ISSN 2042-2695

CENTRE *for* ECONOMIC PERFORMANCE

CEP Discussion Paper No 1451

October 2016

The Loss of Production Work: Evidence from Quasi-Experimental Identification of Labour Demand Functions

Elias Einiö

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Abstract
This paper examines changes in the structure of labour demand in plant-level panel data. I exploit variation in wages across local labour markets induced by the collapse of Finland's Soviet-dependent industry in the early 1990s to identify a labour demand model for plants producing for non-Soviet markets, which were not directly affected by the Soviet shock. I find a labour demand shift against workers in production occupations which accelerates in the 2000s, when industry patterns begin to diverge. Industry heterogeneity suggests that variation in industry structure may partly explain the differential development of wages and employment across countries.

Keywords: Labour demand function, occupation, offshoring, manufacturing, panel data, production work, technical change
JEL codes: F16; J23; J24; O33

This paper was produced as part of the Centre's Labour Markets Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

Acknowledgements
I thank Manuel Bagues, Peter Fredriksson, Kari Hämäläinen, Steve Machin, Kristiina Huttunen, Andrea Ichino, Tuomas Pekkarinen, Steve Pischke, Roope Uusitalo, John Van Reenen and seminar participants at the XIII Brucchi Luchino Workshop, EEA-ESEM, HECER, London School of Economics, RES Annual Congress, and 10th Nordic Summer Institute in Labor Economics for their helpful comments and suggestions, and Matti Mitrunen and Jaakko Nelimarkka for the excellent research assistance. The data used in this article are confidential but the author's access is not exclusive.

Elias Einiö, VATT Institute for Economic Research and Centre for Economic Performance, London School of Economics.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

Development in the structure of labour demand is one of the fundamental factors driving changes in the distribution of wages and employment. Labour demand shifts have been offered as an explanation for the increased wage inequality in the 1980s (e.g., Katz and Murphy, 1992). And a common view among economists is that one of the major triggering causes for the “polarization” of the labour markets in the 1990s and 2000s has been the declining relative demand for middle-skilled occupations engaged in routine task-intensive work (e.g., Autor, Levy, and Murnane, 2003; Autor, Katz, and Kearney, 2008; Acemoglu and Autor, 2011). But empirical measurement of these shifts has proven to be difficult and evidence of their magnitude and time pattern is far from conclusive.

In order to trace changes in the structure of labour demand, labour demand functions need to be identified. A major challenge for identifying these from observed prices and quantities arises from the simultaneity of labour demand and supply. Although this problem has been well acknowledged in the literature (e.g., Wright, 1928; Frisch, 1933), addressing it has proven to be hard due to a lack of good sources of exogenous variation in wages. For example, at the level of a local labour market, an instrument affecting local labour supply is also likely to affect aggregate local income, which in turn will shift the local labour demand curve (Card and Altonji, 1990; Angrist, 1995). Therefore, in the presence of such income effects, a randomly distributed labour supply shock may not solve the simultaneity problem in the estimation of local demand curves. Even if confounding local income effects can be eliminated, a major threat for identification arises from simultaneous technology responses of companies to product demand shocks (e.g., Bustos, 2011).

Prior research has provided some evidence of changes in the structure of labour demand in the 2000s by showing that both the relative employment and wages of the middle-skilled have declined (e.g., Autor et al., 2008). A related strand of research has provided evidence of demand shifts by showing that major demand shifters, such as technology and trade, have affected the structure of employment and wages.[1] But measures of the magnitude of these shifts based on well-identified empirical labour demand models are scant. There is a specific lack of evidence based on data from the mid-1990s onwards, since when middle-skilled workers have experienced massive relative employment losses (Goos and Manning, 2007; Autor, Katz, and Kearney, 2008;

[1] See e.g. Firpo, Fortin, and Lemieux (2011), Autor et al. (2013), Michaels, Natraj, and Van Reenen (2014), Ebenstein et al. (2014), Hummels et al. (2014), Autor et al. (2014), Goos, Manning, and Salomons (2014), and Autor, Dorn, and Hanson (2015).

Goos, Manning, and Salomons, 2009).[2]

The aim of this study is to provide evidence of the magnitude and time pattern of recent changes in the structure of labour demand by tracking shifts in plant-level labour demand schedules. To gain identification, I exploit the dramatic collapse in Finland's Soviet-dependent industry in the early 1990s as a large-scale natural experiment. I estimate labour demand schedules for plants producing for western markets, whose product demand was little affected by the collapse of Soviet import demand, but which were exposed to a local labour supply shock as the downsizing of Soviet-dependent industry released workers.[3] In this setting, the collapse of Soviet trade generated a situation where plants operating in the same western product market faced a differential unit labour cost shock because of the differential historic Soviet specialization of their neighbouring industry. I employ spatial variation in the magnitude of these local general equilibrium effects stemming from the widespread and scattered geographical distribution of Soviet-dependent production.[4]

The paper contributes to literature estimating labour demand models. To my knowledge, there are no prior studies using causal designs to identify labour demand functions at the level of a plant or industry. Previous industry-level studies have used panel techniques relying on the assumptions that relative wages are constant or variation in them is exogenous within industries (e.g. Berman, Bound, and Grilliches, 1994; Haskel and Slaughter, 2002; Baltagi and Rich, 2005), which are not completely credible. One concern is that industry variation in wages is at least partly induced by technology responses to product market shocks that simultaneously shift labour demand. My research design mitigates biases arising from such endogenous technology responses, because plants producing for western markets had stable product demand. Moreover, as the abolition of the Fenno-Soviet trade agreement was caused by an unexpected, external political process, the shock induced by it can also be plausibly viewed as being

[2] Ciccone and Peri (2005) estimate local labour demand curves from labour supply shocks across US states induced by changes in child labour and compulsory school attendance laws. They find a technology-induced demand shift towards more educated workers over the period 1950-1990. For studies estimating demand shifts from aggregate time series data, see e.g. Katz and Murphy (1992), Autor et al. (2008), and Dustmann, Ludsteck, and Schönberg (2009). See also Borjas (2003), who exploits supply shifts across education-experience groups arising from variation in immigrant flows across these groups.

[3] While the collapse of Soviet trade induced significant spatial divergence in output, it induced little spatial divergence in employment, indicating significant spatial rigidities in the national labour market.

[4] The empirical strategy utilises variation in trade shocks across local labour markets arising from historic industry specialization, as in Topalova (2010) and Autor, Dorn, and Hanson (2013). A distinct feature of it is that it exploits local general equilibrium effects on plants not directly affected by the initial shock. For previous work using empirical strategies based on the rise and fall of the Soviet regime and former Eastern Bloc, see e.g. Friedberg (2001), Glitz (2012), Borjas and Doran (2012), and Falck et al. (2013). Dustmann, Schönberg, and Stuhler (2015) exploit local labour supply shocks from changes in commuting restrictions at the German-Czech border to examine effects on native German wages and employment.

independent of productivity development among Finnish producers in western markets. By focusing on the manufacturing sector, the research design mitigates concerns about confounding local income effects resulting from the trade shock, because the scope of manufacturing product markets is typically global, or at least national. To add further credence to the research design, I show that the results are robust when fixed effects for relatively small geographic areas are included. And I can show that the results are not driven by plants supplying inputs for neighbouring Soviet-dependent industry.

To implement the empirical strategy, I employ unique Finnish data on plant inputs, unit labour costs, and product-level outputs. The estimated labour demand model implies significant (relative) demand shifts against production workers over the past three decades. The fall is especially sharp in the 2000s. The results also suggest that the demand patterns begin to diverge dramatically between industries in this period (little industry differentials emerge in the earlier periods). This has the important implication that countries with a different industry structure may experience differential development in the aggregate structure of labour demand (and, as a result, in wage and employment distribution) even if their industries face the same industry-specific technology and trade shocks. A simple calculation predicts the largest fall in the relative demand for production labour for the US industry structure. Finally, I find evidence that the labour demand shift against production occupations is most rapid in industries experiencing the largest increases in ICT investment and offshoring.

While the empirical strategy proposed in this study provides credible estimates of *within-plant* shifts in the structure of labour demand, it does not cover all components of the aggregate labour demand shift. However, within-plant shifts are likely to constitute the major component in the evolution of the structure of labour demand in the Finnish manufacturing sector, because incumbent plants cover over 93% of new investment in the sector in the observation period. Moreover, sectoral shifts are unlikely to be a significant factor because the share of manufacturing employment to total employment has declined only by a decadal rate of 1.4 percentage points in Finland since mid-1990s.[5] While my analysis excludes non-manufacturing sectors, manufacturing production occupations accounted for over 70% of all middle-income employment in the early 1990s, and therefore are a key group for understanding the extent to which demand shifts in the middle of the skill distribution have driven the employment polarization observed in many countries in recent decades (e.g., Goos, Manning, and Salomons, 2009).

[5] Employment share is calculated from the *Annual National Accounts* maintained by Statistics Finland. It was 14.2% in 2008, which is the last year in the plant-level panel data.

The work is organised as follows. I start by documenting the task and occupational structure of manufacturing labour input in section 2. The plant-level labour demand model is presented in section 3 and section 4 describes the data. Section 5 provides the details of the empirical strategy based on the asymmetric downsizing of Soviet-dependent industry, while section 6 presents the results and several robustness checks verifying the identification strategy. The final section concludes.

2 Manufacturing Occupations and Tasks

Previous literature has documented a striking loss of middle-skilled employment in the UK (Goos and Manning, 2007), US (Autor et al., 2008), and Europe (Goos et al., 2009). In some countries, this employment polarization has also coincided with rising relative wages at the top and bottom ends of the wage distribution. The principal suspected cause of this development offered by many economists is the declining relative demand for middle-skilled labour in routine task-intensive occupations (e.g. Autor et al., 2003; Acemoglu and Autor, 2011). These occupations comprise two major worker groups – production workers in manufacturing and clerical occupations. My analysis focuses on the former group, which accounted for around 70% of middle-income employment in the early 1990s (clerical occupations accounted for around 14%) and since then has experienced massive relative employment losses (Goos et al., 2009).

The focus on production occupations has two major advantages. First, extensive and detailed data on manufacturing inputs and outputs required for estimating plant-level labour demand models are readily available for several decades. The second advantage lies in the clear occupation and task structure in manufacturing, as shown in table 1, which is based on the worker-level data on taxable wage income and occupation and job task data of Acemoglu and Autor (2011).[6] The table displays income shares and job task indices for three major occupational categories: production workers, professionals (including managers), and clerical and service workers. The first column, displaying income shares, indicates that manufacturing labour input is highly concentrated in the first two categories, with production workers accounting for around 56.5% and professionals around 36.6%, while clerical and service occupations account for only 7.1%.

[6] For details of the data construction, see online appendix A section A.1.

Table 1: Manufacturing Occupations and Tasks

		Job Task Indices					
		Routine		Non-Routine			
Occupation	Taxable Wage Income Share 1995 (%)	Manual	Cogni-tive	Cognitive Analytic	Cognitive Interper-sonal	Manual Physical	Manual Interper-sonal
Production Workers	56.5	1.27	0.20	-0.28	-0.55	1.13	-1.09
Non-Production Workers	43.5	-0.32	0.11	0.68	0.20	-0.40	-0.07
Professionals (including Managers)	36.6	-0.35	0.07	0.91	0.34	-0.40	-0.04
Clerical and Service Workers	7.1	-0.18	0.34	-0.54	-0.52	-0.34	-0.23

Notes: Data on worker-level taxable wage income and occupation from the researcher-use sample of the FLEED. Task measures are based on the job task data of Acemoglu and Autor (2011).

The rest of the table displays the job task indices. Consistent with prior work using US data (see Acemoglu and Autor, 2011), the table indicates that production work is highly routine (manual) task-intensive.[7] Production workers also score highly in the non-routine manual physical task dimension, which is unsurprising given that work on the factory floor often requires moving and handling tools, machines, and production items. On the other hand, work by professionals is highly non-routine cognitive task-intensive, while the small clerical and service worker category scores relatively lowly along all task indices, with the highest score in the routine cognitive task category.

These observations indicate that manufacturing work is characterised by a clear occupation and task structure, with production and professional occupations accounting for around 93% of labour input. These worker groups are also clearly separated by the key task dimensions, with the former group specialised in routine manual and non-routine physical manual tasks and the latter group specialised in cognitively demanding non-routine tasks. This suggests that the declining relative demand for middle-skilled labour in routine task-intensive occupations should be specifically identifiable in manufacturing data. The next two sections present an econometric framework and empirical strategy for identifying such changes in plant-level panel data.

3 Econometric Model

I consider a manufacturing plant producing output y by combining production and professional labour services and capital. I assume that each unit of professional labour service carries a fixed proportion of clerical and service labour. The manufacturer minimises variable costs given the unit cost of production labour service w_L and pro-

[7] A corresponding table for 2-digit occupations shows that all 10 production occupations rank above professional, clerical and service occupations along this task measure (see online appendix table A1).

fessional labour service w_H. With quasi-fixed capital k, the variable cost function for plant i located in local labour market r and operating in industry j in year t is

$$
\begin{aligned}
&C\left(y_{ijrt}, w_{Lrt}, w_{Hrt}, k_{ijrt}, \boldsymbol{A}_{jt}\right) \\
&\quad = \min_{L,H}\left(w_{Lrt}L_{ijrt} + w_{Hrt}H_{ijrt} \colon \{L_{ijrt}, H_{ijrt}\} \in V\left(y_{ijrt}, k_{ijrt}, \boldsymbol{A}_{jt}\right)\right)
\end{aligned}
$$

where L_{ijrt} is the production labour service input; H_{ijrt} is the professional labour service input; and $V\left(y_{ijrt}, k_{ijrt}, \boldsymbol{A}_{jt}\right)$ is the input requirement set allowing for industry-specific productivity terms $\boldsymbol{A}_{jt}$.[8] Assuming translog costs and applying Shephard's lemma yields the following input cost share equation

$$
\begin{aligned}
\frac{\partial lnC_{ijrt}}{\partial ln(w_{Lrt})} = s_{ijrt} = \beta_L \ln(w_{Lrt}) + \beta_H \ln(w_{Hrt}) + \beta_K \ln\left(k_{ijrt}\right) \\
+\beta_Y \ln\left(y_{ijrt}\right) + \sum_h \gamma_{jt}^{(h)} \ln\left(A_{jt}^{(h)}\right),
\end{aligned}
\tag{1}
$$

where the production labour cost share s_{ijrt} is a function of primary input demand variables: the unit costs of production and professional labour service, capital stock and output. The last term on the right-hand side represents the effects on the labour input mix of the productivity factors affecting the structure of labour demand, such as technology and labour inputs in foreign affiliates. Rising $A_{jt}^{(h)}$ in industry j reduces the relative demand for production labour in year t if $\gamma_{jt}^{(h)} < 0$ and is biased towards production labour if $\gamma_{jt}^{(h)} > 0$. The model allows for differences in unit labour costs across local labour markets r, which may arise if local labour markets are sufficiently isolated so that local unit labour cost shocks are not diffused across production localities immediately.

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

$$
s_{ijrt} = \alpha_i + \beta_L \ln(w_{Lrt}/w_{Hrt}) + \beta_K \ln\left(k_{ijrt}/y_{ijrt}\right) + \sum_h \gamma_{jt}^{(h)} \ln\left(A_{jt}^{(h)}\right) + \epsilon_{ijrt}\,. \tag{2}
$$

[8] Perfect complementarity between professional and clerical and service labour implies $w_H = (1-a)\overline{w}_H + a\underline{w}_H$, where $\overline{w}_H$ and $\underline{w}_H$ are the unit costs of professional and clerical and service labour, respectively, and a is the amount of clerical and service labour input in one unit of professional labour service. This assumption is motivated by the fact that, in the manufacturing sector, workers in clerical and service occupations are mainly engaged in activities that provide assistance and support to workers in professional occupations (see online appendix table A1). It is unlikely to have major implications in the empirical implementation because clerical and service occupations account for only a small fraction of the labour input in the manufacturing sector.

Here all demand shifters $A_{jt}^{(h)}$ are in general not observed. Credible identification of the causal effects of all demand shifters would also require an empirical strategy providing exogenous variation in each of them. Instead of estimating all parameters $\gamma_{jt}^{(h)}$, I recover the demand shift term by replacing it with industry×year fixed effects: $\mu_{jt} = \sum_h \gamma_{jt}^{(h)} \ln\left(A_{jt}^{(h)}\right)$. Time variation in μ_{jt} represents the net effect of the demand shifters on within-plant changes in the labour input mix within industry j. Taking the first differences from t to $t+1$ to eliminate plant fixed effects yields the key estimating equation:

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

where $\tau_{jt} = \mu_{j,t+1} - \mu_{jt}$ represent average within-plant changes in the relative demand for production labour from year t to $t+1$ in industry j. It is worth noting that, in the translog model, the substitution elasticity between production and professional labour service is not fixed across plants, industries or years as it varies with the labour cost share.[9] While it is a short-run (plant-level) parameter, the model controls for capital substitution and thus estimates of τ_{jt} recover long-run within-plant demand shifts (i.e. demand shift estimates accounting for adjustments in the capital stock).

4 Data

The main 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, which includes all manufacturing plants with at least 20 employees over the period 1980-2008. These plants account for around 82% of aggregate manufacturing output in this period. The LDPM provides detailed information on annual outputs and inputs, including value added, capital stock, and labour costs for production and non-production labour (including wage bill and employer contributions such as compulsory insurance payments).[10] Importantly, the data provide information on hours worked by these worker groups, which facilitates the calculation of plant-level hourly labour costs by worker group, and information on the location of a

[9] More specifically, the substitution elasticity is

$$\sigma_{LH}\left(X_{ijrt}, \epsilon_{ijrt}; \xi\right) = 1 - \frac{\beta_L}{s_{ijrt}\left(1 - s_{ijrt}\right)} = 1 - \frac{\beta_L}{\left(X_{ijrt}\xi' + \epsilon_{ijrt}\right)\left(1 - X_{ijrt}\xi' - \varepsilon_{ijrt}\right)}$$

where $X_{ijrt} = \left(1, \ln(w_{Lrt}/w_{Hrt}), \ln\left(k_{ijrt}/y_{ijrt}\right), \ln\left(A_{jt}^{(1)}\right), \ln\left(A_{jt}^{(2)}\right), \dots\right)$ and $\xi = \left(\alpha_i, \beta_L, \beta_K, \gamma_{jt}^{(1)}, \gamma_{jt}^{(2)}, \dots\right)$. While β_L and β_K are assumed to be fixed, the model allows for heterogeneity in the elasticity of substitution across plants and industries and over time due to variation in $\alpha_i, \gamma_{jt}^{h}, X_{ijrt}$, and ϵ_{ijrt}.

[10] The non-production labour input corresponds to the professional labour service input in the model of section 3 (these terms are used interchangeably hereafter).

plant at the level of a municipality.

The LDPM data are amended with the plant-level 1988 Commodity Statistics Survey (CSS) and OECD International Trade by Commodity Statistics (ITCS) data. The CSS covers around 91% of aggregate LDPM output in 1988 and provides information on plant-level outputs and inputs by 6-digit HS commodity. These data are used to calculate a plant's share of national output by commodity before the collapse of Soviet trade. These output shares combined with data on exports from Finland to the Soviet Union by 6-digit HS commodity drawn from the ITCS are used to construct measures of Soviet specialization below. The CSS data are linked to the LDPM with unique plant codes. Online appendix A provides further details of the data construction and summary statistics for relevant samples used in the analysis.

5 Empirical Strategy

The main econometric challenge in identifying the relative production labour demand equation (3) arises from the simultaneity of the labour cost share s_{ijrt} and relative unit cost w_{Lijrt}/w_{Hijrt}. A potential source of confounding variation is a correlated production labour-biased productivity shock that shifts the relative labour demand curve. Such a shock may simultaneously affect the labour share and relative unit cost and will therefore induce bias in the OLS estimates of β_L. A second potential source of bias are unobserved shocks to product demand which may cause omitted variable bias. A third potential source of bias is measurement error, which tends to attenuate the OLS estimates towards zero. While this concern may be less pronounced in industry-level data, it may be specifically relevant in applications based on plant-level data.

To identify the model, I employ an empirical strategy based on the unexpected abolition of the trade agreement between Finland and the Soviet Union in December 1990. I exploit the local general equilibrium effects of the shock on unit labour costs faced by plants producing for western markets, whose sales did not rely on Soviet import demand. These plants did not face collapsing product markets, but they were indirectly affected by the shock as the downsizing of the neighbouring Soviet-dependent industry released workers, and as a result, affected local wages.

5.1 Fenno-Soviet Trade

Trade between the Soviet Union and Finland was based on agreements between the Soviet regime and the Finnish government. One of the main goals of these agreements was to guarantee the balance of trade. As a result of the collapse of the Soviet regime, the real value of Finnish exports to the former Soviet Union fell from 2.52 billion euro

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 Kyrgyz Republic). Sources: Exports: ITCS database, OECD. Manufacturing output: Official Statistics of Finland (OSF): Annual national accounts, Statistics Finland.

in 1990 to 0.90 billion euro in 1991 – a drop corresponding to around 2.7% of manufacturing output in 1990 (figure 1).

The structure of Soviet-dependent production in Finland was determined by the trade agreements and it was concentrated in relatively few commodities. In 1990, the 256 largest 6-digit HS commodity classes, constituting around 10% of the types of commodities exported to the Soviet Union, accounted for 92% of all Finnish exports to the Soviet Union. Telephonic and telegraphic switching apparatus was the most exported commodity, accounting for 5.7% of Soviet exports and 0.4% of total 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 (e.g. rubber boots), and food (e.g. infant cereals). [11]

5.2 Measures of Soviet Specialization

The empirical strategy exploits the fact that Soviet-dependent industry was widespread and highly scattered across the country. As a result of this, the magnitude of the Soviet trade shock varied considerably across production localities depending on the degree of historic local Soviet specialization.

I calculate pre-collapse exposure to Soviet trade at the level of a plant and locality. The former is used to identify plants in western markets, while the latter measures the size of local Soviet-dependent industry before the abolition of the trade agreement and is used as an instrument for relative wages. I measure local 1990 Soviet specialization

[11] Online appendix table B1 displays the top 15 export commodity classes to the Soviet Union in 1990. These commodities covered around 34% of Finnish exports to the Soviet Union.

as

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

where $I(r)$ denotes the set of plants in a production locality 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

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

is a measure of plant-level Soviet specialization in 1990. Here the nominator is a plant's Soviet exports predicted by the plant's pre-collapse output shares by commodity. Scaling by output yields the plant-level predicted output share of Soviet exports. I define producers in western markets as plants with $PSS_{i,1990} < 0.001$.[12] In equation (4), the measure of local Soviet specialization is constructed in a similar way, but the nominator and denominator are summed over plants located in the relevant production locality r. To calculate these measures, I draw pre-collapse Soviet imports by commodity, $SI_{m,1990}$, from the ITCS, and calculate the pre-collapse plant-level commodity output shares, $\omega_{im,1988}$, from the CSS. Both data are based on the 6-digit HS commodity classification.

Figure 2 displays the geographic variation in municipality-level Soviet specialization in 1990 by quintile.[13] The figure illustrates that Soviet-dependent industry is widespread and highly scattered across the country prior to the collapse of the Soviet Union. The figure also displays the spatial distribution of producers in western markets used in the estimation sample. It shows that production for western markets is also widespread and found in localities with low and high exposure to Soviet import demand.[14] Importantly, the fine spatial scale of the data and substantial geographic variation in historic Soviet-dependent production allows identification using variation within relatively small spatial units (i.e., by administrative regions (*maakunta*), which are displayed in the figure). In this setting, the collapse of Soviet trade generates a situation where producers in the same western product market experience a differential local shock because of differential historic Soviet specialization in neighbouring industries.

[12] Around 28% of plants fulfil this criterion in 1990.

[13] Plant location is only available at the level of a municipality. However, Finnish municipalities are relatively small geographic units with a median area of 749 km^2. In 1990, there were 460 municipalities.

[14] Summary statistics separately for plants in the high- and low-exposure areas are provided in online appendix table A3.

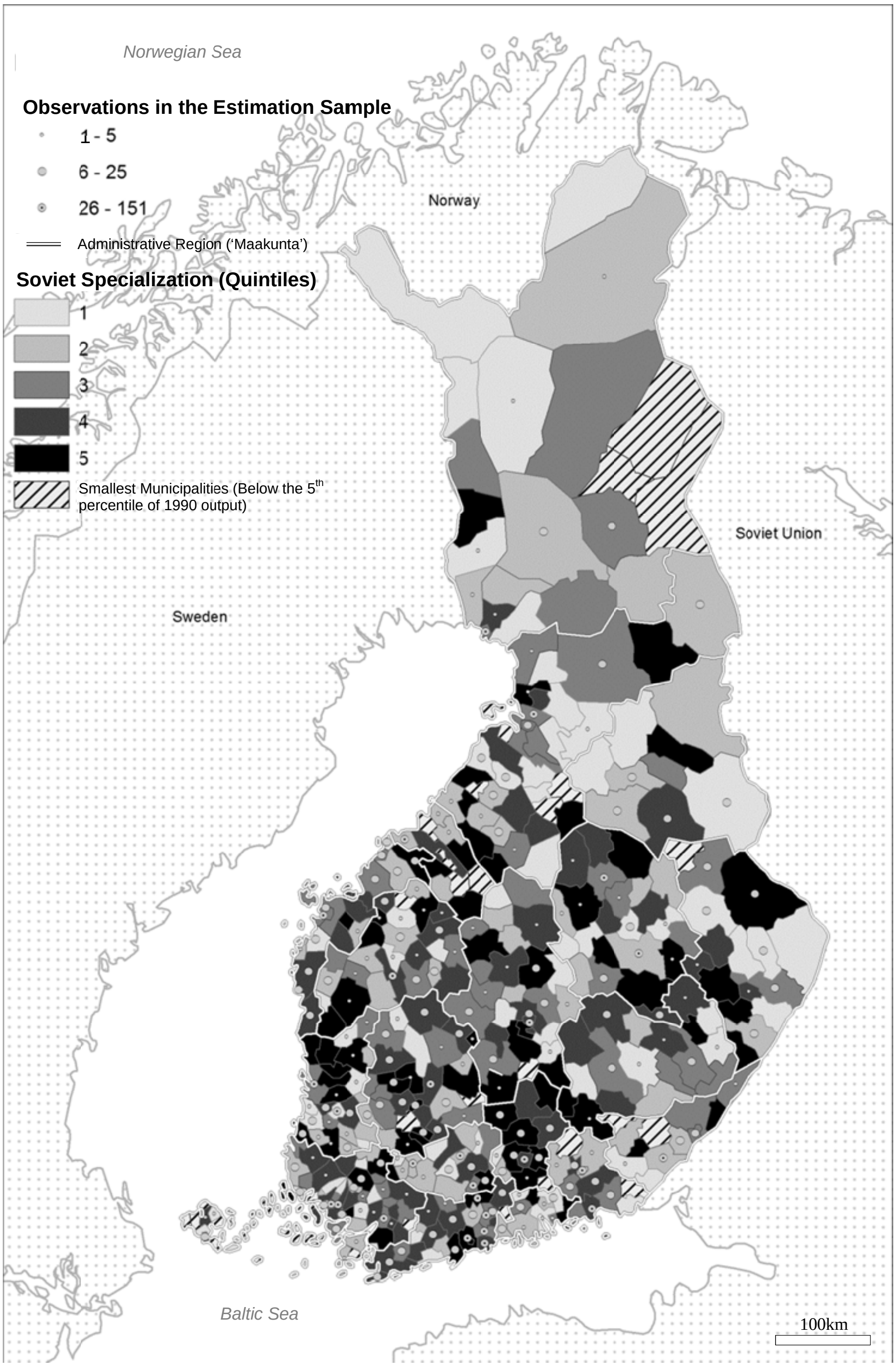

Figure 2: Soviet Specialization Quintiles by Municipality in Finland, 1990

Notes: Local Soviet specialization is the ratio of a municipality's predicted Soviet exports to the municipality's gross output (*LSS* in equation (4)).

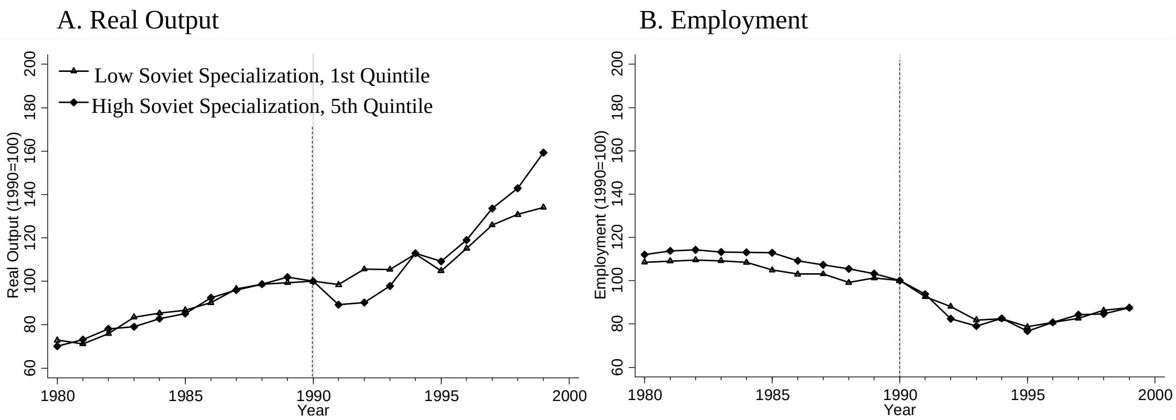

Figure 3: Output and Employment in Municipalities with Low and High Soviet Specialization

Notes: Real output and employment calculated from the Finnish annual manufacturing plant census data (for details of the data, see online appendix A). Local Soviet specialization 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. The 20^{th} and 80^{th} percentiles of it are 0.54% and 6.14%, respectively.

5.3 Local Soviet Trade Shocks

Figure 3 displays the development of manufacturing output (Panel A) and employment (Panel B) in the least (1^{st} *LSS* quintile) and most (5^{th} *LSS* quintile) exposed areas. Panel A shows highly similar output growth patterns in these two areas before the abolition of the trade agreement in December 1990. As Soviet trade collapses in 1991, the regional output patterns diverge dramatically, with an around 10% drop in the most exposed area and only a very small decline in the least exposed area. In the most exposed area, output stays at a low level until 1992 but grows considerably faster compared to the least exposed area in 1993 and 1994. The most exposed area catches up with the least exposed area by 1994. Notably, despite the large shock to output, local employment is very little affected (Panel B). This suggests that workers did not relocate from the areas that were hit hardest by the shock to the least affected areas. This indicates that the bulk of the labour market adjustments occurred locally.

This is supported by OLS and municipality fixed effects regressions of annual plant-level changes in employment on the plant-level measure of Soviet specialization in 1990 displayed in table 2. Both the OLS and FE estimates in columns 1 and 4 indicate significant re-allocation of employment towards less dependent plants in the period 1990-1991. Importantly, the FE estimates suggest considerable re-allocation *within* local labour markets.

Table 2: Plant-Level Soviet Specialization 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. 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 specialization (PSS_i in equation (5)) times 100. The specifications in columns 4-6 control for municipality fixed effects. Municipalities falling below the 5th percentile of 1990 output are excluded. Standard errors clustered by municipality are in parentheses. The number of observations is 3003, 2965, 2678, 2371, 2153, and 1845 for the 1989, 1990, 1991, 1992, 1993, and 1994 samples, respectively. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively.

To examine the local adjustment patterns by worker group, columns 2, 3, 5, and 6 display estimates separately for production and non-production workers. Looking at the FE specifications in columns 5 and 6, the estimates indicate significant reallocation towards less dependent plants for both labour categories in the period 1990-1991. A notable observation is that the initial change in the structure of employment at the margin of adjustment is around 0.079/(0.079+0.059) $\approx$ 0.572 in terms of production worker employment share, while the average production worker employment share among plants in western markets is around 0.782. This suggests that the instantaneous effect of the local Soviet trade shock was to disproportionately increase the available local supply of non-production labour, and as a result, increase the relative production labour unit cost.

5.4 IV Estimation

Motivated by these observations, I use local Soviet specialization in 1990 as the instrument for the relative production labour unit cost and estimate the model with a two-stage least squares (TSLS) procedure based on the following first-stage equation:

$$\Delta \ln\left(w_{Lijrt}/w_{Hijrt}\right) = f\left(LSS_{r,1990}\right) + \beta_{1K}\Delta \ln\left(k_{ijrt}/y_{ijrt}\right) + \tau_{1jt} + \Delta u_{ijrt}\,. \qquad (6)$$

I estimate the model over the period 1990-1994, covering the years of collapsing output in the high-exposure areas and subsequent recovery period observed in figure 3. $f\left(LSS_{r,1990}\right)$ is a function of the local Soviet specialization instrument. I use a second-order polynomial specification with year-specific coefficients to allow for non-linear, time-varying effects over the adjustment period.[15]

6 Results

This section presents the results for the plant-level labour demand model and the labour demand shifts implied by it. I start by presenting the results for the first-stage effects of historic Soviet specialization on the relative production labour unit cost. I then present the estimates of the parameters of the model recovered by the IV approach and address a number of potential robustness concerns. The third part of this section presents average plant-level changes in the relative demand for production labour by industry over the period 1980-2008 implied by the estimated model. The last part examines the extent to which ICT investment and offshoring explain the estimated industry-level labour demand shifts. Standard errors are corrected for clustering at the plant level in all plant-level estimations.[16]

6.1 First Stage

Figure 4 displays the predicted difference in the annual growth rate of the relative production labour unit cost between the 20th and 80th LSS percentile from the first-stage equation (6) using a sample of plants in western markets with predicted Soviet exports less than 0.1% of plant's total output in 1990 (i.e. $PSS_{i,1990} < 0.001$). The figure indicates that the collapse of Soviet trade induces substantial initial adjustment in the relative production labour unit cost, with an around 5 percentage point higher growth rate in high-exposure areas compared to low-exposure areas in the period 1990-1991.[17] With reference to the findings in section 5.3 that the initial local reallocation of em-

---

[15] Formally, $f\left(LSS_{r,1990}\right) = \sum_{s=1990}^{1994} I(year = s) \cdot \left(\zeta_{s1} \ln\left(LSS_{r,1990}\right) + \zeta_{s2} \ln\left(LSS_{r,1990}\right)^2\right)$, where $I(year = s)$ is an indicator function equal to one in year s and zero otherwise. Because the model is over-identified, I also estimate it with the LIML estimator, which has better asymptotic properties than the TSLS estimator in the case of many instruments (e.g. Angrist and Pischke, 2009).

[16] I also experimented with clustering standard errors by municipality and administrative region ("maakunta"), which gave very similar and in many cases slightly smaller standard errors than clustering by plant.

[17] The 20th and 80th percentiles of local Soviet specialization are 0.54% and 6.14%, respectively. The coefficients (standard errors) for the first-order term of the local Soviet specialization 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 instrument 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.

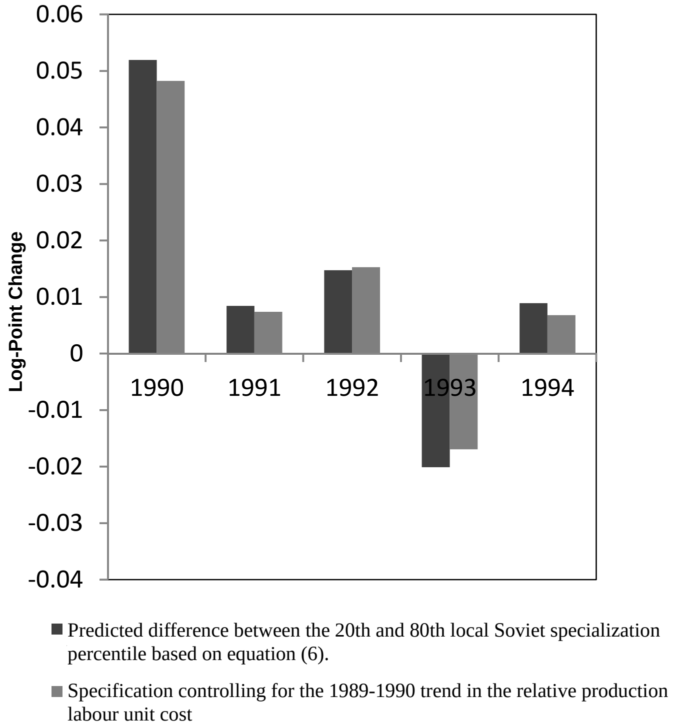

Figure 4: First-Stage Effects on Relative Production Labour Unit Cost Growth,
20th vs. 80th Soviet Specialization Percentile

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

ployment is disproportionately intensive in non-production labour, the divergence in the relative production labour unit cost is driven by a larger relative decline in the unit cost of non-production labour in high-exposure areas. After the instantaneous effect, the growth rate in the relative production labour unit cost continues to be slightly larger in high-exposure areas until 1993, when the growth differential becomes negative. This coincides with the output convergence observed in figure 3.

One may be concerned that auto-correlated local shocks to unit labour costs may have induced the sharp first-stage impacts in the period 1990-1991. To account for this, figure 4 also displays first-stage impacts for a specification including 1989-1990 trends in the relative unit labour cost interacted with year dummies as controls.[18] Controlling for pre-collapse trends has very little impact on the pattern of the effects, lending further credibility to the interpretation that the first-stage variation in the relative unit labour cost is induced by the sudden collapse of Soviet trade rather than by unobserved correlated local factors.

[18] In this specification, the coefficients (standard errors) for the first-order term of the local Soviet specialization 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 instrument 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.

6.2 Parameters of the Plant-Level Labour Demand Model

Table 3 presents parameter estimates for the cost share equation (3) based on the 1990-1994 sample of plants in western markets. The first column displays OLS coefficients, while the rest of the table displays IV and LIML estimates based on the local Soviet specialization instrument. The OLS coefficient on the relative unit labour cost is 0.088 and suggests an elasticity of substitution between production and professional labour of 0.598 at the sample mean of the production labour cost share of 0.676.

As discussed above, the OLS coefficient may be confounded by several potential sources of bias, including unobserved correlated technology shocks and measurement error in hourly wage data. To account for them, column 2 displays TSLS estimates with equation (6) as the first stage. The coefficient on the relative production labour unit cost is highly significant and almost twice as large as the corresponding OLS estimate. The direction of the bias is consistent with attenuation due to measurement error, although it is worth noting that a positive, but smaller, bias from a correlated technology shock reducing the relative demand for production labour cannot be ruled out.

The specification in column 2 treats capital intensity as exogenous. Although the capital stock is likely to adjust more slowly than the labour input, it may to some extent be jointly determined with the labour input mix. To break the potential link between the current production labour share and capital intensity, the specification in column 3 uses capital intensity in the year $t-2$ as an instrument for its concurrent change. This instrument is based on the assumption that current shocks to the labour input mix do not affect capital intensity two years earlier. Allowing for endogenous capital intensity has very little impact on the coefficient on the relative unit labour cost. The coefficient on capital intensity is -0.019 and suggests statistically significant complementarity between capital and professional labour. In this specification, the coefficient on the relative unit labour cost is 0.146 and implies a plant-level short-run elasticity of substitution between production and professional labour service of around 0.333.[19]

[19] As expected, this short-run plant-level elasticity estimate is smaller than typically found for more- and less-educated labour in aggregate-level studies. For example, Katz and Murphy (1992) who estimate a labour demand model using aggregate US data recover a substitution elasticity estimate of 1.41 between college and high school labour. They use substitution elasticities in the range of 0.5 to 4 for alternative demand shift scenarios. As discussed above, although the estimation framework of section 3 recovers an estimate for the short-run substitution elasticity, it controls for capital substitution and thus provides estimates of long-run demand shifts within plants (i.e. demand shift estimates accounting for adjustments in capital stock).

Table 3: Estimates for the Production Labor Cost Share Equation, Plants in Western Markets, 1990-1994

	OLS	IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				TSLS			
Δ log (Relative Production Labor Unit Cost)	0.088***	0.156**	0.146**	0.148**	0.144**	0.154**	0.162**
	(0.008)	(0.062)	(0.058)	(0.057)	(0.059)	(0.056)	(0.055)
Δ log (Capital Intensity)	-0.008***	-0.008***	-0.019**	-0.020*	-0.020*	-0.023*	-0.022*
	(0.002)	(0.002)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)
				LIML			
Δ log (Relative Production Labor Unit Cost)	0.088***	0.186**	0.166**	0.166**	0.160**	0.177**	0.187**
	(0.008)	(0.092)	(0.080)	(0.076)	(0.077)	(0.077)	(0.075)
Δ log (Capital Intensity)	-0.008***	-0.008***	-0.019*	-0.020*	-0.021*	-0.024*	-0.023*
	(0.002)	(0.002)	(0.010)	(0.012)	(0.012)	(0.014)	(0.014)
Instruments:							
Local Soviet Specialization in 1990		Yes	Yes	Yes	Yes	Yes	Yes
Capital Intensity in *t-2*			Yes	Yes	Yes	Yes	Yes
Angrist-Pischke TSLS 1st Stage F-Statistic for Endogenous Regressors:							
Δ log (Relative Production Labor Unit Cost)		2.705	2.530	2.852	2.587	2.528	2.552
Δ log (Capital Intensity)			6.283	4.363	4.413	4.387	4.254
Obs.	2881	2881	2813	2760	2760	2719	2694

Notes: Panel-robust standard errors are in parentheses. The sample excludes plants with plant-level Soviet specialization (*PSS* in equation (5)) more than 0.001. The outcome is the change in the production labour cost share. Local Soviet specialization is the ratio of a municipality's predicted Soviet exports to the municipality's gross output (*LSS* in equation (4)). All regressions include time×industry dummies (coefficients omitted). The specification in column 4 adds the log of energy-intensity (the cost of energy inputs divided by value added) in 1990 interacted with year dummies as control variables. The specifications in column 5 add administrative region (maakunta) dummies as control variables. The specification in column 6 adds logs of 1989 production and non-production worker wages as control variables, while the specification in column 7 corresponds to the specification in column 6 but excludes plants with predicted input supply to local Soviet industry more than 20% of output. Relative production labour unit cost is treated as endogenous in columns 2-7, while capital intensity is treated as endogenous in columns 3-7. The 90%, 95%, and 99% confidence levels are denoted by *, **, and ***, respectively.

6.3 Robustness Checks

The abolition of the trade agreement did not only affect Soviet demand for Finnish products, but it also resulted in a collapse in Finnish imports from the Soviet Union, the bulk of which were energy inputs.[20] Gorodnichenko, Mendoza, and Tesar (2012) have emphasised the adverse effects on the competitiveness of the Finnish economy of the collapse in Soviet trade because it inflated the energy prices faced by the Finnish manufacturing sector. Rising energy costs affected the competitiveness of energy-intensive plants the most. To examine the robustness of the results against potential labour demand responses to the rise in energy prices, I add a control for energy intensity in 1990 (i.e. the costs of energy inputs divided by value added) in column 4 of table 3. This has virtually no effect on the point estimates, suggesting that changes in energy prices are unlikely to confound the results.[21]

As discussed above, the estimations employ a sample of plants that were not directly exposed to Soviet import demand. A potential threat for identification, however, is that plants producing for the domestic market were exposed to differential local product demand shocks because of correlated local income effects of the Soviet import demand shock.[22] If such shocks were large enough, this may have resulted in endogenous technology adjustment as a response to them. I account for the potential income effects in local product markets by including dummies for administrative regions (*maakunta*), the boundaries of which are given in figure 2. I believe that this specification effectively controls for local product market effects because manufacturing product markets typically have an international or at least a national scope. Therefore, the product demand faced by plants operating in the same administrative region and industry is likely to be the same. Column 5 displays the results for a specification including the administrative region dummies. Reassuringly, this has negligible impacts on the coefficients, which suggests that local product market effects are unlikely to be a major source of bias.

To further investigate whether spatial selection by plant-level productivity may drive the results, column 6 adds controls for plant-level production and non-production la-

[20] 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).

[21] Finland also experienced a banking crisis in the early 1990s. Because capital flows were free within the country, it seems unlikely that plants operating in the same industry would have faced systematically different shocks to the supply of credit due to the crises. This would seem even more unlikely among plants in the same industry and within the same relatively small geographic region.

[22] See, e.g. Altonji and Card (1991) and Angrist (1995), who raise the concern about simultaneous income effects in the context of labour demand model estimation.

bour unit costs in 1989. These variables control for confounding variation from differences in plant-level production and non-production labour productivity. Adding these controls has little impact on the estimates, suggesting that biases arising from selection of plants by labour productivity into production localities with significant or little Soviet-dependent industry are unlikely to be a major concern. I also experimented with a specification adding plant-level changes in the relative production labour unit cost from 1989 to 1990 and the size of the neighboring industry in the same municipality as controls.[23] These specifications also gave very similar results, suggesting that autocorrelated trends in relative wages and selection by the size of the local industry are unlikely to drive the results.

The IV strategy is based on the assumption that the trade shock in the local Soviet-dependent industry was not correlated with technology shocks among local western producers. One may be concerned that the collapse in output in Soviet-dependent industry may have adversely affected plants producing inputs for it. Significant product demand shocks through input supply linkages may have induced endogenous technology adaption, which may bias the estimates. To examine whether such spreading of the shock drives the results, I use information on 1988 plant-level inputs by 6-digit HS commodity from the CSS to predict the plant-level output shares of inputs supplied to the local Soviet-dependent industry.[24] Column 7 displays results for a specification corresponding to column 6 but excluding plants with predicted input supply to the local Soviet-dependent industry larger than 20% of output. This restriction excludes only 25 observations, indicating that very few plants producing for western markets were extensive producers of 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.

Finally, the IV specifications in columns 3-7 are based on 11 excluded instruments. The relatively low first-stage F-statistics raise the concern that the asymptotic properties of the TSLS estimator may be poor due to weak instruments (e.g. Bound, Jaeger, and Baker, 1995; Stock, Wright, and Yogo, 2002). In order to examine the robustness of the results against the potential inconsistency that this may cause, I estimate the model with the LIML estimator, which has better asymptotic properties in such a setting (see

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

[24] To calculate this measure, I first approximate the amount of input m used in Soviet-dependent production in plant i by $\hat{x}^s_{im} = x_{im} PSS_i$, where x_{im} is the plant's usage of input m in 1988 and PSS_i is the 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 the plant's predicted output share of inputs supplied to local Soviet production is $PSIS_i = \left(\sum_m \theta_{im} \hat{X}^s_{rm}\right) / y_i$, where θ_{im} is the plant's local output share of commodity m.

Angrist and Pischke, 2009). The LIML estimates have slightly lower precision but are of a similar magnitude as the corresponding TSLS estimates. To further examine this issue, I estimated the model with the HFUL estimator of Hausman et al. (2012), which is a heteroskedasticity-robust version of the Fuller estimator. This also gave very similar estimates. Overall, these results suggest that weak instruments are unlikely to be a major source of bias.

6.4 Changes in the Relative Demand for Production Labour by Industry

This section presents changes in the relative demand for production labour implied by the estimated model. To derive a demand shift series, I recover τ_{jt} by taking the expectations of both sides of equation (3) conditional on industry and year, which yields

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

The index of the relative demand for production labour in year t relative to year 1980 is then $\hat{\mu}_{jt}^{1980} = \sum_{s=1980}^{t-1} \hat{\tau}_{js}$ for $t >$1980, where $\hat{\tau}_{js}$ are calculated from equation (7) by using estimates for β_L and β_K from table 3 and replacing the expectation terms with the corresponding means from the 1980-2008 LDPM sample. I use the TSLS estimates in column 3, where both coefficients have high precision. However, the results are robust in a wide range of IV estimates in table 3.

Figure 5 displays the indexes of the relative demand for production labour by 2-character NACE industry and an aggregate series constructed by averaging the industry series with annual industry labour cost as a weight. The aggregate series shows a 7.1 percentage point decline in the relative demand for production labour between 1980 and 2008. This corresponds to a relative decadal reduction of 2.5 percentage points of production labour input and explains around 42% of the overall decline in the production labour cost share, which was around 16.8 percentage points over the same period. Production labour demand fell in each decade of the observation period, although the pattern of the shift differs considerably across decades. In the 1980s, the decadal demand shift is around 2.8 percentage points. Although the trend continues to be negative between 1989 and 1999, the decadal pace of the shift decelerates to 1.2 percentage points in this period. A striking observation is that the demand shift accelerates sharply in the 2000s. Between 1999 and 2008, the pace of the shift corresponds to a decadal reduction of 2.9 percentage points.

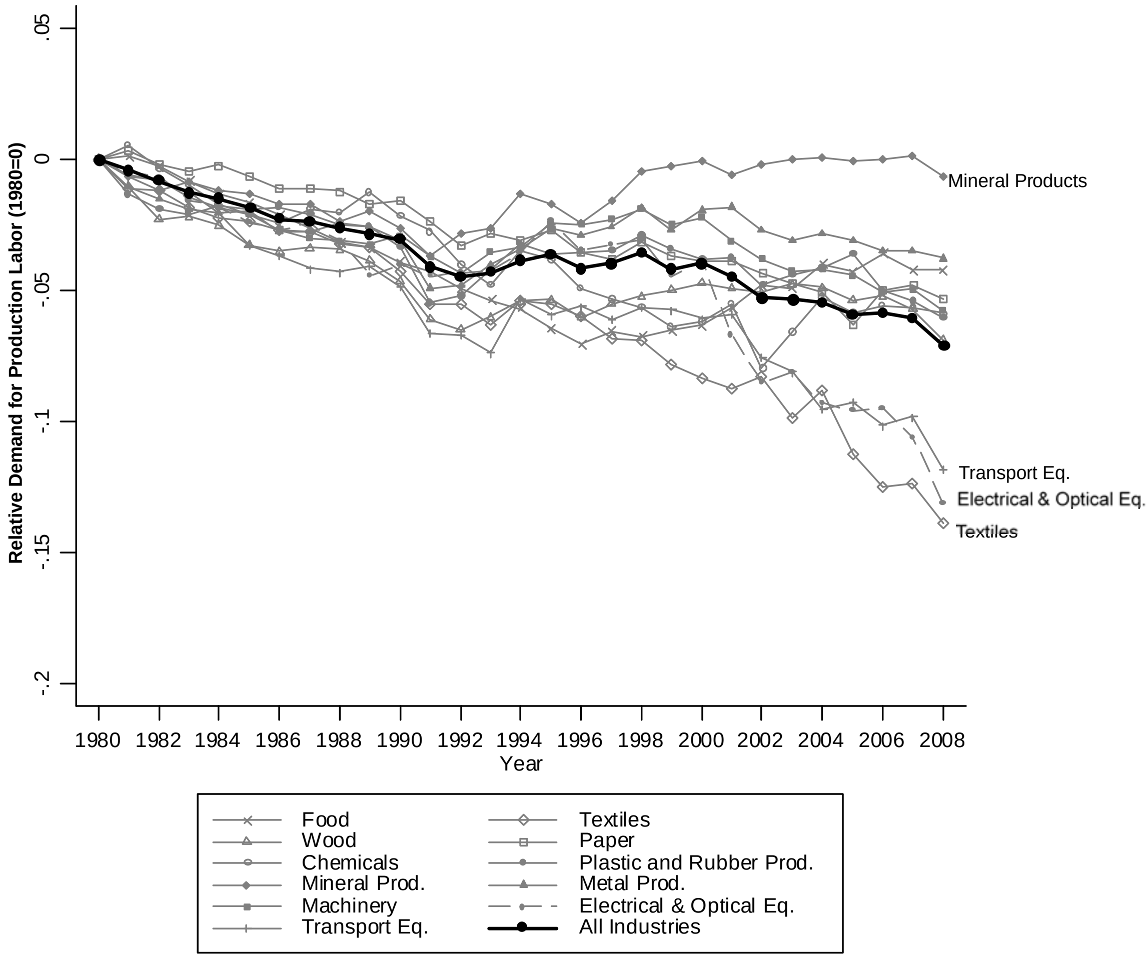

Figure 5: Changes in Relative Production Labour Demand by Industry

Notes: The series are based on relative production labour demand indices by 2-digit industry calculated from equation (7) for the 1980-2008 LDPM sample by imposing the TSLS estimates in column 3 of table 3. Industry indices are aggregated to 2-character NACE level with industry labour cost as a weight.

While the pace of the overall demand shift was fairly similar in the 1980s and 2000s, figure 5 reveals that the underlying industry patterns of the shift are very different in these periods. Table 4 demonstrates these differences. It shows the decadal reduction in the relative demand for production labour and the production labour cost share for each decade by industry. In the 1980s, the demand shift is fairly similar across industries, ranging between -1.2 and -4.4 percentage points. This is consistent with previous work, 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). However, the industry dispersion increases considerably over the observation period. The standard deviation of the decadal industry demand shift rises from 1.0 in 1980-1989 to 2.0 in 1989-1999, and reaches its peak of 3.0 in 1999-2008. In the latter period, the largest fall in the relative demand for production labour occurs in electrical and optical equipment (8.7 percentage points) and textiles (6.0 percentage points). Other industries experiencing significant shifts in the 2000s are transport equipment, machinery and

Table 4: Decadal Changes in Relative Production Labour Demand and Production Labour Cost Share (%)

	1980-2008		1980-1989		1989-1999		1999-2008	
	Demand	Cost Share	Demand	Cost Share	Demand	Cost Share	Demand	Cost Share
All Industries	-2.5	-6.0	-2.8	-6.1	-1.2	-4.3	-2.9	-6.0
Textiles	-4.9	-6.5	-3.4	-3.1	-4.1	-6.8	-6.0	-7.5
Electrical and Optical Equipment	-4.7	-13.3	-4.4	-13.6	0.0	-8.9	-8.7	-13.8
Transport Equipment	-4.2	-1.2	-4.1	-5.0	-1.5	5.3	-6.1	-4.1
Wood	-2.5	-2.9	-3.9	-5.7	-1.0	2.2	-1.9	-4.9
Rubber and Plastic Products	-2.2	-1.5	-2.6	-3.3	-0.8	2.0	-2.6	-3.1
Chemicals	-2.1	-3.9	-1.2	-4.7	-4.7	-2.7	0.5	-3.4
Machinery and Equipment	-2.1	-5.4	-3.2	-6.5	0.7	-4.6	-3.3	-3.7
Paper, Publishing, and Printing	-1.9	-3.3	-1.7	-5.1	-1.8	-0.6	-1.7	-3.6
Food, Beverages, and Tobacco	-1.5	-1.3	-3.4	-2.9	-2.9	-1.0	2.3	0.5
Metal Products	-1.3	-1.4	-2.6	-3.6	-0.1	0.4	-1.1	-0.6
Non-Metallic Mineral Products	-0.2	-1.2	-2.0	-0.7	1.6	-0.2	-0.4	-2.4

Notes: Changes in demand are based on the relative production labour demand index by 2-digit industry calculated from equation (7) for the 1980-2008 LDPM sample by imposing the TSLS estimates in column 3 of table 3. Industry indices are aggregated to 2-character NACE level with industry labour cost as a weight. Production labour cost shares are calculated from the 1980-2008 LDPM sample. All changes have been converted to decadal rates.

equipment, and rubber and plastic products, while the structure of labour demand tilts slightly towards production labour in food, beverages and tobacco products and chemicals in this period.

6.5 Labour Demand Shift for Alternative Industry Structures

The sharply rising dispersion across industries has an important implication for cross-country comparisons as it implies that countries with a differential industry structure would experience differential aggregate evolution of the structure of labour demand even if the industry-specific effects of technology and trade were equivalent across countries. To demonstrate this, table 5 displays changes in the measure of the relative production labour demand based on a similar weighting procedure as in table 4, but using 2-digit industry labour costs for different countries from the OECD STAN database as a weight in the aggregation. In this table, differences emerge only due to variation in industry structure across countries. All OECD countries for which sufficient data were available for the calculations are included. It is worth noting that the figures for Finland are slightly different than in table 4 for two reasons. First, the table excludes manufacturing n.e.c. (NACE 36) and recycling (NACE 37), for which data were una-

Table 5 : Decadal Changes in Relative Production Labour Demand Based on Alternative Industry Specialization (%)

	1980-2007	1980-1989	1989-1999	1999-2007
US	-2.9	-3.2	-2.0	-3.3
UK	-2.7	-3.0	-2.3	-2.4
Italy	-2.6	-3.0	-1.8	-2.8
Korea	-2.6	-3.1	-1.5	-3.0
Germany	-2.6	-3.1	-1.5	-3.0
France	-2.5	-3.0	-2.0	-2.4
Denmark	-2.5	-2.9	-1.9	-2.2
Netherlands	-2.4	-2.8	-2.1	-1.9
Finland	-2.3	-2.8	-1.4	-2.5
Greece	-2.3	-2.9	-2.5	-0.9
Austria	-2.3	-2.8	-1.3	-2.5
Spain	-2.2	-3.0	-1.8	-1.5

Notes: The table displays changes in the aggregate production labour demand index, which is calculated by aggregating 2-digit labour demand indices with industry labour costs for a country indicated by the row labels as a weight. All changes are converted to decadal rates. The industries used for calculation cover manufacturing 2-digit industries with the exception that manufacturing n.e.c. and recycling, for which data was unavailable for several countries, are excluded. For the same reason, the last year used for calculations is 2007. Industry labour cost data are drawn from the OECD STAN database.

vailable for several countries. Second, the table considers changes up to 2007 because data for 2008 were missing for several countries.

Although countries differ significantly in their industry specialization, the demand shifts across alternative industry specializations are very similar for the period 1980-1989, when industries experience similar relative labour demand shifts. The moderately rising dispersion induces some differentials between 1989 and 1999, when the demand shift is largest for Greece (-2.5 percentage points) and smallest for Austria (-1.3 percentage points). However, between 1999 and 2007, when the industry patterns diverge sharply, considerable differentials emerge between countries. The decline is largest for the US, which shows a decadal reduction of 3.3 percentage points. The demand shift is also rapid for Korea and Germany. On the other hand, the reduction is only 0.9 and 1.5 percentage points for Greece and Spain, respectively.

These large differences suggest that variation in industry specialization may have resulted in considerably differential evolution of the structure of labour demand across countries in recent years. It also raises the question of to what extent it is linked to increasing international trade. The trade-based explanation for the demand shift suggests that the demand for routine task-intensive production work has declined most in industries most susceptible to international outsourcing and offshoring (see Acemoglu and Autor, 2011; Blinder and Krueger, 2013). An alternative hypothesis outlines that the pace of skill- or task-biased technical change has diverged between industries. In the next section, I investigate the relative importance of these two factors in explaining the industry labour demand patterns.

6.6 The Role of Offshoring and ICT

To assess the role of ICT and offshoring I estimate the following industry regression:

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

Here, $\hat{\mu}_{j,t+s}$ is the estimate of relative production labour demand 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 relative production labour demand. To account for the potential time gap before the effects are fully realised, I also estimate the model for s =1,2. The model also includes controls for industry fixed effects and industry-specific trends to account for differences in permanent unobserved heterogeneity across industries and industry time trends. All the industry regressions are weighted by industry labour cost and the standard errors are clustered by industry.

I measure ICT by computer and programming expenses, which are available by 2-digit industry for the period 1995-2008 in the Industrial Statistics on Manufacturing maintained by Statistics Finland.[25] Following Feenstra and Hanson (1996) and many subsequent studies, I use industry imports of industrial intermediate inputs as a proxy for offshoring and international outsourcing. This variable is calculated from the 2-digit industry input-output tables maintained by Eurostat and available for the period 1995-2007.[26]

OLS estimates. The first column of table 6 presents OLS estimates of the coefficients of concurrent ICT and offshoring for a specification controlling for industry fixed effects and time trends, while the second and third columns present OLS estimates for similar specifications with *s* set equal to 1 and 2, respectively. The specifications in columns 1 and 2 do not detect any impacts of offshoring and ICT on relative production labour demand. However, in column 3, with a two-year gap between the regressors and the outcome, the coefficient on offshoring is negative and significant at the 5% risk level and the coefficient on ICT is negative and marginally significant. The results are very similar when year dummies are included (columns 4-6), although, when moving from

[25] 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.

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

Table 6: The Effect of Offshoring and ICT on Relative Production Labour Demand, OLS Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$\hat{\mu}_t$	$\hat{\mu}_{t+1}$	$\hat{\mu}_{t+2}$	$\hat{\mu}_t$	$\hat{\mu}_{t+1}$	$\hat{\mu}_{t+2}$
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: OLS estimates weighted by industry labour 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 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.

column 3 to column 6, the precision of the coefficient on ICT declines due to the decline in the degrees of freedom.

IV estimates. In order to reduce the potential biases arising from measurement error and to break any potential link between lagged ICT and offshoring and unobserved shocks to the structure of labour demand in Finnish industry, I use the US industry use of computer services and US imports of intermediate inputs from the same industry as instruments for Finnish industry ICT and offshoring.[27] The results are displayed in table 7. In panel A, treating offshoring as the endogenous regressor, the IV estimate for offshoring is insignificant across all specifications, although, for specifications based on the two-year gap between the regressors and the outcome (columns 3 and 6), the point estimates are similar compared to the corresponding OLS estimates. In panel B, treating ICT as the endogenous regressor, the coefficient on ICT in column 3 is negative, significant, and larger than the corresponding OLS estimate in table 6. The point estimate in column 6 is also larger than the corresponding OLS estimate, although the precision of the estimation is lower due to the reduced strength of the first stage. When moving from panel A to panel C, treating both ICT and offshoring as endogenous variables, the coefficient on offshoring in column 3 increases from -0.022 to -0.027 and is significant at the 5% risk level. The coefficient on ICT is also highly significant in column 3 of panel C. In the last three columns of panel C, the model including all fixed effects is more demanding due to lower degrees of freedom, as a result of which the precision of the estimation is considerably lower than in columns 1-3. It is worth not-

[27] 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 a sufficiently strong first stage.

Table 7: The Effect of Offshoring and ICT on Relative Production Labour Demand, IV Estimates.

	(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	0.009	-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 labour 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 B2. 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: 16.47 (columns 1-3) and 7.312 (columns 4-6). Panel B: 4.523 (columns 1-3) and 3.569 (columns 4-6). 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).

ing, however, that the point estimate for offshoring in column 6 is larger than any other corresponding coefficient in tables 6 and 7.

To put the size of these estimates into perspective, I calculated the predicted average effect of offshoring on the relative labour demand shift from the model using the two-year time gap. 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 labour cost as a weight times the coefficient on the relevant explanatory variable. With the smallest significant coefficient on offshoring of –0.018 in column 6 of panel B, changes in offshoring explain around one third of the overall decline in the predicted relative production labour demand between 2000 and 2008. The smallest significant coefficient on ICT of -0.009 in column 3 of panel A indicates an effect of the same magnitude.

Overall, these results indicate that offshoring has been a significant factor behind the declining relative demand for production labour in the 2000s. The results are somewhat weaker for ICT investment, but suggest that it has also had adverse effects on relative production labour demand in this period.

7 Summary and Conclusions

This paper developed a new approach for identifying plant-level labour demand functions and measuring within-plant shifts in the structure of labour demand. Identification was based on spatial variation in unit labour costs arising from asymmetric product market shocks caused by the collapse of Soviet-dependent industry in the early 1990s in Finland. By employing detailed product-level data on plants' inputs and outputs, I identified Finnish plants producing for western markets, for which product demand did not collapse as a result of the Soviet trade shock. Among these plants, the collapse of Soviet trade generated a situation where plants operating in the same western product market faced a differential unit labour cost shock because of the differential historic Soviet specialization of their neighbouring industry.

A novel feature of this empirical design is that it exploits local general equilibrium effects on the part of the economy that is not directly affected by the initial shock. In the context of labour demand function estimation, this alleviates concerns about biases induced by endogenous technology adjustment to sudden product market shocks.[28] The results indicate a significant demand-driven decline in the production worker labour share. Demand shifts away from workers in production occupations especially sharply during the 2000s. In this period, within-plant demand shifts induce around a 2.9 percentage point decadal decline in the production labour input share and account for around half of the overall decline in it. I also find that industry patterns in the structure of labour demand begin to diverge considerably since the mid-1990s. And that offshoring and ICT are significant factors driving these changes.

The study contributes both substantively and methodologically to the literature examining changes in the structure of labour demand. It provides model-based quasi-

[28] While the Soviet-dependent industry was hit by a large product demand shock, the plants producing for western markets faced steady product demand.

experimental estimates of within-plant changes in the structure of labour demand which are consistent with the view that recent employment polarization has been driven by the loss of demand for middle-skilled occupations in routine task-intensive jobs (see Acemoglu and Autor, 2011). Moreover, the finding that the industry patterns of the labour demand shift have diverged recently implies that countries with different industry structure have likely experienced differential changes in the structure of labour demand. The empirical approach developed in this paper can be employed in future studies to identify labour demand models at the level of a plant or detailed industry when asymmetric product demand shocks affecting only a subset of producers are available.

References

Acemoglu, Daron, and David Autor. 2011. Skills, tasks and technologies: implications for employment and earnings. In *Handbook of Labour Economics. Vol. 4,* ed. Ashenfelter, Orley, and David Card. Amsterdam: Elsevier.

Altonji, Joseph G., and David Card. 1991. The effects of immigration on the labour market outcomes of less-skilled natives. In *Immigration, Trade, and the Labour Market*, ed. Abowd, John, and Richard Freeman. Chicago: University of Chicago Press.

Angrist, Joshua D. 1995. The economic returns to schooling in the West Bank and Gaza strip. *American Economic Review* 85, no. 5:1065-87.

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics: an empiricist's companion.* Princeton: Princeton University Press.

Hummels, David, Rasmus Jørgensen, Jakob R. Munch, and Chong Xiang. 2014. The wage effects of offshoring: evidence from Danish matched worker-firm data, *American Economic Review* 104, no. 6:1597-629.

Autor, David H., and David Dorn. 2013. The growth of low skill service jobs and the polarization of the U.S. labour market. *American Economic Review* 103, no. 5:1553-97

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. The China syndrome: local labour market effects of import competition in the United States. *American Economic Review* 103, no. 6:2121–68.

Autor, David H., David Dorn, and Gordon H. Hanson. 2015. Untangling trade and technology: evidence from local labour markets. *Economic Journal* 125:621-46.

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song. 2014. Trade adjustment: worker-level evidence. *Quarterly Journal of Economics* 129, no. 4:1799-860.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. Trends in US wage inequality: revising the revisionists. *Review of Economics and Statistics* 90, no. 2:300-23.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. The skill content of recent technological change: an empirical exploration. *Quarterly Journal of Economics* 118, no. 4:1279-333.

Baltagi, Badi H., and Daniel P. Rich. 2005. Skill-biased technical change in US manufacturing: a general index approach. *Journal of Econometrics* 126:549-70.

Berman, Eli, John Bound, and Zvi Griliches. 1994. Changes in the demand for skilled labour within U.S. manufacturing: evidence from the Annual Survey of Manufacturers. *Quarterly Journal of Economics* 109, no. 2:367-97.

Berman, Eli, John Bound, and Stephen Machin. 1998. Implications of skill-biased technical change: international evidence. *Quarterly Journal of Economics* 113, no. 4:1245-79.

Blinder, Alan S., and Alan B. Krueger. 2013. Alternative measures of offshorability: a survey approach. *Journal of Labour Economics* 31, no. 2:S97-S128.

Borjas, George J. 2003. The labour demand curve is downward sloping: reexamining the impact of immigration on the labour market. *Quarterly Journal of Economics* 118, no 4:1335-74.

Borjas, George J., and Kirk B. Doran. 2012. The collapse of the Soviet Union and the productivity of American mathematicians. *Quarterly Journal of Economics* 127, no. 3:1143-203.

Bound, John, David A. Jaeger, and Regina M. Baker. 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American Statistical Association* 90:443-50.

Bustos, Paula. 2011. Trade liberalization, exports, and technology upgrading: evidence on the impact of MERCOSUR on Argentinian firms. *American Economic Review* 101, no. 1:304-40.

Ciccone, Antonio, and Giovanni Peri. 2005. Long-run substitutability between more and less educated workers: evidence from US states, 1950–1990. *Review of Economics and Statistics* 87, no. 4:652-63.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg. 2009. Revisiting the German wage structure. *Quarterly Journal of Economics* 124, no. 2:843-81.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler. 2015. Labour supply shocks and the dynamics of local wages and employment. Unpublished manuscript, University College London, London.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips. 2014. Estimating the impact of trade and offshoring on American workers using the Current Population Surveys. *Review of Economics and Statistics* 96, no. 4:581–95.

Falck, Oliver, Christina Guenther, Stephan Heblich, and William R. Kerr. 2013. From Russia with love: the impact of relocated firms on incumbent survival. *Journal of Economic Geography* 13, 3:419-49.

Feenstra, Robert C., and Gordon H. Hanson. 1996. Globalization, outsourcing, and wage inequality. *American Economic Review* 86, no. 2:240-45.

Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2011. Occupational tasks and changes in the wage structure. IZA Discussion Papers 5542.

Friedberg, Rachel M. 2001. The impact of mass migration on the Israeli labour market. *Quarterly Journal of Economics* 116, no. 4:1373-408.

Frisch, Ragnar 1933. *Pitfalls in the Statistical Construction of Demand and Supply Curves*. Leipzig: Hans Buske, Verlag.

Glitz, Albrecht. 2012. The labour market impact of immigration: a quasi-experiment exploiting immigrant location rules in Germany. *Journal of Labour Economics* 30, no. 1:175-213.

Goos, Maarten, and Alan Manning. 2007. Lousy and lovely jobs: the rising polarization of work in Britain. *Review of Economics and Statistics* 89, no. 1:118-33.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. Job polarization in Europe. *American Economic Review* 99, no. 2:58-63.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: routine-biased technological change and offshoring. *American Economic Review* 104, no. 8:2509-26.

Gorodnichenko, Yuriy, Enrique G. Mendoza, and Linda L. Tesar. 2012. The Finnish Great Depression: from Russia with love. *American Economic Review* 102, no. 4:1619-43.

Haskel, Jonathan E., and Matthew J. Slaughter. 2002. Does the sector bias of skill-biased technical change explain changing skill premia? *European Economic Review* 46:1757-83.

Hausman, Jerry A., Whitney K. Newey, Tiemen Woutersen, John C. Chao, and Norman R. Swanson. 2012. Instrumental variable estimation with heteroskedasticity and many instruments. *Quantitative Economics* 3, no. 2:211-55.

Machin, Stephen, and John Van Reenen. 1998. Technology and changes in the skill structure: evidence from seven OECD countries. *Quarterly Journal of Economics* 113, no. 4:1215-44.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. Has ICT polarized skill demand? evidence from eleven countries over twenty-five years. *Review of Economics and Statistics* 96, no. 1:60-77.

Stock, James H., Jonathan H. Wright, and Motohiro Yogo. 2002. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics* 20, no. 4:518-29.

Timmer, Marcel, Ton van Moergastel, Edwin Stuivenwold, Gerard Ypma, Mary O'Mahony , and Mari Kangasniemi. 2007. EU KLEMS growth and productivity accounts version 1.0. EU KLEMS Consortium, University of Groningen, Groningen.

Topalova, Petia. 2010. Factor immobility and regional impacts of trade liberalization: evidence on poverty from India. *American Economic Journal: Applied Economics* 2, no. 4:1-41.

Wright, Philip G. 1928: *The Tariff on Animal and Vegetable Oils.* New York: MacMillan.

[For Online Publication Unless Otherwise Requested]

Appendix A. Data and Summary Statistics

A.1 Finnish Linked Employer-Employee and Job Task Index Data

I use information on annual earnings and occupation from the research-use sample of the Finnish Linked Employer-Employee Data (FLEED) to obtain wage bill shares by 2-digit occupation. The FLEED sample includes individuals aged 15-64 and contains information on annual earnings and occupation at the 2-digit level of the ISCO-88 classification. I use data from Acemoglu and Autor (2011) to obtain job task indices. The Acemoglu-Autor data are based on the 4-digit SOC-2000 classification. I use the 4-digit correspondence table from the US National Crosswalk Service Center to obtain indices for the 4-digit ISCO-88 classification.[29] After this, average task measures by 2-digit ISCO-88 occupations were calculated with occupation-specific US employment from the Acemoglu-Autor data as weights. These task measures and corresponding FLEED income shares sorted by the routine manual task intensity are displayed in table A1.

A.2 Longitudinal Database of Plants in Finnish Manufacturing

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 (AISS). For the years 1980-1994, the AISS covers all plants with at least 5 employees, and for the years 1995-2008 it covers plants whose parent company had at least 20 employees. Therefore, all plants with at least 20 employees are covered over the whole observation period of 1980-2008. I restrict the analysis sample to these plants to maintain consistency over time. These plants cover around 82% of national manufacturing output in the observation period.

[29] webdata.xwalkcenter.org/ftp/DOWNLOAD/xwalks/SOC2000xISCO88.zip

Table A1: Manufacturing Occupations and Tasks

Occupation	Taxable Wage Income Share 1995 (%)	Job Task Indices: Routine: Manual	Routine: Cognitive	Non-Routine: Cognitive Analytic	Non-Routine: Cognitive Interpersonal	Non-Routine: Manual Physical	Non-Routine: Manual Interpersonal
A. Broad Occupations							
Production Workers	56.5	1.27	0.20	-0.28	-0.55	1.13	-1.09
Professionals and Managers	36.6	-0.35	0.07	0.91	0.34	-0.40	-0.04
Clerical and Service Workers	7.1	-0.18	0.34	-0.54	-0.52	-0.34	-0.23
B. Production Occupations							
Machine operators and assemblers	12.9	1.96	0.56	-0.44	-0.59	0.92	-1.28
Stationary plant and related operators	8.6	1.68	0.33	-0.07	-0.42	0.94	-1.13
Precision and related trades workers	2.5	1.32	0.65	-0.24	-0.95	0.43	-1.05
Skilled agricultural and fishery workers	0.5	1.30	-1.31	-0.84	-0.65	1.17	-1.29
Drivers and related water traffic operators	2.3	1.22	0.35	-0.70	-0.91	2.17	-0.46
Other craft and related trades workers	3.7	1.03	0.15	-0.54	-0.56	0.35	-1.10
Labourers in manufacturing and construction	3.8	0.89	0.16	-0.73	-0.45	1.00	-1.15
Metal, machinery and related trades workers	19.8	0.82	-0.03	-0.08	-0.53	1.46	-1.04
Extraction and building trades workers	2.4	0.74	-0.49	-0.18	-0.33	1.38	-0.89
C. Non-production Occupations							
Physical and engineering science assoc. prof.	10.4	0.46	0.41	0.58	-0.26	0.17	-0.57
Customer services clerks	0.3	0.34	1.35	-0.77	-0.34	-0.35	0.24
Sales and services elementary occupations	1.3	0.20	-0.77	-1.49	-1.12	0.10	-0.86
Personal and protective services workers	0.8	0.11	-0.42	-0.74	-0.23	0.18	0.21
Life science and health associate professionals	1.4	-0.03	0.57	0.92	1.07	-0.01	1.17
Life science and health professionals	0.3	-0.09	0.53	1.23	1.30	-0.01	1.32
Office clerks	3.9	-0.28	0.90	-0.32	-0.54	-0.57	-0.25
Corporate managers	6.3	-0.62	-0.66	0.90	1.57	-0.56	0.57
Physical and engineering science professionals	8.5	-0.63	0.26	1.56	0.08	-0.71	-0.69
Salespersons and demonstrators	0.8	-0.69	-0.18	0.19	0.13	-0.44	0.27
Managers of small enterprises	0.4	-0.73	-1.30	0.87	1.29	-0.25	0.61
Other associate professionals	5.9	-0.76	0.17	0.43	0.03	-0.65	0.34
Other professionals	3.2	-1.03	-0.36	1.16	0.51	-0.88	0.69
Teaching professionals	0.2	-1.05	-1.01	1.15	1.36	-1.05	1.57

Notes: Data from the FLEED and Acemoglu and Autor (2011).

The LDPM provides information on value added, capital stock, and labour costs and work hours for production and non-production workers. The labour costs include wage bill and employer contributions such as compulsory insurance payments. The category “production worker” includes all persons directly engaged in production or the related activities of the establishment. These include packers, service staff, maintenance staff, construction staff, machinists and stokers, for example. Low-level supervisors involved in actual production are included in this category. The category “non-production worker” refers to all other employees not directly engaged in production. These are typically employees engaged in supervision, sales, technical services and administration. The LDPM also provides information on the location of a plant at the level of a municipality.

A.3 Commodity Statistics Survey and OECD ITCS Data

I use the Commodity Statistics Survey (CSS) to obtain plant-level output shares by commodity. I use the 1988 file, which provides information on outputs and inputs used by plants by 6-digit commodity in the 1988 Harmonized System (HS) classification. The CSS sampling frame corresponds closely to the LDPM sampling frame and the data cover around 91% of aggregate LDPM output in 1988. The data are linked to LDPM with unique plant codes.[30]

Data on Finland's exports to the former Soviet Union area are drawn from the OECD ITCS database using the 6-digit HS commodity classification. The data used for calculating measures of Soviet-import dependence are for the year 1990 and cover exports from Finland to the former Soviet Union. Soviet exports are linked to plant-level commodity output shares by 6-digit HS codes (the CSS and ITCS are both based on the same 1988 HS commodity classification).

A.4 Summary Statistics for Relevant Samples

Appendix table A2 presents summary statistics for the relevant samples drawn from the LDPM. The first column gives the sample means and standard deviations for the 1990-1994 baseline sample. The sample is constructed by excluding plant-year observations falling into the first or last year of a plant's existence in the LDPM panel to avoid observations for 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 specialization measure, the sample excludes the smallest municipalities falling below the 5^{th} output percentile.[31]

The second column displays statistics for plants in western markets, which are identified by restricting plant-level predicted 1990 Soviet exports to 0.1% of 1990 output (i.e. *PSS* in equation (5) less than 0.001). This sample is used to estimate equation (3) and it covers around 28% of plants in the 1990-1994 baseline sample.

[30] The data are based on an annual survey targeting all manufacturing plants with a parent company with 10 or more employees.

[31] This drops out the 19 smallest municipalities, accounting for around 0.1% of aggregate LDPM output in 1990.

Table A2: Summary Statistics

	1990-1994 Baseline Sample				1980-2008 Sample	
	All		Plants in Western Markets		All	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Labour Cost, Total	3,247	6,244	3,103	6,177	3,221	7,880
Labour Cost, Non-production labour	1,204	2,843	1,140	2,940	1,205	4,740
Labour Cost, Production labour	2,042	3,811	1,963	3,595	2,016	4,227
Employment, Total	128	220	122	228	127	235
Employment, Non-production labour	38	84	35	85	36	102
Employment, Production labour	91	149	87	152	91	155
Hours, Total	205	344	193	342	210	387
Hours, Non-production labour	63	141	58	143	61	175
Hours, Production labour	142	224	135	216	148	249
Production Labour Cost Share	0.676	0.161	0.701	0.171	0.691	0.168
Production Labour Employment Share	0.746	0.145	0.762	0.153	0.757	0.153
Production Labour 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	58.64	2.062	8.172	2.429	170.5
Nominal Production Labour Unit Cost	13.1	3.21	13.41	3.31	12.79	6.680
Nominal Non-Production Labour Unit Cost	18.4	4.8	18.53	5.3	17.92	9.110
Nominal Prod. Labour Unit Cost, 1989	10.63	2.560	10.78	2.640	10.65	2.592
Nominal Non-Prod. Labour Unit Cost,	15.60	4.214	15.44	4.508	15.57	4.184
Relative Production Labour 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 Specialization 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. The number of observations for 1989 production labour unit cost, 1989 non-production labour unit cost, 1990 energy intensity, log of energy intensity, and plant-level Soviet specialization are, respectively: a – 7453, 7434, 7362, 7407, and 7479; b – 2851, 2838, 2808, 2852, and 2881; c –57543, 57210, 56209, 69471, and 52857.

The second block of statistics contains summary statistics for the 1980-2008 sample, covering the full LDPM observation window. This sample is used to calculate the measures of relative production labour demand shift (equation (7)).

Appendix table A3 tabulates 1989 sample means for plants producing for non-Soviet markets located in municipalities with local Soviet specialization below and above the median of 0.030.

Table A3: Summary Statistics by Local Soviet Specialization, Plants in Western Markets, 1989

	Plants in Municipalities Below Median Local Soviet Specialization		Plants in Municipalities Above Median Local Soviet Specialization	
	Mean	Std. Dev.	Mean	Std. Dev.
Labour Cost, Total	2,571	5,492	2,432	4,591
Labour Cost, Non-production labour	877	2,283	881	2,314
Labour Cost, Production labour	1,694	3,446	1,551	2,544
Employment, Total	118	216	114	205
Employment, Non-production labour	31	77	31	74
Employment, Production labour	87	146	83	143
Hours, Total	199	369	184	288
Hours, Non-production labour	54	141	52	124
Hours, Production labour	144	240	132	185
Production Labour Cost Share	0.725	0.156	0.709	0.176
Production Labour Employment Share	0.788	0.136	0.774	0.155
Production Labour 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 Labour Unit Cost	10.51	2.72	10.84	2.73
Nominal Non-Production Labour Unit Cost	15.03	4.40	15.60	4.71
Relative Production Labour 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 specialization 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: Plants with plant-level Soviet specialization (PSS_i in equation (5)) less than or equal to 0.001. 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.

Appendix B. Additional Tables and Figures

Table B1: 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 B2: The Effect of Offshoring and ICT on Relative Production Labour 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 labour 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 first-stage F-statistics: Panel A: 14.37 (columns 1-3) and 6.775 (columns 4-6). Panel B: 3.251 (columns 1-3) and 3.947 (columns 4-6). Panel C: 16.158 for offshoring and 5.992 for ICT (columns 1-3) and 5.195 for offshoring and 3.362 for ICT (columns 4-6).

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1450	Marcus Biermann	Trade and the Size Distribution of Firms: Evidence from the German Empire
1449	Alessandro Gavazza Simon Mongey Giovanni L. Violante	Aggregate Recruiting Intensity
1448	Emmanuel Amissah Spiros Bougheas Fabrice Defever Rod Falvey	Financial System Architecture and the Patterns of International Trade
1447	Christian Fons-Rosen Vincenzo Scrutinio Katalin Szemeredi	Colocation and Knowledge Diffusion: Evidence from Million Dollar Plants
1446	Grace Lordan Jörn-Steffen Pischke	Does Rosie Like Riveting? Male and Female Occupational Choices
1445	Stephen J. Redding David E. Weinstein	A Unified Approach to Estimating Demand and Welfare
1444	Anna Valero John Van Reenen	The Economic Impact of Universities: Evidence from Across the Globe
1443	Marta De Philippis	STEM Graduates and Secondary School Curriculum: Does Early Exposure to Science Matter?
1442	Thierry Mayer Marc J. Melitz Gianmarco I.P. Ottaviano	Product Mix and Firm Productivity Responses to Trade Competition
1441	Paul Dolan Georgios Kavetsos Christian Krekel Dimitris Mavridis Robert Metcalfe Claudia Senik Stefan Szymanski Nicolas R. Ziebarth	The Host with the Most? The Effects of the Olympic Games on Happiness

1440	Jörn-Steffen Pischke	Wage Flexibility and Employment Fluctuations: Evidence from the Housing Sector
1439	Brian Bell John Van Reenen	CEO Pay and the Rise of Relative Performance Contracts: A Question of Governance
1438	Fadi Hassan Paolo Lucchino	Powering Education
1437	Evangelia Leda Pateli	Local and Sectoral Import Spillovers in Sweden
1436	Laura Kudrna Georgios Kavetsos Chloe Foy Paul Dolan	Without My Medal on My Mind: Counterfactual Thinking and Other Determinants of Athlete Emotions
1435	Andrew B. Bernard Andreas Moxnes Yukiko U. Saito	Production Networks, Geography and Firm Performance
1434	Zack Cooper Stephen Gibbons Matthew Skellern	Does Competition from Private Surgical Centres Improve Public Hospitals' Performance? Evidence from the English National Health Service
1433	Nicholas Bloom Raffaella Sadun John Van Reenen	Management as a Technology?
1432	Andrew B. Bernard Toshihiro Okubo	Product Switching and the Business Cycle
1431	Fabrice Defever Alejandro Riaño	Protectionism through Exporting: Subsidies with Export Share Requirements in China

The Centre for Economic Performance Publications Unit
Tel 020 7955 7673 Fax 020 7404 0612
Email info@cep.lse.ac.uk Web site http://cep.lse.ac.uk