Appendix to *The March of The Techies: Technology, Trade, and Job Polarization in France, 1994-2007*

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http://people.virginia.edu/~jh4xd/March_of_the_Techies.htm

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# A Data Sources

## A.1 The DADS Poste

The annual declaration of social data (DADS) is a mandatory requirement to all businesses with employees, where employers provide information on employees in each of their establishments. The declaration file serves both fiscal and social administrative purposes. For each employee the following information must be declared: the nature of the work and qualification, the occupation in which the paid work has been made, the starting and closing dates of the period of paid work, the number of paid hours, the terms of employment (full time, part time), the amount paid, etc.

All employers and their employees are covered by the DADS declaration with the exception of self-employed and government bodies, domestic services (section 97-98 of NAF rev. 2) and employees in businesses outside French territory (section 99 of NAF rev. 2). However, local authorities and public-employed hospital staff are included since 1992. Public institutions of industrial and commercial nature are also included.

Since 1993, DADS data was revised to allow a comprehensive processing of all employees. In 2002, some data processing improvements were introduced, including:

- An enhanced verification of the sector of activity of the establishment and its location.
- Better codification of the socio-professional category (PCS). This involves an superior processing of the profession headings provided 'in clear text" by the computerised coding systems for survey responses (the SICORE application) developed by INSEE. Failures in the automatic coding process (1 in 12 employees on average) are then partly manually processed.

These improvements cause small breaks, or "jumps", in aggregate occupational share time series between 2001 and 2002. The breaks are miniscule in relative terms for occupations that have large shares of employment, and they do not alter the trends. For smaller occupations the breaks are not completely negligible, but still do not change the overall trends. The breaks are also manifested in relative wages of occupations. As with occupational employment shares, these changes are negligible for large occupations, and not large for smaller occupations. See below in this appendix on how we splice aggregate series.

## A.2 DADS Poste, private and permanent sample

The DADS Poste dataset includes about 3.3 million private and public firms, operating in different years. Each firm is assigned to a particular legal category (*catégorie juridique*). Category 4 and 7 defines legal entities governed by public law. These firms are Public Industrial and Commercial Establishment such as SNCF, RATP, Banque de France, etc. or all bodies of the public functions: state, local authorities and hospitals and their dependent establishments. Category 9 defines private law associations. We define a private firm as those belonging to any categories other than 4, 7 or 9. There are 458,000 "public" firms and about 2.9 million private firms in the DADS poste. We identified 310,713 private firms that are permanently in the sample: they report strictly positive hours in all years from 1994 to 2007. Table 18 reports the number and percentages of hours and firms in the French private and public sectors.

Table 18: Hours and number of firms in the private and public sectors (various years)

| Sector | Year | Hours | | Firms | |
|---|---|---|---|---|---|
| | | Number | Percent of total | Number | Percent of total |
| Private | 1994 | 21944417107 | 75.1 | 1089725 | 85.8 |
| | 2002 | 25089302080 | 77.1 | 1224084 | 81.6 |
| | 2007 | 26419823084 | 76.2 | 1320109 | 82.5 |
| Public | 1994 | 7286385816 | 24.9 | 180009 | 14.2 |
| | 2002 | 7441299453 | 22.9 | 276468 | 18.4 |
| | 2007 | 8253869786 | 23.8 | 280534 | 17.5 |

In our dataset, we keep information on all private sector workers. In Table 18, we show that the private sector represents 77% of hours and 82% of firms in 2002. We do not identify a trend in private sector shares of hours or of firms.

In Table 19 we focus on the private sector sample. We report the number of hours and manufacturing and nonmanufacturing firms in the private sector and in the sample of firms that are permanent. In 2002, the sample of permanent firms represents 25.4% of the total number of private firms and about 50% of the total number paid in the private sector. The share of firms in the permanent sample declines somewhat over the sample, but the share of hours worked in the permanent firm sample is stable. The shares of manufacturing and nonmanufacturing are similar in the permanent firm sample as in the entire private sector, with slightly larger sahes in manufacturing in the permanent sample. The manufacturing sector represents about 15% of the total number of firms and about 30% of the total number of hours paid in 2002.

## A.3 The INSEE definitions of "techies" (PCS 38 and PSC 47)

### A.3.1 PCS 38, technical managers and engineers

This occupational category includes employees having an executive position and performing a technical activity. These employees are responsible of management of technical activities and/or of tasks that require in-depth scientific knowledge. The category includes employees who engage in

- Studies, research and development in areas involving exact and natural sciences other than social sciences: agronomy, computers, architecture, urban planning, but not statistical and actuarial calculations.
- Production and product manufacturing, conducting projects.
- The sale of professional equipment, building and civil engineering, intermediate goods and computers.
- Related functions of production which include production planning and scheduling, methods (industrialization), purchasing, logistics, quality control, maintenance of equipment and the environment. In the case of industrial purchases, this PCS category includes only cases in which the activity requires technical skills: industry buyers, construction buyers, and buyers of

Table 19: Private and private permanent samples (various years, percentage in parentheses)

| | Private Sample | | | Permanent Private Sample | | |
|---|---|---|---|---|---|---|
| | Total | Manufacturing | Non-Manufacturing | Total | Manufacturing | Non-Manufacturing |
| Number of firms | | | | | | |
| 1994 | 1089725 | 149359 | 940366 | 310713 | 48062 | 262651 |
| | | (13.7 ) | (86.3 ) | (28.5 ) | (15.5 ) | (84.5 ) |
| 2002 | 1224084 | 150568 | 1073516 | 310713 | 48062 | 262651 |
| | | (12.3 ) | (87.7 ) | (25.4 ) | (15.5 ) | (84.5 ) |
| 2007 | 1320109 | 143503 | 1176606 | 310713 | 48062 | 262651 |
| | | (10.9) | (89.1) | (23.5) | (15.5) | (84.5) |
| Number of hours | | | | | | |
| 1994 | 21944417107 | 6605332784 | 15339084323 | 10571272113 | 3557642396 | 7013629717 |
| | | (30.1 ) | (69.9) | (48.2 ) | (33.7 ) | (66.3 ) |
| 2002 | 25089302080 | 6839688425 | 18249613655 | 12234985433 | 3798055460 | 8436929973 |
| | | (27.3 ) | (72.7 ) | (48.8 ) | (31.0 ) | (69.0 ) |
| 2007 | 26419823084 | 6353186775 | 20066636309 | 12627277437 | 3656060865 | 8971216572 |
| | | (24.0) | (76.0 ) | (47.8) | (29.0) | (71.0) |

Authors' Calculation.

services using heavy equipment. It does not include other buyers, whose function is primarily to optimize their purchases based on commercial considerations (this is allocated to PCS 37).

- IT and telecommunications.
- Transport (technical or specific operating activities).

### A.3.2 PCS 47, technicians

This professional category includes workers who apply in their activities knowledge or technological practices of industrial type. These workers do not have an executive position. Only technicians and supervisors defined by the collective agreement belong to this category. Under some collective agreements such as in the chemical and agro-food industries, assistant technicians, laboratory assistants, etc.—which would otherwise be included in PCS 47—are categorised as skilled industrial workers, i.e. PCS 62.

As with the technical managers and engineers in PCS 38, a breakdown is made according to the function performed by the technician. First, the role exercised differentiates technicians foremen and supervisors. While the latter mainly have supervisory responsibilities, technicians have mainly a design role, support, advice or expertise. Some technicians have supervisory responsibilities, but they are secondary to their technological skills. Technicians can participate in the production, operation and maintenance, but their role is in principle distinct from foremen and supervisors. As for technical managers and engineers in PCS 38, PCS 47 covers several functional areas such as

- Studies, research and development, and methods.

- Manufacturing and quality control.
- Functions related to production (scheduling-programming-logistics, maintenance, environment).

# B Matching DADS with the Custom Data

The French customs dataset and the DADS database are matched on an annual basis using the SIREN identifier of the French firm. The SIREN number is issued by INSEE when a firm registers its business in France. It is a simple serial number, made up of 9 digits (except in the case of public bodies). It does not reflect the nature of the company. It is assigned only once and is not removed from the register until the moment when the legal entity ceases to exist (death or cessation of all activity for an individual, cessation of activity for a corporate body).

Table 20: Share of the value of trade that is matched with the DADS Poste dataset

| | Permanent Private Sample | | Private Sample | |
|---|---|---|---|---|
| year | Export | Import | Export | Import |
| 1994 | 43 | 43 | 91 | 93 |
| 1995 | 44 | 44 | 91 | 93 |
| 1996 | 44 | 44 | 90 | 92 |
| 1997 | 44 | 43 | 90 | 92 |
| 1998 | 44 | 43 | 89 | 91 |
| 1999 | 44 | 45 | 88 | 91 |
| 2000 | 45 | 45 | 88 | 90 |
| 2001 | 44 | 46 | 88 | 89 |
| 2002 | 45 | 47 | 88 | 88 |
| 2003 | 46 | 48 | 87 | 87 |
| 2004 | 47 | 48 | 87 | 88 |
| 2005 | 48 | 48 | 85 | 86 |
| 2006 | 47 | 47 | 85 | 85 |
| 2007 | 47 | 47 | 85 | 86 |
| Average 1994-2007 | 45.1 | 45.6 | 88.0 | 89.4 |

Authors' computations

Table 20 shows that our matched sample of private firms covers 88% of imports and 89.4% of exports. Since some private firms are registered abroad, they are not required to declare to the DADS Poste. This explains the imperfect match between the two datasets. The permanent private sample, which represents less than 11% of the total number of firms contribute to 45% of the share of imports and exports.

# C Contribution of polarization to inequality: splicing around 2001/2002 break

We splice the series $x$ for some occupation from 2001 backwards in two steps. Define the change in some series $x$ for some occupation in 2000–2001 as $\Delta_{00-01}$; the change in the series for some occupation in 2002–2003 is $\Delta_{02-03}$; and the average of the two is $\Delta = (\Delta_{00-01} + \Delta_{02-03})/2$. The first step is

$$x_t^{splice} = \begin{cases} x_t - x_{2001} + x_{2002} - \Delta & \text{for} \quad t \leq 2001 \\ x_t & \text{for} \quad t \geq 2002 \end{cases} . \tag{10}$$

The first step (equation 10) does not take into account the fact that the sum of employment shares or wage bill shares may not be exactly 1 in $t \leq 2001$. To correct for this in the second step we divide each spliced share series by the total of spliced shares in each year: $x_{ot}^{splice,correct} = x_{ot}^{splice} / \sum_o x_{ot}^{splice}$. In the case of splicing relative wages, (10) does not maintain the following property, that the weighted average of relative wages equals exactly one, i.e. $\overline{\omega}_t = \sum_o S_{ot}\omega_{ot} = 1$. To correct for this in the second step we divide the spliced relative wage by the weighted average of spliced relative wages, in each year: $\omega_{ot}^{splice,correct} = \omega_{ot}^{splice} / \sum_o S_{ot}^{splice,correct}\omega_{ot}^{splice}$.

# D Contribution of polarization to occupational inequality

We measure occupational inequality—wage inequality across occupations—in year $t$ by the weighted standard deviation of relative occupational wages:

$$\sigma_t = \sqrt{\sum_o S_{ot} \left(\omega_{ot} - \overline{\omega}_t\right)^2} = \sqrt{\sum_o S_{ot} \left(\omega_{ot} - 1\right)^2} , \tag{11}$$

where $S_{ot}$ is the employment share of occupation $o$, $\omega_{ot}$ is the wage of occupation $o$ divided by the overall average wage, and $\overline{\omega}_t$ is the weighted average of relative wages, which is, by construction, always equal to 1. This measure is equivalent to the (weighted) coefficient of variation, and has the virtue of being scale independent, and thus invariant to general trends in nominal wages (see Cowell (2008)).

We compute $\omega_{ot}$ as the ratio of the wage bill of occupation $o$ to the employment share of occupation $o$. We splice these share series around the 2001/2002 break in the series, which is caused by data reclassification in 2002. In an alternative procedure we splice the relative wage series and the employment share series; this does not alter the results significantly. We describe the splicing procedure below.

Thus computed, occupational inequality (11) increased from 0.485 in 1994 to 0.514 in 2007. The increase occurs until 2001, after which occupational inequality is relatively stable. The change in $\sigma_t$ from 1994 to 2007 is due to both changes in relative wages and employment shares. To gauge the contribution of occupational polarization (more generally, changes in occupational employment shares) to occupation inequality we can follow two calculations.

1. Fix wages, let employment shares evolve as in the data. Compute (11) in 2007 as if we had the same wages of 1994:

$$\sigma_{2007|w_{1994}} = \sqrt{\sum_o S_{o,2007} \left(\omega_{o,\mathbf{1994}} - 1\right)^2} .$$

Compare $\sigma_{2007} - \sigma_{1994}$ to $\sigma_{2007|w_{1994}} - \sigma_{1994}$. The ratio $r_1 = \left(\sigma_{2007|w_{1994}} - \sigma_{1994}\right) / \left(\sigma_{2007} - \sigma_{1994}\right)$ tells us the contribution of occupational polarization to occupational inequality.

2. Fix employment shares, let wages evolve as in the data. Compute the weighted standard deviation of relative wages in 2007 using the employment shares of 1994:

$$\sigma_{2007|h_{1994}} = \sqrt{\sum_o S_{o,\mathbf{1994}} \left(\omega_{o,2007} - 1\right)^2} \ .$$

Compare $\sigma_{2007} - \sigma_{1994}$ to $\sigma_{2007|h_{1994}} - \sigma_{1994}$. The ratio $r_2 = \left(\sigma_{2007|h_{1994}} - \sigma_{1994}\right) / \left(\sigma_{2007} - \sigma_{1994}\right)$ tells us the contribution of changes in occupational wages to occupational inequality; $1 - r_2$ tells us the contribution of occupational polarization to occupational inequality.

The first calculation yields $r_1 = 1.53$, and the second calculation yields $1 - r_2 = 1.24$. These results are obtained when splicing employment shares and relative wage series. When splicing employment shares and wage bill shares (computing relative wages as their ratio), the numbers are slightly smaller: $r_1 = 1.43$ and $1 - r_2 = 1.14$.

# E Properties of the model

In this section of the appendix we show how relative employment varies with $\theta$, the distributional parameter associated with ICT services in the functions $\widetilde{H}$ and $\widetilde{M}$ , and with $r$, the cost of ICT capital services.

## E.1 Cross-sectional variation in relative employment

How does cross-sectional variation in $\theta$ affect the composition of employment within firms? We answer this question by differentiating the relative employment equations with respect to $\theta$,

$$\frac{\partial}{\partial \theta}\left(\frac{H}{L}\right) = \frac{-\beta}{1-\alpha-\beta} \frac{p_C^{\sigma+1} w_H^{\sigma} w_L}{\left(\theta p_C w_H^{\sigma} + (1-\theta)\, p_C^{\sigma} w_H\right)^2} < 0$$

$$\frac{\partial}{\partial \theta}\left(\frac{M}{L}\right) = \frac{-\alpha}{1-\alpha-\beta} \frac{p_C^{\eta+1} w_M^{\eta} w_L}{\left(\theta p_C w_M^{\eta} + (1-\theta)\, p_C^{\eta} w_M\right)^2} < 0$$

For both $H$ and $M$, higher $\theta$ is associated with lower employment relative to $L$. The reason is that as the importance of ICT in producing high- and medium-skill tasks rises, the labor that is required to work with ICT capital falls. Since there is no direct effect of $\theta$ on the productivity of $L$, the ratios $H/L$ and $M/L$ decline with $\theta$. The effect of $\theta$ on $\frac{H}{M}$ can not be signed:

$$\frac{\partial}{\partial \theta}\left(\frac{H}{M}\right) = \frac{\beta}{\alpha} \frac{p_C^{\sigma+1}\left(p_C^{\sigma-\eta} w_H w_M^{\eta} - 1\right)}{\left(\theta p_C w_H^{\sigma} + (1-\theta)\, p_C^{\sigma} w_H\right)^2}$$

The term in parentheses in the numerator is of ambiguous sign, so the derivative is of ambiguous sign. The effect is more likely to be positive the higher is $w_H$ or $w_M$, and the lower is $p_C$.

The parameter $\theta$ is an indicator of the importance of ICT services in production. The share $S^{ICT}$ of ICT in unit cost $b$, which is also the elasticity of cost with respect to $p_C$, is a fairly complex function,

$$S^{ICT} = \frac{p_C}{b}\frac{\partial b}{\partial p_C} = \frac{\theta p_C w_M w_H \left[\alpha\left(1-\theta\right)p_C^{\sigma} w_M^{\eta-1} + \beta\left(1-\theta\right)p_C^{\eta} w_H^{\sigma-1} + \left(\alpha+\beta\right)\theta p_C w_M^{\eta-1} w_H^{\sigma-1}\right]}{\left[\theta p_C w_H^{\sigma} + \left(1-\theta\right)p_C^{\sigma} w_H\right]\left[\theta p_C w_M^{\eta} + \left(1-\theta\right)p_C^{\eta} w_M\right]}.$$

This share is increasing in $\theta$:

$$\frac{\partial S^{ICT}}{\partial \theta} = \frac{p_C}{b}\frac{\partial^2 b}{\partial p_C \partial \theta} = \frac{\alpha\left(p_C w_M\right)^{\eta+1}}{\left(\theta p_C w_M^{\eta} + \left(1-\theta\right)p_C^{\eta} w_M\right)^2} + \frac{\beta\left(p_C w_H\right)^{\sigma+1}}{\left(\theta p_C w_H^{\sigma} + \left(1-\theta\right)p_C^{\sigma} w_H\right)^2} > 0$$

Given that $S^{ICT}$ is increasing in $\theta$, it is not surprising that the share of techie workers in total employment, $T/(T+L+M+H)$, can also be shown to be increasing in $\theta$.

## E.2 Polarization with falling ICT prices

We next turn to the effect of falling ICT prices on relative employment. Since $\sigma - 1 < 0$ and $\eta - 1 > 0$, we find that a drop in $r$ leads to a polarization in employment, with $H$ rising relative to $M$ and $L$, and $M$ falling relative to $H$ and $L$,

$$\frac{\partial}{\partial r}\left(\frac{H}{L}\right) = \frac{\beta}{1-\alpha-\beta}\frac{\left(\sigma-1\right)\theta\left(1-\theta\right)p_C^{\sigma} w_H^{\sigma} w_L}{\left(\theta p_C w_H^{\sigma} + \left(1-\theta\right)p_C^{\sigma} w_H\right)^2} < 0$$

$$\frac{\partial}{\partial r}\left(\frac{M}{L}\right) = \frac{\alpha}{1-\alpha-\beta}\frac{\left(\eta-1\right)\theta\left(1-\theta\right)p_C^{\eta} w_M^{\eta} w_L}{\left(\theta p_C w_M^{\eta} + \left(1-\theta\right)p_C^{\eta} w_M\right)^2} > 0$$

$$\frac{\partial}{\partial r}\left(\frac{H}{M}\right) = \frac{\beta}{\alpha}\frac{p_C^{\sigma-\eta}\left[-\left(1-\theta\right)\left(\eta-1\right)p_C^{\sigma} w_H w_M^{\eta} - w_H^{\sigma}\left\{\theta\left(\eta-\sigma\right)p_C w_M^{\eta} + \left(1-\theta\right)\left(1-\sigma\right)p_C^{\eta} w_M\right\}\right]}{\left(\theta p_C w_H^{\sigma} + \left(1-\theta\right)p_C^{\sigma} w_H\right)^2} < 0$$

The intuition is straightforward: since ICT is a complement to $H$ but a substitute for $M$, a drop in $r$ leads to greater employment of $H$ and less of $M$.

We now turn to a key question which helps motivate our empirical specification below: is the polarizing effect of falling $r$ stronger within firms where ICT is more important? Mathematically, is the cross derivative $\frac{\partial^2}{\partial r \partial \theta}\left(\frac{H}{M}\right)$ negative? The expression for $\frac{\partial^2}{\partial r \partial \theta}\left(\frac{H}{M}\right)$ is quite complex:

$$\frac{\partial^2}{\partial r \partial \theta}\left(\frac{H}{M}\right) = r^{\sigma-\eta}\frac{\beta}{\alpha}\frac{A-B}{\left[-\theta r w_H^{\sigma} - \left(1-\theta\right)r^{\sigma} w_H\right]^3}$$

where the cubed term in the denominator is negative, and

$$A = r^{\eta} w_H^{\sigma} w_M\left(\sigma-1\right)\left[\theta r w_H^{\sigma} - \left(1-\theta\right)r^{\sigma} w_H\right]$$

$$B = r^{\sigma} w_H w_M^{\eta}\left[\theta r w_H^{\sigma}\left(2\sigma-\eta-1\right) - \left(1-\theta\right)\left(\eta-1\right)r^{\sigma} w_H\right]$$

Given the assumptions $\eta > 1$ and $1 > \sigma > 0$, the term $B$ is necessarily negative. If $A > 0$, then $A - B > 0$ and the derivative is therefore negative. This is what intuition suggests: for higher levels of $\theta$, the polarizing effect of a fall in $r$ is greater. However, $A$ need not be positive, though $A - B > 0$ is still possible when $A < 0$. The condition $A - B > 0$ can be analyzed further by writing it out, and dividing both sides by the positive quantity $r^{\eta} w_H^{\sigma} w_M$, to obtain

$$(\sigma - 1) \left[\theta r w_H^{\sigma} - (1-\theta) r^{\sigma} w_H\right] > r^{\sigma-\eta} w_H^{1-\sigma} w_M^{\eta-1} \left[\theta r w_H^{\sigma} (2\sigma - \eta - 1) - (1-\theta)(\eta - 1) r^{\sigma} w_H\right]$$

When will this inequality be satisfied? Since the RHS is strictly negative, a sufficient but not necessary condition is that $\sigma \to 1$, so that the LHS $\to 0$. An alternative sufficient condition is that $\left[\theta r w_H^{\sigma} - (1-\theta) r^{\sigma} w_H\right] < 0$, which will hold for small enough values of $\theta$. Without tediously examining various configurations of the parameter space, we conclude that if the importance of ICT in production $\theta$ is not too high, and/or if ICT is not too complementary with high-skilled labor $H$, then $\frac{\partial^2}{\partial r \partial \theta}\left(\frac{H}{M}\right) < 0$: the polarizing effect of falling prices for ICT is stronger in firms where ICT is more important.

Aside from the effects on within-firm relative labor demand, a drop in $r$ can change economy-wide relative labor demand by reducing costs more rapidly for firms that use ICT more intensively. This effect follows from $\frac{\partial^2 b}{\partial p_C \partial \theta} > 0$ shown above.

# F Estimation methodology

Our estimation strategy for the within firm changes in occupational structure and the between differences in employment growth equations can be summarized as follow:

- For each equations, we have two regressions for manufacturing and nonmanufacturing firms
- Dependent variable is growth in hours, 2002-2007 or the ex-techie share of hours of the twelve large non-techie occupations
- Explanatory variables are levels of techies (share of hours), trade (imports and exports, scaled by total firm wage bill), and log hours in 2002 for the growth equations. Adding the log total hours to the within equations hardly affects the estimates.
- Estimator is weighted two stage least squares.
- Instruments are lagged techies, trade, and log hours 1994-1998.
- Observations weighted by firm hours in 2002.
- Heteroskedasticity robust covariance matrix.

### F.0.1 Instrument validity

**Choice of instrument.** To answer the question about how many instruments are valid, we implement a sequence of "difference-in-Sargan" tests, also known as $C$ tests.[48] We assume that the 1994 lag is a valid instrument, and we then sequentially add more recent lags (1995, 1996, etc.). The incremental increase in the usual overidentification Sargan test statistic is distributed as a $\chi_m^2$, where $m$ is the number of added instruments, which is 7 in our case. The null hypothesis is that the additional instruments are valid, conditional on the previous ones being valid. Failure to reject the null at each increment is taken as evidence for the validity of the added instruments. The results indicate that in non-manufacturing no more than six lags, including 1994–1999, should be used; in manufacturing the procedure indicates no more than four lags, including 1994–1997, should be used. We chose the average of five.

[48] Convenient references for the "difference-in-Sargan" test include Hayashi (2000), pages 218–221 and 232–234, and Ruud (2000), Chapter 22.

Importantly, the lag for which the $C$ stat exceeds conventional critical values is also the lag that is the first to have a Hansen $J$ statistic that exeeds conventional critical values. This is not generally true, but in our case it is. This implies that the overidentification test is not rejected at standard levels of significance for six lags in nonmanufacturing and for four lags in manufacturing. In manufacturing, using five lags from 1994 to 1998 gives a $p$-value for the $J$ test of 0.03.[49] This is particularly reassuring, because it implies that as a set, lags 1994–1998 can be considered exogenous *a priori*. We chose five lags in both sectors for symmetry.

To answer the question about how many valid instruments to use, we use the procedure proposed by Donald and Newey (2001). The purpose of the Donald-Newey procedure is to select the most efficient set of instruments, and the procedure involves minimizing the mean squared error (MSE) of a weighted average of the estimates of interest, relative to a benchmark estimate.[50] Our benchmark uses only the 1994 lags of $\mathbf{X}$. We consider the simple average of the MSE criterion across the seven elements of $\boldsymbol{\beta}$. When we add lags of $\mathbf{X}$ sequentially and compare the MSE to that of using only 1994, we find that the minimum MSE is attained with six or seven lags, which includes 1999 or 2000, respectively.

To summarize, our two procedures give slightly different answers, with the difference-in-Sargan procedure suggesting using 1994–1998 lags and the Donald-Newey procedure suggesting an additional year or two. We choose to be conservative, and thus proceed by using the 1994–1998 lags as our set of instruments in both the manufacturing and nonmanufacturing sectors.

**Are the instruments strong?** We report in Table 6 of the main text the Shea partial $R^2$. The results leave no question that the first stage is strong.

**Exclusion restriction and exogeneity** An implication of exogeneity is that the instruments must statisfy the exclusion restriction (not relevant except through their influence on the endogenous regressors). We conduct a specification test that addresses this implication. We can directly test part of our exogeneity assumptions, because 2002–2007 changes in techies and trade are among the changes in firm characteristics included in the composite error term, $u_{it}$, and we have data on these changes. As a test of the null hypothesis that these observable changes are uncorrelated with the instruments, we regress 2002–2007 changes in techies and trade on the full set of instruments. The explanatory power of these regressions is near zero: the regressions' $R^2$'s are tiny, and $F$ tests fail to reject the null of no linear relationship.

While reassuring, these regression tests of instrument exogeneity fail to address potential correlation between the instruments and changes in *unobservable* firm characteristics such as revenue or capital and intermediates intensity. However, given the very low correlation between changes and lagged levels in the variables we do observe, it seems reasonable to expect that the correlation between changes in different variables and our instruments would also be small.

One of the things we are worried about is how serial correlation in the errors of the structural model in levels affects the 2SLS estimator of the change-on-levels regression. The structural model in levels can be written as

$$\ln h_{ft} = \beta_f + D_f \cdot t + \mathbf{W}_{ft}\gamma + \varepsilon_{ft} \ , \tag{12}$$

[49] Adding 1999 and 2000 lags increases the $p$-value somewhat to 0.06.

[50] Of the two minimum MSE criteria proposed by Donald and Newey (2001), we use the Mallows criteria, which proves to be more robust.

where $h$ is total firm hours, $\beta_f$ is a firm fixed effect, $D$ is a firm specific trend in $s$, $\mathbf{W}$ is a set of firm characteristics and $\varepsilon$ is the error term. We take first differences of (12) to get

$$\Delta \ln h_{ft} = D_{ft} + \Delta \mathbf{W}_{ft}\boldsymbol{\gamma} + \Delta\varepsilon_{ft} = D_{ft} + u_{ft} \ , \tag{13}$$

where $u_{ft} = \Delta \mathbf{W}_{ft}\boldsymbol{\gamma} + \Delta\varepsilon_{ft}$ is a composite error. We model the firm-specific trend $D_{ft}$ as a function of the initial *level* of techies and trade in time $t$. Therefore, we estimate

$$\Delta \ln h_{ft} = \mathbf{X}_{ft}\beta + u_{ft} \ , \tag{14}$$

where $\mathbf{X}$ is a subset of the list of variables $\mathbf{W}$. In practice, we add to (14) industry fixed effects.

Within $u_{ft}$, there is $\Delta\varepsilon_{ft}$. What are the consequences of serial correlation in $\varepsilon_{ft}$? Since we cannot assume $E\left(\mathbf{X}_{ft}\varepsilon_{ft}|\beta_f\right) = 0$, then $\mathbf{X}$ is endogenous and OLS is a biased and inconsistent estimator of $\beta$. This is one of the motivations for using instruments for $\mathbf{X}$. Our instruments are lagged values. Here we characterize the consequences of serial correlation in $\varepsilon_{ft}$.

To make progress, we add the particular timing to (14), and structure to the serial correlation. Here $\Delta$ is the change from 2002 to 2007, and $t = 2002$. Our instruments are the set of lagged values of $\mathbf{X}$, where the latest one is in 1998, i.e. in $t-4$, and the earliest one is in 1994, i.e. in $t-8$. In other words, our instrument set is $\mathbf{X}_{f,t-4}, ...\mathbf{X}_{f,t-8}$. Let $E\left(\mathbf{X}_{ft}\varepsilon_{ft}|\beta_f\right) = \eta \neq 0$, and suppose that $\varepsilon_{ft}$ follows an AR(1) process

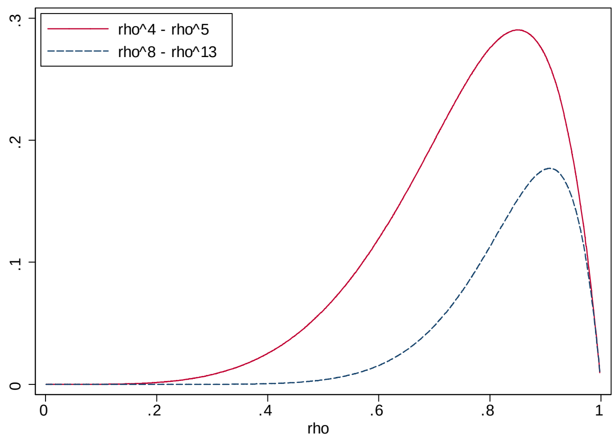
$$\varepsilon_{ft} = \rho\varepsilon_{ft-1} + v_{ft} \ , \tag{15}$$

where $\rho \in (0,1)$ and $v$ is white noise.

To ease notation, we ignore the firm-level index, which is inconsequential for what follows, unless $\rho$ and $\eta$ systematically covary across firms, which is unlikely. For $\mathbf{X}_{t-4}$ to be a valid instrument we need $E\left(\mathbf{X}_{t-4}\Delta\varepsilon_t\right) = 0$, but this is not the case:

$$\begin{aligned}
E\left(\mathbf{X}_{t-4}\Delta\varepsilon_t\right) &= E\left[\mathbf{X}_{t-4}\left(\varepsilon_{t+5} - \varepsilon_t\right)\right] \\
&= E\left[\mathbf{X}_{t-4}\varepsilon_{t+5}\right] - E\left[\mathbf{X}_{t-4}\varepsilon_t\right] \\
&= E\left[\mathbf{X}_{t-4}\left(\rho^9\varepsilon_{t-4} + \sum_{j=0}^{8}\rho^j v_{t+5-j}\right)\right] - E\left[\mathbf{X}_{t-4}\left(\rho^4\varepsilon_{t-4} + \sum_{j=0}^{3}\rho^j v_{t-j}\right)\right] \\
&= \rho^9 E\left[\mathbf{X}_{t-4}\varepsilon_{t-4}\right] - \rho^4 E\left[\mathbf{X}_{t-4}\varepsilon_{t-4}\right] \\
&= \rho^9 E_{\beta_f}\left[E\left(\mathbf{X}_{t-4}\varepsilon_{t-4}|\beta_f\right)\right] - \rho^4 E_{\beta_f}\left[E\left(\mathbf{X}_{t-4}\varepsilon_{t-4}|\beta_f\right)\right] \\
&= \left(\rho^9 - \rho^4\right)\eta \\
&= -\eta\left(1-\rho^5\right)\rho^4 < 0 \ .
\end{aligned}$$

Similar calculations give $E\left(\mathbf{X}_{t-5}\Delta\varepsilon_t\right) = -\eta\left(1-\rho^5\right)\rho^5$,...$E\left(\mathbf{X}_{t-8}\Delta\varepsilon_t\right) = -\eta\left(1-\rho^5\right)\rho^8$. We see that longer lags give lower correlation, so bias with respect to longer lags is smaller. We also see that the relationship to $\rho$ is non-monotonic, where both $\rho = 0$ and $\rho = 1$ give zero correlation of $\mathbf{X}_{t-s}$ with $\Delta\varepsilon_t$, for any $s = 4, 5...8$. For $\rho \in (0,1)$ we get a non-zero correlation, with a maximum of $E\left(\mathbf{X}_{t-4}\Delta\varepsilon_t\right) \approx -\eta \cdot 0.29$ at $\rho \approx 0.85$ and a maximum of $E\left(\mathbf{X}_{t-8}\Delta\varepsilon_t\right) \approx -\eta \cdot 0.18$ at $\rho \approx 0.9$; see figure below. Note that one needs rather high $\rho$ to get large values of $E\left(\mathbf{X}_{t-s}\Delta\varepsilon_t\right)$, $s = 4, 5, ...8$.




Inconsistency of 2SLS is the result of the non-zero product of $(1-\rho^5)\,\rho^5$ with $\eta$. We expect $\eta = E\left(\mathbf{X}_{ft}\varepsilon_{ft}|\beta_f\right)$ to be small. First, most of the cross-firm variation in technological and other shocks (and in unobservables, too) is absorbed in the $\beta_f$ firm fixed effects; see (4) and (9). Second, $\mathbf{X}_{ft}$ are firm characteristics and as such they are unlikely to respond much to contemporaneous firm level shocks. Therefore, we think that it is reasonable to say that this source of inconsistency is not a major concern.

# G Extensive and intensive margins and evaluation of the effects

Here we explain how we calculate the extensive and intensive margin effects of techies and trade when we use the interaction specification given by equation (6). The extensive and intensive margin effects depend on both estimated parameters and data, and Section G.3 explains where in the sample we evaluate the effects that we report in Tables 10, 11, and 14 through 17.

In what follows, $\Delta y$ can be either the firm-level growth in hours ($\Delta \ln h_{ft}$) or the change in ex-techie share of hours of the twelve large non-techie occupations ($\Delta s_{fot}$).

## G.1 Extensive margins

### G.1.1 Techies

Comparing the mean of $\Delta s$ when $techpos = 0$ and $techpos = 1$,

$$\mathbb{E}\left[\Delta s_{fot}|techpos_{t-1}=1\right] - \mathbb{E}\left[\Delta s_{fot}|techpos_{t-1}=0\right]$$

$$= \beta_1 tech_{t-1} + \beta_2$$

$$+ \left(\beta_7 imp_{t-1} + \beta_8 imppos_{t-1} + \beta_9 exp_{t-1} + \beta_{10} exppos_{t-1}\right) \times tech_{t-1}$$

$$+ \left(\beta_{11} imp_{t-1} + \beta_{12} imppos_{t-1} + \beta_{13} exp_{t-1} + \beta_{14} exppos_{t-1}\right).$$

This can be evaluated at – among other points – the different combinations of the trade variables, *imppos* and *exppos*.

| | $exppos_{t-1}=0$ | $exppos_{t-1}=1$ |
|---|---|---|
| $imppos_{t-1}=0$ | $\beta_1 tech_{t-1}+\beta_2$ | $\beta_1 tech_{t-1}+\beta_2$ <br> $+(\beta_9 exp_{t-1}+\beta_{10})\times tech_{t-1}$ <br> $+(\beta_{13} exp_{t-1}+\beta_{14})$ |
| $imppos_{t-1}=1$ | $\beta_1 tech_{t-1}+\beta_2$ <br> $+(\beta_7 imp_{t-1}+\beta_8)\times tech_{t-1}$ <br> $+(\beta_{11} imp_{t-1}+\beta_{12})$ | $\beta_1 tech_{t-1}+\beta_2$ <br> $+(\beta_7 imp_{t-1}+\beta_8+\beta_9 exp_{t-1}+\beta_{10})\times tech_{t-1}$ <br> $+(\beta_{11} imp_{t-1}+\beta_{12}+\beta_{13} exp_{t-1}+\beta_{14})$ |

#### G.1.2 Imports

$$\begin{aligned}&\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=1\right]-\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=0\right]\\&=\beta_3 imp_{t-1}+\beta_5\\&+(\beta_7 imp_{t-1}+\beta_8)\times tech_{t-1}\\&+(\beta_{11} imp_{t-1}+\beta_{12})\times techpos_{t-1}.\end{aligned}$$

Since the model contains no interactions between the two trade variables, we only need evaluate the extensive import margin at zero or positive levels of techies:

$$\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=1,techpos_{t-1}=0\right]-\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=0,techpos_{t-1}=0\right]=\beta_3 imp_{t-1}+\beta_5,$$

and

$$\begin{aligned}&\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=1,techpos_{t-1}=1\right]-\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=0,techpos_{t-1}=1\right]\\&=\beta_3 imp_{t-1}+\beta_5\\&+(\beta_7 imp_{t-1}+\beta_8)\times tech_{t-1}\\&+(\beta_{11} imp_{t-1}+\beta_{12}).\end{aligned}$$

#### G.1.3 Exports

Similarly,

$$\mathbb{E}\left[\Delta s_{fot}|exppos_{t-1}=1\right]-\mathbb{E}\left[\Delta s_{fot}|exppos_{t-1}=0\right]$$
$$=\beta_4 exp_{t-1}+\beta_6$$
$$+\left(\beta_9 exp_{t-1}+\beta_{10}\right)\times tech_{t-1}$$
$$+\left(\beta_{13} exp_{t-1}+\beta_{14}\right)\times techpos_{t-1}.$$

So

$$\mathbb{E}\left[\Delta s_{fot}|exppos_{t-1}=1,techpos_{t-1}=0\right]-\mathbb{E}\left[\Delta s_{fot}|exppos_{t-1}=0,techpos_{t-1}=0\right]=\beta_4 exp_{t-1}+\beta_6,$$

and

$$\mathbb{E}\left[\Delta s_{fot}|exppos_{t-1}=1,techpos_{t-1}=1\right]-\mathbb{E}\left[\Delta s_{fot}|exppos_{t-1}=0,techpos_{t-1}=1\right]$$
$$=\beta_4 exp_{t-1}+\beta_6$$
$$+\left(\beta_9 exp_{t-1}+\beta_{10}\right)\times tech_{t-1}$$
$$+\left(\beta_{13} exp_{t-1}+\beta_{14}\right).$$

## G.2 Intensive margins

### G.2.1 Techies

All else equal, if $tech_{t-1}$ changes by $\Delta tech_{t-1}$, then $\Delta s_{fot}$ changes by

$$\Delta\mathbb{E}\left[\Delta s_{fot}|techpos_{t-1}=1\right]=\left(\beta_1+\beta_7 imp_{t-1}+\beta_8 imppos_{t-1}+\beta_9 exp_{t-1}+\beta_{10} exppos_{t-1}\right)\times\Delta tech_{t-1},$$

which can also be evaluated at various combinations of the two trade indicators.

| | $exppos_{t-1}=0$ | $exppos_{t-1}=1$ |
|---|---|---|
| $imppos_{t-1}=0$ | $\beta_1\times\Delta tech_{t-1}$ | $(\beta_1+\beta_9 exp_{t-1}+\beta_{10})\times\Delta tech_{t-1}$ |
| $imppos_{t-1}=1$ | $(\beta_1+\beta_7 imp_{t-1}+\beta_8)\times\Delta tech_{t-1}$ | $(\beta_1+\beta_7 imp_{t-1}+\beta_8+\beta_9 exp_{t-1}+\beta_{10})\times\Delta tech_{t-1}$ |

### G.2.2 Imports

Similarly, if $\Delta tech_{t-1}=\Delta exp_{t-1}=0$, then

$$\Delta\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=1\right]=\left(\beta_3+\beta_7 tech_{t-1}+\beta_{11} techpos_{t-1}\right)\times\Delta imp_{t-1}.$$

Then

$$\Delta\mathbb{E}\left[\Delta s_{fot}|imppos_{t-1}=1,techpos_{t-1}=0\right]=\beta_3\times\Delta imp_{t-1},$$

and

$$\Delta \mathbb{E}\left[\Delta s_{fot} | imppos_{t-1} = 1, techpos_{t-1} = 1\right] = (\beta_3 + \beta_7 tech_{t-1} + \beta_{11}) \times \Delta imp_{t-1}.$$

### G.2.3 Exports

Finally, if $\Delta tech_{t-1} = \Delta imp_{t-1} = 0$, then

$$\Delta \mathbb{E}\left[\Delta s_{fot} | exppos_{t-1} = 1\right] = (\beta_4 + \beta_9 tech_{t-1} + \beta_{13} techpos_{t-1}) \times \Delta exp_{t-1}.$$

Then

$$\Delta \mathbb{E}\left[\Delta s_{fot} | exppos_{t-1} = 1, techpos_{t-1} = 0\right] = \beta_4 \times \Delta exp_{t-1},$$

and

$$\Delta \mathbb{E}\left[\Delta s_{fot} | exppos_{t-1} = 1, techpos_{t-1} = 1\right] = (\beta_4 + \beta_9 tech_{t-1} + \beta_{13}) \times \Delta exp_{t-1}.$$

## G.3 Evaluating the effects

- We need to pick values of $tech_{t-1}$, $imp_{t-1}$, and $exp_{t-1}$ at which to evaluate effects at both margins
- In addition, we need to pick values of $\Delta tech_{t-1}$, $\Delta imp_{t-1}$, and $\Delta exp_{t-1}$ at which to evaluate the intensive margin effects
- For comparability across PCS codes, the computed effects are be scaled by variation in the occupation share. In particular
  - For the extensive margin effects, we calculate all values at the median of the strictly positive values and then divide by the median of the ex-techie share.
  - For the intensive margin effects, we also evaluate levels at the median of the strictly positive values. The changes $\Delta tech_{t-1}$, $\Delta imp_{t-1}$, and $\Delta exp_{t-1}$ are evaluated as the difference between the $25^{th}$ and $75^{th}$ percentiles of the strictly positive values, that is, $p_{75}(x) - p_{25}(x)$, and then divide by the $25^{th}$ - $75^{th}$ percentile range of the ex-techie share.

# H Approximating $\Delta\widehat{\lambda}_f$ by using $\widehat{g}_f$

Here we describe how we use predicted values of firm employment growth (from employment growth regreesions) to predict changes in firm employment shares.

The change in the employment share of firm $f$ from period 1 to period 2 is

$$\Delta \lambda_f = \frac{h_{f2}}{H_2} - \frac{h_{f1}}{H_1} \ ,$$

where

$$H_t = \sum_f h_{ft}$$

is total employment in time $t$. Firm employment growth of firm $f$ from period 1 to period 2 is

$$g_f = \frac{h_{f2} - h_{f1}}{h_{f1}} \ .$$

$\Delta\lambda_f$ can be written as

$$\Delta\lambda_f = \frac{h_{f2}}{H_2} - \frac{h_{f1}}{H_1} = \frac{h_{f1}\,(1+g_f)}{H_2} - \frac{h_{f1}}{H_1}\ ,$$

so we can predict

$$\widehat{\Delta\lambda}_f = \frac{h_{f1}(1+\widehat{g}_f)}{H_2} - \frac{h_{f1}}{H_1}\ ,$$

where $h_{f1}$, $H_1$ and $H_2$ are all data.

# I Regression Results

As discussed in the previous section, the estimated effects reported in the main text are functions of estimated regression results and the data. In Tables 21 through 26 below we report the regression results.

Table 21: Growth regressions (nonmanufacturing)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| techies | 0.042 | 0.042 | 0.058 | 0.574*** |
| | *0.160* | *0.158* | *0.150* | *0.220* |
| positive techies | 0.107* | 0.103 | 0.124** | 0.075 |
| | *0.063* | *0.068* | *0.060* | *0.061* |
| exports | -0.019 | -0.018 | -0.019 | 0.004 |
| | *0.018* | *0.018* | *0.019* | *0.017* |
| positive exports | -0.107 | -0.123* | -0.057 | -0.123 |
| | *0.069* | *0.069* | *0.077* | *0.127* |
| imports | 0.001 | 0.007 | | 0.004 |
| | *0.007* | *0.007* | | *0.012* |
| positive imports | -0.040 | -0.013 | | 0.028 |
| | *0.069* | *0.104* | | *0.115* |
| imports of intermediate inputs | | -0.023* | | |
| | | *0.012* | | |
| positive imports of intermediate inputs | | 0.004 | | |
| | | *0.097* | | |
| imports from China | | | 0.019 | |
| | | | *0.024* | |
| positive imports from China | | | -0.046 | |
| | | | *0.141* | |
| imports from high income countries | | | 0.006 | |
| | | | *0.009* | |
| positive imports from high income countries | | | 0.010 | |
| | | | *0.081* | |
| imports from other countries | | | 0.005 | |
| | | | *0.014* | |
| positive imports from other countries | | | -0.118 | |
| | | | *0.113* | |
| techies × exports | | | | 0.391 |
| | | | | *0.355* |
| techies × positive exports | | | | 0.019 |
| | | | | *0.634* |
| techies × imports | | | | -0.244 |
| | | | | *0.183* |
| techies × positive imports | | | | -1.143 |
| | | | | *0.764* |
| positive techies × exports | | | | -0.059** |
| | | | | *0.024* |
| positive techies × positive exports | | | | 0.034 |
| | | | | *0.235* |
| positive techies × imports | | | | 0.012 |
| | | | | *0.023* |
| positive techies × positive imports | | | | -0.010 |
| | | | | *0.217* |
| Observations | 261,196 | 261,196 | 261,196 | 261,196 |
| $R^2$ | 0.005 | 0.005 | 0.005 | 0.002 |

Table 22: Growth regressions (manufacturing)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| techies | 0.337*** | 0.340*** | 0.352*** | 0.206 |
| | *0.103* | *0.103* | *0.106* | *0.225* |
| positive techies | 0.188*** | 0.185*** | 0.155*** | 0.256*** |
| | *0.056* | *0.056* | *0.057* | *0.065* |
| exports | -0.004 | -0.003 | -0.002 | 0.021 |
| | *0.005* | *0.005* | *0.005* | *0.037* |
| positive exports | 0.023 | 0.017 | 0.048 | -0.093 |
| | *0.054* | *0.053* | *0.049* | *0.128* |
| imports | 0.006 | 0.010 | | -0.017 |
| | *0.006* | *0.009* | | *0.031* |
| positive imports | -0.042 | 0.166 | | 0.223* |
| | *0.067* | *0.129* | | *0.133* |
| imports of intermediate inputs | | -0.008 | | |
| | | *0.012* | | |
| positive imports of intermediate inputs | | -0.199** | | |
| | | *0.097* | | |
| imports from China | | | 0.079 | |
| | | | *0.060* | |
| positive imports from China | | | -0.021 | |
| | | | *0.047* | |
| imports from high income countries | | | 0.017** | |
| | | | *0.009* | |
| positive imports from high income countries | | | -0.014 | |
| | | | *0.056* | |
| imports from other countries | | | -0.027** | |
| | | | *0.012* | |
| positive imports from other countries | | | -0.106** | |
| | | | *0.053* | |
| techies × exports | | | | -0.053 |
| | | | | *0.042* |
| techies × positive exports | | | | -0.935 |
| | | | | *0.580* |
| techies × imports | | | | 0.047 |
| | | | | *0.074* |
| techies × positive imports | | | | 1.158* |
| | | | | *0.631* |
| positive techies × exports | | | | -0.014 |
| | | | | *0.039* |
| positive techies × positive exports | | | | 0.227 |
| | | | | *0.247* |
| positive techies × imports | | | | 0.017 |
| | | | | *0.039* |
| positive techies × positive imports | | | | -0.439 |
| | | | | *0.272* |
| Observations | 47,808 | 47,808 | 47,808 | 47,808 |
| $R^2$ | 0.018 | 0.017 | 0.018 | 0.013 |

Table 23: Within regressions (nonmanufacturing; baseline)

| | 37 | 46 | 54 | 55 | 56 | 62 | 63 | 64 | 67 | 68 |
|---|---|---|---|---|---|---|---|---|---|---|
| techies | 0.1200*** | 0.0474** | -0.0442* | -0.0649** | 0.0155* | -0.0578 | -0.0250 | -0.0337** | 0.0572** | -0.0406** |
| | *0.0457* | *0.0186* | *0.0241* | *0.0321* | *0.0093* | *0.0471* | *0.0204* | *0.0146* | *0.0245* | *0.0162* |
| positive techies | 0.0105 | -0.0105 | 0.0022 | 0.0052 | -0.0053 | 0.0270** | 0.0070 | -0.0001 | 0.0037 | -0.0082** |
| | *0.0092* | *0.0078* | *0.0075* | *0.0083* | *0.0068* | *0.0113* | *0.0047* | *0.0039* | *0.0067* | *0.0034* |
| imports | 0.0026** | -0.0020* | 0.0015 | 0.0018* | -0.0001 | 0.0006 | -0.0018* | -0.0018*** | 0.0010 | -0.0006 |
| | *0.0011* | *0.0012* | *0.0014* | *0.0010* | *0.0005* | *0.0017* | *0.0010* | *0.0006* | *0.0012* | *0.0006* |
| positive imports | 0.0081 | 0.0131 | 0.0040 | -0.0104 | -0.0082 | -0.0162 | 0.0016 | 0.0149* | 0.0002 | -0.0177 |
| | *0.0118* | *0.0090* | *0.0109* | *0.0066* | *0.0058* | *0.0112* | *0.0064* | *0.0081* | *0.0077* | *0.0122* |
| exports | 0.0102** | -0.0007 | 0.0049** | -0.0014 | 0.0008 | -0.0098** | -0.0008 | -0.0004 | -0.0014 | -0.0036*** |
| | *0.0048* | *0.0023* | *0.0020* | *0.0012* | *0.0012* | *0.0048* | *0.0011* | *0.0010* | *0.0022* | *0.0014* |
| positive exports | 0.0024 | 0.0062 | -0.0398*** | 0.0112 | -0.0037 | -0.0034 | -0.0028 | 0.0000 | -0.0090 | 0.0350 |
| | *0.0109* | *0.0118* | *0.0145* | *0.0081* | *0.0088* | *0.0088* | *0.0057* | *0.0074* | *0.0108* | *0.0156* |
| Observations | 76,731 | 119,470 | 170,219 | 73,198 | 55,464 | 33,650 | 114,246 | 50,376 | 49,418 | 106,631 |
| $R^2$ | 0.049 | 0.012 | 0.021 | 0.010 | 0.019 | 0.028 | 0.002 | 0.012 | 0.043 | 0.005 |

## Table 24: Within regressions (nonmanufacturing; interactions)

| | 37 | 46 | 54 | 55 | 56 | 62 | 63 | 64 | 67 | 68 |
|---|---|---|---|---|---|---|---|---|---|---|
| techies | 0.0283 | 0.0191 | -0.0227 | 0.0009 | 0.0193 | 0.0609* | 0.0102 | -0.0736* | 0.0371 | -0.0318* |
| | *0.0214* | *0.0243* | *0.0261* | *0.0252* | *0.0183* | *0.0358* | *0.0411* | *0.0382* | *0.0344* | *0.0174* |
| positive techies | 0.0221*** | -0.0111 | 0.0007 | 0.0018 | -0.0031 | 0.0217*** | 0.0048 | 0.0009 | 0.0126 | -0.0091** |
| | *0.0075* | *0.0094* | *0.0090* | *0.0102* | *0.0078* | *0.0075* | *0.0048* | *0.0056* | *0.0094* | *0.0043* |
| imports | 0.0009 | -0.0020 | 0.0026 | -0.0012 | 0.0035 | 0.0011 | 0.0001 | -0.0005 | -0.0036 | -0.0015 |
| | *0.0028* | *0.0025* | *0.0042* | *0.0022* | *0.0030* | *0.0051* | *0.0018* | *0.0017* | *0.0029* | *0.0014* |
| exports | -0.0041 | -0.0013 | -0.0028 | -0.0005 | -0.0100 | 0.0054 | -0.0022 | -0.0006 | 0.0065** | 0.0001 |
| | *0.0031* | *0.0030* | *0.0022* | *0.0029* | *0.0062* | *0.0062* | *0.0034* | *0.0019* | *0.0029* | *0.0018* |
| positive imports | 0.0120 | 0.0317* | -0.0303* | 0.0005 | -0.0372* | 0.0449* | -0.0122 | -0.0112 | 0.0004 | 0.0281** |
| | *0.0167* | *0.0184* | *0.0180* | *0.0117* | *0.0225* | *0.0267* | *0.0171* | *0.0093* | *0.0127* | *0.0142* |
| positive exports | -0.0007 | -0.0486** | 0.0240 | 0.0057 | 0.0506** | -0.0443 | 0.0095 | 0.0182 | 0.0300** | -0.0211 |
| | *0.0250* | *0.0199* | *0.0175* | *0.0195* | *0.0237* | *0.0409* | *0.0311* | *0.0118* | *0.0134* | *0.0183* |
| techies × imports | 0.0530 | 0.0032 | 0.0358 | -0.0427* | -0.0101 | -0.0582 | -0.0203 | 0.0131* | -0.0237* | 0.0119 |
| | *0.0656* | *0.0271* | *0.0232* | *0.0229* | *0.0090* | *0.0920* | *0.0299* | *0.0078* | *0.0129* | *0.0076* |
| techies × positive imports | 0.0622 | -0.0232 | -0.0936 | 0.0543 | 0.0262 | -0.1630** | -0.0461 | 0.0228 | 0.0291 | 0.0845 |
| | *0.0746* | *0.0966* | *0.1060* | *0.0514* | *0.0313* | *0.0687* | *0.0490* | *0.0487* | *0.0722* | *0.0527* |
| techies × exports | 0.0701 | -0.0212 | -0.0109 | 0.0360* | 0.0135 | -0.0515 | 0.0182 | -0.0001 | -0.0138 | -0.0033 |
| | *0.0640* | *0.0244* | *0.0216* | *0.0200* | *0.0113* | *0.0583* | *0.0231* | *0.0077* | *0.0141* | *0.0073* |
| techies × positive exports | 0.0723 | 0.0996 | 0.0395 | -0.1600** | -0.0438 | 0.0146 | -0.0022 | 0.0350 | 0.0156 | -0.0998* |
| | *0.0740* | *0.0948* | *0.1080* | *0.0769* | *0.0338* | *0.0587* | *0.0327* | *0.0234* | *0.0505* | *0.0569* |
| positive techies × imports | -0.0010 | 0.0000 | -0.0044 | 0.0065 | -0.0032 | 0.0015 | -0.0002 | -0.0021 | 0.0067 | 0.0002 |
| | *0.0057* | *0.0043* | *0.0054* | *0.0043* | *0.0035* | *0.0080* | *0.0035* | *0.0022* | *0.0041* | *0.0019* |
| positive techies × positive imports | -0.0157 | -0.0279 | 0.0559 | -0.0165 | 0.0264 | -0.0519 | 0.0192 | 0.0308 | -0.0007 | -0.0618* |
| | *0.0239* | *0.0278* | *0.0344* | *0.0180* | *0.0258* | *0.0319* | *0.0212* | *0.0201* | *0.0196* | *0.0333* |
| positive techies × exports | 0.0071 | 0.0055 | 0.0085* | -0.0035 | 0.0097 | -0.0081 | -0.0004 | -0.0004 | -0.0099* | -0.0035 |
| | *0.0072* | *0.0056* | *0.0047* | *0.0038* | *0.0068* | *0.0091* | *0.0032* | *0.0030* | *0.0058* | *0.0032* |
| positive techies × positive exports | -0.0049 | 0.0574* | -0.0798** | 0.0169 | -0.0511* | 0.0471 | -0.0150 | -0.0269 | -0.0434* | 0.0741* |
| | *0.0319* | *0.0318* | *0.0382* | *0.0227* | *0.0266* | *0.0451* | *0.0354* | *0.0206* | *0.0248* | *0.0407* |
| Observations | 76,731 | 119,470 | 170,219 | 73,198 | 55,464 | 33,650 | 114,246 | 50,376 | 49,418 | 106,631 |
| $R^2$ | 0.068 | 0.011 | 0.018 | 0.007 | 0.017 | 0.039 | 0.000 | 0.010 | 0.043 | |

Table 25: Within regressions (manufacturing; baseline)

| | 37 | 46 | 48 | 54 | 62 | 63 | 64 | 67 |
|---|---|---|---|---|---|---|---|---|
| techies | 0.0409 | 0.0962** | -0.0263** | -0.0318 | -0.1380** | -0.0027 | 0.0114*** | 0.0212 |
| | *0.0324* | *0.0462* | *0.0115* | *0.0424* | *0.0674* | *0.0181* | *0.0039* | *0.0630* |
| positive techies | 0.0079 | 0.0134 | -0.0109 | -0.0118 | -0.0933 | 0.0092 | 0.0091 | 0.1060 |
| | *0.0106* | *0.0127* | *0.0187* | *0.0104* | *0.0520* | *0.0181* | *0.0039* | *0.0781* |
| imports | 0.0000 | -0.0004 | 0.0004 | 0.0012 | -0.0014 | 0.0006 | -0.0002 | -0.0009 |
| | *0.0012* | *0.0019* | *0.0005* | *0.0008* | *0.0027* | *0.0018* | *0.0002* | *0.0032* |
| positive imports | 0.0051 | 0.0092 | 0.0149* | -0.0061 | 0.1720* | 0.0898** | 0.0069* | -0.3120* |
| | *0.0100* | *0.0157* | *0.0090* | *0.0096* | *0.1030* | *0.0365* | *0.0039* | *0.1600* |
| exports | -0.0010 | 0.0000 | -0.0001 | -0.0005 | 0.0073 | 0.0011 | 0.0004** | -0.0066 |
| | *0.0010* | *0.0011* | *0.0004* | *0.0009* | *0.0051* | *0.0013* | *0.0002* | *0.0063* |
| positive exports | 0.0186** | -0.0032 | -0.0015 | 0.0038 | -0.1470* | -0.0516* | -0.0027 | 0.2100* |
| | *0.0083* | *0.0126* | *0.0085* | *0.0078* | *0.0789* | *0.0267* | *0.0036* | *0.1200* |
| Observations | 20,244 | 27,944 | 20,413 | 31,882 | 35,168 | 26,750 | 12,649 | 31,778 |
| $R^2$ | 0.062 | 0.024 | 0.005 | 0.028 | 0.009 | | 0.004 | |

Table 26: Within regressions (manufacturing; interactions)

| | 37 | 46 | 48 | 54 | 62 | 63 | 64 | 67 |
|---|---|---|---|---|---|---|---|---|
| techies | -0.0543 | 0.0768 | 0.0353 | 0.0780 | 0.2170 | -0.2390*** | -0.0623* | -0.3740 |
| | *0.0592* | *0.0606* | *0.1250* | *0.0680* | *0.2260* | *0.0741* | *0.0331* | *0.2970* |
| positive techies | 0.0428*** | 0.0150 | -0.0332 | -0.0275* | -0.2030** | 0.0756*** | 0.0260*** | 0.1990 |
| | *0.0166* | *0.0169* | *0.0497* | *0.0161* | *0.0858* | *0.0222* | *0.0078* | *0.1270* |
| imports | -0.0105 | -0.0086 | 0.0015 | -0.0046 | 0.0020 | -0.0157* | 0.0002 | 0.0067 |
| | *0.0057* | *0.0084* | *0.0041* | *0.0047* | *0.0152* | *0.0082* | *0.0024* | *0.0171* |
| exports | 0.0034 | -0.0064 | -0.0036 | 0.0139 | -0.0208 | 0.0150 | 0.0034 | 0.0218 |
| | *0.0084* | *0.0083* | *0.0049* | *0.0087* | *0.0199* | *0.0180* | *0.0042* | *0.0245* |
| positive imports | 0.0365 | 0.0194 | -0.0100 | 0.0350 | -0.4150** | 0.0646 | 0.0145 | 0.4590* |
| | *0.0317* | *0.0379* | *0.0250* | *0.0235* | *0.1700* | *0.0525* | *0.0138* | *0.2640* |
| positive exports | 0.0233 | -0.0041 | 0.0021 | -0.0381* | 0.3130* | 0.0336 | -0.0038 | -0.4630* |
| | *0.0335* | *0.0382* | *0.0212* | *0.0198* | *0.1660* | *0.0531* | *0.0150* | *0.2560* |
| techies × imports | -0.0184 | 0.0019 | -0.0074 | 0.0275 | -0.0612 | -0.0216 | -0.0004 | 0.0765* |
| | *0.0195* | *0.0235* | *0.0069* | *0.0328* | *0.0449* | *0.0149* | *0.0031* | *0.0439* |
| techies × positive imports | 0.1980* | -0.0211 | -0.0283 | -0.0082 | -1.8960** | 0.0294 | 0.0645* | 2.0460 |
| | *0.1190* | *0.1880* | *0.0998* | *0.1230* | *0.8930* | *0.2020* | *0.0377* | *1.2560* |
| techies × exports | -0.0019 | 0.0045 | 0.0019 | -0.0094 | 0.0198 | 0.0035 | -0.0003 | -0.0152 |
| | *0.0105* | *0.0116* | *0.0039* | *0.0150* | *0.0290* | *0.0065* | *0.0013* | *0.0308* |
| techies × positive exports | -0.0724 | 0.0269 | -0.0367 | -0.1150 | 1.5220** | 0.2320 | 0.0105 | -1.6400 |
| | *0.1090* | *0.1910* | *0.0845* | *0.1050* | *0.7480* | *0.1580* | *0.0238* | *1.0200* |
| positive techies × imports | 0.0141* | 0.0084 | 0.0001 | 0.0013 | 0.0063 | 0.0204** | -0.0005 | -0.0201 |
| | *0.0074* | *0.0108* | *0.0046* | *0.0076* | *0.0201* | *0.0099* | *0.0027* | *0.0226* |
| positive techies × positive imports | -0.0643 | -0.0151 | 0.0339 | -0.0416 | 0.8860** | -0.0054 | -0.0195 | -1.0850* |
| | *0.0520* | *0.0686* | *0.0466* | *0.0490* | *0.3930* | *0.1080* | *0.0191* | *0.5970* |
| positive techies × exports | -0.0037 | 0.0051 | 0.0033 | -0.0127 | 0.0261 | -0.0141 | -0.0029 | -0.0282 |
| | *0.0091* | *0.0090* | *0.0052* | *0.0084* | *0.0248* | *0.0183* | *0.0043* | *0.0304* |
| positive techies × positive exports | 0.0018 | 0.0053 | -0.0005 | 0.0598 | -0.6910** | -0.1120 | 0.0007 | 0.9330* |
| | *0.0489* | *0.0644* | *0.0342* | *0.0380* | *0.3410* | *0.0966* | *0.0192* | *0.5120* |
| Observations | 20,244 | 27,944 | 20,413 | 31,882 | 35,168 | 26,750 | 12,649 | 31,778 |
| $R^2$ | 0.060 | 0.021 | 0.002 | 0.012 | | | 0.004 | |