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The Loss of Production Work: Identification of Demand Shifts Based on Local Soviet Trade Shocks †

Elias Einiö*

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Abstract

This paper examines changes in the structure of labor demand in panel data on Finnish manufacturing plants. I exploit general equilibrium effects on unit labor costs in local labor markets induced by the 1990 collapse of Fenno-Soviet trade to identify labor demand schedules for plants producing for the non-Soviet markets, which were not directly affected by the fall of Soviet-import demand. The estimated model implies that the relative demand for non-interpersonal, manual task-intensive production labor activities is stagnant in the 1990s, but starts to decline rapidly in the early 2000s, coinciding with a surge of imported intermediate inputs. In this period, the industry patterns of the shift also begin to diverge. Offshoring and ICT explain both one-third of the overall shift.

JEL classification: F16; J23; J24; O33.
Keywords: Labor demand; Occupations; Tasks; Technical change; ICT; Trade; Offshoring; Manufacturing; Panel data.

1 Introduction

Changes in the structure of labor demand are one of the key drivers of disparities in wages and employment across workers with different occupations and skills. Studies in various countries have associated the rising labor market inequality of the 1980s with increases in the relative demand for skill (Katz and Murphy, 1992; Katz, Loveman, and Blanchflower, 1993; Dustman, Ludsteck, and Schönberg, 2009) and the subsequent employment polarization of the 1990s and early 2000s with the fall in the relative demand for routine work (Autor, Levy, and Murnane, 2003; Goos and Manning, 2007; Autor, Katz, and Kearney, 2008; Goos, Manning, and Salomons, 2009).[1] Although there is a wide consensus among

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[1] Changes in the structure of wages and employment have also been associated with changing structure of labor supply (e.g., Card and Lemieux, 2001), and with labor market institutions such as minimum wages (e.g., Lee, 1999; Card and DiNardo, 2002; Machin, Manning and Rahman, 2003; Autor, Manning and Smith, 2014) and deunionization (e.g., Fortin and Lemieux, 1997; Machin, 1997).

Figure 1: Aggregate Exports to the Former Soviet Union Area from Finland, 1987-2002

Notes: Until 1990, the series cover exports to the Soviet Union from Finland. From 1991 onwards, the series cover exports to the same geographic area as in 1990: In 1991, they include exports to the Soviet Union, Estonia, Latvia, and Lithuania; from 1992 onwards, they include exports to Armenia, Azerbaijan, Belarus, Estonia, Lithuania, Latvia, Russia, Uzbekistan, Tajikistan, Turkmenistan, Kyrgyzstan, Kazakhstan, and Ukraine (the name of Kyrgyzstan changed in 1993 to the Republic of Kyrgyz). Exports are from the OECD ITCS database. Manufacturing output is from the Official Statistics of Finland.

economists that changes in the structure of labor demand have played an important role in shaping the labor markets in the past three decades, evidence on the patterns of the demand shifts based on quasi-experimental identification of labor demand curves is rare.

The main challenge in identifying demand curves from observed prices and quantities arises from the simultaneity of demand and supply. Although this problem has been well acknowledged in the literature (e.g., Wright, 1928; Frisch, 1933), addressing it in the context of labor markets has proven to be difficult due to a lack of good sources of exogenous variation in labor supply. In this study, labor demand curves are identified from variation in unit labor costs arising from a large-scale manufacturing trade shock, which was caused by the unexpected abolition of the bilateral trade agreement between Finland and the Soviet Union by the Soviet regime in December 1990. As a result of the collapse of Soviet trade, the real value of Finnish exports to the former Soviet Union area fell from 2.52 billion euro in 1990 to 0.90 billion euro in 1991 – a drop corresponding to around 2.7% of manufacturing output in 1990 (figure 1). I exploit the differential local magnitude of this shock stemming from spatial variation in the historic output share of local Soviet export commodity production. In municipalities with a high output share of Soviet exports, manufacturing output fell by around 10% from 1990 to 1991, while it changed only a little in municipalities with a low output share of Soviet exports (panel A of figure 2). Despite this large spatial divergence in output, the shock induced relatively small geographic variation in employment (panel B of figure 2). My analysis indicates that the initial consequence of this rigid spatial adjustment was to induce significant re-allocation of employment within local labor markets to plants that were producing for the non-Soviet markets, and to induce spatial variation in unit labor costs, which facilitates identification of plant-level labor

A. Real Output B. Employment

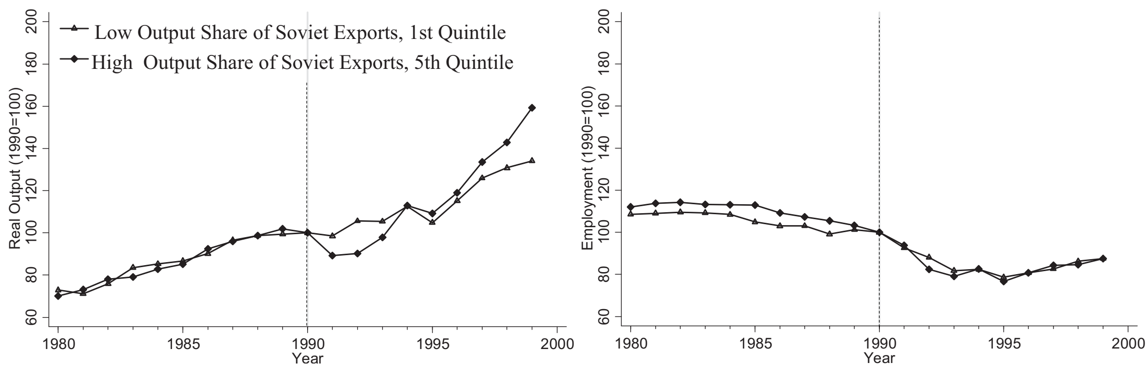

Figure 2: Output and Employment in Municipalities with Low and High Output Share of Predicted Soviet Exports

Notes: Real output and employment calculated from the Finnish annual manufacturing plant census data (LDPM). Predicted Soviet exports are municipality's Soviet exports in 1990 predicted by the 1988 municipality-level 6-digit commodity output structure. The 20^{th} and 80^{th} percentiles of it are 0.54% and 6.14%, respectively.

demand schedules.

The paper contributes to the literature concerned with identifying labor demand curves and quantifying shifts in the structure of labor demand (e.g., Katz and Murphy, 1992; Johnson, 1997). A lack of good instruments for labor prices in labor demand equations has led most of the previous studies to rely on the assumption that they are equal across industries (Berman, Bound and Grilliches, 1994), or that observed variation in them arises solely from differences in the structure of labor supply across industries defined at a more or less aggregate level (Baltagi and Griffin, 1988; Haskel and Slaughter 2002; Baltagi and Rich, 2005).[2] However, variation in labor prices is unlikely to be independent of technology shocks, which are one of the main suspected sources of confounding variation in estimation of labor demand curves. To account for this, Ciccone and Peri (2005) exploit variation in labor prices arising from changes in school attendance and child labor laws in their analysis of state-level labor demand in the US. While their approach accounts for confounding variation from local technology shocks that may simultaneously shift labor demand (to the extent that state policies are independent of expected labor demand patterns), a labor supply shock will also increase aggregate local income and demand for local products which in turn has an effect on labor demand (Card and Altonji, 1990; Angrist, 1995). This implies that any instrument inducing a labor supply shock in a local labor market also shifts the aggregate local labor demand curve, and hence results in a simultaneity bias in its estimation.

The main contribution of this study to the literature aiming to identify labor demand

[2] For a survey of earlier studies estimating labor demand relations, see Hamermesh (1990).

models is threefold. First, to my knowledge, this paper is the first study identifying plant-level labor demand curves in a quasi-experimental setting based on local labor market consequences of a large-scale manufacturing shock. My empirical strategy utilises geographic variation in the magnitude of a trade shock stemming from historic industry specialization, as in Topalova (2010), who examines the impacts on local poverty of local shocks from tariff reductions in India, and Autor, Dorn, and Hanson (2013), who analyse the impacts of increasing Chinese import penetration on local labor markets in the US. A distinct feature of my research setting is that the abolishment of the Fenno-Soviet trade agreement was caused by an unexpected, external political process – the breakdown of the Soviet regime – and therefore the shock induced by it can be plausibly viewed as being highly independent of productivity development in the Finnish industry.

Second, as previous research provides evidence that plants adapt to abrupt trade shocks by changing their technologies (Bustos, 2011), I eliminate the confounding effects of endogenous technology adaption by exploiting general equilibrium price effects within local labor markets on plants producing for the non-Soviet markets, which were not directly hit by the collapse of Soviet-import demand. To identify this group of plants, I merge unique data on plant-level outputs to data on Finnish exports to the Soviet Union, both at the level of the 6-digit *Harmonized System* product categories. Moreover, I address the concern that negative product demand shocks on the local Soviet-dependent industry may have adversely affected neighboring plants producing inputs for it by employing detailed product-level data on the structure of input usage in the Soviet-dependent industry. I also account for the potentially confounding effects of the decline in the supply of low-priced Soviet energy inputs, which was the main component of Soviet-export supply to Finland.[3]

Third, by focusing on establishments in the tradable sector, I circumvent the potential biases that may arise from local demand effects in the non-tradable sector. The abolition of the Fenno-Soviet trade agreement provides a particularly useful setting for controlling for these effects because the Finnish Soviet-dependent industry was widespread and highly scattered across space. I also control for unobserved regional effects within relatively small geographic units, which adds further credence to the interpretation that the collapse of Soviet trade did not induce confounding location-specific demand effects at the level of spatial scale employed in the analysis.

To preview the results, the identified labor demand model implies that the relative de-

[3] Gorodnichenko, Mendoza, and Tesar (2012) have emphasized the adverse effects on the Finnish economy of increasing energy prices stemming from the collapse of the supply of Soviet energy inputs.

mand for non-interpersonal, manual task-intensive production labor activities is stagnant in the 1990s, but starts to decline rapidly in the early 2000s, coinciding with a surge of imported intermediate inputs. Moreover, in this period, the industry patterns of the shift diverge dramatically. This raises the question of to what extent increased offshoring of production labor activities have contributed to it. While there is a growing body of work suggesting significant labor market consequences of trade using data from the 2000s, work examining the impacts of both trade and technology is scant and the existing few studies provide to some extent mixed results.[4] Moreover, to my knowledge, there is no prior analysis of the effects of these two factors on explicit measures of the structure of labor demand based on quasi-experimental identification of demand curves. To provide such evidence, I relate industry offshoring and ICT to the estimated industry indices of the relative production labor demand. The results indicate significant adverse effects of these variables with both explaining around one-third of the overall decline in the relative demand for production labor in the 2000s. The findings are robust when shocks to imported inputs and technology in US manufacturing are used as instruments for Finnish offshoring and ICT.

The work is organized as follows. Section 2 presents a conceptual framework and discusses the econometric approach for identifying relative labor demand curves based on local shocks induced by the collapse of Soviet-import demand. Section 3 presents the data and section 4 documents the task content of production and non-production job activities. Section 5 presents results for the plant-level labor demand model and indices of the relative production labor demand implied by it. Section 6 examines the impacts of offshoring and ICT on the demand shift, while section 7 concludes.

2 Estimating Changes in the Structure of Labor Demand

2.1 Conceptual Framework and Econometric Model

I consider a manufacturing plant producing output y by combining capital and labor services. Manual task-intensive production labor services are used in the production line.

[4] Michaels, Natraj, and Van Reenen, (2014) and Goos, Manning, and Salomons (2014) provide evidence that technology has significantly affected job polarization while they find no clear evidence of trade on it. Autor, Dorn, and Hanson (forthcoming) provide evidence of significant effects of both rising Chinese import competition and historic specialization in routine-intensive job tasks on the structure of employment. For recent studies examining the impacts of *trade* on the labor markets, see Ebenstein, Harrison, McMillan, and Phillips (2014), Autor, Dorn and Hanson (2013), Autor, Dorn, Hanson and Song (2014), and Ashournia, Munch and Nguyen (2014). Previous literature examining the impacts of *technology* on the structure of wages and employment includes e.g., Bartel, Ichniowski and Shawn (2007), and Autor and Dorn (2013). For contributions to these strands of literature based on data from earlier periods see e.g. Berman, Bound and Grilliches (1994), Doms, Dunne and Troske (1997), Autor, Katz and Krueger (1997), Berman, Bound and Machin (1998), Machin and Van Reenen (1998), Feenstra and Hanson (1999), Autor, Levy and Murnane (2003), and Michaels (2008).

Cognitively and analytically demanding professional (non-production) labor services are used in management, business planning, and specialized technical and engineering work. Each unit of professional service carries a fixed proportion a of clerical services. The manufacturer minimizes variable costs given the unit labor costs of production labor services w_L and non-production labor services $w_H = (1-a)\cdot \overline{w}_H + a \cdot \underline{w}_H$, where $\overline{w}_H$ and $\underline{w}_H$ are the unit labor costs of professional and clerical labor services. With quasi-fixed capital k, the variable cost function for plant i located in a local labor market r and operating in industry j in year t is

$$C\left(y_{ijrt}, w_{Lrt}, w_{Hrt}, k_{ijrt}, A_{jt}\right) = \min_{L,H}\left(w_{Lrt}L_{ijrt} + w_{Hrt}H_{ijrt} : \left\{L_{ijrt}, H_{ijrt}\right\} \in V\left(y_{ijrt}, k_{ijrt}, \mathbf{A}_{jt}\right)\right),$$

where L_{ijrt} is the production labor input; H_{ijrt} is the non-production labor input; and $V\left(y_{ijrt}, k_{ijrt}, \mathbf{A}_{jt}\right)$ is the input requirement set allowing for industry-specific factors $\mathbf{A}_{jt}$ affecting plant-level productivity. Assuming translog costs and applying Shephard's lemma yields the production labor cost share equation:

$$\frac{\partial \ln C_{ijrt}}{\partial ln(w_{Lrt})} = s_{ijrt} = \beta_L ln\left(w_{Lrt}\right) + \beta_H ln\left(w_{Hrt}\right) + \beta_K ln\left(k_{ijrt}\right) + \beta_Y ln\left(y_{ijrt}\right) + \boldsymbol{\gamma}_{jt} \ln\left(\mathbf{A}_{jt}\right). \tag{1}$$

Here $\boldsymbol{\gamma}_{jt} \ln\left(\mathbf{A}_{jt}\right)$ represents differentials in the relative demand for production labor associated with industry-specific methods of production. $\mathbf{A}_{jt}$ includes various elements that may shift relative labor demand, such as factors related to technology and international organization of production (that is, inputs in foreign affiliates, for example). The elements of $\boldsymbol{\gamma}_{jt}$ are time-varying industry-specific effects, γ^h_{jt}, of the labor demand shifters, A^h_{jt}, indexed by h. Rising A^h_{jt} in industry j reduces the relative demand for production labor in year t if $\gamma^h_{jt} < 0$ and is biased towards production labor if $\gamma^h_{jt} > 0$. The specification also allows for differential unit labor costs across local labor markets, w_{Lrt} and w_{Hrt}. Spatial variation in unit labor costs may arise if local labor markets are sufficiently isolated so that price shocks are not diffused across the national labor market in the short run.

To empirically implement equation (1), I allow for unobserved heterogeneity across plants and include plant fixed effects to account for it. Assuming homogeneity of degree one in prices $(\beta_H + \beta_L = 0)$ and constant returns to scale $(\beta_K + \beta_Y = 0)$ yields the following empirical specification:

$$s_{ijrt} = \beta_L \, ln\left(w_{Lrt}/w_{Hrt}\right) + \beta_K ln\left(k_{ijrt}/y_{ijrt}\right) + \boldsymbol{\gamma}_{jt} \, ln\left(\mathbf{A}_{jt}\right) + \alpha_i + \varepsilon_{ijrt} . \tag{2}$$

Here, all elements of $\mathbf{A}_{jt}$ are in general not observed. Instead of estimating $\boldsymbol{\gamma}_{jt}$, I recover $\boldsymbol{\gamma}_{jt} \ln\left(\mathbf{A}_{jt}\right)$ by replacing it with industry$\times$year fixed effects: $\mu_{jt} = \boldsymbol{\gamma}_{jt} \ln\left(\mathbf{A}_{jt}\right)$. Taking first differences from t to $t+1$ to eliminate α_i gives the key estimating equation

$$\Delta s_{ijrt} = \beta_L \Delta ln\left(w_{Lrt}/w_{Hrt}\right) + \beta_K \Delta ln\left(k_{ijrt}/y_{ijrt}\right) + \tau_{jt} + \Delta\varepsilon_{ijrt} , \tag{3}$$

where $\tau_{jt} = \mu_{j,t+1} - \mu_{jt}$ represents, conditional on capital intensity, the average change in the relative demand for production labor from year t to $t+1$ in industry j.

Many previous studies have acknowledged that input prices may be highly endogenous in input demand equations. In the context of this study, such endogeneity may arise from local technology shocks, for example, that simultaneously affect the structure of employment and relative unit labor cost. Another potential source of bias is measurement errors which may be present in hourly labor cost data and would attenuate the OLS estimates towards zero.

Due to the lack of suitable instruments for labor input prices, many previous studies have employed indirect methods of controlling for them. Grilliches (1969) and Berman, Bound, and Grilliches (1994) assume sufficient labor mobility for the price of skilled labor to be equalized across industries and regions. On the contrary, in their industry-level regression analysis of cost share equations, Baltagi and Rich (2005) include relative input prices due to their concern that excluding them will induce larger biases in the estimates of the relative factor demand shifts.

In contrast to these previous studies, this paper employs a quasi-experimental research design to identify the parameters of the cost share equation. Before discussing the empirical strategy in more detail, it is worth noting that the plant-level specification in equation (3) controls for numerous unobserved sources of potentially confounding variation. First, the specification controls for plant fixed effects and hence is robust to any persistent unobserved heterogeneity which may arise, for example, from time-invariant differences in technology or quality of labor, or from other unobserved factors that affect the labor input mix across plants, industries, or local labor markets. Second, the specification includes year$\times$industry dummies, which control for differential shifts in unobserved industry factors affecting the structure of labor demand. However, these features of the empirical model do not eliminate the potentially confounding within-industry variation over time in the unobserved factors.

2.2 Identification Based on Local Soviet Trade Shocks

Identification of β_L in the cost share equation (3) requires exogenous variation in the structure of available supply of labor to comparable plants. To achieve this, I employ an empirical strategy based on the unexpected abolishment of the trade agreement between Finland and the Soviet Union in December 1990 which induced a large negative shock to Soviet-dependent manufacturing. The real value of Finnish exports to the former Soviet Union area fell from 2.52 billion euro in 1990 to 0.90 billion euro in 1991, and the drop corresponded to around 2.7% of manufacturing output in 1990.

The Soviet Union imported 2650 different 6-digit commodities from Finland in 1990, but Soviet-import demand was concentrated in a relatively narrow group of commodities and the distribution of the value of trade is very skewed, with the top 15 Soviet-import commodities accounting for around 34% of Soviet exports and the 265 commodities in the top 10% accounting for around 92% of them. Online appendix table A1 displays the 15 largest Soviet-import commodities in 1990. The telephonic or telegraphic switching apparatus is the most exported commodity, covering 5.7% of Soviet exports and 0.4% of manufacturing output. Other major commodity categories include specific transportation equipment (e.g. railway cars and vessels), various paper industry products (e.g., paper and chemical wood pulp), textiles (rubber boots), and food (infant cereals).

My IV strategy exploits variation in unit labor costs among plants that produce goods for the *non-Soviet* markets and those arising from the asymmetric local Soviet-trade shock, whose magnitude depends on the historic size of the local Soviet-dependent industry. A negative shock to the local Soviet-dependent industry reduces its demand for labor. This shifts local labor demand curve inwards and reduces unit labor costs in the local labor market, provided that capital does not adjust immediately and the workforce is not completely mobile. As the unit labor costs decline, plants producing for the non-Soviet markets move along the labor demand schedules. This facilitates the identification of the empirical model.

The key identifying assumption of this estimation strategy is that the magnitude of the local Soviet trade shock is uncorrelated with technological adjustment among the plants producing for the non-Soviet markets. Provided that this assumption holds, the validity of which is supported by an extensive robustness analysis presented below, variation in the size of the local Soviet-dependent industry induces exogenous variation in local unit labor costs. Finally, to gain identification of the model in equation (3), which requires variation in the *relative* production labor unit cost, the effect of the local Soviet trade shock on the production and nonproduction labor unit costs must be sufficiently disproportionate. The empirical analysis below indicates that this condition holds with the nonproduction labor unit cost adjusting more quickly to the initial shock than the production labor unit cost.

2.2.1 Local and Plant-Level Soviet-Import Dependence

To implement this strategy, I measure local 1990 Soviet-import dependence by

$$LSID_{r,1990} = \frac{\sum_{i\in I(r)}\sum_{m}\omega_{im,1988}SI_{m,1990}}{\sum_{i\in I(r)} y_{i,1990}} = \frac{\sum_{i\in I(r)} PSID_i y_{i,1990}}{\sum_{i\in I(r)} y_{i,1990}} \tag{4}$$

where $I(r)$ denotes the set of plants in a local labor market r; $SI_{m,1990}$ is total imports of commodity m from Finland to the Soviet Union in 1990; $\omega_{im,1988}$ is the fraction of production of commodity m in plant i to national production of commodity m in 1988; $y_{i,1990}$ is output by plant i in 1990; and

$$PSID_{i,1990} = \frac{\sum_{m}\omega_{im,1988}SI_{m,1990}}{y_{i,1990}} \tag{5}$$

is plant-level Soviet-import dependence. To calculate these measures, I draw data on exports from Finland to the Soviet Union in 1990 from the 6-digit commodity International Trade by Commodity Statistics (ITCS) of the OECD based on the Harmonized System 1988 classification (HS88). In order to approximate plant-level Soviet exports, I calculate commodity output shares, $\omega_{im,1988}$, from data on 1988 plant-level output by 6-digit HS88 commodity from the plant-level Commodity Statistics Survey provided by Statistics Finland. The survey covers around 91% of Finnish manufacturing output in 1988, and it lists all products produced by a plant at the 6-digit level.

In the measure of local Soviet-import dependence, geographic variation arises from spatial differentials in the structure of commodity production in 1988: Localities that produce historically a larger fraction of commodities exported to the Soviet Union in the last year of the trade agreement are predicted to be more dependent on Soviet-import demand. Figure 3 displays variation in Soviet-import dependence across municipalities. The figure illustrates that Soviet specialization is neither clustered in one specific area of the country nor concentrated in the eastern part of the country closer to the Soviet border, but rather the historical industry specialization induces substantial spatial variation in Soviet-import dependence across the whole country. The figure also displays the spatial distribution of plants producing for the non-Soviet markets used in the plant-level IV analysis.[5] Importantly, these plants are widespread and found in both low- and high-exposure localities.

2.2.2 Re-Allocation of Employment

Observations from figure 2 suggest that the collapse of Soviet trade did not have long-term adverse economic consequences in terms of output and employment in the highly dependent area. They also suggest that the impacts of it did not diffuse completely throughout the national labor market. The incomplete adjustment of the workforce across localities has the important implication that as a result of it local shocks induced spatial variation in unit labor costs among plants producing for the non-Soviet markets.

To shed more light on the adjustment in the labor markets, table 1 presents OLS and area fixed effects estimates from a regression of annual plant-level changes in employment on the plant-level measure of Soviet-import dependence multiplied by 100. The OLS estimate for total employment in the period 1989-1990 is slightly negative and statistically insignificant, while the coefficient for the period 1990-1991 indicates a large and statistically significant re-allocation of employment from more dependent plants to less dependent plants. The coefficients for later periods in the remaining rows are substantially smaller and statistically insignificant.

These estimates indicate that the collapse of Soviet trade had a significant instantaneous impact on the structure of employment by re-allocating workforce from plants dependent on Soviet trade to plants less dependent on it. Column 4 of table 1 displays corresponding estimates from a regression controlling for municipality fixed effects. Estimates in this column are based on within-municipality variation in plant-level Soviet-import dependence and hence provide a descriptive measure of the *local* re-allocation of employment. The FE estimate for the period 1990-1991 indicates significant initial re-allocation within local labor markets, while the estimates for other periods are, again, substantially smaller in magnitude and statistically insignificant.

[5] For a detailed description of the estimation sample used in the plant-level IV estimations, and of other samples used in the analysis, see section 3.

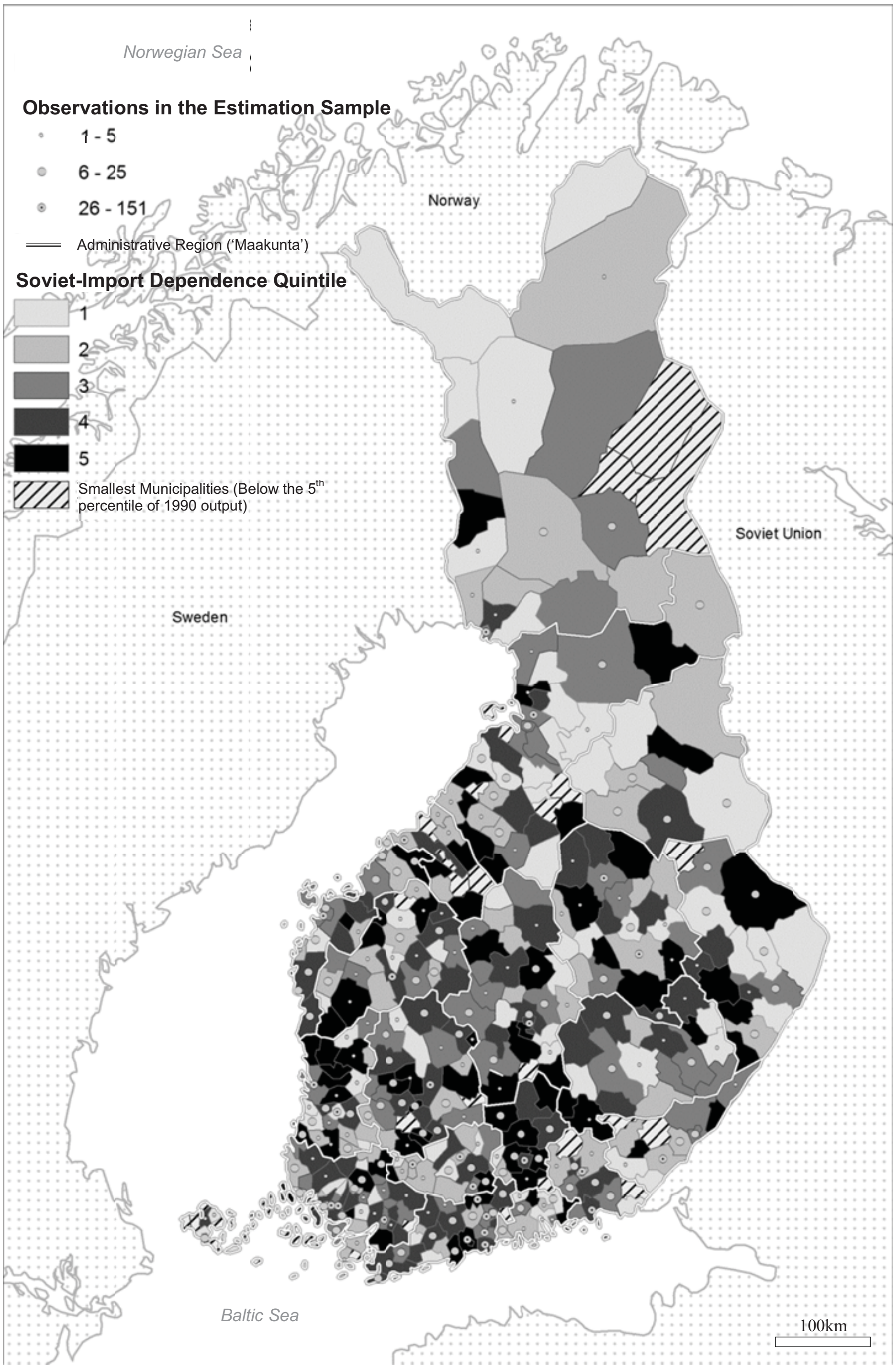

Figure 3: Soviet-Import Dependence Quintiles by Municipality in Finland, 1990

Notes: Local Soviet-import dependence is based on equation (4). It is the fraction of a municipality's Soviet exports in 1990 predicted by the 1988 6-digit commodity output structure to the municipality's 1990 output.

Table 1: Plant-Level Soviet-Import Dependence and Annual Employment Growth, 1989-1995

	OLS			Area FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	All workers	Production workers	Non-Production Workers	All workers	Production workers	Non-Production Workers
1989-1990	-0.045	-0.024	-0.021	-0.079	-0.042	-0.036
	(0.038)	(0.018)	(0.022)	(0.057)	(0.026)	(0.034)
1990-1991	-0.123**	-0.072**	-0.051*	-0.138**	-0.079**	-0.059**
	(0.052)	(0.029)	(0.027)	(0.054)	(0.029)	(0.029)
1991-1992	-0.045	-0.028	-0.017	-0.052	-0.038	-0.014
	(0.036)	(0.025)	(0.013)	(0.035)	(0.025)	(0.012)
1992-1993	0.011	0.012	-0.001	0.001	0.003	-0.002
	(0.019)	(0.014)	(0.007)	(0.020)	(0.014)	(0.008)
1993-1994	-0.033	-0.023	-0.010	-0.059	-0.043	-0.015
	(0.049)	(0.037)	(0.014)	(0.053)	(0.039)	(0.016)
1994-1995	-0.011	-0.002	-0.008	-0.008	-0.001	-0.007
	(0.024)	(0.018)	(0.010)	(0.024)	(0.019)	(0.012)

Notes: LDPM plants with at least 20 employees. Municipalities falling below the 5th percentile of 1990 output are excluded. Standard errors clustered by municipality are in parentheses. Coefficients are from plant-level regressions of the annual change in employment in a worker group (displayed in the column title) on plant-level 1990 Soviet-import dependence ($PSID_i$ in equation (5)) times 100. Specifications in columns 4-6 control for municipality fixed effects. Number of observations is 3003, 2965, 2678, 2371, 2153, and 1845 for the 1989, 1990, 1991, 1992, 1993, and 1994 samples, respectively.

The results in columns 2-3 and 5-6 display OLS and FE estimates separately for production and non-production employment. Looking at the FE specifications in columns 5-6, the correlation coefficients indicate that, in the period 1990-1991, in a plant with one standard deviation higher Soviet-import dependence, employment growth was $0.079 \times 0.174 \times 100 \approx 1.37$ employees slower in production occupations, while it was $0.059 \times 0.174 \times 100 \approx 1.03$ employees slower in non-production occupations. These estimates suggest that the instantaneous effect of the shock was to increase the local relative supply of non-production workers available for plants producing for the non-Soviet markets: The change in the structure of employment at the margin in terms of production worker employment share was around $0.079/(0.079+0.059) \approx 0.572$, while the average production worker employment share in plants with low Soviet-import dependence was 0.782.

2.3 IV Estimation

Motivated by these observations, I use local Soviet-import dependence in 1990 as the instrument for the relative production labor unit cost and identify the coefficient on it in equation (3) with a two-stage least squares (TSLS) procedure based on the following first-stage equation:

$$
\begin{aligned}
\Delta ln\left(w_{Lrt}/w_{Hrt}\right) = \sum_{s=1990}^{1994}\left(\zeta_{1s} ln\left(\mathrm{LSID}_{r,1990}\right)+\zeta_{2s} ln\left(\mathrm{LSID}_{r,1990}\right)^{2}\right)\cdot I(year=s) \\
+\beta_{1K}\,\Delta ln\left(k_{ijrt}/y_{ijrt}\right)+\tau_{1jt}+\Delta\varepsilon_{1ijrt}\,,
\end{aligned}
\tag{6}
$$

where $I(year = s)$ is an indicator function equal to one in year s and zero otherwise. I estimate the model over the period 1990-1994, covering years of collapsing output in the high-exposure areas and the subsequent recovery period observed in figure 2. The specification includes interaction terms for the logarithm of local Soviet-import dependence and year to allow for differential impacts over this adjustment period. I also estimate specifications including a second order term for the log of *LSID* to improve the fit of the first-stage regression and the precision of the IV estimation. The IV model has ten excluded instruments, which raises concerns about the inconsistency of the TSLS estimator with many instruments when some of the instruments are weak. To assess the potential bias that this may induce, I follow Angrist and Pischke (2009) and examine the robustness of the TSLS estimates by estimating the model with the LIML estimator, which has better asymptotic properties in the case of many instruments.

In the IV model based on equations (3) and (6), capital intensity is treated as an exogenous variable. One may be concerned, however, that measurement errors in capital stock data may bias the OLS coefficient on it. I examine the robustness of the results against this potential source of bias by exploiting the fact that the IV model is over-identified, which allows me to employ variation in capital intensity induced by the *LSID* instrument to identify the coefficient on it. This approach is based on the same key identifying assumption as the identification of β_L: Its validity hinges on whether, conditional on unobserved heterogeneity at the plant level and 2-digit industry trends, production labor-biased technology shocks (correlated with capital intensity) among the population of plants producing for the non-Soviet markets are uncorrelated with the size of the neighbouring Soviet-dependent industry in 1990 as predicted by the 1988 local structure of commodity production. One may also be concerned that simultaneous input and output choices may confound the estimates of the coefficient on capital intensity. While such simultaneity is less likely to arise from endogenous capital adjustment, which is likely to be more sluggish than adjustments in labor inputs, I cannot completely rule out the possibility that idiosyncratic shocks to labor input mix may affect the output. However, instrumenting current change in capital intensity with the *LSID* instrument is likely to mitigate such concerns. To further examine the robustness of the results against such a potential link between idiosyncratic labor input patterns and productivity, I use lagged capital intensity in $t - 2$ as an instrument for its current change.

3 Annual Census of Manufacturers

The main plant-level data source of this study is the Longitudinal Database of Plants in Finnish Manufacturing (LDPM) provided by Statistics Finland. The LDPM is based on the Annual Industrial Structures Survey, and it compiles comprehensive information on the economic activity of all manufacturing plants over the period 1980-2008 which fulfil the survey employment criteria: Until 1994, all plants with at least 5 employees were surveyed; from 1995 onwards, plants whose parent company had at least 20 employees were surveyed. Hence, in every year, the survey frame covers all plants with at least 20 employees.[6]

The LDPM provides detailed annual output and input information including value added; labor costs on production and non-production labor (wage bill and employer contributions such as compulsory insurance payments); hours worked by these worker groups; investment in machinery and equipment; and location (municipality). Plant-level hourly labor costs of a worker group are calculated as the ratio of total labor cost to total hours within the worker group.

Figure 4 displays aggregate changes in the LDPM sample of plants employing at least 20 persons over the period 1980-2008. Over the 1980s, non-production employment is stable while production employment declines. During the recession in the early 1990s, a major initial cause of which was the collapse of Soviet trade (see, e.g., Gorodnichenko et al., 2012), the decline of production employment accelerates and also non-production employment starts to contract. During the recovery period in the 1990s, employment improves in both groups with non-production employment reaching the pre-recession levels by 2000. In the 2000s, non-production employment is stable while production employment starts to decline again. In sum, the figures indicate that the overall contraction of manufacturing employment over the period 1980-2008 is due to the declining employment in production occupations.

Table 2 displays summary statistics for the relevant samples drawn from the LDPM. As explained above, the sampling frame changed in 1995. For consistency over time, I include

[6] The LDPM sample of plants with at least 20 employees covers around 82% of total manufacturing employment in the period 1980-2008.

only plants with at least 20 employees which are covered in the sample frame over the whole observation period.

The first block of statistics is based on the sample covering the period 1990-1994 used to estimate equation (3). The sample is constructed by excluding from the LDPM data plant-year observations falling into the first or last year of a plant's existence in the panel to avoid observations from years in which plants may have entered or exited the market in the middle of the year. To reduce noise in the municipality-level Soviet-import dependence measure, the sample excludes municipalities falling below the 5th output percentile.[7] The first column shows sample means and standard deviations for plants fulfilling these criteria. The second column displays statistics for plants that produce for the non-Soviet markets which are identified by restricting plant-level predicted 1990 Soviet exports to 0.1% of 1990 output (that is, PSID in equation (5) less than 0.001). These plants cover around 38% of all plants in this sample, and they have slightly lower employment, slightly larger capital stock, and slightly higher wages for both worker groups, on the average. Their average production worker cost and employment share are a bit higher than among all plants. The 1990 municipality-level Soviet-import dependence is 0.040 for low-dependence plants, on the average, which is of a relatively similar magnitude compared to the full estimation sample mean of 0.048. This indicates that plants that were not directly dependent on Soviet-import demand were, on the average, located in municipalities that housed a sizeable local Soviet-dependent industry. Overall, these comparisons suggest that plants producing for the non-Soviet markets are fairly similar, on the average, as plants in the full estimation sample.

The second block of statistics labelled "Analysis Sample" displays summary statistics for the sample used to calculate relative production labor demand shifts in section 5.4. The sample used in this simulation relaxes some of the restrictions imposed in the estimation sample: The sample does not exclude observations by 1990 plant-level Soviet-import dependence; it includes also plants located in the smallest municipalities; and it includes observation over a wider period, 1980-2008.

[7] This drops 19 smallest municipalities covering around 0.1% of aggregate LDPM output in 1990.

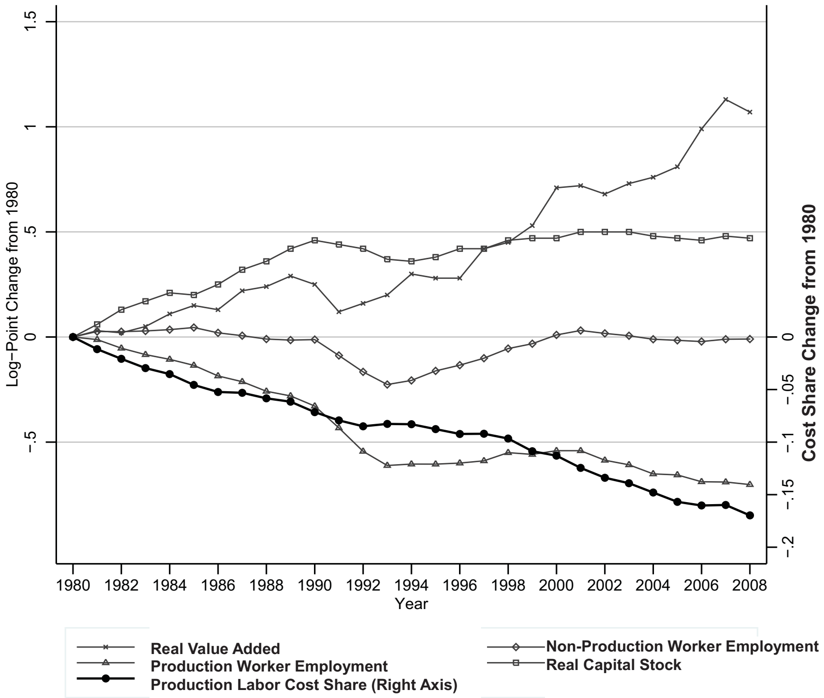

Figure 4: Aggregate Trends in Finnish Manufacturing
Notes: Data from the LDPM.

Notably, plants with low Soviet-import dependence in the estimation sample have very similar structure of employment and wage bill compared to the analysis sample. The means for these samples are, to a large extent, of a very similar magnitude for most of the variables. One exception is energy intensity, which is 0.141 in the low-dependence estimation sample and 0.322 in the analysis sample. However, variation in energy prices over time is likely to affect the comparability of this measure, as the means are based on different observation windows in these samples. Indeed, differentials in the 1990 energy intensity are much less pronounced. These observations suggest that plants with low Soviet-import dependence are not, on the average, of significantly different size and do not differ significantly in their input mix in 1990-1994 compared to the full analysis sample.

A key requirement for the validity of the IV procedure is that plants producing for the non-Soviet markets are comparable across highly- and less-dependent localities. To examine the credibility of this assumption, online appendix table A2 tabulates 1989 sample means for plants producing for the non-Soviet markets located in municipalities with local Soviet-import dependence below and above the median of 0.030. In sum, in the former group, the average local 1990 Soviet-import dependence is 0.016, while it is 0.065 in the latter group, indicating a substantial difference in the relative size of neighbouring Soviet-dependent industry. Plants in the low-exposure area are slightly larger in terms of output and inputs, on the average, but have very similar production-worker intensity in terms of wage-bill, employment, and hours share compared to plants in the high-exposure area. Average unit labor costs for both worker groups are also of a very similar magnitude across samples. Overall, plants producing for the non-Soviet markets located in low- and high-exposure areas seem to be fairly similar in terms of the variables in the empirical model and other available observable characteristics. This lends further credibility to the assumption that the size of the neighbouring Soviet-dependent industry is uncorrelated with technology in plants producing for the non-Soviet markets.

While the LDPM provides fairly detailed information on output and inputs, the breakdown of labor input in it is limited to production and non-production worker categories. For the interpretability of the results, it would be useful to know what workers in these groups do for work. To shed light on this question, I next examine the task content of production and non-production jobs.

4 Manufacturing Occupations and Tasks

In order to examine the task content of manufacturing jobs, I calculate task indices for production and non-production workers by using the occupational task measure data of Acemoglu and Autor (2011), who build on the work of Autor, Levy, and Murnane (2003). Finnish data on occupations were drawn from the research-use sample of the Finnish Linked Employer-Employee Data (FLEED) maintained by Statistics Finland which covers one-third of the working-age population and contains information on occupation at the 2-digit level of the ISCO-88 classification. Each 2-digit occupation in FLEED was assigned to production and non-production categories according to the LDPM definition.[8] The Acemoglu-Autor data provides job task indices at the level of 4-digit occupation based on the SOC-2000 classification. To obtain task measures for 2-digit occupations, weighted averages of the 4-digit task measures were calculated with occupation-specific US employment used as weights.[9]

[8] The production worker category includes operators, assemblers, workers, and laborers; the non-production worker category includes professionals, managers, salespersons, and clerks. As a robustness exercise, I also assigned each 4-digit ISCO-88 occupation to production and non-production categories. This exercise indicated that all 2-digit occupations observed in manufacturing included only either production or non-production 4-digit occupations.

[9] The 2-digit job task indices were linked to FLEED with the correspondence table from the US National Crosswalk Service Center (webdata.xwalkcenter.org/ftp/DOWNLOAD/xwalks/SOC2000xISCO88.zip, accessed: 1.7.2013)

Table 2: Summary Statistics

	Estimation Sample, 1990-1994				Analysis Sample, 1980-2008	
	All		Low Soviet-Import Dependence		All	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Labor Cost, Total	3,247	6,244	3,103	6,177	3,221	7,880
Labor Cost, Non-production labor	1,204	2,843	1,140	2,940	1,205	4,740
Labor Cost, Production labor	2,042	3,811	1,963	3,595	2,016	4,227
Employment, Total	128	220	122	228	127	235
Employment, Non-production labor	38	84	35	85	36	102
Employment, Production labor	91	149	87	152	91	155
Hours, Total	205	344	193	342	210	387
Hours, Non-production labor	63	141	58	143	61	175
Hours, Production labor	142	224	135	216	148	249
Production Labor Cost Share	0.676	0.161	0.701	0.171	0.691	0.168
Production Labor Employment Share	0.746	0.145	0.762	0.153	0.757	0.153
Production Labor Hour Share	0.738	0.147	0.755	0.157	0.753	0.154
Real Capital Stock (2000 Prices)	9,496	30,644	10,248	30,020	7,992	30,333
Real Output (2000 Prices)	21,464	73,049	22,323	55,242	22,456	101,492
Real Value Added (2000 Prices)	7,012	19,023	6,675	15,030	7,184	34,339
Capital Intensity	2.242	58.644	2.062	8.172	2.429	170.5
Nominal Production Labor Unit Cost	13.1	3.21	13.41	3.31	12.79	6.680
Nominal Non-Production Labor Unit Cost	18.4	4.8	18.53	5.3	17.92	9.110
Nominal Prod. Labor Unit Cost, 1989	10.63	2.560	10.78	2.640	10.65	2.592
Nominal Non-Prod. Labor Unit Cost, 1989	15.60	4.214	15.44	4.508	15.57	4.184
Relative Production Labor Unit Cost	0.743	0.214	0.764	0.225	0.738	0.227
Energy Intensity	0.114	1.657	0.141	0.593	0.322	42.30
Energy Intensity, 1990	0.080	0.139	0.106	0.176	0.084	0.195
Soviet-Import Dependence in 1990:						
Plant	0.052	0.174	0	0	0.054	0.170
Municipality	0.048	0.075	0.040	0.060	0.048	0.096
Municipality, Log Levels	-3.458	0.978	-3.712	1.110	-3.452	0.969
Observations	7,479[a]		2,881[b]		70,806[c]	

Notes: Monetary values are in thousand euro. a – Number of observations for 1989 production labor unit cost, 1989 non-production labor unit cost, 1990 energy intensity, and log of energy intensity are 7453, 7434, 7362, and 7407, respectively. b – Number of observations for 1989 production labor unit cost, 1989 non-production labor unit cost, 1990 energy intensity, and log of energy intensity are 2851, 2838, 2808, and 2852, respectively. c – Number of observations for 1989 production labor unit cost, 1989 non-production labor unit cost, 1990 energy intensity, log of energy intensity, and plant-level Soviet-import dependence are 57543, 57210, 56209, 69471, and 52857, respectively.

Task measures by 2-digit occupation sorted by the routine manual task intensity are displayed in table 3. In sum, production work contains clearly more routine manual and non-routine physical tasks compared to non-production work: All ten 2-digit production occupations rank above non-production occupations along these task measures. Moreover, in the interpersonal manual category, all production occupations rank below non-production occupations except drivers and related water traffic operators, covering only around 2.3% of the manufacturing wage bill. These observations indicate that production occupations are clearly more intensive in routine manual and non-routine physical tasks compared to

Table 3: Manufacturing Occupations and Tasks

		Job Task Index						Taxable Wage Income Share 1995 (%)	
		Routine		Non-Routine					
Occupation	ISCO	Manual	Cognitive	Cognitive Analytic	Cognitive Interpersonal	Manual Physical	Manual Interpersonal	Total	Within Worker Group
Production Occupations									
Machine operators and assemblers	82	1.96	0.56	-0.44	-0.59	0.92	-1.28	12.9	22.9
Stationary plant and related operators	81	1.68	0.33	-0.07	-0.42	0.94	-1.13	8.6	15.2
Precision and related trades workers	73	1.32	0.65	-0.24	-0.95	0.43	-1.05	2.5	4.4
Skilled agricultural and fishery workers	61	1.30	-1.31	-0.84	-0.65	1.17	-1.29	0.5	0.8
Drivers and related water traffic operators	83	1.22	0.35	-0.70	-0.91	2.17	-0.46	2.3	4.1
Other craft and related trades workers	74	1.03	0.15	-0.54	-0.56	0.35	-1.10	3.7	6.6
Labourers in manufacturing and construction	93	0.89	0.16	-0.73	-0.45	1.00	-1.15	3.8	6.7
Metal, machinery and related trades workers	72	0.82	-0.03	-0.08	-0.53	1.46	-1.04	19.8	35.1
Extraction and building trades workers	71	0.74	-0.49	-0.18	-0.33	1.38	-0.89	2.4	4.2
Non-production Occupations									
Physical and engineering science assoc. professionals	31	0.46	0.41	0.58	-0.26	0.17	-0.57	10.4	23.8
Customer services clerks	42	0.34	1.35	-0.77	-0.34	-0.35	0.24	0.3	0.6
Sales and services elementary occupations	91	0.20	-0.77	-1.49	-1.12	0.10	-0.86	1.3	2.9
Personal and protective services workers	51	0.11	-0.42	-0.74	-0.23	0.18	0.21	0.8	1.9
Life science and health associate professionals	32	-0.03	0.57	0.92	1.07	-0.01	1.17	1.4	3.2
Life science and health professionals	22	-0.09	0.53	1.23	1.30	-0.01	1.32	0.3	0.8
Office clerks	41	-0.28	0.90	-0.32	-0.54	-0.57	-0.25	3.9	9.0
Corporate managers	12	-0.62	-0.66	0.90	1.57	-0.56	0.57	6.3	14.4
Physical and engineering science professionals	21	-0.63	0.26	1.56	0.08	-0.71	-0.69	8.5	19.5
Salespersons and demonstrators	52	-0.69	-0.18	0.19	0.13	-0.44	0.27	0.8	1.9
Managers of small enterprises	13	-0.73	-1.30	0.87	1.29	-0.25	0.61	0.4	0.8
Other associate professionals	34	-0.76	0.17	0.43	0.03	-0.65	0.34	5.9	13.5
Other professionals	24	-1.03	-0.36	1.16	0.51	-0.88	0.69	3.2	7.3
Teaching professionals	23	-1.05	-1.01	1.15	1.36	-1.05	1.57	0.2	0.5
Production Occupations		1.27	0.20	-0.28	-0.55	1.13	-1.09	56.5%	100.0%
Non-production Occupations		-0.32	0.11	0.68	0.20	-0.40	-0.07	43.5%	100.0%

Notes: Data from the FLEED. Task measures are based on Acemoglu and Autor (2011) occupational job task content data.

non-production occupations.

Production jobs also contain considerably fewer cognitive analytic tasks: The ranking along this measure shows that all ten 2-digit professional and managerial occupations are within the ten most cognitive analytic intensive occupations. Although the ranking in this category does not perfectly separate the two worker groups as three non-production clerical and service occupations fall below some of the production occupations, the cognitive analytic intensive professional and managerial occupations cover around 83 percent of the non-production wage bill, implying that non-production labor activities are clearly more cognitive analytic intensive compared to production labor activities as indicated by average task measures for these two broader groups. The non-routine cognitive interpersonal task category separates also the worker groups relatively well: Three non-production occupations that fall below some production occupations (customer service clerks, sales and service elementary occupations, and office clerks) cover only around 5.5% of the manufacturing wage bill.

These observations indicate that production workers are highly specialized in non-interactive, manual tasks and their work activities are clearly less analytic cognitive task-intensive compared to non-production work. These clear distinctions have the important implication that changes in the relative demand for production labor are indicative of changes in the relative demand for non-interactive, manual task-intensive labor activities. These tasks are also among those that are likely the most susceptible to being replaced by computer-aided machines.[10] Moreover, as they require little face-to-face interaction and physical presence in a specific location (e.g., near to the customer) – task features that have been broadly conceived as one of the main restrictions for offshoring (e.g., Blinder and Krueger 2013) – they also are likely to be among those labor activities that are the most prone to being offshored.

5 Results

This section presents the results of the cost share equation analysis. I start by presenting the results for the first-stage effects of local Soviet-import dependence on the relative production labor unit cost among plants producing for the non-Soviet markets. I then present the estimates of the labor cost share equation parameters recovered from variation

[10] While the non-routine manual physical tasks typically require manual dexterity and spatial orientation at which computer-aided machines have traditionally not been so good, the capability of computers to perform such tasks involving pattern recognition, operating vehicles, and handling irregularly-shaped objects, for example, has improved considerably over the past couple of decades; hence, these tasks may not have been as immune to computerization in recent years as they may have been before.

induced by the local Soviet trade shocks and address a number of potential robustness concerns. The last part of this section presents simulation results for average plant-level changes in the relative demand for production labor over the period 1980-2008 based on the identified model. Standard errors are corrected for clustering at the plant level in all plant-level estimations.[11]

5.1 First-Stage

Figure 5 displays the first-stage impacts of the *LSID* instrument on the annual change in the relative production labor unit cost based on equation (6) in a sample of plants with predicted Soviet exports less than 0.1% of plant's total output in 1990. It shows the predicted difference in the annual growth of the relative production labor unit cost between the 20th and 80th *LSID* percentiles, fixing other variables.[12]

The figure indicates that the collapse of Soviet trade induces substantial initial adjustments in unit labor costs with around 5 percentage points faster increase in the relative unit cost of production labor in the high-exposure area compared to the low-exposure area from 1990 to 1991. The rise in the relative production labor price is induced by a larger relative decline in the unit cost of non-production labor, which is in line with the findings of section 2 suggesting that the initial local reallocation of labor is more intensive in non-production labor than the average plant-level structure of employment among plants producing for the non-Soviet markets. After the large instantaneous impact from 1990 to 1991, the growth in the relative production labor unit cost continues to be slightly faster in the high-exposure area until 1993 when some convergence emerges, coinciding with a period of output convergence between the two areas observed in figure 2.

One may be concerned that auto-correlated local shocks to unit labor costs may have induced the sharp first-stage impacts in the period 1990-1991. To account for this, figure 5 also displays first-stage impacts of the instrument for a specification including 1989-1990

[11] I also experimented with clustering standard errors by municipality and region ("maakunta" displayed in figure 3) which gave very similar and in many cases smaller standard errors than clustering by plant.

[12] For this specification, the coefficients (standard errors) for the first-order term of the local Soviet-import dependence instrument interacted with a dummy for the year 1990, 1991, 1992, 1993, and 1994 are 0.084 (0.038), 0.008 (0.029), 0.007 (0.030), -0.026 (0.031), and -0.002 (0.047), respectively, while the corresponding coefficients (standard errors) for the second-order terms of the instruments are 0.010 (0.004), 0.000 (0.003), -0.002 (0.003), -0.002 (0.003), and -0.003 (0.005), respectively, with 2881 observations used in the estimation. The 20th and 80th percentiles of local Soviet-import dependence are 0.54% and 6.14%, respectively.

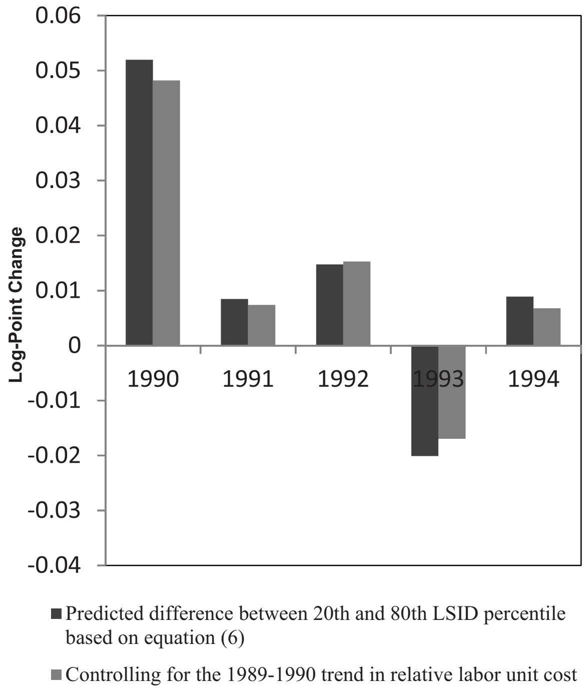

Figure 5: First-Stage Effects on Relative Production Labor Unit Cost Growth, 20th vs. 80th Soviet-Import Dependence Percentile

Notes: Effects are the difference between predicted values between 20th and 80th local Soviet-import dependence percentiles from equation (6), fixing other variables.

trends in the relative unit labor cost interacted with year as controls.[13] This has very little impact on the pattern of adjustment lending further credibility for the interpretation that the first-stage variation in the relative unit labor cost is induced by the sudden collapse of Soviet trade rather than by unobserved correlated local factors.

5.2 Production Labor Cost Share Equation

Table 4 presents coefficients on the relative production labor unit cost and capital intensity for the cost share equation (3) based on a sample of plants with predicted Soviet exports less than 0.1% of plant's total output in 1990.[14] The first column displays OLS coefficients, while the rest of the table displays IV estimates based on the local Soviet-import dependence $\times$ year dummy instruments. Following Angrist and Pischke (2009), in the second panel of the table, I also report estimates for the LIML estimator, which has better asymptotic properties in the many instruments setting. Columns 2-3 show results for specifications

[13] For this specification, the coefficients (standard errors) for the first-order term of the local Soviet-import dependence instrument interacted with a dummy for the year 1990, 1991, 1992, 1993, and 1994 are 0.077 (0.038), 0.007 (0.028), 0.011 (0.030), -0.023 (0.031), and -0.004 (0.045), respectively, while the corresponding coefficients (standard errors) for the second-order terms of the instruments are 0.009 (0.004), 0.000 (0.003), -0.001 (0.003), -0.002 (0.003), and -0.003 (0.005), respectively, with 2829 observations used in the estimation.

[14] For the corresponding estimates based on a sample also including plants with higher plant-level Soviet-import dependence, see online appendix table A3.

where the relative production labor unit cost is treated as the endogenous variable, while specifications in columns 5-8 treat both the relative production labor unit cost and capital intensity as endogenous.

The OLS coefficient on the relative unit labor cost is 0.088, while the corresponding TSLS estimates range from 0.144 to 0.215. Provided that the direction of the potential simultaneity bias is upwards because a technology shock favouring non-production labor tends to inflate their relative wages, the smaller positive OLS estimate is in line with a relatively larger attenuation bias that tends to drive estimates towards zero. This is not surprising as wage data are commonly suspected to have a relatively large error component.

The largest and the most imprecise TSLS estimate is in column 2 using the first-order term of local Soviet-import dependence interacted with year dummies as instruments (that is, ζ_{2s} are set equal to zero in equation (6)). The estimates in column 3 are based on a specification including the second-order term of local Soviet-import dependence interacted with year dummies as instruments. The inclusion of the second-order terms improves the precision of the estimation considerably, lowering the standard error by almost one-third, and reduces the coefficient to 0.156.

The specifications in columns 2 and 3 treat capital intensity as an exogenous variable. However, as discussed in section 2, it cannot be completely ruled out that the coefficient on it may be confounded by measurement error, or by idiosyncratic shocks to the labor input mix due to random variation in recruitment patterns, for example. In columns 4-5, I examine the robustness of the results against these potential sources of biases by exploiting the fact that the IV model based on equations (3) and (6) is over-identified which allows me to employ variation in capital intensity induced by the *LSID* instrument to identify the coefficient on it.

Column 4 displays estimates based on this approach. It employs the same set of instruments as the model in column 3 but treats both the relative unit labor cost and capital intensity as endogenous variables. Moving from column 3 to column 4 increases the number of endogenous regressors, while the number of excluded instruments is fixed. This lowers the precision of the estimation, as expected, with the largest reduction for the coefficient on capital intensity. The coefficient declines to –0.047, and although it is significant only at the 10% confidence level, the point estimate is more negative than the corresponding estimate in column 3, suggesting a positive bias in column 3, where capital intensity is treated as exogenous. To improve the precision of the estimation of the coefficient on capital intensity, the specification in column 5 uses log capital intensity in $t-2$ as an instrument for its current change. This approach is based on the assumption that the lagged capital intensity is uncorrelated with current idiosyncratic relative labor input patterns. With this instrument, the coefficient on capital intensity is -0.019 and has high precision.

Importantly, including the lagged capital intensity instrument has only a little effect on the coefficient on the relative unit labor cost but improves its precision considerably. The coefficient of 0.146 on it implies that, at the sample mean of labor cost share, the own price elasticity is -0.108 for production labor demand and -0.225 for non-production labor demand while the corresponding cross elasticities are 0.108 and 0.225, respectively, implying an elasticity of substitution of 0.225 – (– 0.108) = 0.333.[15]

5.3 Robustness Analysis

Controlling for the energy price shock. The abolishment of the trade agreement did not affect only the Soviet demand for Finnish products, but it also resulted in a collapse of Finnish imports from the Soviet Union, the bulk of which were energy inputs.[16] Gorodnichenko, Mendoza, and Tesar (2012) have emphasized the adverse effects on the competitiveness of the Finnish industry of the collapse of Soviet trade due to its positive impacts on the price of energy inputs. Such a price shock affected the competitiveness of energy-intensive plants the most. To examine the robustness of my results against such a shock, I add a control for energy intensity in 1990 (that is, costs of energy inputs divided by value added) in column 6. This has virtually no effect on the point estimates, suggesting that changes in energy prices are unlikely to confound the results.

Region effects. Because the estimations use a sample of plants that were not directly exposed to Soviet-import demand, the results are robust against confounding variation from differential development of productivity across low- and high-dependence establishments. A key threat for identification, however, is that low-dependence plants may have selected into historically highly-dependent localities partly according to unobserved characteristics. It is worth noting, however, that differencing eliminates selection due to permanent unobserved plant, industry, and local characteristics and that the model controls for confounding variation in productivity at the 2-digit industry level over time by including industry$\times$year

[15] In the translog model, the own price elasticity is $\eta_{ii} = (\beta_{ii} + s_i^2 - s_i) / s_i$, the cross price elasticity is $\eta_{ij} = (\beta_{ij} + s_i s_j) / s_i$, and the elasticity of substitutions is $\sigma_{ij} = \eta_{ij} / s_j = \eta_{ji} - \eta_{ii}$.

[16] In the period 1986-1990, fuels and crude oil accounted for around 62% of Soviet imports of manufacturing inputs. Energy inputs are defined here as crude oil and fuels as reported in the statistical book *Foreign Trade 1990, Vol. 2* (The Finnish Board of Customs).

Table 4: Estimates for the Production Labor Cost Share Equation, Plants with Low Soviet-Import Dependence, 1990-1994

	OLS	IV							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					TSLS				
Δ log (Relative Production Labor Unit Cost)	0.088***	0.215**	0.156**	0.170**	0.146**	0.148**	0.144**	0.154**	0.162**
	(0.008)	(0.085)	(0.062)	(0.070)	(0.058)	(0.057)	(0.059)	(0.056)	(0.055)
Δ log (Capital Intensity)	-0.008***	-0.008***	-0.008***	-0.047*	-0.019**	-0.020*	-0.020*	-0.023*	-0.022*
	(0.002)	(0.002)	(0.002)	(0.027)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
					LIML				
Δ log (Relative Production Labor Unit Cost)	0.088***	0.249**	0.186**	0.189**	0.166**	0.166**	0.160**	0.177**	0.187**
	(0.008)	(0.111)	(0.092)	(0.087)	(0.080)	(0.076)	(0.077)	(0.077)	(0.075)
Δ log (Capital Intensity)	-0.008***	-0.008***	-0.008***	-0.058	-0.019*	-0.020*	-0.021*	-0.024*	-0.023*
	(0.002)	(0.002)	(0.002)	(0.036)	(0.010)	(0.012)	(0.012)	(0.014)	(0.014)
Instruments:									
Log (Municipality Soviet-Import Dependence in 1990) ×Year		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log (Municipality Soviet-Import Dependence in 1990)^2×Year			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log(Capital Intensity Lagged Two Years)						Yes	Yes	Yes	Yes
Angrist-Pischke TSLS 1st Stage F-Statistic for Endogenous Regressors:									
Δ log (Relative Production Labor Unit Cost)		3.186	2.705	2.980	2.530	2.852	2.587	2.528	2.552
Δ log (Capital Intensity)				1.639	6.283	4.363	4.413	4.387	4.254
Obs.	2881	2881	2881	2881	2813	2760	2760	2719	2694

Notes: Panel-robust standard errors are in parentheses. The sample excludes plants with plant-level Soviet-import dependence (*PSID* in equation (5)) more than 0.001. The outcome is the change in the production labor cost share. Municipality Soviet-import dependence is the ratio of a municipality's predicted Soviet exports to the municipality's gross output (*LSID* in equation (4)). All regressions include time×industry dummies (coefficients omitted). Specifications in columns 6-9 control for the log of energy intensity (costs of energy inputs divided by value added) in 1990 interacted with year dummies as control variables. Specifications in columns 7-9 add region dummies as control variables. The specification in column 8 adds logs of 1989 production and nonproduction worker wages as control variables. The specification in column 9 corresponds to the specification in column 8 excluding plants with predicted output share of commodities supplied to local Soviet production more than 20%. Relative production worker wage is treated as endogenous in columns 2-8, while capital intensity is treated as endogenous in columns 4-8. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively.

fixed effects. To gain further control over the potential unobserved trends, I estimate a specification including dummies for administrative regions ("maakunta"), boundaries of which are displayed in figure 3. Restricting identifying variation within these areas has negligible impacts on the coefficients. This suggests that local production labor-biased productivity shocks are unlikely to be a major source of bias.

Selection by labor productivity and size of the local industry. To further investigate whether spatial selection by plant-level productivity may drive the results, column 8 adds controls for plant-level production and non-production labor unit costs in 1989. These variables control for differences in plant-level labor productivity within the two worker groups, which may arise from variation in technologies and quality of labor across plants, for example. Adding these controls has little impact on the estimates, suggesting that biases arising from differences in labor productivity or the quality of labor between low-dependence plants in highly- and less- exposed localities are unlikely to be a major concern. I also experimented with a specification adding plant-level changes in the relative production labor unit cost from 1989 to 1990 and the size of the neighboring industry in the same municipality as controls. Also these specifications gave very similar results suggesting that auto-correlated trends in relative wages and selection by the size of the local industry are unlikely to drive the results.[17]

Local input-output linkages. The IV strategy is based on the assumption that the trade shock on local Soviet-dependent industry was not correlated with technology shocks in local plants producing for the non-Soviet markets. One may be concerned that the collapse of output in Soviet-dependent industry may have adversely affected plants producing inputs for it. This may have forced these plants to change production technologies in order to adapt to new market environment which may confound the IV results. To examine whether such spreading of the shock through local input-output linkages drive the results, I draw data on 1988 plant-level inputs by 6-digit HS88 commodity from the Commodity Statistics Survey to predict the plant-level output share of commodities supplied as inputs to the local Soviet-dependent industry.[18] Column 9 displays results for a specification

[17] In this specification, the TSLS estimate (standard error) was 0.160 (0.062) for the relative production labor unit cost and -0.022 (0.013) for capital intensity.

[18] To calculate this measure, I first approximate the amount of input *m* used in Soviet-dependent production in plant *i* by $\hat{x}^s_{im} = x_{im} PSID_i$, where x_{im} is plant's usage of input *m* in 1988 and $PSID_i$ is plant's predicted output share of Soviet exports (see equation (5)). Then the predicted usage of input *m* in Soviet-dependent production in locality *r* is $\hat{X}^s_{rm} = \sum_{i \in I(r)} \hat{x}^s_{im}$ and plant's predicted output share of inputs supplied to local Soviet production is $\hat{y}^s_i = \left(\sum_m \theta_{im} \hat{X}^s_{rm}\right) / y_i$, where θ_{im} is plant's local output share of commodity *m*. For further details of the plant-level Commodity Statistics survey, see section 2.2.

corresponding to column 8 but excluding plants with predicted output share of inputs used by the local Soviet-dependent industry larger than 20%. This excludes only 25 observations indicating that very few plants are producing extensively inputs for local Soviet export production. Importantly, excluding these plants has little impact on the results, suggesting that demand effects through local input-output linkages are unlikely to confound the results.

Robustness against weak instruments. The IV specifications in columns 5-9 are based on eleven excluded instruments. In order to examine the robustness of the results against the potential inconsistency of the TSLS estimator that may arise with many instruments when some of the instruments are weak, I follow Angrist and Pischke (2009) and estimate the model with the LIML estimator, which has better statistical properties in the many instruments setting. For the specifications in columns 5-9, the LIML estimates of the coefficient on the relative production labor unit cost have lower precision, but they are, in general, of a similar magnitude as the corresponding TSLS estimates. I also estimated the model with the HFUL estimator of Hausman et al. (2012), which is a heteroskedasticity-robust version of the Fuller estimator, and this gave also very similar estimates as the corresponding TSLS procedure. In sum, results based on these alternative estimators are consistent with the TSLS estimates, suggesting that weak instruments are not a major source of bias. In the industry-level analysis below, I use the TSLS estimates in column 5 where both coefficients have high precision, but the results are robust in the range of IV estimates in table 4.

5.4 Changes in the Relative Demand for Production Labor

This section presents indices of the relative demand for production labor implied by the estimates of β_L and β_K. To derive a demand shift series for the full analysis sample over the whole observation window 1980-2008, I recover τ_{jt} by taking expectations of both sides of equation (3) conditional on industry and year, which yields

$$\tau_{jt} = E\left[\Delta s_{ijrt} \mid j,t\right] - \beta_L E\left[\Delta ln\left(w_{Lrt}/w_{Hrt}\right) \mid j,t\right] - \beta_K E\left[\Delta ln\left(k_{ijrt}/y_{ijrt}\right) \mid j,t\right]. \tag{7}$$

The index of the relative demand for production labor in year t relative to year 1980 is then $\hat{\mu}_{jt}^{1980} = \Sigma_{s=1980}^{t-1}\hat{\tau}_{js}$ for $t > 1980$, where $\hat{\tau}_{js}$ are calculated from equation (7) by imposing β_L and β_K to be equal to the corresponding preferred parameter estimates in column 5 of table 4 and by replacing expectations by sample means from the full analysis sample.

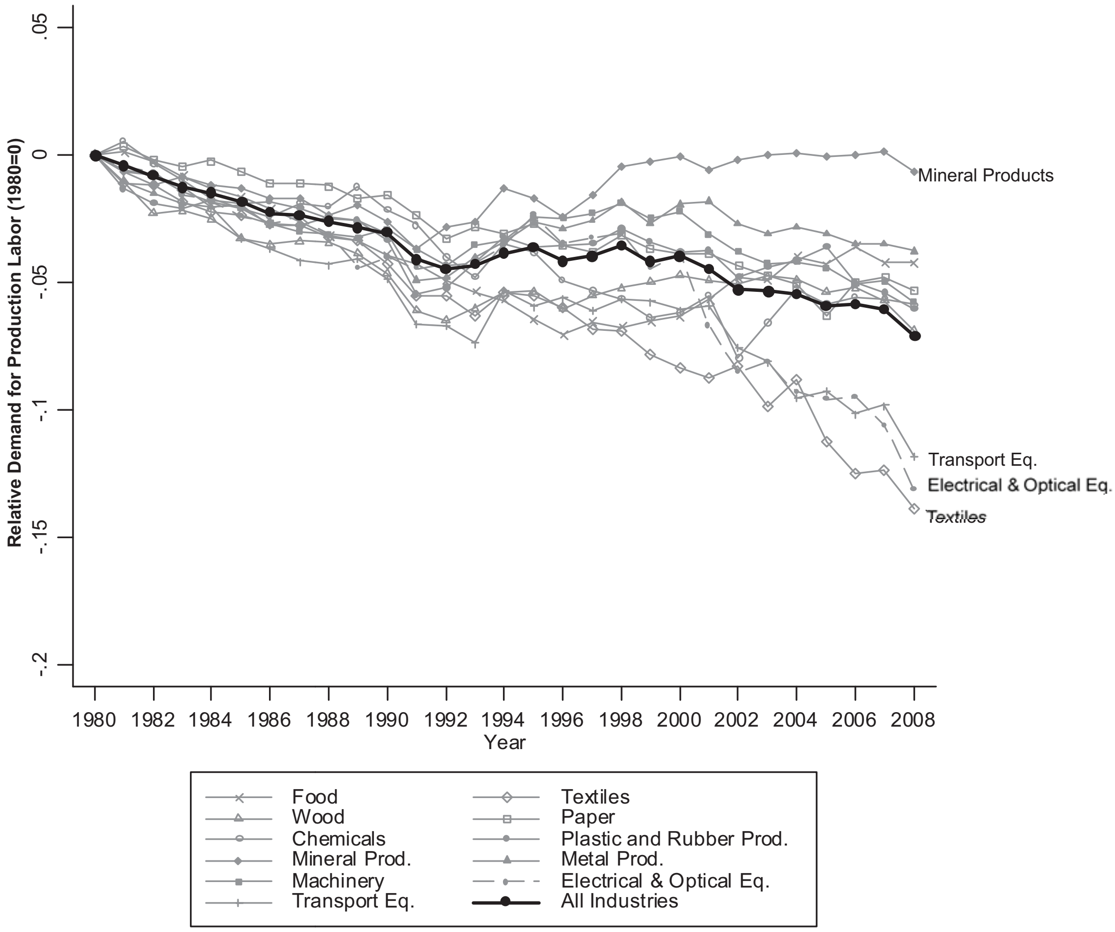

Figure 6: Relative Demand for Production Labor by Industry (1980=0)

Notes: Series are based on relative production labor demand indices by 2-digit industry calculated from equation (7) for the full analysis sample by imposing the TSLS estimates in column 5 of table 4. 2-digit series are aggregated to 2-character level and to all industries with industry labor costs as weights.

Figure 6 displays the indexes of the relative demand for production labor by 2-character industry and an aggregate series which is the average of the industry figures weighted by annual industry labor cost. Overall, the aggregate decline in the fraction of production labor cost to total labor cost associated with the labor demand shift is 7.1 percentage points from 1980 to 2008, implying an average decadal contraction rate of 2.5 percentage points. From 1980 to 1989, the relative demand declines with a decadal contraction rate of 3.1 percentage points, while the contraction rate reduces to 1.2 in the 1990s. The fall of the relative production labor demand accelerates again in the 2000s, with a decadal contraction rate of 3.9 percentage points over the period 2000-2008.

The patterns of the relative production labor demand shift are strikingly similar across industries in the 1980s, whereas considerable differences emerge in the late 1990s and in the 2000s. Over the period 1995-2008, the relative demand declines the most in transport equipment, textiles, and electrical and optical equipment with decadal contraction rates of 4.5, 6.4, and 8.3 percentage points, respectively, while it declines the least in metal products, food, beverages and tobacco products, and mineral products, with the two latter industries experiencing a small increase.

The prevalent and uniform decline of the relative production labor demand in the 1980s is in line with the broad literature suggesting that pervasive technical change was a major driver of the structure of employment and wages in the 1980s (e.g., Berman, Bound, and Machin, 1998). The increasing industry dispersion in the 2000s cannot, however, be explained by uniform technological change across industries. Alternative hypotheses outline that the patterns of production labor-saving technological change have diverged or that the rise of international trade has differentially affected the composition of labor demand across industries. I next investigate the relative importance of these two potential sources of shifts in the structure of labor demand.

6 Offshoring, ICT, and the Relative Demand for Production Work

6.1. Trends in Imports of Intermediate Inputs and ICT investment in Finland

This section examines to what extent technology and offshoring of production activities explain the declining relative production labor demand in figure 6. I start by showing in figure 7 the ratio of imported intermediate manufacturing inputs to manufacturing output and the ratio of manufacturing ICT and software investment to manufacturing output over the observation period.

The imported intermediate input share is stagnant in the early 1980s, while the ICT and software investment share more than doubles over the same period, thus rising from 0.45% in 1980 to 1.14% in 1989, which is in line with the rising role of computer-aided technologies in that period. In the early 1990s, the rise of the ICT and software investment share stagnates and even begins to slowly decline until 1997, while the imported intermediate input share rises from 9% in the late 1980s to 18% in 2008. The sharpest rise in the imported intermediate input share is observed in the period 2003-2007 with a staggering decadal growth of 10.4 percentage points.

6.2 Impacts of Offshoring and ICT on the Relative Demand for Production Labor

To assess to what extent ICT and offshoring of production activities have contributed to changes in the composition of labor demand, I estimate the following industry regression:

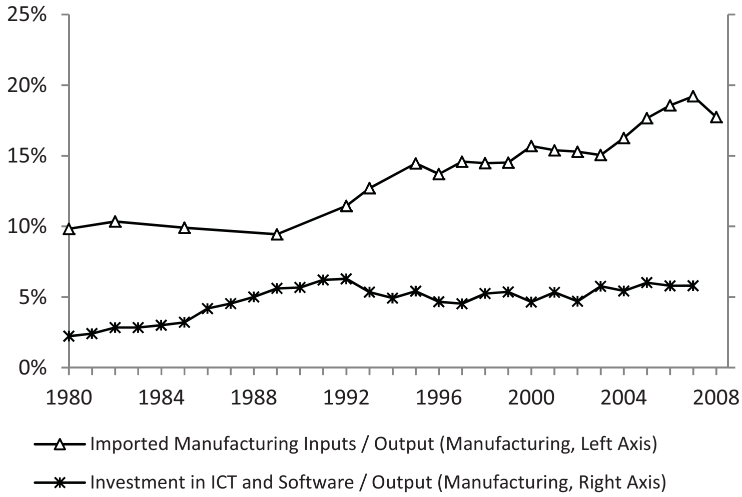

Figure 7: Imported Intermediate Manufacturing Inputs and ICT, 1980-2008

Data Sources:
GDP, and manufacturing output: *Annual National Accounts*, Official Statistics of Finland.
ICT Investment: *EU KLEMS Growth and Productivity Accounts: November 2009 Release, updated March 2011 (Timmer et al. 2007)*
Imports of intermediate inputs 1980-1993: *Supply and Use Tables (1980, 1982, 1985, 1989, 1992, 1993)*, Statistics Finland
Imports of intermediate inputs 1995-1999: *Supply and Use Tables 1995-2000*, Statistics Finland.
Imports of intermediate inputs 2000-2008: *Supply and Use Tables 2000-2008*, Statistics Finland.

$$\hat{\mu}_{j,t+s} = \gamma_1 log(ICT_{jt}) + \gamma_2 log(OFFSHORING_{jt}) + \alpha_j + \delta_t + \xi_j t + \upsilon_{jt} . \qquad (8)$$

Here, $\hat{\mu}_{j,t+s}$ is the estimated relative production labor demand index in 2-digit industry j in year $t+s$. When $s=0$, estimates of γ_1 and γ_2 recover the impacts of concurrent ICT and offshoring on the relative production labor demand. In order to break the potential correlation between labor input choice, ICT, and offshoring that may arise as a result of, say, a productivity shock biased towards non-production services if, for example, non-production services are more complementary with ICT or outsourced production, I also estimate the model for $s=1,2$. The specification includes fixed industry effects, fixed year effects, and industry-specific trends. The former controls for permanent unobserved heterogeneity in the structure of labor demand across industries while the latter controls for differential trends in unobserved industry factors. All industry regressions are weighted by industry labor cost and standard errors are clustered by industry.

I measure ICT by computer and programming expenses[19], which are available at the 2-digit industry level from the Industrial Statistics on Manufacturing maintained by Statistics Finland for the period 1995-2008. Following the seminal paper by Feenstra and Hanson (1996) and many subsequent studies, I use industry imports of industrial intermediate

[19] These include costs of equipment and programming; consulting related to automatic data processing; design and programming of software; activities related to computer operations and data processing; database hosting; repair and maintenance of office equipment and computers; other data processing services, e.g., software engineering services; and IT-software maintenance and consulting.

Table 5: Offshoring, Technology, and Relative Production Labor Demand: OLS Estimates

Dependent variable:	(1) μ_t	(2) μ_{t+1}	(3) μ_{t+2}	(4) μ_t	(5) μ_{t+1}	(6) μ_{t+2}
Offshoring	0.010	-0.000	-0.020***	-0.000	-0.009	-0.017***
	(0.010)	(0.007)	(0.007)	(0.010)	(0.007)	(0.006)
ICT	-0.007	-0.006	-0.009*	-0.005	-0.002	-0.009
	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Observations	171	171	171	171	171	171

Notes: Estimates weighted by industry labor cost. Standard errors clustered by industry are in parentheses. All specifications control for the log of industry R&D expenditure. Columns 1-3 include industry fixed effects and industry time trends, while columns 4-6 add year dummies. Offshoring is measured as the log of imported industrial intermediate inputs. ICT is measured as the log of computer and programming expenses. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively.

inputs as a proxy for offshored production activities, drawn from the 2-digit industry input-output tables maintained by Eurostat. These data are available for the period 1995-2007.[20]

Basic results. The first column of table 5 presents OLS estimates of the coefficients on concurrent ICT and offshoring for a specification controlling for industry fixed effects and trends, while the second column shows results for a specification based on a one-year time gap between the regressors and the outcome. These specifications do not detect impacts of offshoring and ICT on the relative production labor demand. However, in column 3, the coefficient on offshoring based on the two-year time gap is substantially larger negative compared to the estimates in column 1 and 2, and significant at the 5 percent risk level, while the coefficient on ICT is also negative and marginally significant. The results are very similar when year dummies are included (columns 4-6), although ICT is insignificant for the two-year time gap specification in column 6.

IV estimates. While the two-year time gap between the explanatory variables and outcome and the inclusion of industry fixed effects and controls for industry-specific time trends may reduce the potential biases arising from reverse causality and omitted variables, computer and programming expenses and imports of intermediate inputs may be noisy measures of industry ICT and offshoring. Hence, the OLS estimates may be prone to attenuation bias arising from measurement errors in these variables. It cannot be ruled out completely, either, that autocorrelation in unobserved industry shocks may induce confounding bias in the estimates, if such correlation is sufficiently persistent.

In order to reduce the potential biases arising from measurement errors and to break the

[20] Data after 2007 uses a considerably coarser industry classification and hence cannot be used to extend the 2-digit data used in this study.

potential correlation between lagged ICT and offshoring and unobserved industry shocks in the relative production labor demand, I use US industry use of computer services and imports of intermediate inputs from the same industry as instruments for the Finnish ICT and offshoring.[21] The results are displayed in table 6. Panel A shows results for specifications treating offshoring as the endogenous regressor; panel B shows results for specifications treating ICT as the endogenous regressor; and panel C treats both variables as endogenous. Columns 1-3 display results for specifications including industry fixed effects and industry-specific time trends, while columns 4-6 add year dummies to add further control over variation in unobserved characteristics over time.

In panel A, the IV estimate on offshoring is insignificant in specifications using the concurrent (column 1) and one-year leaded (column 2) outcome, while in the model based on a two-year time gap between the explanatory variables and the outcome (column 3), the estimate is considerably more negative, although statistically insignificant. All coefficients on offshoring are negative when year dummies are included in the model (columns 4-6), although the precision of the estimation is reduced considerably. In panel B treating ICT as the endogenous regressor, the coefficient on ICT based on the two-year time gap is significant and more negative than the corresponding OLS estimate in table 5. It is also worth noting that the magnitude of the coefficient on offshoring in column 3 is largely unchanged when moving from panel A to panel B, but the estimate becomes highly significant due to the improved precision of the estimation.

In column C treating both offshoring and ICT as endogenous, the pattern of coefficients on offshoring is, to a large extent, similar to that of the corresponding coefficients in panel A, but here the coefficient on offshoring in column 3 is significant at the 5 percent risk level. The point estimate increases when year dummies are included, although the precision of the estimation in columns 4-6 is considerably reduced due to lower degrees of freedom. The coefficient on the ICT measure is also significant in column 3, but this finding does not hold in the more demanding specification in column 6 controlling for year dummies.

[21] US computer services are inputs from NAICS industry 5415 ("computer systems design and related services") drawn from the BLS nominal use tables lagged one year. US offshoring is imported intermediate inputs from own industry drawn from the BEA import matrixes. I also experimented with imported inputs from all manufacturing industries, but this instrument did not provide sufficiently strong first-stage.

Table 6: Offshoring, Technology, and Relative Production Labor Demand: IV Estimates

Dependent variable:	(1) μ_t	(2) μ_{t+1}	(3) μ_{t+2}	(4) μ_t	(5) μ_{t+1}	(6) μ_{t+2}
		A. Endogenous Variable: Offshoring				
Offshoring	0.010	0.009	-0.022	-0.021	-0.025	-0.029
	(0.019)	(0.013)	(0.017)	(0.027)	(0.030)	(0.023)
ICT	-0.007	-0.006	-0.009*	-0.004	-0.001	-0.009
	(0.007)	(0.007)	(0.005)	(0.007)	(0.004)	(0.005)
1st Stage:						
US Offshoring	0.422***	0.422***	0.422***	0.255**	0.255**	0.255**
	(0.104)	(0.104)	(0.104)	(0.094)	(0.094)	(0.094)
		B. Endogenous Variable: ICT				
Offshoring	0.010	-0.001	-0.020***	-0.003	-0.014	-0.018**
	(0.009)	(0.006)	(0.006)	(0.008)	(0.009)	(0.007)
ICT	-0.001	0.005	-0.024**	0.006	0.021	-0.012
	(0.007)	(0.012)	(0.011)	(0.023)	(0.021)	(0.019)
1st Stage:						
US computer services	0.370**	0.370**	0.370**	0.343*	0.343*	0.343*
	(0.174)	(0.174)	(0.174)	(0.181)	(0.181)	(0.181)
		C. Endogenous Variables: Offshoring and ICT				
Offshoring	0.012	0.010	-0.027**	-0.030	-0.037	-0.032
	(0.016)	(0.010)	(0.011)	(0.108)	(0.060)	(0.033)
ICT	-0.003	-0.003	-0.019**	0.021	0.033	-0.002
	(0.010)	(0.010)	(0.009)	(0.077)	(0.050)	(0.022)
1st Stage for Offshoring:						
US Offshoring	0.371***	0.371***	0.371***	0.216**	0.216**	0.216**
	(0.086)	(0.086)	(0.086)	(0.098)	(0.098)	(0.098)
US Computer Services	0.183**	0.183**	0.183**	0.161*	0.161*	0.161*
	(0.068)	(0.068)	(0.068)	(0.090)	(0.090)	(0.090)
1st Stage for ICT:						
US Offshoring	-0.279*	-0.279*	-0.279*	-0.011	-0.011	-0.011
	(0.141)	(0.141)	(0.141)	(0.258)	(0.258)	(0.258)
US Computer Services	0.355**	0.355**	0.355**	0.356**	0.356**	0.356**
	(0.168)	(0.168)	(0.168)	(0.159)	(0.159)	(0.159)
Observations	171	171	171	171	171	171

Notes: Estimates weighted by industry labor cost. Standard errors clustered by industry are in parentheses. All specifications control for the log of industry R&D expenditure. For results excluding R&D expenditure, see online appendix table A4. Columns 1-3 include industry fixed effects and industry time trends while columns 4-6 add year dummies. Offshoring is measured as the log of imported industrial intermediate inputs. ICT is measured as the log of computer and programming expenses. US computer services is the log of inputs from NAICS industry 5415 ("computer systems design and related services") lagged one year. US offshoring is the log of imported industrial intermediate inputs from own industry. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively. Angrist-Pischke F-Statistics: In panel A, 16.47 (columns 1-3) and 7.312 (columns 4-6); in panel B, 4.523 (columns 1-3) and 3.569 (columns 4-6); in panel C, 19.398 for offshoring and 5.838 for ICT (columns 1-3), and 5.057 for offshoring and 2.247 for ICT (columns 4-6).

To put the size of the impacts of offshoring and ICT on the relative demand for production labor into perspective, figure 7 plots the predicted average contribution of these two factors to the estimated demand shift. I employ a conservative approach and choose the smallest values of the impact estimates with sufficiently high precision based on the models using the two-year time gap. For offshoring, I use the estimate of –0.018 in column 6 of panel B. The coefficients on ICT in this specification and in the corresponding specification in panel C have relatively large standard errors. Hence, I use the coefficient value

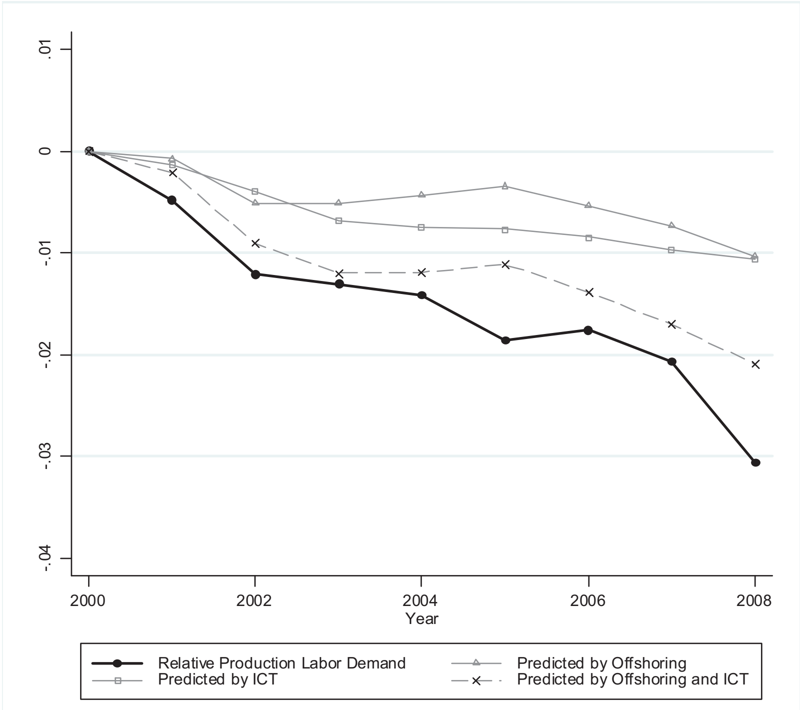

Figure 7: Relative Production Labor Demand Shift Predicted by ICT and Offshoring, 2000-2008
Notes: The predicted effect in year *t* is calculated as the weighted average of log changes of ICT (offshoring) from 1998 to *t*-2 with industry labor costs as weights times the coefficient on ICT (offshoring) in equation (8). The coefficient values used are -0.009 for ICT and -0.018 for offshoring.

of -0.009 identified with better precision in four out of eight specifications in tables 5 and 6. The predicted effect in year t is calculated as the weighted average of log changes from 1998 to $t-2$ of a relevant explanatory variable with industry labor costs as weights times the coefficient on the relevant explanatory variable.

Overall, the preferred estimates imply that offshoring and ICT explain around 2.1 percentage points of the 3.1 percentage point decline in the relative production labor demand over the period 2000-2008. The individual contribution of these variables is of a very similar magnitude, with ICT explaining around 35% of the overall demand shift and offshoring explaining around 34% of it.

In sum, the results of this section suggest that ICT and offshoring in the manufacturing sector have had an equally important role in shaping the demand side of the labor markets in recent years. They also indicate that these two commonly suspected sources of skill- or task-biased labor demand shifts explain the bulk of the recent decline in the relative demand for non-interpersonal, manual task-intensive production labor activities.

7 Conclusions

This paper examined changes in the relative demand for production labor in Finnish manufacturing. To track the demand shifts, plant-level labor demand schedules were identified from spatial variation in unit labor costs arising from a large-scale manufacturing trade shock, which was caused by the abolishment of the bilateral trade agreement between

Finland and the Soviet Union. The analysis employed detailed product-level data on inputs and outputs to identify plants that were producing for the non-Soviet markets and that were indirectly affected by the shock as the downsizing of the neighboring Soviet-dependent industry affected unit labor costs in local labor markets. These plants were used in estimations to avoid biases that may arise from endogenous technology adjustment in the Soviet-dependent industry which was severely hit by the collapse of trade. The analysis also controlled for local demand effects on these plants that may arise from the declining input demand in the Soviet-dependent industry and for numerous other potential sources of confounding variation.

The identified model of plant-level labor demand implies that the relative demand for production labor declines by 7.1 percentage points in terms of production labor cost share over the period 1980-2008. I identify two rapid phases of the demand shift. The first is observed in the 1980s, when the relative production labor demand declines with a virtually uniform rate across industries. A second phase of the rapid demand shift is observed in the 2000s, coinciding with a surge of imported intermediate input. An industry-level analysis relating ICT and offshoring to industry-level indices of the demand shift indicates that both of these variables have a significant negative impact on the relative production labor demand and both explain around one-third of its decline in the 2000s.

I believe that the findings of this study are relevant to understand recent changes in the task content of work as my analysis of individual-level data on wage and occupation indicates that production workers are highly specialized in non-interactive, manual task-intensive job activities whereas non-production workers are specialized in analytic and cognitive task-intensive job activities. Hence, the decline in the relative demand for production labor implies demand-driven relative decline in manual job activities requiring little human interaction. The results are also relevant to understand the recent polarization patterns in the labor markets because a notable fraction of middle-income labor input is provided by workers in production occupations.[22]

The article contributes both methodologically and substantively to the literature examining the forces shaping the labor markets. I proposed a novel empirical strategy for estimat-

[22] Mitrunen (2013) shows that the polarization of employment in the Finnish labor market has been to a large extent driven by two groups of production workers: machine operators and assemblers (ISCO 82); and metal, machinery and related trades workers (ISCO 72). Table 1 in Goos, Manning, and Salomons (2009) based on data from 16 European countries indicates that around 71% of middle-income occupations are related to production work and that the same two production worker groups that have driven polarization in Finland have experienced the largest declines in the European-level employment shares over the period 1993-2006.

ing labor demand models based on local general equilibrium effects on establishments whose neighboring industry experiences an abrupt product demand shock. The results of the study provide direct evidence that the relative demand for production job activities has declined sharply in the 2000s, and that the recent rise of trade has contributed significantly to this development. The findings also suggest that technological change has not lost its key role as one of the main drivers of the structure of labor demand.

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Online Appendix

Table A1: Top 15 Soviet Export Commodities in 1990

Commodity	USD	% of Soviet Exports	% of Total Exports	% of Manufacturing Output
Telephonic or telegraphic switching apparatus	193,322,285	5.7	0.8	0.4
Prefabricated buildings	107,956,401	3.2	0.5	0.2
Railway cars n.e.s., open, with sides > 60 cm high	105,420,520	3.1	0.5	0.2
Floating, submersible drilling or production platform	89,001,175	2.6	0.4	0.2
Paper, fine, woodfree, 40 - 150 g/m2, uncoated	88,540,280	2.6	0.4	0.2
Chemical wood pulp, dissolving grades	77,287,466	2.3	0.3	0.2
Apparatus, for carrier-current line systems, n.e.s.	68,536,926	2.0	0.3	0.1
Tankers	65,452,989	1.9	0.3	0.1
Paper, fine, wood-containing, uncoated, n.e.s.	62,427,258	1.9	0.3	0.1
Cyclic amides, derivatives, n.e.s., salts thereof	54,585,407	1.6	0.2	0.1
Infant foods of cereals, flour, starch or milk, retail	53,068,693	1.6	0.2	0.1
Paper, multi-ply, clay coated, n.e.s.	50,486,437	1.5	0.2	0.1
Boots, sole rubber or plastic upper leather, n.e.s.	45,988,073	1.4	0.2	0.1
Railway tank cars	45,646,409	1.4	0.2	0.1
Warships, lifeboats, hospital ships, vessels n.e.s.	44,675,870	1.3	0.2	0.1

Notes: Data from OECD ITCS Database. Figures represent total exports from Finland to the Soviet Union in 1990 for 6-digit HS88 categories. "N.e.s." stands for "not especially specified."

Table A2: Summary Statistics by Local Soviet-Import Dependence, Plants with Low Soviet-Import Dependence, 1989

	Plants in Municipalities Below Median Local Soviet-Import Dependence		Plants in Municipalities Above Median Local Soviet-Import Dependence	
	Mean	Std. Dev.	Mean	Std. Dev.
Labor Cost, Total	2,571	5,492	2,432	4,591
Labor Cost, Non-production labor	877	2,283	881	2,314
Labor Cost, Production labor	1,694	3,446	1,551	2,544
Employment, Total	118	216	114	205
Employment, Non-production labor	31	77	31	74
Employment, Production labor	87	146	83	143
Hours, Total	199	369	184	288
Hours, Non-production labor	54	141	52	124
Hours, Production labor	144	240	132	185
Production Labor Cost Share	0.725	0.156	0.709	0.176
Production Labor Employment Share	0.788	0.136	0.774	0.155
Production Labor Hour Share	0.784	0.140	0.768	0.161
Real Capital Stock (2000 Prices)	9,743	30,841	6,989	21,111
Real Output (2000 Prices)	21,462	51,714	15,553	36,049
Real Value Added (2000 Prices)	6,704	17,055	5,638	15,867
Capital Intensity	1.813	3.962	1.592	2.939
Nominal Production Labor Unit Cost	10.51	2.72	10.84	2.73
Nominal Non-Production Labor Unit Cost	15.03	4.40	15.60	4.71
Relative Production Labor Unit Cost	0.738	0.219	0.730	0.192
Energy Intensity	0.136	0.329	0.090	0.198
Energy Intensity, 1990	0.123	0.156	0.117	0.559
Soviet-Import Dependence in 1990:				
Plant	0.000	0.000	0.000	0.000
Municipality	0.016	0.009	0.065	0.070
Municipality, Log Levels	-4.446	0.976	-2.897	0.457
Observations	366[a]		357[b]	

Notes: Data are for estimation sample plants with plant-level Soviet-import dependence ($PSID_i$ in equation (5)) less than or equal to 0.001. Local exposure refers to $LSID_i$ in equation (4). a –Number of observations for 1990 energy intensity and log of energy intensity are 364, and 365, respectively. b – Number of observations for 1990 energy intensity, and log of energy intensity are 350 and 349, respectively.

Table A3: Estimates for the Production Labor Cost Share Equation, All Plants, 1990-1994

	OLS	IV							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				TSLS					
Δ log (Relative Production Labor Unit Cost)	0.099***	0.325*	0.117*	0.127*	0.128**	0.112**	0.095*	0.124**	0.126**
	(0.005)	(0.167)	(0.063)	(0.065)	(0.061)	(0.057)	(0.056)	(0.060)	(0.060)
Δ log (Capital Intensity)	-0.007***	-0.008***	-0.007***	-0.028	-0.022**	-0.025**	-0.024**	-0.026**	-0.025**
	(0.001)	(0.002)	(0.001)	(0.018)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
				LIML					
Δ log (Relative Production Labor Unit Cost)	0.099***	0.452	0.148	0.153	0.146	0.117	0.089	0.135	0.139
	(0.005)	(0.333)	(0.173)	(0.123)	(0.106)	(0.099)	(0.089)	(0.092)	(0.092)
Δ log (Capital Intensity)	-0.007***	-0.008***	-0.008***	-0.031	-0.022**	-0.025**	-0.025**	-0.026**	-0.026**
	(0.001)	(0.002)	(0.001)	(0.022)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Instruments:									
Log (Municipality Soviet-Import Dependence in 1990) ×Year		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log (Municipality Soviet-Import Dependence in 1990)^2×Year			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log(Capital Intensity Lagged Two Years)						Yes	Yes	Yes	Yes
Angrist-Pischke TSLS 1st Stage F-Statistic for Endogenous Regressors:									
Δ log (Relative Production Labor Unit Cost)		0.994	1.365	1.518	1.700	1.892	1.916	1.725	1.724
Δ log (Capital Intensity)				2.938	13.48	8.144	8.425	8.790	8.621
Obs.	10360	10360	10360	10360	10187	10036	10036	9948	9901

Notes: The outcome is the change in the production labor cost share. Panel-robust standard errors are in parentheses. Municipality Soviet-import dependence is the ratio of a municipality's predicted Soviet exports to the municipality's gross output (LSID in equation (4)). All regressions include time×industry dummies (coefficients omitted). Specifications in columns 6-8 control for the log of energy intensity (costs of energy inputs divided by value added) in 1990 interacted with year dummies as control variables. Specifications in columns 7-8 add region dummies as control variables. The specification in column 8 adds logs of 1989 production and nonproduction worker wages as control variables. The specification in column 9 corresponds to the specification in column 8 excluding plants with predicted output share of commodities supplied to local Soviet production more than 20%. Relative production labor unit cost is treated as endogenous in columns 2-8, while capital intensity is treated as endogenous in columns 4-8. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively.

Table A4: Offshoring, Technology, and Relative Production Labor Demand: Alternative IV Estimates Excluding R&D Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$\hat{\mu}_t$	$\hat{\mu}_{t+1}$	$\hat{\mu}_{t+2}$	$\hat{\mu}_t$	$\hat{\mu}_{t+1}$	$\hat{\mu}_{t+2}$
			A. Endogenous Variable: Offshoring			
Offshoring	0.010	0.010	-0.023	-0.020	-0.018	-0.021
	(0.019)	(0.014)	(0.017)	(0.023)	(0.043)	(0.031)
ICT	-0.008	-0.008	-0.009**	-0.004	-0.003	-0.009
	(0.006)	(0.007)	(0.004)	(0.006)	(0.004)	(0.005)
1st Stage:						
US Offshoring	0.414***	0.414***	0.414***	0.248**	0.248**	0.248**
	(0.109)	(0.109)	(0.109)	(0.095)	(0.095)	(0.095)
			B. Endogenous Variable: ICT			
Offshoring	0.009	-0.003	-0.018**	-0.004	-0.017*	-0.016*
	(0.008)	(0.005)	(0.007)	(0.008)	(0.010)	(0.008)
ICT	-0.001	0.007	-0.025**	0.008	0.025	-0.014
	(0.006)	(0.014)	(0.011)	(0.024)	(0.021)	(0.022)
1st Stage:						
US computer services	0.348*	0.348*	0.348*	0.305*	0.305*	0.305*
	(0.193)	(0.193)	(0.193)	(0.154)	(0.154)	(0.154)
			C. Endogenous Variables: Offshoring and ICT			
Offshoring	0.013	0.012	-0.029***	-0.028	-0.027	-0.028
	(0.015)	(0.011)	(0.010)	(0.034)	(0.058)	(0.035)
ICT	-0.003	-0.004	-0.018*	0.020	0.030	-0.005
	(0.010)	(0.010)	(0.009)	(0.044)	(0.041)	(0.020)
1st Stage for Offshoring:						
US Offshoring	0.355***	0.355***	0.355***	0.207*	0.207*	0.207*
	(0.089)	(0.089)	(0.089)	(0.099)	(0.099)	(0.099)
US Computer Services	0.184**	0.184**	0.184**	0.157	0.157	0.157
	(0.076)	(0.076)	(0.076)	(0.093)	(0.093)	(0.093)
1st Stage for ICT:						
US Offshoring	-0.329**	-0.329**	-0.329**	-0.060	-0.060	-0.060
	(0.133)	(0.133)	(0.133)	(0.259)	(0.259)	(0.259)
US Computer Services	0.358*	0.358*	0.358*	0.336**	0.336**	0.336**
	(0.195)	(0.195)	(0.195)	(0.141)	(0.141)	(0.141)
Observations	171	171	171	171	171	171

Notes: Estimates weighted by industry labor cost. Standard errors clustered by industry are in parentheses. Columns 1-3 include industry fixed effects and industry time trends while columns 4-6 add year dummies. Offshoring is measured as the log of imported industrial intermediate inputs. ICT is measured as the log of computer and programming expenses. US computer services is the log of inputs from NAICS industry 5415 ("computer systems design and related services") lagged one year. US offshoring is the log of imported industrial intermediate inputs from own industry. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively.

Angrist-Pischke F-Statistics:

Panel A: 14.37 (columns 1-3) 6.775 (columns 4-6)

Panel B: 3.251 (columns 1-3) 3.947 (columns 4-6)

Panel C (Outsourcing, ICT): 16.158 5.992 (columns 1-3) 5.195 3.362 (columns 4-6).