.58) | (1.76) | (1.85) | (1.75) | (1.69) | (1.57) |
| | Panel C: country-year fixed effects and foreign variables | | | | | | | |
| Low-skill wage | 2.41 | 3.04** | 4.05*** | 5.08*** | 3.82** | 2.80* | 2.55 | 1.62 |
| | (1.50) | (1.52) | (1.55) | (1.54) | (1.55) | (1.65) | (1.76) | (1.77) |
| High-skill wage | 0.41 | -2.12 | -3.30** | -2.95** | -4.08*** | -5.03*** | -5.07*** | -3.71** |
| | (1.53) | (1.50) | (1.48) | (1.46) | (1.56) | (1.56) | (1.52) | (1.58) |
| Labor productivity | -1.77 | -0.61 | -0.92 | -2.15 | 0.35 | 2.07 | 2.57 | 1.78 |
| | (1.64) | (1.65) | (1.61) | (1.58) | (1.60) | (1.71) | (1.76) | (1.78) |
| Fixed effects | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 46461 | 47136 | 48172 | 48773 | 49236 | 49810 | 50857 | 52253 |
| Firms | 3156 | 3202 | 3277 | 3324 | 3361 | 3406 | 3484 | 3584 |

Marginal effects; Standard errors in parentheses. Each panel represents a different regression. All regressions contain controls for GDP gap, stocks and spillovers, for which we do not report the coefficients. The independent variables (wages, labor productivity, GDP gap and spillovers) are lagged by the number of periods indicated in lag, except for the stock variables which are always lagged by 2 periods. Estimation is done by conditional Poisson regressions fixed-effects (HHG). Panel A regressions contain firm and industry-year fixed effects. Panels B and C add country-year fixed effects. In Panel C the macroeconomic variables are their foreign normalized values previously definted. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.12:** Placebo regressions: long leads

| Dependent variable | Auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | | | Foreign | | |
| | $t+5$ | $t+10$ | $t+15$ | $t+5$ | $t+10$ | $t+15$ | $t+5$ | $t+10$ | $t+15$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | -0.34 | -1.77 | -1.39 | -0.41 | -1.35 | -1.71** | 0.65 | 2.44 | 0.81 |
| | (0.79) | (1.08) | (1.13) | (0.66) | (0.83) | (0.78) | (1.32) | (1.78) | (1.95) |
| High-skill wage | 1.83** | 0.53 | -0.64 | 0.12 | 0.68 | -0.33 | 2.62** | -1.36 | -1.67 |
| | (0.89) | (1.54) | (1.27) | (0.58) | (0.89) | (0.81) | (1.19) | (2.03) | (2.03) |
| GDP gap | -0.91 | 3.36 | 3.24 | -4.01 | -0.34 | 7.88*** | 2.05 | 7.82* | 5.61 |
| | (8.66) | (6.29) | (5.70) | (3.17) | (2.64) | (3.04) | (4.14) | (4.41) | (4.12) |
| Labor productivity | -1.04 | 1.27 | -0.38 | 0.61 | -0.07 | -0.57 | -2.33* | -4.24*** | -2.51 |
| | (1.14) | (1.91) | (1.73) | (0.77) | (0.94) | (0.96) | (1.29) | (1.47) | (1.54) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 51124 | 59393 | 62059 | 51506 | 59917 | 62670 | 51124 | 59393 | 62059 |
| Firms | 3850 | 4177 | 4284 | 3859 | 4183 | 4290 | 3850 | 4177 | 4284 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are led by 5 periods (Columns (1), (4) and (5)) 10 periods (Columns (2), (5) and (8)) or 15 periods (Columns (3), (6) and (9)), except the stock variables which are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Columns (1)-(3) include firm and industry year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9), the macroeconomi variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p <$ 0.05; *** $p < 0.01$

**Table A.13:** Predicted wages

| Dependent variable | Auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | 2.38*** | 1.77** | 2.40*** | 1.60* | 1.47 | 1.61* | 3.79*** | 4.03*** | 3.78*** |
| | (0.80) | (0.81) | (0.81) | (0.92) | (1.01) | (0.93) | (1.28) | (1.37) | (1.29) |
| High-skill wage | -2.77*** | -4.79*** | -2.81*** | -3.38*** | -3.78*** | -3.39*** | -4.35*** | -3.79** | -4.34*** |
| | (0.81) | (1.08) | (0.82) | (1.01) | (1.38) | (1.02) | (1.31) | (1.52) | (1.32) |
| GDP gap | -4.90* | -4.23* | -4.95* | 4.10 | 4.09 | 4.11 | -0.86 | -0.36 | -0.81 |
| | (2.56) | (2.51) | (2.56) | (6.78) | (6.79) | (6.78) | (4.45) | (4.51) | (4.49) |
| Labor productivity | | 2.92*** | | | 0.59 | | | -0.92 | |
| | | (0.95) | | | (1.54) | | | (1.48) | |
| GDP per capita | | | 0.12 | | | 0.02 | | | -0.02 |
| | | | (0.10) | | | (0.12) | | | (0.14) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 49174 | 49174 | 49174 | 48773 | 48773 | 48773 | 48773 | 48773 | 48773 |
| Firms | 3329 | 3329 | 3329 | 3324 | 3324 | 3324 | 3324 | 3324 | 3324 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). We estimate for each country an AR(1) process with time trends for wages, labor productivity, and GDP per capita. We then use the estimated process to predict with the information available at time t-2 the average values between the years t+2 and t+7, which are in turn the independent variables in these regressions. Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Stock and spillover variables are calculated with respect to the dependent variable. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

## Table A.14: Minimum wage

| Dependent variable | Auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Minimum wage | 2.10*** | 1.85*** | 2.11*** | 1.79** | 1.92** | 1.92* | 2.15* | 2.20* | 0.92 |
| | (0.62) | (0.63) | (0.78) | (0.88) | (0.92) | (1.04) | (1.17) | (1.24) | (1.38) |
| High-skill wage | -1.88*** | -2.50*** | -1.86** | -3.69*** | -3.17*** | -3.46** | -3.35** | -3.19* | -5.35*** |
| | (0.66) | (0.79) | (0.82) | (1.01) | (1.22) | (1.40) | (1.36) | (1.84) | (1.85) |
| GDP gap | -2.99 | -3.89 | -2.96 | 7.05 | 7.72 | 7.55 | 2.79 | 2.97 | -2.52 |
| | (2.46) | (2.55) | (2.74) | (6.42) | (6.50) | (7.00) | (4.72) | (5.21) | (6.10) |
| Labor productivity | | 1.22 | | | -0.94 | | | -0.20 | |
| | | (0.79) | | | (1.48) | | | (1.62) | |
| GDP per capita | | | -0.04 | | | -0.47 | | | 4.11* |
| | | | (1.22) | | | (1.98) | | | (2.49) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 49129 | 49129 | 49129 | 48757 | 48757 | 48757 | 47577 | 47577 | 47577 |
| Firms | 3326 | 3326 | 3326 | 3322 | 3322 | 3322 | 3237 | 3237 | 3237 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed effects regressions (HHG). Columns (1)-(3) include firm and year-industry fixed effects, while (4)-(9) include firm, year-industry, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

## Table A.17: Citations-weighted patents

| Dependent variable | Citations-weighted auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic+Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | 2.06** | 1.79 | 3.28*** | 1.28 | 1.62 | 3.53** | 3.39** | 4.16** | 3.80* |
| | (1.00) | (1.10) | (1.14) | (1.22) | (1.45) | (1.50) | (1.72) | (1.87) | (2.21) |
| High-skill wage | -2.38** | -2.88*** | -0.97 | -3.26** | -2.41* | -1.71 | -4.00** | -3.02 | -3.77** |
| | (0.96) | (0.99) | (1.07) | (1.27) | (1.30) | (1.40) | (1.64) | (1.89) | (1.76) |
| GDP gap | -3.80 | -4.47 | -0.74 | 0.53 | 1.75 | 4.62 | -0.69 | 1.01 | 0.11 |
| | (3.15) | (3.36) | (3.26) | (7.80) | (7.97) | (7.98) | (5.06) | (5.47) | (5.71) |
| Labor productivity | | 1.15 | | | -1.90 | | | -1.63 | |
| | | (1.23) | | | (2.29) | | | (1.80) | |
| GDP per capita | | | -3.54** | | | -5.60** | | | -0.71 |
| | | | (1.63) | | | (2.35) | | | (2.61) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | | | |
| Fixed effects | F+IY | F+IY | F+IY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 49174 | 49174 | 49174 | 48773 | 48773 | 48773 | 48773 | 48773 | 48773 |
| Firms | 3329 | 3329 | 3329 | 3324 | 3324 | 3324 | 3324 | 3324 | 3324 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Patents are citations-weighted: we add to each patent the number of citations received within 5 years normalized by technological field and year of application. Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.15:** Five-year difference estimation

| Dependent Variable | Δ Arcsinhauto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic + Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Panel A: Firms which patented at least once in 1995-2013* | | | | | | | | | |
| Δ Low-skill wage | 0.94*** | 0.91*** | 0.98*** | 0.70** | 0.59 | 0.49 | 1.10** | 0.74 | 0.46 |
| | (0.27) | (0.29) | (0.32) | (0.34) | (0.37) | (0.43) | (0.49) | (0.56) | (0.61) |
| Δ High-skill wage | -0.95*** | -1.00*** | -0.91*** | -0.99*** | -1.21*** | -1.14*** | -1.20** | -1.62*** | -1.60*** |
| | (0.25) | (0.28) | (0.28) | (0.35) | (0.40) | (0.38) | (0.51) | (0.58) | (0.54) |
| Δ GDP gap | -1.45 | -1.55 | -1.38 | -0.19 | -0.50 | -0.36 | -0.41 | -1.27 | -1.80 |
| | (1.07) | (1.07) | (1.15) | (2.18) | (2.19) | (2.22) | (1.42) | (1.65) | (1.74) |
| Δ Labor productivity | | 0.12 | | | 0.50 | | | 0.75 | |
| | | (0.39) | | | (0.59) | | | (0.56) | |
| Δ GDP per capita | | | -0.10 | | | 0.54 | | | 1.22* |
| | | | (0.44) | | | (0.60) | | | (0.66) |
| Fixed effects | IY | IY | IY | CY + IY | CY + IY | CY + IY | CY + IY | CY + IY | CY + IY |
| Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 35310 | 35310 | 35310 | 35280 | 35280 | 35280 | 35280 | 35280 | 35280 |
| Firms | 3531 | 3531 | 3531 | 3528 | 3528 | 3528 | 3528 | 3528 | 3528 |
| *Panel B: Firms which patented at least twice in 1995-2013* | | | | | | | | | |
| Δ Low-skill wage | 1.87*** | 1.86*** | 1.87*** | 1.42*** | 1.40** | 1.26* | 2.43*** | 1.96** | 1.74* |
| | (0.43) | (0.47) | (0.53) | (0.54) | (0.60) | (0.70) | (0.76) | (0.88) | (0.96) |
| Δ High-skill wage | -1.74*** | -1.75*** | -1.74*** | -1.88*** | -1.92*** | -2.00*** | -2.36*** | -2.91*** | -2.79*** |
| | (0.39) | (0.44) | (0.45) | (0.56) | (0.64) | (0.61) | (0.77) | (0.89) | (0.84) |
| Δ GDP gap | -2.38 | -2.39 | -2.37 | -2.06 | -2.11 | -2.19 | -0.81 | -1.92 | -2.29 |
| | (1.46) | (1.47) | (1.60) | (3.20) | (3.24) | (3.28) | (2.09) | (2.46) | (2.61) |
| Δ Labor productivity | | 0.02 | | | 0.09 | | | 0.96 | |
| | | (0.60) | | | (0.94) | | | (0.89) | |
| Δ GDP per capita | | | -0.01 | | | 0.42 | | | 1.28 |
| | | | (0.71) | | | (0.98) | | | (1.06) |
| Fixed effects | IY | IY | IY | CY + IY | CY + IY | CY + IY | CY + IY | CY + IY | CY + IY |
| Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 22650 | 22650 | 22650 | 22630 | 22630 | 22630 | 22630 | 22630 | 22630 |
| Firms | 2265 | 2265 | 2265 | 2263 | 2263 | 2263 | 2263 | 2263 | 2263 |

Note: Marginal effects; Standard errors in parentheses. Estimation is done by OLS. $t = 2000 - 2009$: The dependent variable is the difference between the arcsinh of the sum of yearly auto95 patents in $t$ to $t+4$ and the arcsinh of the sum of yearly auto95 patents in $t-5$ to $t-1$. Columns (1)-(3) include industry-year fixed effect, while (4)-(9) include industry-year and country-year fixed effects. In Columns (7) to (9) the macroeconomic variables are the normalized foreign variables previously defined. All the independent variables are the sum of yearly counterparts from $t-4$ to $t$. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.18:** Wages and deflators

| Dependent variable | Auto95 | | | | |
|---|---|---|---|---|---|
| Sector | Manufacturing | | | Total | |
| Deflator | Manufacturing PPI, conversion in 2005 | US manufacturing PPI, conversion every year | GDP deflator, conversion in 1995 | Manufacturing PPI, conversion in 1995 | US manufacturing PPI, conversion every year |
| | (1) | (2) | (3) | (4) | (5) |
| *Foreign:* | | | | | |
| Low-skill wage | 5.00*** | 4.24*** | 4.88** | 5.23* | 4.75** |
| | (1.51) | (1.41) | (1.93) | (2.80) | (2.03) |
| High-skill wage | -2.68* | -3.60** | -2.58* | -2.58 | -3.43 |
| | (1.38) | (1.42) | (1.48) | (2.27) | (2.23) |
| GDP gap | 1.53 | 0.49 | 1.40 | 0.15 | -0.52 |
| | (4.78) | (4.82) | (4.84) | (4.42) | (4.55) |
| Labor productivity | -2.40 | -1.10 | -2.32 | -2.85 | -2.24 |
| | (1.51) | (1.56) | (1.62) | (3.06) | (2.90) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY | F+IY+CY |
| Observations | 48773 | 48773 | 48773 | 48773 | 48773 |
| Firms | 3324 | 3324 | 3324 | 3324 | 3324 |

Note: All regressions include firm fixed effects, industry-year fixed effects and country-year fixed effects. Columns (1) to (3) use manufacturing wages and Columns (4) and (5) on total wages. In Column (1), macroeconomic variables are deflated with the local manufacturing PPI and converted to USD in 2005. In Columns (2) and (5) they are converted to USD every year and deflated with the US manufacturing PPI. In Column (3), macroeconomic variables are deflated with the local GDP deflator and converted to USD in 1995. In Column (4), macroeconomic variables are deflated with the local manufacturing PPI and converted to USD in 1995. In all columns, the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

**Table A.19:** Firm bin size - year fixed effects

| Dependent Variable | Auto95 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Domestic + Foreign | | | | | | Foreign | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Low-skill wage | 3.03*** | 2.78*** | 3.56*** | 2.31** | 2.70** | 3.57*** | 4.34*** | 5.51*** | 4.36** |
| | (0.79) | (0.84) | (0.95) | (0.98) | (1.12) | (1.24) | (1.31) | (1.54) | (1.77) |
| High-skill wage | -2.29*** | -2.70*** | -1.77** | -2.85*** | -2.01* | -2.02* | -4.52*** | -2.87* | -4.50*** |
| | (0.71) | (0.77) | (0.79) | (0.94) | (1.07) | (1.04) | (1.32) | (1.47) | (1.40) |
| GDP gap | -3.32 | -3.89 | -2.11 | 3.95 | 5.01 | 6.11 | -0.68 | 1.78 | -0.63 |
| | (2.67) | (2.78) | (2.83) | (6.76) | (6.80) | (7.06) | (4.54) | (4.81) | (5.15) |
| Labor productivity | | 0.99 | | | -1.92 | | | -2.67* | |
| | | (0.90) | | | (1.77) | | | (1.62) | |
| GDP per capita | | | -1.46 | | | -3.09 | | | -0.04 |
| | | | (1.30) | | | (1.90) | | | (2.06) |
| Stocks / Spillovers | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed effects | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY | F+IY |
| | BY | BY | BY | BY | BY | BY | BY+CY | BY+CY | BY+CY |
| Observations | 49935 | 49935 | 49935 | 49890 | 49890 | 49890 | 49890 | 49890 | 49890 |
| Firms | 3329 | 3329 | 3329 | 3326 | 3326 | 3326 | 3326 | 3326 | 3326 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Firms are classified into five bins by the stock of total patents in 1995 with 25th, 50th, 75th and 95th percentiles as four thresholds. Columns (1)-(3) include firm, indsutry-year (IY) and bin-year (BY) fixed effects, while (4)-(9) include firm, indsutry-year, bin-year and country-year fixed effects. In Columns (7) to (9) the macroeconomic variables are the normalized foreign variables previously defined. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

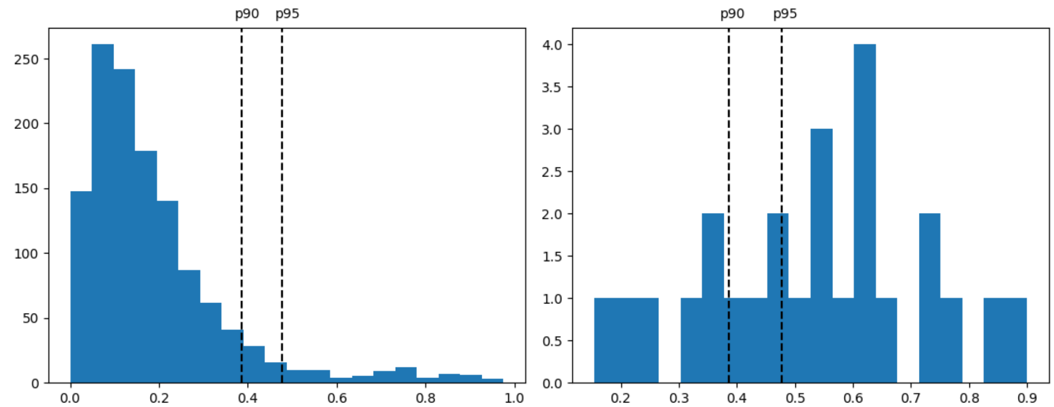
## A.2 Details on the classification of automation patents

We derived the exact list of keywords in Table 1 after experimenting extensively with variations around them and looking at the resulting classification of technology categories and the associated patents. Relative to the original list of technologies given in the SMT, we did not include keywords related to information network, as these seem less related to the automation of the production process and the patents containing words such as "local area network" do not appear related to automation. We also did not count all laser patents as they are not all related to automation—but we obtain patents related to automation using laser technologies thanks to our other keywords. Furthermore, the Y section of the CPC classification is organized differently from the rest and is only designed to provide additional information. As a result, we ignore Y codes throughout.

### A.2.1 Statistics on the classification

Table A.1 gives summary statistics on the prevalence of automation keywords across technology categories in machinery, $p(t)$, as well as the prevalence of the 4 main subgroups of keywords: automat*, robot, numerical control (CNC) and labor. The $95^{th}$ and $90^{th}$ percentile for the prevalence of automation keywords for 6-digit codes in machinery define the thresholds used to categorize auto95 and auto90 patents. The distributions are quite similar for the C/IPC 6 digit codes and for pairs of IPC 4 digit codes (see also the histograms below). As expected, the distributions are significantly shifted to the right for combinations of C/IPC 4-digit codes with G05 or G06. All prevalence measures are right-skewed particularly for 6-digit codes and 4-digit pairs, and even more for the robot and CNC patents. The automat* keywords are also more common as the prevalence of automat* is significantly higher than for the other keywords. Yet, the difference narrows somewhat in the right tail: the $95^{th}$ percentile for 6 digit codes is 29.4% for automat* and 13.7% and 12.7% for robot and CNC. In fact, the thresholds (5 and 2) used in the definition of the automat* keywords were chosen so that the distributions of the prevalence measures are somewhat comparable. The right tails of the distribution are similar for the prevalence of the robot and CNC keywords.

Figure A.4.a gives the histograms of the prevalence of automation keywords for machinery technology categories which are pairs of C/IPC 4-digit codes. The histograms are very similar to those of C/IPC 6 digit codes in Figure 1. Figure A.4.b shows the histograms for all combinations of machinery C/IPC 4-digit codes with G05 or G06. The distribution is considerably shifted to the right, in line with expectations since G05




**(a)** For all pairs of C/IPC 4 digit codes within machinery with 100 patents

**(b)** For combinations of IPC4 in machinery with G05 G06 and at least 100 patents

**Figure A.4:** Histograms of the prevalence of automation keywords. The p90 and p95 lines are those of the 6 digit distribution and mark the thresholds used to define auto90 and auto95 technological categories.

proxies for control and G06 for algorithmic, two set of technologies which have been used heavily in automation. There are, however, many fewer combination of these types, and accordingly fewer patents can be characterized as automation innovations this way.

### A.2.2 How are auto90 and auto95 patents identified?

Given that our classification procedure is relatively complex, we assess here which features dominate. To do so, we focus on the set of $15,212,134$ biadic patent applications in 1997-2011 (corresponding to the $3,187,536$ patent families which have patent applications in at least two countries), since this corresponds to the set on which we run our main regressions. There are $310,458$ auto95 patent applications corresponding to $61,768$ patent families (and similarly $541,693$ auto90 patent applications corresponding to $107,237$ patent families). Table A.20.a gives the share of biadic patents which are identified through a C/IPC 6 digit code, a pair of 4-digit codes or a combination of 4-digit code with G05/G06 (the shares sum up to more than 100% since patents may be identified as automation innovations in several ways). 6-digit codes are the most relevant since they identify close to 80% of either auto90 or auto95 patents alone.

Similarly, one may wonder which keywords are the most important in identifying automation patents. To assess that, we define robot95 patents as patents which contain a technology category with a prevalence of "robot" keywords above the threshold used to

**Table A.20:** Identification of automation technology categories

**(a)** Type of C/IPC codes identifying auto90 and auto95 patents

| Ipc codes / Patents | Auto90 | Auto95 |
|---|---|---|
| Matches ipc6 | 78.2% | 78.7% |
| Matches ipc4 pair | 17.3% | 24.3% |
| Matches ipc4 - G05/G06 combination | 47.7% | 47.8% |

Note: Share of innovations classified as automation innovation through ipc6 codes, ipc4 pairs or ipc4 - G05/G06 pairs. Statistics computed on biadic patents from 1997-2011.

**(b)** Auto patents and subcategories of automation innovations

| Sources / Patents | Auto80 | Auto90 | Auto95 |
|---|---|---|---|
| Auto80 | 100.0% | 100.0% | 100.0% |
| Automat*80 | 36.2% | 53.1% | 72.1% |
| CNC80 | 5.0% | 8.0% | 13.2% |
| Robot80 | 12.0% | 19.2% | 33.6% |
| Auto90 | 62.4% | 100.0% | 100.0% |
| Automat*90 | 21.6% | 34.6% | 56.0% |
| CNC90 | 2.2% | 3.6% | 6.3% |
| Robot90 | 7.8% | 12.5% | 21.8% |
| Auto95 | 35.8% | 57.3% | 100.0% |
| Automat*95 | 4.4% | 7.1% | 12.4% |
| CNC95 | 1.6% | 2.5% | 4.4% |
| Robot95 | 6.3% | 10.2% | 17.7% |

Note: Share of auto95 (auto90 and auto80, respectively) innovations which are also classified as automat*80/90/95, CNC80/90/95, and robot80/90/95 innovations. Statistics computed on biadic patents from 1997-2011.

define auto95 (namely 0.4766), therefore those patents are a subset of the auto95 patents. We define CNC85, automat*95, robot90, CNC90, automat*90, robot80, CNC80 and automat*80 similarly. The other keywords are much less common. Table A.20.b reports the share of auto95, auto90 and auto80 patents which belong to each subcategory. "Automat*" is the most important keyword since 72% of auto95 patents are also automat*80 patents. "Robot" matters as well with 33.6% of auto95 patents which are robot80 and 17.7% which are even robot95 (more than automat*95). CNC does not matter much: only 13% of auto95 patents are CNC80.

### A.2.3 Stability of the classification

To assess the stability of our classification, we redo exactly the same exercise but instead of using EPO patents from 1978 to 2017, we restrict attention to EPO patents from the first half of the sample (1978-1997), the second half (1998-2017) or the period of our main regression analysis (1997-2011). There is a modest increase in the share of patents with automation keywords within each technology category. At the C/IPC 6-digit level in machinery, the share of patents with an automation keyword increases on average from 0.19 in the first half of the sample to 0.21 in the second half. Nevertheless, the ranking of codes is remarkably stable as shown in Table A.21which reports the correlations of the prevalence measures for the different time periods.

**Table A.21:** Correlation between the prevalence of automation keywords for different periods

| | Prevalence of automation keywords using patents during the period: 1978-2017 | 1997-2011 | 1978-1997 | 1998-2017 |
|---|---|---|---|---|
| 1978-2017 | 1 | . | . | . |
| 1997-2011 | 0.9863 | 1 | . | . |
| 1978-1997 | 0.9693 | 0.9321 | 1 | . |
| 1998-2017 | 0.9885 | 0.992 | 0.9241 | 1 |

Notes: Correlation matrix for the prevalence of automation keywords by C/IPC 6-digit codes in machinery using EPO patents over different time periods. We exclude catch-all categories made at the 4-digit level.

**Table A.22:** Confusion table for different classification periods

| Confusion Matrix | | Auto95 based on the 1998-1997 classification | | Auto95 based on the 1998-2017 classification | | Auto95 based on the 1997-2011 classification | | Total |
|---|---|---|---|---|---|---|---|---|
| | | Yes | No | Yes | No | Yes | No | |
| Auto95 based on | Yes | 240,194 | 70,264 | 280,047 | 30,411 | 262,972 | 47,486 | 310,458 |
| the 1978-2017 | No | 53,137 | 14,848,539 | 25,186 | 14,876,490 | 26,368 | 14,875,308 | 14,901,676 |
| classification | Total | 293,331 | 14,918,803 | 305,233 | 14,906,901 | 289,340 | 14,922,794 | 15,212,134 |

Notes: The statistics are always computed on patents from 1997-2011.

Further, focusing on the same set of biadic patent applications in 1997-2011, Table A.22 shows confusion tables on the classification of patents as auto95 according to each of the classification period. Regardless of the time period used the number of automation patents stays roughly constant. In particular, 85% of the baseline auto95 patents are still auto95 if we run the classification over the years 1997-2011. This common set of patents then represent 91% of all biadic patents classified as auto95 patents when using the period 1997-2011 instead of the full sample.

## A.3 Comparison with Mann and Puettmann (2020)

We considered the machinery (according to our definition) of Mann and Puettmann (2020, henceforth MP) and them as auto95 or not (at the family level). We have a lower share of automation patents (18.5% for auto90 and 10% for auto90) than MP who have 30.8%. 70% of our auto95 patents are classified as automation patents by MP (to analyze this number, it is useful to note that their algorithm has a 17% false negative error rate on the training set), while we classify 22.7% of their automation patents as auto95. Therefore, our measure of automation is generally stricter than theirs although it is not a perfect subset.

To facilitate comparison, we computed the share of automation patents at the C/IPC

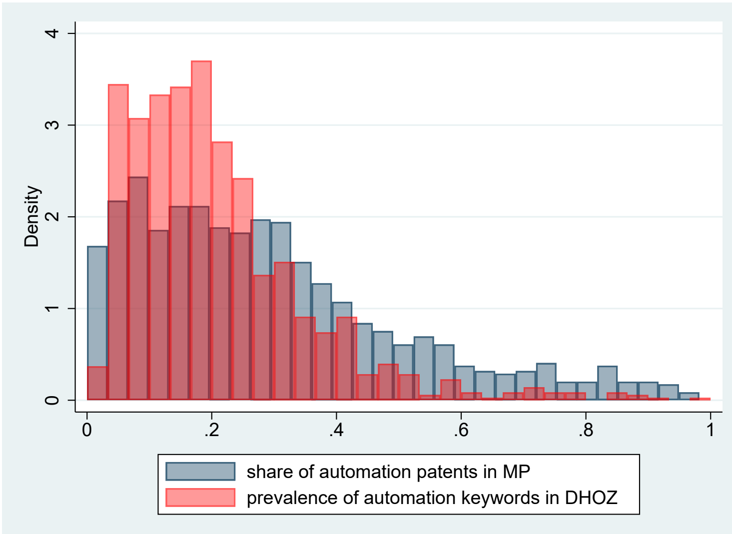



**Figure A.5:** Histograms of the share of automation patents in MP and of the prevalence of automation keywords in this paper at the 6 digit level in machinery.

60digit level according to their classification and compare this number with our measure of the prevalence of automation keywords. The correlation between these two measures is high (at 0.58). Figure A.5 shows the histograms of the two distributions. Our prevalence measure is more skewed and has a fatter tail (with a kurtosis of 7 versus 3.5), as such it more clearly identifies a set of outliers among 6-digit C/IPC codes.

We compute the difference between our prevalence measure and their share of automation patents and look at the codes with the highest and lowest values (focusing on codes with at least 100 patents in both their dataset and our EPO dataset). Table A.23 lists the 6 codes with the largest positive difference (among auto95 codes) and the 6 codes with the largest (in absolute value) negative difference (among non-auto90 codes). 3 of the codes with a high difference belong to the manipulator subclass (B25J), they correspond to joints (B25J17), gripping heads (B25J15) and accessories of manipulators (B25J19). MP classify a large share of these patents as automation but our prevalence number is even higher. In their definition of automation patents, MP specify that they exclude innovations which only refer to parts of a machine. This accounts for some of the patents in these codes that they do not classify as automation. D01H9 corresponds to "arrangements for replacing or removing bobbins, cores, receptacles, or completed packages at paying-out or take-up stations" for textile machines. The share of automation patents in MP is low at 0.38, however their "raw share" (computed before they exclude certain patents) is quite high at 0.71. The excluded patents are not chemical or phar-

**Table A.23:** Outliers 6-digit C/IPC codes in the comparison between our measure and MP's measure

| C/IPC 6 digit code | Simplified description | Prevalence of automation keywords (DHOZ) | Share of automation patents (MP) |
|---|---|---|---|
| | *Positive outliers (among auto95 codes)* | | |
| B25J17 | Manipulators (joints) | 0.84 | 0.54 |
| D01H9 | Textile machines (arrangements for replacing or removing various elements) | 0.62 | 0.38 |
| B65B2210 | Specific aspects of packaging machines | 0.48 | 0.25 |
| B25J15 | Manipulators (gripping heads) | 0.71 | 0.50 |
| B23P23 | Metal working machines (specified combinations n.e.c) | 0.67 | 0.46 |
| B25J19 | Manipulators (accessories) | 0.89 | 0.69 |
| | *Negative outliers (among non-auto 90 codes)* | | |
| B66B2201 | Control systems of elevators | 0.19 | 0.97 |
| B66B3 | Elevators (signalling and indicating device applications) | 0.19 | 0.92 |
| B41J23 | Typerwriters / printing machines (power drive) | 0.08 | 0.82 |
| B66B1 | Elevators (control systems) | 0.16 | 0.89 |
| B41J19 | Typerwriters / printing machines (characters and line spacing mechanisms) | 0.14 | 0.84 |
| B41J5 | Typerwriters / printing machines (controlling character selection) | 0.21 | 0.91 |

Note: This table lists the 6 auto95 codes with the largest positive difference between the prevalence of automation keywords in our data and the share of automation patents according to MP in their data; and the 6 non-auto90 codes with the largest negative difference between the two measures. We restrict attention to codes with at least 100 patents in both datasets.

maceutical patents (as emphasized in the paper), but belong to the "other" technological field (according to the Hall-Jaffe-Trajtenberg classification). The same situation occurs for B65B2210 (which is about packaging machines) where their raw automation score is actually at 0.63 and the patents excluded by MP are not chemical. B23P23 is a machine tool subclass (specifically "Machines or arrangements of machines for performing specified combinations of different metal-working operations not covered by a single other subclass") which often involves CNC technologies.

The non-auto90 codes where MP find a high share of automation patents but for which we have a comparatively low prevalence measure are easily identifiable. Among the top 6, half are in the subclass B66B which corresponds to elevators and the other half are in the subclass B41J which corresponds to typewriters and printing machines. In fact, the first 34 6-digit C/IPC codes belong to either B66B, B41J or the subclass B65H which is about handling thin or filamentary material and also involves patents associated with printing machines. It is not surprising that our classifications differ for these types of innovation, since they do correspond to processes perform independently of human action (in line with MP's criterion); yet elevators and printers do not (or at least no longer) replace humans in existing tasks.

## A.4 Redoing ALM

We detail how we build the variables used in Section 2.6 and provide further results.

### A.4.1 Data for the ALM exercise

Except for the automation measures, we take the variables directly from ALM. We refer the reader to that paper for a detailed explanation. The task measures are computed using the 1977 *Dictionary of Occupational Titles* (DOT) which measure the tasks content of occupations. Occupations are then matched to industries using the Census Integrated Public Micro Samples 1% extracts for 1960, 1970 and 1980 (IPUMS) and the CPS Merged Outgoing Rotation Group files for 1980, 1990 and 1998 (MORG). The task change measure at the industry level reflects changes in occupations holding the task content of each occupation constant, which ALM refer to as the extensive margin. Since tasks measures do not have a natural scale, ALM concert them into percentile values corresponding to their rank in the 1960 distribution of tasks across sectors, so that the employment-weighted means of all tasks measure across sectors in 1960 is 50. Our analysis starts in 1970 and drops a few sectors but we keep the original ALM measure to facilitate comparison. As in ALM, the dependent variable in Table 3 corresponds to 10 times the annualized change in industry's tasks inputs to favor comparison across periods of different lengths. Computerization $\Delta C_j$ is measured as the change per decade in the percentage of industry workers using a computer at their jobs between 1984 and 1997 (estimated from the October Current Population Survey supplements). For all regressions, observations are weighed by the employment share in each sector.

To map patents to sectors we proceed in 4 steps. First, we build a mapping between C/IPC 4 digit codes and the SIC sector that holds the patent (inventing sector). To do that, we use Autor et al. (2020) who match 72% of domestic USPTO corporate patents to firms in Compustat. This allows us to assign a 4-digit SIC sector to this subset of patents. We match the USPTO patents to our patent family data from PATSTAT, which we use to get the full set of C/IPC codes of the family. We then restrict attention to granted patents in machinery applied for in the period 1976-2010. Each patent family for which we have a sector creates a link between its C/IPC codes and that sector. We weigh that link inversely to the number of 6-digit C/IPC codes in the patent. Counting these connections allows us to build a weighted concordance table between 656 4-digit C/IPC codes and 397 SIC codes (at different levels of aggregation), where the industries refer to the industry of invention / manufacturing.

**Table A.24:** Sectors with the highest and lowest shares of automation patents

| ind6090 | Title | Auto95 | ind6090 | Title | Auto95 |
|---|---|---|---|---|---|
| | *Sectors with the highest share of automated patents in machinery* | | | *Sectors with the lowest share of automated patents in machinery* | |
| 756 | Automotive services and repair shops | 0.111 | 801 | Bowling alleys, billiard and pool parlors | 0.043 |
| 206 | Household appliances; Radio, TV & communications equipment; Electric machinery, equipment & supplies; Not specified electrical machinery, equipment & supplies | 0.109 | 802 | Misc. entertainment and recreation services | 0.048 |
| | | | 100 | Meat products | 0.049 |
| | | | 101 | Dairy products | 0.049 |
| 470 | Water supply and irrigation | 0.101 | 102 | Canned and preserved fuits and vegetables | 0.049 |
| 271 | Iron and stell foundaries | 0.098 | 110 | Gain mill products | 0.049 |
| 212 | Misc. plastic products | 0.096 | 111 | Bakery products | 0.049 |
| 130 | Tobacco manufactures | 0.095 | 112 | Sugar and confectionary products | 0.049 |

Auto95 is the share of automation patents in machinery (95th threshold) in 1980-1998.

Second, to obtain the sector of use we rely on the 1997 "investment by using industries" table from the BEA (at the most disaggregated level, 180 commodities for 123 industries) which gives the flows of investment from commodities to industry available at www.bea.gov/industry/capital-flow-data. Beforehand, we assign commodities to industries using the 1997 make table at the detailed level from the BEA (available at www.bea.gov/industry/historical-benchmark-input-output-tables) which gives the commodities produced by each industry.[32] We dropped commodities associated with the construction sector which are structures. Combining the two BEA tables, we obtain an investment flow table at the industry level. We combine that table with the C/IPC to industry of manufacturing table previously derived to get an C/IPC to industry of use table mapping 656 4-digit C/IPC codes into 966 SIC industries.

Third, we allocate patent families fractionally to their C/IPC 4-digit codes and use the previous table to assign them to an industry of use in the SIC classification (having restricted attention to the C/IPC codes which appear in the table). Fourth, we use a concordance table from the US Census Bureau from SIC industries to the Census industries from 1990 (ind90) given by Scopp (2003) and ALM concordance table from ind90 to consistent Census industries (ind6090) in order to allocate patents to their industry of use in ALM's classification.

Finally, for each sector and time period, we compute the sums of automation patents and machinery patents and take the ratio to be our measure of automation intensity. We exclude sectors with less than 50 machinery patents (so that the number of sectors varies across time periods). Table A.24 shows the sectors with the highest and lowest

[32] Since our industries are in SIC 1987, we use concordance tables from the IO industries to NAICS 1997 provided by the BEA and then the weighed concordance table between NAICS 1997 and SIC 1987 from David Dorn's website https://www.ddorn.net/data.htm which we complete with a concordance table from the Census available here (www.census.gov/eos/www/naics/concordances/concordances.html). To generate weights in the mapping between IO industries and NAICS 1997 and to disaggregate the NAICS industries from the capital flow table, we use CBP data from 1998 (https://www.census.gov/data/datasets/1998/econ/cbp/1998-cpb.html).

shares of automation patents in machinery.

To compute the share of automation patents in machinery according to the industry of manufacturing / invention, we proceed as above but skip step 3 with the investment flow table. Once patents are assigned to a SIC industry of manufacturing, we use the same concordance tables to assign patents to an ind6090 industry of manufacturing.

Finally, in robustness checks, we also use an alternative mapping from patents to sectors based on Lybbert and Zolas (2014) who provide a concordance table between IPC codes at the 4-digit level and NAICS 1997 6-digit industry codes. The concordance table is probabilistic (so that each code is associated with a sector with a certain probability). The Lybbert and Zolas concordance tables are derived by matching patent texts with industry descriptions, and as such they cannot *a priori* distinguish between sector of use and industry of manufacturing. We checked, however, that patents associated with “textile and paper machines” for instance are associated with the textile and paper sectors and not with the equipment sector. In addition, it has the advantage of providing a much more direct mapping between C/IPC codes and industries. We attribute patents to sectors fractionally in function of their C/IPC codes. To assign patents to the consistent Census industry codes used by ALM, we first use a Census concordance table (https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html) to go from NAICS 1997 to Census industry codes 1990, and then again use ALM concordance table.

**Table A.25:** Changes in routine task intensity and different measures of sectoral automation

| Dependent variable | Δ Routine cognitive | | | | | Δ Routine manual | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Automation share (using industry) | -146.44*** (26.72) | -179.22*** (34.33) | -154.22*** (33.70) | | -75.32*** (14.58) | -120.22*** (28.18) | -84.40** (35.03) | -58.62* (34.34) | | -53.91*** (15.56) |
| Automation share (manufacturing industry) | | | -25.85*** (8.29) | | | | | -26.65*** (8.44) | | |
| Automation share (Lybbert and Zolas) | | | | -26.66*** (4.83) | | | | | -17.09*** (3.90) | |
| Δ Computer use 1984 - 1997 | -17.70*** (4.74) | -19.02*** (5.93) | -19.28*** (5.65) | -17.74** (6.79) | -17.77*** (4.81) | -19.43*** (5.00) | -28.15*** (6.05) | -28.42*** (5.76) | -11.53** (5.48) | -18.97*** (5.13) |
| $R^2$ | 0.24 | 0.30 | 0.37 | 0.39 | 0.22 | 0.19 | 0.24 | 0.32 | 0.29 | 0.15 |
| Observations | 124 | 90 | 90 | 69 | 124 | 124 | 90 | 90 | 69 | 124 |

Standard errors are in parentheses. Each column presents a separate OLS regression of ten times the annual change in industry-level task input between 1980 and 1998 (measured in centiles of the 1960 task distribution) on the share of automation patents in machinery and the annual percentage point change in industry computer use during 1984 - 1997 and a constant. In columns (1) to (5) the dependent variable is the change in routine cognitive tasks and in columns (6) to (10) the change in routine manual tasks. The automation share measures correspond to the share of automation patents in machinery using different mappings between C/IPC codes and industries. "Using industry" allocates patents to their sector of use and "Manufacturing industry" to their sector of manufacturing following the method described in the paper. "Lybbert and Zolas" uses a concordance table from Lybbert and Zolas (2014). Automation patents are auto95 patents for all columns except (5) and (10) which use auto90 patents. Estimates are weighted by mean industry share of total employment in FTEs in 1980 and 1998. * p<0.1; ** p<0.05; *** p<0.01

### A.4.2 Additional results

Table A.25 looks at alternative ways to map patents to sectors focusing on the consolidated time period 1980-1998. Columns (1) and (6) reproduce the previous results for this time period (and contrary to Figure 4 control for computerization). In Columns (3) and (8), we add the share of automation patents in machinery where we allocate patents to the manufacturing sector (the inventing sector) instead of the using sector (i.e. we skip the capital flow table step when computing our automation variable at the sectoral level). We restrict attention to sectors where there are at least 50 machinery patents with both measures, which reduces the number of sectors. We also find a negative effect and the coefficient on the share of automation patents in the using sector is not too much altered relative to Columns (2) and (7) which carry our initial regression on the same set of sectors. In Columns (4) and (9), we instead map patents to sectors based on a concordance table from Lybbert and Zolas (2014) between 4 digit C/IPC codes and sectors. This method has the advantage of mapping more directly patents to sectors but cannot distinguish between manufacturing and using sectors. We still find that sectors with a high share of automation patents experienced a decline in routine tasks. Finally, Columns (5) and (10) use the share of auto90 patents in machinery to measure automation in the sector of use. The results are similar but with smaller coefficients than in Columns (1) and (6).

## A.5 Macroeconomic variables

Our main source of macroeconomic variables is the *World Input Output Database (WIOD)* from Timmer et al. (2015) which contains information on hourly wages (low-skill, middle-skill and high-skill) for the manufacturing sector and the total economy from 1995 to 2009 for 40 countries. It further contains information on GDP deflators and PPIs both for manufacturing and for the whole economy. They employ the ISCED skill-classification, where category 1+2 denote low-skill (no high-school diploma in the US) 3+4 denote middle-skill (high-school but not completed college) and 5+6 denotes high-skill (college and above). Switzerland is not included in the WIOD database and we add data on skill-dependent wages, productivity growth and price deflators using data obtained directly from *Federal Statistical Office of Switzerland.*

We supplement this data with data from *UNSTAT* on exchange rates and GDP (and add Taiwan from the *Taiwanese Statistical office*). We calculate the GDP gap as the deviations of log GDP from HP-filtered log GDP using a smoothing parameter of 6.25. To compute the offshoring variable we follow Timmer et al. (2014) and compute the share of foreign value added in manufacturing from the WIOD 2013 (except for Switzerland where we use the 2016 release and assign to the years 1995-1999 the same value as in 2000). For the nominal interest rate, we use the yield on 10-year government bonds with data from the OECD for AT AU BE CA CH DE DK ES FI FR GB IE IT JP NL PT SE US and from the IMF for KR GR LU.

The primary data source for the hourly minimum wage data is *OECD Statistics.*[33] For the US, we use data from FRED for state minimum wages and calculate the nation-level minimum wage as the weighed average of the state-by-state maximum of state minimum and federal minimum wages, where the weight is the manufacturing employment in a given state. Further, the UK did not have an official minimum wage until 1999. Before 1993, wage councils set minimum wages in various industries (see Dickens, Machin and Manning, 1999). We compute an employment-weighed industry average across manufacturing industries and use the 1993 nominal value for the four years in our sample (1995-1998) with no minimum wage. Finally, Germany did not have a minimum wage during the time period we study. Instead, we follow Dolado et al. (1996) and use the collectively bargained minimum wages in manufacturing which effectively constitute law once they have been implemented. These data come from personal correspondence with Sabine Lenz at the *Statistical Agency of Germany.*

## A.6 Firm-level patent weights

We give further details on the firm level patent weights. As mentioned in the text, we only count patents in machinery because some of the biggest innovators in automation technologies are large firms which produce a wide array of products with different specialization patterns across industries. Further, we exclude firms which have more than half of their patents in countries for which we do not have wage information.

In Europe, firms can apply both at national patent offices and at the EPO, in which case they still need to pay a fee for each country where they seek protection. We count a

[33] Not all countries have government-imposed hourly minimum wages. Spain, for instance, had a monthly minimum wage of 728 euros in 2009. To convert this into hourly wage we note that Spain has 14 "monthly" payments a year. Further, workers have 6 weeks off and the standard work week is 38 hours. Consequently we calculate the hourly minimum wages as monthly minimum wage$\times 14/[(52-6)\times 38]$, which in 2009 is 5.83 euros per hour. We perform similar calculations, depending on individual work conditions, for other countries with minimum wages that are not stated per hour: Belgium, Brazil, Israel, Mexico, Netherlands, Poland and Portugal.

patent as being protected in a given European country if it is applied for either directly in the national office or through the EPO. In addition, we take the following steps in order to deal with EP patents. We assign EP patents to countries when they enter into the national phase. A firm's untransferred EP patents are assigned using information on where that firm previously transferred its EP patents. If a firm does not have any already transferred EP patents, we assign the patent based on a firm's direct patenting history in EPO countries. Untransferred EP patents that are still left are assigned to countries based on the EPO-wide distribution of transfers. We also drop a firm if more than half of its patents are EP patents assigned using the EPO-wide distribution.

Finally, as mentioned in the text we only count patents in families with at least one (non self-) citation. Including all patents generally increases the weight of the country with the most patents, in line with the finding that poor quality patents tend to be protected in fewer countries. However, further increasing the threshold from 1 to more citations does not significantly change the distribution of weights.

## A.7 Macroeconomic interpretation of the regression coefficients

To better understand the magnitude of our coefficients and the effect of spillovers and stock variables, we run a simulation where we uniformly and permanently decrease the skill-premium by 10% between 1995 and 2009 in all countries and use our results to recompute the share of automation innovations in machinery. Importantly, we stress that one *must not* interpret the result of this simulation as predictive notably because a change in innovation should in turn affect the skill premium. Yet, our analysis could be used to calibrate a model which predicts that the direction of innovation reacts to changes in the skill premium. We focus on a changes in the skill-premium as it is easier to interpret than a change in low-skill wages keeping high-skill wages constant.

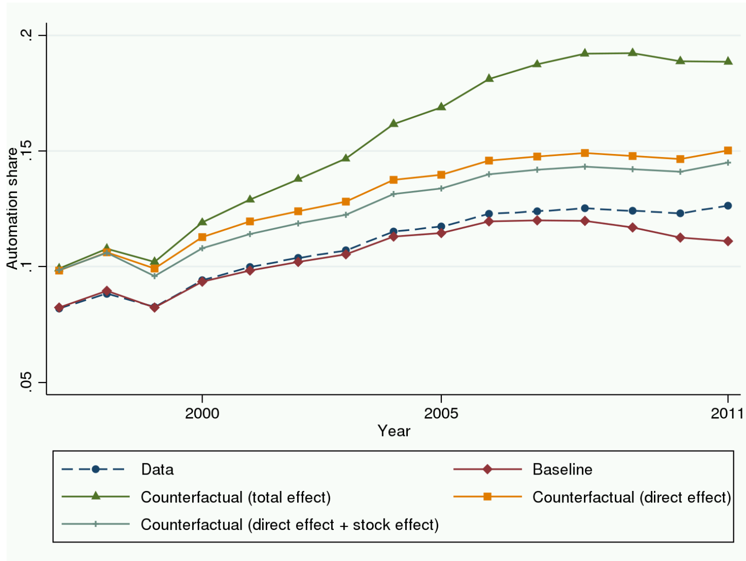
Specifically, we simulate the regression results reported in Figure A.6. We regress both auto95 innovations and all machinery innovations except auto95 on the inverse of the skill premium, the GDP gap, stock and spillover variables and firm and industry-year fixed effects. We consider separately the stocks and spillovers of auto95 innovations, machinery except auto95 innovations and all other innovations.

Figure A.6 reports the results averaged over 500 simulations (using the median gives similar results).[34] We first compute the direct effect of a decrease in the skill premium

[34] The figure reports the share of automation patents for the firms in our regression sample. This differs from Figure 3 since the latter reports the share of automation patents for all firms.

| Dependent variable | Auto95 | Mach.\auto95 |
|---|---|---|
| | (1) | (2) |
| Low-skill / High-skill wages | 2.38*** | 0.25 |
| | (0.67) | (0.51) |
| GDP gap | -4.80* | -2.96** |
| | (2.64) | (1.36) |
| Stock automation | -0.16*** | 0.14*** |
| | (0.05) | (0.03) |
| Stock mach.\auto95 | 0.35*** | 0.26*** |
| | (0.06) | (0.03) |
| Stock other | 0.35*** | 0.26*** |
| | (0.06) | (0.04) |
| Spillovers automation | 1.04*** | -0.13 |
| | (0.36) | (0.21) |
| Spillovers mach.\auto95 | 1.14* | 2.25*** |
| | (0.60) | (0.38) |
| Spillovers other | -1.68** | -1.92*** |
| | (0.73) | (0.49) |
| Fixed effects | F+IY | F+IY |
| Observations | 49174 | 154965 |
| Firms | 3329 | 10367 |

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed effects regressions (HHG). All regressions include firm and year-industry fixed effects and include dummies for no stocks or no spillovers. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$




**(a)** Supporting regression **(b)** Simulation result

**Figure A.6:** Simulation of a permanent and global 10% decrease in the skill premium on the share of automation innovations in machinery

(keeping stocks and spillover variables constant) on the share of automation innovations in machinery. This is captured by the gap between the data curve and the counterfactual (direct effect) curve. This gap reflects the elasticity of 2.38 of auto95 innovations with respect to the inverse skill premium (with an elasticity of 0.25 for other machinery innovations). Taking into account the response of firms' own innovation stocks slightly decreases the effect of low-skill wages reflecting the negative effect of the automation stock on auto95 innovations and its positive effect on other machinery innovations.

We then assess the importance of knowledge spillovers by recomputing the spillover variables for the auto95 innovations and other machinery innovations (but not the non-machinery innovations). This involves two complications. First, our model only applies to the number of innovations and not their location. To allocate innovations to countries, we assign the simulated innovations proportionally to the firm's inventor weights (used to construct the spillover variables). Second, firms in our sample account for only 58% of all biadic innovations in 1997-2011. We assume that the other firms respond similarly so that when we assign simulated innovations to countries, we increase innovations by out-of-sample firms to keep the ratio of in-sample to out-of-sample innovations constant.

The overall effect of an increase in the inverse skill premium is then captured by the gap between the baseline curve and the counterfactual one. The baseline curve and the data series differ because the baseline is an average while the data series is only one possible realization. Knowledge spillovers increase the overall elasticity of the share of automation patents with respect to low-skill wages. The average share of automation innovations in machinery between 1997 and 2011 increases by 4.8 p.p. from 10.5% to 15.3%. This is 2.7 p.p. more than the direct effect. This 4.8 p.p. increase can be compared to the 4.4 p.p. increase in the data over the same time period.

To further interpret the 4.8 p.p increase, we use the results of Section 2.6. Using the coefficients from Columns (1) and (6) in Table A.25 (which gives the correlation between tasks changes and the share of automation innovation in 1980-1998), we see that, over a decade, such an increase would be associated with a decline in routine cognitive tasks of 7 centiles and a decline in routine manual tasks of 5.8 centiles. Over this time period, routine cognitive and manual tasks declined at 4.8 and 2.4 centiles per decade. Although one should not interpret these numbers as causal, they indicate that the effect of the skill premium on automation innovations is economically significant.

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