Exposure(s) to Trade and Earnings Dynamics*

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Abstract

How do local labor markets shape the response to trade shocks? Do workers whose employers' are more exposed to negative trade shocks fair equally poorly across markets or is there something distinct about the experience of workers in more affected markets? To make progress on these questions, we study the impact of a massive trade shock—the collapse of the Finnish-Soviet bilateral trade agreement on December 6th, 1990—on the earnings trajectories of Finnish workers. Combining newly digitized data on Finnish firms' licensed exports to the USSR in 1989 with matched employer-employee data from that same year, we construct two distinct measures of trade exposure: (i) a worker-level measure of trade exposure, equal to the share of USSR exports in the sales of that worker's employer; and (ii) a market-level measure of trade exposure, equal to the average exposure in a market. We find that more exposed workers within a labor market systematically experience lower earnings after the shock and that the negative effect of worker-level exposure is larger in more exposed markets, consistent with the predictions of a model of earnings dynamics with significant downward wage rigidity. Whereas the direct effect of worker-level exposure dissipates in the medium run, the negative interaction effect between worker- and market-level exposures does not, a form of local scarring.

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1 Introduction

A national labor market there is not. When imports surge in some sectors, either because of domestic tariff cuts or foreign productivity gains, regions with employment concentrated in those sectors systematically experience worse labor-market outcomes (e.g. Topalova, 2010, Autor et al., 2013, and Kovak, 2013). But how do local labor markets actually shape the response to trade shocks? Are workers exposed to negative trade shocks fairing equally poorly across regions or is there something systematically different about the experience of those workers in the most negatively affected markets?

The answers to the previous questions have obvious policy implications. If empirical findings from so-called “shift-share” designs are merely about a greater number of workers being negatively exposed in the most affected regions, then national trade assistance programs designed to compensate all workers whose jobs have been lost to trade, such as those currently in place in the US, may be well suited. If instead, such empirical findings partly reflect the fact that similar workers experience larger earnings losses in these regions, then there is scope for trade assistance programs to inherit characteristics of place-based policies, with assistance to displaced workers conditioning on local labor-market conditions.

To make progress on these questions, we focus on a massive trade shock---the collapse of the Finnish-Soviet bilateral trade agreement towards the end of 1990---for which we are not only able to measure the exposure of local labor markets---by measuring USSR exports from Finnish plants located in this market in 1989---but also the exposure of individual workers within each of those markets---by matching individual workers to plants in 1989. This allows us to study how the earnings trajectories of Finnish workers vary with their own exposure to the USSR shock as well as the exposure of the local labor market to which they belong.[1]

Our main empirical conclusions are as follows. First, more exposed workers, i.e. those employed by plants with higher fractions of their sales to the USSR in 1989, experience slower earnings growth from 1990 to 2000. Second, the negative effect of worker-level exposure is substantially and significantly larger in more exposed labor markets, i.e. those in which average exposure to the USSR is higher in 1989. Third, while the direct effect of worker-level exposure dissipates in the medium run, the differential impact of worker-level exposure in more relative to less exposed labor markets persists throughout the sample period, a form of local scarring.

[1] Gorodnichenko et al. (2012) argue that the collapse of Finnish Soviet trade in the presence of wage rigidities played a central role in the Finnish Great Depression in 1991-1993.

Section 2 presents the historical background of the Finnish-USSR trade relationship and its termination, documents differences in exposure to the USSR shock across Finnish local labor markets, and describes their incidence through a standard difference-in-difference strategy. On December 6th, 1990, the Soviet Union unilaterally canceled the five-year trade agreement that had been signed in the previous year. This cancelation and the severity and duration of the resulting trade collapse took Finland by surprise. To measure the exposure of Finnish local labor markets, we have digitized firm-level reports of transactions with the Soviet Union for the year 1989 from the Office of Licenses (Lisenssivirasto) and linked these to the Longitudinal Data on Plants in Finnish Manufacturing (LDPM). This allows us to measure the share of USSR exports in the sales of plants located in any Finnish municipality and, in turn, to define market-level exposure to the USSR shock as the weighted average of USSR export shares across plants in a municipality, with weights equal to the plants' employment share. We show that local labor markets that were more exposed to the USSR shock experienced lower average earnings in the post-shock years—consistent with previous empirical work—and higher unemployment rates—in contrast to traditional trade theory in which labor-market adjustment results in full employment.

Motivated by the previous findings, as well as the institutional features of the Finnish labor market, Section 3 develops a simple model of worker-level earnings dynamics in the presence of wage rigidity. In a labor market, the total number of workers is fixed and plants vary in terms of the fraction of sales that they export.[2] In this environment, we provide an analytic characterization of the expected dynamic path of earnings for each worker in response to a one-time negative export shock as a function of her own exposure, defined as the share of USSR exports in the sales of the plant employing her at the time of the shock, and the exposure of her market, defined as in Section 2 as the weighted average of plants' USSR export shares.

On impact, exposed plants reduce their labor demand by an amount proportional to their export shares before the shock, whereas wages do not adjust. As a result, more exposed workers immediately experience higher unemployment probabilities and lower expected earnings, independent of the exposure of their local labor markets. Over time, though, a larger pool of unemployed lowers job-finding rates and wages in more exposed markets. The job-finding-rate effect magnifies the decreases in earnings experienced by workers with greater exposure, since displaced workers face a lower probability of transitioning back to employment in more exposed markets. The wage effect works in the

[2]Empirically, we find little migration responses to local-labor market exposure, consistent with previous empirical work.

opposite direction. For workers with greater exposure, who are more likely to be unemployed at all dates, the earnings losses in terms of foregone wages are lower in more exposed markets. As a result, the negative effect of worker-level exposure is larger in more exposed markets if the job-finding-rate effect dominates the wage effect, which occurs when downward wage rigidities are substantial.

Section 4 describes our main empirical findings. Guided by the previous theoretical results, we explore the relationship between earnings, at the worker-level, and our two measures of trade exposure, at the worker- and market-level. Our first set of results replicates the same difference-in-difference strategy as in Section 2, but with both earnings and exposure now defined at the worker- rather than market-level. The idea is to compare the earnings trajectories, both before and after the USSR shock, of workers with similar observable characteristics—including the market in which they are initially employed at the time of the shock—but different exposure to this shock due to differences in the USSR exports of their employer. We find that more exposed workers experience large declines in earnings, with their earnings bottoming out around the same time that trade with the USSR does. In 1992, a worker at the 90th percentile of exposure (conditional on positive exposure) experiences an average decline in earnings of 732 euros (denominated in 2010 euros) compared to a worker at 10th percentile; this decline represents about 3% of average annual income in 1992.

Our second, and most novel set of results use a triple-difference that compares how the previous double-difference—in the changes in earnings between more and less exposed workers within a local labor market—varies with the exposure of the market in which workers are located. We find that the decline in earnings experienced by more exposed workers are greater, as well as more persistent, in more exposed markets. Going back to the comparison of workers at the 90th and 10th percentile (of worker-level exposure) in 1992, our results imply an earnings gap of 658 euros in the municipality at the 10th percentile (of market-level exposure), but a gap of about 790 euros in the municipality at the 90th percentile, a 20% increase. The previous results are robust to a variety of controls and alternative specifications.

Our empirical analysis is related to a large shift-share literature using differences in market exposure (the share) to analyze the impact of trade and other negative labor demand shocks (the shift) on market-level outcomes. Well-known examples include Blanchard and Katz (1992), Topalova (2010), Autor et al. (2013), Kovak (2013) and Kovak and Dix-Carneiro (2017). Our work differs both because we directly observe the market level shock, rather than construct it using regional shares and national shocks, and because we focus on worker-level outcomes, as in Autor et al. (2014) and Yagan (2019). Although we share the same focus on worker-level outcomes as in these two papers, we differ from them in that for each worker, we are able to observe two measures of exposure: a market-level measure, similar to theirs, and a more granular worker-level measure, obtained from matching workers to plants and plants to USSR exports. This allows us to study whether workers directly exposed to a shock fair equally poorly across markets.[3]

Our empirical analysis is also related to the displacement literature, e.g. Jacobson et al. (1993), Couch and Placzek (2010), Davis and von Wachter (2011), Farber (2017), Schmieder et al. (2019), and Huckfeldt (Forthcoming). While the previous papers compare labor-market outcomes for workers who differ in terms of ex-post characteristics—comparing those who are fired in a mass-layoff event to workers who do not separate from their employer for any reason over a period of time—we compare workers who differ in terms of ex-ante characteristics—comparing workers whose plants have different shares of sales to the USSR in 1989, prior to the USSR collapse. We also control for time-varying local-labor-market conditions, thereby identifying the differential effect of worker-level exposure within but not across local labor markets. Our results can be viewed as the spatial counterpart of the business cycle analysis of Davis and von Wachter (2011), Farber (2017), Schmieder et al. (2019), and Huckfeldt (Forthcoming). We find that negative plant-level demand shocks induce greater and more persistent earnings declines in more exposed labor markets whereas they find that job displacement during a national recession induces greater earnings losses.

From a theoretical standpoint, most of the trade literature is static and implicitly focuses on the long-run, steady-state consequences of trade shocks; see, e.g., Stolper and Samuelson (1941), Feenstra and Hanson (1996), Grossman and Rossi-Hansberg (2008), and Costinot and Vogel (2010). An important exception is the seminal work of Artuç et al. (2010), later expanded by Caliendo et al. (2019), who emphasize transitional dynamics due to moving costs in the presence of idiosyncratic preference shocks across workers. An implication of such frictions is that changes in employment should be larger in the long-run than in the short-run, as workers wait for beneficial idiosyncratic shocks before moving. In contrast, our theoretical framework, which builds on a very large macro literature that emphasizes nominal rigidities—see, e.g, Keynes (1925), Friedman (1953), Akerlof et al. (1996), Blanchard and Galí (2010), Schmitt-Grohé and Uribe (2016)—predicts larger employment changes in the long-run than in the short-run, something we also document empirically.[4] In emphasizing the role of nominal rigidities in a trade context, our

[3] A potential limitation of our dataset is that it does not include information about input-output linkages between plants (e.g. Dhyne et al. 2021). Such linkages may also affect the heterogeneity of exposure to various foreign shocks across workers, as in Adao et al. (2021) and Alfaro-Urena et al. (2021).

[4] For evidence of downward wage rigidities, see, e.g., Fortin (1996), Fehr and Goette (2005), Barattieri et

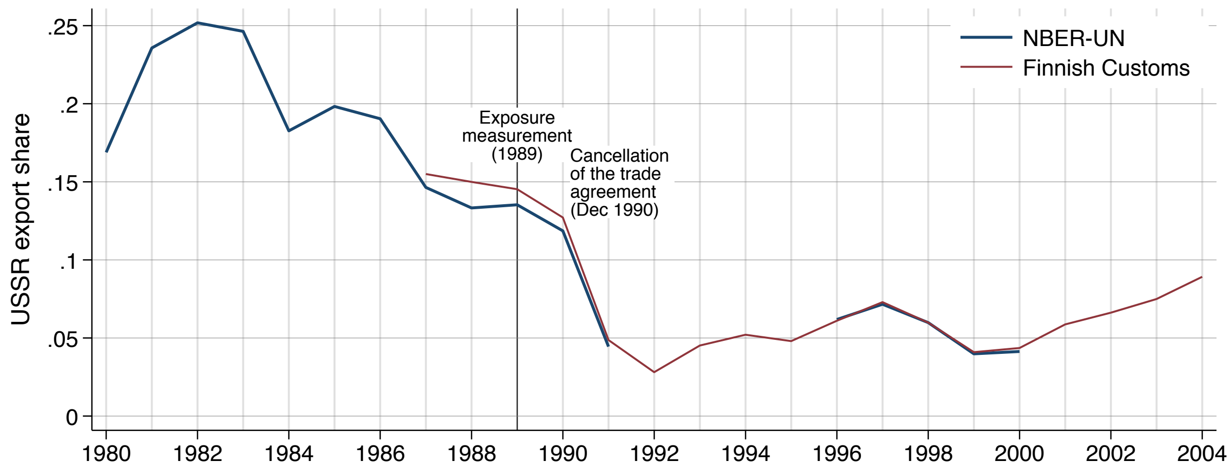


Figure 1: The USSR Shock

Notes: Figure 1 reports the share of Finnish exports sold to the USSR from 1980 to 2004.

analysis also relates to Rodríguez-Clare et al. (2020).

2 Background

2.1 The Collapse of the Finnish-Soviet Trade Agreement

Finland and the Soviet Union had a series of bilateral trade deals between 1951 and 1990. At its peak in the early- and mid-1980s, more than a quarter of Finland's exports went to the Soviet Union. As discussed in Eloranta and Ojala (2005) and Sutela (2005, 2014), the Finnish-Soviet trade agreement was in many ways similar to those between the Soviet Union and Eastern European communist countries. The composition of trade was agreed at the governmental level, and the aim was to keep trade strictly balanced each year. Finland's imports from the Soviet Union consisted almost entirely of energy, mostly crude oil, that was valued at world prices. In return, Finland primarily exported manufacturing goods, as described in Figure B.1 in Appendix B.1. Consequently, the world energy prices and Finland's energy use largely determined the total value of Finnish exports. This link between energy prices and Finland's exports to the USSR is visible in Figure 1, which shows a substantial increase in the Soviet export share following the second oil crisis and a decline in the 1980s as energy prices decreased.

On December 6th, 1990, the Soviet Union unilaterally canceled the five-year trade

al. (2014), and Kaur (2019). Dickens et al. (2007) argue that Finland is exceptional in the extent of downward wage rigidity.

agreement that had been signed in the previous year. While exports to the USSR had declined since the mid-1980s—and the entire Soviet block was in turmoil—it appears that this turn of events took the Finnish political and business elite by surprise. In the words of Sutela (2014, 134): "*That it was evident that the Soviet Union was collapsing was not of any importance: there were friends at the Soviet Ministry of Foreign Trade who claimed that everything would be fine after a short period of uncertainty*." In line with this argument, the minutes of internal discussions of a significant export cartel suggest that some of the most experienced people engaged in the Eastern trade expected the decline in the Soviet trade to be temporary (Eloranta and Ojala, 2005). Furthermore, none of the economic forecasts published in 1990 anticipated that exports to the USSR would collapse in the next year (Möttönen, 2002). The value of Finnish exports to the USSR, however, decreased from €3.6bn in 1990 to €1.2bn in 1991 (in 2010 euros). In 1992, exports to the newly formed Russian Federation were only €800m. In percentage terms, USSR exports went from about 14% before the collapse of the trade agreement to about 5%, as described in Figure 1. This unexpected drop is what we will refer to as the "USSR shock" in the rest of our analysis.

2.2 Market-Level Exposure to the USSR Shock

Not all local labor markets in Finland were equally exposed to the USSR shock. There was significant variation in export shares to the USSR across firms and products as well as significant variation the employment shares of these firms and products across Finnish municipalities, which we will exploit throughout our empirical analysis.

The Finnish authorities tightly controlled trade with the Soviet Union. Firms were obliged to formally notify the Office of Licenses (Lisenssivirasto) of all transactions with the Soviet Union; Lisenssivirasto published these transactions in biweekly reports. These reports include information on the exporting firm, 6-digit product, value, currency, and date of the transaction. In co-operation with the Central Archives for Finnish Business Records, we have digitalized all of these reports for the year 1989.[5]

As a first step towards measuring exposure to the USSR shock across local labor markets, we have linked the export information to the Longitudinal Data on Plants in Finnish Manufacturing (LDPM). In 1989, the sampling frame of LDPM included all manufacturing plants that had at least five employees. Firms were legally required to answer the survey, which included questions about their inputs, outputs, and background character-

[5] In total, these data include information on 3,380 transactions with a total value of €3.7bn in 2010 euros. For comparison, Finland's exports to the USSR in 1989 were €4.29bn and €4.24bn according to the Finnish Customs and NBER-UN ("Feenstra") databases, respectively.

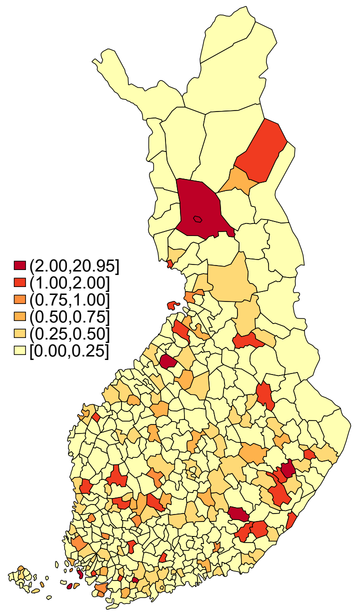


Figure 2: Local Labor Market Exposure to the USSR Shock

Notes: This figure reports (100 times) the exposure S_m to the USSR shock across Finnish municipalities. S_m is defined as the weighted sum of plant exposure in municipality m, with plant exposure equal to its ratio of USSR exports to gross output and weight equal to the plant's employment share in the municipality.

istics, including the municipalities in which their plants are located.[6]

For each plant j in our dataset, we then define exposure to the USSR trade shock as $s_j \equiv x_{j,89}/q_{j,89}$, where $x_{j,89}$ is the value of exports to the USSR from plant j in 1989 as measured by our export data and $q_{j,89}$ is the value of gross output of this plant in 1989.[7] Armed with the previous measure, we can define a municipality or local labor market m's exposure to the USSR trade shock as the weighted average of the exposure of plants located in market m, $S_m \equiv \sum_{j \in \mathcal{J}_m} \omega_j s_j$, with weights equal to the employment share of plant j in market m.

Figure 2 displays how exposure in 1989 varies across Finland's 431 municipalities. Although many municipalities have low levels exposure to the USSR shock, including

[6]We use either firm names and product codes or annual reports of export cartels to link firm-level exports to manufacturing plants (see the Data Appendix for details). In total, we are able to link 71% of the total value in our export data to manufacturing plants included in the LDPM data.The remaining 29% are mostly construction companies, wholesalers, and trading companies, which were also active in the USSR trade, but are not included in the LDPM. Furthermore, we cannot match to firms that changed their names after 1989.

[7]We directly observe the value of gross output $q_{j,89}$ in LDPM. To construct $x_{j,89}$ we start from the value of exports in 1989 of the firm owning plant j disaggregated by 6-digit products, which we directly observe in the Lisenssivirasto. For single plant firms, we then simply set $x_{j,89}$ equal to the total value of exports across all 6-digit products. For multi-plant firms, we weigh the exports of each 6-digit product by the share of gross-output accounted by plant j for this product, which we also observe in LDPM.

15 municipalities without any exposure, $S_m = 0$, there is substantial variation across municipalities, with exposures at the 75th and 90th percentiles reaching 0.30 and 0.66, respectively. Table B.1 in Appendix B.2 reports how other municipality characteristics, also measured in 1989, vary with exposure to the USSR shock. Not surprisingly given the nature of the Finnish-Soviet trade agreement, market exposure, S_m, is positively correlated with the share of municipality employment within the manufacturing sector. It is also positively correlated with the share of the working-age population (18-64 years old) with at least a secondary education and negatively correlated with the average age of the working-age population (both measured in 1989).

2.3 Market-Level Incidence of the USSR Shock

As already mentioned in our Introduction, when imports surge in some sectors, either because of domestic tariff cuts or foreign productivity gains, regions with employment concentrated in those sectors systematically experience worse labor market outcomes (e.g. Topalova, 2010, Autor et al., 2013, and Kovak, 2013). When exports collapse, we therefore expect a similar negative impact on more exposed Finnish municipalities.

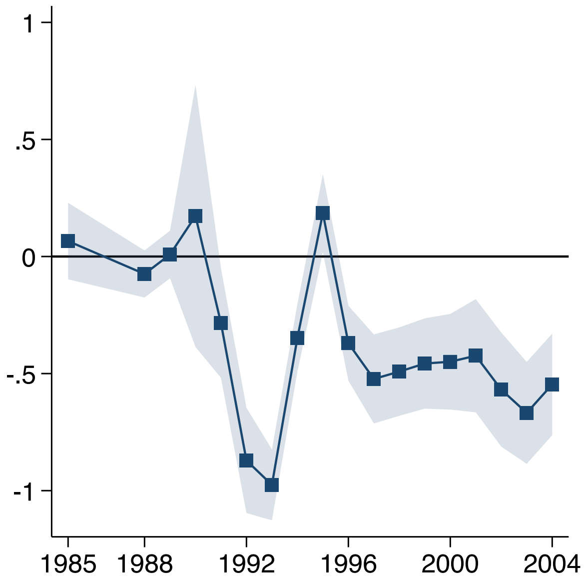
To investigate whether this is indeed the case in this context, we separately estimate the following linear model for each year t in our sample,

$$\Delta Y_{mt} = \beta_t S_m + \text{Controls}'_m \zeta_t + \varepsilon_{mt}, \tag{1}$$

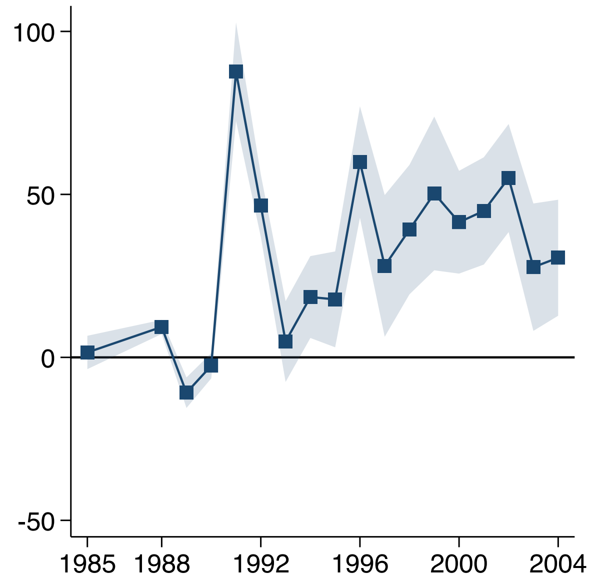
where $\Delta Y_{mt} \equiv Y_{mt} - \overline{Y}_m^{pre}$ is the difference between the value of the outcome variable of interest, Y_{mt}, and its average value in the pre-period (up to and including 1989), $\overline{Y}_m^{pre}$; and Controls$_m$, is a vector of controls that include the three municipality characteristics described above (share of employment in manufacturing, share of population with at least secondary education, and average age); and ε_{mt} is a market-and-year-specific shock. The coefficient of interest is β_t, which we estimate using OLS.

Our sample period covers the so-called Finnish Great Depression from 1991-1993, a period that was marked not only by the collapse of the USSR, but also by a severe financial crisis. The identifying assumption is that at any given date t, conditional on our vector of controls, exposure to the USSR S_m is orthogonal to the market-specific shock ε_{mt}. This allows financial shocks to have differential effects across municipalities, perhaps due to differences in bank exposure, but not in a way that is systematically correlated with exposure to the USSR.[8]

[8] This identifying assumption will play no role in our main empirical analyses. In Section 4, all regressions remain estimated year-by-year, but at the worker level and including municipality fixed effects.



(a) Average Earnings



(b) Unemployment Rate

Figure 3: Local Labor Market Impact of the USSR Shock

Notes: Figures 3a and 3b report the OLS estimates of β_t in equations (1) when Y_{mt} is equal to the log of the average earnings of the working-age population and the unemployment rate times 100, respectively, in municipality m and year t.

Figure 3 reports the OLS estimates of β_t in equation (1) along with their 95 percent confidence intervals for two labor market outcomes: (i) average earnings (Figure 3a) and (ii) the unemployment rate (Figure 3b). Average earnings are computed as the log of average total earnings, as measured by tax records, among 18–64 year-old residents of each municipality. Unemployment rates are defined as the share of unemployed persons living in the municipality out of municipality's labor force at the end of each year.[9]

Consistent with prior empirical work, we find that local labor markets that were more exposed to the USSR shock experienced statistically significant declines in labor earnings and increases in unemployment following the trade collapse. In Figures 3a and 3b, the relative decline in earnings peaks in 1992 and 1993, shortly after the nadir of Finnish-Soviet trade, whereas the peak in the relative increase in unemployment coincides with the nadir in 1991. In terms of magnitude, our coefficient estimates imply that the collapse of the Finnish-USSR trade deal was associated with a decrease in earnings in 1993 of

[9] We have constructed these municipality-level measures using individual-level data covering the entire Finnish population (see Section 4.2).

approximately 0.6 percent in the municipality at the 90th percentile of exposure ($S_m = 0.66$) relative to the 10th percentile ($S_m = 0.005$) and an increase in the difference of their unemployment rates in 1991 of 0.57 percentage points. After declining from their peaks, these adverse effects are persistent throughout our sample period (with the exception of the earnings effect in 1995).[10]

As shown in Appendix B.3, the same qualitative patterns hold across a variety of alternative specifications that allow for different vectors of controls as well as different measures of labor-market exposure.

3 Exposures to Trade and Earnings Dynamics: Theory

In a frictionless labor market featuring flexible wages, unemployment rates should be unaffected by local negative shocks. In practice, Finnish unemployment rates increased in markets more exposed to the USSR shock. Motivated by the previous evidence, we now develop a simple model of a local labor market in which, in response to a large negative trade shock, slow downward wage adjustment creates unemployment along the transition path. We then use this model to characterize how workers' exposure to the trade shock shapes the dynamic path of their earnings as well as how this effect varies with the exposure of their local labor market.

3.1 The Model

We focus on a labor market m comprising a fixed number of workers, indexed by $i \in \mathcal{I}_m$, and a fixed number of plants, indexed by $j \in \mathcal{J}_m$. Time is continuous and indexed by t.

Workers. Workers are either employed or unemployed. We let E_{mt} and U_{mt} denote the numbers of employed and unemployed workers, respectively, in the market in period t. Their sum is equal is to the total number of workers in that market,

$$E_{mt} + U_{mt} = N_m. \tag{2}$$

[10]It is reassuring to note that the small decrease in earnings and increase in unemployment between 1985 and 1988 as well as the increase in earnings and decrease in unemployment between 1988 and 1989 are both consistent with the institutional design of the Finnish-USSR trade pact described above. Finland imported oil from the USSR at market prices and trade was required to be bilaterally balanced each year. Hence, before the collapse of the trade agreement in December of 1989, decreases in oil prices harmed labor markets with higher values of S_m—since exports to the Soviet Union fell—and increases in oil prices had the opposite effect. The decline in oil prices between 1985 and 1988 decreased earnings and increased unemployment in labor markets with higher values of S_m and the subsequent rise in oil prices between 1988 and through 1989 had the opposite effect.

For any worker i, we let e_{it} denote her employment status at date t. It is equal to one if worker i is employed and zero otherwise. If employed by plant j at date t, worker i receives a wage W_{mt} and faces an endogenous probability $\lambda_{jt}dt$ of switching from employment to unemployment at date $t + dt$. If unemployed, she does not receive a wage and faces an endogenous probability $\kappa_t dt$ of switching from unemployment to employment at date $t + dt$.

Plants. Plant j's labor demand at time t is given by

$$\ell_{jt}(W_{mt}) = \phi_{jt} W_{mt}^{-\sigma},$$

where $\phi_{jt} > 0$ is a plant-specific labor demand shifter and $\sigma > 0$ is the elasticity of labor demand, which we assume is common across plants.[11] At any date t, we assume that employment in plant j is equal to its demand, $E_{jt} = \ell_{jt}(W_t)$. Hence, total employment in market m satisfies

$$E_{mt} = \Phi_{mt} W_{mt}^{-\sigma}, \tag{3}$$

where $\Phi_{mt} \equiv \sum_{j \in \mathcal{J}_m} \phi_{jt}$ is the market-level labor demand shifter.[12]

Between any consecutive dates t and $t + dt$, a constant fraction λdt of existing worker-plant matches is destroyed. If plant j is growing ($\dot{E}_{jt}/E_{jt} \geq 0$) or downsizing at a rate lower than λ ($-\lambda \leq \dot{E}_{jt}/E_{jt} \leq 0$) over the same time period, λ coincides with the total separation rate of plant j. If instead plant j is downsizing at rate greater than λ ($\dot{E}_{jt}/E_{jt} \leq -\lambda$), then its total separation rate is equal to $-\dot{E}_{jt}/E_{jt}$. Hence the separation rate for plant j at time t, λ_{jt}, can be expressed compactly as

$$\lambda_{jt} = \max\{\lambda, -\frac{\dot{E}_{jt}}{E_{jt}}\}. \tag{4}$$

In turn, the job finding rate in market m is given by

$$\kappa_{mt} = \max\left\{0, \frac{\dot{E}_{mt} + \lambda_{mt} E_{mt}}{U_{mt}}\right\} \tag{5}$$

[11]Each plant's iso-elastic labor demand can be obtained from a model in which plants behave as price-takers in good and labor markets, employ workers and a fixed factor according to a Cobb-Douglas production function with labor share $1 - 1/\sigma > 0$, and maximize profits period-by-period (and hence, trivially, the present discounted sum of all profits). Alternatively, each plant's labor demand can be obtained from a model in which plants behave as price-takers in labor markets, are monopolistically competitive in goods markets (with $\sigma > 1$ the elasticity of substitution between goods), produce with labor alone, and maximize profits period-by-period.

[12]This requires total population N_m to be large enough so that $E_{mt} \leq N_m$, an assumption that we maintain throughout this section.

where $\lambda_{mt} = \sum_{j \in \mathcal{J}_m} \lambda_{jt} \left(E_{jt}/E_{mt} \right)$ is the market's separation rate.

Wages. Wages adjust slowly. Between t and $t + dt$, the change in wages W_t satisfy

$$\dot{W}_{mt} = \gamma(\overline{W}_{mt} - W_{mt}) \tag{6}$$

where $\overline{W}_{mt} \equiv (N_m/\Phi_{mt})^{-1/\sigma}$ denotes the market-clearing wage at which full employment obtains and $\gamma \geq 0$ determines the speed of wage adjustment.[13]

3.2 Earnings Dynamics

We assume that the local labor market is in steady state just before date 0, with the wage equal to the market-clearing wage, $W_{m0} = \overline{W}_{m0}$, and labor supply equal to labor demand, $E_{m0} = N_m$. At date 0, it experiences a one-time, permanent negative labor demand shock, which is how we think of the USSR shock. Plants may be more or less exposed to the shock. For each plant $j \in \mathcal{J}_m$, we let ϕ_j denote the level of plant j's demand before the shock and $\phi'_j \equiv \left(1 - s_j\right) \phi_j$ its demand after the shock, with $s_j \in [0, 1]$ denoting its exposure. For each worker $i \in \mathcal{I}_m$, we define *worker exposure* s_i as the exposure of the plant $j(i)$ employing that worker, i.e., $s_i = s_{j(i)}$. Consistent with our empirical analysis in Section 2, we then define *market exposure* S_m as the weighted average of plants located in market m, with weights equal to the initial employment share of each plant in that market, i.e. $S_m \equiv \sum_{j \in \mathcal{J}_m} s_j (E_{j0}/E_{m0}) \in [0, 1]$. By construction, S_m is also equal to the average across workers of worker-level exposure, $S_m \equiv \sum_{i \in \mathcal{I}_m} s_i / E_{m0}$.

Unemployment and Wages. To characterize the path of workers' earnings after the shock, it is convenient to start by solving for the path of wages and unemployment, $\{W_{mt}\}$ and $\{U_{mt}\}$, in the local labor market. After the shock, the market-clearing wage jumps from $\overline{W}_{m0} = (N_m/\Phi_m)^{-1/\sigma}$ to $\overline{W}_{m0^+} = (N_m/\Phi'_m)^{-1/\sigma}$, where it remains ever thereafter, with $\Phi_m \equiv \sum_{j \in \mathcal{J}_m} \phi_j$ and $\Phi'_m \equiv \sum_{j \in \mathcal{J}_m} \phi'_j = \Phi_m(1 - S_m)$ denote market-level demands pre- and post-shock.[14] Market-level wages $\{W_t\}$, however, respond sluggishly. They are

[13] For expositional purposes, we ignore the asymmetry between upward and downward wage adjustments. Since we focus next on negative labor demand shocks in which wages only adjust downward, upward wage rigidity (or lack thereof) is irrelevant for our analysis. Appendix A.2 demonstrates that all of our results extend to a generalized environment in which wages adjust downward until the unemployment rate converges to a fixed but not necessarily zero value. Appendix A.3 further discusses how our results extend to environments in which the wages of incumbent workers are (fully) rigid, but those of new hires are not.

[14] For any variable x_t, we use the notation $x_{0^+} \equiv \lim_{t \to^+ 0} x_t$.

given by the unique solution to the first-order linear differential equation (6) with initial condition $W_{m0} = \overline{W}_{m0}$,

$$W_{mt} = \left(\frac{N_m}{\Phi_m}\right)^{-\frac{1}{\sigma}} \left[e^{-\gamma t} + (1 - e^{-\gamma t})(1 - S_m)^{\frac{1}{\sigma}}\right], \text{ for all } t > 0, \tag{7}$$

which converges to the new market-clearing wage at rate γ and is strictly decreasing in S_m at any date $t > 0$. Substituting equilibrium wages into equation (3) pins down equilibrium employment levels $\{E_{mt}\}$, whereas substituting those into equation (2) pins down unemployment levels $\{U_{mt}\}$, which are given by

$$U_{mt} = N_m \left\{1 - (1 - S_m)\left[e^{-\gamma t} + (1 - e^{-\gamma t})(1 - S_m)^{\frac{1}{\sigma}}\right]^{-\sigma}\right\}, \text{ for all } t. \tag{8}$$

The unemployment rate (U_{mt}/N_m) rises upon impact in proportion to S_m, declines over time, and is strictly increasing in S_m at any date $t > 0$, consistent with our empirical results above.

Workers' Earnings. Building on the characterization of market-level outcomes, we now turn to our model's implications for worker-level earnings.

Let π_{it} denote the probability that a worker $i \in \mathcal{I}_m$ who was employed by plant $j(i)$ at date 0 is employed by *any* plant $j \in \mathcal{J}_m$ at date $t > 0$. At date 0^+, right after the shock, the job destruction rate in equation (4) implies

$$\pi_{i0^+} = 1 - s_i. \tag{9}$$

At any subsequent date $t > 0$, the employment status of each worker over time $\{e_{it}\}$ is a two-state continuous Markov chain with a time-varying transition probability from unemployment to employment equal to the job-finding rate κ_{mt} (as described in equation 5) and a transition probability from employment to unemployment equal to the exogenous separation rate λ (since wages are falling, all plants are expanding and $\lambda_{jt} = \lambda$, by equation 4). Hence, π_{it} satisfies the following first-order differential equation,

$$\dot{\pi}_{it} = \kappa_{mt}(1 - \pi_{it}) - \lambda\pi_{it} = \kappa_{mt} - (\lambda + \kappa_{mt})\,\pi_{it}. \tag{10}$$

Combining equations (3), (4), (5), (7), and (8), we can solve for the job-finding rate κ_{mt} and then use equations (9) and (10) to solve for π_{it} as a function of worker i's exposure s_i and the exposure of her market S_m, as we do in Appendix A.1. Expected earnings at each date

$t > 0$ for a worker i is then simply given by $y_{it} = \pi_{it} W_{mt}$, with the market wage given by equation (7).

Proposition 1 characterizes the impact of a worker's exposure s_i on the path of her expected earnings as well as how this impact varies with the exposure of her market S_m.

Proposition 1. *In response to a negative shock at $t = 0$, (i) more exposed workers always experience declines in expected earnings ($dy_{it}/ds_i < 0$ for all $t > 0$); (ii) these declines are larger in more exposed markets ($d^2 y_{it}/ds_i dS_m < 0$ for all $t > 0$) if wages are sufficiently rigid (γ low enough); but (iii) smaller declines in more exposed markets are possible ($d^2 y_{it}/ds_i dS_m > 0$ for some $t > 0$) if wages are sufficiently flexible (γ high enough).*

That more exposed workers have lower expected earnings is intuitive. They are more likely to lose their job at date 0. Being unemployed at date 0, in turn, lowers the probability of being employed at all future dates. Since all workers receive the same wage at a given point in time, this leads to lower expected earnings for more exposed workers.[15]

The interaction between worker and market exposure is more subtle. More exposed markets have lower wages, as can be seen from equation (7), as well as lower job-finding rates at every date, as we prove in Appendix A.1. The job-finding-rate effect magnifies the decreases in earnings experienced by workers with greater exposure s_i in markets with higher exposure S_m, since workers facing a higher probability of unemployment at any date $T \geq 0$ now also face a lower probability of transitioning back to employment at any date $t > T$. The wage effect works in the opposite direction. For workers with greater exposure s_i, who are more likely to be unemployed at all dates, the earnings losses in in terms of foregone wages are lower in markets with higher exposure S_m. As a result, a negative interaction effect $d^2 y_{it}/ds_i dS_m < 0$ arises when the job-finding-rate effect dominates the wage effect, which happens when γ is low enough and wages respond little to the shock, whereas a positive interaction effect $d^2 y_{it}/ds_i dS_m > 0$ arises when the wage effect dominates, which may only happen when γ is high enough.[16]

[15] In the long-run, the probability of being employed is independent of employment status just after date 0. So, the direct effect of workers' exposure fully dissipates asymptotically: $\lim_{t\to\infty} dy_{it}/ds_i = 0$.

[16] Proposition 1 focuses on expected earnings rather than the log of expected earnings. The log case is straightforward. Under the assumption of a common market wage, the wage effect cancels out and only the job-finding-rate effect remains: $d^2 \log y_{it}/(ds_i dS_m) < 0$ at any date $t > 0$. Equally straightforward is the impact of market exposure on expected earnings: $dy_{it}/dS_m < 0$ for all $t > 0$, both because of lower wages and higher unemployment.

4 Exposures to Trade and Earnings Dynamics: Evidence

Guided by the previous theoretical results, we now turn to our empirical analysis of the relationship between the path of Finnish workers' earnings over the 1985-2004 period, y_{it}, and their exposures to the USSR shock, s_i and S_m.

4.1 Empirical Design

We first examine the incidence of worker exposure to the USSR shock, s_i, on annual earnings, y_{it}, and then study how the previous incidence varies across markets with different exposure, S_m.

For the first part of our empirical analysis, we follow closely earlier work using longitudinal worker-level data to estimate the impact of negative labor demand shocks at various time horizons (Jacobson et al., 1993; Davis and Wachter, 2011; Autor et al., 2014; Yagan, 2019). The idea is to compare changes in the earnings trajectories of workers who are more and less exposed but similar in terms of other observable characteristics. This is the worker-level counterpart of the difference-in-difference strategy conducted in Section 2.3. For each sample year t, we separately estimate the following linear regression model,

$$\Delta y_{it} = \beta_t s_i + \text{Controls}_i' \zeta_t + \varepsilon_{it}, \tag{11}$$

where $\Delta y_{it} \equiv y_{it} - \overline{y}_i$ is the difference between worker i's earning at date t, y_{it}, and her pre-period average, $\overline{y}_i$; s_i denotes worker i's exposure to the USSR shock; Controls_i is a vector of initial worker characteristics; and ε_{it} is a worker-and-year specific shock. Both the sample of workers and their characteristics are fixed across all years.

We interpret β_t as the causal effect of worker exposure to the USSR shock, consistent with our previous theoretical analysis. Alternatively, β_t could reflect different pre-existing trends (e.g., a downward pre-1989 earnings trend for workers initially employed in severely exposed plants) or omitted contemporaneous shocks (e.g., greater financial vulnerability of the industries or plants that disproportionately employ more exposed workers in 1989 interacting with the Finnish Depression). We favor a causal interpretation of β_t both because we find no evidence of pre-existing trends and because we control for a rich set of initial worker characteristics, including municipality and manufacturing dummy variables.

The second and most novel part of our empirical analysis focuses on the heterogeneous incidence of worker exposure, s_i, across markets with different exposure, S_m. As discussed in Proposition 1, depending on how rigid wages are, the consequences of workers' exposure to the USSR shock may be magnified or dampened in markets that are themselves more exposed to the shock. To shed light on this issue, we estimate the following augmented model,

$$\Delta y_{it} = \beta_t s_i + \gamma_t (s_i \times S_m) + \text{Controls}_i' \zeta_t + \varepsilon_{it}, \tag{12}$$

where S_m is measured exactly as in Section 2.3. Except for the new interaction term, $s_i \times S_m$, all variables are the same as in our earlier regression. The idea is therefore to compare how the difference between the earnings trajectories of more and less exposed workers varies with the exposure of the market, S_m, a triple- rather than double-difference strategy.

4.2 Worker-Level Data

Our worker-level data are drawn from various administrative registers made available to us by Statistics Finland. The main registers, described in more details below, cover Finland's entire working-age population in 1985 and in every year from 1988 to 2004. Using each worker's personal identification number to merge data from different registers, we can observe workers' earnings and demographic characteristics, which we use in our baseline analysis, as well as employment status, which we will use in the next section. Importantly, each employed worker also has a firm and plant identifier, which we can use to match workers to plants from the LDPM dataset described in Section 2.2.

Worker-Level Outcomes. Our primary outcome variable is annual earnings, y_{it}. It is equal to the total annual wage and salary income as reported to the Finnish Tax Authority in year t. In order to limit the influence of outliers, we follow Autor et al. (2014) and winsorize annual income at the top 1% within each year. In subsequent regressions in Section 4.6 we also consider the change in the number of days of employment during a year, Δn_{it}, which we construct using information on employment spells as recorded in the Pension Register. A limitation of this employment measure is that it does not include information on hours and is likely to over-estimate the employment of people working irregular shifts.

Worker-Level Controls. Our vector of worker-level controls, Controls_i, includes various characteristics of worker i in 1989. As mentioned above, Controls_i includes indicator variables for each of Finland's 431 municipalities (equal to 1 if worker i is located in a municipality in 1989 and 0 otherwise) as well as a manufacturing sector indicator variable (equal to 1 if worker i is employed in manufacturing in 1989 and 0 otherwise). In addition to the previous municipality and sector dummies, Controls_i includes the following socio-demographic characteristics: gender, year of birth, 5 levels of education, 5 fields of education, 3 native languages, and a decile indicator variable for worker earnings in 1989.[17] Finally, Controls_i includes decile indicator variables for various characteristics of the plant employing worker i in 1989: gross output, capital-labor ratio, average hourly wage for blue-collar workers, average monthly wage for white-collar workers, and average annual earnings of workers in the plant, all evaluated in 1989.[18]

Worker Sample. We focus on workers in the private sector with high labor force attachment before the collapse of the USSR and who remain of working-age throughout the period we examine. We define an individual to have a high labor force attachment if her annual earnings were at least the equivalent of 1,600 annual hours of work at the "minimum wage," following Autor et al. (2013). Since there is no mandated minimum wage in Finland, we measure the "minimum wage" as the first percentile of hourly wages among blue collar manufacturing workers for each year in 1985, 1988, and 1989.[19] We limit the sample to those born in 1945–1967. These birth cohorts were 18–40 years old at the start of our examination pre-period in 1985 and 37–59 years old at the end of our follow-up period in 2004. Although worker exposure is positive only for those workers employed in LDPM plants, our sample includes both workers employed in LDPM plants and those employed in all non-public sectors in 1989. After eliminating workers from the previous birth cohorts who are not in the private sector in 1989 or do not have high labor force attachment, we end up with a total of 627,070 individuals corresponding to 34 percent of these birth cohorts.

[17] The five education levels are: less than lower secondary or unknown, lower secondary, upper secondary, lower tertiary, and higher tertiary. The five fields of education: general, arts, and teaching; commercial and business administration; technical; other; and unknown or missing. The three native languages are: Finnish, Swedish, and other.

[18] Since gross output, capital-labor ratio, average hourly wage for blue-collar workers, and average monthly wage for white-collar workers are only available for LDPM plants, we add a missing category to each of these decile dummy variables, which we assign to any worker not employed by an LDPM plant in 1989.

[19] We observe the distribution of blue-collar manufacturing wages by year using the Confederation of Finnish Industry and Employers (TT) wage data, which covers approximately 75% of manufacturing employees. The resulting annual income cutoff for inclusion in our high-labor-force-attachment sample is €8,896 for 1985, €9,453 for 1988, and €9,318 for 1989, all in 2010 euros.

Table 1: Worker controls, 1989

	Baseline sample (1)	All private sector workers (2)
A: Employer characteristics		
Average annual earnings	26,517	25,583
	(7,430)	(7,553)
Average hourly blue-collar wages (LDPM)	7.9	7.8
	(1.7)	(1.7)
Average hourly white-collar wages (LDPM)	11.0	10.9
	(2.1)	(2.2)
Output (LDPM)	67.4	64.3
	(155.6)	(152.4)
Capital-labor ratio (LDPM)	102.8	97.7
	(220.1)	(212.3)
B: Worker socio-demographics		
Year of birth	1953.8	1955.1
	(5.9)	(6.5)
Female	0.35	0.39
First language Finnish	0.95	0.94
First language Swedish	0.05	0.05
Other first language	0.003	0.003
Less than secondary/unknown degree	0.32	0.30
Lower secondary degree	0.37	0.38
Upper secondary degree	0.20	0.22
Lower tertiarydegree	0.05	0.05
Higher tertiary degree	0.06	0.06
General, arts or teaching degree	0.06	0.07
Business degree	0.16	0.16
Technical degree	0.36	0.34
Degree in other fields	0.10	0.13
Degree unknown / missing	0.32	0.30
Annual earnings	28,354	25,336
	(13,101)	(13,483)
C: Sector of employment		
Manufacturing	0.35	0.39
Observations	627,070	830,639

Notes: This table shows means and standard deviations (in parentheses) of background characteristics measured in 1989 for our main sample of "attached workers" (column 1) and all private sector workers (column 2).

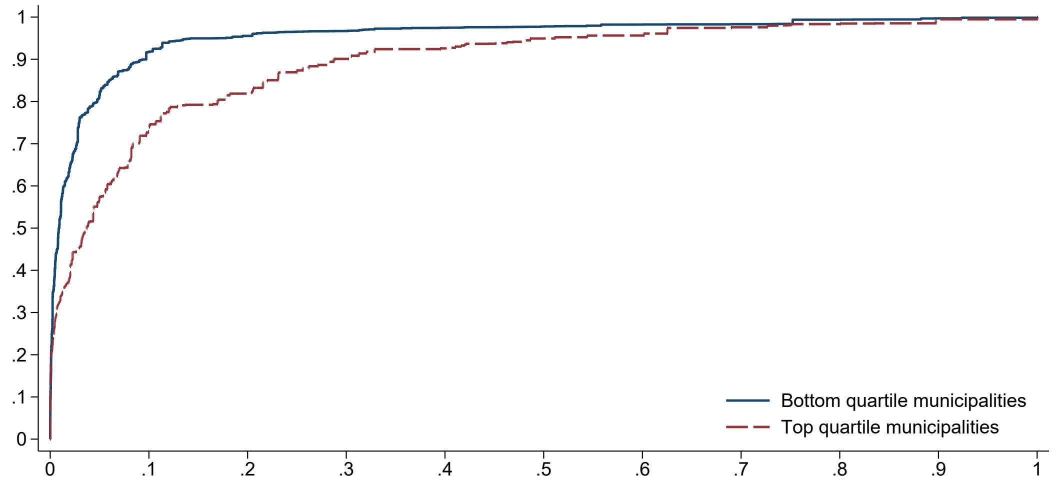


Figure 4: Worker-Level Exposure

Notes: Distribution of worker-level exposure conditional on $s_i > 0$ in the municipalities in the bottom (solid line) and top (dashed line) quartile of market-level exposure.

4.3 Worker-Level Exposure to the USSR Shock

Following our previous theoretical analysis, we define a worker i's exposure, s_i, as the exposure of the plant j that employs her in 1989. Figure 4 displays a histogram of worker exposure (conditional on $s_i > 0$) among municipalities in the top and bottom quartiles of market exposure, S_m. Exposure to Soviet exports was extremely skewed both because only 30% of workers in our sample are employed in LDPM plants in 1989—and only LDPM plants have positive exposure—and because within LDPM plants only 13% exported to the USSR in 1989 (although these plants employed 43% of the workers in LDPM plants). Even among exposed plants, exposure was uneven. For most plants participating in the Eastern trade, exports to the USSR constituted less than a tenth of their total output. At the other end, 30 plants (employing 2,842 workers) exported more than half of their production to the Soviet Union in 1989.

Table B.2 in Appendix B.2 presents characteristics of manufacturing plants by their USSR exposure. Compared to other plants, those exporting to the USSR were larger, paid higher wages, and more often belonged to multi-plant firms. Among the plants exporting to the USSR, the more exposed ones tended to be smaller and less capital-intensive than those less reliant on the Eastern trade. Table B.3 in Appendix B.2 reports worker characteristics in 1989 by their plants' exposure to the USSR export market. Workers in more and less exposed plants within manufacturing are balanced on age and gender. In comparison to other manufacturing workers, those working in more exposed plants are more educated and, given their level of education, more likely to have obtained a degree

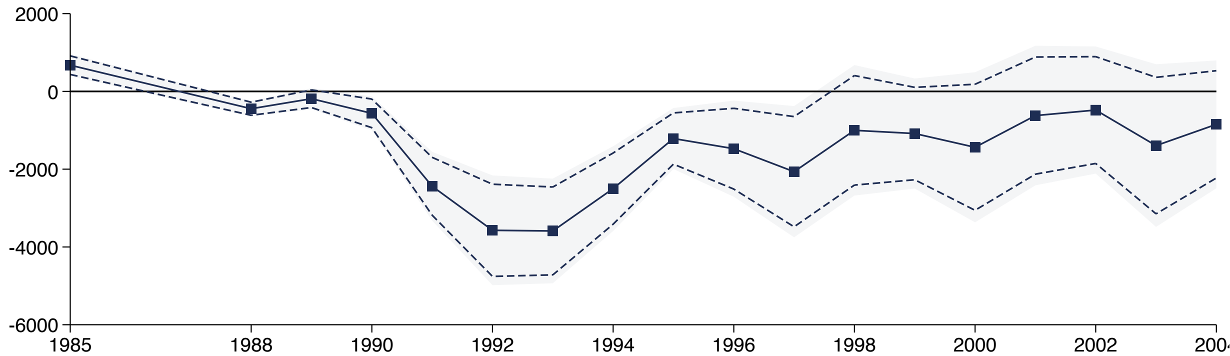


Figure 5: Estimated effect of worker-level exposure ($\hat{\beta}_t$)

Notes: Predicted $\hat{\beta}_t$ and its 90% and 95% confidence intervals estimated from (11) with robust standard errors clustered by 1989 municipality

in a technical field. We control for the time-varying impact of these worker characteristics in our baseline empirical specifications.

4.4 Worker-Level Incidence of the USSR Shock

This section presents the paper's main empirical results: the estimated earnings effects of the USSR trade collapse on more relative to less exposed workers, s_i, and how this varies across markets with different exposure, S_m.

Worker-Level exposure and earnings dynamics. Figure 5 displays the predicted effects of worker exposure s_i to the USSR trade collapse, $\hat{\beta}_t$, estimated using regression (11) together with its 90% and 95% confidence intervals, which are based on standard errors clustered by 1989 municipality.

More exposed workers experience statistically significant declines in labor earnings following the trade collapse. In Figure 5, the relative decline in earnings peaks in 1992 and 1993, coinciding with the nadir of Finnish-Soviet trade. The 1992 estimate implies that a worker at the 90th percentile of exposure (conditional on positive exposure) experiences a decline in earnings of 732 euros (denominated in 2010 euros) compared to a worker at the 10th percentile, which is equivalent to approximately 3 percent of the average income of workers in our sample. This effect is highly statistically significant.

Between 1993 and 1995 the annual earnings losses of more exposed workers decline (in absolute value). In spite of this, more exposed workers' earnings remain lower throughout our sample period, although this differences become statistically insignificant in 1998 and remains so through the end the sample period.

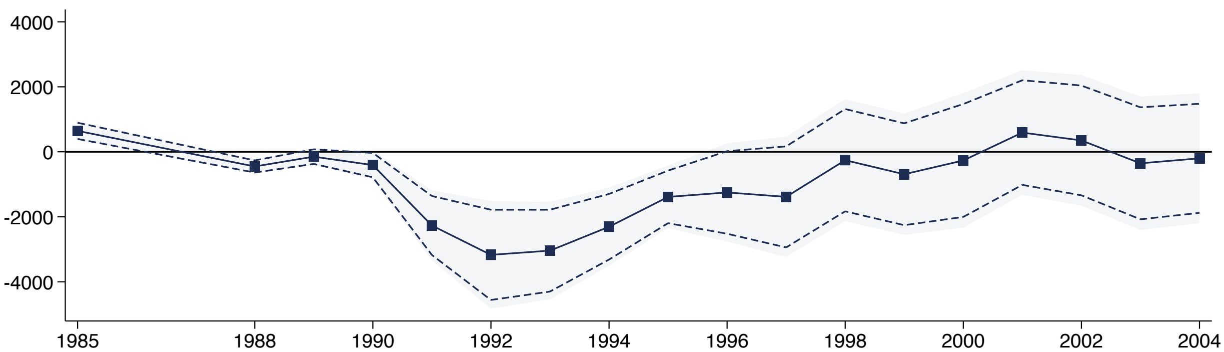
The estimated effects of worker exposure in the pre-trade collapse period show no evidence of pre-existing differential trends.[20] Instead, consistent with our municipality-level results in Section 2.3, we observe changes in estimates that are consistent with the institutional details of the Finnish-Soviet trade agreement; see Footnote 10. Before the the collapse of the Finnish-Soviet trade agreement, more exposed workers' earnings decline when oil prices fall (as they did between 1985 and 1988) and increase when oil prices rise (as they did between 1988 and 1989).

The negative and persistent effects of worker-level exposure is consistent with results in the mass-layoff literature and with Autor et al. (2014). Relative to Autor et al. (2014), our measure of exposure is more granular: we focus on plant-level exposure as compared to industry-level exposure and control for municipality-time effects. Relative to the mass-layoff literature, we compare workers who differ in terms of ex-ante characteristics (workers whose plants have different shares of sales to the USSR in 1989, prior to the USSR collapse) as opposed to comparing workers who differ in terms of ex-post characteristics (workers who are fired in a mass-layoff event relative to those who do not separate from their employer for any reason over a period of time).

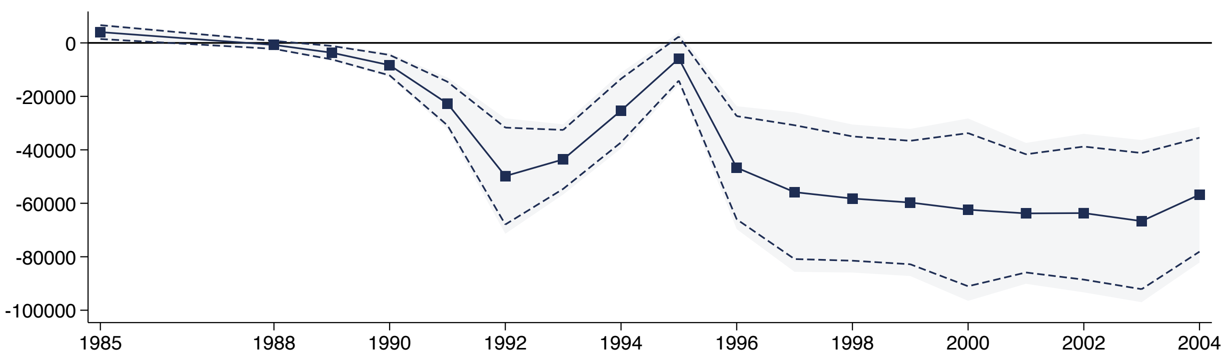
Interaction between Worker- and Market-Level Exposures. Figure 6 displays our more novel empirical results: the predicted effects $\hat{\beta}_t$ of worker exposure s_i together with the heterogeneous incidence $\hat{\gamma}_t$ of worker exposure across markets with different exposure, $s_i \times S_m$, estimated using regression (12).

Panel A of Figure 6 plots the estimate of $\hat{\beta}_t$ from regression (12) as well as the 90% and 95% confidence intervals. Panel B plots the estimate of $\hat{\gamma}_t$, along with its respective 90 and 95% confidence intervals. All confidence intervals are based on standard errors clustered by 1989 municipality. As in Figure 5, Panel A of Figure 6 documents that conditional on the interaction $s_i \times S_m$, workers with higher exposure s_i experienced substantial and statistically significant declines in labor earnings following the trade collapse, which peak in 1992 and 1993. Unlike Figure 5, these declines converge quickly to zero: $\hat{\beta}_t$ becomes statistically insignificant by 1996 and economically zero by 1998. This implies that within a local labor market with very low exposure S_m, the annual earnings change between the pre-shock years and 1998 (and all subsequent years) are no different for more and less exposed workers. Consistent with our theory, workers who are fired in respose to the trade collapse in low-exposure markets quickly find employment.

[20]By construction, the sum of the estimated coefficients across pre-shock years (1985, 1988, and 1989) is zero. Pre-trends, if they exist, would be identified by a decrease (or increase) in estimated coefficients across these three years.



(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure 6: Baseline Earnings Results

Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ and their 90% and 95% confidence intervals estimated from (12) with robust standard errors clustered by 1989 municipality

Panel B of Figure 6 documents that within a local labor market that is more exposed, worker exposure leads to both larger and more persistent earnings declines. A higher value of the interaction $s_i \times S_m$ reduces earnings in all post-shock years except for 1995.[21] Going back to the comparison of workers at the 90th and 10th percentile of worker-level exposure (conditional on positive exposure) in 1992, our results imply a greater decline in earnings of 658 euros for the more exposed worker in the municipality at the 10th percentile of market-level exposure, but a greater decline of about 790 euros for the more exposed worker in the municipality at the 90th percentile, a 20% increase.

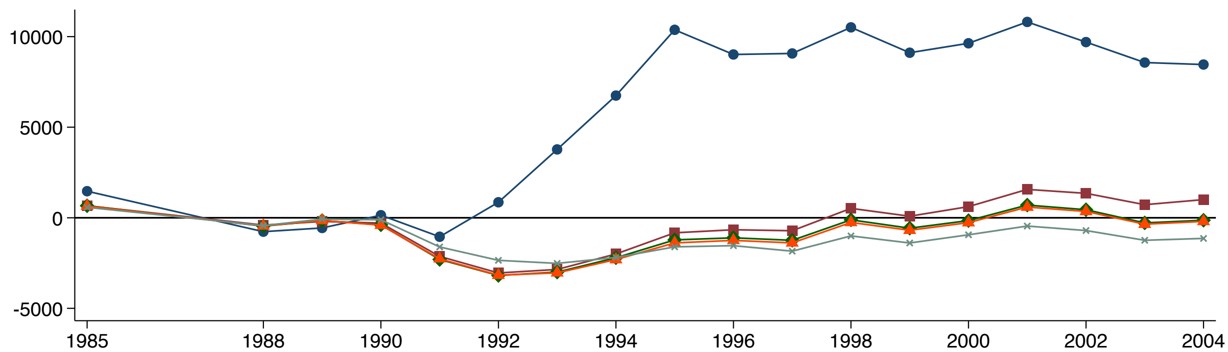
The result that a negative worker-level trade shock has larger and more persistently negative earnings effects in more exposed municipalities is novel in the trade literature. The mass-layoff literature—see, e.g., Davis and von Wachter (2011), Farber (2017), and Schmieder et al. (2019)—obtains a related result: a worker fired in a mass layoff experiences larger and more persistent earnings declines if that layoff ocurred during a recession (a period with higher unemployment rates) at the national level. Relative to the mass-layoff result, which leverages time variation alone, we exploit both time and market variation. Our results, therefore, can be viewed as the spatial counterpart of this business cycle analysis. Moreover, our identification assumption does not require that the composition of mass layoffs is not systematically related to the state of the business cycle. Instead, we require that the composition of more relative to less exposed workers is not systematically related to the exposure of the local labor market.

4.5 Sensitivity Analysis

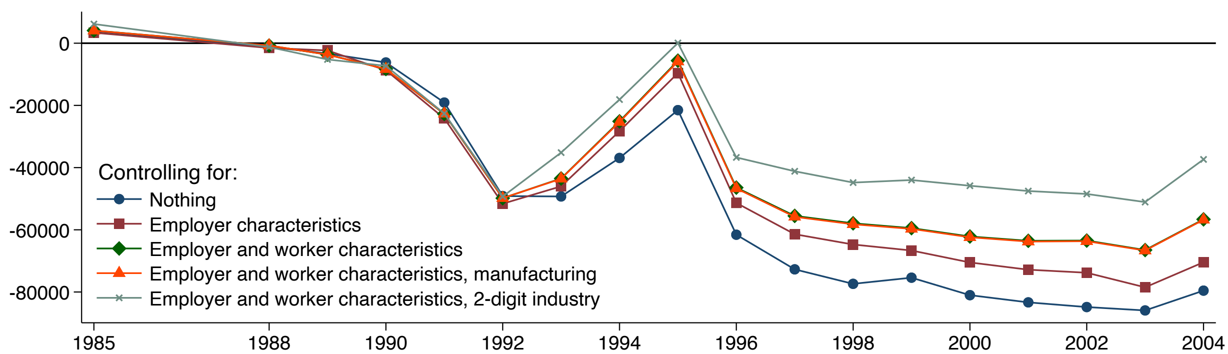
Our baseline results in Figure 6 are robust to a variety of alternative specifications that allow for different controls, different worker samples, and relative rather than absolute levels of earnings.

Set of Controls. Figure 7 presents results as we progressively add controls. We start with no controls (except for municipality effects), add employer characteristics, then add worker socio-demographic characteristics, then add a manufacturing effect, and finally add a richer set of industry controls than in our baseline (industry effects at the two-digit level). Our estimates of $\widehat{\gamma}_t$ (the interaction effect of worker and local labor market exposure) are broadly stable across all sets of controls. With no controls, our baseline

[21] Reconciling the results of Figure 5 and Panel A of Figure 6 is straightforward. The persistent effects within a local labor market identified in Figure 5 arise because of the omission of the interaction between s_i and S_m—which is positively correlated with s_i by construction—since this interaction term has a negative effect on earnings.



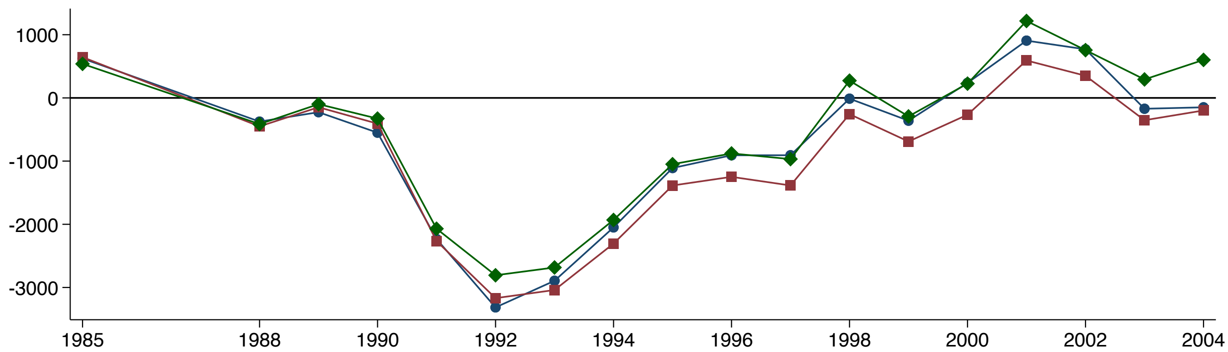
(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



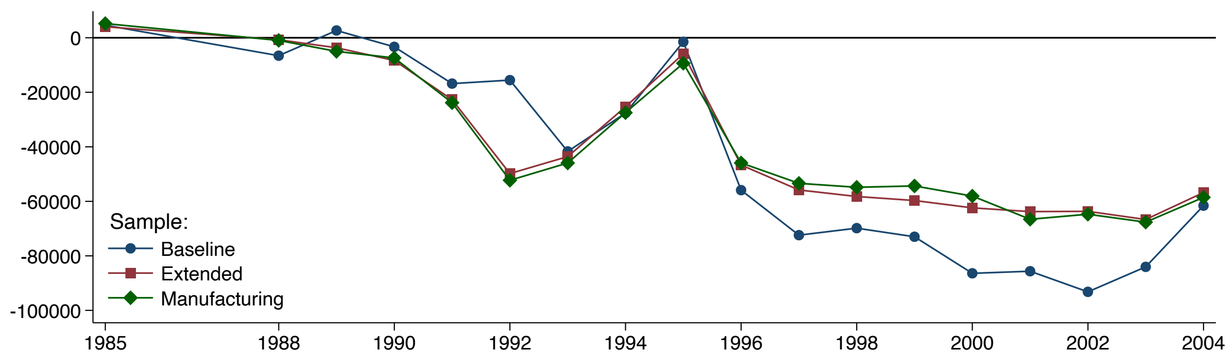
(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure 7: Sensitivity to Controls

Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ estimated from (12) with alternative vectors of controls, Controls$_i$. The curves with blue circles only include municipality indicator variables; red squares additionally include employer characteristics; green diamonds additionally include worker socio-demographic characteristics; orange triangles additionally include a manufacturing indicator variable (thereby replicating our baseline specification); and grey xs additionally include two-digit industry indicator variables.



(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



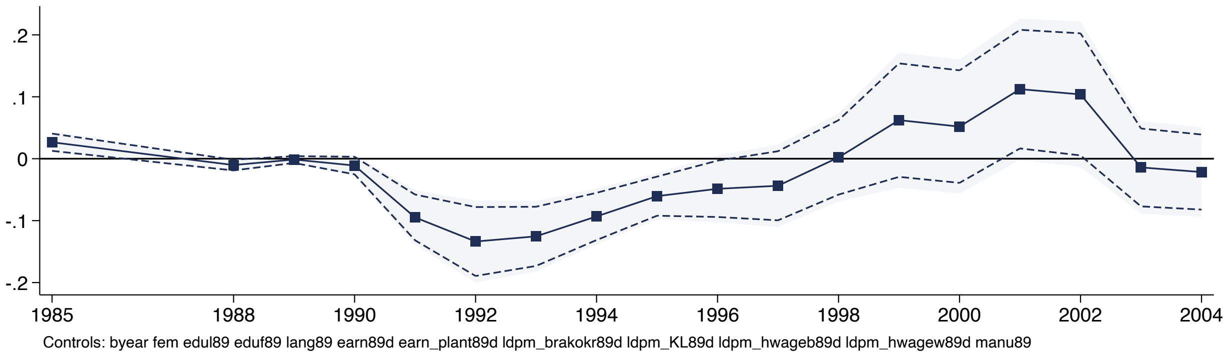
(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure 8: Sensitivity to Worker Sample

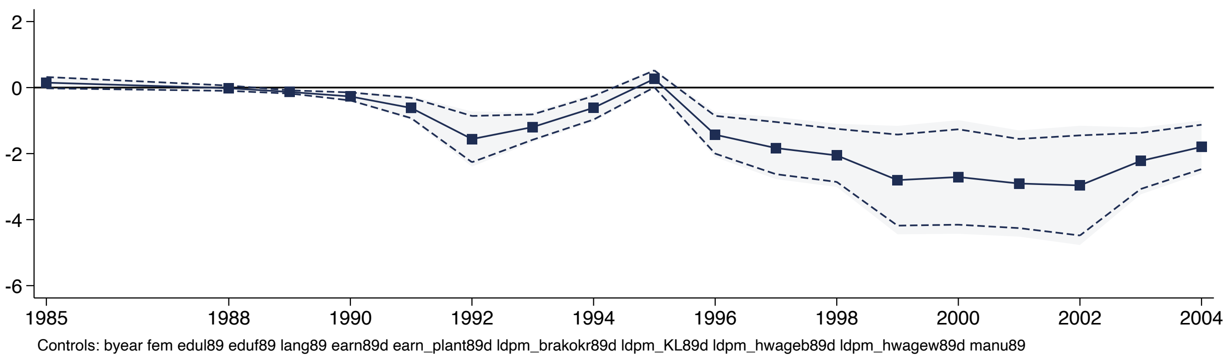
Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ estimated from (12) with different samples of workers. The blue circles represent our baseline sample. The red squares represent the larger sample that additionally includes workers who do not meet our high-labor-force-attachment criterion. Finally, the green diamonds represent the smaller sample that includes only workers initially employed in manufacturing.

controls, or an extended set of controls in which we include two-digit industry effects we find a negative and persistent interaction between worker exposure and municipality exposure. Our estimates of $\widehat{\beta}_t$ (the direct effect of worker exposure) are stable conditional on including employer exposure. Employer exposure is important because more exposed plants are larger and pay higher wages; during the financial crises of the Finnish great depression workers in these types of plants—whether or not they are exposed to Soviet trade—experience smaller earnings declines.

Worker Sample. Figure 8 varies our baseline worker sample. We consider our baseline sample but also a smaller sample of workers employed only in manufacturing in 1989 as well as a larger sample of workers who do not meet our definition of high attachment



(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure 9: Relative Earnings Specification

Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ estimated from (12) defining the dependent variable as $\Delta y_{it} \equiv y_{it}/\overline{y}_i$ instead of as $\Delta y_{it} \equiv y_{it} - \overline{y}_i$.

to the labor force in the years preceding the trade shock. Across samples, our results are very similar.

Relative vs. Absolute Earnings. Our baseline empirical specifications identify the impact of worker-level exposure and its heterogeneity across markets with different levels of market exposure on changes in absolute earnings: $\Delta y_{it} \equiv y_{it} - \overline{y}_i$. In Figure 9, we replace our baseline dependent variable with relative changes in earnings, $\Delta y_{it} \equiv y_{it}/\overline{y}_i$, which is more similar to the approach in Autor et al., 2014. This specification comes closer to a log change, yet—as in our baseline—does not drop observations with zero earnings. Results are qualitatively very similar to those in our baseline; of course, quantitative coefficient values cannot be compared directly across specifications.

In our baseline, we measure municipality exposure on the full working-age population. In Figure B.2 in Appendix B.3 we instead measure municipality exposure only on our baseline estimation sample. The resulting values of local labor market exposure are higher (so that the quantitative coefficient estimates are correspondingly lower) yet the qualitative pattern of estimates is otherwise identical to our baseline. Finally, as shown in Figure 2, there are a small number of municipalities with very high values of exposure. In Figure B.3 in Appendix B.3 we winsorize municipality exposure at the top percentile and results are again very similar to in our baseline.

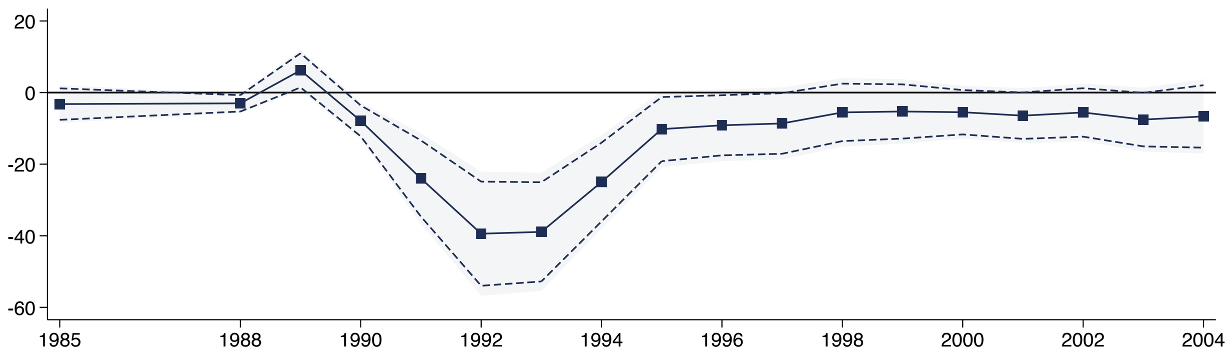
4.6 Earning versus Employment Dynamics

To this point, we have focused on earning dynamics. We have provided empirical evidence that (i) more exposed workers experience greater earnings decline in the response to the USSR shock and that (ii) these earnings declines are larger (in absolute value) in more exposed markets, a form of local scarring. While the two previous predictions are consistent with the model of Section 3.2, an additional implication of this model is that local scarring arises because more exposed workers, who are more likely to become unemployed in the response to the shock, are also less likely to be re-employed in markets that are more exposed. Formally, our model predicts that the probability of employment π_{it} of worker i at any date t satisfies: $d\pi_{it}/ds_i < 0$ and $d^2\pi_{it}/ds_i dS_m < 0$.[22] We conclude our empirical analysis by turning to these additional predictions about employment dynamics.

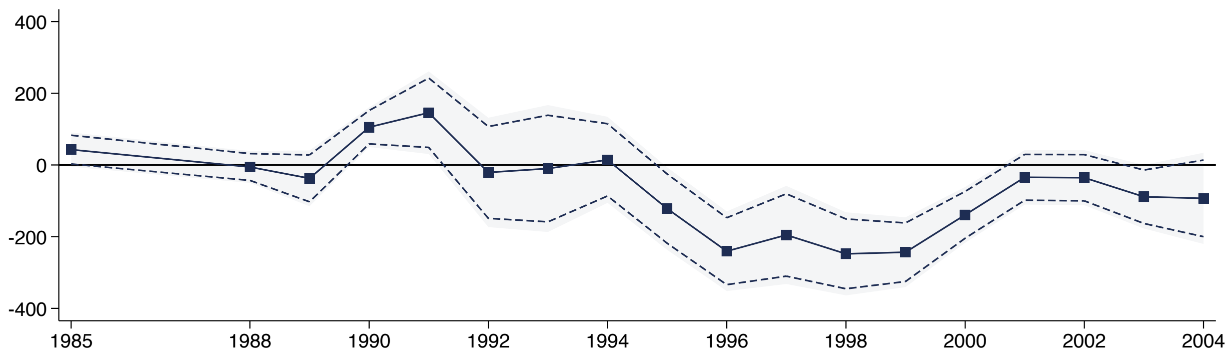
To do so, we repeat our baseline empirical specification, as described in equation (12), using changes in days employed Δn_{it} rather than earnings Δy_{it} as our dependent variable. According to our model, changes in those should be equal, on average, to changes in employment probabilities.[23] Figure 10 displays the predicted effects on employment $\hat{\beta}_t$ of worker exposure s_i together with the heterogeneous incidence $\hat{\gamma}_t$ of worker exposure across markets with different exposure, $s_i \times S_m$, estimated using regression (12). In line with our model and our baseline earnings results, we find a negative impact $\hat{\beta}_t$ of worker-level exposure on employment that peaks around 1992-1993 and dissipates in the medium-run. Although there is a positive and statistically significant estimate of $\hat{\gamma}_t$ in 1990 (recall that the shock occurs at the very end of this year) and 1991, it turns negative thereafter. Interestingly, in contrast to the earnings results, the interaction effect $\hat{\gamma}_t$ also converges to zero in the medium-run, consistent with downward-wage adjustment in the

[22]The sign of the cross-derivative here is unambiguous, unlike in Proposition 1, because it only depends on the job-finding rate effect and not the wage effect described in Section 3.2.

[23]As already noted in Section 4.2, this measure of employment does not include information on hours. So it is likely to over-estimate the employment of people working irregular shifts.



(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure 10: Days Employed Specification

Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ estimated from (12) defining the dependent variable as $\Delta n_{it} \equiv n_{it} - \overline{n}_i$ instead of as $\Delta y_{it} \equiv y_{it} - \overline{y}_i$, where n_{it} is days employed and y_{it} is earnings in year t for individual i.

medium-run.[24]

5 Concluding Remarks

What role do local labor markets play in propagating trade shocks? Is recent empirical evidence about significant differences in the incidence of trade shocks across local labor markets merely reflecting the fact that more exposed markets are inhabited by a greater share of equally affected workers or is there something distinct about the experience of workers exposed to trade in the more exposed markets? From a policy perspective, are national trade assistance programs well suited to compensate workers for the adverse

[24]Our extended model in which incumbent-worker wages are fully rigid—presented in Appendix A.3—can generate a more negative interaction effect for earnings than for employment, as observed in Figures 6 and 10.

consequences of globalization or should such programs inherit characteristics of place-based policies, with assistance to displaced workers conditioning on local labor-market conditions?

To make progress on these questions, we have combined employer-employee data and our own digitized export data to construct worker- and market-level exposures to a massive trade shock, the collapse of the Finnish-Soviet Trade Agreement. Theoretically, we have characterized analytically how these two measures of exposure shape worker-level dynamics in a model with downward wage rigidity. Our main empirical finding, consistent with the presence of significant wage rigidity, is that the negative effect of worker-level exposure to the USSR shock on earnings is substantially and significantly larger in more exposed labor markets in the short and long run, a form of local scarring.

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A Theoretical Appendix

A.1 Proof of Proposition 1

Consider a market with exposure S. We first characterize the job-finding rate in that market and establish its monotonicity with respect to S. Equations (3), (4), (5), (7), and (8) imply that the job-finding rate at any $t > 0$ is equal to

$$\kappa_{mt} = \frac{\left[e^{-\gamma t}(1-S_m)^{-\frac{1}{\sigma}} + (1-e^{-\gamma t})\right]^{-\sigma}(\lambda+\sigma\gamma) - \left[e^{-\gamma t}(1-S_m)^{-\frac{1}{\sigma}} + (1-e^{-\gamma t})\right]^{\frac{\sigma+1}{\sigma}}\sigma\gamma}{1-\left[e^{-\gamma t}(1-S_m)^{-\frac{1}{\sigma}} + (1-e^{-\gamma t})\right]^{-\sigma}}. \tag{A.1}$$

This can be rearranged more compactly as $\kappa_t = \tilde{\kappa}(x_{mt})$, with $\tilde{\kappa}(x_{mt}) \equiv [x_{mt}(\lambda+\sigma\gamma) - x_{mt}^{\frac{\sigma+1}{\sigma}}\sigma\gamma]/(1-x_{mt})$ and $x_{mt} \equiv \left[e^{-\gamma t}(1-S_m)^{-\frac{1}{\sigma}} + (1-e^{-\gamma t})\right]^{-\sigma}$, where $x_{mt} \in [1-S_m, 1]$ measures the employment share E_{mt}/N_m at date t, which is decreasing in S_m for all $t > 0$. Note also that $\tilde{\kappa}'(x_{mt}) = [\lambda+\sigma\gamma+\gamma h(x_{mt})]/\left(1-x_{mt}\right)^2$, with $h(x_{mt}) \equiv x_{mt}^{\frac{1}{\sigma}}[x_{mt}-(\sigma+1)]$. Since $h(1) = -\sigma$ and $h'(x_{mt}) = \frac{\sigma+1}{\sigma}x_{mt}^{\frac{1-\sigma}{\sigma}}(x_{mt}-1) \le 0$ for all $x_{mt} \in [1-S_{mt}, 1]$, we must have $\tilde{\kappa}'(x_{mt}) \ge [\lambda+\sigma\gamma+\gamma h(1)]/\left(1-x_{mt}\right)^2 > 0$. Combining this observation with the monotonicity of x_{mt} with respect to S_m, we conclude that $\kappa_{mt} = \tilde{\kappa}(x_{mt})$ is strictly decreasing in S_m for all $t > 0$.

Next, consider a worker with exposure s_i in a market with exposure S_m. The employment probability of this worker is given by the unique solution to (10) whose initial condition satisfies (9),

$$\pi_{it} = 1 - s_i e^{-\int_0^t(\lambda+\kappa_{mv})dv} - \lambda\int_0^t e^{-\int_v^t(\lambda+\kappa_{mz})dz}dv. \tag{A.2}$$

It is strictly decreasing in s_i; and since κ_{mt} is strictly decreasing in S_m for all t, it is also strictly decreasing in S_m.

Since earnings are equal to W_{mt} if a worker is employed and 0 otherwise, expected earnings are equal to

$$y_{it} = W_{mt}\pi_{it}, \tag{A.3}$$

with the market wage given by equation (7),

$$W_{mt} = \left(\frac{N_m}{\Phi_m}\right)^{-\frac{1}{\sigma}}\left[e^{-\gamma t} + (1-e^{-\gamma t})(1-S_m)^{\frac{1}{\sigma}}\right].$$

Equations (A.2) and (A.3) immediately imply

$$\frac{dy_{it}}{ds_i} = -W_{mt}e^{-\int_0^t(\lambda+\kappa_{mv})dv} < 0,$$

as argued in point (i) of Proposition 1.

The cross-derivative with respect to s_i and S_m, in turn, satisfies

$$\frac{d^2y_{it}}{ds_i dS_m} = \left[-\frac{d\ln W_{mt}}{dS_m} + \int_0^t (\frac{d\kappa_{mv}}{dS_m})dv\right] \times W_{mt}e^{-\int_0^t(\lambda+\kappa_{mv})dv},$$

the sign of which depends on whether the positive wage effect ($-d\ln W_{mt}/dS_m > 0$) dominates the negative job-finding-rate effect ($\int_0^t(\frac{d\kappa_{mv}}{dS_m})dv < 0$). Differentiating (7) and (A.1) with respect to S_m implies

$$-\frac{d\ln W_{mt}}{dS_m} = \frac{1}{\sigma}(1-e^{-\gamma t})(1-S_m)^{\frac{1}{\sigma}-1}x_{mt}^{\frac{1}{\sigma}},$$

$$\frac{d\kappa_{mv}}{dS_m} = -\frac{e^{-\gamma t}x_{mv}^{\frac{\sigma+1}{\sigma}}\left[\lambda+\sigma\gamma+\gamma x_{mv}^{\frac{1}{\sigma}}\left[x_{mv}-(\sigma+1)\right]\right]}{(1-x_{mv})^2(1-S_m)^{\frac{1}{\sigma}+1}}.$$

At $\gamma = 0$, we therefore get

$$-\frac{d\ln W_{mt}}{dS_m}\bigg|_{\gamma=0} = 0,$$

$$\frac{d\kappa_{mv}}{dS_m}\bigg|_{\gamma=0} = -\lambda/S_m^2 < 0.$$

Point (ii) of Proposition 1 follows from the two previous equations and the fact that both $-d\ln W_{mt}/dS_m$ and $\int_0^t(\frac{d\kappa_{mv}}{dS_m})dv$ are continuous in γ.

To establish point (iii), we consider first-order Taylor expansions of $-d\ln W_{mt}/dS_m$ and $\int_0^t(\frac{d\kappa_{mv}}{dS_m})dv$ around $t = 0$,

$$-\frac{d\ln W_{mt}}{dS_m} = \frac{\gamma}{\sigma}(1-S_m)^{\frac{1-\sigma}{\sigma}}t + o(t),$$

$$\int_0^t(\frac{d\kappa_{mv}}{dS_m})dv = -(\lambda/{S_m}^2)t + o(t).$$

For $\gamma > \lambda\sigma(1-S_m)^{\frac{\sigma-1}{\sigma}}/S_m^2$, the two previous equations imply the existence of $T > 0$ such that for all $t \in (0,T)$, we have $\frac{d^2y_{it}}{ds_i dS_m} > 0$, as argued in point (iii).

A.2 Extension to Positive Steady-State Unemployment

The goal of this Appendix is to show that the main results of Section 3 generalize to an environment in which the wage adjustment process maintains positive unemployment in the steady state. In particular, we generalize the definition of $\overline{W}_{mt}$ in equation (6) to allow for a steady-state unemployment rate of $u \in [0, 1)$:

$$\overline{W}_{mt} \equiv \left(\frac{N_m(1-u)}{\Phi_{mt}} \right)^{-1/\sigma}$$

We assume that the local labor market is in steady state just before date 0, with the wage given by $W_{m0} = \overline{W}_{m0}$ and with employment equal to $E_{m0} = (1-u)N_m$. In this case, the equations that characterize market- and worker-level outcomes following the trade shock at date $t = 0$ are little changed from our baseline. After the shock, the long-run wage jumps from $\overline{W}_{m0} = (N_m(1-u)/\Phi_m)^{-1/\sigma}$ to $\overline{W}_{m0^+} = (N_m(1-u)/\Phi'_m)^{-1/\sigma}$ whereas the market wage and unemployment rate are given by

$$W_{mt} = \left(\frac{N_m(1-u)}{\Phi_m} \right)^{-\frac{1}{\sigma}} \left[e^{-\gamma t} + (1 - e^{-\gamma t})(1 - S_m)^{\frac{1}{\sigma}} \right], \text{ for all } t > 0,$$

and

$$U_{mt} = N_m \left\{ 1 - (1 - S_m)(1-u) \left[e^{-\gamma t} + (1 - e^{-\gamma t})(1 - S_m)^{\frac{1}{\sigma}} \right]^{-\sigma} \right\}, \text{ for all } t > 0$$

in place of equations (7) and (8). On impact, the unemployment rate rises from u to $u + S_m(1-u)$, since a share S_m of the employed are fired. Whereas equations (9) and (10) remain unchanged, the job-finding rate—equation (A.1)—generalizes to

$$\kappa_{mt} = \frac{\left[e^{-\gamma t}(1 - S_m)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t}) \right]^{-\sigma} (\lambda + \sigma\gamma) - \left[e^{-\gamma t}(1 - S_m)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t}) \right]^{\frac{\sigma+1}{\sigma}} \sigma\gamma}{(1-u)^{-1} - \left[e^{-\gamma t}(1 - S_m)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t}) \right]^{-\sigma}}$$

which can be expressed more compactly as $\kappa_t = \tilde{\kappa}(x_{mt})$, with $\tilde{\kappa}(x_{mt}) \equiv [x_{mt}(\lambda + \sigma\gamma) - x_{mt}^{\frac{\sigma+1}{\sigma}} \sigma\gamma] / \left((1-u)^{-1} - x_{mt} \right)$. The mathematical definition of $x_{mt} \in [1 - S_m, 1]$ remains unchanged; however it now measures the share of the maximum employment share that is employed at date t: $x_{mt}(1-u) = E_{mt}/N_m$. Finally, if $u \in [0, \min\{\lambda/\gamma, 1\})$, then $\kappa'(x) > 0$ and all of our baseline results follow.[25]

[25] If $\lambda/\gamma < 1$ and $u > \lambda/\gamma$, then for sufficiently high values of $t > T$, we have $\kappa'(x) < 0$. In this case, our results hold for all $t \in (0, T)$.

A.3 Extension to Incumbent Wage Rigidity

The goal of this Appendix is to show that the main results of Section 3 generalize to an environment in which incumbent wages are more rigid than new hire wages. More specifically, we consider the same model as in Section 3.1, except for the fact that W_t now refers to the wage paid to all new hires at date t. Once hired by plant j at date t, we assume that worker i receives $W_{it} = W_t$ throughout her tenure at that plant. In the limit case where $\gamma \to \infty$, new hire wages are fully flexible, whereas incumbent wages are fully rigid.[26]

The wages of new hires $\{W_t\}$ and the unemployment levels $\{U_t\}$ remain given by equations (7) and (8),

$$W_t = \left(\frac{N}{\Phi}\right)^{-\frac{1}{\sigma}} \left[e^{-\gamma t} + (1 - e^{-\gamma t})(1-S)^{\frac{1}{\sigma}}\right], \text{ for all } t > 0,$$

$$U_t = N \left\{1 - (1-S)\left[e^{-\gamma t} + (1 - e^{-\gamma t})(1-S)^{\frac{1}{\sigma}}\right]^{-\sigma}\right\}, \text{ for all } t.$$

Likewise, the probability of employment π_{jt} continues to satisfy (9) and (10),

$$\pi_{j0^+} = 1 - s_j,$$

$$\dot{\pi}_{jt} = \kappa_t(1 - \pi_{jt}) - \lambda \pi_{jt} = \kappa_t - (\lambda + \kappa_t)\, \pi_{jt},$$

with the job-finding-rate given by equation (A.1),

$$\kappa_t = \frac{\left[e^{-\gamma t}(1-S)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t})\right]^{-\sigma} (\lambda + \sigma\gamma) - \left[e^{-\gamma t}(1-S)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t})\right]^{\frac{\sigma+1}{\sigma}} \sigma\gamma}{1 - \left[e^{-\gamma t}(1-S)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t})\right]^{-\sigma}}.$$

This implies that probabilities of employment are the same as in the baseline model of Section 3.1 and given by (A.2)

$$\pi_{jt} = 1 - s_j e^{-\int_0^t (\lambda + \kappa_v) dv} - \lambda \int_0^t e^{-\int_v^t (\lambda + \kappa_z) dz} dv.$$

The only difference between expected earnings in the two models come from the expected

[26] It is worth noting that we maintain the same assumption on the plant separation rate as in our baseline model: exposed plants fire workers at date 0 in proportion to their export sales shares and thereafter separate from workers at the exogenous rate λ. Since wages fall in response to the shock at date 0, this assumption rules out the possibility that plants fire higher wage workers in order to rehire lower wage labor. Given the institutional features of the Finnish labor market, we view this assumption a reasonable.

wage received by a worker employed at date t.

To this point, the baseline model of Section 3.1 and the present model yield identical results. We next turn to deriving expected earnings, where the two models diverge. In particular, with fixed incumbent wages, expected earnings at date t depend not only on the value of W_t at that date, but also its value in all previous dates. Let $t(w)$ denote the date at which a wage $w \in [W', W]$ is being offered to new hires. Inverting equation (7) gives

$$t(W) = \frac{1}{\gamma} \ln \left[\frac{1-(1-S)^{\frac{1}{\sigma}}}{w/W-(1-S)^{\frac{1}{\sigma}}} \right]. \tag{A.4}$$

For any $w \in [W', W]$, denote by $H_{jt}(w)$ the probability that a worker i initially employed by plant j at date 0 receives a wage $W_{it} \leq w$. $H_{jt}(w)$ depends on whether t is less than or greater than $t(w)$. If $t < t(w)$, then the probability of worker i receiving less than w is simply the probability of her being unemployed and receiving a wage of zero, since wages for the employed have not yet fallen to w at date t. If $t \geq t(w)$, then the probability of her receiving more than w is the product of the probability of her being employed at date $t(w)$ times the probability of her not losing her job between $t(w)$ and t; the probability she earns less than w is then 1 minus this. Summarizing this discussion,

$$H_{jt}(w) = \begin{cases} 1-\pi_{jt} & \text{for all } w \in [W', W] \text{ and } t < t(w), \\ 1-\pi_{jt(w)} e^{-\lambda[t-t(w)]} & \text{for all } w \in [W', W] \text{ and } t \geq t(w). \end{cases} \tag{A.5}$$

The expected earnings Y_{jt} of workers initially employed by plant j at date 0 are then equal to

$$Y_{jt} = W(1-s_j)e^{-\lambda t} + \int_{W_t}^{W} w dH_{jt}(w)dw.$$

Differentiating (A.5) and substituting in the previous expression implies, after a change of variable,

$$Y_{jt} = W(1-s_j)e^{-\lambda t} + \int_0^t W_v \left[\dot{\pi}_{jv} + \lambda \pi_{jv}\right] e^{-\lambda[t-v]} dv.$$

Combining this expression with (10) and (A.2), we obtain, after rearrangements,

$$Y_{jt} = s_j \left[-W_t e^{-\int_0^t (\lambda+\kappa_z)dz} + \int_0^t e^{-\int_0^v (\lambda+\kappa_z)dz} \dot{W}_v dv \right] + Y_t,$$

where $Y_t \equiv We^{-\lambda t} + e^{-\lambda t} \int_0^t \left(1 - e^{-\int_0^v (\lambda+\kappa_z)dz} - \int_0^v \kappa_z e^{-\int_z^v (\lambda+\kappa_r)dr} dz\right) W_v \kappa_v e^{\lambda v} dv$ is independent of j.

Although expected earnings differs from our baseline model, where it is simply equal to $W_t \pi_{jt}$, we still obtain results (i) and (ii) of Proposition 1, as we now show. Differentiating the previous expression with respect to s_j, we get

$$\frac{dY_{jt}}{ds_j} = -W_t e^{-\int_0^t (\lambda+\kappa_z)dz} + \int_0^t e^{-\int_0^v (\lambda+\kappa_z)dz} \dot{W}_v dv < 0,$$

as argued in point (i) of Proposition 1. The cross-derivative with respect to s_j and S, in turn, satisfies

$$\frac{d^2Y_{jt}}{ds_j dS} = \left[-\frac{d \ln W_t}{dS} + \int_0^t (\frac{d\kappa_v}{dS}) dv \right] \times W_t e^{-\int_0^t (\lambda+\kappa_v)dv}$$
$$- \int_0^t \left\{ \left[-\frac{d \ln \dot{W}_v}{dS} + \int_0^v (\frac{d\kappa_z}{dS}) dz \right] e^{-\int_0^v (\lambda+\kappa_z)dz} \dot{W}_v \right\} dv.$$

At $\gamma = 0$, we are back to the baseline model with fully rigid wages (both for incumbent and new hires), with

$$\frac{d^2Y_{jt}}{ds_j dS} = \int_0^t (\frac{d\kappa_v}{dS}) dv \times W_t e^{-\int_0^t (\lambda+\kappa_v)dv} < 0.$$

Point (ii) of Proposition 1 therefore still holds by the same continuity argument.

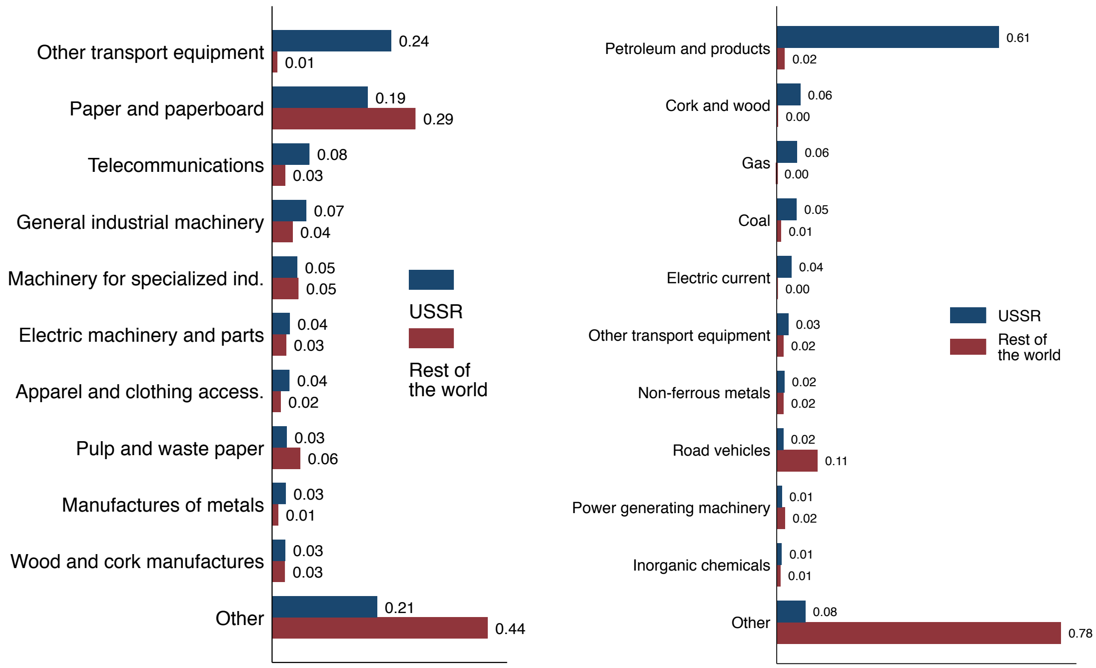
The only part of Proposition 1 that no longer holds in the present environment is point (iii). Around $t = 0$, a first-order Taylor expansion now implies

$$\frac{d^2Y_{jt}}{ds_j dS} = -\left(\frac{N}{\Phi}\right)^{-\frac{1}{\sigma}} \frac{\lambda}{S^2} t + o(t).$$

It follows that $\frac{d^2Y_{jt}}{ds_j dS} < 0$ if t is small enough. Intuitively, the wage effect is weaker here than in our baseline model, since wages of incumbent workers do not decline; hence, the job-finding-rate effect, which is common in the two models, is more likely to dominate.

B Empirical Appendix

B.1 The Composition of Finland's Exports and Imports



(a) Exports **(b)** Imports

Figure B.1: Composition of Finland's Exports and Imports

B.2 Characteristics by Exposure in 1989

Table B.1: Correlation Between Municipality-Level Exposure and 1989 Characteristics

	1. S_m	2. $Manu_m$	3. Edu_m	4. Age_m
1. Exposure (S_m)	1.00	0.27	0.08	-0.08
2. Share in manufacturing ($Manu_m$)		1.00	0.19	-0.24
3. Share with secondary degree or more (Edu_m)			1.00	-0.68
4. Average age (Age_m)				1.00

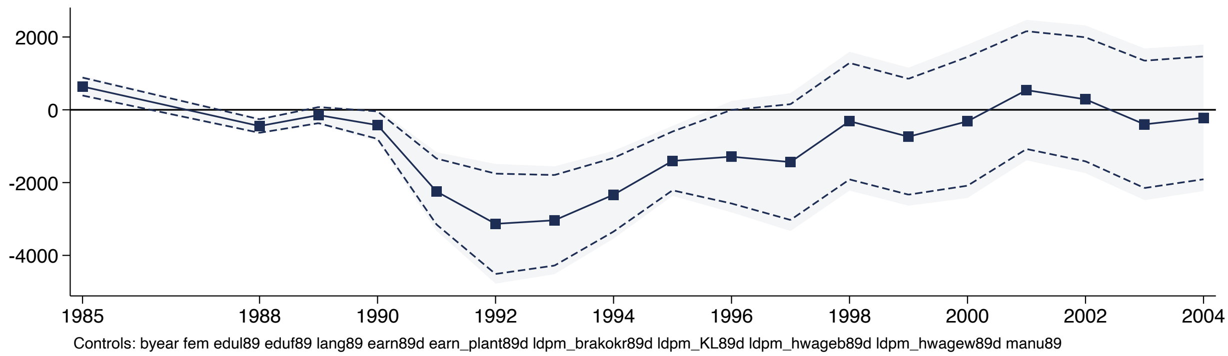
Table B.2: LDPM Plants by Exposure to USSR Exports, 1989

		By share of output exported to the USSR in 1989			
	All	0%	0–10%	10–50%	50–100%
A: Plant characteristics					
Gross output	8,207	4,991	33,860	38,277	15,615
Value-added	2,770	1,725	11,140	11,906	6,013
No. of workers	58.9	38.3	221.8	245.7	144.0
Value-added per worker	44.0	42.2	58.5	45.7	41.0
Share of blue-collar workers	0.74	0.74	0.71	0.72	0.73
Blue-collar average wages	8.2	8.1	9.0	8.7	8.6
White-collar average wages	11.8	11.8	12.4	12.0	12.0
Capital / labor ratio	60.3	59.2	70.5	57.1	41.5
Plant age	10.5	10.2	12.9	12.6	12.5
Multiplant firm	0.31	0.25	0.82	0.67	0.58
Share of ouput exported to the USSR	0.01	0.00	0.02	0.24	0.82
B: Group characteristics					
Share of output	1.00	0.54	0.39	0.06	0.01
Share of workers	1.00	0.58	0.36	0.05	0.01
Share of USSR exports	1.00	0.00	0.30	0.44	0.26
No. of plants	6,865	5,989	734	99	43
No. of workers	404,462	229,507	162,787	24,327	6,192

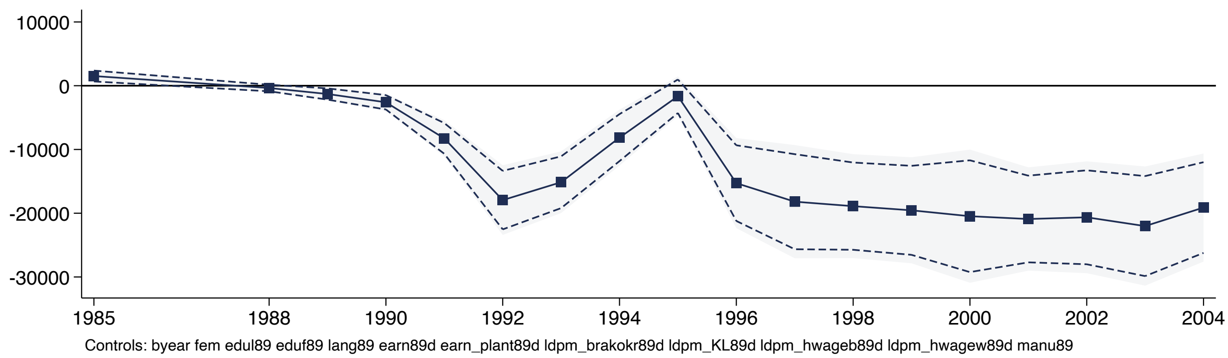
Table B.3: Individual Characteristics by Exposure to USSR Exports, 1989

	Manufacturing					Other industries
		By plant exposure				
	All	0%	0–10%	10–50%	50–100%	
A: Demographics						
Female	0.28	0.29	0.25	0.28	0.31	0.47
Age	35.4	35.2	35.9	35.8	35.7	35.4
First language Finnish	0.96	0.95	0.97	0.96	0.97	0.94
C: Level of education						
Less than secondary / unknown	0.33	0.33	0.32	0.30	0.23	0.27
Secondary	0.44	0.44	0.43	0.45	0.44	0.35
Advanced vocational	0.15	0.15	0.14	0.14	0.17	0.22
College	0.09	0.08	0.10	0.11	0.16	0.16
D: Field of education						
Technical	0.50	0.48	0.53	0.55	0.62	0.25
Other	0.16	0.17	0.14	0.14	0.15	0.45
Unknown	0.33	0.33	0.32	0.30	0.23	0.27
E: Earnings						
Annual earnings						
Earnings growth, 1985–89						

B.3 Sensitivity Analysis



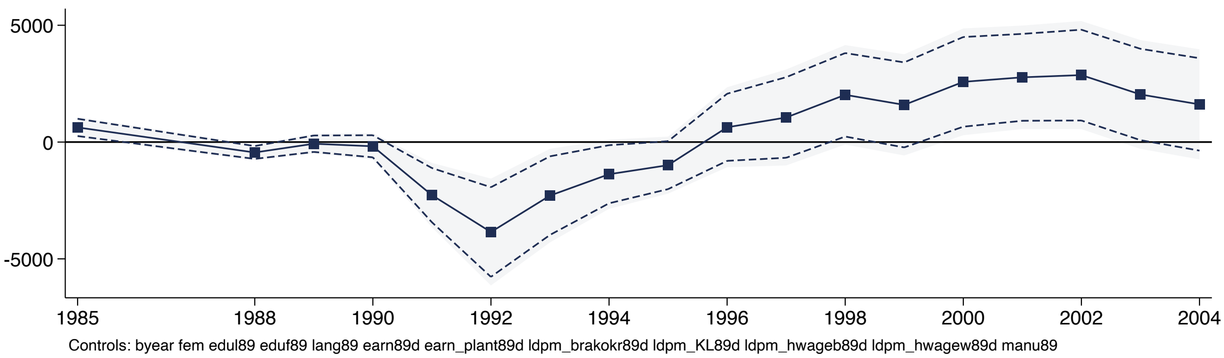
(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



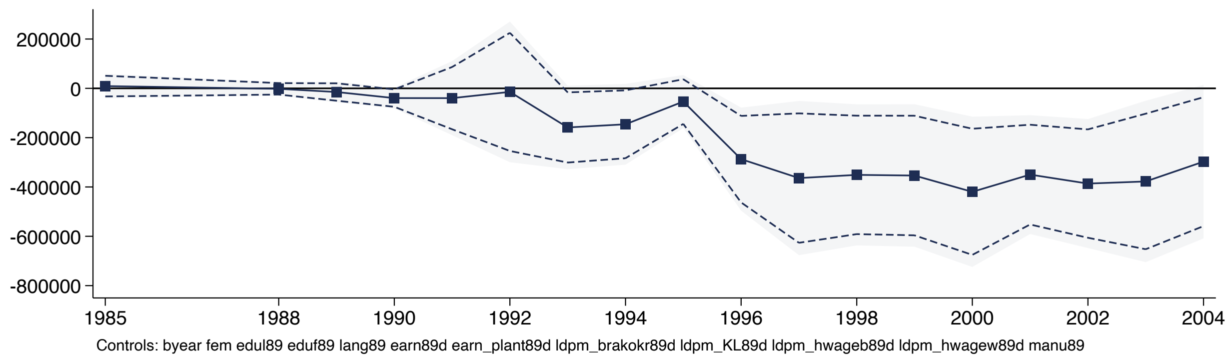
(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure B.2: Sensitivity to Measuring Market-Level Exposure on the Attached Sample

Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ estimated from (12) defining labor-market exposure on the baseline sample rather than the full working-age population.



(a) Estimated effect of worker-level exposure ($\hat{\beta}_t$)



(b) Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

Figure B.3: Sensitivity to Winsorizing Market-Level Exposure

Notes: Predicted $\hat{\beta}_t$ and $\hat{\gamma}_t$ estimated from (12) winsorizing labor-market exposure at the top percentile

Table B.4: Sensitivity: Estimated effect of worker-level exposure ($\hat{\beta}_t$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1985	1,469	663	666	645	579	639	627	697	0.027	538
	(288)	(198)	(152)	(151)	(137)	(149)	(224)	(203)	(0.008)	(206)
1988	-766	-403	-461	-451	-431	-446	-445	-476	-0.010	-414
	(117)	(110)	(113)	(113)	(114)	(113)	(167)	(148)	(0.005)	(113)
1989	-562	-204	-155	-148	-74	-146	-71	-124	-0.001	-99
	(234)	(158)	(136)	(136)	(113)	(134)	(214)	(193)	(0.003)	(183)
1990	142	-292	-387	-408	-110	-420	-179	-161	-0.011	-327
	(281)	(240)	(227)	(228)	(239)	(230)	(288)	(278)	(0.009)	(237)
1991	-1,046	-2,131	-2,301	-2,265	-1,610	-2,244	-2,272	-2,581	-0.095	-2,070
	(616)	(563)	(552)	(551)	(504)	(551)	(705)	(677)	(0.022)	(526)
1992	856	-3,047	-3,183	-3,169	-2,348	-3,132	-3,852	-4,466	-0.134	-2,806
	(925)	(855)	(844)	(844)	(763)	(838)	(1,166)	(1,038)	(0.034)	(804)
1993	3,775	-2,851	-2,998	-3,040	-2,516	-3,035	-2,292	-2,717	-0.125	-2,683
	(953)	(821)	(766)	(765)	(657)	(756)	(1,023)	(998)	(0.029)	(713)
1994	6,747	-1,998	-2,206	-2,306	-2,189	-2,334	-1,377	-1,502	-0.093	-1,931
	(931)	(672)	(613)	(613)	(582)	(615)	(756)	(725)	(0.023)	(600)
1995	10,377	-829	-1,220	-1,386	-1,606	-1,404	-988	-949	-0.060	-1,049
	(999)	(571)	(488)	(491)	(472)	(491)	(623)	(584)	(0.019)	(494)
1996	9,015	-661	-1,107	-1,249	-1,539	-1,288	633	223	-0.049	-879
	(1,130)	(857)	(768)	(772)	(612)	(781)	(873)	(881)	(0.028)	(782)
1997	9,071	-714	-1,244	-1,386	-1,842	-1,436	1,053	543	-0.044	-968
	(1,279)	(1,024)	(941)	(945)	(741)	(966)	(1,048)	(1,093)	(0.034)	(936)
1998	10,513	520	-114	-257	-1,001	-313	2,023	1,438	0.002	273
	(1,277)	(1,059)	(949)	(956)	(716)	(973)	(1,086)	(1,133)	(0.037)	(1,001)
1999	9,114	86	-575	-690	-1,390	-739	1,592	1,009	0.062	-293
	(1,261)	(1,080)	(945)	(952)	(743)	(967)	(1,106)	(1,134)	(0.056)	(980)
2000	9,634	615	-155	-266	-938	-316	2,579	1,996	0.052	226
	(1,382)	(1,207)	(1,049)	(1,056)	(805)	(1,075)	(1,167)	(1,177)	(0.055)	(1,055)
2001	10,811	1,568	703	593	-456	541	2,772	2,201	0.112	1,217
	(1,278)	(1,154)	(971)	(978)	(728)	(984)	(1,130)	(1,121)	(0.058)	(972)
2002	9,700	1,349	445	351	-704	288	2,867	2,207	0.104	756
	(1,385)	(1,196)	(1,018)	(1,026)	(808)	(1,036)	(1,181)	(1,194)	(0.060)	(993)
2003	8,569	724	-281	-353	-1,242	-399	2,038	1,466	-0.014	292
	(1,397)	(1,185)	(1,044)	(1,047)	(873)	(1,063)	(1,188)	(1,213)	(0.038)	(1,052)
2004	8,461	1,004	-135	-199	-1,138	-221	1,614	1,214	-0.022	602
	(1,327)	(1,111)	(1,021)	(1,020)	(872)	(1,026)	(1,203)	(1,177)	(0.037)	(1,016)
Outcome	BL	BL	BL	BL	BL	BL	BL	BL	Relative	BL
Sample	BL	BL	BL	BL	BL	BL	BL	BL	BL	all
Measure for S_m	BL	BL	BL	BL	BL	BL	Wins.	trimmed	BL	BL
Controls:										
Employer char.	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
Worker char.	no	no	yes	yes	yes	yes	yes	yes	yes	yes
Manufacturing	no	no	no	yes	no	yes	yes	yes	yes	yes
2-digit industry	no	no	no	no	yes	no	no	no	no	no
N	627,070	627,070	627,070	627,070	627,069	627,070	627,070	626,712	627,070	830,639

Table B.5: Sensitivity: Estimated interaction effect between worker- and market-level exposures ($\hat{\gamma}_t$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1985	3,878	3,386	4,079	4,044	6,172	1,518	9,151	-1,399	0.149	5,207
	(3,210)	(2,109)	(1,585)	(1,574)	(1,151)	(519)	(25,435)	(19,141)	(0.104)	(2,184)
1988	-1,163	-1,521	-757	-739	-1,238	-359	-1,892	1,966	-0.019	-962
	(940)	(901)	(906)	(910)	(910)	(313)	(14,120)	(9,769)	(0.049)	(773)
1989	-3,328	-2,324	-3,666	-3,653	-5,218	-1,298	-14,853	-6,164	-0.132	-4,982
	(2,496)	(1,816)	(1,537)	(1,530)	(1,181)	(537)	(21,403)	(16,018)	(0.030)	(2,196)
1990	-6,189	-8,691	-8,287	-8,321	-7,283	-2,600	-39,562	-33,976	-0.269	-7,394
	(2,502)	(3,413)	(2,310)	(2,315)	(1,976)	(683)	(21,434)	(16,926)	(0.074)	(2,486)
1991	-19,076	-24,171	-22,741	-22,680	-22,602	-8,267	-39,680	10,280	-0.617	-23,829
	(4,512)	(4,640)	(4,962)	(4,957)	(4,269)	(1,465)	(76,671)	(52,775)	(0.187)	(4,091)
1992	-49,145	-51,608	-49,830	-49,806	-49,288	-17,946	-14,454	85,541	-1.560	-52,275
	(9,457)	(10,150)	(11,014)	(11,016)	(9,726)	(2,789)	(145,563)	(78,152)	(0.426)	(8,446)
1993	-49,273	-46,012	-43,496	-43,583	-35,160	-15,138	-158,674	-77,287	-1.197	-45,922
	(10,903)	(7,734)	(6,689)	(6,700)	(7,405)	(2,468)	(86,443)	(61,917)	(0.233)	(5,953)
1994	-36,898	-28,271	-25,124	-25,330	-18,113	-8,139	-145,786	-109,035	-0.613	-27,468
	(14,778)	(8,800)	(7,220)	(7,232)	(8,180)	(2,241)	(83,594)	(69,009)	(0.217)	(6,626)
1995	-21,511	-9,591	-5,593	-5,875	79	-1,650	-53,620	-51,274	0.264	-9,362
	(12,841)	(7,370)	(4,989)	(5,007)	(5,616)	(1,599)	(55,022)	(40,492)	(0.155)	(4,550)
1996	-61,575	-51,351	-46,432	-46,672	-36,725	-15,280	-287,221	-199,874	-1.428	-45,919
	(19,730)	(14,433)	(11,715)	(11,733)	(10,855)	(3,607)	(106,653)	(93,265)	(0.347)	(10,303)
1997	-72,712	-61,408	-55,522	-55,822	-41,170	-18,192	-363,905	-256,659	-1.833	-53,395
	(24,293)	(18,244)	(15,217)	(15,218)	(12,947)	(4,532)	(159,532)	(148,211)	(0.480)	(12,714)
1998	-77,378	-64,716	-57,912	-58,215	-44,803	-18,893	-350,944	-234,657	-2.054	-54,837
	(22,634)	(17,766)	(14,119)	(14,130)	(12,353)	(4,160)	(145,993)	(135,639)	(0.488)	(12,851)
1999	-75,392	-66,658	-59,454	-59,698	-43,994	-19,546	-353,513	-236,412	-2.803	-54,346
	(22,870)	(18,018)	(14,029)	(14,036)	(11,980)	(4,245)	(147,404)	(133,619)	(0.838)	(12,506)
2000	-81,005	-70,486	-62,150	-62,387	-45,820	-20,468	-419,651	-297,934	-2.709	-58,057
	(26,974)	(21,894)	(17,397)	(17,403)	(14,235)	(5,329)	(155,501)	(138,399)	(0.878)	(15,052)
2001	-83,330	-72,822	-63,533	-63,768	-47,529	-20,909	-349,823	-231,175	-2.907	-66,568
	(21,413)	(18,305)	(13,434)	(13,440)	(10,908)	(4,133)	(122,961)	(100,635)	(0.821)	(12,199)
2002	-84,837	-73,793	-63,458	-63,659	-48,472	-20,641	-386,153	-256,666	-2.964	-64,720
	(24,496)	(20,210)	(15,120)	(15,128)	(13,039)	(4,478)	(133,525)	(117,110)	(0.922)	(13,260)
2003	-85,921	-78,489	-66,502	-66,654	-51,078	-22,021	-377,597	-255,840	-2.221	-67,635
	(24,887)	(20,611)	(15,477)	(15,475)	(13,426)	(4,769)	(167,049)	(150,420)	(0.517)	(13,908)
2004	-79,560	-70,429	-56,636	-56,773	-37,356	-19,115	-297,237	-203,916	-1.798	-58,538
	(21,924)	(18,250)	(12,964)	(12,953)	(10,240)	(4,326)	(158,908)	(138,301)	(0.408)	(12,446)
Outcome	BL	BL	BL	BL	BL	BL	BL	BL	Relative	BL
Sample	BL	BL	BL	BL	BL	BL	BL	BL	BL	all
Measure for S_m	full	full	full	full	full	baseline	winsorized	trimmed	full	full
Controls:										
Employer char.	no	yes	yes	yes	yes	yes	yes	yes	yes	yes
Worker char.	no	no	yes	yes	yes	yes	yes	yes	yes	yes
Manufacturing	no	no	no	yes	no	yes	yes	yes	yes	yes
2-digit industry	no	no	no	no	yes	no	no	no	no	no
N	627,070	627,070	627,070	627,070	627,069	627,070	627,070	626,712	627,070	830,639