

# Exposure(s) to Trade and Earnings Dynamics: Evidence from the Collapse of Finnish-Soviet Trade\*

Arnaud Costinot  
MIT

Matti Sarvimäki  
Aalto

Jonathan Vogel  
UCLA

This Version: June 2022

## Abstract

How do local labor markets shape the response to trade shocks? Do workers whose employers are more exposed to negative trade shocks fare equally poorly across markets or is there something distinct about their experience in the most negatively 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 the earnings trajectories of Finnish workers. Combining newly-digitized data on Finnish firms’ licensed exports to the USSR with matched employer-employee data, we construct measures of both worker and market exposure to the USSR shock. We find that more exposed workers within a labor market experience systematically lower earnings after the shock and that the negative effect of worker exposure is persistently larger in more exposed markets, a form of local scarring. We develop a simple model of labor market dynamics with wage rigidity that rationalizes the previous empirical results and generates new theoretical predictions about the dynamic response of employment and wages, all broadly consistent with the Finnish experience.

---

\* Author contacts: [costinot@mit.edu](mailto:costinot@mit.edu), [matti.sarvimaki@aalto.fi](mailto:matti.sarvimaki@aalto.fi), and [jvogel@econ.ucla.edu](mailto:jvogel@econ.ucla.edu). We thank Rodrigo Adao, David Atkin, Ariel Burstein, Dave Donaldson, Kristiina Huttunen, Felix Tintelnot, and numerous seminar participants for helpful comments. Sarvimäki also thanks OP-Pohjola Group Research Foundation for financial support.

# 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 faring 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 social programs designed to compensate workers for the adverse consequences of globalization, 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 these programs to inherit characteristics of place-based policies, with assistance conditioning on local labor-market conditions, as advocated by [Austin et al. \(2018\)](#).

To make progress on these questions, we focus on a massive trade shock: the collapse of the Finnish-Soviet bilateral trade agreement. Combining newly-digitized data on Finnish firms’ licensed exports to the USSR with matched employer-employee data, we are able to construct measures of both worker and market exposure to the USSR shock and use them 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. Our main empirical finding is that while more exposed workers systematically experience lower earnings after the shock, the negative effect of worker exposure is persistently larger in more exposed markets, a form of local scarring.

Section 2 first describes the historical background of the Finnish-USSR trade relationship and its termination. On December 6th, 1990, the Soviet Union unilaterally canceled the five-year trade agreement that had been signed the previous year. This cancelation and the severity and duration of the resulting trade collapse took Finland by surprise. Finnish plants, however, varied greatly in the intensity of their exports to the USSR, which we document by digitizing firm-level reports of transactions with the Soviet Union for the year 1989 from the Office of Licenses (Lisenssivirasto) and linking these to the Longitudinal Data on Plants in Finnish Manufacturing (LDPM). This heterogeneity allows us, in turn, to create two distinct measures of exposure to the USSR shock: (i) *worker expo-*

*sure*, equal to the share of USSR exports in the sales of the plant in which a worker is employed, and (ii) *market exposure*, equal to the weighted average of USSR export shares across plants in a municipality, with weights equal to each plants' employment share.

Section 3 describes our main empirical findings about the impact of worker and market exposures to the USSR shock on the path of worker annual earnings. Our first result focuses on the the impact of worker exposure using a double-difference strategy that compares 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. 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. Among workers with positive exposure, going from the 10th to the 90th percentile of exposure to the USSR shock lowers average earnings in 1992 by 732 euros, or about 3% of average annual income in that year.

Our second, and most novel result uses a triple-difference that compares how the previous double-difference—in the earnings changes of more and less exposed workers—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 exposure in 1992, our results imply an earnings gap of 658 euros if they are located in the municipality at the 10th percentile of market exposure, but a gap of about 790 euros in the municipality at the 90th percentile, a 20% increase. The previous finding is robust to a variety of controls and alternative specifications.

Motivated by the previous findings, as well as the institutional features of the Finnish labor market, Section 4 develops a minimalistic model of labor market dynamics in the presence of wage rigidity. We provide an analytic characterization of the dynamic responses of wages, employment, and earnings to a one-time negative export shock as a function of market and worker exposures, both defined as in our earlier empirical analysis. 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, however, works in the 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 exposure on earnings is larger in more exposed markets if the job-finding-rate effect dominates the wage effect, which occurs when downward wage rigidities are substantial. The opposing implications for earnings of the job-finding-rate and wages effects, and the role played by wage rigidity in shaping their relative importance, are the key analytic insights of our simple model.

In addition to offering a structural interpretation of our main empirical findings on the impact of worker and market exposures on earnings, we also generate new theoretical predictions about the dynamic response of employment and wages to trade shocks in the presence of wage rigidity, distinct from those of existing models in the trade literature, and for which we also find support in the data. Specifically, we document that in line with the previous discussion, more exposed workers within a labor market are systematically employed fewer days and that this negative effect of worker exposure is larger in more exposed markets. We also find that market exposure to the USSR tends to reduce the number of days worked, but only in the short run, while steadily reducing hourly wages throughout the post-period.

## Related Literature

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, e.g., [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 fare equally poorly across markets.<sup>1</sup>

The trade shock that we focus on, the collapse of the Finnish-Soviet bilateral trade

---

<sup>1</sup>As should be clear, exposure to the USSR shock in our analysis always refers to direct export exposure, not import exposure or indirect export exposure through input-output linkages. In practice, Finnish workers and markets may also be differentially exposed because Finnish plants or their suppliers vary in the intensity of their imports from the USSR, mostly oil. Unfortunately, our dataset does not include information about oil purchases or input-output linkages between plants, as in [Adao et al. \(2021\)](#), [Alfaro-Urena et al. \(2021\)](#), and [Dhyne et al. \(2022\)](#), which prevents us from further exploring such considerations.

agreement, has featured prominently in analyses of the Finnish Great Depression, e.g., [Honkapohja and Koskela \(1999\)](#), [Jonung et al., eds \(2009\)](#), [Gorodnichenko et al. \(2012\)](#), and [Gulan et al. \(2021\)](#). The previous papers have studied whether the USSR shock contributed significantly to the collapse of Finnish GDP over that time period, which they explore using aggregate and sector data. In this paper we shed light instead on the distributional consequences of the USSR shock and the extent to which they might have been more severe within the most negatively affected markets, which we explore using firm-level exports to the USSR and matched employer-employee data.<sup>2</sup>

Our empirical analysis is also related to the displacement literature pioneered by [Jacobson et al. \(1993\)](#). Through the lens of our model, one can view of our regressions as the reduced-forms of 2SLS regressions, whose first stages would regress a dummy for being fired on measures of exposure to the USSR shock and whose second stages would regress earnings on a dummy for being fired, similar to the regressions considered in the displacement literature. Interpreted in this way, our main empirical results provide the spatial counterpart of the business cycle analysis of [Davis and von Wachter \(2011\)](#), [Korkeamäki and Kyrrä \(2014\)](#), [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.<sup>3</sup>

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, e.g., [Dix-Carneiro \(2014\)](#), [Caliendo et al. \(2019\)](#), and [Traiberman \(2019\)](#), who emphasize transitional dynamics due to moving costs in the presence of idiosyncratic preference shocks across workers. An implication of such frictions is that in response to a negative labor demand shock, declines in employment should be larger in the long run than in the short run, as workers wait for beneficial idiosyncratic shocks before moving out of the negatively impacted sector or region, whereas declines in wages should be larger in the short run than in the long run, as labor supply slowly adjusts downward. This is the same type of transitional dynamics that arises in the model with

---

<sup>2</sup>The USSR shock is also used by [Einiö \(2018\)](#) as a shifter of the labor supply faced by Finnish plants in industries that do not export to the USSR, which he uses to estimate the elasticity of their labor demand.

<sup>3</sup>The heterogeneous effects that we document across local labor markets also resonate well with the findings by [Hyman \(2018\)](#) that returns to trade adjustment assistance program tend to be lower in regions with higher unemployment rates. Through the lens of our model, both our findings and his derive from the fact that it is harder to find jobs in the most negatively affected markets.

search frictions and bargaining à la Helpman et al. (2010), as shown in Helpman and Itskhoki (2015). In contrast, our theoretical framework emphasizes wage rigidities, following a very long tradition in the macro literature, see, e.g., Keynes (1925), Friedman (1953), Akerlof et al. (1996), Blanchard and Galí (2010), Schmitt-Grohé and Uribe (2016) as well as recent quantitative work by Rodríguez-Clare et al. (2020). As mentioned above, this generates the opposite dynamics with larger employment changes in the short run than in the long run and larger wage changes in the long run than the short run, for which we find support in the data.<sup>4</sup> These novel findings point towards very different, and largely unexplored, structural determinants of the consequences of international trade, from the speed of wage adjustment to the extent of labor market churning.

## 2 Historical Background and Data

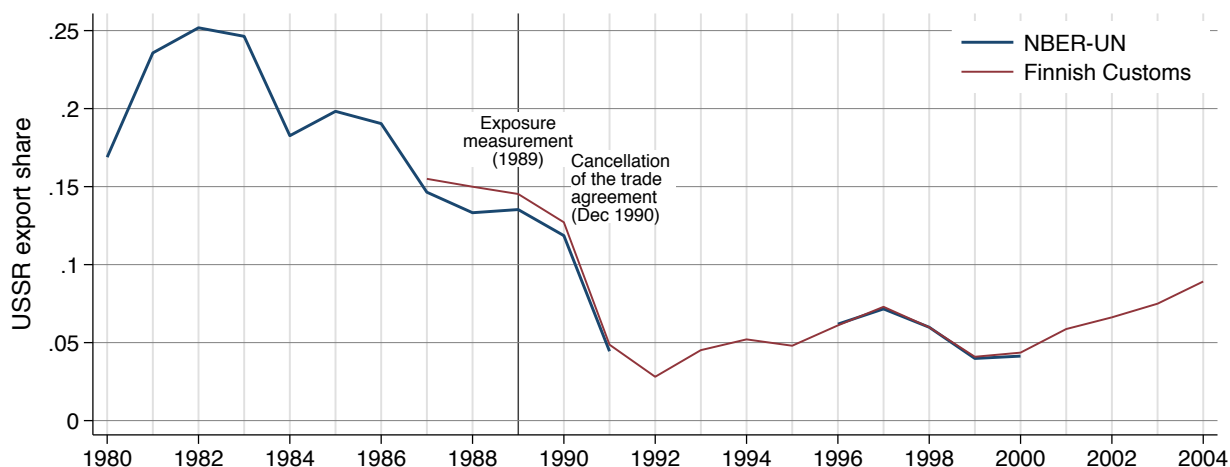
### 2.1 The Collapse of the Finnish-Soviet Trade Agreement

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 A.1 in Appendix A.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 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*

---

<sup>4</sup>For direct evidence of downward wage rigidities, see, e.g., Fortin (1996), Fehr and Goette (2005), Barattieri et al. (2014), and Kaur (2019).



**Figure 1: The USSR Shock**

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

*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 3.6 billion in 1990 to 1.2 billion euros in 1991 (in 2010 euros). In 1992, exports to the newly formed Russian Federation were only 800 million. 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 and persistent drop is what we will refer to as the “USSR shock” in the rest of our analysis.

## 2.2 Exposure(s) to the USSR Shock

To measure exposure to the USSR shock, we first combine data about exports to the USSR at the firm-and-product level with data on gross-output at the plant-and-product level. Using these two pieces of information, we infer the shares of USSR exports in gross output at the plant-level. We then match plants to municipalities and workers to create two distinct measures of exposure to the USSR shock, one at the market level and one at the worker level, which will be at the core of our empirical analysis.



**Firm-and-Product Data.** 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 bi-weekly 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.<sup>5</sup> This provides us with the value of exports to the USSR of product  $p$  by firm  $f$  in 1989, which we denote  $x_{fp,1989}$ .

**Plant-and-Product Data.** We have linked the previous exports data with 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 characteristics, including the municipalities in which their plants are located.<sup>6</sup> For each plant  $j$  in the LDPM, we directly observe the value of gross output at the plant-and-product level, which we denote  $q_{jp,1989}$ .

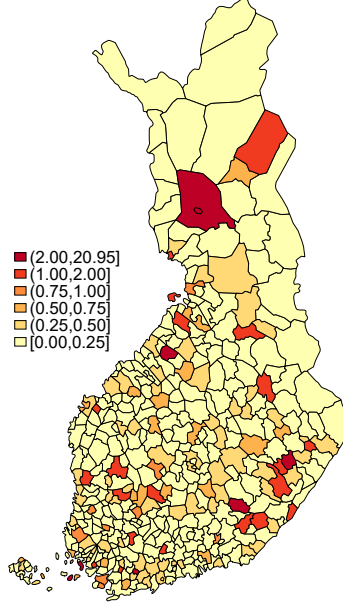
**Plant Export Intensity.** Consider a plant  $j$  belonging to a firm  $f$  that appears in both LDPM and Lisenssivirasto's records. If plant  $j$  belongs to a single-plant firm, we also directly observe the value of USSR exports at the plant-product-level,  $x_{jp,1989} = x_{fp,1989}$ . We can therefore compute the share of USSR exports in gross output at the plant level as  $s_j \equiv x_{j,1989}/q_{j,1989}$ , where  $x_{j,1989} \equiv \sum_p x_{jp,1989}$  and  $q_{j,1989} \equiv \sum_p q_{jp,1989}$  denote the total value of exports and gross output, respectively. If instead plant  $j$  belongs to a multi-plant firm, we do not directly observe the value of USSR exports at the plant level. We instead indirectly infer it from the firm-level values,  $x_{fp,1989}$ , using the following proportionality rule,  $x_{jp,1989} \equiv x_{fp,1989} \times (q_{jp,1989}/q_{fp,1989})$ . Given these inferred export measures, we again compute the share of USSR exports in gross output for each plant as  $s_j \equiv x_{j,1989}/q_{j,1989}$ . For each plant  $j$  that belongs to a firm  $f$  that does not appear in either LDPM or Lisenssivirasto's records, we simply set  $s_j = 0$ . Table A.1 in Appendix

---

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

<sup>6</sup>We use either firm names and product codes or annual reports of export cartels to link firm 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.



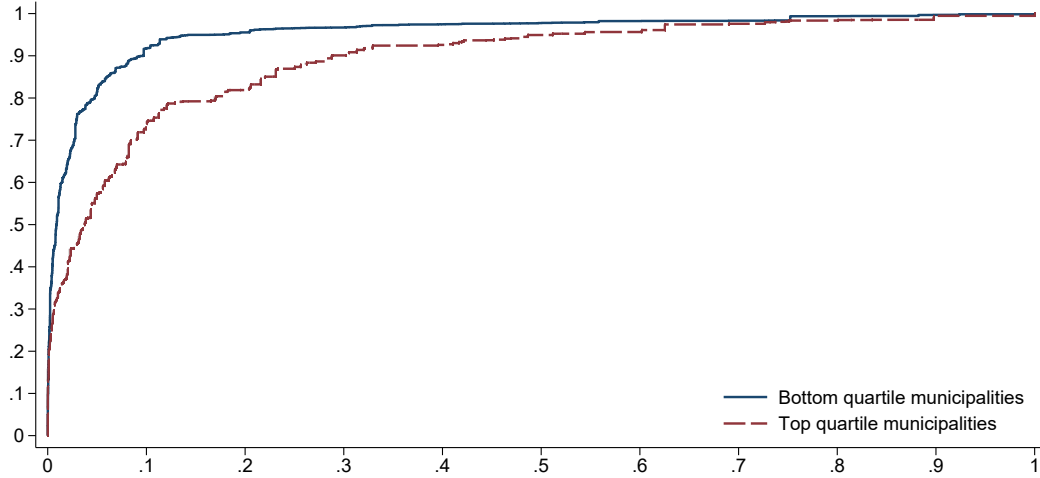


**Figure 2:** Local Labor Market Exposure to the USSR Shock

*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.

[A.2](#) summarizes how characteristics of LDPM plants vary with their USSR export intensity,  $s_j$ . 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, those exporting more tended to be smaller and less capital-intensive than those less reliant on the Eastern trade.

**Market Exposure to the USSR Shock.** For each Finnish municipality  $m$ , we observe the set of plants  $j \in \mathcal{J}_{m,1989}$  located in that municipality as well as the employment share of each of these plants  $\omega_{j,1989}$ , available from the population linked employer-employee data discussed below. We then define market exposure to the USSR shock,  $S_m$ , as the employment-weighted average of the export intensity of market  $m$ 's plants,  $S_m \equiv \sum_{j \in \mathcal{J}_{m,1989}} \omega_{j,1989} s_j$ . [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 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 A.2](#) in [Appendix A.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 and the fact that we match our ex-



**Figure 3: Worker Exposure**

*Notes:* Distribution of worker exposure ( $s_i$ ) in our baseline estimation sample, as defined in Section 3.2, conditional on  $s_i > 0$  in the municipalities in the bottom (solid line) and top (dashed line) quartile of market exposure ( $S_m$ ).

port information to firms in LDPM, 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).

**Worker Exposure to the USSR Shock.** For each Finnish worker  $i$ , we directly observe a personal identification number and a firm and plant identifier, made available to us by Statistics Finland, which we can use to match workers to their employers in 1989. We then define worker exposure to the USSR shock,  $s_i$ , as the export intensity of the plant  $j$  in which she is employed,  $s_i \equiv s_j$ . Figure 3 displays the distributions 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 are employed in LDPM plants in 1989 and because only 13% of LDPM plants exported to the USSR in that same year (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, a small number of plants exported more than half of their production to the Soviet Union in 1989. Table A.3 in Appendix A.2 reports how worker characteristics in 1989 vary with exposure to the USSR export market. Within manufacturing, more and less exposed workers are balanced on age and

gender. In comparison to other manufacturing workers, more exposed workers have higher incomes, are more educated and, given their level of education, more likely to have obtained a degree in a technical field. We control for the time-varying impact of these worker characteristics in our baseline empirical specifications.

## 2.3 Other Data

Our worker data are drawn from various administrative registers also 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.

**Worker Outcomes.** Our primary outcome variable (in Section 3) is annual earnings,  $y_{i,t}$ . It is equal to the total annual wage and salary income received by worker  $i$  as reported to the Finnish Tax Authority in year  $t$ . In order to compare the levels of earnings across years, we deflate all earnings to 2010 euros using the markka-euro exchange rate and Finland’s Cost-of-living index. In order to limit the influence of outliers, we also follow [Autor et al. \(2014\)](#) and winsorize annual income at the top 1% within each year. In subsequent regressions (in Section 4) we also consider the change in the number of days of employment during a year, 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 and under-estimate their hourly wages. Given this limitation, we complete our analysis with survey data from the Confederation of Finnish Industry (TT) that cover large firms in manufacturing and construction industries.<sup>7</sup> For workers who receive an hourly wage, the TT gathers data on hours worked and total compensation in quarter four of each year. Dividing total compensation by hours worked, we construct a worker sample of hourly wages. We later refer to this subset of workers as the hourly-wage sample.

**Worker Observables.** We observe gender, year of birth, and native language, in the Population Register, and level and field of education, in the Register of Completed Education

---

<sup>7</sup>In 2000, these companies employed about one third of all private-sector employees in Finland; answering the survey is compulsory for the member companies with more than thirty employees and voluntary for smaller companies.

and Degrees. In addition to these socio-demographic characteristics, we also observe a range of characteristics of the plant employing each worker: municipality, industry, average annual earnings of workers in the plant (from the Finnish Tax Authority), as well as plant gross output, and capital-labor ratio. We offer summary statistics in Section 3.2 below.

### 3 Exposures to Trade and Earnings Dynamics

The goal of our empirical analysis is to study the causal relationship between worker and market exposures to the USSR shock,  $s_i$  and  $S_m$ , and the path of Finnish workers' earnings  $y_{i,t}$  over the 1985-2004 period. We proceed in two steps. 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,  $S_m$ .

#### 3.1 Empirical Designs

**Double-Difference Strategy.** For the first part of our empirical analysis, we follow closely earlier work using longitudinal worker 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. For each sample year  $t$ , we separately estimate the following linear regression model,

$$\Delta y_{it} = \beta_t s_i + \text{Controls}_i' \zeta_t + \varepsilon_{it}, \quad (1)$$

where  $\Delta y_{it} \equiv y_{it} - \bar{y}_i$  is the difference between worker  $i$ 's earning at date  $t$ ,  $y_{it}$ , and her pre-period average (across the years 1985, 1988, and 1989),  $\bar{y}_i$ ;  $s_i$  denotes worker  $i$ 's exposure to the USSR shock;  $\text{Controls}_i$  is a long vector of initial worker characteristics; and  $\varepsilon_{it}$  is a worker-and-year specific shock. Both the sample of workers and their characteristics are fixed across all years.

We interpret  $\beta_t$  as the causal effect of worker exposure to the USSR shock. Alternatively,  $\beta_t$  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  $\beta_t$  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.

**Triple-Difference Strategy.** 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,  $S_m$ . We estimate the following augmented model,

$$\Delta y_{it} = \beta_t s_i + \gamma_t (s_i \times S_m) + \text{Controls}_i' \zeta_t + \varepsilon_{it}, \quad (2)$$

where  $S_m$  denotes municipality  $m$ 's exposure to the USSR shock. 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.

## 3.2 Worker Sample and Controls

**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 the pre-period (i.e, 1985, 1988, and 1989).<sup>8</sup> 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.

---

<sup>8</sup>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 euros for 1985, 9,453 euros for 1988, and 9,318 euros for 1989, all in 2010 euros.

**Table 1: Worker controls, 1989**

	“Attached workers”			All private sector (4)
	Baseline sample (1)	Manu- facturing (2)	Hourly wage (3)	
<i>A: Employer characteristics</i>				
Average annual earnings	26,517 (7,430)	26,400 (6,018)	26,774 (5,211)	25,583 (7,553)
Output (LDPM)	67.4 (155.6)	69.2 (158.7)	86.6 (173.3)	64.3 (152.4)
Capital-labor ratio (LDPM)	102.8 (220.1)	86.3 (137.9)	118.4 (203.6)	97.7 (212.3)
<i>B: Worker socio-demographics</i>				
Year of birth	1953.8 (5.9)	1953.6 (5.8)	1953.8 (5.9)	1955.1 (6.5)
Female	0.35	0.30	0.21	0.39
First language Finnish	0.95	0.95	0.97	0.94
First language Swedish	0.05	0.04	0.03	0.05
Other first language	0.003	0.002	0.001	0.003
Less than secondary / unknown degree	0.32	0.34	0.42	0.30
Lower secondary degree	0.37	0.43	0.55	0.38
Upper secondary degree	0.20	0.15	0.03	0.22
Lower tertiary degree	0.05	0.04	0.00	0.05
Higher tertiary degree	0.06	0.05	0.00	0.06
General, arts or teaching degree	0.06	0.03	0.01	0.07
Business degree	0.16	0.09	0.02	0.16
Technical degree	0.36	0.48	0.49	0.34
Degree in other fields	0.10	0.05	0.06	0.13
Degree unknown / missing	0.32	0.34	0.42	0.30
Annual earnings	28,354 (13,101)	27,765 (11,508)	26,229 (7,231)	25,337 (13,483)
<i>C: Sector of employment</i>				
Manufacturing	0.36	1.00	0.70	0.33
Observations	627,070	222,611	140,860	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), the subset of those only working in manufacturing in 1989 (column 2), those included in our hourly-wage sample (column 3), and all private sector workers (column 4).

**Worker Controls.** Our vector of worker controls,  $\text{Controls}_i$ , includes various characteristics of worker  $i$  in 1989 built from the worker observables listed in Section 2.3. Specifically,  $\text{Controls}_i$  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,  $\text{Controls}_i$  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.<sup>9</sup> Finally,  $\text{Controls}_i$  includes decile indicator variables for various characteristics of the plant employing worker  $i$  in 1989: gross output, capital-labor ratio, and average annual earnings of workers in the plant, all evaluated in 1989.<sup>10</sup> Table 1 offers summary statistics for worker controls among workers in our baseline sample (column 1), among the subset of our sample initially employed in manufacturing (column 2), among workers in the hourly wage sample (column 3), and among all private sector workers (column 4).

### 3.3 Worker Exposure to the USSR Shock and Earnings Dynamics

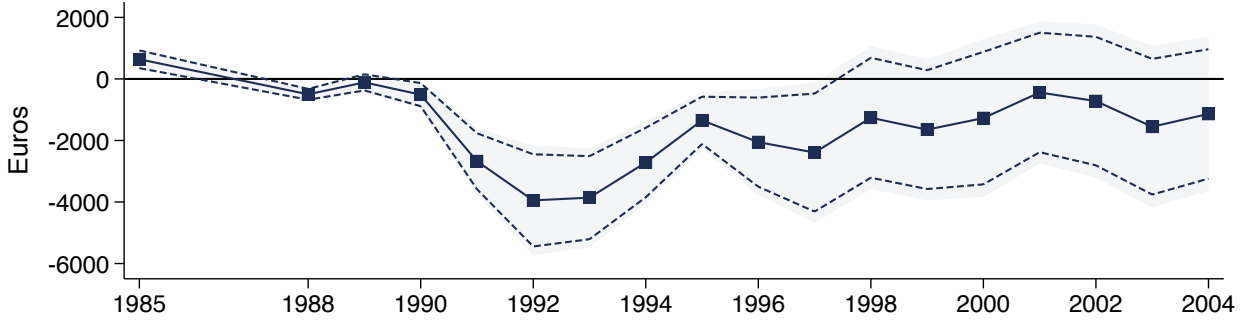
We first report the estimated earnings effects of the USSR shock on workers with different exposure  $s_i$  using our double-difference strategy. Figure 4 displays the OLS estimates of  $\beta_t$  in equation (1) together with the 90% and 95% confidence intervals, which are based on standard errors clustered by 1989 municipality.

More exposed workers experience statistically significant declines in labor earnings following the trade collapse. In Figure 4, 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 809 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. Another way to interpret the magnitude of  $\beta_t$  is to think of equation (1) as the reduced-form of a 2SLS regression, whose first stage would regress a dummy for being fired on exposure to the USSR shock and whose second stage would regress earnings on a dummy for being fired, similar to the regression considered in the

<sup>9</sup>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.

<sup>10</sup>Since gross output and capital-labor ratio are only available for LDPM plants, we add a missing category, which we assign to workers not employed by an LDPM plant in 1989.





**Figure 4:** Direct Effect of Worker Exposure ( $s_i$ ) on Earnings

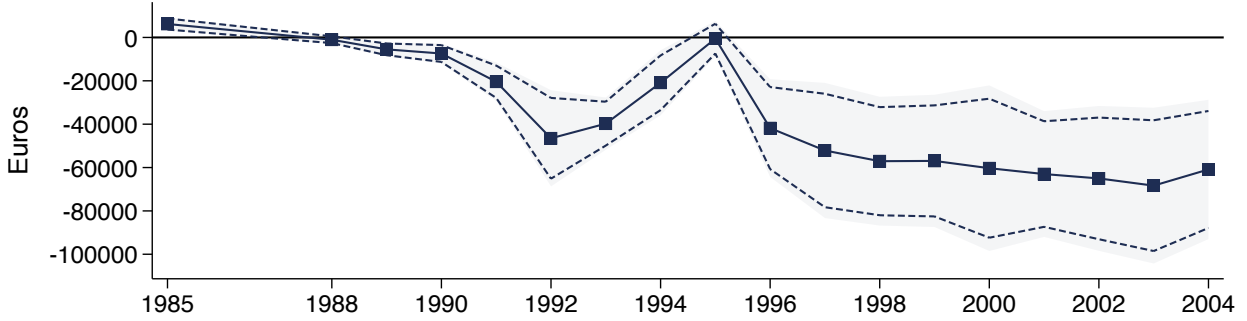
*Notes:* This figure reports the OLS estimates of  $\beta_t$  in equation (1), with 90% and 95% confidence intervals (dashed and shaded, respectively) computed with robust standard errors clustered by 1989 municipality.

mass layoff literature. As a simple back-of-the-envelope calculation, let us assume that, consistent with the model of Section 4.1, the probability that worker  $i$  is fired in response to the USSR shock is equal to her exposure  $s_i$ . Under this assumption, the first stage coefficient is equal to one and the estimated impact of worker exposure on earnings in 1992,  $\hat{\beta}_{1992} = -3,858$ , implies a decline in earnings of 3,858 euros for a worker who is fired in response to the USSR shock, or approximately 15 percent of average annual income.

After bottoming out in 1992, Figure 4 shows that the annual earnings losses of more exposed workers become less severe between 1993 and 1995. In spite of this, more exposed workers' earnings remain lower throughout our sample period, although this difference becomes statistically insignificant in 1998 and remains so through the end of the sample period. Prior to 1989, Figure 4 also shows no evidence of pre-existing differential trends.<sup>11</sup> Instead, we observe changes in estimates that are consistent with the institutional details of the Finnish-Soviet trade agreement. 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 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).

Qualitatively, the negative response of workers' earnings to exposure to the USSR shock is broadly in line with the results of Autor et al. (2014) about the impact of the China shock. Although we focus on a decrease in exports rather than a surge in imports, both can be thought of as negative labor demand shocks—which is how we will

<sup>11</sup>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.



**Figure 5:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Earnings

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (2), with 90% and 95% confidence intervals (dashed and shaded, respectively) computed with robust standard errors clustered by 1989 municipality.

model the USSR shock in Section 4—with negative expected effects on earnings. The key distinction between our empirical results and those of Autor et al. (2014) is the level of aggregation at which worker exposure is measured. We leverage variation in plant export intensity, while controlling for municipality-time effects, as opposed to relying on industry variation. This added granularity will guide our modeling choices in Section 4.

### 3.4 Do Local Labor Markets Shape the Incidence of the USSR Shock?

We now explore how the estimated earnings effects of the USSR shock on workers with different exposure  $s_i$  vary across markets with different exposure  $S_m$  using the triple-difference strategy described in Section 3.1. Figure 5 describes our main empirical finding. It displays the OLS estimates of  $\gamma_t$  in equation (2); the new OLS estimates of  $\beta_t$ , now also estimated using equation (2), can be found in Figure A.2 in Appendix A.3.

Figure 5 shows that within more exposed local labor markets, worker exposure leads to both larger and more persistent earnings declines, a form of local scarring. Since the OLS estimate of  $\gamma_t$  is negative and statistically different from zero, a higher value of the interaction term  $s_i \times S_m$  reduces earnings in all post-shock years except for 1995. Going back to the comparison of workers at the 90th and 10th percentiles of worker 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 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 empirical finding that a negative worker trade shock has larger and more persistently negative earnings effects in more exposed municipalities can be viewed as the spatial counterpart of earlier results in the labor literature about the heterogeneous im-

pact of mass lay-offs over the business cycle, see, e.g., [Davis and von Wachter \(2011\)](#), [Korkeamäki and Kyrrä \(2014\)](#), [Farber \(2017\)](#), [Schmieder et al. \(2019\)](#), and [Huckfeldt \(Forthcoming\)](#). They show that a worker fired in a mass layoff experiences larger and more persistent earnings declines if that layoff occurred during a national recession. We show a similar result in the cross-section of Finnish municipalities, with  $S_m$  playing the role of the severity of the recession in that earlier literature.<sup>12</sup>

### 3.5 Sensitivity Analysis

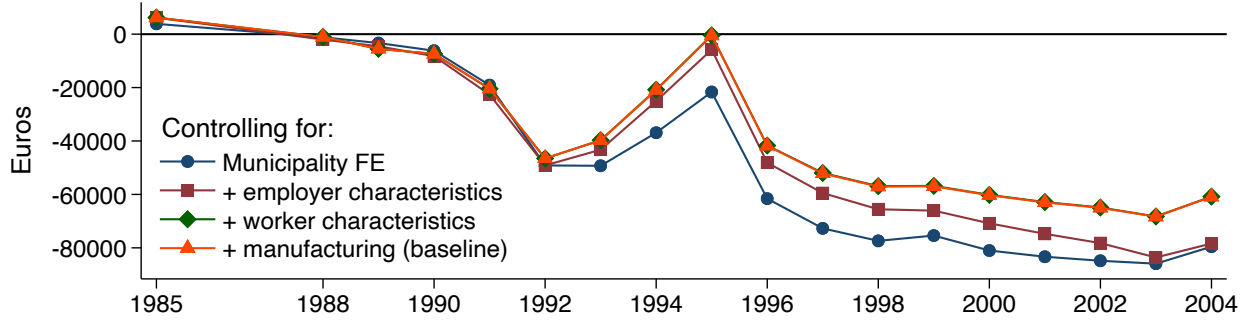
The baseline results from the triple-difference strategy presented in [Figure 5](#) are robust to a variety of alternative specifications. We summarize these additional results here.

**Alternative Worker Controls.** Panel (a) of [Figure 6](#) presents results as we progressively add worker characteristics, starting with only municipality controls and building up to the baseline vector  $\text{Controls}_i$  in the estimating equation (2). We start with no controls (except for municipality effects), add employer characteristics, then add worker socio-demographic characteristics, then add a manufacturing effect (thereby replicating our baseline specification). Our OLS estimates of  $\gamma_t$  (the interaction effect of worker and local labor market exposure) are broadly stable across all sets of controls. For each specification, we find a negative and persistent interaction between worker and market exposures to the USSR shock.

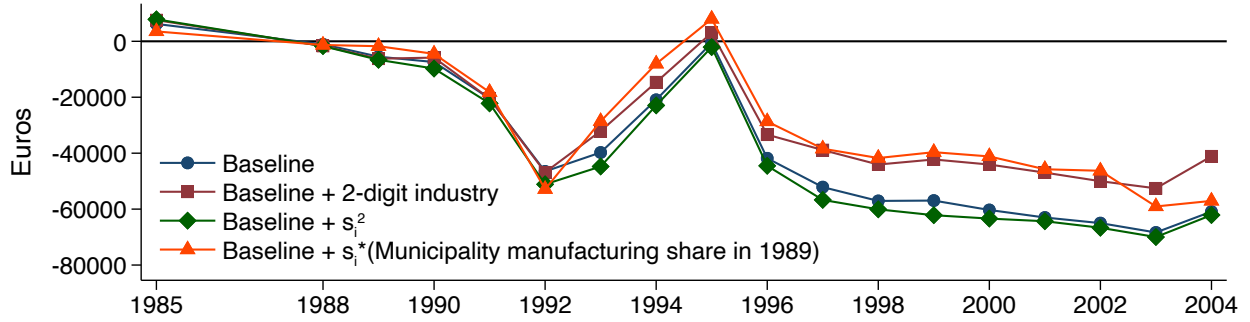
Panel (b) of [Figure 6](#) presents results as we add controls over-and-above those included in the baseline analysis. One concern is that industries are experiencing different wage and employment trends not fully captured by the manufacturing fixed effect included in  $\text{Controls}_i$ . To address this, we replace the manufacturing fixed effect with two-digit industry fixed effects. A second concern more related to the identification of

---

<sup>12</sup>One further distinction between these existing results and ours relates to the comparison of “treated” and “untreated” workers. Here, as well as in the double-difference strategy, we compare workers who differ in terms of ex-ante characteristics (e.g., workers whose plants have different shares of exports to the USSR in 1989, prior to the USSR shock) as opposed to comparing workers who differ in terms of ex-post characteristics (e.g., 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). This distinction has implications for the strength of the exclusion restriction invoked in the empirical analysis. In our double-difference strategy, we require that growth rates in the returns to unobserved worker characteristics are not systematically correlated with the exposure of the worker’s plant in 1989, whereas the mass-layoff literature requires that they are not systematically different in plants with and without mass layoffs. In our triple-difference strategy, we additionally require that the difference in growth rates in the returns to unobserved worker characteristics in more relative to less exposed plants is not systematically related to the exposure of the local labor market whereas the mass-layoff literature additionally requires that the difference in these growth rates across plants with and without mass-layoff events is not systematically related to the state of the national business cycle.



(a) Interaction Effect of Worker and Market exposures ( $s_i \times S_m$ ) on Earnings, with Fewer Controls



(b) Interaction Effect of Worker and Market exposures ( $s_i \times S_m$ ) on Earnings, with Additional Controls

### Figure 6: Sensitivity to Alternative Worker Controls

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (2) with alternative vectors of controls,  $\text{Controls}_i$ . In the top panel, we estimate (2) including only include municipality indicator variables; then additionally include employer characteristics; then additionally include worker socio-demographic characteristics; and finally additionally include a manufacturing indicator variable, thereby replicating our baseline specification. In the bottom panel, the we estimate the baseline specification; then replace the manufacturing indicator with two-digit industry indicators; then separately include  $s_i^2$  as a control; and then separately add  $s_i \times (\text{Share of municipality's workers in manufacturing in 1989})$  as a control.

$\gamma_t$  is that the interaction  $\gamma_t(s_i \times S_m)$  is picking up any potentially non-linear direct effects of worker exposure,  $s_i$ , since  $s_i$  is correlated with  $S_m$  by construction. To address this, we include not only the direct effect of worker exposure  $s_i$ , but also the direct effect squared  $s_i^2$ .<sup>13</sup> Finally, another concern related to the identification of  $\gamma_t$  is that the interaction  $\gamma_t(s_i \times S_m)$  is picking up the heterogeneous effects of worker exposure across municipalities that differ in various characteristics that are correlated with municipality exposure  $S_m$ . To address this, we include not only the interaction of interest  $s_i \times S_m$ , but also the interaction between worker exposure and the municipality characteristic most correlated with  $S_m$ , the initial manufacturing share of employment in municipality  $m$  in 1989. For each specification, we find a negative and persistent interaction between worker and market exposures to the USSR shock.

**Other Robustness Checks.** Our baseline results are also robust to a variety of alternative specifications including using relative rather than the absolute level of earnings, allowing for different worker samples, and using different measures of municipality exposure. We summarize these additional results here and report the counterpart of Figure 5 for each of these specifications in Appendix A.4.

In our baseline empirical specification we identify the impact of worker exposure and its heterogeneity across markets with different levels of market exposure on changes in absolute earnings:  $\Delta y_{it} \equiv y_{it} - \bar{y}_i$ . Figure A.3 instead replaces the dependent variable in equation (2) with relative changes in earnings,  $\Delta y_{it} \equiv y_{it}/\bar{y}_i$ , following Autor et al. (2014). This specification comes closer to a log change, while still not dropping observations with zero earnings. Results are qualitatively very similar to those in our baseline, with estimates  $\gamma_t$  converging to a negative value in the long-run.

Figure A.4 goes back to our baseline specification, but considers alternative worker samples. 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 to the labor force in the years preceding the trade shock. Again, our results are very similar across alternative samples.

For our baseline analysis, we have defined market exposure as  $S_m \equiv \sum_{j \in \mathcal{J}_{m,1989}} \omega_{j,1989} s_j$  with  $\omega_{j,1989}$  the share of plant  $j$  in market  $m$ 's total employment. This is equivalent to defining market exposure  $S_m$  as the employment-weighted average of workers' exposure using the full working-age population in each municipality. In Figure A.5 we instead recompute market exposure as the employment-weighted average of workers' exposure

---

<sup>13</sup>This concern does not extend to non-linear direct effects of  $S_m$ , since we include municipality effects in our first-difference estimating equation.

using only workers included in our baseline sample (as described in column 1 of Table 1). Since only workers in this sample have strictly positive exposure to the USSR shock, market exposure is mechanically higher and our point estimates are correspondingly lower, but they follow the same qualitative patterns as in Figure 5. Our final exercise deals with the fact that a small number of municipalities has very high values of exposure (as shown in Figure 2). In Figure A.6, we winsorize municipality exposure at the top percentile. Since this reduces  $S_m$ , the average value of market exposure is mechanically lower and our point estimates are correspondingly higher, but again follow the same pattern as in Figure 5.

## 4 Can Wage Rigidity Explain the Impact of the USSR Shock?

In a frictionless labor market, more and less exposed workers should experience similar changes in earnings in response to negative labor demand shocks. In Figures 4 and 5, we have documented instead that in response to the USSR shock, more exposed workers have experienced declines in earnings relative to other workers and that these declines have been larger in more exposed markets. What is the source of frictions driving these patterns?

In this section, we propose to focus on a channel that is under-explored in the trade literature, but potentially salient in many countries, including Finland: the existence of downward wage rigidity.<sup>14</sup> Intuitively, if wages only slowly adjust downward in response to negative shocks, then unemployment will be observed in the short run and more exposed workers, who are more likely to lose their jobs, will experience longer unemployment spells and larger decreases in earnings. Furthermore, if workers are located in more exposed markets, one may expect unemployment effects and, in turn, earnings losses to be more severe.

Section 4.1 develops the simplest model of labor market dynamics that formalizes these ideas and rationalizes our previous empirical results. It also derives additional theoretical predictions about the dynamic response to trade shocks that arise in a model with wage rigidity and distinguish its predictions from those of existing dynamic models. Sections 4.2 and 4.3 conclude with empirical evidence supporting these additional theoretical predictions.

---

<sup>14</sup>According to the the International Wage Flexibility Project, downward wage rigidity is particularly severe in Finland; see Dickens et al. (2007). Böckerman et al. (2006) also document a lack of downward nominal wage adjustments (and only limited inflation) during the Finnish Great Depression of 1991-1993.

## 4.1 Labor Markets Dynamics, Trade Shocks, and Wage Rigidity

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

**Workers.** Workers are either employed or unemployed. We let  $E_t$  and  $U_t$  denote the numbers of employed and unemployed workers, respectively, in the market in period  $t$ . Their sum is equal to the total number of workers in that market,

$$E_t + U_t = N. \quad (3)$$

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  $W_t$  and faces an endogenous probability  $\lambda_{jt}dt$  of switching from employment to unemployment at date  $t + dt$ . If not employed, 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

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

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.<sup>15</sup> 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

$$E_t = \Phi_t W_t^{-\sigma}, \quad (4)$$

where  $\Phi_t \equiv \sum_{j \in \mathcal{J}} \phi_{jt}$  is the market labor demand shifter.<sup>16</sup>

---

<sup>15</sup>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.

<sup>16</sup>This requires total population  $N$  to be large enough so that  $E_t \leq N$ , an assumption that we maintain throughout this section.



**Job Destruction and Job Creation.** Between any consecutive dates  $t$  and  $t + dt$ , a constant fraction  $\lambda dt$  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  $\lambda$  ( $-\lambda \leq \dot{E}_{jt}/E_{jt} \leq 0$ ) over the same time period,  $\lambda$  coincides with the total separation rate of plant  $j$ . If instead plant  $j$  is downsizing at rate greater than  $\lambda$  ( $\dot{E}_{jt}/E_{jt} \leq -\lambda$ ), then its total separation rate is equal to  $-\dot{E}_{jt}/E_{jt}$ . Hence the separation rate for plant  $j$  at time  $t$ ,  $\lambda_{jt}$ , can be expressed compactly as

$$\lambda_{jt} = \max\left\{\lambda, -\frac{\dot{E}_{jt}}{E_{jt}}\right\}. \quad (5)$$

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

$$\kappa_t = \max\left\{0, \frac{\dot{E}_t + \lambda_t E_t}{U_t}\right\} \quad (6)$$

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

**Wage Rigidity.** The key feature of the model is that wages adjust slowly. Between  $t$  and  $t + dt$ , the change in wages  $W_t$  satisfy

$$\dot{W}_t = \gamma(\bar{W}_t - W_t) \quad (7)$$

where  $\bar{W}_t \equiv (N/\Phi_t)^{-1/\sigma}$  denotes the market-clearing wage at which full employment obtains and  $\gamma \geq 0$  determines the speed of wage adjustment.<sup>17</sup>

**Trade Shocks.** We assume that the local labor market is in steady state just before date 0, with the wage equal to the market-clearing wage,  $W_0 = \bar{W}_0$ , and labor supply equal to labor demand,  $E_0 = N$ . At date 0, it experiences a one-time, permanent, negative labor demand shock, which is the theoretical counterpart of the trade shock in earlier sections. Plants may be more or less affected by the shock. For each plant  $j \in \mathcal{J}$ , we let  $\phi_j$  denote the level of plant  $j$ 's demand before the shock and  $\phi'_j \equiv (1 - s_j) \phi_j$  its demand after the shock, with  $s_j \in [0, 1]$  denoting its exposure. Consistent with our empirical analysis in Section 3, we define worker exposure  $s_i$  as the exposure of the plant  $j(i)$  employing that

---

<sup>17</sup>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. We also ignore the distinction between incumbent and new hire wage rigidity. Appendix B.4 shows that Propositions 1 and 2 extend to environments in which the wages of incumbent workers are (fully) rigid, but those of new hires are not. Finally, Appendix B.5 provides conditions under which our results extend to a generalized environment in which wages adjust downward until the employment rate converges to a fixed value potentially below one.

worker, i.e.,  $s_i = s_{j(i)}$ , and market exposure  $S$  as the weighted average of plants located in the market, with weights equal to the initial employment share of each plant in that market, i.e.  $S \equiv \sum_{j \in \mathcal{J}} s_j (E_{j0}/E_0) \in [0, 1]$ .<sup>18</sup>

**Predicted Impact of Trade Shocks.** In this environment, we can characterize in closed-form the full path of market wages,  $W_t$ , and employment,  $E_t$ . Given those, we can then solve, again in closed-form, for each worker’s probability of employment  $\pi_{it}$ —that is, the probability that a worker  $i \in \mathcal{I}$  who was employed by plant  $j(i)$  at date 0 is employed by *any* plant  $j \in \mathcal{J}$  at date  $t > 0$ —as well as expected earnings  $y_{it} = \pi_{it}W_t$  at any point in time. We do so in Appendix B. Propositions 1 and 2 summarize the main properties of the market- and worker-level impact of trade shocks predicted by our model.

**Proposition 1** (Market-Level Impact). *In response to a negative trade shock at  $t = 0$ , more exposed markets experience: (i) declines in wages ( $dW_t/dS \leq 0$  for all  $t \geq 0$ ), with wages slowly adjusting downward ( $\dot{W}_t \leq 0$  for all  $t \geq 0$ ) toward a new lower market-clearing wage ( $\lim_{t \rightarrow \infty} W_t \equiv \bar{W}_{0+} < \bar{W}_0$ ); and (ii) declines in employment ( $dE_t/dS \leq 0$  for all  $t \geq 0$ ), with employment jumping down at impact ( $E_{0+} < E_0$ ) before adjusting upward slowly ( $\dot{E}_t \geq 0$  for all  $t \geq 0$ ) toward full employment ( $\lim_{t \rightarrow \infty} E_t = N$ ).*

In response to a negative labor demand shock, workhorse dynamic models with flexible wages used in the trade literature—e.g., Artuç et al. (2010), Dix-Carneiro (2014), Caliendo et al. (2019), and Traiberman (2019)—would suggest larger wage declines in the short run than in the long run combined with larger employment declines in the long run than in the short run. The reason is that workers in these models are subject to idiosyncratic preference shocks and so, even if employment becomes less attractive in a market, there is option value in waiting for a better draw. Thus the overall effect of the shock on employment takes a long time to unfold. For the same reason, the initial drop in wages in the negatively affected market dissipates over time as labor supply slowly adjusts downward.<sup>19</sup> The same type of transitional dynamics arises in the model with search frictions and bargaining à la Helpman et al. (2010), as shown in Helpman and Itskhoki (2015). Proposition 1, while entirely unsurprising given our assumptions, predicts the exact opposite dynamics. Since wages are rigid, they slowly adjust downward, which lowers employment in the short run, but not in the long-run. We turn to these predictions in Section 4.3.

<sup>18</sup>By construction,  $S$  is also equal to the average across workers of worker exposure,  $S \equiv \sum_{i \in \mathcal{I}} s_i / E_0$ .

<sup>19</sup>Depending on the specific application, markets could be regions, sectors (including household production), or a combination thereof.

**Proposition 2** (Worker-Level Impact). *In response to a negative trade shock at  $t = 0$ , more exposed workers experience: (i) declines in expected employment ( $d\pi_{it}/ds_i \leq 0$  for all  $t \geq 0$ ), with larger declines in more exposed markets ( $d^2\pi_{it}/ds_idS \leq 0$  for all  $t \geq 0$ ); and (ii) declines in expected earnings ( $dy_{it}/ds_i \leq 0$  for all  $t \geq 0$ ), with larger declines in more exposed markets ( $d^2y_{it}/ds_idS \leq 0$  for all  $t \geq 0$ ) if wages are sufficiently rigid ( $\gamma$  low enough).*

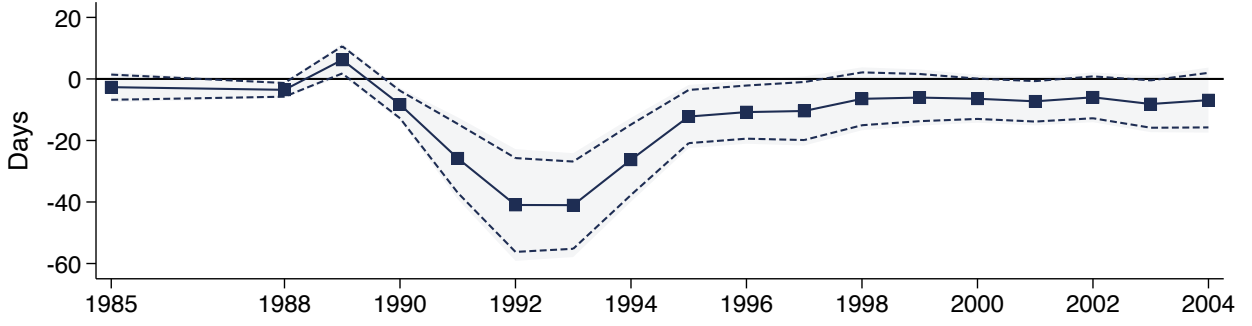
Part (ii) of Proposition 2 rationalizes the empirical evidence presented in Section 3. That more exposed workers have lower expected employment and earnings is intuitive. They are more likely to lose their job at date 0. Being unemployed at date 0, in turn, lowers the probability of being employed at 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.<sup>20</sup>

Interestingly, Proposition 2 shows that the interaction between worker and market exposure is more subtle and requires extra conditions. More exposed markets have lower wages as well as lower job-finding rates at every date, as we prove in Appendix B.2. The job-finding-rate effect magnifies the decreases in employment and 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, however, works in the opposite direction. For workers with greater exposure  $s_i$ , who are more likely not to be employed at all dates, the earnings losses in terms of foregone wages are lower in markets with higher exposure  $S_m$ . As a result, a negative interaction effect  $d^2y_{it}/ds_idS_m < 0$  arises when the job-finding-rate effect dominates the wage effect, which happens when  $\gamma$  is low enough and wages respond little to the shock.<sup>21</sup>

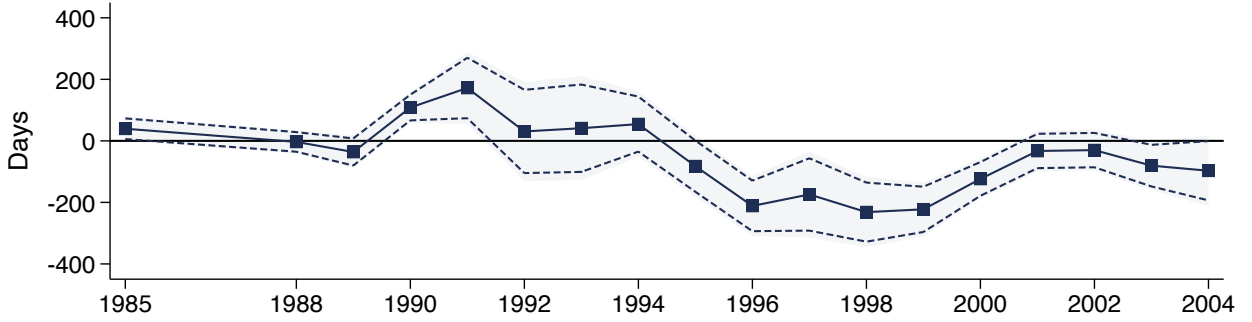
The flip-side of the previous discussion is that local scarring effects should be more pronounced when looking at employment rather than earnings, since the wage effect is absent. This is reflected in part (i) of Proposition 2, which does not require any qualification. We also note that while one might have expected the earnings of exposed workers to be negatively affected by the USSR shock in alternative economic environments with monopsony power, bargaining or other form of rent sharing, it is less clear why, absent other frictions, these considerations would lead to systematic drops in employments, with greater declines in more exposed markets. Next we investigate this theoretical prediction empirically.

<sup>20</sup>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:  $\lim_{t \rightarrow \infty} d\pi_{it}/ds_i = 0$  and  $\lim_{t \rightarrow \infty} dy_{it}/ds_i = 0$ .

<sup>21</sup>In contrast, when  $\gamma$  is high enough, one can show that the interaction effect between  $s_i$  and  $S$  is positive:  $d^2y_{it}/ds_idS > 0$ . The formal argument can be found in Appendix B.3.



(a) Direct Effect of Worker Exposure ( $s_i$ ) on Days Employed



(b) Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Days Employed

**Figure 7: Exposures to Trade and Employment Dynamics**

Notes: Figure 7a reports the OLS estimate of  $\beta_t$  in equation (8), whereas figure 7b reports the OLS estimates of  $\gamma_t$  in the same equation. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.

## 4.2 Exposures to Trade and Employment Dynamics

We now repeat our baseline empirical specification, as described in equation (2), using changes in days employed  $\Delta n_{it}$  rather than earnings  $\Delta y_{it}$  as our dependent variable,

$$\Delta n_{it} = \beta_t s_i + \gamma_t (s_i \times S_m) + \text{Controls}'_i \zeta_t + \varepsilon_{it}, \quad (8)$$

According to our model, expected changes in  $\Delta n_{it}$  should equal changes in employment probabilities  $\Delta \pi_{it}$ , which should be decreasing in both worker exposure  $s_i$  and the interaction between worker and market exposure  $s_i \times S_m$ .<sup>22</sup>

Figure 7 displays the OLS estimates of  $\beta_t$  and  $\gamma_t$ , with  $\beta_t$  now measuring the predicted effect on days employed of worker exposure  $s_i$  and  $\gamma_t$  the predicted effect of the interaction between worker and market exposures  $s_i \times S_m$ . Consistent with Proposition 2, and in line with the baseline earnings results presented in Figure 5, the OLS estimate of  $\beta_t$  is

<sup>22</sup>As already noted in Section 3.2, this measure of employment does not include information on hours. So it is likely to over-estimate the employment of people working irregular shifts.

negative; it peaks around 1992-1993 and dissipates in the medium run. Although the OLS estimate of  $\gamma_t$  is positive and statistically significant in 1990 (recall that the shock occurs at the very end of this year) and 1991, it turns negative thereafter, again consistent with Proposition 2. 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 medium-run, a point we come back to below.<sup>23</sup>

### 4.3 Market Exposure and Labor Market Dynamics

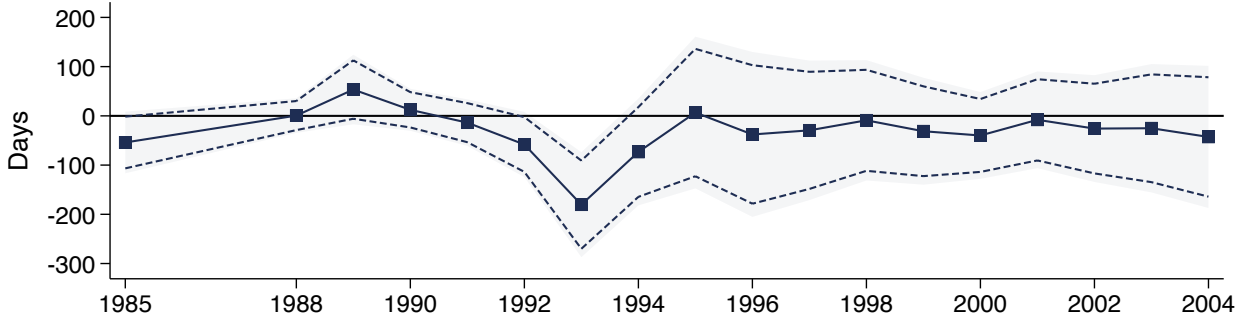
To this point, we have focused empirically on the effect of worker exposure  $s_i$  as well as its interaction with market exposure  $s_i \times S_m$ . The model with wage rigidity presented in Section 4.1, however, makes additional predictions about the direct effect of market exposure  $S_m$  on market wages and employment. As described in Proposition 1, our model predicts that the market-level wage is lower in more exposed markets at all dates  $t > 0$ ,  $dW_t/dS_m < 0$ , and adjusts slowly from the pre-demand-shock level to its lower long-run lower level. Our model also predicts that the market-level employment rate is lower in more exposed markets at all dates  $t > 0$ , falls upon impact, and rises over time. We now turn to these additional predictions.<sup>24</sup>

**Market Exposure and Employment Dynamics.** We first return to the double-difference strategy described in equation (1), but use market-level exposure  $S_m$  rather than worker-level exposure  $s_i$  as our main independent variable, now omitting municipality dummy variables from the vector of controls. The idea is to compare changes in the employment trajectories of workers whose labor markets are more and less exposed but who are similar in terms of other observable characteristics. For each sample year  $t$ , we now separately estimate the following linear regression model,

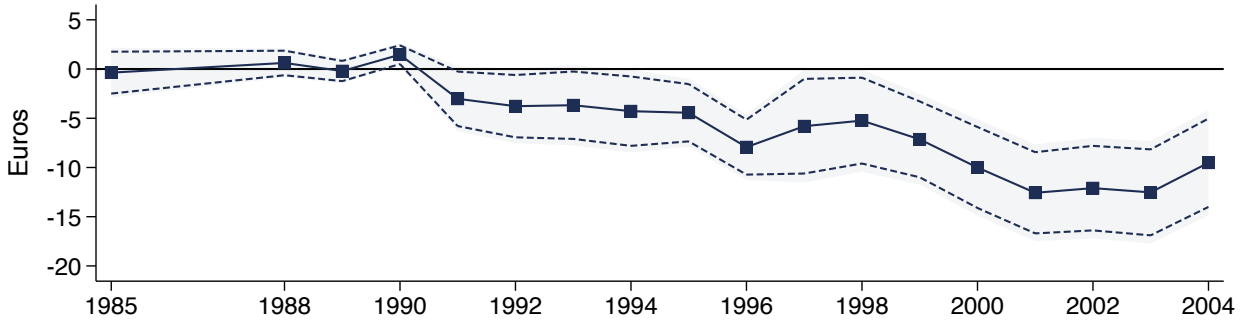
$$\Delta n_{it} = \beta_t S_m + \text{Controls}'_i \zeta_t + \varepsilon_{it}, \quad (9)$$

<sup>23</sup>The sensitivity of our employment results to the same alternative specifications as in Section 3.5 can be found in Appendix A.5.

<sup>24</sup>This final part of our empirical analysis, solely leveraging heterogeneity in exposure across markets, is most closely related to earlier empirical work by Kovak and Dix-Carneiro (2017), on the regional impact of Brazil's trade liberalization, and recent work by Autor et al. (2021), on the persistence of market exposure to the China shock. An attractive feature of the collapse of the Finnish-Soviet trade agreement is that it was a one-time shock, which occurred on December 6th, 1990. This helps us interpret our empirical results, consistent with our theoretical predictions, as the impulse response to the USSR shock rather than as a combination of evolving trade shocks and their impulse responses. We return to the comparison between our results and those of Kovak and Dix-Carneiro (2017) below.



(a) Direct Effect of Market Exposure ( $S_m$ ) on Days Employed



(b) Direct Effect of Market Exposure ( $S_m$ ) on Hourly Wage

**Figure 8: Market Exposure and Labor Market Dynamics**

*Notes:* Figure 8a reports the OLS estimate of  $\beta_t$  in equation (9). Figure 8b reports the OLS estimate of  $\beta_t$  in equation (10) estimated on the hourly-wage sample rather than our baseline sample. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.

where  $\Delta n_{it}$  refers to changes in days employed for worker  $i$ ,  $\text{Controls}_i$  is our baseline vector of worker controls excluding the municipality dummy variable, and  $S_m$  is market exposure for worker  $i$ . Note that although the treatment of interest is defined at the market level, we continue to estimate (9) at the worker level in order to control for time-varying impacts of worker observables and potential changes in worker composition across markets (as in all previous regressions, standard errors will be clustered at the market level).

Panel (a) of Figure 8 displays the OLS estimate of  $\beta_t$  in equation (9). Although the drop in employment is smoother than the one-time jump that our stylized model predicts, the results are broadly consistent with the predictions of Proposition 1. We find that the impact of market exposure on employment is negative, peaks around 1993, and dissipates in the medium run. According to the model, this dissipation should result from a steady decline in the market wage.

**Market Exposure and Wage Dynamics.** We unfortunately do not observe the hourly wage rate of all workers in our baseline sample (and even our measure of days worked is not without issues, as discussed above). To study hourly wages, we therefore turn to the smaller, more restrictive sample of manufacturing workers described as the “hourly wage sample” in Section 2.3 for which such data is available.<sup>25</sup> We repeat our market specification, as described in equation (9), using changes in hourly wages  $\Delta W_{it}$  rather than days worked  $\Delta n_{it}$  as our dependent variable,

$$\Delta W_{it} = \beta_t S_m + \text{Controls}'_i \zeta_t + \varepsilon_{it}, \quad (10)$$

Panel (b) of Figure 8 displays the OLS estimate of  $\beta_t$  in equation (9). In line with Proposition 1, we find a negative and statistically significant impact of market exposure on wages, which exhibits a slow and steady decline consistent with downward wage rigidity.

As mentioned above, these estimated effects of market exposure on the joint dynamics of employment and wages are broadly consistent with our theory of downward wage rigidity but inconsistent with the workhorse framework of international trade and labor market adjustment with flexible wages. The slow and persistent decline in market-level wages displayed in Panel (b) of Figure 8 is also reminiscent of the pattern of formal-sector wages documented across Brazilian local labor markets in response to tariff cuts by Kovak and Dix-Carneiro (2017), which they interpret as evidence of agglomeration economies and slow capital adjustments. The employment response that we document, however, is very different. Whereas Kovak and Dix-Carneiro (2017) document a slow and persistent decline in formal employment, Panel (a) displays a recovery of employment in the medium run. These distinct empirical findings may reflect differences in labor-market institutions, with wage rigidity being more salient in Finland than Brazil.<sup>26</sup>

Needless to say that we do not interpret the results of the previous regressions as establishing that the considerations from which our simple model abstracts—from monopoly power to matching frictions and rent-sharing—are unimportant for understanding

---

<sup>25</sup>In order for a worker  $i$  to be included in the year  $t$  regression sample, she must meet our definition of high attachment to the labor force in the years preceding the trade shock (as in our baseline regressions), be in the hourly-wage sample in 1989, and be in the hourly-wage sample in year  $t$ . Conditioning on being in the hourly-wage sample in year  $t > 1989$  introduces issues of selection that are not present in our baseline analysis. To show that this selection issue may not markedly affect our wage results, in Appendix A.6 we show that estimating equation (9) using the hourly-wage sample yields results similar to estimating the same specification using our baseline sample.

<sup>26</sup>These differences may also reflect the distinct measures of employment that we use, with ours covering the universe of Finnish workers as opposed to the subset of formal workers in the Brazilian economy, as well as differences in empirical specifications, with our worker-level regressions allowing us to control for time-varying effects of worker-level observables and compositional changes in the labor force.



the labor market impact of trade shocks.<sup>27</sup> Rather, we view the fact that adding one key ingredient, downward wage rigidity, into an otherwise minimalistic model can help explain a variety of qualitative features of the dynamic responses of earnings, employment, and wages as a positive signal about the value of further exploring its implications, perhaps in combination with these other considerations.

## 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 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 most exposed markets? From a policy perspective, are national social programs well suited to compensate workers for the adverse consequences of globalization or should such programs inherit characteristics of place-based policies, with assistance to negatively affected workers conditioning on local labor-market conditions?

To make progress on these questions, we have combined newly-digitized export data with employer-employee data to construct measures of worker and market exposure to a massive trade shock, the collapse of the Finnish-Soviet Trade Agreement. Empirically, we have documented that worker exposure to the USSR shock lowers earnings throughout the post period, but persistently more so in more exposed markets, a form of local scarring that provides a potential rationale for place-based unemployment insurance and trade adjustment assistance programs.

Motivated by these empirical findings, we have developed a simple model of labor market dynamics with downward wage rigidity. We have characterized analytically how worker and market exposure shape the path of worker earnings in response to a negative labor demand shock and shown that it can rationalize the observed response of earnings to the USSR shock. We have also derived additional theoretical predictions about the response of employment and wages for which we find support in the data. In particular, we have shown that workers in more exposed markets experience slowly declining wages together with negative employment effects that dissipate in the medium run.

While the transitional dynamics predicted by a model with wage rigidity is intuitive, it is radically different from that predicted by workhorse models in the trade literature, in which wage declines are largest in the short run and employment declines are largest

---

<sup>27</sup>In fact, we do observe that average wages at the plant-level go down for more exposed plants relative to less exposed plants, consistent with models of monopsony, bargaining or rent-sharing at the plant-level.

in the long run. A model with wage rigidity also points towards very different structural determinants of the distributional consequences of trade, namely how fast wages adjust and how much churning there is in the labor market. If the speed of wage adjustment or the steady-state job destruction and creation rates are high, then the difference between the earnings path of exposed and unexposed workers should be small and the pain of a negative labor demand shock should be broadly shared within a local labor market. The converse should hold if the same rates are low. This opens the intriguing possibility that some of the adverse distributional consequences of the China shock in the United States might have been magnified, at least in part, by the low inflation rate or the decline in business dynamism in the US.

The previous examples illustrate some of the many ways in which the introduction of rigid wages may improve our understanding of the consequences of trade liberalization, both qualitatively and quantitatively. Much remains to be done.

## References

- Adao, Rodrigo, Paul Carrillo, Arnaud Costinot, Dave Donaldson, and Dina Pomeranz,** “Imports, Exports, and Earnings Inequality: Measures of Exposure and Estimates of Incidence,” *mimeo MIT*, 2021.
- Akerlof, George A., William R. Dickens, and George L. Perry,** “The Macroeconomics of Low Inflation,” *Brookings Papers on Economic Activity*, 1996, 27 (1), 1–76.
- Alfaro-Urena, Alonso, Isabela Manelici, and Jose P Vasquez,** “The Effects of Multinationals on Workers: Evidence from Costa Rican Microdata,” Technical Report 2021.
- Artuç, Erhan, Shubham Chaudhuri, and John McLaren,** “Trade Shocks and Labor Adjustment: A Structural Empirical Approach,” *American Economic Review*, June 2010, 100 (3), 1008–1045.
- Austin, Benjamin A., Edward L. Glaser, and Lawrence H. Summers,** “Jobs for the Heartland: Place-Based Policies in 21st Century America,” *NBER Working Paper 24548*, 2018.
- Autor, David, David Dorn, and Gordon H. Hanson,** “On the Persistence of the China Shock,” *Brookings Papers on Economic Activity*, 2021.
- Autor, David H., David Dorn, and Gordon H. Hanson,** “The China syndrome: Local labor market effects of import competition in the United States,” *American Economic Review*, 2013, 103 (6), 2121–2168.
- , —, —, —, and **Jae Song,** “Trade Adjustment: Worker-Level Evidence,” *Quarterly Journal of Economics*, 2014, 129 (4), 1799–1860.
- Barattieri, Alessandro, Susanto Basu, and Peter Gottschalk,** “Some Evidence on the Importance of Sticky Wages,” *American Economic Journal: Macroeconomics*, January 2014, 6 (1), 70–101.
- Blanchard, Olivier and Jordi Galí,** “Labor Markets and Monetary Policy: A New Keynesian Model with Unemployment,” *American Economic Journal: Macroeconomics*, April 2010, 2 (2), 1–30.
- Blanchard, Olivier Jean and Lawrence F. Katz,** “Regional Evolutions,” *Brookings Papers on Economic Activity*, 1992, 23 (1), 1–76.

- Böckerman, Petri, Seppo Laaksonen, and Jari Vainiomäki**, “Micro-level evidence on wage rigidities in Finland,” 2006. Working paper. Labour Institute for Economic Research.
- Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro**, “Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock,” *Econometrica*, May 2019, 87 (3), 741–835.
- Costinot, Arnaud and Jonathan Vogel**, “Matching and Inequality in the World Economy,” *Journal of Political Economy*, 2010, 118 (4), 747–786.
- Davis, Steven J. and Till von Wachter**, “Recessions and the Costs of Job Loss,” *Brookings Papers on Economic Activity*, 2011, pp. 1–72.
- **and Till Von Wachter**, “Recessions and the Costs of Job Loss,” *Brookings Papers on Economic Activity*, 2011, 2.
- Dhyne, Emmanuel, Ken Ayumu Kikawa, Toshiaki Komatsu, Magne Mogstad, and Felix Tintelnot**, “How Do Firms Respond to Demand Shocks? A Network Perspective,” *mimeo University of Chicago*, 2022.
- Dickens, William T., Lorenz Goette, Erica L. Groshen, Steinar Holden, Julian Messina, Mark E. Schweitzer, Jarkko Turunen, and Melanie E. Ward**, “How Wages Change: Micro Evidence from the International Wage Flexibility Project,” *Journal of Economic Perspectives*, June 2007, 21 (2), 195–214.
- Dix-Carneiro, Rafael**, “Trade Liberalization and Labor Market Dynamics,” *Econometrica*, 2014, 82 (3), 825–885.
- Einiö, Elias**, “Estimating Labor Demand Elasticities from Asymmetric Product Market Shocks,” *mimeo VATT Institute for Economic Research*, 2018.
- Eloranta, Jari and Jari Ojala**, “Converta - A Finnish Conduit in the East-West Trade,” in Jari Eloranta and Jari Ojala, eds., *East-West Trade and the Cold War*, Jyväskylä Studies in Humanities, 2005.
- Farber, Henry S.**, “Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey,” *Journal of Labor Economics*, 2017, 35 (S1), S235–S272.
- Feenstra, Robert C. and Gordon H. Hanson**, “Globalization, Outsourcing, and Wage Inequality,” *The American Economic Review, Papers and Proceedings*, 1996, 86 (2), 240–245.

- Fehr, Ernst and Lorenz Goette**, "Robustness and real consequences of nominal wage rigidity," *Journal of Monetary Economics*, May 2005, 52 (4), 779–804.
- Fortin, Pierre**, "The Great Canadian Slump," *Canadian Journal of Economics*, November 1996, 29 (4), 761–787.
- Friedman, Milton**, "The Case for Flexible Exchange Rates," in Milton Friedman, ed., *Essays in Positive Economics*, University of Chicago Press, 1953, pp. 157–203.
- Gorodnichenko, Yuriy, Enrique G. Mendoza, and Linda L. Tesar**, "The Finnish Great Depression: From Russia with Love," *American Economic Review*, 2012, 102 (4), 1619–44.
- Grossman, Gene M. and Esteban Rossi-Hansberg**, "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, 2008, 98 (5), 1978–1997.
- Gulan, Adam, Markus Haavio, and Juha Kilponen**, "Can large trade shocks cause crises? The case of the Finnish-Soviet trade collapse," *Journal of International Economics*, 2021, 131, 103480.
- Helpman, E. and O. Itskhoki**, "Trade Liberalization and Labor Market Dynamics with Heterogeneous Firms," *mimeo Harvard University*, 2015.
- , —, and **S. Redding**, "Inequality and Unemployment in a Global Economy," *Econometrica*, 2010, 78 (4), 1239–1283.
- Honkapohja, Seppo and Erkki Koskela**, "The Economic Crisis of the 1990s in Finland," *Economic Policy*, 1999, 14 (29), 401–436.
- Huckfeldt, Christopher**, "Understanding the Scarring Effect of Recessions," *American Economic Review*, Forthcoming.
- Hyman, Benjamin G.**, "Can Displaced Labor be Retrained? Evidence from Quasi-Random Assignment to Trade Adjustment Assistance," *mimeo*, 2018.
- Jacobson, Louis S., Robert J. Lalonde, and Daniel G. Sullivan**, "Earnings Losses of Displaced Workers," *American Economic Review*, 1993, 83 (4), 685–709.
- Jonung, Lars, Jaakko Kiander, and Pentti Vartia, eds**, *The great financial crisis in Finland and Sweden: The nordic experience of financial liberalization*, Edward Elgar Publishing, 2009.
- Kaur, Supreet**, "Nominal Wage Rigidity in Village Labor Markets," *American Economic Review*, October 2019, 109 (10), 3585–3616.

**Keynes, John Maynard**, "The Collected Writings of John Maynard Keynes," in Donald Moggridge, ed., *The Economic Consequences of Mr. Churchill*, New York: St. Martin's Press, 1925, pp. 207–230.

**Korkeamäki, Ossi and Tomi Kyyrä**, "A distributional analysis of earnings losses of displaced workers in an economic depression and recovery," *Oxford Bulletin of Economics and Statistics*, 2014, 76 (4), 565–588.

**Kovak, Brian**, "Regional Effects of Trade Reform: What is the Correct Measure of Liberalization?," *American Economic Review*, 2013, 103 (5), 1960–76.

— **and Rafael Dix-Carneiro**, "Trade Liberalization and Regional Dynamics," *American Economic Review*, 2017, 107 (10), 2908–2946.

**Möttönen, Tuomas**, "Idänkaupan ennusteet 1987-1991," 2002. ETLA Discussion Paper 833.

**Rodríguez-Clare, Andrés, Mauricio Ulate, and José P. Vásquez**, "New-Keynesian Trade: Understanding the Employment and Welfare Effects of Trade Shocks," NBER Working Papers 27905, National Bureau of Economic Research, Inc October 2020.

**Schmieder, Johannes F., Till von Wachter, and Joerg Heining**, "The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany," Mimeo, UCLA 2019.

**Schmitt-Grohé, Stephanie and Martín Uribe**, "Downward Nominal Wage Rigidity, Currency Pegs, and Involuntary Unemployment," *Journal of Political Economy*, 2016, 124 (5), 1466–1514.

**Stolper, Wolfgang F. and Paul A. Samuelson**, "Protection and Real Wages," *Review of Economic Studies*, 1941, 9 (1), 58–73.

**Sutela, Pekka**, "Finnish trade with the USSR: Why was it different?," 2005. BOFIT, Bank of Finland.

— , *Trading with the Soviet Union: The Finnish Experience 1944-1991*, Helsinki: Aleksanteri Institute, 2014.

**Topalova, Petia**, "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India," *American Economic Journal: Applied Economics*, 2010, 2 (4), 1–41.

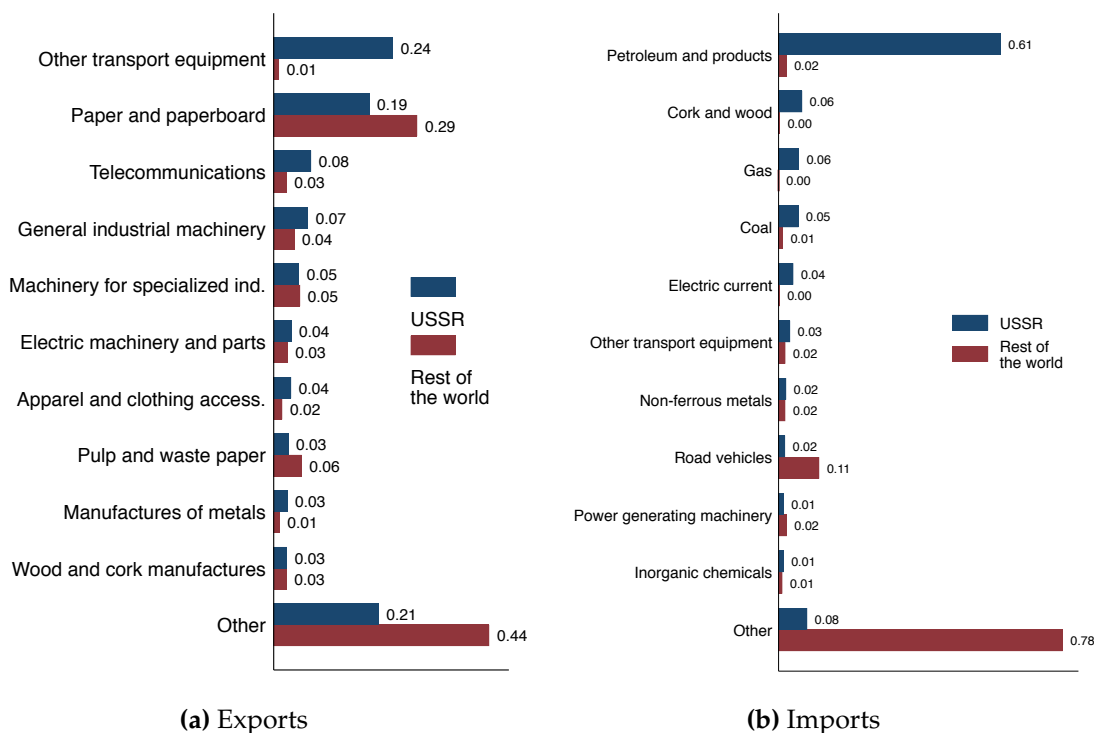
**Traiberman, Sharon**, "Occupations and Import Competition: Evidence from Denmark," *American Economic Review*, December 2019, 109 (12), 4260–4301.

**Yagan, Danny**, "Employment Hysteresis from the Great Recession," *Journal of Political Economy*, 2019, 127 (5), 2505–2558.



# A Empirical Appendix

## A.1 The Composition of Finland's Exports and Imports



**Figure A.1:** Composition of Finland's Exports and Imports, 1989

*Notes:* Panel (a) reports the shares of Finnish exports to the USSR accounted by different sectors (in blue) as well as the same shares for Finnish exports to the Rest of the World (in red). Panel (b) reports the shares of Finnish imports to the USSR (in blue) and imports to the Rest of the World (in red). Both panels refer to year 1989.

## A.2 Characteristics by Exposure in 1989

**Table A.1:** LDPM Plants by USSR Export Intensity, 1989

		By share of gross output exported to the USSR in 1989			
	All	0%	0–10%	10–50%	50–100%
<i>A: Plant characteristics</i>					
Gross output	8,207	4,991	33,860	38,277	15,615
Value-added	2,770	1,725	11,140	11,906	6,013
Number 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
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
Multi-plant firm	0.31	0.25	0.82	0.67	0.58
Share of output exported to the USSR	0.01	0.00	0.02	0.24	0.82
<i>B: Group characteristics</i>					
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

*Notes:* This table reports how characteristics of LDPM plants vary with their export intensity (Panel a) as well as the shares of output, employment, and USSR exports accounted by groups of plants with different export intensity (Panel b).

**Table A.2:** Correlation Between Market 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

*Notes:* This table reports the correlation between market exposure to the USSR shock and other municipality characteristics.

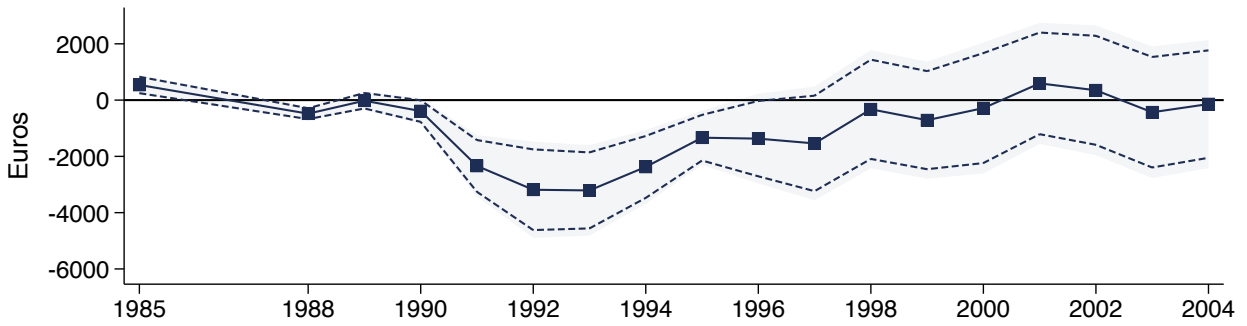
**Table A.3:** Worker Characteristics by Worker-Level Exposure to USSR Shock, 1989

		By worker-level exposure			
	All	0%	0–10%	10–50%	50–100%
<i>A: Employer characteristics</i>					
Average annual earnings	26,517 (7,430)	26,228 (7,738)	28,493 (4,328)	28,412 (4,611)	27,910 (5,235)
Output (LDPM)	67.4 (155.6)	34.7 (167.0)	115.3 (134.2)	95.5 (78.0)	60.8 (41.5)
Capital-labor ratio (LDPM)	102.8 (220.1)	99.1 (263.0)	111.0 (157.6)	94.1 (83.0)	75.3 (50.1)
<i>B: Worker socio-demographics</i>					
Year of birth	1953.8 (5.9)	1953.9 (5.9)	1953.2 (5.7)	1953.2 (5.8)	1953.3 (5.4)
Female	0.35	0.36	0.26	0.28	0.31
First language Finnish	0.95	0.94	0.97	0.96	0.97
First language Swedish	0.05	0.06	0.03	0.04	0.02
Other first language	0.003	0.003	0.002	0.001	0.004
Less than secondary/unknown degree	0.32	0.32	0.33	0.30	0.23
Lower secondary degree	0.37	0.37	0.42	0.45	0.44
Upper secondary degree	0.20	0.20	0.14	0.14	0.17
Lower tertiary degree	0.05	0.05	0.05	0.05	0.09
Higher tertiary degree	0.06	0.06	0.06	0.06	0.07
General, arts or teaching degree	0.06	0.06	0.03	0.02	0.03
Business degree	0.16	0.17	0.08	0.08	0.08
Technical degree	0.36	0.34	0.51	0.55	0.62
Degree in other fields	0.10	0.11	0.05	0.05	0.04
Degree unknown / missing	0.32	0.32	0.33	0.30	0.23
Annual earnings	28,354 (13,101)	28,260 (13,412)	29,017 (10,711)	28,823 (10,693)	28,828 (11,842)
<i>C: Sector of employment</i>					
Manufacturing	0.36	0.26	0.98	1.00	1.00
Observations	627,070	546,055	67,714	10,459	2,842

Notes: This table reports how characteristics of workers in our baseline sample vary with their exposure to the USSR shock.

### A.3 Effect of Worker Exposure: Earnings Regression (2)

Figure A.2 displays the OLS estimate of  $\beta_t$  in equation (2). As in Figure 4, Panel A of Figure 5 documents that even after conditioning 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. Compared to Figure 4, however, these declines converge quickly to zero: the OLS estimate of  $\beta_t$  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.<sup>28</sup>



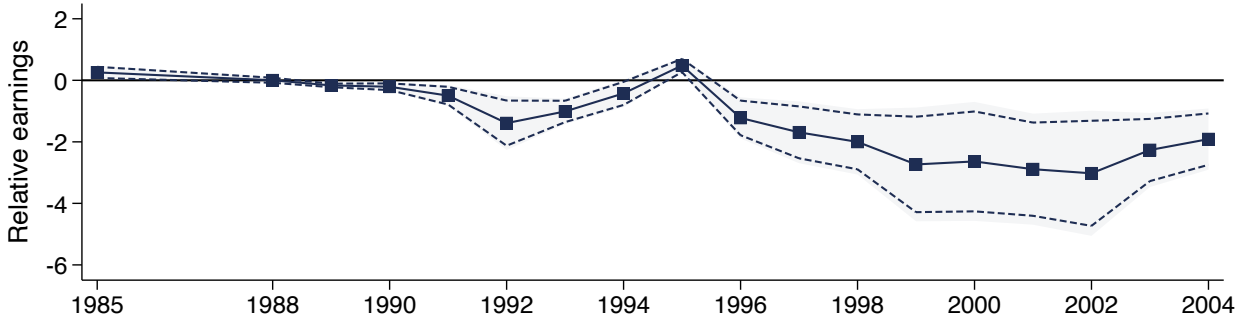
**Figure A.2:** Direct Effect of Worker Exposure ( $s_i$ ) on Earnings (Triple-Difference Specification)

*Notes:* Figure A.2 reports the OLS estimate of  $\beta_t$  in equation (2), with the 90% and 95% confidence intervals (dashed and shaded, respectively) computed with robust standard errors clustered by 1989 municipality.

<sup>28</sup>Reconciling the results of Figure 4 and Panel A of Figure 5 is straightforward. The persistent effects within a local labor market identified in Figure 4 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.

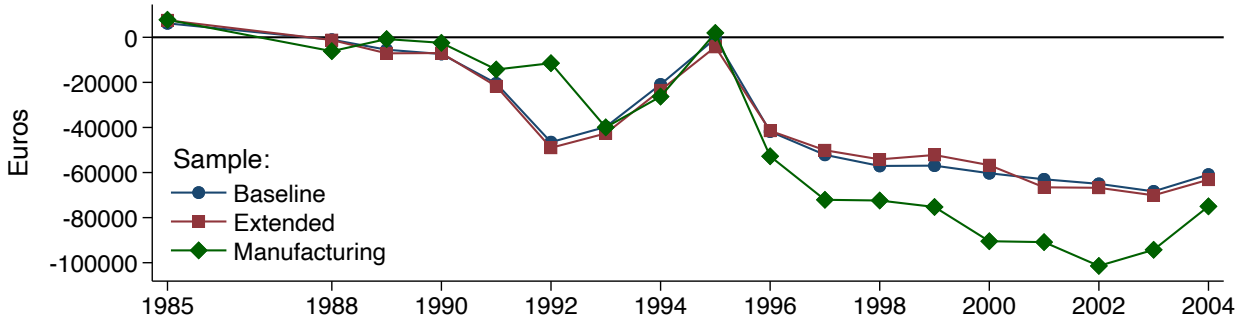
## A.4 Sensitivity Analysis: Earnings Regression (2)

We present additional robustness checks for the OLS estimates of  $\gamma_t$  in our baseline earnings regression (2). For visual clarity, in figures featuring multiple sensitivity results we do not include confidence intervals. Point estimates and standard errors associated with these figures (and our baseline results from Figure 5) are reported in Table A.4.



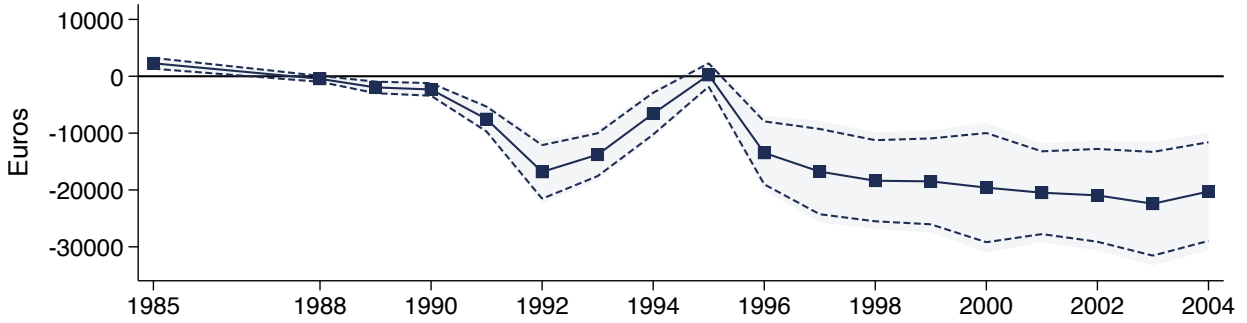
**Figure A.3:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Relative Earnings

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (2) defining the dependent variable as  $\Delta y_{it} \equiv y_{it}/\bar{y}_i$  instead of as  $\Delta y_{it} \equiv y_{it} - \bar{y}_i$ , with the 90% and 95% confidence intervals (dashed and shaded, respectively) computed with robust standard errors clustered by 1989 municipality.



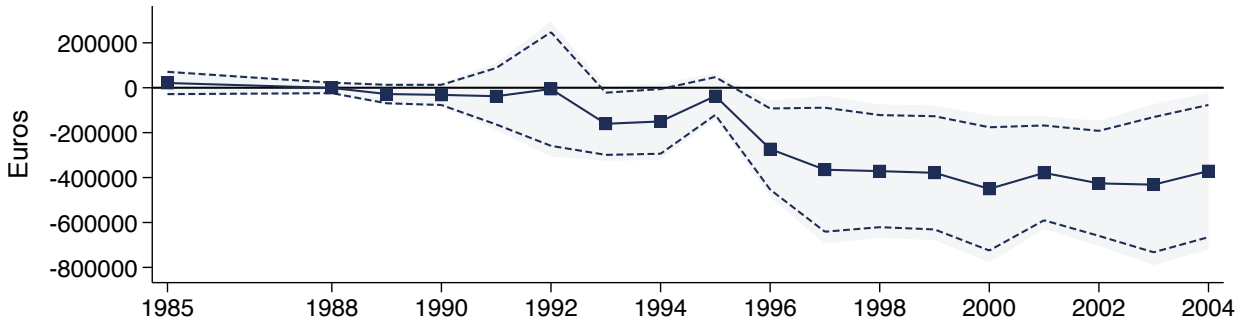
**Figure A.4:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Earnings (Alternative Worker Samples)

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (2) 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.



**Figure A.5:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Earnings (Alternative Measure of Market Exposure)

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (2) defining labor-market exposure on the baseline sample rather than the full working-age population. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.



**Figure A.6:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Earnings (Winsorizing Market Exposure)

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (2) winsorizing labor-market exposure at the top percentile. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.

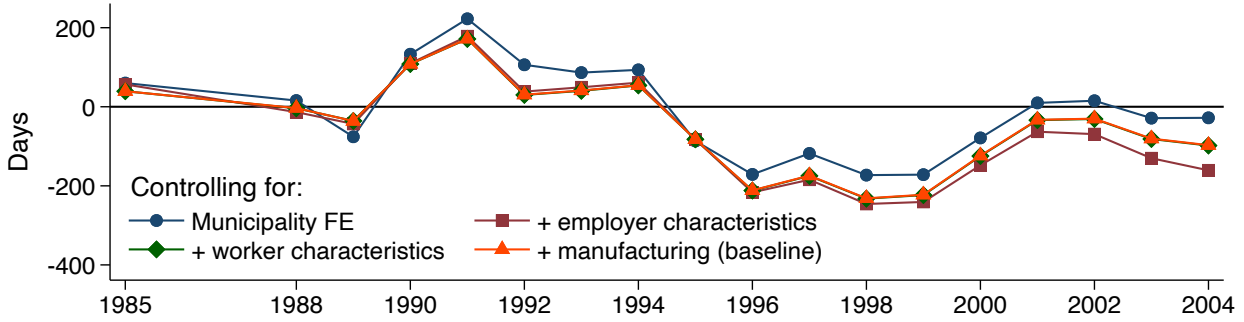
**Table A.4: Earnings Sensitivity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1985	3,878 (3,210)	5,842 (2,170)	6,227 (1,551)	6,212 (1,547)	7,583 (1,003)	7,859 (1,712)	3,537 (1,964)	7,579 (2,410)	7,792 (6,788)
1988	-1,163 (940)	-425 (1,030)	-1,054 (947)	-1,047 (947)	-1,660 (921)	-1,719 (1,004)	-1,306 (1,160)	-1,196 (778)	-6,142 (3,836)
1989	-3,328 (2,496)	-5,965 (2,104)	-5,494 (1,649)	-5,489 (1,648)	-6,206 (1,014)	-6,610 (1,579)	-1,746 (1,652)	-7,102 (2,462)	-777 (5,195)
1990	-6,189 (2,502)	-6,865 (2,137)	-7,391 (2,353)	-7,407 (2,351)	-5,811 (2,269)	-9,737 (2,306)	-4,480 (3,077)	-6,979 (2,553)	-2,437 (8,541)
1991	-19,076 (4,512)	-18,646 (4,125)	-20,446 (4,548)	-20,420 (4,535)	-20,452 (3,996)	-22,191 (5,237)	-18,167 (7,008)	-21,690 (3,555)	-14,278 (10,023)
1992	-49,145 (9,457)	-48,541 (9,624)	-46,522 (11,335)	-46,512 (11,327)	-46,847 (9,881)	-51,118 (12,428)	-52,864 (12,260)	-49,026 (8,494)	-11,467 (27,324)
1993	-49,273 (10,903)	-47,776 (10,153)	-39,704 (6,156)	-39,752 (6,153)	-32,081 (6,679)	-44,756 (8,118)	-28,610 (7,932)	-42,628 (5,234)	-39,936 (22,622)
1994	-36,898 (14,778)	-34,729 (13,903)	-20,797 (7,711)	-20,908 (7,662)	-14,625 (8,588)	-22,915 (9,500)	-8,042 (6,191)	-23,472 (6,896)	-26,288 (35,816)
1995	-21,655 (12,154)	-18,242 (11,159)	-421 (4,242)	-536 (4,173)	3,059 (5,163)	-2,067 (5,415)	8,006 (4,779)	-4,256 (3,750)	1,957 (24,128)
1996	-61,575 (19,730)	-57,222 (18,357)	-41,698 (11,586)	-41,803 (11,508)	-33,380 (11,035)	-44,514 (13,570)	-28,665 (8,348)	-41,464 (10,012)	-52,770 (43,453)
1997	-72,712 (24,293)	-67,231 (22,831)	-51,969 (15,993)	-52,133 (15,906)	-38,868 (13,778)	-56,697 (18,418)	-38,387 (12,073)	-50,091 (13,148)	-72,089 (59,438)
1998	-77,378 (22,634)	-70,887 (20,948)	-56,900 (15,237)	-57,067 (15,156)	-44,052 (13,135)	-60,078 (17,464)	-41,721 (10,641)	-54,140 (13,663)	-72,400 (60,145)
1999	-75,392 (22,870)	-68,463 (20,914)	-56,800 (15,634)	-56,936 (15,565)	-42,237 (13,113)	-62,171 (17,837)	-39,628 (10,885)	-52,202 (13,894)	-75,276 (59,032)
2000	-81,005 (26,974)	-72,587 (24,561)	-60,171 (19,556)	-60,304 (19,485)	-44,053 (15,803)	-63,385 (21,536)	-41,159 (13,718)	-56,710 (16,909)	-90,457 (69,648)
2001	-83,330 (21,413)	-73,835 (18,690)	-62,861 (14,872)	-62,992 (14,800)	-46,941 (11,803)	-64,324 (16,897)	-45,745 (10,038)	-66,541 (13,548)	-90,861 (57,552)
2002	-84,837 (24,496)	-74,079 (21,491)	-64,895 (17,112)	-65,006 (17,051)	-50,006 (14,527)	-66,663 (19,240)	-46,282 (11,520)	-66,753 (14,987)	-101,408 (61,918)
2003	-85,921 (24,887)	-73,332 (21,980)	-68,260 (18,383)	-68,345 (18,332)	-52,568 (15,689)	-69,983 (20,714)	-59,040 (15,322)	-70,100 (16,412)	-94,260 (64,857)
2004	-79,560 (21,924)	-65,023 (19,067)	-60,806 (16,447)	-60,883 (16,397)	-41,118 (12,628)	-62,109 (18,775)	-57,047 (15,593)	-63,179 (15,577)	-74,994 (58,685)
Sample	BL	BL	BL	BL	BL	BL	BL	All	Manuf.
Controlling for:									
Emp.	no	yes	yes	yes	yes	yes	yes	yes	yes
Worker	no	no	yes	yes	yes	yes	yes	yes	yes
Manu	no	no	no	yes	no	yes	yes	yes	yes
2-d ind.	no	no	no	no	yes	no	no	no	no
$s_i^2$	no	no	no	no	no	yes	no	no	no
$s_i^2 \times M_{89}$	no	no	no	no	no	no	yes	no	no
N	627,070	627,070	627,070	627,070	627,070	627,070	627,070	830,639	222,607

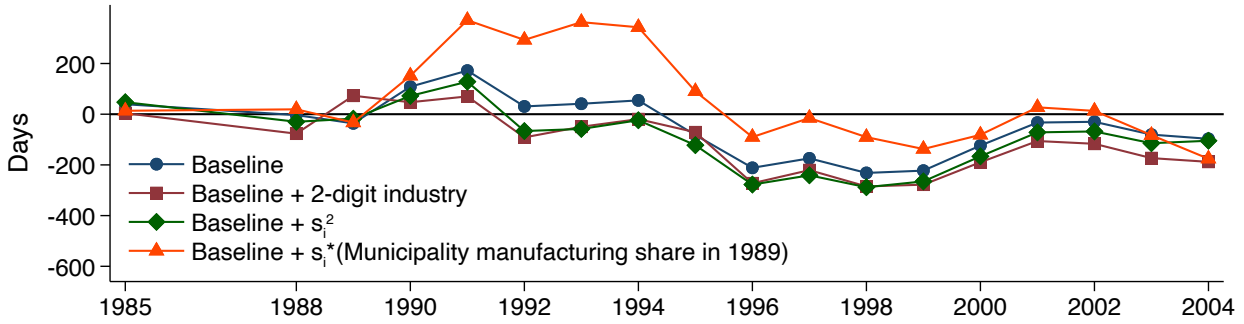
*Notes:* Sample: *BL* (baseline), *All* (not restricted by high-labor-force-attachment criterion), *Manuf.* (initially employed in manufacturing). Controls: Emp. and Worker indicate the inclusion of employer and worker characteristics, Manu and 2-d ind. indicate manufacturing and 2-digit industry indicators, and  $M_{89}$  is the municipality manufacturing share in 1989.

## A.5 Sensitivity Analysis: Days Worked Regression (8)

We present our sensitivity analysis for our employment earnings regression (8) in Figures A.7-A.10. For visual clarity, in figures featuring multiple sensitivity results we do not include confidence intervals. Point estimates and standard errors associated with these figures (and our baseline results from Figure 7) are reported in Table A.5.



(a) Interaction Effect of Worker and Market exposures ( $s_i \times S_m$ ) on Employment, with Fewer Controls

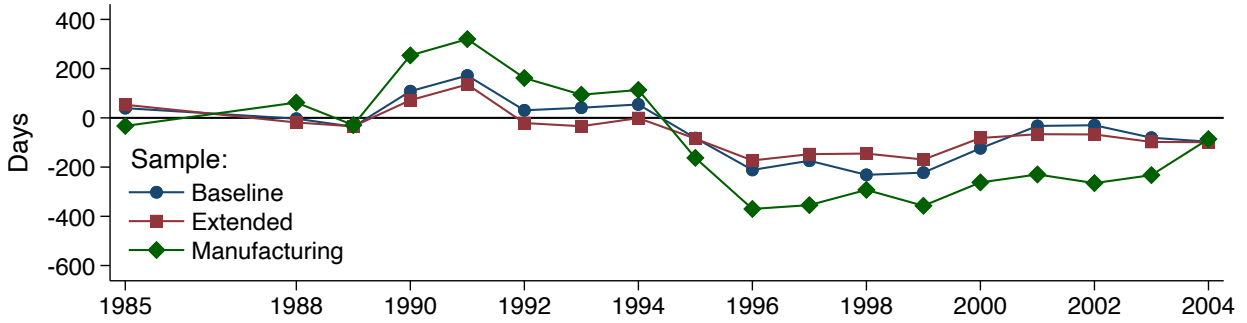


(b) Interaction Effect of Worker and Market exposures ( $s_i \times S_m$ ) on Employment, with Additional Controls

**Figure A.7: Employment Sensitivity: Controls**

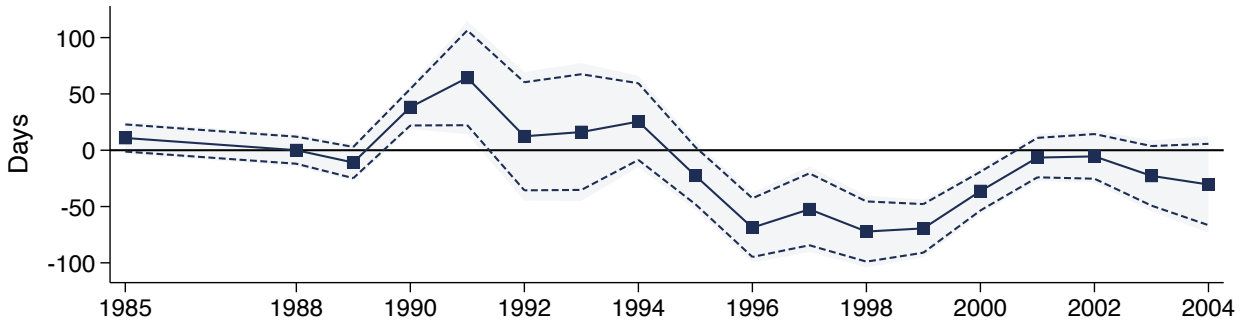
*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (8) with alternative vectors of controls,  $\text{Controls}_i$ . In the top panel, we estimate (8) including only include municipality indicator variables; then additionally include employer characteristics; then additionally include worker socio-demographic characteristics; and finally additionally include a manufacturing indicator variable, thereby replicating our baseline specification. In the bottom panel, the we estimate the baseline specification; then replace the manufacturing indicator with two-digit industry indicators; then separately include  $s_i^2$  as a control; and then separately add  $s_i \times (\text{Share of municipality's workers in manufacturing in 1989})$  as a control.





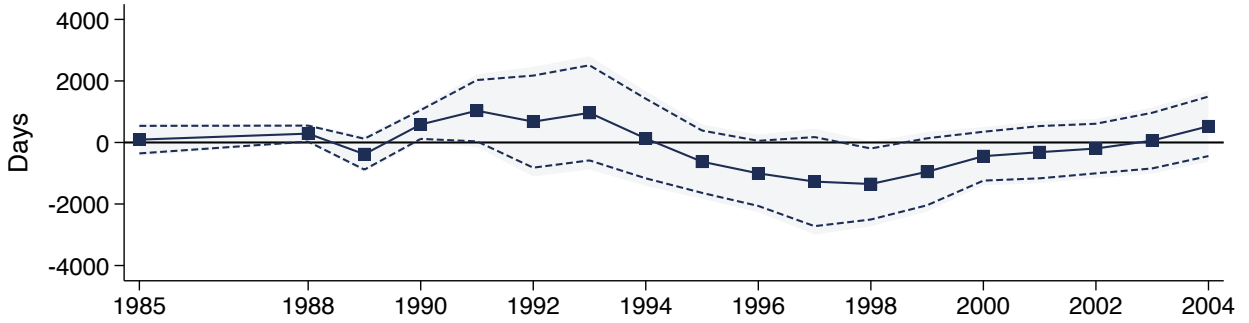
**Figure A.8:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Employment (Alternative Worker Samples)

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (8) 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.



**Figure A.9:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Employment (Alternative Measure of Market Exposure)

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (8) defining labor-market exposure on the baseline sample rather than the full working-age population. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.



**Figure A.10:** Interaction Effect of Worker and Market Exposure ( $s_i \times S_m$ ) on Employment (Winsorizing Market Exposure)

*Notes:* This figure reports the OLS estimates of  $\gamma_t$  in equation (8) winsorizing labor-market exposure at the top percentile. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.

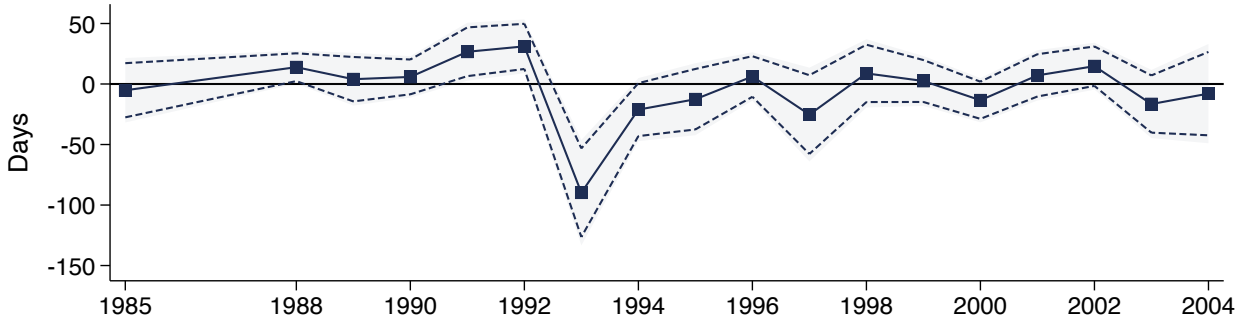
**Table A.5: Employment Sensitivity**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1985	60.0 (18.2)	33.2 (20.1)	39.3 (20.4)	39.4 (20.4)	3.9 (22.3)	47.3 (19.6)	13.6 (23.9)	53.2 (29.1)	-32.8 (55.0)
1988	15.8 (22.1)	27.7 (24.4)	-3.7 (19.7)	-3.3 (19.4)	-76.7 (13.3)	-29.7 (22.4)	19.3 (29.0)	-18.7 (19.0)	62.1 (38.8)
1989	-75.8 (24.8)	-60.9 (19.2)	-35.6 (27.1)	-36.1 (26.8)	72.8 (30.0)	-17.6 (28.8)	-32.9 (29.4)	-34.5 (28.7)	-29.3 (81.5)
1990	133.0 (29.9)	126.6 (28.1)	108.1 (25.5)	108.5 (25.4)	47.3 (16.7)	72.2 (32.8)	151.6 (47.8)	71.9 (24.9)	253.8 (39.1)
1991	222.6 (73.5)	200.1 (66.3)	171.6 (59.9)	172.1 (59.7)	70.2 (38.0)	128.3 (71.7)	370.8 (149.0)	135.8 (51.7)	320.0 (107.2)
1992	106.2 (100.2)	70.3 (90.5)	30.0 (82.6)	30.7 (82.2)	-91.4 (59.4)	-66.4 (88.7)	293.1 (177.4)	-21.1 (72.4)	161.9 (147.7)
1993	86.5 (100.2)	43.5 (89.6)	40.3 (86.7)	41.2 (86.3)	-49.4 (72.6)	-58.0 (97.3)	363.1 (198.1)	-33.9 (73.5)	94.1 (148.1)
1994	93.4 (64.0)	49.1 (59.0)	54.1 (54.3)	54.6 (54.4)	-19.4 (71.9)	-23.8 (64.1)	343.0 (118.8)	-0.9 (56.7)	113.4 (185.3)
1995	-86.5 (50.8)	-118.1 (50.3)	-82.3 (50.6)	-82.3 (50.6)	-71.2 (53.1)	-122.1 (56.6)	90.3 (60.7)	-84.4 (51.4)	-162.6 (200.3)
1996	-171.0 (51.0)	-199.5 (50.9)	-211.9 (49.7)	-211.5 (49.9)	-272.4 (66.1)	-277.5 (57.3)	-90.0 (57.0)	-173.1 (53.9)	-370.1 (158.6)
1997	-118.0 (68.0)	-141.1 (73.3)	-174.8 (71.0)	-174.1 (71.5)	-220.5 (83.9)	-241.0 (81.6)	-15.0 (63.7)	-147.5 (69.9)	-354.5 (226.6)
1998	-172.9 (51.8)	-191.8 (55.0)	-232.3 (58.0)	-231.6 (58.3)	-284.9 (70.9)	-288.0 (65.5)	-90.5 (58.5)	-144.9 (56.4)	-292.5 (203.8)
1999	-171.7 (40.6)	-185.9 (41.1)	-223.4 (44.3)	-222.5 (44.7)	-278.0 (56.7)	-265.0 (55.8)	-137.3 (56.6)	-169.4 (45.9)	-357.1 (131.6)
2000	-78.7 (28.7)	-86.8 (26.9)	-124.6 (32.9)	-123.7 (33.3)	-189.5 (44.6)	-166.2 (38.9)	-81.3 (49.7)	-81.7 (32.7)	-262.3 (93.2)
2001	9.8 (30.1)	8.4 (27.0)	-33.7 (33.6)	-32.8 (33.9)	-105.8 (46.9)	-71.7 (37.4)	27.1 (43.8)	-66.4 (31.7)	-229.8 (93.3)
2002	15.2 (36.2)	21.8 (30.7)	-30.8 (33.9)	-30.0 (33.9)	-116.7 (42.3)	-68.0 (37.8)	13.1 (50.1)	-67.4 (31.2)	-265.2 (91.3)
2003	-28.7 (50.3)	-13.7 (46.2)	-81.5 (41.2)	-80.5 (41.1)	-173.2 (39.3)	-114.4 (45.4)	-82.8 (56.4)	-97.8 (34.2)	-232.6 (111.9)
2004	-28.0 (79.0)	-1.2 (78.6)	-98.1 (58.8)	-97.0 (58.5)	-187.9 (44.8)	-104.7 (60.7)	-175.6 (54.1)	-98.8 (40.8)	-86.1 (152.6)
Sample	BL	BL	BL	BL	BL	BL	BL	All	Manuf.
Controlling for:									
Emp.	no	yes	yes	yes	yes	yes	yes	yes	yes
Worker	no	no	yes	yes	yes	yes	yes	yes	yes
Manu	no	no	no	yes	no	yes	yes	yes	yes
2-d ind.	no	no	no	no	yes	no	no	no	no
$s_i^2$	no	no	no	no	no	yes	no	no	no
$s_i^2 \times M_{89}$	no	no	no	no	no	no	yes	no	no
N	627,070	627,070	627,070	627,070	627,070	627,070	627,070	830,639	222,607

Notes: Sample: *BL* (baseline), *All* (not restricted by high-labor-force-attachment criterion), *Manuf.* (initially employed in manufacturing). Controls: Emp. and Worker indicate the inclusion of employer and worker characteristics, Manu and 2-d ind manufacturing and 2-digit industry indicators, and  $M_{89}$  municipality manufacturing share in 1989.

## A.6 Sensitivity Analysis: Hourly-Wage Sample

As we describe in Section 4.3, in estimating the wage regression (10) for year  $t$ , we must restrict our sample to workers in the hourly-wage sample both in 1989 and year  $t$ . Conditioning on being in the hourly-wage sample in year  $t > 1989$  introduces issues of selection that are not present in our baseline analysis. Here, our objective is to show that this may not bias our estimates displayed in Panel (b) of Figure 8. To do so, we focus on the market employment regression, which, unlike the wage regression, we can estimate in both our baseline sample and the hourly-wage sample. Figure A.11 displays the predicted effects on employment  $\hat{\beta}_t$  of market exposure  $S_m$  estimated using regression (9) on the hourly-wage sample. Comparing these estimates to Panel (b) of Figure 8, we see similar results across samples, suggesting that sample selection into the year  $t$  hourly-wage sample does not substantially affect our employment results.



**Figure A.11:** Market Employment: Sensitivity to Hourly-Wage Sample

*Notes:* This figure reports the OLS estimate of  $\beta_t$  in equation (9) estimated on the hourly-wage sample rather than our baseline sample. The 90% and 95% confidence intervals (dashed and shaded, respectively) are computed with robust standard errors clustered by 1989 municipality.

## B Theoretical Appendix

### B.1 Proof of Proposition 1

After the shock, the market-clearing wage jumps from  $\bar{W}_0 = (N/\Phi)^{-1/\sigma}$  to  $\bar{W}_{0+} = (N/\Phi')^{-1/\sigma}$ , where it remains ever thereafter, with  $\Phi \equiv \sum_{j \in \mathcal{J}} \phi_j$  and  $\Phi' \equiv \sum_{j \in \mathcal{J}} \phi'_j = \Phi(1 - S)$  denoting market-level demands pre- and post-shock. In turn, market-level wages  $\{W_t\}$  are given by the unique solution to the first-order linear differential equation (7) with initial condition  $W_0 = \bar{W}_0$ ,

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

Proposition 1 part (i) directly follows. Substituting equilibrium wages into equation (4) pins down equilibrium employment levels  $\{E_t\}$ ,

$$E_{mt} = \begin{cases} N_m & , \text{ for } t = 0, \\ N_m(1 - S_m) \left[ e^{-\gamma t} + (1 - e^{-\gamma t})(1 - S_m)^{\frac{1}{\sigma}} \right]^{-\sigma} & , \text{ for all } t > 0. \end{cases} \quad (\text{B.2})$$

Proposition 1 part (ii) directly follows, with  $E_{0+} = N_m(1 - S_m)$ .

### B.2 Proof of Proposition 2

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

Let  $\pi_{it}$  denote the probability that a worker  $i \in \mathcal{I}$  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 (5) implies

$$\pi_{i0+} = 1 - s_i. \quad (\text{B.3})$$

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  $\kappa_t$  (as described in equation 6) and a transition probability from employment to unemployment equal to the exogenous separation rate  $\lambda$  (since wages are falling, all plants are expanding and  $\lambda_{jt} = \lambda$ , by

equation 5). Hence,  $\pi_{it}$  satisfies the following first-order differential equation,

$$\dot{\pi}_{it} = \kappa_t(1 - \pi_{it}) - \lambda\pi_{it} = \kappa_t - (\lambda + \kappa_t)\pi_{it}. \quad (\text{B.4})$$

Combining equations (4), (5), (6), (B.1), and (B.2), we can solve for the job-finding rate  $\kappa_t$ . At any date  $t$ , we have

$$\kappa_t = \frac{\left[ e^{-\gamma t}(1-S)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t}) \right]^{-\sigma} (\lambda + \sigma\gamma) - \left[ e^{-\gamma t}(1-S)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t}) \right]^{\frac{\sigma+1}{\sigma}} \sigma\gamma}{1 - \left[ e^{-\gamma t}(1-S)^{-\frac{1}{\sigma}} + (1 - e^{-\gamma t}) \right]^{-\sigma}}. \quad (\text{B.5})$$

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

Next, consider a worker with exposure  $s_i$  in a market with exposure  $S$ . The employment probability of this worker is given by the unique solution to (B.4) whose initial condition satisfies (B.3),

$$\pi_{it} = 1 - s_i e^{-\int_0^t (\lambda + \kappa_v) dv} - \lambda \int_0^t e^{-\int_v^t (\lambda + \kappa_z) dz} dv. \quad (\text{B.6})$$

The employment probability is strictly decreasing in  $s_i$ ; and since  $\kappa_t$  is strictly decreasing in  $S$  for all  $t$ , it is also strictly decreasing in  $S$ . Since earnings are equal to  $W_t$  if a worker is employed and 0 otherwise, expected earnings are equal to

$$y_{it} = W_t \pi_{it}, \quad (\text{B.7})$$

with the market wage given by equation (B.1),

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

Differentiating equation (B.6) implies

$$\begin{aligned}\frac{d\pi_{it}}{ds_i} &= -e^{-\int_0^t(\lambda+\kappa_v)dv} < 0, \\ \frac{d^2\pi_{it}}{ds_idS} &= \int_0^t \left(\frac{d\kappa_v}{dS}\right)dv \times e^{-\int_0^t(\lambda+\kappa_v)dv} < 0.\end{aligned}$$

Proposition 2 part (i) directly follows.

Finally, differentiating equation (B.7) implies

$$\begin{aligned}\frac{dy_{it}}{ds_i} &= -W_t e^{-\int_0^t(\lambda+\kappa_v)dv} < 0, \\ \frac{d^2y_{it}}{ds_idS} &= \left[ -\frac{d \ln W_t}{dS} + \int_0^t \left(\frac{d\kappa_v}{dS}\right)dv \right] \times W_t e^{-\int_0^t(\lambda+\kappa_v)dv}.\end{aligned}$$

The sign of  $\frac{d^2y_{it}}{ds_idS}$  depends on whether the positive wage effect,  $-d \ln W_t / dS > 0$ , dominates the negative job-finding-rate effect,  $\int_0^t (\frac{d\kappa_v}{dS})dv < 0$ . Differentiating (B.1) and (B.5) with respect to  $S$  implies

$$\begin{aligned}-\frac{d \ln W_t}{dS} &= \frac{1}{\sigma}(1 - e^{-\gamma t})(1 - S)^{\frac{1}{\sigma}-1} x_t^{\frac{1}{\sigma}}, \\ \frac{d\kappa_v}{dS} &= -\frac{e^{-\gamma t} x_v^{\frac{\sigma+1}{\sigma}} [\lambda + \sigma\gamma + \gamma x_v^{\frac{1}{\sigma}} [x_v - (\sigma + 1)]]}{(1 - x_v)^2 (1 - S)^{\frac{1}{\sigma}+1}}.\end{aligned}$$

At  $\gamma = 0$ , we therefore get

$$\begin{aligned}-\frac{d \ln W_t}{dS} \Big|_{\gamma=0} &= 0, \\ \frac{d\kappa_v}{dS} \Big|_{\gamma=0} &= -\lambda/S^2 < 0.\end{aligned}$$

Proposition 2 part (ii) follows from the two previous equations and the fact that both  $-d \ln W_t / dS$  and  $\int_0^t (\frac{d\kappa_v}{dS})dv$  are continuous in  $\gamma$ .

### B.3 Footnote 21

In Footnote 21, we have argued that  $\frac{d^2 y_{it}}{ds_i dS} > 0$  is possible if  $\gamma$  is large enough. To show this, we consider first-order Taylor expansions of  $-d \ln W_t / dS$  and  $\int_0^t (\frac{d\kappa_v}{dS}) dv$  around  $t = 0$ ,

$$\begin{aligned} -\frac{d \ln W_t}{dS} &= \frac{\gamma}{\sigma} (1 - S)^{\frac{1-\sigma}{\sigma}} t + o(t), \\ \int_0^t (\frac{d\kappa_v}{dS}) dv &= -(\lambda / S^2) t + o(t). \end{aligned}$$

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

### B.4 Extension: Incumbent versus New Hire Wage Rigidity

The goal of this Appendix is to show that the results in Propositions 1 and 2 in Section 4.1 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 4.1, 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  $\gamma \rightarrow \infty$ , new hire wages are fully flexible, whereas incumbent wages are fully rigid.<sup>29</sup>

The wages of new hires  $\{W_t\}$  and the employment levels  $\{E_t\}$  remain given by equations (B.1) and (B.2),

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

Proposition 1 therefore remains unchanged, provided that  $W_t$  is now interpreted as the wage of new hires rather than the wage of all employed workers. Likewise, the probabil-

---

<sup>29</sup>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  $\lambda$ . 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 as reasonable.



ity of employment  $\pi_{it}$  continues to satisfy (B.3) and (B.4),

$$\begin{aligned}\pi_{i0+} &= 1 - s_i, \\ \dot{\pi}_{it} &= \kappa_t(1 - \pi_{it}) - \lambda\pi_{it} = \kappa_t - (\lambda + \kappa_t)\pi_{it},\end{aligned}$$

with the job-finding-rate given by equation (B.5),

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

This implies that probabilities of employment are the same as in the baseline model of Section 4.1 and given by (B.6)

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

Proposition 2 part (i) is therefore also unchanged. The only difference between expected earnings in the two models come from the expected wage received by a worker employed at date  $t$ .

To this point, the baseline model of Section 4.1 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 (B.1) gives

$$t(W) = \frac{1}{\gamma} \ln \left[ \frac{1 - (1-S)^{\frac{1}{\sigma}}}{w/W - (1-S)^{\frac{1}{\sigma}}} \right]. \quad (\text{B.8})$$

For any  $w \in [W', W]$ , denote by  $H_{it}(w)$  the probability that a worker  $i$  receives a wage  $W_{it} \leq w$ .  $H_{it}(w)$  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,

$$H_{it}(w) = \begin{cases} 1 - \pi_{it} & \text{for all } w \in [W', W] \text{ and } t < t(w), \\ 1 - \pi_{it(w)} e^{-\lambda[t-t(w)]} & \text{for all } w \in [W', W] \text{ and } t \geq t(w). \end{cases} \quad (\text{B.9})$$

The expected earnings  $Y_{it}$  of worker  $i$  is then equal to

$$y_{it} = W(1 - s_i) e^{-\lambda t} + \int_{W_t}^W w dH_{it}(w) dw.$$

Differentiating (B.9) and substituting in the previous expression implies, after a change of variable,

$$y_{it} = W(1 - s_i) e^{-\lambda t} + \int_0^t W_v [\dot{\pi}_{iv} + \lambda \pi_{iv}] e^{-\lambda[t-v]} dv.$$

Combining this expression with (B.4) and (B.6), we obtain, after rearrangements,

$$y_{it} = s_i \left[ -W_t e^{-\int_0^t (\lambda + \kappa_z) dz} + \int_0^t e^{-\int_0^v (\lambda + \kappa_z) dz} \dot{W}_v dv \right] + y_t,$$

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

Although expected earnings differs from our baseline model, where it is simply equal to  $W_t \pi_{it}$ , we still obtain part (ii) of Proposition 2, as we now show. Differentiating the previous expression with respect to  $s_i$ , we get

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

as argued in part (ii) of Proposition 2. The cross-derivative with respect to  $s_i$  and  $S$ , in turn, satisfies

$$\begin{aligned} \frac{d^2 y_{it}}{ds_i dS} &= \left[ -\frac{d \ln W_t}{dS} + \int_0^t \left( \frac{d \kappa_v}{dS} \right) dv \right] \times W_t e^{-\int_0^t (\lambda + \kappa_v) dv} \\ &\quad - \int_0^t \left\{ \left[ -\frac{d \ln \dot{W}_v}{dS} + \int_0^v \left( \frac{d \kappa_z}{dS} \right) dz \right] e^{-\int_0^v (\lambda + \kappa_z) dz} \dot{W}_v \right\} dv. \end{aligned}$$

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

$$\frac{d^2 y_{it}}{ds_i dS} = \int_0^t \left( \frac{d \kappa_v}{dS} \right) dv \times W_t e^{-\int_0^t (\lambda + \kappa_v) dv} < 0.$$

Part (ii) of Proposition 2 therefore still holds by the same continuity argument.

## B.5 Extension: Positive Steady-State Unemployment

The goal of this Appendix is to show that the main results of Section 4 generalize to an environment in which the wage adjustment process maintains positive unemployment in the steady state. Specifically, we now assume that  $\bar{W}_t$  in equation (7) is such that

$$\bar{W}_t \equiv \left( \frac{N(1-u)}{\Phi_t} \right)^{-1/\sigma},$$

where  $u \in [0, 1)$  denotes the steady-state unemployment rate. The model of Section 4 corresponds to the special case  $u = 0$ .

In line with our baseline analysis, we assume that the local labor market is in steady state just before date 0, with the wage given by  $W_0 = \bar{W}_0$  and with employment equal to  $E_0 = (1-u)N$ . After the shock, the long-run wage jumps from  $\bar{W}_0 = (N(1-u)/\Phi)^{-1/\sigma}$  to  $\bar{W}_{0+} = (N(1-u)/\Phi')^{-1/\sigma}$ . In turn, the market wage and employment are given by

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

and

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

Proposition 1 therefore continues to hold without qualification.

On impact, the unemployment rate jumps from  $u$  to  $u + S(1-u)$ , since a share  $S$  of the employed are fired. Whereas equations (B.3) and (B.4) remain unchanged, the job-finding rate—equation (B.5)—generalizes to

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

which can be expressed more compactly as  $\kappa_t = \tilde{\kappa}(x_t)$ , with  $\tilde{\kappa}(x_t) \equiv [x_t(\lambda + \sigma\gamma) - x_t^{\frac{\sigma+1}{\sigma}} \sigma\gamma] / ((1-u)^{-1} - x_t)$  and  $x_t \equiv E_t / [N(1-u)] \in [1-S, 1]$ . If  $u \in [0, \min\{\lambda/\gamma, 1\})$ , then  $\kappa'(x) > 0$  and Proposition 2 continues to hold without qualification. If  $\lambda/\gamma < 1$  and  $u > \lambda/\gamma$ , then for sufficiently high values of  $t > T$ , we have  $\kappa'(x) < 0$ . In this case, the same results only hold for  $t \in (0, T)$ .