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## The Costs of Job Displacement and the Demand for Industry-Specific Human Capital

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# The Costs of Job Displacement and the Demand for Industry-Specific Human Capital

Maor Milgrom\*

February 22, 2025

## Abstract

It is well established that job displacement leads to large and persistent earnings losses, but the reasons for these long-term losses remain unclear. A leading theory ties earnings losses to the demand laid-off workers face for their industry-specific human capital, yet evidence in support of this theory is lacking. This paper proposes a novel method for estimating the demand for workers' industry-specific skills. I proxy for the worker's skill set with her occupation, and measure how industry-specific her occupation is by the share of the occupation that is employed in her industry. The demand for the worker's industry-specific skills is then estimated by the industry growth rate. Applying this measure, I test for heterogeneity in the costs of displacement for manufacturing workers in Israel. I show that workers laid off from shrinking industries who held highly industry-specific occupations suffer from substantially greater earnings losses, as predicted by the theory. Within shrinking industries, these workers experience earnings losses that are 76% higher than workers in occupations with low industry-specificity. These losses in earnings are driven by a persistent effect on employment, as workers with industry-specific occupations are 2.5 times more likely to exit the labor market in the years following displacement. The findings are robust to within-firm analysis, indicating that these results are not explained by a loss of firm wage premiums. (*JEL* J24, J31, J63, J65)

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# 1 Introduction

The effects of job loss have long been a central topic in the field of labor economics. In their seminal work, [Jacobson et al. \(1993\)](#) studied Pennsylvania’s deindustrialization in the early 1980s, a period marked by widespread closures of steel mills and coal mines ([Reisinger and Lewandowski 1998](#)). They found that displaced workers suffered substantial and persistent earnings losses. This result has since been replicated in numerous settings and countries, establishing the fact that this is a general phenomenon, not an idiosyncratic event. The persistence and magnitude of these earnings losses present a striking pattern that economists have struggled to explain. Over the past 30 years, researchers have attempted to identify the fundamental causes and mechanisms, yet with little success.<sup>1</sup>

These long-term earnings losses have significant implications for policymakers. Understanding their causes is important when designing assistance programs for workers after firm closures, when deciding whether to intervene to prevent impending mass layoffs, and especially when considering broad policy measures that could lead to substantial job displacement, such as trade liberalization ([Autor et al. 2013](#)) and automation ([Acemoglu et al. 2020](#)). To effectively minimize displacement costs, policymakers must understand the underlying mechanisms to apply appropriate policies and target the workers who would benefit from them.

The empirical evidence on displacement costs also poses a major challenge to standard economic theory. Canonical models of the labor market (e.g., [Katz and Murphy 1992](#)), where wages and employment levels are determined by supply and demand in frictionless markets, cannot explain these persistent effects. In response, several theories have been proposed. A leading explanation is the theory of industry-specific human capital (ISHC), originating with [Becker \(1964\)](#) and developed by [Neal \(1995\)](#). According to this theory, wages, in part, reflect compensation for skills that are specific to industries. Displacement may lead to a drop in earnings, if the worker is unable to find another job where these skills are valued, or if the demand for these specific skills has declined. When testing this theory empirically, the researcher faces two major challenges. The first is to identify which workers possess skills that are industry-specific. Not every employee of the steel industry, for example, holds skills that are specific to that industry. The second challenge is assessing the market demand for those specific skills.

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<sup>1</sup>To quote [Lachowska et al. \(2020, pp. 3231\)](#): “Longitudinal data on workers’ earnings have established the magnitude of displaced workers’ earnings losses, but little evidence exists on the reasons underlying these losses”.

In this paper, I propose a novel, and simple, approach for identifying both elements. To identify the workers that hold industry-specific skills, I use the worker’s occupation to proxy for her skills, and define the *industry-specificity* (IS) measure of her occupation as the share of that occupation that is employed in her industry. The higher the concentration of an occupation in an industry, the more industry-specific is her human capital, and the more her “investment” is tied to that industry. Then, I estimate the demand for a worker’s industry-specific skills with the growth rate of that industry. If the industry is soaring, there will be vast demand for workers with skills specific to the industry. If it’s declining, demand will be low. Putting together both components, we have an approach that allows to directly examine the contribution of workers’ ISHC to their post-displacement losses, and to test the predictions of the ISHC theory. Namely, I expect the worker’s earnings losses to be larger, if both of the following conditions hold: Her occupation was highly specific to her industry, and that industry is shrinking.

I test this hypothesis on workers laid off from the manufacturing sector in Israel, using administrative longitudinal data. I follow the empirical strategy laid out by Jacobson, LaLonde, and Sullivan (1993, JLS henceforth) for estimating the causal effects of displacement, by tracking the recovery of workers who were laid off as part of a mass layoff or plant closure, and comparing their earnings trajectories to a comparable group of workers who were not displaced. To estimate the average treatment effects, I run a Stacked Difference-in-Differences (DiD) regression model (Cengiz et al. 2019). I then extend the model to a triple-differences model (DDD), and test for heterogeneity in the costs of displacement by industry growth and the occupations’ industry-specificity levels.

I use employer-employee matched data from the Israeli Tax Authority. The tax records track individuals and firms over time, and include information on earnings, employment, and industry. These records are merged with other sources to incorporate data on sex, ethnicity, age, and education, allowing me to control in my analysis for important labor market variables. The dataset covers the entire workforce for the years 1990-2019, and enables the identification of events of mass layoffs and firm closures. Information on workers’ occupations comes from surveys that are matched to the administrative dataset. These include the Israeli Censuses of 1995 and 2008, each of which surveys 14% of the population, and the smaller Labor Force Surveys (LFS). In order not to restrict the analysis to the years in which workers were surveyed, I impute the occupation variable using the following assumption: If a worker remains in the same firm for which I have data on occupation from a different year, I assume she remains in the same occupation.

I begin the analysis by replicating the main findings in the job displacement literature.

I find strong and persistent effects of job loss. After one year, the average treatment effect on earnings for displaced workers (the ATT) is 31%, and it remains above 7% ten years later. Displacement leads to a large fall in employment levels in the short run, but recovery is relatively quick, as employment losses are at 2%-4% in the long run. Losses in monthly wages (conditional on working) are significantly smaller in the short run, but persist in the long run at around 4%. For all outcome variables, the estimated pre-trends are negligible, strengthening our confidence in the estimates of the DiD research design.

Turning to examine heterogeneous treatment effects, I show that conditional on being laid off from a declining industry, having an industry-specific occupation has a large negative effect on displaced workers, matching the hypothesis. In shrinking industries, I find that an increase of one Std Dev in the IS measure equals 1/3 of the ATT in these industries, both in the short run and in the long run. Averaging across all post-displacement periods, high IS workers<sup>2</sup> in shrinking industries lose 76% more than low IS workers. In contrast, there is no effect of IS in growing industries. I also find large heterogeneity in the effect of IS. In the short run, the difference between the displacement effects at the 90th percentile and the 10th percentile of the IS distribution is over half the size of the ATT. In the long run, that gap equals 82% of the ATT. I then repeat the analysis separately by education level. The results show that the costs associated with having a significantly industry-specific occupation are concentrated among lower-education workers.

How important is the ISHC channel in explaining the overall effects of displacement? I find that workers with high IS, but low industry growth, account for 35% of the ATT on earnings, and 40% of the ATT on employment, even though this group constitutes only 22% of laid-off workers. I then show that the driving force behind these estimated effects is the fact that high IS workers experience large losses in employment. I conduct a counterfactual analysis, holding wages fixed at their pre-displacement level, and imputing their earnings based on changes in employment levels. For high IS workers who were laid off from shrinking industries, employment losses account for over 70% of the losses in earnings in the long run. These workers are also 2.5 times more likely to exit the labor market in the years following displacement. Overall, the evidence points to the ISHC mechanism as a key contributor to the persistent effects of displacement.

A potential concern with the empirical strategy is that laid-off workers with highly industry-specific occupations may have been concentrated in distinct types of firms or labor markets. For instance, they may be more likely to be employed by worst firms or in a market with particular poor conditions. If the recovery of displaced workers is dependent

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<sup>2</sup>I define workers as high IS if their occupation's industry-specificity is above 10%.

on firm-specific shocks, or on highly-localized market conditions that are hard to account for even if controlling for the geographical region, it could introduce bias into the results. To address this concern, I modify the DDD model and conduct a *within-firm* analysis: I compare workers from the same firm, who were laid off during the same mass layoff event, but whose occupations differ in their IS level. The results of this analysis mirror the main findings, mitigating potential concerns. Finally, to validate the use of the IS measure, I test whether a relationship exists between possessing industry-specific skills and industry tenure, as predicted by [Becker \(1964\)](#). Indeed, I find that workers with high IS remain longer in their industry, and that conditional on switching employers, they are more likely to end up at another job in the same industry.

In addition to the ISHC theory, several other theories attempt to explain the effects of job displacement.<sup>3</sup> A prominent explanation focuses on the loss of firm wage premiums (commonly interpreted as rents), as the displaced are forced to switch to lower-paying firms ([Topel 1990](#); [Schmieder et al. 2023](#)); A second theory stipulates that the large earnings losses are due to compensation schemes that tie wages to tenure (e.g., backloaded compensation), as the “bonus” for longevity is lost upon displacement ([Lazear 1981](#)); And job ladder models emphasize the loss of a high-quality match between the worker and the firm, as workers displaced from stable jobs are likely to require time to find similarly high-quality matches ([Jovanovic 1979](#)). These theories, including ISHC, are not mutually exclusive, as earnings losses can be the result of several factors working simultaneously. Notwithstanding, I argue that the ISHC theory explains my findings better than the competing theories, and I show results that significantly weaken alternative explanations. Specifically, I show that longer tenure is not a strong predictor of earnings losses in this setting, and demonstrate through within-firm analysis that firm-level factors, such as AKM-style firm wage premiums, do not drive the results.

This paper relates to the extensive literature estimating the earnings losses of displaced workers. The original work by [Jacobson et al. \(1993\)](#) has since been replicated and extended in different settings, including [Couch and Placzek \(2010\)](#) for Connecticut, [Davis and von Wachter \(2011\)](#) for the U.S., [Lachowska et al. \(2020\)](#) for Washington state, [Raposo et al. \(2021\)](#) for Portugal, and [Schmieder et al. \(2023\)](#) for Germany. In addition, several studies showed suggestive evidence in support of the ISHC explanation for this phenomenon.<sup>4</sup> Notably among them, [Carrington \(1993\)](#) and [Neal \(1995\)](#) found that workers who switched industries after displacement suffered greater losses. Following that work, other studies found

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<sup>3</sup>See [Carrington and Fallick \(2017\)](#) for an extensive survey.

<sup>4</sup>For example, studies have found that earnings losses of displaced workers are higher in industries where on-the-job training is common ([Carrington and Zaman 1994](#); [Schoeni et al. 1997](#)).



that larger earnings losses are associated with switching occupations (Huckfeldt 2022), job titles (Raposo et al. 2021), or “skill portfolios” (Poletaev and Robinson 2008). The main limitation of these papers is that they condition on the worker’s endogenous decision of switching or remaining in her industry or occupation, which may lead to selection bias.

I contribute to this literature by proposing a measure of the demand for workers’ industry-specific skills that is predetermined (in relation to displacement), and does not require conditioning on an outcome. Closer to this paper, recent work has shown that earnings losses are larger when displaced workers have fewer outside options (Caldwell and Danieli 2024), and when there is greater skill mismatch between their previous occupation and locally prevalent occupations (Macaluso 2023).<sup>5</sup> In contrast to these studies, this paper focuses on the role that industries, and particularly divergent industry growth patterns, play in determining the demand for workers with specific skills.<sup>6</sup>

A recent paper by Schmieder et al. (2023) challenges the ISHC explanation, finding that occupation and industry switches have little explanatory power once controlling for changes in firm wage premiums. However, like occupational switching, moving to lower-paying firms is an endogenous outcome, making it problematic to control for.<sup>7</sup> Furthermore, while I also find that displacement reduces firm wage premiums, this decline does not explain the losses I attribute to the ISHC channel. Comparing workers from the same firm and mass layoff event, but with different levels of industry-specific skills, reveals persistent ISHC effects when holding fixed origin-firm wage effects.

The remainder of the paper proceeds as follows: I begin by presenting the theory of industry-specific human capital and its predictions regarding displaced workers. Section 3 presents the empirical strategy, while Section 4 provides background information on the Israeli manufacturing sector. Section 5 describes the data and definitions used in the analysis. Section 6 presents the results. Section 7 discusses how the results fit competing theories on the costs of displacement. Section 8 concludes.

## 2 Theory: Specific Human Capital and Job Loss

In one of his most famous contributions to economic theory, Becker (1964) set out a theory of human capital. Among its many components, it included a distinction between

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<sup>5</sup>Blien et al. (2021) similarly find larger earnings losses among workers displaced from more routine-intensive occupations.

<sup>6</sup>My work relates to Helm et al. (2023), who examine how the overall decline of the manufacturing sector differentially affects low- and high-wage workers.

<sup>7</sup>Indeed, Schmieder et al. (2023) themselves acknowledge that “the associations... do not necessarily imply causal relationships if workers with larger or smaller wage losses tend to select different employers after job loss” [pp. 1242].

*general* human capital and *specific* human capital. In Becker’s model, both types are the result of on-job training, a costly investment made by the firm and/or the worker, to increase the worker’s productivity. According to Becker, general training is defined as training that affects productivity at any firm or job, while specific training increases productivity only in a specific firm. For our purposes, the training aspect is not of importance, but rather the outcome: Different workers develop and accumulate a different stock of skills. Furthermore, workers with general human capital are not dependent on a specific firm to collect the returns on that investment. In contrast, with specific human capital, “Workers develop a stock of firm-specific skills whose rental price is tied to the demand conditions for that firm’s product or services” (Carrington and Fallick 2017, pp. 691). Becker then adds a third category - human capital that is not specific only to a specific firm, but to “... a set of firms defined by product, type of work, or geographical location” [pp. 27]. This type of human capital follows the logic of the firm-specific human capital, only the “unit” is replaced. Extending Becker’s logic, industry-specific human capital is the case where workers develop skills that are specific to an industry, and whose *rental price* is tied to the demand conditions for that industry’s product or services.

Although Becker did not refer directly to the costs of job loss, his distinction between different types of human capital provides a possible, and commonly referenced,<sup>8</sup> explanation for this phenomenon: Since general human capital is completely transferable, it will not be “lost” when a worker switches employers.<sup>9</sup> In contrast, firm-specific human capital is always lost with displacement, assuming the worker does not return to that firm. In between those two, we have industry-specific human capital. Consider a worker who received on-job training in a textile factory, and was later laid off. If her next job is outside the textile industry, she is likely not to receive a return for these skills, and will experience a reduction in wages. If she does find a job within the industry, those skills still have value. However, she may still incur a loss, because the value she receives for that skill set will depend on the market demand for those skills. If the textile industry is in decline, there will be lower demand for textile-specific skills and the displaced worker will suffer losses, even if she stays in the industry.<sup>10</sup> The concept of specific human capital can also explain post-displacement losses in *employment*. If workers’ reservation wages are tied to past wages (Koenig et al.

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<sup>8</sup>According to Carrington and Fallick (2017), Becker’s theory is “[t]he theory most commonly associated with the earnings losses of displaced workers” [pp. 688].

<sup>9</sup>Returns for general human capital can also depend on market conditions. For example, Davis and von Wachter (2011) found that displacement effects are larger in recessions.

<sup>10</sup>An additional reason for these losses is skill depreciation. However, that cannot explain the large immediate drop in earnings following displacement (assuming the depreciation is somewhat continuous) unless the pre-displacement wages were not being adjusted to the concurrent skill level (for example, due to wage rigidity).

2016), or just slow to adjust, then workers whose specific skill set is in low demand will receive offers that constitute a significant cut in wages, and they may choose to remain out of the labor market

This theory, therefore, predicts earnings losses for workers with human capital that is specific to an industry in decline. The key to predicting the earnings losses of such a displaced worker lies in evaluating the demand for her skills.

## 3 Research Design

### 3.1 Measures of ISHC and its demand

The idea that industry-specific human capital plays an important role in explaining earnings losses is not new, and was suggested already by [Jacobson et al. \(1993\)](#) and [Neal \(1995\)](#). However, to provide empirical support for this conjecture, we must overcome two major challenges. The first is to identify which workers possess industry-specific human capital, and to infer how specific it is. For example, a weaver in the textile industry is likely to possess skills that are more industry-specific than those of a truck driver employed in the same industry. The second challenge is to assess the market demand for those specific skills.

I begin with the first challenge. Since I do not have information on workers' skills, I proxy for them, using their self-reported occupation. Then, to identify which workers hold industry-specific skills, I introduce the occupation's industry-specificity (IS) measure, defined as the share of the occupation employed by each industry. The higher the concentration of an occupation in an industry, the more industry-specific is the worker's human capital, and the more her "market value" is dependent on that industry. In a sense, this continuous measure of an occupation's industry-specificity is a way to position each individual on the scale between general and specific human capital. The second challenge is to assess the demand for a worker's specific skills. To do so, I focus on the state of the industry from which she was laid off. If the industry is soaring, there will be vast demand for workers with skills specific to the industry. If it's declining, demand will be low. Putting together both components, we have a method that allows us to empirically examine the relationship between ISHC and displacement.

This leads to the hypothesis of this paper, which posits that a displaced worker will experience larger earnings losses if both of the following conditions hold: Her occupation is highly specific to her industry, and that industry is declining.

### 3.2 Average displacement effects

To estimate average treatment effects of displacement, I will follow JLS in what became the standard approach for examining displacement effects. The JLS method stands on two pillars. First, the treated group includes only workers laid off in mass layoffs and firm closure events. There are two main advantages to this restriction: (i) It helps isolate layoffs from quits – in many administrative datasets, including the Israeli tax data, we observe workers separating from firms, but not the underlying cause. Separation during a period of significant contraction reduces the likelihood that these workers are quitting; (ii) It reduces potential selection – a main threat to the identification of the displacement effects are cases where workers were displaced due to lackluster performance on an unobservable level. For workers of this type, it would be nearly impossible to find an adequate control group. Restricting the treatment group to mass layoffs and closures reduces the potential selection, as it is unlikely that all the workers displaced were unobservably bad. Furthermore, mass layoffs and closures are usually perceived as a shock to the firm, i.e., as circumstances beyond the control of the worker.<sup>11</sup>

The second pillar of the JLS research design is constructing a control group of comparable workers, designed to provide us with the counterfactual path for the treated workers, had they not been displaced. These workers were employed in firms that did not go through a mass layoff, and I require these workers to remain with the firm for three additional years, to serve as a “stable employment” counterfactual. JLS used a staggered difference-in-differences (DiD) regression model, which I will adopt and expand upon. By using DiD, we remove any common trends underlying the data, plus we account for any time-invariant worker characteristics.

In my setting, displacement events took place in different calendar years. To obtain a single estimate for the average displacement effects, the common practice is to pool all displacement events and run a staggered DiD regression. However, pooling events across years requires caution, as pointed out in the recent Differences-in-Differences literature (e.g., [Goodman-Bacon 2021](#); [Borusyak et al. 2021](#); [Sun and Abraham 2021](#)). In this paper I follow the Stacked Regression approach ([Gormley and Matsa 2011](#); [Cengiz et al. 2019](#)). At the core of this approach is the creation of cohort-specific datasets, each dataset including the treated and control workers for the layoff events of a specific calendar year. These cohort-specific datasets are then *stacked* together, and the DiD regression is estimated on the stacked dataset. In practice, this entails saturating the model’s control variables (including

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<sup>11</sup>The online Business Dictionary gives the following definition for a displaced worker: “Eligible worker who has been permanently laid off... due to the firm’s failure or plant closure”.

the model’s fixed effects) by indicators for the cohort-specific dataset. This ensures that the comparison group used is within the cohort, and prevents the use of past treated units as effective controls (Baker et al. 2022).<sup>12</sup> I apply the Stacked Regression approach using a Poisson regression model. The common practice in the literature (e.g., Lachowska et al. 2020) is to use a log-linear model, in order to derive the semi-elasticities of the outcomes with respect to treatment. However, for outcome variables that include zeros, this results in those observations being dropped. Two of my main outcome variables, earnings and employment, have a significant share of zero values, because many displaced workers have periods of non-employment following displacement. Therefore, instead of a log-linear model, I use an exponential (Poisson) regression model, where the coefficients represent percentage changes (i.e., semi-elasticities) (Silva and Tenreyro 2006).<sup>13</sup>

Formally, let  $i$  be a worker,  $t$  a calendar year, and  $D_i$  a binary indicator for a displaced (treated) worker. In my sample, each worker is assigned to a specific displacement year  $c$  (cohort): A treated worker if she was displaced in this year, and a control worker if she can serve as a counterfactual for this year (i.e., has been with the firm at least three years, and will not separate from the firm in the following two years). Let  $p$  represent periods, defined as years relative to displacement year. Note the period variable is defined for the control group as well. We get the following specification:

$$y_{ip} = \exp\left(\sum_{p=-6}^{10} \alpha_{c(i)p} + \sum_{p=-6}^{10} \beta_p \cdot D_i + \theta_i + x_{ic(i)p}\pi + z_{j(i)}\psi_{c(i)t(i,p)}\right) + \varepsilon_{ip}, \quad (1)$$

where the outcome  $y_{ip}$  (earnings, employment, or wages) is non-negative, and for the error term I assume  $E[\varepsilon_{ip} | \alpha_{c(i)p}, \theta_i, D_i, x_{ic(i)}, z_{j(i)}] = 0, \forall p$ . The vector  $\alpha_{cp}$  represents cohort by period fixed effects, which allows the control group to evolve on a separate trend by displacement year. The coefficients of interest are  $\beta_p$ , that estimate the regression-adjusted differences in outcomes between displaced and non-displaced (control) workers. In addition,  $\theta_i$  are workers fixed effects,  $x_{icp}$  includes quadratic and cubic terms in age, which may vary by cohort,<sup>14</sup> and  $z_j$  is a vector of firm-level controls (size and industry) interacted by year-

<sup>12</sup>Cengiz et al. (2019) explain that “by aligning events by event-time (and not calendar time), it is equivalent to a setting where the events happen all at once and are not staggered; this prevents negative weighting of some events that may occur with a staggered design” (Online Appendix D, pp. 44).

<sup>13</sup>Cohn et al. (2021) show that using a Poisson model for instances where the dependent variable is zero-valued is superior to other common practices used by economists, such as adding a constant to the outcome and then estimating log-linear regressions, or applying the inverse hyperbolic sine to the outcome, as these produce estimates “with no natural interpretation that can easily have the wrong sign” [pp. 1]. See also Bellemare and Wichman (2020).

<sup>14</sup>Following Card et al. (2016), I recenter the quadratic and cubic terms around age 40. This normalization is used based on evidence that the age profile is flat at age 40.

cohort fixed effects, to allow for specific trends by industry and firm size. As we can see, the model’s control variables (in particular the  $\alpha$ ’s) are saturated in cohort-specific indicators, following the Stacked Regression approach (Baker et al. 2022).<sup>15</sup>

For  $\beta_p$  to represent the *causal* effect of displacement on the treated (ATT), it requires the identifying assumption that absent of displacement, the time path of displaced workers’ earnings (in terms of percentage changes) would have remained parallel to the time path of non-displaced workers’ earnings. This assumption can be tested in the pre-displacement periods, as we would like to see no observed “effect” of displacement on the outcomes prior to displacement, but must be assumed for post-displacement periods. Note that most of the literature on displacement effects shows evidence of a *dip* in earnings in the 1-2 years prior to displacement (including Jacobson et al. 1993, Schmieder et al. 2023 and Lachowska et al. 2020), a limited violation of the parallel assumption. This is usually interpreted as evidence that these firms were struggling even before executing the mass layoff, leading them to reduce hours or wages.

### 3.3 Heterogeneous effects by IS and industry growth

To test the hypothesis of this paper, I will extend the DiD model to allow for heterogeneous treatment effects (HTE) by the occupation’s industry-specificity and the rate of industry growth. My main specification is the traditional DiD model with heterogeneous treatment effects, which leads to a model equivalent to a Triple-Differences regression (or difference-in-difference-in-differences, DDD). For illustration, let me focus on a binary case, in which I compare the displacement effects for workers with an industry-specific occupation (henceforth ISOCC) to workers with a general occupation (GOCC). The DDD model essentially compares the outcomes for these two types of displaced workers, after subtracting from each group their counterfactual outcome, estimated using their respective control groups. The difference between the two (separately estimated) effects of displacement tells us whether displacement has a stronger impact on one of the groups. Olden and Møen (2020) show that for a causal interpretation, the DDD estimator requires a (single) modified parallel trends assumption: That in the absence of treatment, the difference between the outcomes of the ISOCC workers in the treated group and the control groups, equals (or “trends similarly”) to the difference between the (counterfactual) outcomes of the treated and control GOCC workers.

Formally, let  $IS_{ok}$  denote the level of industry-specificity of occupation  $o$  at industry  $k$ ,

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<sup>15</sup>The individual fixed effects are not saturated, since by construction each individual belongs to a single cohort. In addition, note that I cannot include year fixed effects in this model, since the calendar year is predetermined when I control for each combination of cohort X period.

assigned to worker  $i$  at her pre-displacement job, and let  $G_k$  denote the growth level of that industry. To allow for heterogeneous treatment effects by these factors, I extend Eq. 1, as follows:

$$\begin{aligned}
y_{ip} = \exp & \left( \underbrace{\sum_{p=-4}^6 \alpha_{c(i)p} + \sum_{p=-4}^6 \beta_p D_i + \theta_i + x_{ic(i)p} \pi}_{\text{Baseline displacement equation}} + \right. \\
& \underbrace{\sum_{p=-4}^6 \gamma_p \text{IS}_{o(i)k(i)} + \sum_{p=-4}^6 \delta_p G_{k(j(i))} + \sum_{p=-4}^6 \zeta_p (\text{IS}_{o(i)k(i)} \times G_{k(j(i))})}_{\text{Industry-specificity and growth main effects}} + \\
& \left. \underbrace{\sum_{p=-4}^6 \eta_p (D_i \times \text{IS}_{o(i)k(i)}) + \sum_{p=-4}^6 \lambda_p (D_i \times G_{k(j(i))}) + \sum_{p=-4}^6 \phi_p (D_i \times \text{IS}_{o(i)k(i)} \times G_{k(j(i))})}_{\text{Heterogeneous treatment effects}} \right) + \varepsilon_{ip}
\end{aligned} \tag{2}$$

As before,  $\beta_p$  gives the dynamic main effect of displacement,  $\gamma_p$  and  $\delta_p$  give the main effect of IS and G, respectively, and  $\zeta_p$  is the interaction between them. The vectors  $\eta_p$  and  $\lambda_p$  represent the dynamic additional effects of IS and industry growth for displaced workers, respectively.<sup>16</sup> Our coefficient of interest is  $\phi_p$ , that tells us whether there are heterogeneous displacement effects by the interaction of IS levels with industry growth. According to the hypothesis, I predict  $\phi_p > 0$  in post-displacement periods, i.e., that job displacement will lead to larger losses when both the growth of industry  $k$  is lower, and the industry-specificity of occupation  $o$  is higher.<sup>17</sup> While Eq. 2 represents the full model, I will also focus on the dynamics specific to industries in different states. Specifically, I split the industries into categories of growing and shrinking industries (to be defined in Section 5.2), and estimate

<sup>16</sup>In contrast to Eq. 1, I do not include in this equation firm-level controls, due to power considerations.

<sup>17</sup>The reader may have noticed that while the parallel trends assumption for the DDD model stated above related to a binary heterogeneity variable, in practice I defined continuous measures for industry-specificity and industry growth. Callaway et al. (2024) define the required assumptions for a continuous treatment variable to estimate the average treatment effects, and it is possible to apply their approach to the DDD model. The authors, however, stress that with a continuous treatment variable, stronger assumptions are required to recoup a causal estimate. First, a *strong* parallel trends assumption must hold, which essentially requires that for any level of treatment, all units must follow the same path they would have followed if assigned to that level. The second and more problematic issue, is that we must assume no selection into treatment level. Since the DiD coefficients are by definition local treatment effects for the treated (ATT), selection into treatment level is a non-issue in the binary treatment case. However, with many levels of treatment, this is a strong assumption to make. For example, if we are examining the effect of the dosage level of Advil on headaches, we need to assume that the effect at any dosage is the same for individuals who usually take two Advil pills, and for those who take five pills (Example given by Cunningham (2021)).



the following model, separately for each category:

$$y_{ip} = \exp \left( \underbrace{\sum_{p=-4}^6 \alpha_{c(i)p} + \sum_{p=-4}^6 \beta_p D_i + \theta_i + x_{ic(i)p} \pi}_{\text{Baseline displacement equation}} + \underbrace{\sum_{p=-4}^6 \gamma_p \text{IS}_{o(i)k(i)}}_{\text{IS main effect}} + \underbrace{\sum_{p=-4}^6 \eta_p (D_i \times \text{IS}_{o(i)k(i)})}_{\text{HTE by industry-specificity}} \right) + \varepsilon_{ip} \quad (3)$$

Here,  $\eta_p$  is the dynamic additional effect of the IS measure on the displacement effects. For shrinking industries, I predict  $\eta_p < 0$ . For growing industries, the relationship is ambiguous. Lastly, note that for the entire analysis, I cluster standard errors at the pre-displacement firm level,<sup>18</sup> since the treatment, displacement, occurs at that level.

## 4 The Manufacturing Sector in Israel

The empirical analysis in this paper centers around mass layoffs in the Israeli manufacturing sector.<sup>19</sup> Since the establishment of the state of Israel in 1948, the Israeli economy was characterized by heavy government involvement. The government took on responsibility for the promotion of employment opportunities in all regions of the country, and did so by assisting in the development of industries (Levi-Faur 1996). This included various protectionist measures, as well as subsidized loans and grants (Katz 2018), to encourage the opening of factories in remote areas of Israel. In 1985, Israel began shifting to a more market-based economy, when the Economic Stabilization Plan was adopted. This followed a decade of economic stagnation and increasing government deficit, which had culminated in hyperinflation in 1984-1985. As part of this shift, Israel began removing trade barriers. With relation to the manufacturing sector, the key trade reform was the adoption of the Exposure Plan in 1991. The program opened the Israeli market to imports from the emerging Far East, by removing trade regulations and reducing customs duties. Its declared goals were to improve the welfare of consumers through lower prices and access to a larger variety of goods, while forcing the local industries to become more efficient (Elbert, 2003). The reform covered most manufacturing industries, with only a few exemptions. This reform led to a rapid decline in many low-tech manufacturing industries, including textiles, glass products,

<sup>18</sup>For treated workers, the pre-displacement firm is the firm that laid them off. For the control workers, it is their main employer at period 0.

<sup>19</sup>This sector was chosen for both technical and substantial reasons, see Appendix B.2.



and furniture production, resulting in the shutdown of many factories.<sup>20</sup>

While the role the government plays in the modern Israeli economy is limited, there remains an expectation that the state will take an active role in creating jobs (Zimring and Moav 2015). This is particularly true when plants shut down in remote areas of the country, where job opportunities are limited. For example, the threat of closing Pri Galil, a canned food manufacturing plant, in 2011, led to months of media coverage and parliament committee meetings, focused on how to assist the workers in their recovery process. The crisis culminated with the plant receiving government assistance in the amount of 18 million ILS, or 4.7 million USD (Avital 2012). This example highlights the prominent role that job loss costs hold in Israeli discourse.

## 5 Data and Definitions

### 5.1 Data

I use Israeli administrative longitudinal data, compiled from several sources by the Israeli Central Bureau of Statistics. Employer-employee matched data originates in Form 126, which every employer in Israel must submit annually to the Israel Tax Authority. This dataset covers all workers of prime working age (25-65) for the years 1990-2019. The work-related variables include annual earnings, monthly employment indicators per employer, employer identifier, and a 2-digit industry identifier (based on the ISIC Rev. 3 classification). Data on demographic variables comes from the Population and Immigration Authority, and includes sex, birth year, religion, ethnicity, and city of residence. Data on schooling and degrees comes from the Ministry of Education.

Because there are no official records in Israel on the occupations of workers, I matched the administrative records to survey data. The main sources for occupation information are the 1995 and 2008 Censuses, each covering approx. 14% of the population in that year, and quarterly Labor Force Surveys (LFS, 2001-2019). Both surveys classify the self-reported occupation using the ISCO-88 classification, at the 3-digit level.

### 5.2 Definitions

#### 5.2.1 Outcome Variables

My analysis will focus on three outcome variables: earnings, employment, and wages. Earnings is defined as the total annual earnings from salaried employment during the calendar

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<sup>20</sup>Appendix Figure A.1 shows the evolution of the high-tech and low-tech manufacturing industries in Israel.

year. If the worker did not work, it receives the value zero. Employment is defined as the number of months worked during the year (0-12). Wages is defined as the average monthly earnings for the months in which the individual worked. If she did not work during the year, wages receives a missing value. Earnings and wages are both in 2019 Israeli shekel (ILS) values. The average exchange rate in 2019 was 1 USD = 3.56 ILS.

### 5.2.2 Industry Growth

I use the term *industry* to describe the 2-digit categories (“divisions”) of the ISIC Rev. 3 classification. The manufacturing sector is composed of 28 industries. I define *industry growth* in terms of the growth rate of the industry’s workforce. While other definitions are possible (e.g., growth in output or gross production), I use the growth of employment for two reasons: (1) It is most commonly used in the literature;<sup>21</sup> (2) It is arguably the most relevant measure for a displaced worker searching for work, since it should be highly correlated with hirings in the industry.<sup>22</sup> Industry growth is computed as the 5-year growth rate of industry employment, centered around the time of layoff.<sup>23</sup> This window was selected to capture both the state of the industry at the time of layoff, as well as to reflect the demand for workers in that industry in the years immediately following. I define an industry as *growing* in year  $t$ , if its growth rate was above the median industry growth of manufacturing industries in that year. I define an industry as *shrinking* if its growth rate is below the median.

Figure 1 ranks manufacturing industries according to their overall growth rate for the years 1995-2008. This figure captures the story of manufacturing in Israel over the past decades. At the top, we have production of computers, electronics, and pharmaceutical products, reflecting the growth of the Israeli hi-tech sector. At the bottom are the low-tech industries that have been rapidly declining, including tobacco products and textiles.

### 5.2.3 The Industry-Specificity of Occupations

An *occupation* is defined as a 3-digit ISCO-88 entry. Examples include semiconductor, stonemason, and plasterer. For each combination of occupation  $o$  and industry  $k$ , I define the occupation’s Industry-Specificity (IS) as the share of the occupation employed by that industry ( $IS_{ok} \in (0, 1]$ ).<sup>24</sup> In parts of the analysis, I will use a binary classification, in which

<sup>21</sup>For example, the very popular Bartik industry shares are computed based on employment shares.

<sup>22</sup>Production growth is naturally correlated with employment growth, but the relation is not necessary. A key example of this is the recent trends in automation.

<sup>23</sup>For example, the industry growth for a certain industry in the year 2000 is defined as the growth in employment between 1997 and 2002. The results are robust to defining industry growth in other ways, see Appendix C.3.3.

<sup>24</sup>The industry-specificity measure is estimated twice, in the 1995 and 2008 censuses. For each year, I assign the industry-specificity measure that is closer in time. It should be noted that the measure is fairly

an occupation-industry combination will be classified as an Industry-Specific Occupation (ISOC) for  $IS \geq 0.1$ ,<sup>25</sup> or as a General Occupation (GOCC) for values below the cutoff. Appendix Figure A.2(a) depicts the distribution of the IS measure for displaced workers, at their pre-displacement employer. The distribution is highly skewed, with a median of 0.057. This distribution implies that the skill set of a large share of the displaced workers was, in fact, not particularly specific to their industry.

A convenient way to summarize each occupation’s level of industry-specificity is by measuring how concentrated it is, using the familiar Herfindahl–Hirschman index (HHI) for concentration.<sup>26</sup> Figure 2 ranks the main manufacturing occupations, grouped at the 2-digit level, by their concentration levels. Diamond workers are at the top, being highly dependent on the diamond manufacturing industry. Other concentrated occupations and their primary employing industries (noted in brackets) include builders (construction), spinners and weavers (textile), and shoemakers (leather and shoes).

To bolster the confidence in the use of the IS measure for examining the heterogeneous effects of job displacement, I assess its validity based on a prediction made by Becker (1964). He predicted that workers with firm-specific human capital will have lower turnover, as these workers would prefer to remain with the only firm that values their specific skills. This prediction can be naturally extended to the case of industry-specific human capital: We expect workers who developed skills specific to an industry to prefer to remain in the industry, where these skills positively influence their productivity, and therefore, their wages. I test this prediction in two ways: First, I examine whether workers with high IS remain longer than other workers in their industry; second, I check whether, upon switching employers, high IS workers are more likely to end up at another job in the same industry. I test both predictions in a sample of non-displaced workers, using a linear regression model. Results are reported in Appendix Table A.2. First, we see a positive association between the IS measure and tenure in an industry. With controls, the coefficient on IS is 0.192 (implying a 5.7 percent increase Per Std Dev of the IS measure), and highly significant.<sup>27</sup> Focusing on job switchers, we see that a higher IS is predictive of remaining in the same industry, matching the hypothesis. With controls, the coefficient on IS is 0.129, or 3.9 percentage points per Std

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stable across the two censuses (see Appendix Figure A.2(b)), and that the results are robust to using an IS measure based solely on either census.

<sup>25</sup>Equivalent to the 60th percentile of the IS distribution.

<sup>26</sup>In fact, there is a direct link between HHI and the IS measure, since the HHI for occupation  $o$  is defined as the sum of the squared employment shares of that occupation over the  $k$  industries, i.e.,  $HHI_o = \sum_k (IS_{ok})^2$ .

<sup>27</sup>The results in Appendix Table A.2 also point to a negative association between industry tenure and industry growth, as well as for the interaction of IS and industry growth. A possible interpretation of this result is that workers in growing industries are in high demand also in other industries, while for declining industries workers remain there as long as possible, especially those with ISHC.

Dev. Appendix Figure A.3 depicts this positive relationship in a non-parametric fashion, using a binned scatter plot.

Lastly, for specific parts of the analysis, I will split the sample into four groups, using the binary definitions from above. Each worker (displaced or not), will be assigned to one of the following groups, based on her IS and industry growth values: ISOCC-Growing, ISOCC-Shrinking, GOCC-Growing, and GOCC-Shrinking. I will refer to these groups as the *ISHC groups*. The reader can undoubtedly see that according to my hypothesis, earnings losses will be the largest for the ISOCC-Shrinking group.

### 5.3 Sample Construction

Following the JLS framework, I construct a treatment group and a control group. The treatment group consists of long-tenured workers who were displaced during mass layoff events, defined as in Schmieder et al. (2023).<sup>28</sup> The control group is composed of comparable long-tenured workers who remained employed in firms with a stable workforce. Due to the limited availability of the occupation variable, I construct two samples. The first, the General Sample, includes all workers in the treated and control groups and will be used to estimate average treatment effects of job displacement. This sample comprises 9,010 treated workers and 23,209 control group workers. The second sample, the Occupation Sample, consists of individuals for whom occupation information prior to displacement is available. This sample will be used to examine heterogeneity in displacement effects based on industry growth and the occupations' industry-specificity levels. It includes 1,727 treated workers and 8,064 control group workers. Further details on the definitions and construction of these samples appear in Appendix B.1.

## 6 Results

### 6.1 Case Study: The Textile Industry

Once a prominent employer in Israel, the textile industry rapidly declined following the removal of trade barriers and the increase in imports from the Far East. I use this industry to illustrate the hypothesis tested in this paper. Because this industry was in decline, I expect workers with industry-specific occupations to incur greater losses than those with more general occupations. In this industry, the top occupations classified as ISOCC are seamster and knitter, while the top GOCC occupations are salesperson, mechanic, and warehouse worker. Appendix Figure A.4 plots the mean earnings for these two groups of laid-off workers,

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<sup>28</sup>See Appendix B.1 for details.

and points to the importance of the ISHC channel. Already in the short run, the drop in earnings is larger for the ISOCC group. More strikingly, in the long run the trajectories diverge: GOCC workers recover to their pre-displacement earnings level within six years, while the ISOCC group has not begun to recover at this stage.

## 6.2 Summary Statistics

Columns 1-4 in Table 1 present basic descriptive statistics for the treated and control groups for both samples. We see baseline differences between the treated workers and the control workers, in both samples: Treated workers are older, have longer firm tenure, are more likely to be Arab, are less educated, and earned less prior to displacement.<sup>29</sup> Appendix Figure A.5 presents the evolution of earnings for the treated and control workers in the General Sample. We see there is a small vertical difference in the pre-periods, that increases substantially after displacement. Columns 5-8 break down the characteristics of the treated (displaced) group, into the four ISHC groups defined in Section 5.2, across the measures of IS and industry growth. The groups are fairly balanced on most demographic variables. However, ISOCC workers earned less, on average,<sup>30</sup> than the GOCC workers in the pre-displacement periods, both in growing and in shrinking industries.

## 6.3 Average Displacement Effects

I begin by examining the overall displacement effects, estimating Eq. 1 on the General Sample. The results are summarized in Table 2. Figure 3 depicts the evolution of  $\beta_p$ , the ATT of displacement on earnings by period. We see the familiar pattern: Displacement leads to large, long-lasting losses. Average earnings losses after one year are 30.6% (equivalent to 46.4k Israeli Shekels (ILS)), 7.3% (or 10k ILS) after six years, and 7% (or 9.7k ILS) after ten years.<sup>31</sup> The total losses over 10 years amount to 176.3K ILS (in net present value), which is equivalent to 1.3 years of earnings for the displaced workers before displacement.<sup>32</sup> Although earnings do gradually recover, they do not return to their previous levels even ten years after displacement. Appendix Table A.1 compares these estimates to those in the

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<sup>29</sup>Note that baseline differences between treated and control workers do not invalidate the DiD approach. As stated in Section 3, the required assumption for identification is having parallel trends between these two groups. In addition, Appendix Figure A.6(a) compares the wage distribution of both groups prior to displacement, and shows a large overlap.

<sup>30</sup>Appendix Figure A.6(b) compares the wage distribution of both groups prior to displacement.

<sup>31</sup>All results are relative to period -1.

<sup>32</sup>Earnings losses in levels are reported in Appendix Table A.3. To obtain losses in levels, I define as the counterfactual earnings level the earnings of the control group, adjusted (vertically) to the earnings level of the treated group, according to the gap between them at period -3. This period was selected because the dip in the earnings of the treated group begins in period -2. For NPV calculations, I used an interest rate of 5%.

literature. There is variation in the estimates found, but the results in this paper are within the range of the findings in the literature.<sup>33</sup> Estimating the ATT for the smaller Occupation Sample, the results are very similar in the short run (coefficient of 29.3% after one year), but larger in the longer run, with an effect of 13.3% after six years (see Appendix Figure A.7).

Next, I repeat the analysis for the other outcome variables, employment and wages.<sup>34</sup> Appendix Figure A.8 reports the results: Employment drops dramatically in the short run, albeit less than earnings, and almost fully recovers within 5-6 years, with losses remaining at 2%-4% in the long run. Losses in monthly wages are significantly smaller, yet persist in the long run at around 4%.<sup>35</sup> How important is the employment variable in explaining the loss of earnings? To assess its contribution, I examine the extent to which earnings drop if only employment is allowed to adjust following displacement, holding wages fixed at their pre-displacement level.<sup>36</sup> I find that 1-2 years after displacement, losses are approx. 80% of the overall effect, meaning employment explains the vast majority of the loss. In the long run, in contrast, employment losses explain only 55% of the overall effect. These results are similar to Schmieder et al. (2023), who find that short-term earnings losses are largely driven by employment losses, while long-run losses are driven by both wages and employment. Other papers found mixed results on the importance of employment and wages (Carrington and Fallick 2017). In addition, Appendix C.1 provides a detailed analysis of displacement's average treatment effect across demographic groups and demonstrates its negative impact on firm wage premiums through an AKM model.

## 6.4 Heterogeneous Effects by IS and Industry Growth

I now turn to the focus of this paper, the relationship between a worker's ISHC, the demand for those skills, and how she is affected by displacement. Figure 4 presents the estimates for  $\phi_p$  from Eq. 2, the coefficient on the interaction of IS and G (industry growth). We see a positive and significant jump in the year following displacement, that remains positive and significant for all post-displacement periods. This means that post-displacement earnings are higher when both the IS level and the industry growth rate increase (or both

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<sup>33</sup>Differences in the estimates can stem from many factors, most notably related to sample construction. For example, Jacobson et al. (1993) and Couch and Placzek (2010) drop workers without positive earnings in each year of the study, which likely attenuates their estimates. On the other hand, Jacobson et al. (1993) and Lachowska et al. (2020) restrict the control group to workers who did not separate from their employers for at least six years after their counterfactual displacement date, which likely inflates the estimates.

<sup>34</sup>Note that conditional on  $i$  being employed,  $Earnings_i = Employment_i \cdot Wage_i$ .

<sup>35</sup>The wage effect should not be interpreted as causal, as this variable is defined only for employed individuals, leading to potential selection bias.

<sup>36</sup>For each worker, I fix wages at their level from period -3 (before the pre-displacement earnings dip) and impute earnings by multiplying this wage by realized employment. I then estimate Eq. 1 using the imputed earnings as the dependent variable.

decrease), and lower otherwise. This result is consistent with my hypothesis, as earnings will be lower for displaced workers with a high IS level, who were displaced from declining (i.e., low growth) industries.<sup>37</sup> Since it is difficult to infer the magnitudes of the effects from a coefficient on an interaction of two continuous variables, I illustrate the predictions of this model. Appendix Figure A.9 plots the regression’s predictions for three levels of industry growth (p(10), p(50), and p(90)), and for intervals of 0.1 in the level of the occupations’ industry-specificity. We learn two things from this figure: First, earnings are on average higher in growing industries; second, the IS gradient is significantly larger (in absolute terms) in industries with a low growth rate.

Breaking down the effect on earnings to its components, I estimate again Eq. 2, with employment and wages as the dependent variables. Appendix Figure A.10 reports the results. There is a positive association between  $IS \times G$  and employment, similar to the pattern for earnings, consistent with the case that high IS workers in shrinking industries suffer from lower employment levels. There is no such relationship for wages. This suggests that the driver of the earnings losses is the effect on employment.

Because the estimated effects of the interaction term in Eq. 2 are consistent with different scenarios, to better understand the relationship between an occupation’s industry-specificity, industry growth and displacement, I estimate Eq. 3 separately for growing and shrinking industries, using the definition from Section 5.2. Figure 5(a) and Table 3 present the estimates for  $\eta_p$ , the additional displacement effect due to the IS measure. For growing industries, there is no additional effect, with estimates close to zero for all periods. In shrinking industries, however, we see a negative and persistent effect, even six years after displacement. The coefficient on IS is -0.35 one year after displacement, implying a 10.4% drop in earnings per Std Dev of the IS measure. After six years, the coefficient is still significant at the 10% threshold, with a coefficient of 0.15, or 4.5% per Std Dev. To put these estimates in perspective, I compare them to the ATT of displacement in shrinking industries (see Table 2), 32.9% and 14.4%, after one year and six years, respectively. A quick calculation finds that one Std Dev increase in the IS measure equals just under one-third of the ATT in shrinking industries, in the short and long runs.

To examine the relationship between the industry-specificity measure and earnings losses in a less parametric manner, I use binned scatter plots. Appendix Figure A.11 depicts this relationship, separately for growing and shrinking industries, one year after displacement

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<sup>37</sup>Note that the estimates for  $\lambda_p$ , the interaction of displacement with industry growth from Eq. 2 are small and insignificant (not reported). This strengthens the interpretation that it is the interaction of IS with industry growth that matters for the displacement effects, and not solely the state of the displacing industry.



(where earnings are relative to their pre-displacement level). There is a strong negative relationship in shrinking industries, as predicted, possibly driven by workers at the top of the IS distribution. We observe no clear relationship in growing industries. These results all support the hypothesis of this paper: ISHC, as measured by the industry-specificity of occupations, leads to significantly larger losses in earnings, conditional on this specific human capital being in low demand, as proxied for by the growth rate of the industry.<sup>38</sup> Finally, for additional analysis of the heterogeneity of the impact of IS on earnings losses, see Appendix C.2. In particular, I present evidence that the costs of having a highly industry-specific occupation are primarily borne by lower-education workers.

#### 6.4.1 Is the ISHC Channel Important?

Up until this point, I have shown that the combination of an industry-specific occupation with a low-growth industry predicts substantially larger earnings losses. However, I have not yet quantified its importance. To that end, I use a common formula from the meta-analysis literature (e.g., [Sánchez-Meca and Marin-Martínez 1998](#)), according to which the overall treatment effect can be approximated by a weighted average of the separate treatment effects of each group, estimated in non-overlapping groups:<sup>39</sup> Accordingly, suppose a sample of size  $N$  is split into  $g$  groups such that  $\sum_{i \in g} N_i = N$ . Let  $S_i \equiv (N_i/N)$  be the share of group  $i$ . If  $\beta$  is the average effect, then  $\beta \approx \sum_{i \in g} S_i \beta_i$ . Dividing both sides by  $\beta$ , I define the *contribution* of group  $i$  to the average effect as following:

$$C_i = \frac{S_i \beta_i}{\beta} \quad (4)$$

where of course,  $\sum_{i \in g} C_i = 1$ .

I apply this formula by estimating Eq. 1 for each ISHC group separately, and computing the contribution of each group, i.e., the share of the displacement effects *explained* by each group. I find that while the ISOC- Shrinking group constitutes 22.5% of all laid-off workers, it explains 35.4% of earnings losses and 40.1% of employment losses. The contribution of this group increases when we attempt to explain losses in the long run. Six years after displacement, it explains 40.2% of earnings losses, and 49.6% of employment losses, suggesting again that ISHC is a key contributor to the *persistent* effect of job loss.

<sup>38</sup>This section’s results were all from dynamic DiD models. Appendix Table A.4 summarizes the relationship between earnings losses, IS, and industry growth using a static DiD model.

<sup>39</sup>It should be noted that this formula is based on the assumption that we are combining independent samples from independent studies, which is not the case here.



## 6.5 Decomposing the Effect of IS on Earnings Losses

Thus far, we have seen that the negative effect of the IS measure on workers' post-displacement earnings is concentrated in shrinking industries. To understand the sources of these losses, I again estimate Eq. 3 separately for growing and shrinking industries, this time with employment months as the dependent variable. Figure 5(b) shows that the effect of IS on employment is very similar to that on earnings, with persistent losses six years after displacement. This suggests that the driving force behind the observed IS effect on earnings losses is employment.

To test this conjecture, I repeat the exercise of estimating the contribution of employment to the overall losses in earnings (see Section 6.3), focusing this time on the ISOC- Shrinking group. I fix workers' wages at their pre-displacement levels, and impute earnings by multiplying that wage level with their actual employment. Figure A.12 depicts the results. Holding wages fixed, earnings for the ISOC- Shrinking group fall by 30.8% after one year, compared to a 40% loss overall. This means that employment explains 78% of short-term losses, similar to the overall contribution of employment found previously. However, the results differ in the long run. After six years, employment still explains 77% of earnings losses for the ISOC- Shrinking group, compared to 55% for the entire sample. This implies that for workers with highly industry-specific skills, lower employment plays a larger role in explaining the *persistence* of losses.

To better understand what drives the changes in employment levels, I estimate the following linear probability model, separately for growing and shrinking industries:

$$y_{ip} = \sum_{p=-4}^6 \alpha_{c(i)p} + \sum_{p=-4}^6 \beta_p D_i + \theta_i + x_{ic(i)p} \pi + \sum_{p=-4}^6 \gamma_p IS_{o(i)k(i)} + \sum_{p=-4}^6 \eta_p (D_i \times IS_{o(i)k(i)}) + \varepsilon_{ip} \quad (5)$$

The dependent variable is either a binary variable for being *out* of the labor market that period ( $\text{Employment}_{ip} = 0$ ), or a binary variable for having *left* the labor market, meaning the worker was not employed from a certain period and onward ( $\text{Employment}_{ip} = 0 \ \forall p' \geq p$ ). Figure 6(a) shows the estimates of  $\eta_p$ , the additional effect of IS for the treated workers, on the likelihood of being out of the labor market. For growing industries, there is no effect in post-displacement periods. In shrinking industries, in contrast, the relationship is very substantial. In the year following displacement, we see an immediate jump to 0.13 (or 3.9 percent increase per Std Dev), and the coefficient only slightly decreases in the

long run. Finally, Figure 6(b) plots the share of workers who left the labor market, by ISHC group. The gap between the ISOCC-Shrinking group and the other groups begins immediately following displacement, and remains throughout. Across all post-periods, the ISOCC-Shrinking workers are 2.5 times more likely to exit the labor market.

A possible concern regarding this result, is that the increased likelihood of leaving the labor market was driven by the characteristics of high-IS workers. For example, if they tend to be older they are more likely to take early retirement. To address this concern, Table 4 reports results from linear probability regressions. While being female and being older does increase the likelihood of exiting the labor market, the interaction of IS with G remains significant and large. Repeating this analysis by ISHC groups, I find the ISOCC-Shrinking group to be much more likely to leave the labor market, even after controlling for workers' characteristics.<sup>40</sup>

These results may seem surprising. The ISHC theory predicts that these workers should expect a pay cut following displacement, perhaps even a substantial one, if demand for their specific human capital is extremely low. But why are these workers exiting the labor market, rather than continuing to work for a lower wage? One possible explanation is that experiencing a large pay cut might be difficult for workers to cope with (e.g., [Greenberg 2006](#); [Drakopoulos and Grimani 2015](#)), to the extent that they prefer not to work entirely. More generally, an expected wage cut can lead to unemployment if the worker's reservation wage is a function of her previous wage ([Koenig et al. 2016](#)), or simply adjusts slowly to the displaced worker's deteriorating job prospects ([Krueger and Mueller 2016](#)). Exiting the labor market, therefore, is a possible outcome when a displaced worker expects to receive lower wages, and consistent with theories that predicts earnings losses.

## 6.6 Robustness: Comparing Workers Within Firms

The results of Section 6 are derived from a heterogeneous treatment effects framework, in which workers with industry-specific occupations were compared to those with more general occupations, after adjusting each group's outcome by subtracting their respective counterfactual outcomes estimated using control groups. A remaining concern, however, is that these two types of workers differ with regard to firm-specific and local market conditions. Although both groups of workers are going through mass layoffs, it is possible that high IS workers are concentrated in worst firms or in a market with particular poor conditions.

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<sup>40</sup>It's interesting to compare these results with those of [Autor et al. \(2013\)](#). They found that areas with higher exposure to import competition from China saw a decline in both wages and in labor force participation, implying that some affected workers exited the labor market. Consistent with my results, they find a stronger negative effect on LFP for older workers, though they find not differential effect by sex.

Specifically, the recovery of displaced workers may be dependent on highly-localized market conditions, which are hard to account for even if restricting the workers to be employed in the same region or city.

To address this concern, I conduct an additional stage of analysis, and propose a modified research design. Here, the comparison is restricted to be *within* a mass layoff, i.e., between workers who were laid off from the same firm at the same time, but who held occupations that differ in their level of industry-specificity. For example, if a mass layoff occurs at a textile factory, I will be comparing the outcomes of tailors to those of drivers.<sup>41</sup> This research design is achieved by modifying the DDD model used above. Formally, I add a vector of firm-period fixed effects ( $\alpha_{j(i)p}$ ) to Eq. 2, which results in limiting the variation used for estimation to come from within the firm-period pair, and therefore, from within mass layoff events:

$$y_{ip} = \exp \left( \underbrace{\sum_{p=-4}^6 \alpha_{j(i)p} + \theta_i + x_{ij(i)p}\pi}_{\text{Baseline displacement equation}} + \underbrace{\sum_{p=-4}^6 \gamma_p \text{IS}_i + \sum_{p=-4}^6 \zeta_p (\text{IS}_i \times \text{G}_{k(j(i))})}_{\text{Industry-specificity and growth main effects}} + \underbrace{\sum_{p=-4}^6 \eta_p (\text{D}_i \times \text{IS}_i) + \sum_{p=-4}^6 \lambda_p (\text{D}_i \times \text{G}_{k(j(i))}) + \sum_{p=-4}^6 \phi_p (\text{D}_i \times \text{IS}_i \times \text{G}_{k(j(i))})}_{\text{Heterogeneous treatment effects}} \right) + \varepsilon_{ip} \quad (6)$$

As before, the coefficient of interest is  $\phi_p$ , the additional effect of the interaction of IS and G for displaced workers. I predict  $\phi_p > 0$  in post-displacement periods.<sup>42</sup> In terms of identification, the inclusion of firm-period fixed effects necessitates a modification to the parallel trends assumption. As the comparison now is between workers within the same firm with different IS levels, the assumption here is that in the absence of treatment, the regression-adjusted outcomes of all treated workers within the same firm follow parallel trends.

For instances when I wish to analyze the effects separately for growing and shrinking

<sup>41</sup>An additional advantage of this approach is that it allows to isolate the impact of the ISHC channel from firm-level explanations, such as the loss of firm wage premiums. This will be discussed further in Section 7.

<sup>42</sup>Note that once I include firm-period fixed effects, the main effect of displacement (and of industry growth) is not identified, since there is no variation in those variables at the firm level. This is by construction, since within each firm in my sample, all workers are either treated or not, and of course, all belong to the same industry. In addition, note that the main effect of the occupation's industry-specificity ( $\gamma_p$ ) will be identified from the control group, as will be its interaction with industry growth ( $\zeta_p$ ), while the cohort-period fixed effects are subsumed by the addition of firm-period fixed effects.

industries, I similarly adjust Eq. 3, by adding firm-period fixed effects:

$$y_{ip} = \exp\left(\sum_{p=-4}^6 \alpha_{j(i)p} + \theta_i + x_{ij(i)p}\pi + \sum_{p=-4}^6 \gamma_p \text{IS}_i + \sum_{p=-4}^6 \eta_p (\text{D}_i \times \text{IS}_i)\right) + \varepsilon_{ip} \quad (7)$$

The coefficient of interest is  $\eta_p$ , and I predict it to be negative for shrinking industries.<sup>43</sup> Finally, because this analysis uses only within-firm variation, it has substantially less power. For this reason, in this analysis I group relative time periods into two-year pairs.

### 6.6.1 Results

Figure A.13 shows that the general relationship found in Section 6 holds here as well. The estimates for  $\phi_p$ , the interaction term of IS and G in Eq. 6, present a clear jump post displacement, and remain positive, and significant, in most periods. This means that for workers with high IS, their post-displacement earnings increase (decrease) with higher (lower) industry growth. The magnitudes of the effects are also very similar to those reported in Figure 4. The same is true for the post-employment levels. Within shrinking industries (Figure A.14), the effect of IS is negative, as predicted. However, the results are noisier than in our main specification, and significant for only part of the post-periods. In terms of magnitudes, the effects in the short run and in the long run are also similar to the main results. In growing industries, there is no effect, as before. Put together, these results suggest that there is no significant bias in the results estimated using the heterogeneous treatment effects research design.<sup>44</sup>

## 6.7 Additional Robustness Tests

Online Appendix C.3 includes supplementary robustness analysis. In Section C.3.1 I examine an alternative to the IS measure, that ignores the roles of industries, and estimates the demand for workers' skill set using solely the growth rate of occupations. I show that this measure explains significantly less of the variation in the effects of displacement, strengthening the argument that industry-specific skills play a central role. In Section C.3.2, I examine whether the driving force behind the results is not the ISHC channel, but rather other pre-displacement workers attributes: low wages, tenure, education level, and age. I show evidence to rule out these alternative explanations. Finally, Section C.3.3 tests the sensitivity of the results to alternative measures of industry growth.

<sup>43</sup>Here as well, the main effects of displacement cannot be identified.

<sup>44</sup>In addition, static versions of these regressions are reported in Appendix Table A.4.

## 7 Discussion: Alternative Theories

In this section, I will describe the other leading theories for post-displacement earnings losses, validate their predictions against the results, and discuss whether I can rule out these theories as alternative explanations to the findings.

The main theories proposed to explain the effects of displacement hold a common thread: Prior to their displacement, these workers were receiving higher wages than they would receive in an average job in the market (i.e., higher than their “market value”). As a result, their next job after displacement would pay them less, on average, leading to a loss in earnings.<sup>45</sup> What separates these theories is the reason given for the “above-market” pre-displacement wage.

One such reason we have already discussed - ISHC. The other leading theories include the loss of rents (Topel 1990), longevity pay (Lazear 1981), and loss of a quality job match (Jovanovic 1979; Lachowska et al. 2020). The rents explanation focuses on workers “losing” high-paying employers after displacement. Originally referring to excess profits shared by firms with market power or union coverage (Hildreth and Oswald 1997),<sup>46</sup> the concept of rents has evolved to encompass firm wage premiums more broadly, as part of a larger emphasis in the literature on firm wage differentials (Abowd et al. 1999; Card et al. 2013). Accordingly, this view attributes displacement losses to workers moving to firms that pay lower premiums (See Schmieder et al. (2023)). The theories related to longevity pay argue that many displaced workers had a salary that was tied to their tenure at the firm. One example is backloaded compensation. Once laid off, these workers lose their “seniority” benefits, and are likely to receive a lower wage. Lastly, according to the job-matching model, a firm-worker match is more likely to survive if it offers a good value for both sides (Jovanovic 1979). When displacement hits, these workers are forced to begin the job-matching process from scratch, and the quality of their next match will likely be lower.

The predictions of these theories are often similar, making it difficult to identify the true mechanism behind the losses. For example, all of these theories, including ISHC, would predict larger losses for workers with longer tenure. Furthermore, layoffs from manufacturing industries, which are the focus of much of the literature, including this paper, may embody several of these mechanisms simultaneously, implying that these theories are not mutually exclusive: Manufacturing industries are often concentrated and unionized, leading to the

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<sup>45</sup>The exception are theories claiming that displacement itself has a scarring effect on the displaced, for example, by harming physical or mental health, which impairs the workers future earning capacity. Black et al. (2015) found mild effects on health, but it is not clear if those translated to effects on future earnings. In addition, Sullivan and Von Wachter (2009) found that displacement increases the risk of mortality.

<sup>46</sup>For example, Kuhn and Sweetman (1998) found that losses are concentrated among unionized workers.

possibility of economic rents; large and established manufacturing firms may set a pay grade in which wage growth and promotions are tied to tenure; a long-tenured worker may signal a high-quality match between the worker and the firm; and finally, manufacturing workers are perhaps more likely to require industry-specific skills than in other sectors. However, the goal of this paper was not to examine the contribution of these alternative theories. Rather, the goal is to establish the connection between the demand for ISHC and the displacement effects. To that end, I will discuss the likelihood that the effects I am attributing to the ISHC theory are in fact driven by alternative mechanisms.

Starting with the theory of longevity pay, additional robustness analysis finds that workers' tenure is not a strong predictor for earnings losses, and that including it in the regression does not affect the IS coefficient (see Appendix C.3.2). With regard to rents, this theory is inconsistent with the results presented in Section 6.6. By including firm-period fixed effects, I rule out any firm-level variable as an explanation for the observed effects, such as firm wage premiums, because they are estimated using variation from within firms.<sup>47</sup> Lastly, consider the job-matching model. Identifying match parameters directly is generally challenging.<sup>48</sup> Nonetheless, I do not expect a positive correlation, within shrinking industries, between the match quality and the IS level. Recall that prior to displacement, high IS workers had lower earnings on average. It would be surprising if low-wage workers had the highest quality match.<sup>49</sup>

## 8 Conclusion

In this paper, I estimated the average displacement effects in manufacturing industries in Israel, using administrative data. The effects of displacement are large and persistent, in line with the literature. I then estimated the heterogeneous treatment effects of displacement by two measures, which together serve as a proxy for the demand for the displaced workers' industry-specific human capital. Matching the prediction of the ISHC theory, I found that earnings losses are substantially larger for workers with industry-specific occupations, conditional on being laid off from declining industries. Namely, the ISHC theory explains over one-third of the ATT for displacement. There is large heterogeneity in the effects of

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<sup>47</sup>Note that this would not be the case if, within a firm, different groups of workers received different levels of rents, and this division was correlated with the IS measure. Although I cannot fully rule out this possibility, if such a division existed, it would likely be highly correlated with tenure. And as I have shown, tenure does not appear to threaten my interpretation of the results.

<sup>48</sup>In Lachowska et al. (2020), what the authors refer to as *matching effects* are in fact the residuals of an AKM-type regression, with firm fixed effects and worker fixed effects.

<sup>49</sup>A relationship between the IS levels and the quality of a match could be due to search frictions. If search frictions are lower when switching jobs within the same industry, then high IS workers, who are more likely to switch jobs within the same industry, would be able on average to achieve a higher match quality.

ISHC, as the gap between the earnings losses for workers at the 90th percentile and the 10th percentile of the IS measure equals more than half of the ATT in the short run, and over 80% of it in the long run. I show that the long-run effects on earnings are driven by employment losses, as the likelihood of leaving the labor market is considerably larger for high IS workers. Put together, these findings suggest that the ISHC mechanism is an important factor in explaining the persistence of earnings losses.

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Table 1: Characteristics table

	<i>Within treated workers:</i>							
	<b>General Sample</b>		<b>Occupation Sample</b>		<b>Shrinking industries</b>		<b>Growing industries</b>	
	Treated	Control	Treated	Control	ISOCC	GOCC	ISOCC	GOCC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	42.7	42.0	45.2	43.8	46.0	45.1	44.7	45.0
Tenure	89.6	83.4	112.5	90.2	115.7	115.9	108.3	105.6
Arab	0.111	0.065	0.114	0.070	0.134	0.107	0.136	0.086
Female	0.225	0.231	0.272	0.270	0.288	0.274	0.219	0.297
Pre-earnings	133,147	142,317	131,689	146,714	119,477	141,124	117,416	138,996
Higher education	0.259	0.310	0.209	0.295	0.208	0.181	0.206	0.268
Periphery	0.477	0.447	0.506	0.472	0.428	0.433	0.655	0.609
N	9,010	23,209	1,727	8,064	389	690	301	347

Note: This table presents summary statistics for the samples used in this paper. Columns 1-2 relate to the General Sample, defined in Appendix B.1.1. Columns 3-8 relate to the Occupation Sample, defined in Appendix B.1.2. Columns 5-8 display statistics according to the ISHC groups, defined in Section 5.2. All the statistics reported are mean values. *Tenure* is the months employed in the firm prior to displacement. *Pre-earnings* are the earnings at period -2. *High-education* indicates having postsecondary education. *Periphery* indicates residing in the Southern or Northern region in Israel.

Table 2: Average displacement effects

	General Sample			Occupation Sample			Occupation Sample Shrinking industries		
	Earnings (1)	Employment (2)	Wages (3)	Earnings (4)	Employment (5)	Wages (6)	Earnings (7)	Employment (8)	Wages (9)
$p \times D$									
-4	0.0569*** (0.0128)	0.00901*** (0.00264)	0.0511*** (0.0117)	0.0942*** (0.0194)	0.0167*** (0.00467)	0.0821*** (0.0178)	0.0898*** (0.0136)	0.0227*** (0.00616)	0.0724*** (0.0121)
-3	0.0532*** (0.0114)	0.0109*** (0.00197)	0.0443*** (0.0107)	0.0649*** (0.0168)	0.00760*** (0.00293)	0.0597*** (0.0156)	0.0442*** (0.00978)	0.00406 (0.00390)	0.0416*** (0.00888)
-2	0.0265*** (0.00805)	0.000746 (0.00141)	0.0262*** (0.00746)	0.0268** (0.0119)	-0.00258 (0.00207)	0.0283** (0.0110)	0.0220*** (0.00721)	-0.00307 (0.00249)	0.0239*** (0.00661)
0	-0.132*** (0.0134)	-0.130*** (0.00876)	-0.00893 (0.0110)	-0.130*** (0.0146)	-0.134*** (0.0113)	-0.00491 (0.0117)	-0.153*** (0.0214)	-0.152*** (0.0138)	0.00783 (0.0193)
1	-0.306*** (0.0205)	-0.264*** (0.0162)	-0.111*** (0.0103)	-0.293*** (0.0230)	-0.250*** (0.0177)	-0.106*** (0.0134)	-0.329*** (0.0351)	-0.261*** (0.0230)	-0.136*** (0.0195)
2	-0.248*** (0.0166)	-0.180*** (0.0105)	-0.104*** (0.00980)	-0.210*** (0.0210)	-0.153*** (0.0124)	-0.0836*** (0.0136)	-0.235*** (0.0323)	-0.158*** (0.0152)	-0.109*** (0.0208)
3	-0.175*** (0.0162)	-0.110*** (0.00903)	-0.0943*** (0.0107)	-0.181*** (0.0205)	-0.108*** (0.0124)	-0.0951*** (0.0132)	-0.196*** (0.0309)	-0.119*** (0.0162)	-0.0970*** (0.0191)
4	-0.139*** (0.0155)	-0.0686*** (0.00852)	-0.0826*** (0.0127)	-0.156*** (0.0204)	-0.0806*** (0.0122)	-0.0812*** (0.0141)	-0.188*** (0.0310)	-0.100*** (0.0178)	-0.0952*** (0.0191)
5	-0.0997*** (0.0160)	-0.0428*** (0.00912)	-0.0607*** (0.0105)	-0.141*** (0.0211)	-0.0626*** (0.0133)	-0.0804*** (0.0151)	-0.161*** (0.0320)	-0.0669*** (0.0184)	-0.0981*** (0.0215)
6	-0.0734*** (0.0160)	-0.0321*** (0.00979)	-0.0440*** (0.0103)	-0.133*** (0.0215)	-0.0611*** (0.0139)	-0.0603*** (0.0178)	-0.144*** (0.0324)	-0.0676*** (0.0191)	-0.0834*** (0.0213)
N	547,621	547,621	514,011	89,552	89,552	87,256	47,070	47,070	45,745

Note: This table presents estimates of  $\beta_p$  from Eq. 1. The dependent variables are, respectively, earnings, employment months, and monthly wages. For columns 1-3, the sample is the General Sample, defined in Appendix B.1.1. For columns 4-9 the sample is the Occupation Sample, defined in Appendix B.1.2. Columns 1-6 use all layoffs in the manufacturing sector, while columns 7-9 examine the effects only in shrinking industries, based on the definitions in Section 5.2. Standard errors are clustered at the pre-displacement firm level. The omitted category is period -1.

Table 3: The effect of IS, by industry growth

	Shrinking industries		Growing industries	
	Earnings (1)	Employment (2)	Earnings (3)	Employment (4)
$p \times D \times IS$				
-4	-0.102** (0.0423)	-0.0767** (0.0303)	0.0354 (0.0436)	0.0278 (0.0300)
-3	-0.0108 (0.0385)	0.00754 (0.0190)	0.00420 (0.0324)	0.0175 (0.0159)
-2	-0.00807 (0.0237)	-0.00127 (0.00639)	-0.0550* (0.0326)	-0.00880 (0.00937)
0	-0.183*** (0.0597)	-0.124*** (0.0455)	-0.00797 (0.0410)	0.0487* (0.0251)
1	-0.348*** (0.0997)	-0.323*** (0.0890)	-0.0481 (0.0881)	-0.0276 (0.0679)
2	-0.251*** (0.0737)	-0.234*** (0.0605)	-0.00541 (0.0633)	0.0352 (0.0397)
3	-0.217** (0.0870)	-0.137** (0.0618)	0.0216 (0.0666)	0.0251 (0.0418)
4	-0.151* (0.0802)	-0.128** (0.0635)	0.00426 (0.0674)	0.0183 (0.0438)
5	-0.184** (0.0907)	-0.100 (0.0642)	0.0688 (0.0763)	0.0358 (0.0500)
6	-0.150* (0.0912)	-0.144** (0.0628)	0.0257 (0.0782)	0.0604 (0.0449)
N	56,463	56,463	51,238	51,238

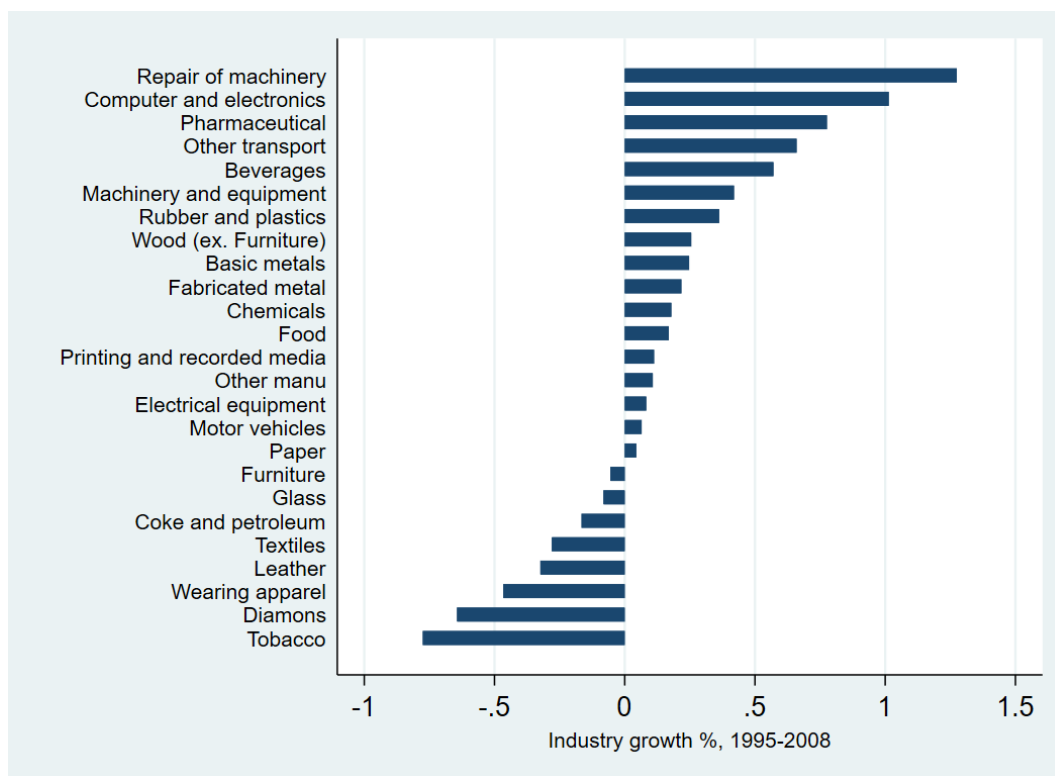
Note: This table presents estimates of  $\eta_p$  from Eq. 3, estimated separately for growing and shrinking industries, as defined in Section 5.2. The dependent variables are earnings, and employment. The sample is the Occupation Sample defined in Appendix B.1.2. Standard errors are clustered at the pre-displacement firm level.

Table 4: The probability of not working

	Out of labor market			Left labor market		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0680*** (0.0216)	0.0742*** (0.0210)	0.0715*** (0.0211)	0.0668* (0.0400)	0.0825** (0.0391)	0.0800** (0.0393)
Age	0.00257*** (0.000225)	0.00250*** (0.000224)	0.00247*** (0.000224)	0.00401*** (0.000516)	0.00363*** (0.000491)	0.00359*** (0.000490)
Pre-Wage (1000s)	-0.00088*** (0.00018)	-0.00058*** (0.00018)	-0.00056*** (0.00018)	-0.00179*** (0.00039)	-0.00141*** (0.00039)	-0.00136*** (0.00039)
Arab	0.0365*** (0.00735)	0.0317*** (0.00716)	0.0312*** (0.00717)	0.0493*** (0.0149)	0.0477*** (0.0140)	0.0470*** (0.0141)
Higher Educ	-0.00591* (0.00343)	-0.00449 (0.00342)	-0.00411 (0.00340)	-0.0137* (0.00716)	-0.00306 (0.00708)	-0.00200 (0.00713)
Treated		0.0473*** (0.0123)	0.0523*** (0.00724)		0.0285 (0.0201)	0.0366*** (0.0121)
<b>Treated × ISOCC-Shrink</b>		0.0791*** (0.0203)			0.0697** (0.0286)	
Treated × ISOCC-Grow		-0.00620 (0.0174)			-0.0363 (0.0261)	
Treated × GOCC-Shrink		0.00160 (0.0151)			0.00302 (0.0246)	
Treated × IS			0.0750*** (0.0238)			0.0328 (0.0325)
Treated × G			0.0324 (0.0372)			0.0265 (0.0537)
<b>Treated × IS × G</b>			-0.390*** (0.116)			-0.442*** (0.165)
Constant	-0.0524*** (0.0103)	-0.0569*** (0.0106)	-0.0571*** (0.0104)	-0.0338 (0.0210)	-0.0551** (0.0221)	-0.0502** (0.0211)
N	58,452	58,452	58,452	9,742	9,742	9,742

Note: This table presents estimates of Eq. 5. In columns 1-3, the analysis is at the individual-year level. The dependent variable receives 1 if the individual is not employed in that year, 0 otherwise. Standard errors are clustered at the pre-displacement firm level. In columns 4-6, the analysis is at the individual level. The dependent variable receives 1 if the individual permanently left the labor market within six years of displacement, 0 otherwise. Standard errors are clustered at the individual level. For all columns, the sample is the Occupation Sample defined in Appendix B.1.1. Controls not reported: year fixed-effects, tenure, female × age, periphery, and the main effects of IS, G, IS × G, and the ISHC groups. In columns 2 and 5, the omitted group is GOCC-Growing.

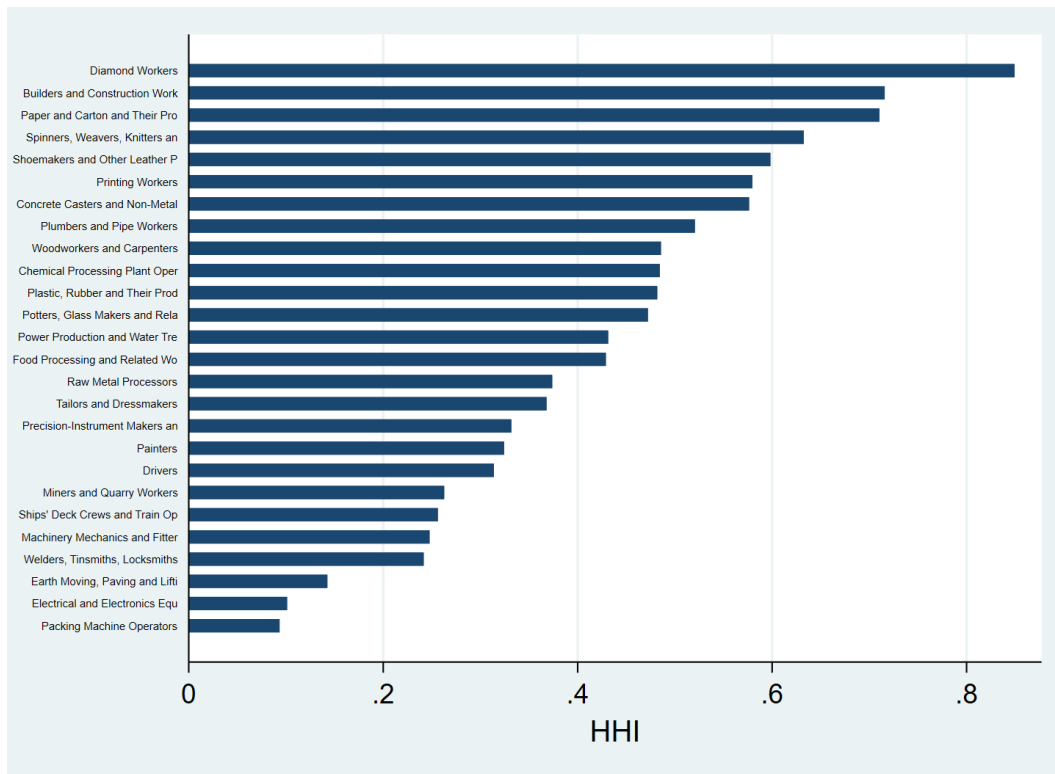
Figure 1: Growing and Shrinking Industries



Note: This figure ranks manufacturing industries according to their growth level. Industries are defined according to the 2-digit categories ("divisions") of the ISIC Rev. 3 classification. Industry growth is defined as the growth of employment in each industry, between the years 1995-2008.

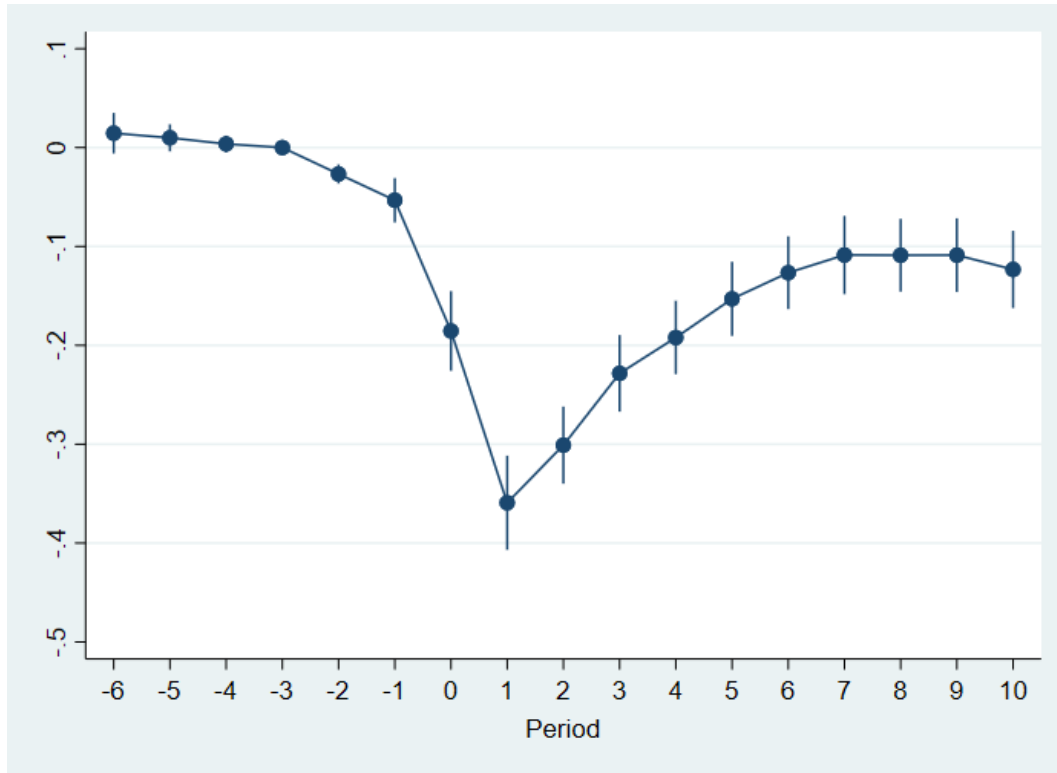


Figure 2: Occupations' Herfindahl–Hirschman index (HHI)



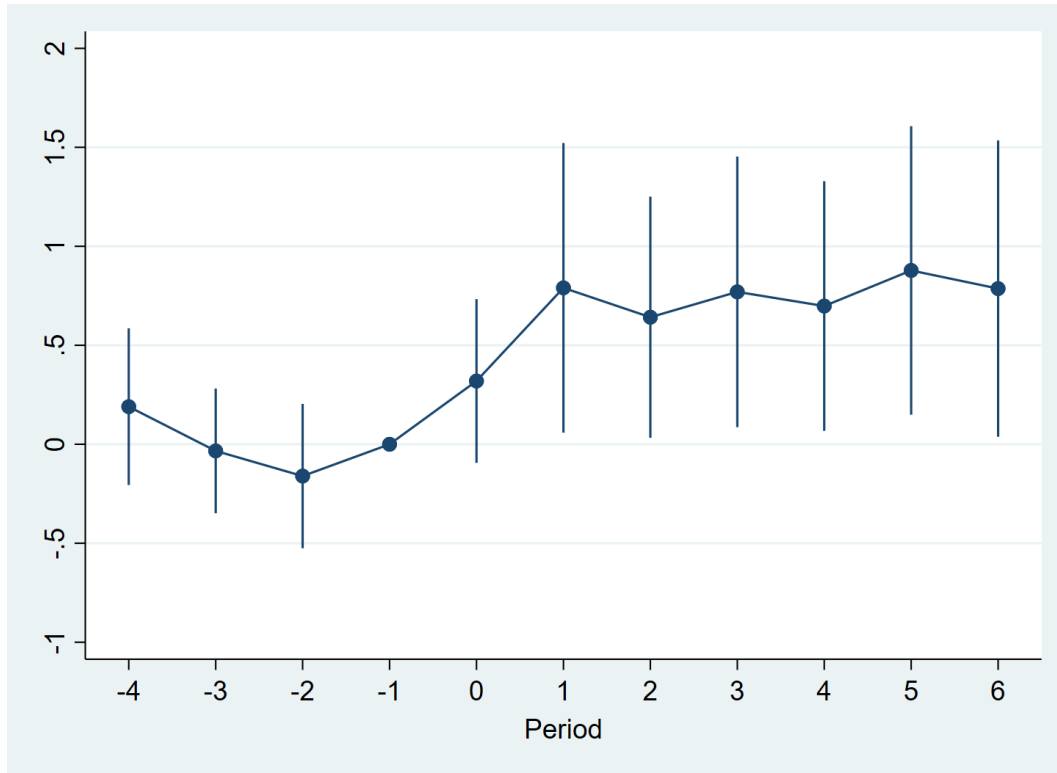
Note: This figure plots the Herfindahl–Hirschman index for the concentration of occupations in industries. Included are occupations from the “Professional workers in industry, construction and other professional workers” category, ISCO-88 classification, at the 2-digit level.

Figure 3: Displacement Effects: Earnings



Note: This figure shows estimates of  $\beta_p$  from Eq. 1. The dependent variable is earnings. The sample is the General Sample defined in Appendix B.1.1. Standard errors are clustered at the pre-displacement firm level.

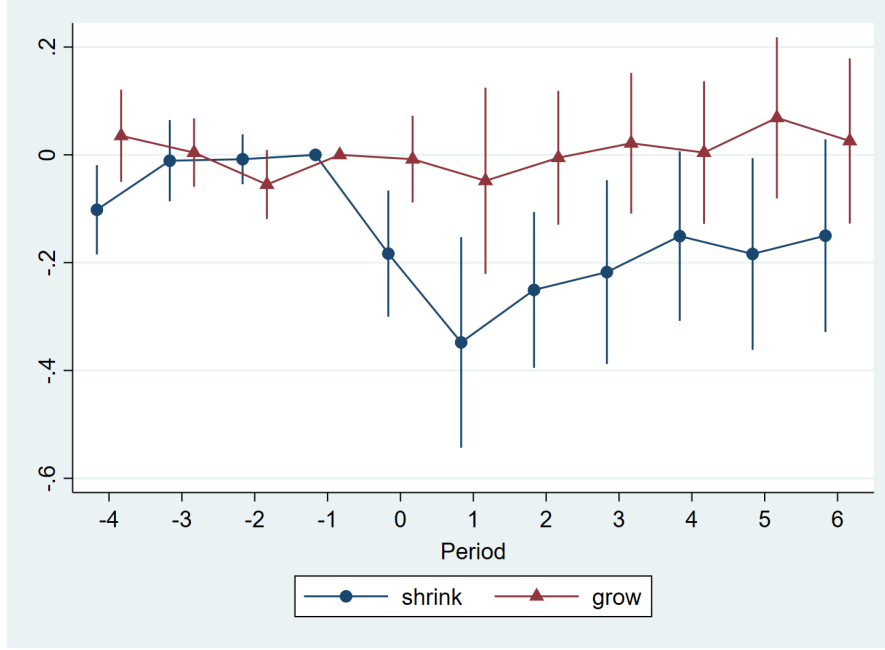
Figure 4: The effect of  $IS \times Growth$  on earnings



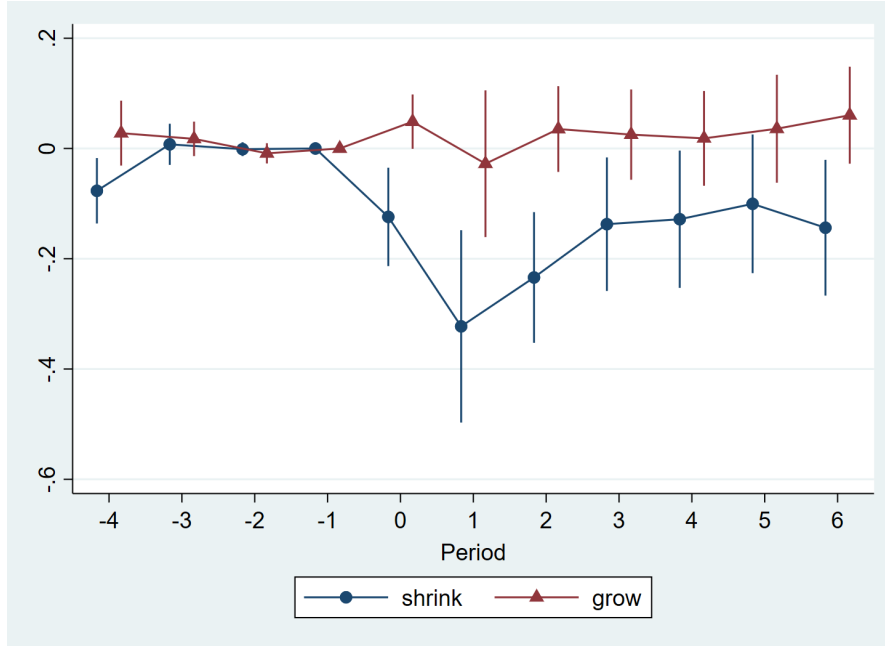
Note: This figure shows estimates of  $\phi_p$  from Eq. 2. The sample is the Occupation Sample defined in Appendix B.1.2. The dependent variable is earnings. Standard errors are clustered at the pre-displacement firm level.

Figure 5: The effects of IS, by industry growth

(a) Earnings



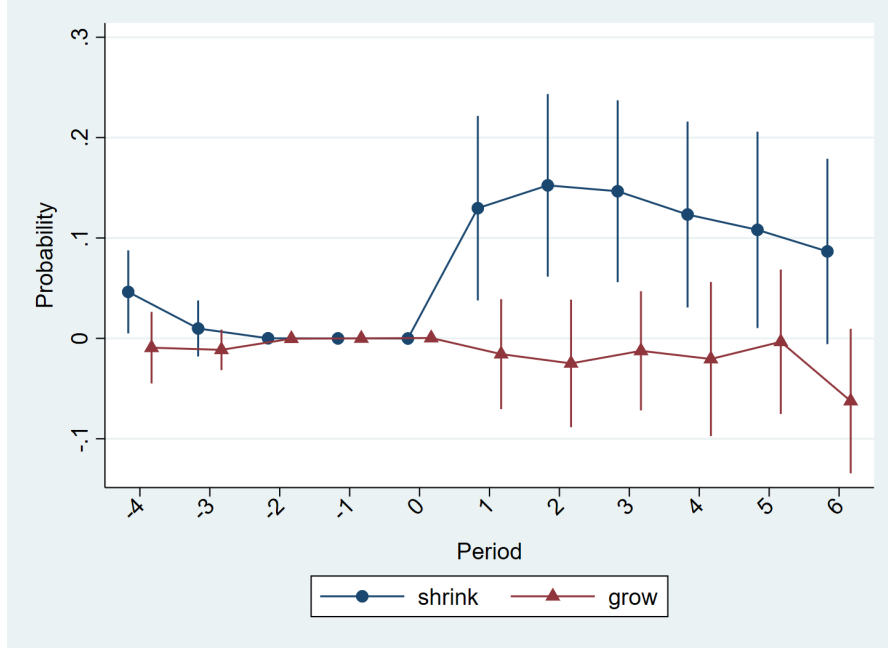
(b) Employment



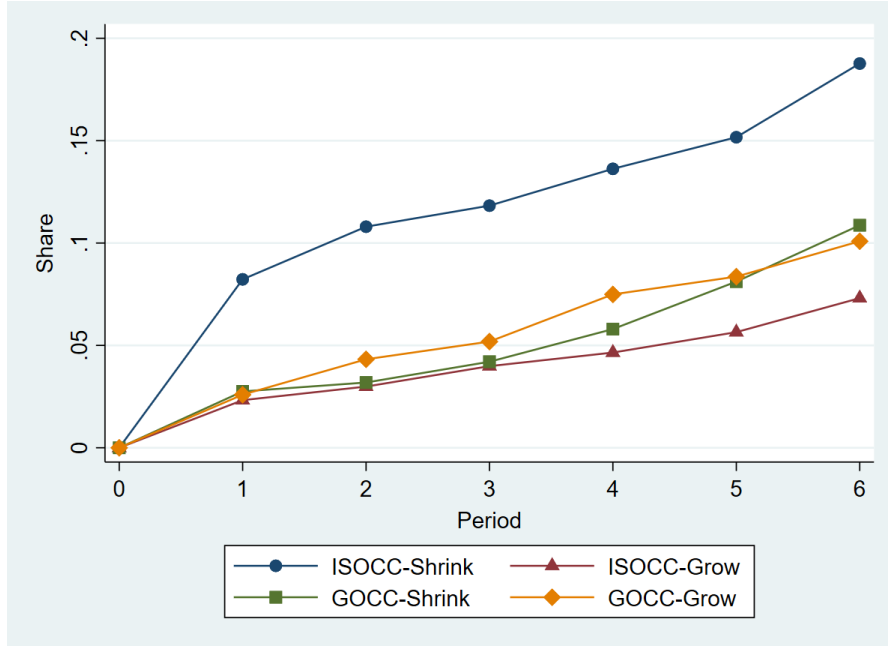
Note: This figure shows estimates of  $\eta_p$  from Eq. 3, estimated separately for growing and shrinking industries, as defined in Section 5.2. The sample is the Occupation Sample defined in Appendix B.1.2. In Panel (a) the dependent variable is earnings, and in Panel (b) the dependent variable is employment months. Standard errors are clustered at the pre-displacement firm level.

Figure 6: IS and exiting the labor market

(a) Out of labor market



(b) Left labor market



Note: Panel (a) shows estimates of  $\eta_p$  from Eq. 5, estimated separately for growing and shrinking industries, as defined in Section 5.2. The dependent variable is *out of labor market*, that receives 1 in period  $p$  if a worker worked zero months in that year, and 0 otherwise. Standard errors are clustered at the pre-displacement firm level. Panel (b) depicts the raw shares of workers who left the labor market, by ISHC group, among the displaced workers. The variable *left labor market* receives 1 in period  $p$  if a worker worked zero months in that year and in all subsequent years, and 0 otherwise. For both Panels, the sample used is the Occupation Sample, defined in Appendix B.1.2.

# Online Appendices

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Appendix C: Extended Analysis and Findings .....	<a href="#">66</a>

## Appendix A    Appendix Tables and Figures

Table A.1: Comparison with literature – the effect of displacement on earnings

Paper	Sample	Period	Short-run effects	Long-run effects
Jacobson et al. (1993)	Pennsylvania	1974-1986	40%	25% (6 years)
Couch and Placzek (2010)	Connecticut	1993-2004	33%	15% (6 years)
Schmieder et al. (2019)	Germany	1975-2009	29%	10% (10 years)
Lachowska et al. (2020)	Washington	2002-2014	49%	15% (5 years)
This paper	Israel	1990-2019	31%	7% (6 years)

Note: This table reports estimates for the ATT of displacement on earnings for several papers in the literature. *Short-run effects* refers to the effect one year after displacement. *Long-run effects* refers to the effects after the number of years listed in the parentheses.

Table A.2: Industry-specificity and switching behavior

	Industry tenure			Stayed in industry		
	(1)	(2)	(3)	(4)	(5)	(6)
Industry-specificity	0.0550*** (0.0138)	0.180*** (0.0175)	0.192*** (0.0151)	0.145*** (0.0169)	0.140*** (0.0253)	0.129*** (0.0253)
Industry growth		-0.801*** (0.0159)	-0.147*** (0.0118)		0.0795*** (0.0153)	0.0804*** (0.0171)
Industry-specificity X Industry growth		-0.712*** (0.0535)	-0.230*** (0.0374)		0.0210 (0.0560)	0.0591 (0.0546)
log(tenure)						-0.0431*** (0.00981)
log(industry-tenure)						0.0941*** (0.00842)
log(wage)			0.284*** (0.0066)			0.00825 (0.00832)
log(size)			0.0336*** (0.0032)			0.0106*** (0.00312)
High education			-0.250*** (0.0085)			0.0394*** (0.0105)
Age			0.114*** (0.0023)			0.00118** (0.000559)
Arab			0.198*** (0.0164)			-0.000405 (0.0187)
Female			0.0564*** (0.0093)			-0.0139 (0.0102)
N	211,437	193,437	193,437	10,475	8,115	8,115

Note: columns 1-3 report results of a linear regression model. The dependent variable is the number of months employed at the current industry. Columns 4-6 report results of a linear probability model, estimated among workers who switched employers. The dependent variable is an indicator for remaining in the same industry. For all columns, the sample used is the control group workers from the Occupation Sample, defined in Appendix B.1.2. Standard errors are clustered at the individual level.



Table A.3: Losses (levels)

	General Sample			Occupation Sample		
	Earnings	Employment	Wages	Earnings	Employment	Wages
	(1)	(2)	(3)	(4)	(5)	(6)
Period						
1	46,389	3.17	1,404	44,837	3.05	1,335
2	38,095	2.13	1,351	32,404	1.85	1,073
3	25,786	1.22	1,244	27,229	1.24	1,249
4	19,626	0.73	1,091	23,119	0.90	1,080
5	13,717	0.44	798	20,862	0.69	1,086
6	9,968	0.33	580	19,615	0.66	823
7	7,521	0.30	148			
8	7,587	0.24	404			
9	7,626	0.22	347			
10	9,703	0.36	384			

Note: This table reports the average losses due to displacement, in levels. Losses are estimated by multiplying the estimates of  $\beta_p$  from Eq. 1 by the *counterfactual earnings level*, defined as the earnings level of the control group, minus the gap between the earnings of the control group and of the treated group at period -3. Columns 1-3 report losses for the General Sample, defined in Appendix B.1.1. Columns 4-6 report losses for the Occupation Sample, defined in Appendix B.1.2.

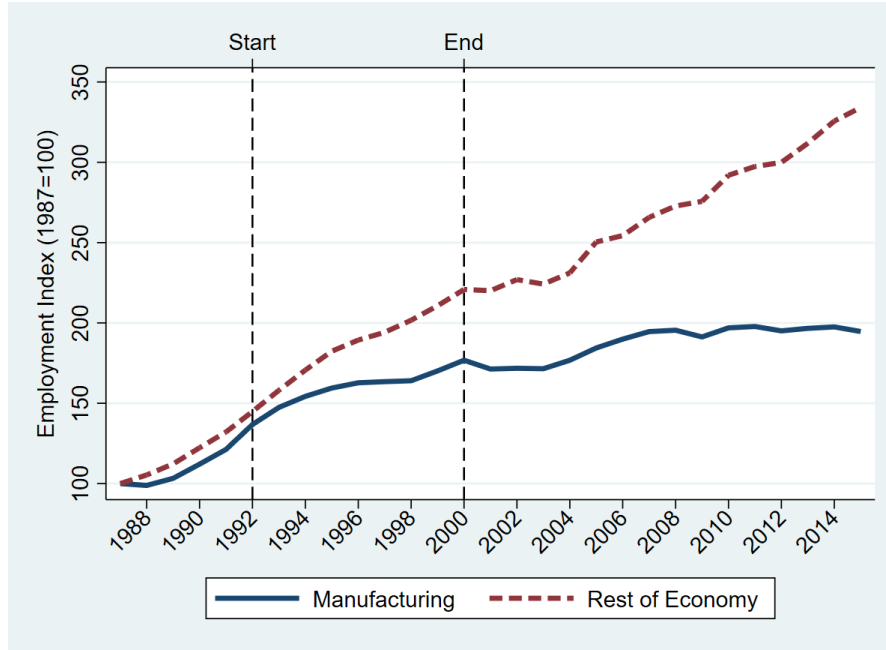
Table A.4: Heterogeneous treatment effects – static model

	DDD model			Within-firm model		
	All (1)	Shrinking (2)	Growing (3)	All (4)	Shrinking (5)	Growing (6)
<i>Dependent variable: earnings</i>						
Post $\times$ D $\times$ IS $\times$ G	1.4902*** (0.4400)			1.0379** (0.4273)		
Post $\times$ D $\times$ IS		-0.3276*** (0.1199)	0.1655 (0.1068)		-0.2280** (0.1152)	-0.0632 (0.0940)
<i>Dependent variable: employment months</i>						
Post $\times$ D $\times$ IS $\times$ G	0.5512*** (0.1785)			0.5404** (0.2184)		
Post $\times$ D $\times$ IS		-0.1722*** (0.0570)	0.0299 (0.0372)		-0.1044 (0.0654)	0.0559 (0.0422)
N	107,701	56,463	51,238	107,677	56,445	51,226

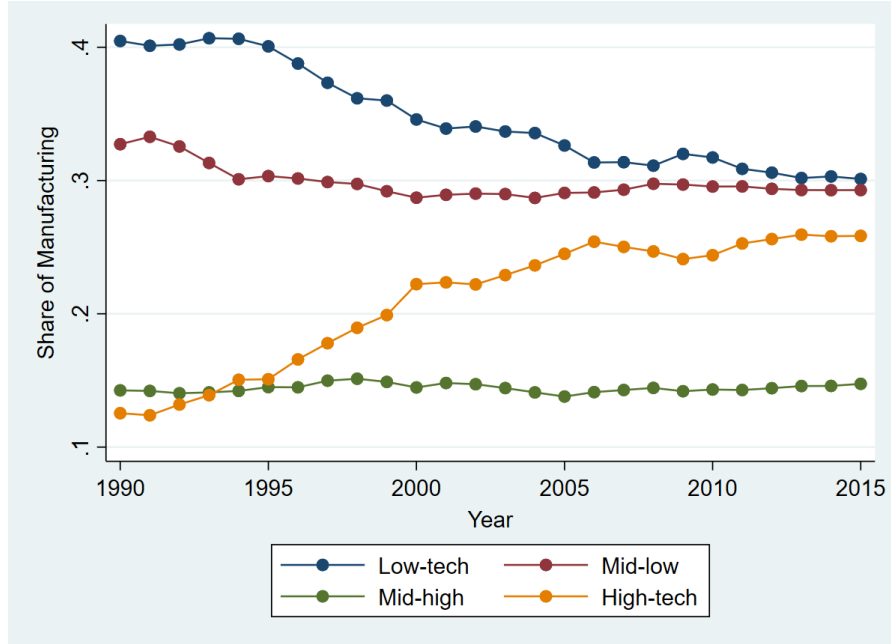
Note: This table presents estimates of static versions of the dynamic event-study regressions presented in this paper. Column 1 mimics Eq. 2, columns 2-3 – Eq. 3, column 4 – Eq. 6, and columns 5-6 – Eq. 7. Shrinking and growing industries are defined in Section 5.2. The sample used is the Occupation Sample, defined in Appendix B.1.2. Standard errors are clustered at the displacing-firm level.

Figure A.1: Trends in the Israeli workforce

(a) Employment and the Exposure Reform



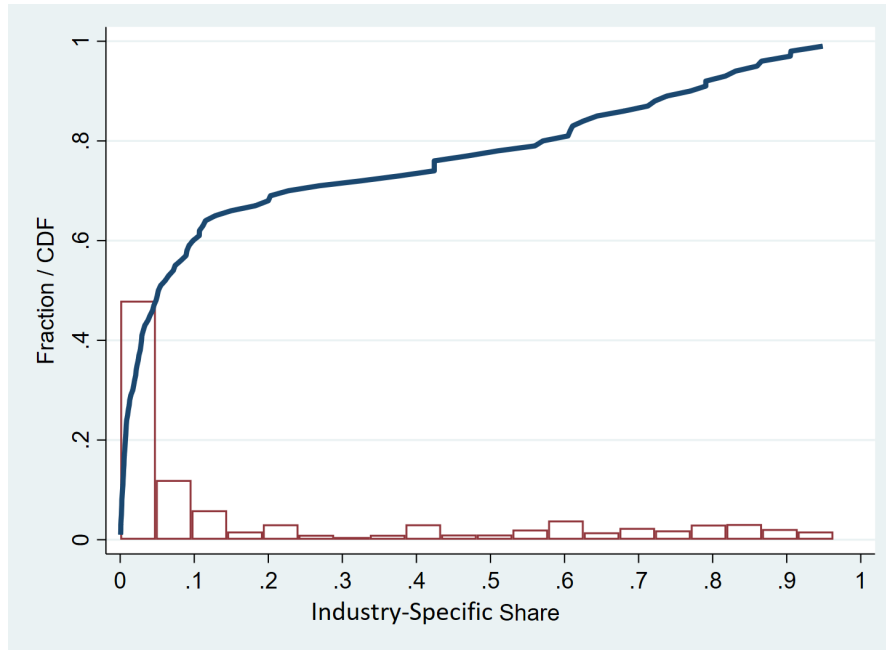
(b) The Manufacturing sector, by technological intensity



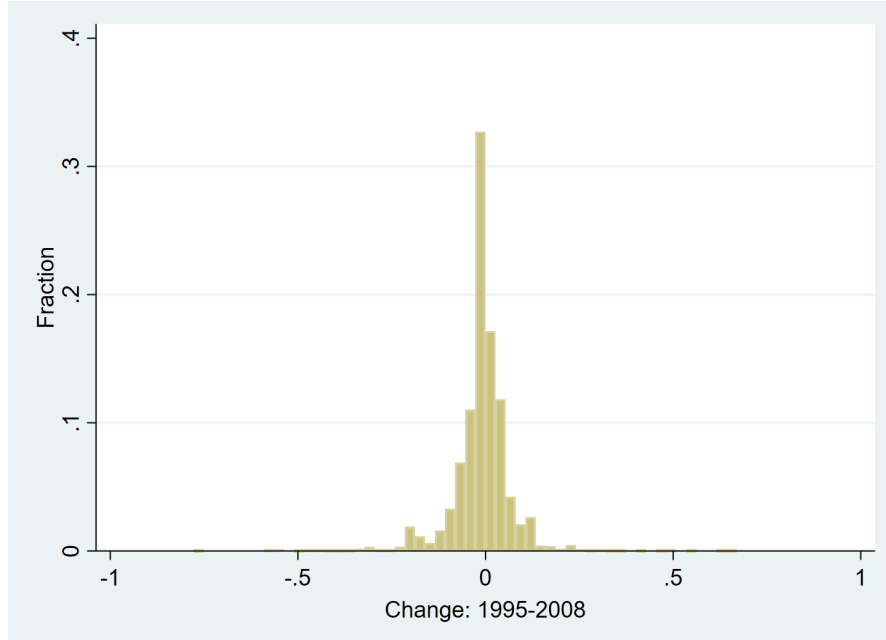
Note: Panel (a) plots the employment growth in the manufacturing sector compared to the rest of the economy. Panel (b) shows a breakdown of the employment in the manufacturing sector, according to the CBS classification of manufacturing industries by technological intensity (CBS 2015).

Figure A.2: The Industry-Specificity measure

(a) The distribution of the IS measure

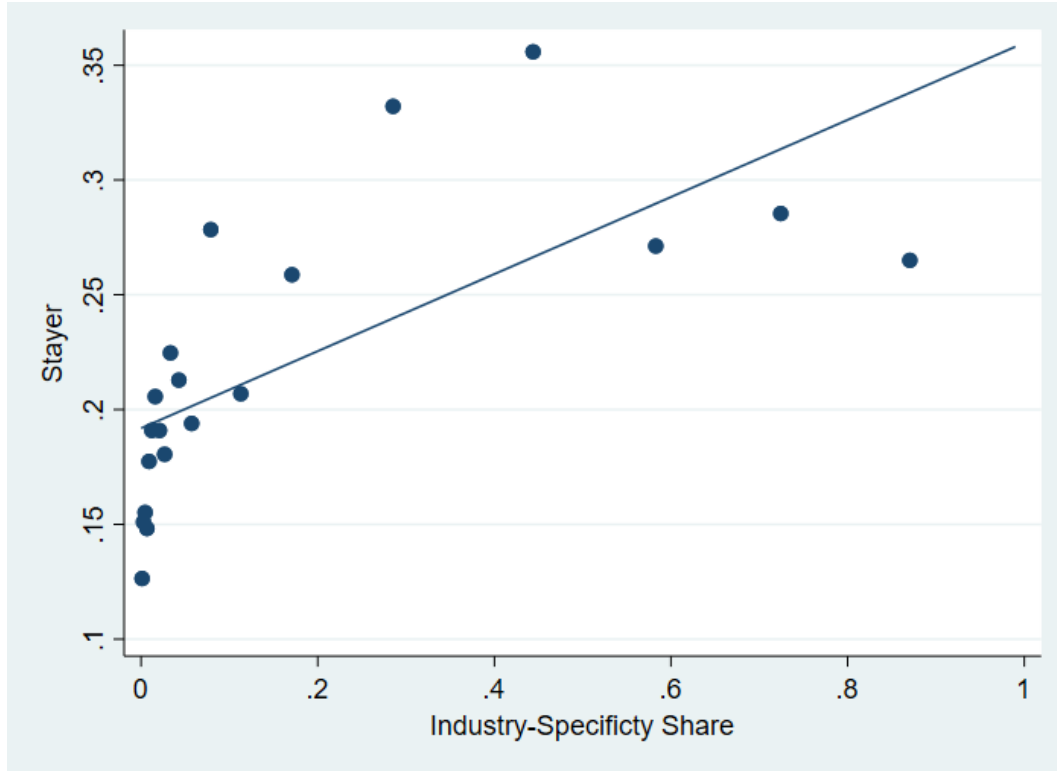


(b) The change in the IS measure between censuses



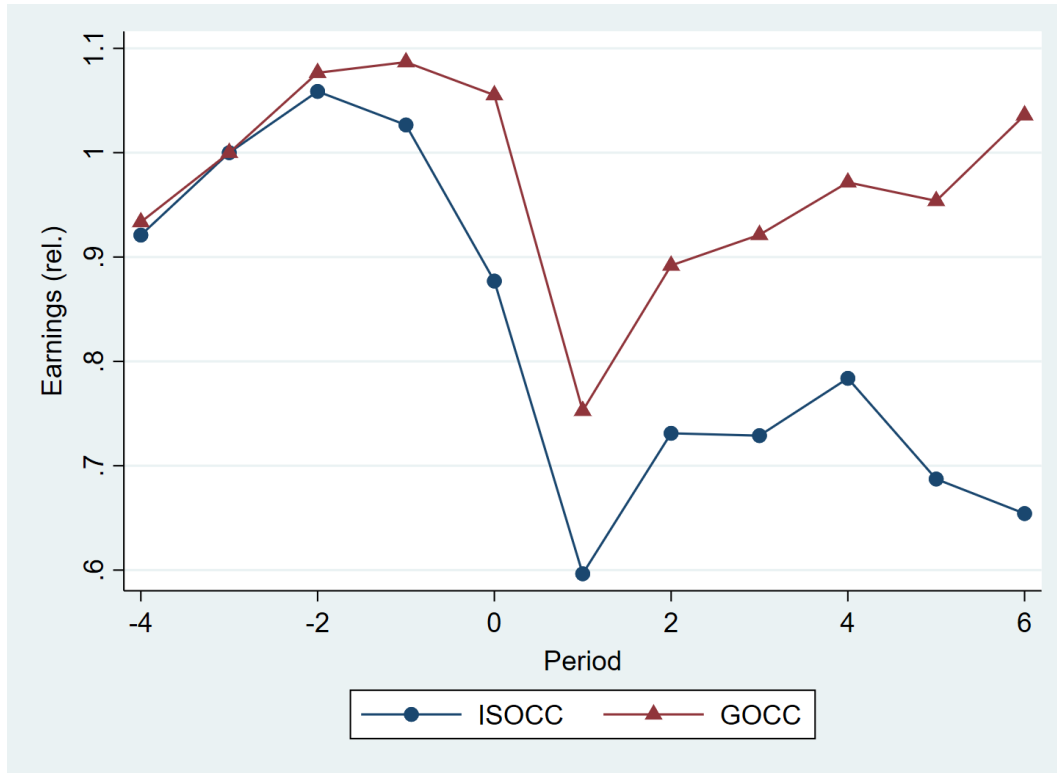
Note: Panel (a) plots the histogram (red bars) and the cumulative distribution function (blue curve) for the occupation's industry-specificity variable at time of displacement, as defined in Section 5.2. Panel (b) plots the histogram of the change in the IS measure for each combination of occupation-industry, between the 1995 census and the 2008 census. The sample is the Occupation Sample defined in Appendix B.1.1.

Figure A.3: Share remaining in industry, conditional on new employer



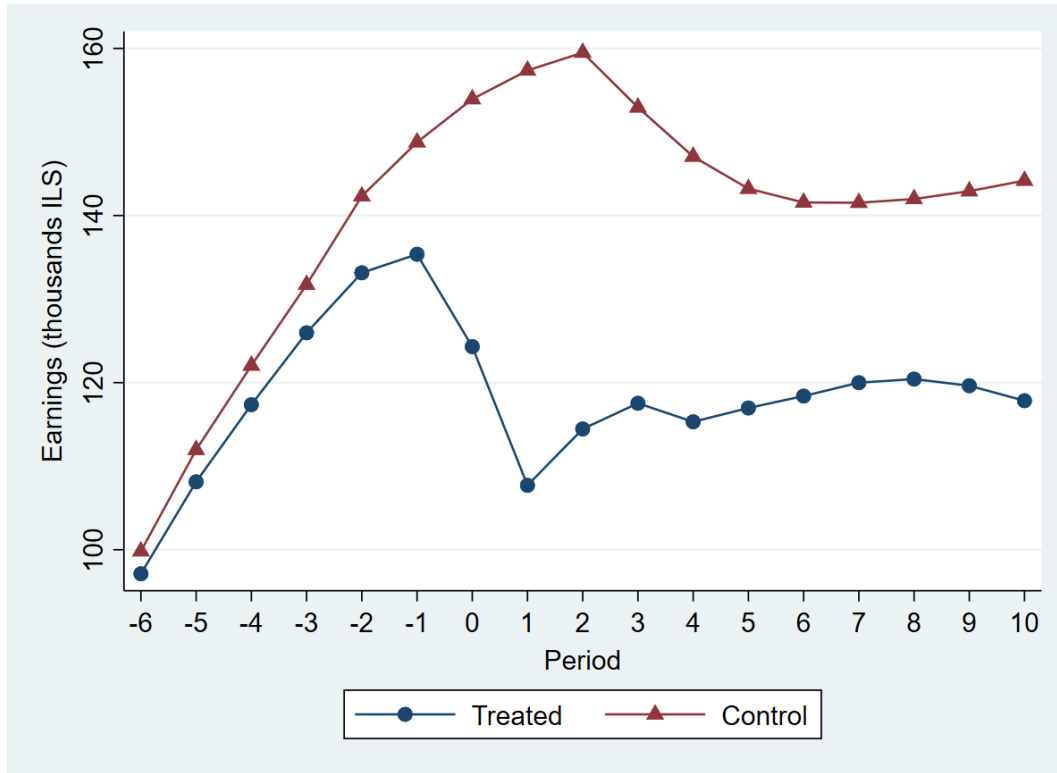
Note: This is a binned scatter plot, applying a bin-scatter least squares estimation using the Stata package *binsreg* (Cattaneo et al. 2019). The sample consists of all workers who switched employers. Workers are grouped into 20 equal-sized bins, according to their occupations' industry-specificity level. The y-axis reports the share of each bin who remained in the same industry in their next job. The estimation procedure includes the following controls: tenure, age, ethnicity, sex, education, wage, and firm size. The curve reports a third-degree polynomial fitting function. Industries are defined according to the 2-digit categories ("divisions") of the ISIC Rev. 3 classification.

Figure A.4: Cast study – the textile industry



Note: The sample is composed of workers displaced from the textile industry. The figure shows average earnings (divided by earnings in the year before displacement) across periods for workers with industry-specific occupations (ISOCC), and with general occupations (GOCC), defined in Section 5.2.

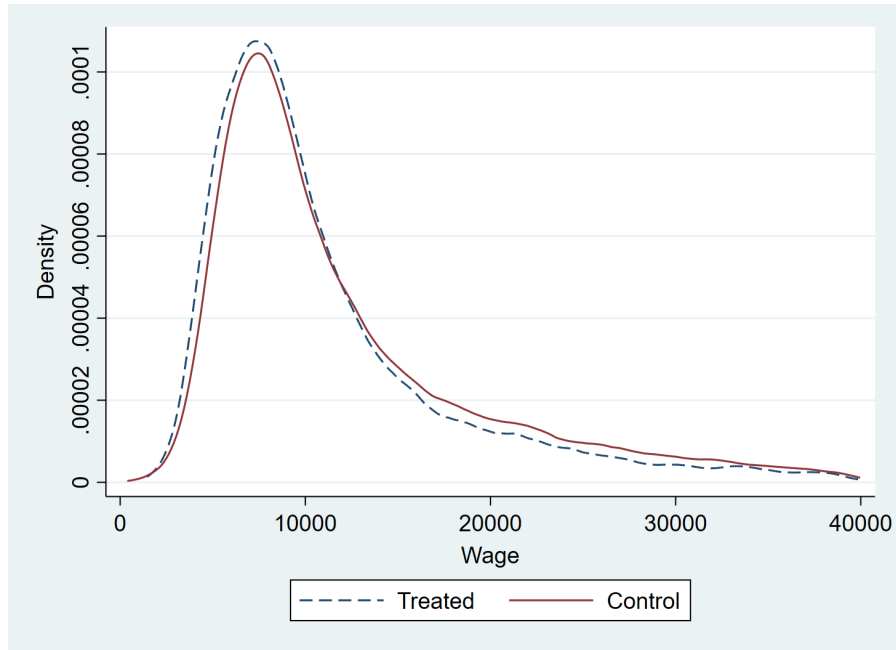
Figure A.5: Earnings means – treated and control workers



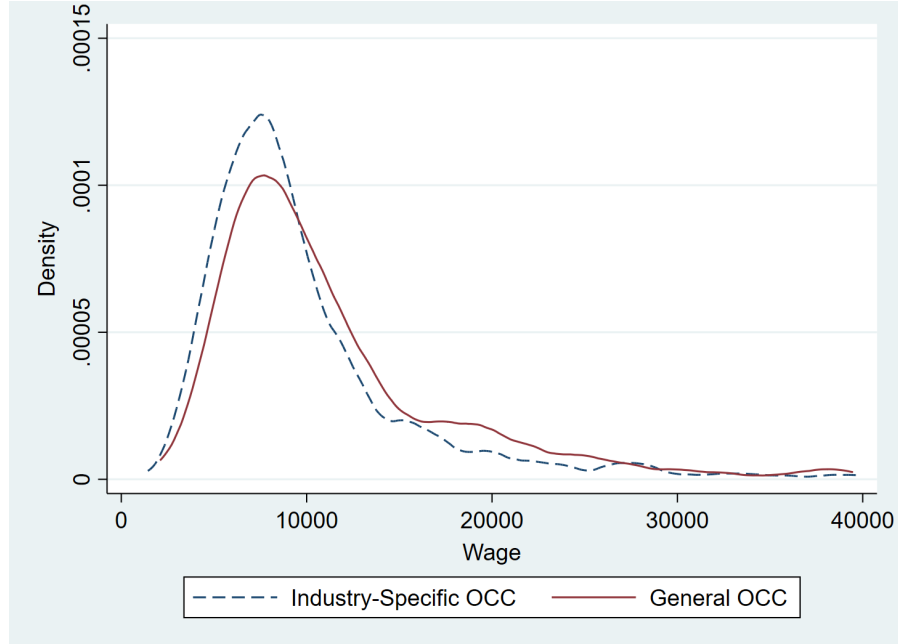
Note: This figure shows raw average earnings across periods for workers in the treated group and in the control group. The sample is the General Sample defined in Appendix B.1.1.

Figure A.6: The distribution of pre-displacement wages

(a) Treated vs. Control



(b) Among treated: ISOCC vs. GOCC

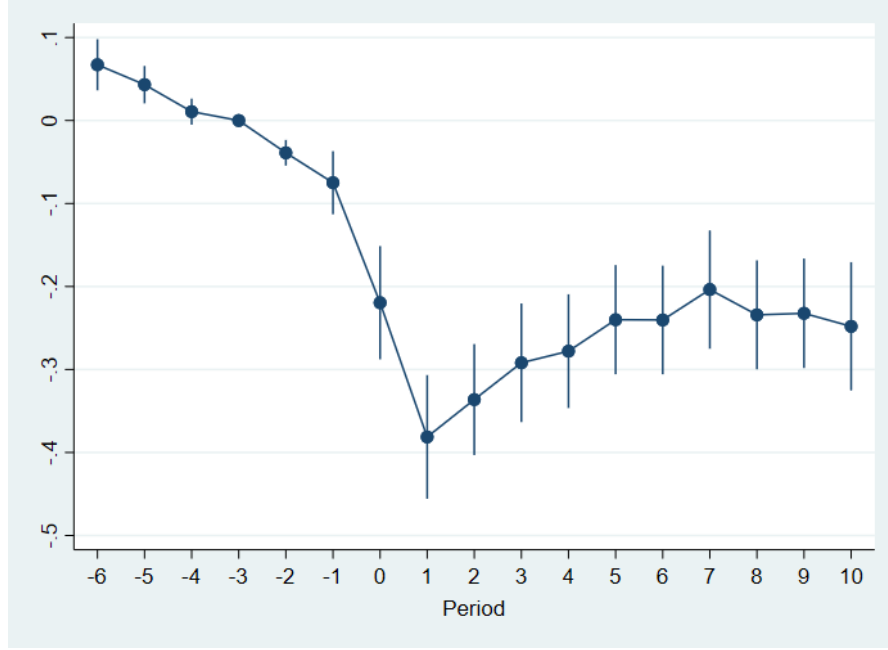


Note: Both panels present density plots of workers wages in period -2. For Panel (a), the sample is the General Sample defined in Appendix B.1.1. Panel (b) uses the Occupation Sample, defined in Appendix B.1.2, and compares between workers with Industry-Specific and General occupations, as defined in Section 5.2.

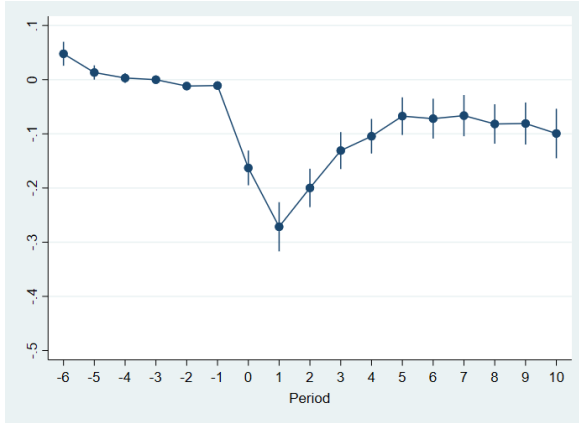


Figure A.7: Displacement effects – Occupation Sample

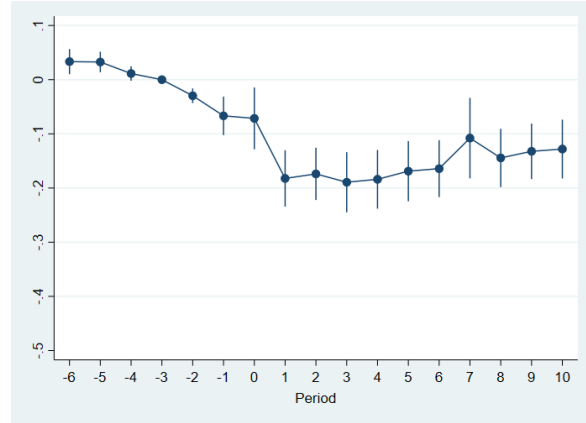
(a) Earnings



(b) Employment months



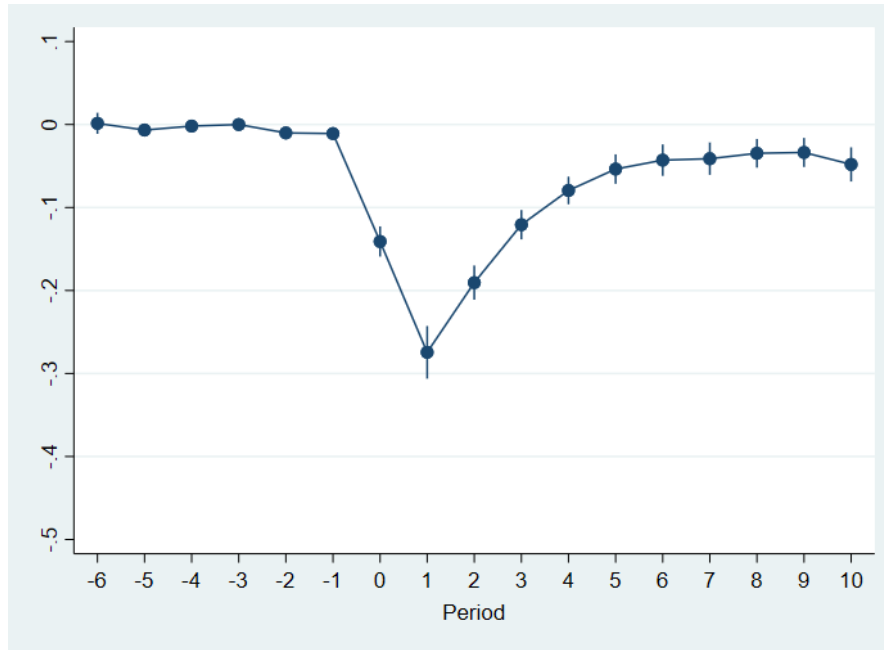
(c) Monthly wages



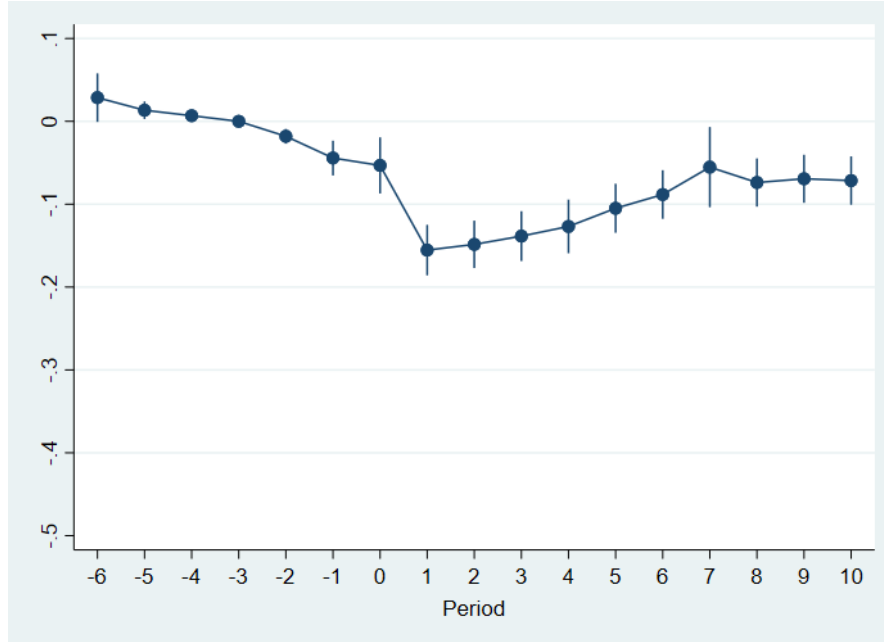
Note: All panels plot estimates of  $\beta_p$  from Eq. 1. The dependent variables are earnings, employment months, and monthly wages, in Panels (a),(b), and (c), respectively. The sample is the Occupation Sample defined in Appendix B.1.2. Standard errors are clustered at the pre-displacement firm level.

Figure A.8: Displacement effects – additional outcomes

(a) Employment months



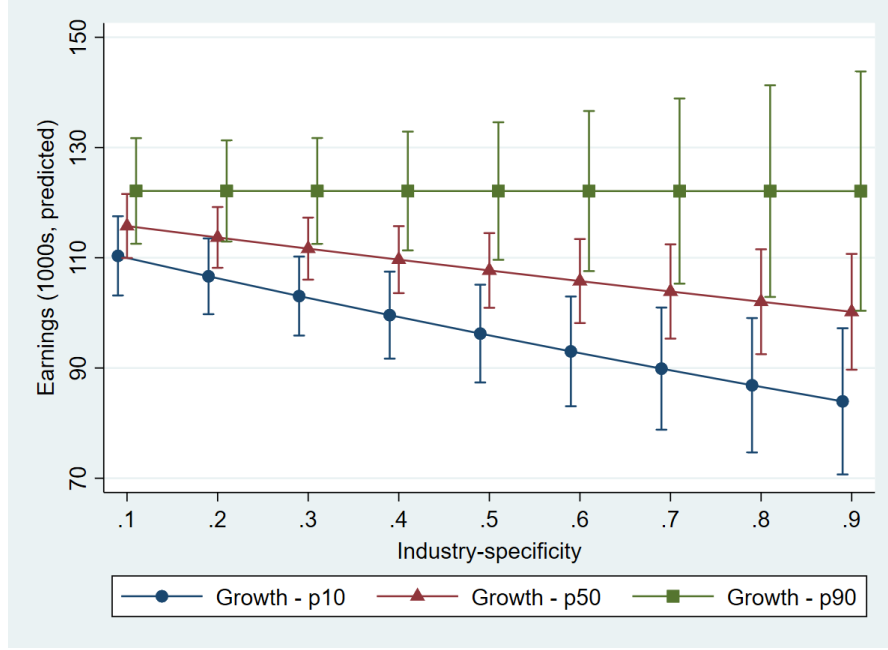
(b) Monthly wages



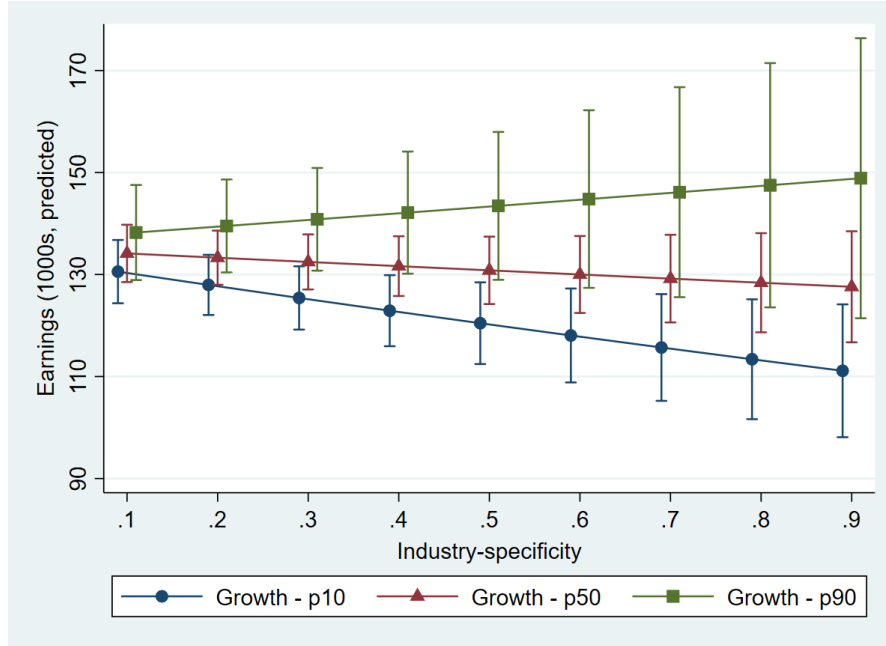
Note: This figure shows estimates of  $\beta_p$  from Eq. 1. In Panel (a), the dependent variable is months of employment. In Panel (b), the dependent variable is monthly wages (conditional on being employed). The sample is the General Sample defined in Appendix B.1.1. Standard errors are clustered at the pre-displacement firm level.

Figure A.9: Predicted earnings, by levels of IS and G

(a) Period 1



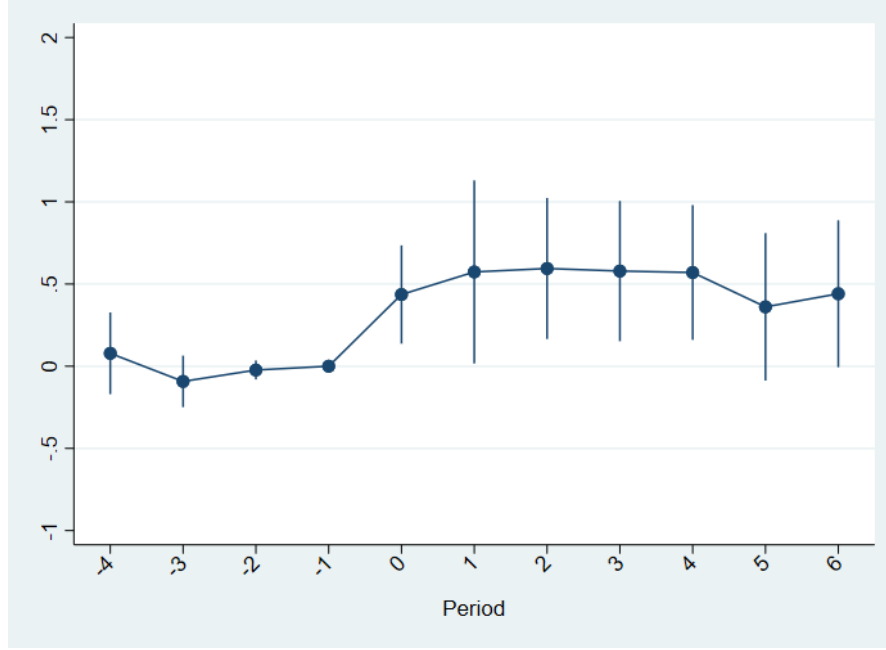
(b) Period 6



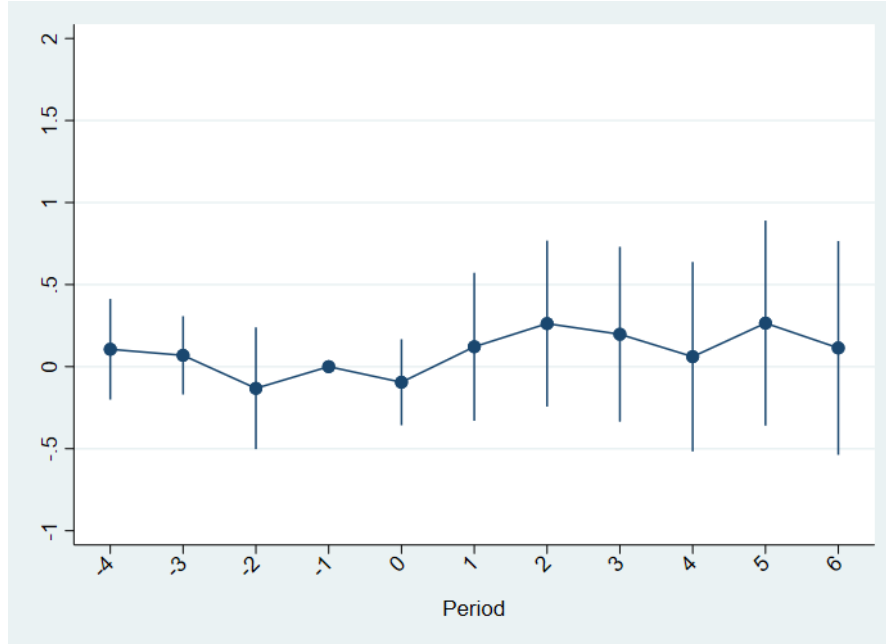
Note: This figure reports the adjusted means (also known as predictive margins) of earnings at different levels of  $IS_i$  and  $G_k(j)$ , following an estimation of Eq. 2. Panel (a) reports the estimates for period 1 (one year post-displacement), and Panel (c) for period 6. The sample is the Occupation Sample defined in Appendix B.1.2. Standard errors are computed using the Delta method.

Figure A.10: The effect of IS X Growth – Breakdown

(a) Employment months



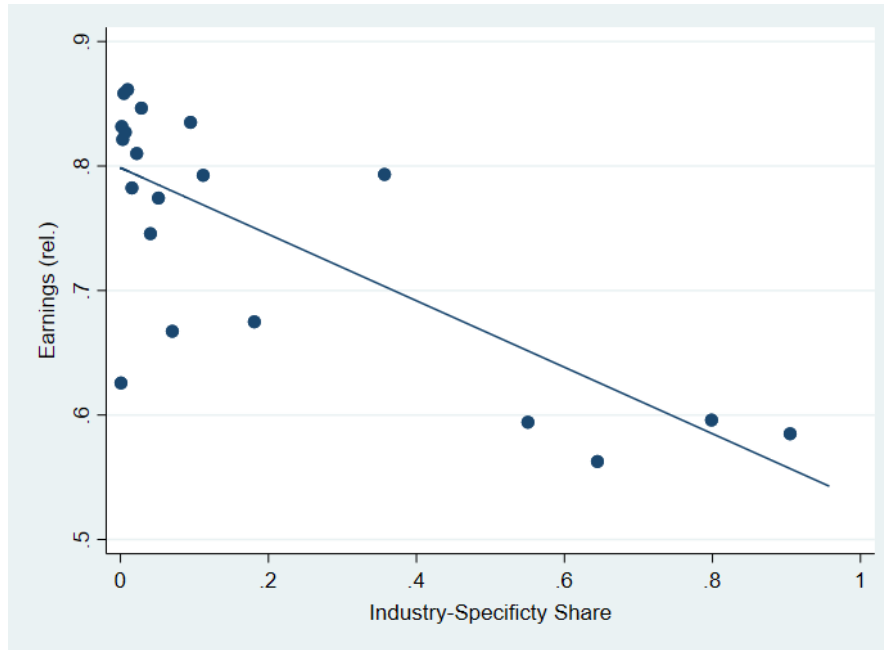
(b) Monthly wages



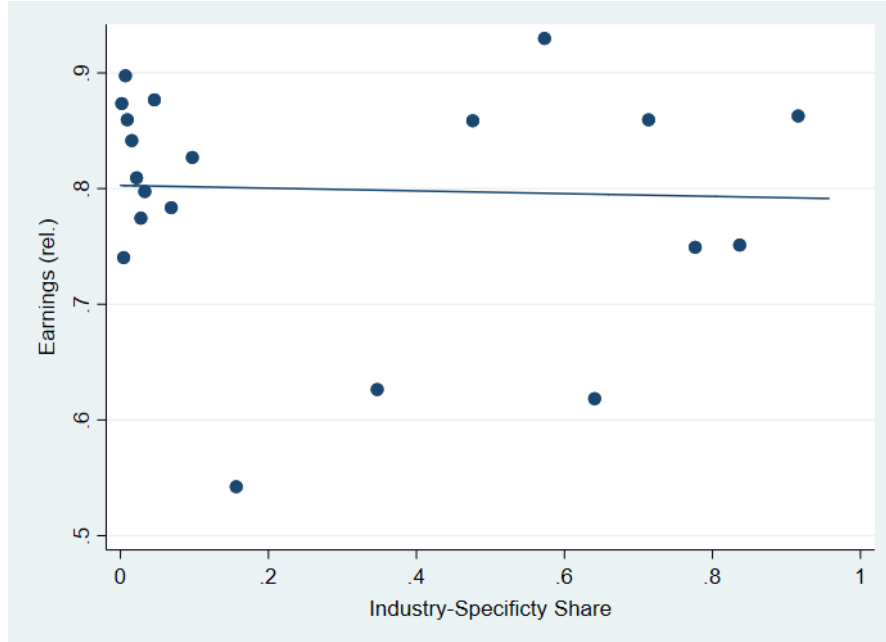
Note: This figure shows estimates of  $\phi_p$  from Eq. 2. The sample is the Occupation Sample defined in Appendix B.1.2. In Panel (a), the dependent variable is employment months. In Panel (b), the dependent variable is monthly wages (conditional on employment). Standard errors are clustered at the pre-displacement firm level.

Figure A.11: Earnings and IS one year after displacement

(a) Shrinking industries

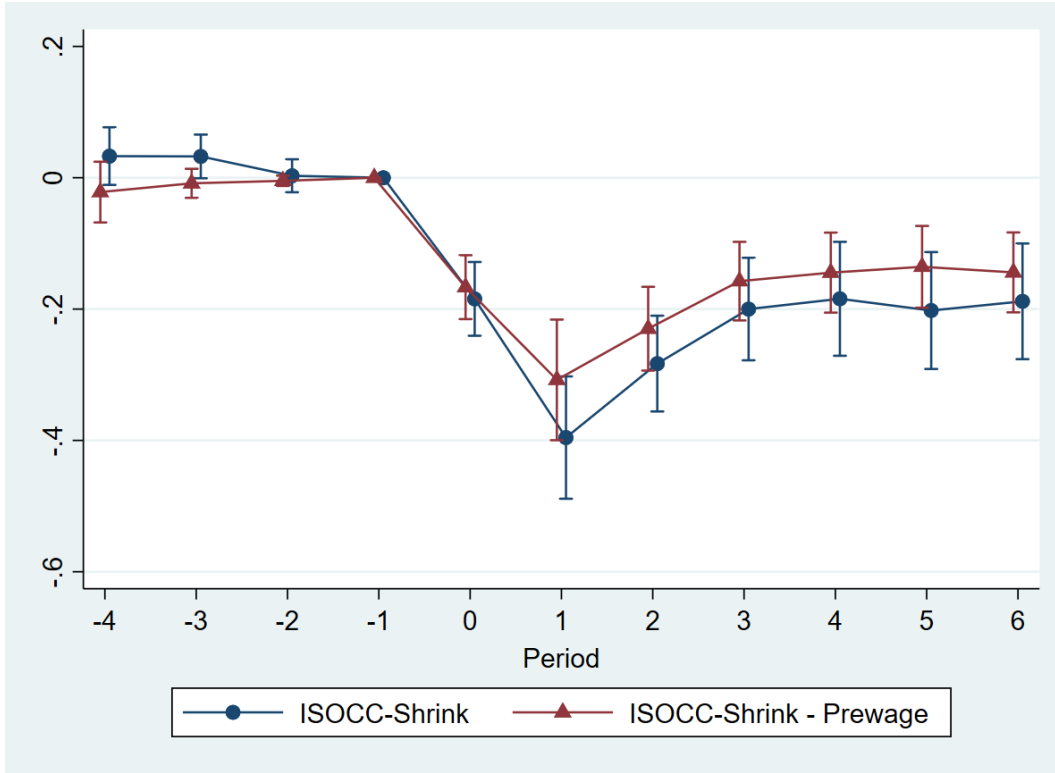


(b) Growing industries



Note: This figure shows binned scatter plots, applying a bin-scatter least squares estimation using the Stata package *binsreg* (Cattaneo et al. 2019). Workers are grouped into 20 equal-sized bins, according to their occupations' industry-specificity level. The y-axis reports the average earnings of workers in each bin one year following displacement, divided by their earnings in the year before displacement. Panel (a) includes workers displaced in shrinking industries, while Panel (b) includes workers laid off in growing industries. Both are defined in Section 5.2. The controls used in the estimation procedure are age, ethnicity, and sex.

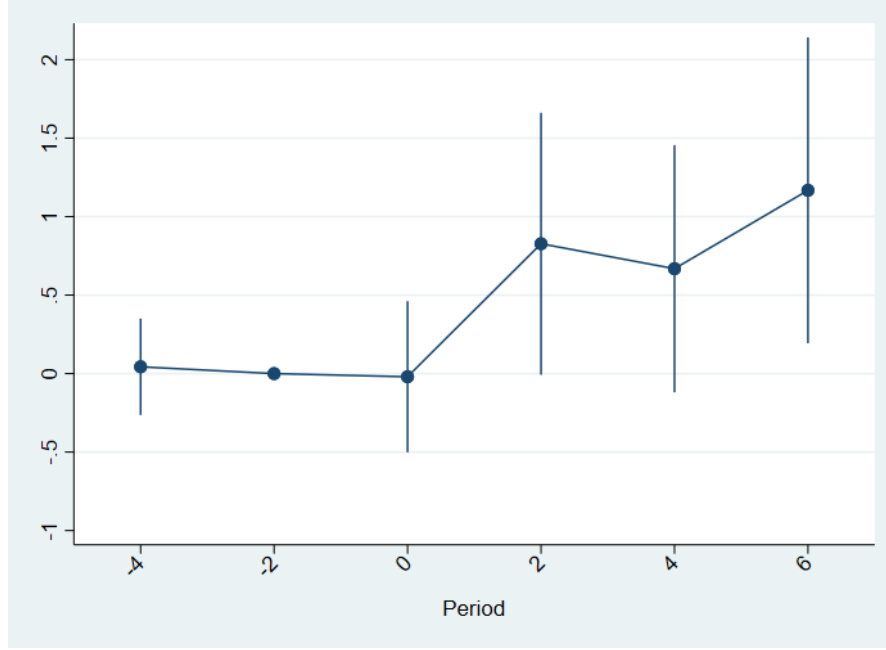
Figure A.12: Earnings losses with fixed wages



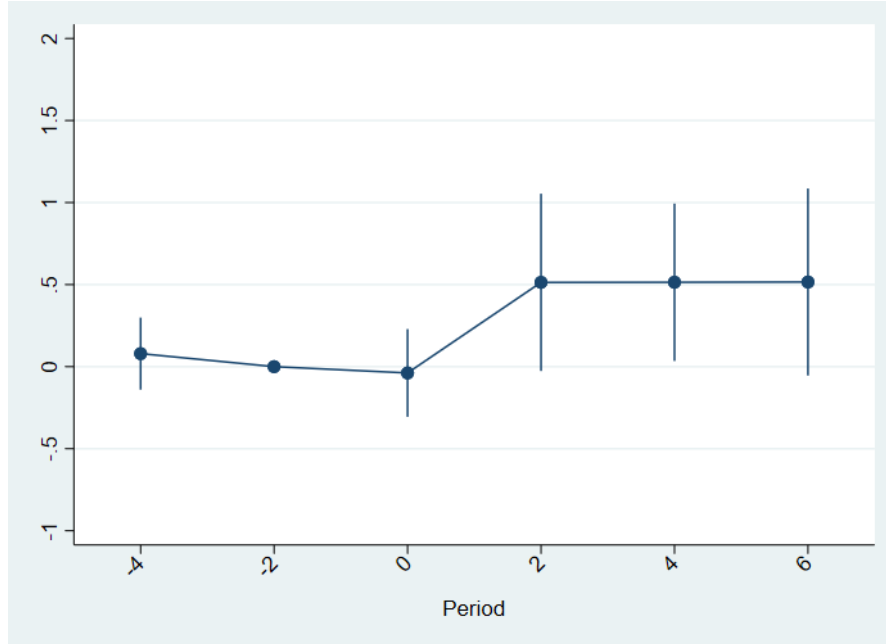
Note: This figure plots estimates of  $\beta_p$  from Eq. 1 for the ISOCC-Shrink group, defined in Section 5.2. For the blue curve the dependent variable is earnings. For the red curve the dependent variable is the employment variable multiplied by the worker's wage at period -3. The sample is the Occupation Sample defined in Appendix B.1.2. Standard errors are clustered at the pre-displacement firm level.

Figure A.13: Within-firm – The effect of  $IS \times G$

(a) Earnings



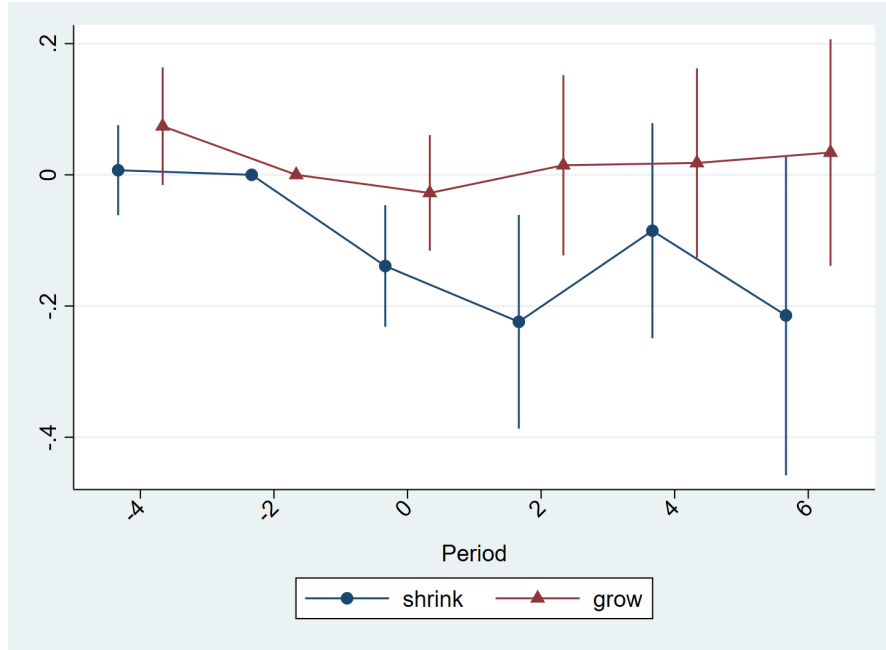
(b) Employment months



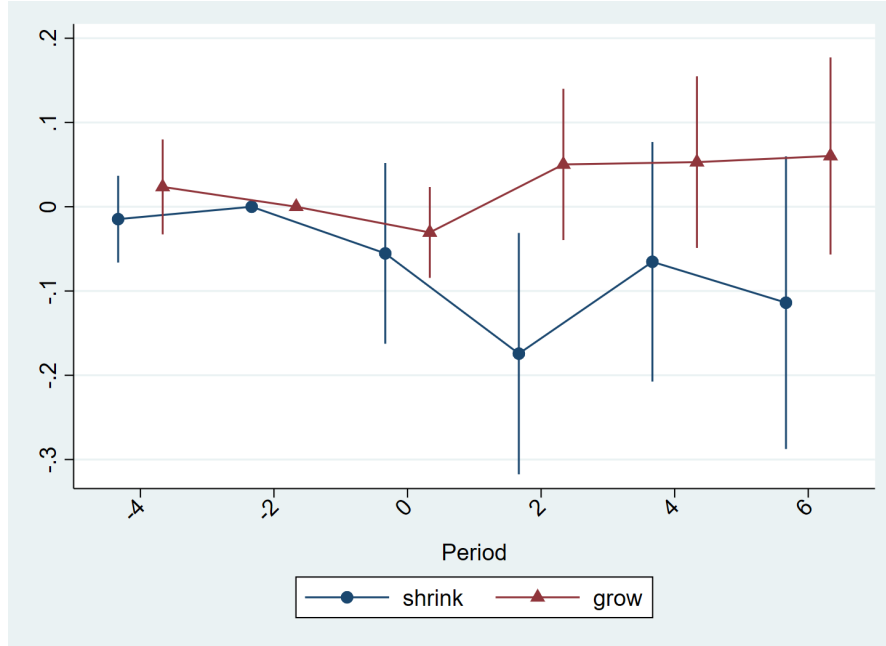
Note: This figure shows estimates of  $\phi_p$  from Eq. 6. The sample is the Occupation Sample defined in Appendix B.1.2. In Panel (a), the dependent variable is earnings. In Panel (b), the dependent variable is employment months. Standard errors are clustered at the pre-displacement firm level. Due to insufficient power, the period variable is grouped into two-year pairs.

Figure A.14: Within-firm – The effect of IS, by industry growth

(a) Earnings



(b) Employment months



Note: This figure shows estimates of  $\eta_p$  from Eq. 7, estimated separately for growing and shrinking, as defined in Section 5.2. The sample is the Occupation Sample defined in Appendix B.1.2. In Panel (a), the dependent variable is earnings. In Panel (b), the dependent variable is employment months. Standard errors are clustered at the pre-displacement firm level. Due to insufficient power, the period variable is grouped into two-year pairs.



## Appendix B Data Appendix

### B.1 Sample construction

#### B.1.1 General Sample

For estimating average treatment effects of displacement (ATT), I construct the following sample, primarily following the definitions used by [Schmieder et al. \(2023\)](#). For every calendar year  $t$ , the sample includes all workers who have stable employment (3+ years tenure with the current firm), and work for firms with 50+ employees in the manufacturing sector. Within this sample, a worker is defined as *displaced*, and assigned to the treatment group, if she separated from her firm during year  $t$  and the firm experienced a *displacing event* (to be defined momentarily) in that year; a worker is assigned to the control group if her firm is not experiencing a displacing event, and she remained with her firm in years  $t+1$  and  $t+2$ . This restriction is aimed at providing a “stable” counterfactual for the displaced worker.<sup>50</sup> This setup gives us, for each calendar year  $t$ , a sample of workers who were either displaced in this year, or can serve as a counterfactual (control) for the displaced workers. I define each of these samples as a *cohort*. Combining these samples into a single dataset, I require that each worker is assigned to a specific cohort: A treated worker if she was displaced this year, and a control worker if she can serve as a counterfactual for this year. As a consequence, treated workers are not allowed to be displaced on two separate occasions, and if non-displaced workers meet the conditions to serve as a control for different displacement years, they are assigned randomly to one of the years. In addition, a treated worker cannot be assigned as a control worker in other cohorts.

**Mass layoffs events:** A firm experiences a *mass layoff* in year  $t$  if it started the year with 50+ workers, contracted by at least 30% (or 20% with 100+ workers separating), and did not fully recover in years  $t+1$  and  $t+2$ .<sup>51</sup> A firm experiences a *closure* in year  $t$  if it started the year with 50+ workers, did not grow by 40% or more before closing, and does not appear again in the dataset in future years. To account for the possibility that what appears to be a mass layoff or a closure is in fact restructuring of workers between entities (or simply a change in the employer identifying number), I track workers to their next job, and drop a “closed” firm from the analysis if 50% or more of its workers moved together to a different firm, and a “mass-layoff” firm if 70% or more of its workers moved together to a different

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<sup>50</sup>The duration of the required stay with a firm will have a strong effect on the results. [Jacobson et al. \(1993\)](#) required six years without separation, leading to a highly positively-selected control group.

<sup>51</sup>I require that firm employment does not return to 90% of its previous level in the following two years. In addition, I require that the firm did not grow in year  $t-1$  by 30% or more, to remove the possibility of cycles, or seasonality, in hirings.

firm.

**Additional restrictions:** To obtain a balanced sample, I require all individuals to appear in the data at least six years before year  $t$ , and ten years after. In addition, to remove outliers, and to ensure that workers had a strong attachment to the labor market prior to displacement, I require that the monthly wages of all workers lie between the 5th and 95th percentiles of the wage distribution in the five years before displacement. Due to the balanced sample restriction, my final dataset includes treated and control workers for cohorts 1995 – 2013. I refer to this sample as the *General Sample*.

### B.1.2 Occupation Sample

As stated above, data on workers' occupations comes from surveys, mostly from the censuses in 1995 and 2008, and from the smaller LFS. These are not panel surveys, implying that for the workers for whom I have an occupation listed, it is usually only for a specific year. To impute the workers' occupations in other years, I make the following assumption: If in year  $t$  worker  $i$  is employed by firm  $j$  and reports that her occupation is  $o$ , I assume she remains with the same occupation for all years in which she is employed by firm  $j$ .<sup>52</sup> After applying this method to all workers in the General Sample, I have a non-missing occupation value at the year of displacement for 10% of the sample (meaning, a 10% coverage rate).<sup>53</sup> Due to the limited availability of occupation data, this sample is significantly smaller. To not restrict it further, the balanced sample used here only restricts workers to appear in the data at least four years before displacement, and six years after.<sup>54</sup> In addition, I drop workers with a managerial occupation. This defines my *Occupation Sample*.

## B.2 Why the Manufacturing Sector?

This paper focuses on layoffs that took place in the manufacturing sector. Manufacturing is the largest non-public sector in Israel, and accounts for over 30% of all mass layoffs in the country. The main reason I restrict the analysis to this sector is technical: The industry variable included in this administrative database, which classifies the economic activity of each firm, is the 2-digit level of the ISIC Rev. 3 classification, named "divisions" in their documentation. The manufacturing sector is composed of 28 2-digit industries, and the 2-digit level appears to be the sensible level to use for the analysis, since its categories match

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<sup>52</sup>Support for this assumption can be found in the analysis of within firm mobility by [Ransom and Oaxaca \(2005\)](#), who found little movement between job titles.

<sup>53</sup>For workers with a reported occupation in more than one year, I assign them the value from the nearest year.

<sup>54</sup>In addition, I do not restrict here the pre-wages to be within the 5th and 95th percentiles of the wage distribution, with the same purpose of not reducing the sample size.

the level of economic activity that an industry-specific skill is likely to refer to. These industries include “Manufacture of tobacco products”, “Manufacture of chemicals and chemical products”, “Manufacture of basic metals”, and “Manufacture of textiles”.<sup>55</sup> Conversely, the available 2-digit level is insufficient in most other sectors. For example, the second largest sector is “Commerce”, but it is composed of only two 2-digit categories, “Retail trading” and “Wholesale trading”. Note that for both categories, the most common occupation is “Salesperson”.<sup>56</sup> Regretfully, the 3-digit industry categories that *could* have helped in distinguishing between different types of salespeople (e.g., those working in “Retail trading of textile, apparel, and shoes”, versus those in “Retail trading of machines and their equipment”), are not available in my dataset.

In addition, concentrating on the manufacturing sector may be desirable, regardless of data limitations. The reason is that manufacturing is the canonical example used when discussing on-job training and industry-specific human capital. For example, [Couch and Placzek \(2010\)](#) write that “manufacturing workers, in particular, are thought to develop more specific skills than others” [pp. 584].

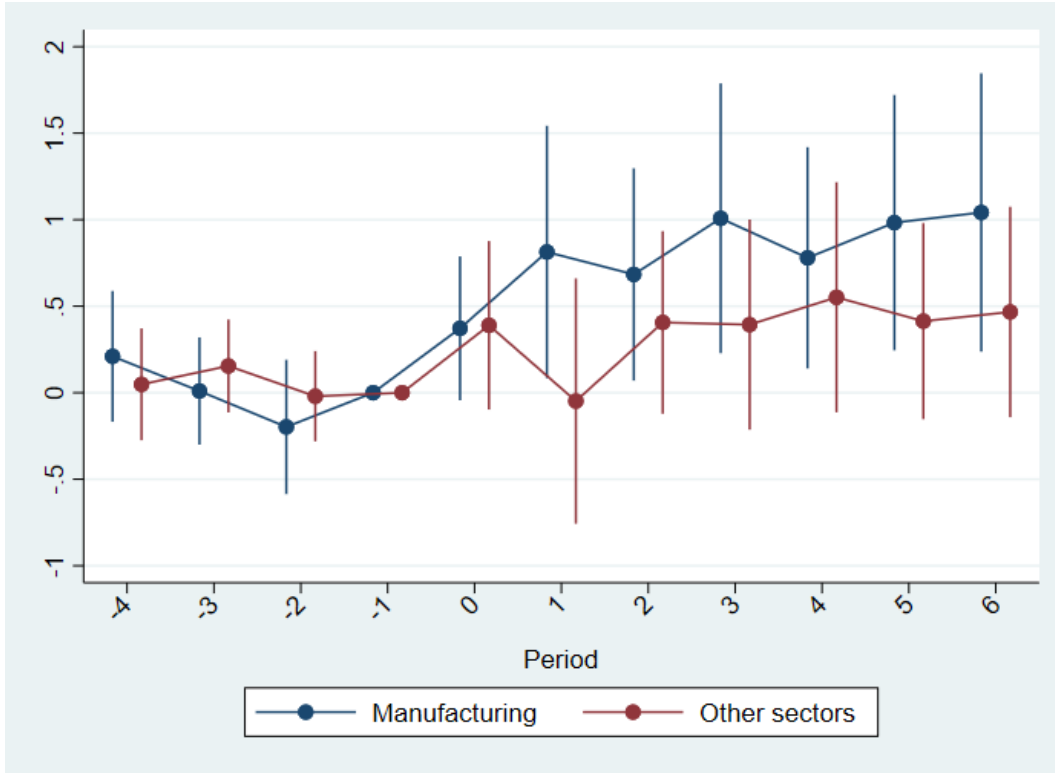
For good measure, Appendix Figure [B.1](#) compares estimates for  $\phi_p$  from Eq. 2, the coefficient on the interaction of IS and industry growth, for the manufacturing sector versus all other sectors combined. We can see the effect is attenuated in other sectors, and not significantly different from zero.

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<sup>55</sup>Taking “Manufacture of textiles” (industry 17) as an example, it collapses the following 3-digit categories: “Spinning, winding and braiding of threads” (170), “Fabric weaving” (171), and “Weaving towels” (172). When analyzing ISHC, I would argue that the 2-digit level (the most detailed level available in the dataset) is the appropriate one.

<sup>56</sup>Similarly, other 2-digit industries include “Health services”, “Welfare and assistance services”, “Education”, “Guards, security, and cleaning activities”, and “communication”.

Figure B.1: The effect of  $IS \times G$  - manufacturing vs. the rest of the economy



Note: This figure shows estimates of  $\phi_p$  from Eq. 2, estimated separately for layoffs from the manufacturing sector, and for layoffs from all other sectors in the economy. The sample is the Occupation Sample defined in Appendix B.1.2. The dependent variable is earnings. Standard errors are clustered at the pre-displacement firm level.

## Appendix C Extended Analysis and Findings

### C.1 Displacement Effects: Additional Results

Appendix Figure C.1 reports the effects of displacement on earnings by different demographic characteristics, and shows that the effect is larger for men, for older workers, and especially for workers with lower education. The effect on Arab workers is stronger only in the short run. In addition, Appendix Figure C.2 presents the average effects of displacement in growing and shrinking industries. We see the earnings losses are larger in shrinking industries, but only in the short run.

#### C.1.1 AKM Analysis

Following Abowd et al. (1999) and Card et al. (2013), I estimate the AKM model: A wage model that includes fixed effects for individual workers and fixed effects for employers. The firm fixed effects are interpreted as firm pay premiums, in the sense that they capture the average differences in wages that different firms pay to similar workers, while the worker fixed effects are interpreted as a measure of the productivity of the worker, after accounting for the type of firms she had worked for. Formally, I estimate the following model:

$$\omega_{it} = \alpha_i + \psi_{J(it)} + Z'_{it}\gamma + \varepsilon_{it} \quad (8)$$

where  $\omega_{it}$  is the log of the monthly wage of worker  $i$  at year  $t$ ,  $\alpha_i$  is a person fixed effect,  $\psi_{J(it)}$  is the firm fixed effect, and  $Z'_{it}\gamma$  are a set of year fixed effects and quartic polynomials age-restricted to be flat at age 40 (Card et al. 2016). I estimate the model using the entire working population in the years 1995-2019, on the sample's largest connected set of firms.

Appendix Figure C.3 presents estimates from this model. We see that displacement leads to a large drop in the quality of firms that workers match with (in terms of their wage premiums). In addition, earnings losses are larger for workers displaced from better firms, and larger for workers of lower quality (as measured in the model).

### C.2 Heterogeneity in the Effects of IS

We have seen that the IS measure has, on average, a large impact on earnings losses. To understand its impact better, I test for the existence of heterogeneity in its effects. Appendix Figure C.4(a) plots predicted values for treated (displaced) workers, within shrinking industries, at different percentiles of the IS distribution. Appendix Figure C.4(b) shows those same predicted earnings in relative terms, compared to the 10th percentile. We see evidence

of large heterogeneity, as the gap between the 10th percentile and the 90th percentile is over 20% one year after displacement (or 24k ILS), and 12.4% after six years (16k ILS). To put the estimated heterogeneity *between* treated workers in perspective, I will compare it to the ATT:<sup>57</sup> one year after displacement, this gap between treated workers at the two edges of the IS distribution is 54% as large as the average gap between treated and control workers (44.8k ILS); and in the long run, six years after displacement, the gap between the 10th percentile and the 90th percentile equals 82% of the average gap between treated and control workers (19.6k ILS). At the same time, only a small gap exists between the median and the 10th percentile. The reason for this is likely the highly skewed distribution of the industry-specific measure (recall Appendix Figure A.2(a)), implying the difference in IS levels is quite small at the bottom half of the distribution.

Another way to examine heterogeneity is by running Eq. 1 separately by IS quintile. Again, this is done within shrinking industries, comparing treated and control workers within the respective quintile. Appendix Figure C.5 reports the results. Panel (a) shows the separate event-study plots, by quintile. Here again, we see small and insignificant differences between the bottom and the middle of the distribution, while there is a large gap between earnings losses at the top quintile and the rest. One year after displacement, workers in the top quintile lose 84% more than workers from the bottom, and 105% more after six years. This suggests that displaced workers with highly industry-specific occupations are more prone to long-term losses. In Panels (b) and (c), each curve plots the coefficients for all quintiles, in absolute values, for a separate period. These plots suggest that there is convexity in the effect of the IS measure on earnings losses. In the short run, the relationship appears to be non-monotonic, as losses are larger in the bottom quintile than in quintiles 2-3. In contrast, in the long run, the losses appear to be an increasing and convex function of IS.<sup>58</sup>

### C.2.1 Displacement Effects by ISHC Groups

Most of the analysis thus far has examined the heterogeneous treatment effects of displacement using the continuous IS measure. In this section I break down the displacement effects by the four ISHC groups defined in Section 5.2, based on dichotomizing the continuous IS measure into *industry-specific occupations* (ISOCC), and *general occupations* (GOCC), and the measure of industry growth into growing and shrinking industries. Following the ISHC hypothesis, I expect losses to be largest for the ISOCC-Shrinking group, which includes workers with highly industry-specific occupations who are in low demand. Appendix Figure

<sup>57</sup>The ATT, in levels, in the Occupation Sample.

<sup>58</sup>In addition, Appendix Figure C.6 presents the outcomes for different intersections of industry-specificity quintiles and industry growth quintiles.

C.7 compares the outcomes from estimating Eq. 1 only for the ISOCC-Shrinking group, to estimating it jointly for the other three groups.<sup>59</sup> For both earnings and employment, losses are significantly larger for the ISOCC-Shrinking group, as predicted. Averaging across all post-displacement periods, the coefficients for the ISOCC-Shrinking group are 82% larger than all other groups, and 76% larger than the GOCC-Shrinking group, the complement group within shrinking industries. The losses are not only larger, but also more persistent in the long run. Focusing on the period six years after displacement, the ISOCC-Shrinking group's losses are more than *double* that of the other groups. The gap is even larger when we focus on employment outcomes. After six years, the average effect for the other three ISHC groups is only -0.047, less than one-third of the effect for the ISOCC-Shrinking group.

### C.2.2 The Effects of IS by Education Levels

An additional interesting place to examine for heterogeneity is by the education level of the worker. Appendix Figure C.10 explores the overall relationship between the IS measure and the education level of workers, at the occupation level. We see that occupations that are highly industry-specific exhibit a lower prevalence of workers with higher education. This result suggests that high-education occupations are less tied to specific industries, providing workers with more employment alternatives when separating from an employer. If this is the case, the enhanced losses experienced by high-IS workers in shrinking industries may be concentrated among low-education workers.

To test the relationship between the effect of IS and education, I again estimate Eq. 3 separately for growing and shrinking industries, but this time separately for each education group - workers with higher education, and without. The estimates for  $\eta_p$ , the additional displacement effect due to the IS measure, are presented in Appendix Figure C.11. It is evidently apparent that the effect on earnings comes from the variation within low-education workers (Panel (b)), matching the conjecture that the costs associated with having a significantly industry-specific occupation is borne mostly by workers with low-education levels.

## C.3 Additional Robustness

### C.3.1 Occupation Growth

The evidence presented thus far supports the argument that the demand for the displaced workers' specific skills is key for explaining their displacement effects, and that this demand can be proxied by a measure that combines their occupation and industry. However,

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<sup>59</sup>Appendix Figure C.8 and Appendix Table C.1 report regression results for the four ISHC groups separately. In addition, Appendix Figure C.9 tests the sensitiveness of the threshold used for dichotomizing the IS measure.

another possible method to proxy for this demand is to look directly at the demand for each occupation, using the occupation growth rate. Ideally, this would be measured with annual occupation data. However, the annual Labor Force Surveys (LFS) are too small for that purpose. Instead, I measure the growth of each occupation using the the two censuses, 1995 & 2008. This means that for each occupation I will have a single value of growth for the entire sample, not allowing for changing trends.

Using this measure, I run a modified version of Eq. 3, with the treatment variable interacted with the occupation growth rate. Appendix Figure C.12(a) shows that the occupation growth does indeed have a positive additional effect on post-displacement earnings. However, the coefficients are small - if an occupation grows by one Std Dev (growth of 65%), earnings are only 3.6% higher in the year after displacement - and not significant in the long run.<sup>60</sup> Comparing these estimates to the ATT of displacement in the Occupation Sample one year after displacement (29.3%, see Table 2), we see that a one Std Dev increase in the measure of occupation growth accounts for 12.3% of the ATT. This is a large effect, but in order of magnitude smaller than the industry-specificity measure in its explanatory power. In addition, I estimate the average displacement effects (Eq. 1) separately for growing and shrinking occupations, using the median growth rate of occupations as the cutoff. In Appendix Figure C.12(b), we see that losses are overall larger for workers in shrinking occupations.

It is important to note that the difference between these two approaches is not merely technical, but addresses a fundamental question about what influences a worker's specific human capital, especially in terms of her earnings potential: Is it only the occupation that matters, or is the employing industry important as well? For example, how different is the demand for a carpenter who worked in the furniture industry to that of a carpenter from the construction sector? These are important questions for understanding the sources of the post-displacement losses in earnings. Given the crudeness of the occupation growth measure, it is difficult to fully compare the two methods. Having said that, the results presented here suggest that a worker's industry matters as well. This can be true for many reasons: connections made in the industry, knowledge regarding future employment opportunities, or simply the different skills required in each industry, even for workers in the same occupation.

### C.3.2 Testing Other Explanations

We have seen that workers with high IS levels had lower wages prior to displacement (Table 1). Due to this, one possible concern is that the low wages are driving the results, not the ISHC. To examine this, I again estimate Eq. 3 in shrinking industries, with earnings as

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<sup>60</sup>The fact that the estimates are noisy could be a consequence of the crudeness of the measure - comparing occupations levels between the two censuses.



the dependent variable, but I replace the IS variable with the *low-earnings* variable, defined as the inverse to the log of earnings in period -2. I then compare the estimates to those of Eq. 3 with the IS variable, as before. The results are presented in Appendix Figure C.13(a). The effect of having low pre-earnings are very small and short-lived, as the estimate is significant only in the first year following displacement. Another possible concern is that the estimates for the IS measure are masking the real culprit, which is the worker's tenure. As reviewed in Section 2, an alternative theory proposed for explaining earnings losses focuses on longevity pay, arguing that many firms tie their pay grade to tenure, which will result in large losses in the case of a layoff. Appendix Figure C.13(b) reports estimates of Eq. 3, where IS is replaced with the log of tenure as the explanatory variable. The results here point in the other direction - higher tenure pushes earnings to *increase* in the short run, with no long-term effect. Finally, I estimate Eq. 3 again, adding the following controls (each interacted with period indicators): low-earnings, tenure, education level and age. The estimates for the coefficient on IS remain unchanged (Appendix Figure C.13(c)). The stability of the IS estimate strongly suggests that the estimated effects are not driven by these other forces.

### C.3.3 Industry Growth: Alternative Definition

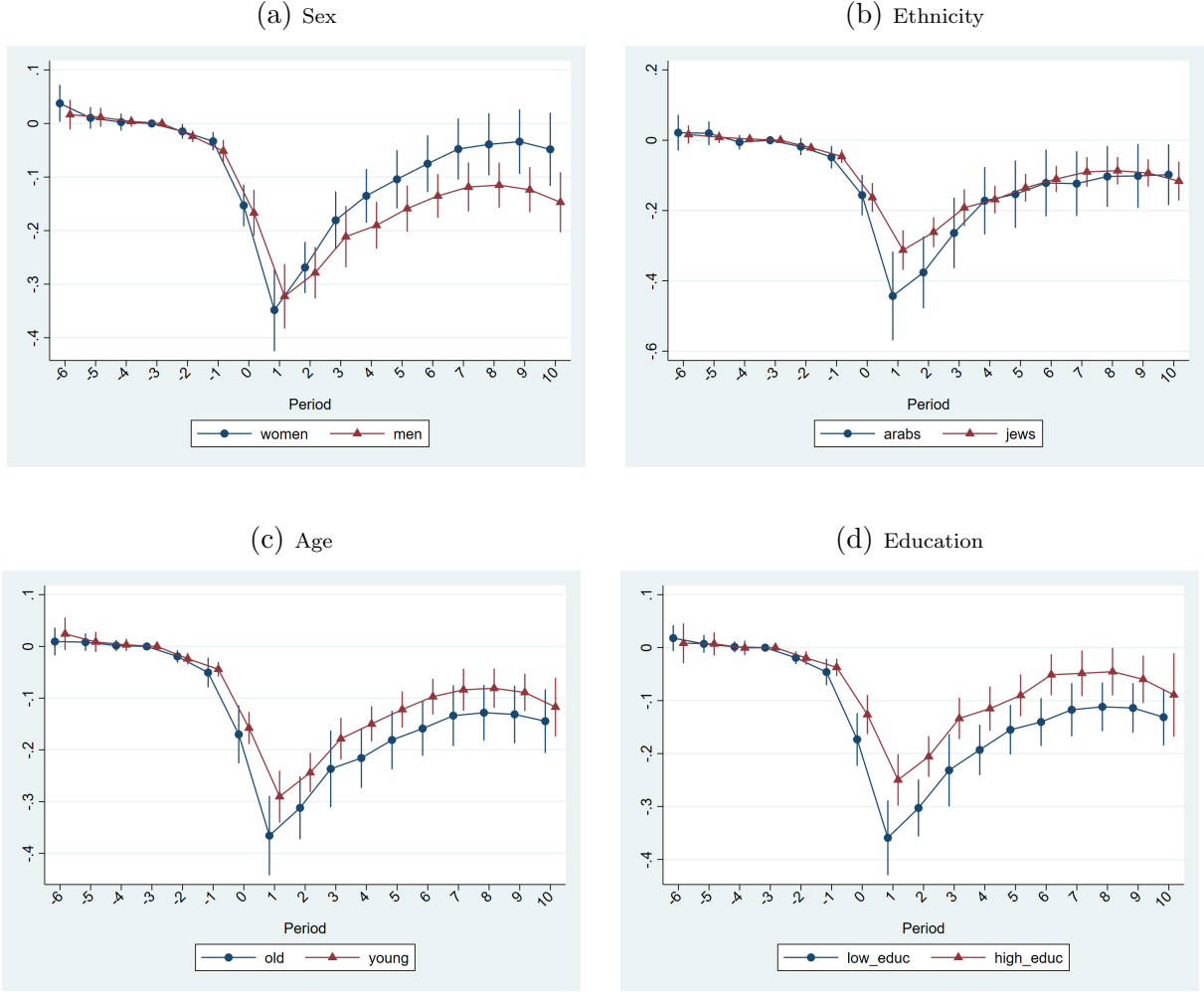
For a worker laid off in year  $t$ , Section 5.2 defines the industry growth rate as the change in her industry's employment level between years  $t - 3$  and  $t + 2$ . This 5-year window was chosen to capture the state of the industry both at displacement and during the job search period. However, including post-displacement years may introduce bias due to reverse causality. For example, if many displaced workers are re-employed in the same industry, their re-employment will affect the industry's employment levels and measured growth. The potential bias is likely negligible because the number of workers displaced in mass layoffs is small compared to the overall workforce size in each industry. Nonetheless, to alleviate possible concerns, I repeat the main analysis with industry growth defined as the change in employment between years  $t - 3$  and  $t$ . Results are presented in Appendix Figure C.14. Panel (a) presents the estimates for  $\phi_p$  from Eq. 2, which is the coefficient for the interaction between IS and industry growth, corresponding to the estimates in Figure 4. Panel (b) reports the estimates for  $\eta_p$ , which reflect the additional displacement effect due to the IS measure. These estimates are computed separately for growing and shrinking industries from Eq. 3, and correspond to Figure 5(a). In both cases, the results are highly significant, and support the hypothesis. In fact, the results point to a stronger negative effect on earnings compared to the results when using the current definition of industry growth.

Table C.1: Displacement effects on earnings, by ISHC group

	Shrinking		Growing	
	ISOCC	GOCC	ISOCC	GOCC
	(1)	(2)	(3)	(4)
$p \times D$				
-4	0.0391* (0.0226)	0.131*** (0.0454)	0.0954*** (0.0166)	0.116*** (0.0361)
-3	0.0364** (0.0173)	0.0944** (0.0410)	0.0678*** (0.0185)	0.102*** (0.0306)
-2	0.00506 (0.0129)	0.0234 (0.0284)	0.0346*** (0.0100)	0.0485* (0.0258)
0	-0.187*** (0.0287)	-0.108*** (0.0264)	-0.0945*** (0.0234)	-0.0822*** (0.0233)
1	-0.400*** (0.0478)	-0.281*** (0.0464)	-0.231*** (0.0391)	-0.215*** (0.0389)
2	-0.289*** (0.0375)	-0.196*** (0.0363)	-0.177*** (0.0297)	-0.164*** (0.0373)
3	-0.208*** (0.0401)	-0.166*** (0.0324)	-0.0966* (0.0497)	-0.158*** (0.0425)
4	-0.193*** (0.0440)	-0.0976*** (0.0309)	-0.131*** (0.0284)	-0.0926** (0.0393)
5	-0.213*** (0.0454)	-0.0837** (0.0329)	-0.121*** (0.0309)	-0.0904** (0.0414)
6	-0.200*** (0.0450)	-0.0891** (0.0366)	-0.108*** (0.0285)	-0.0555 (0.0382)
N	21,285	21,835	35,178	29,403

Note: This table presents estimates of  $\beta_p$  from Eq. 1, run separately for the four ISHC groups defined in Section 5.2. The dependent variable is earnings. The sample is the Occupation Sample, defined in Appendix B.1.2. Standard errors are clustered at the pre-displacement firm level. The omitted category is period -1.

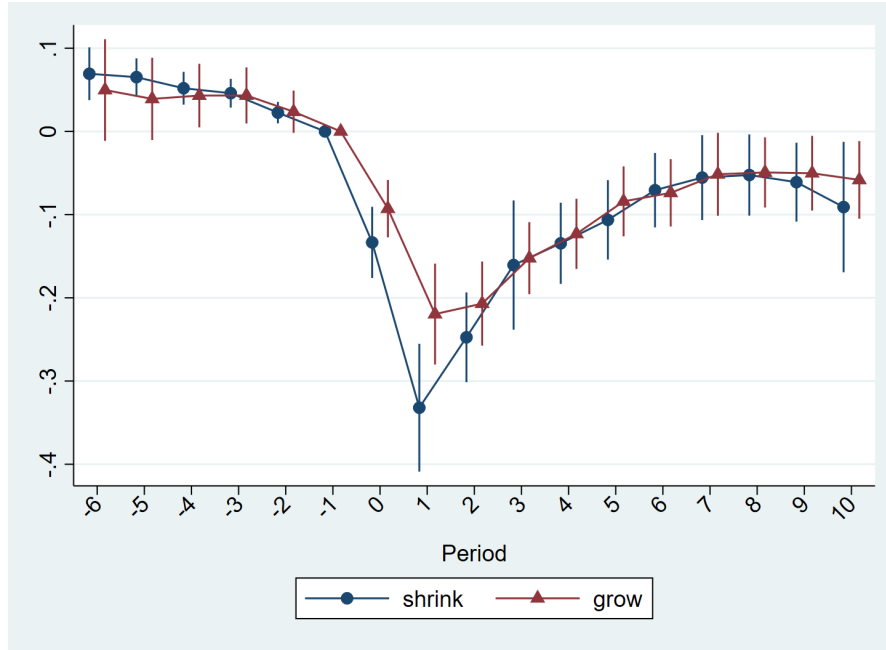
Figure C.1: Displacement effects on earnings, by demographic group



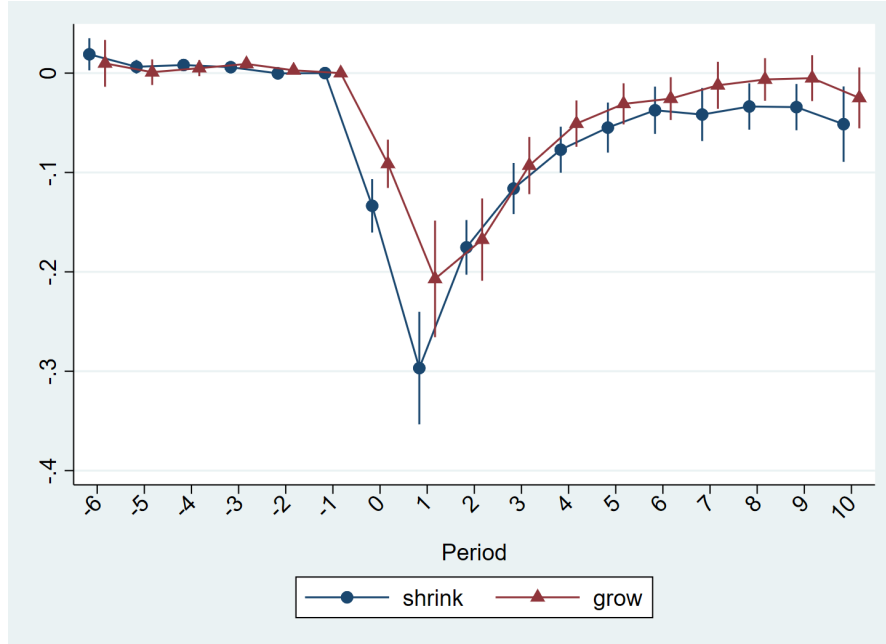
Note: All panels plot estimates of  $\beta_p$  from Eq. 1, run separately for different demographic groups. In Panel (c), the cutoff age is 42, the median age at the time of displacement. For panel (d), workers are classified as *high-educ* if they hold an academic degree, and *low-educ* otherwise. The dependent variable is earnings. The sample is the General Sample defined in Appendix B.1.1. Standard errors are clustered at the pre-displacement firm level.

Figure C.2: Displacement effects on earnings, by industry growth

(a) Earnings



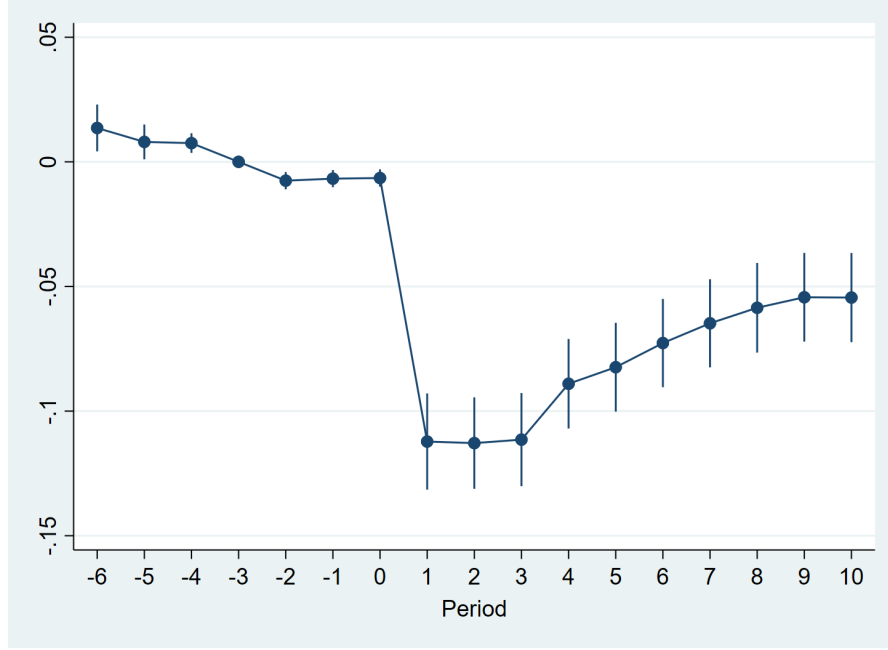
(b) Employment months



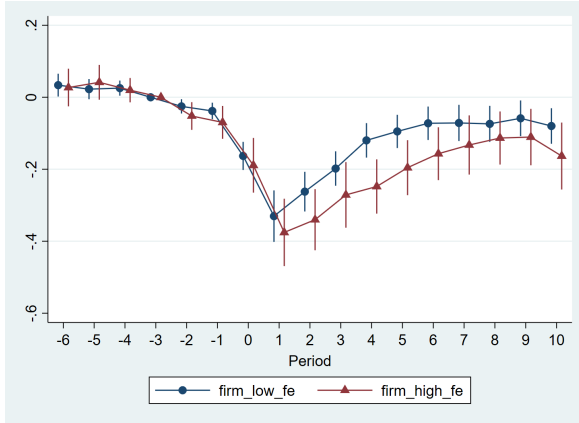
Note: Both panels plot estimates of  $\beta_p$  from Eq. 1, run separately for growing and shrinking industries, as defined in Section 5.2. For Panel (a) the dependent variable is earnings, and for Panel (b) it is employment. The sample is the General Sample defined in Appendix B.1.1. Standard errors are clustered at the pre-displacement firm level.

Figure C.3: Displacement effects – AKM analysis

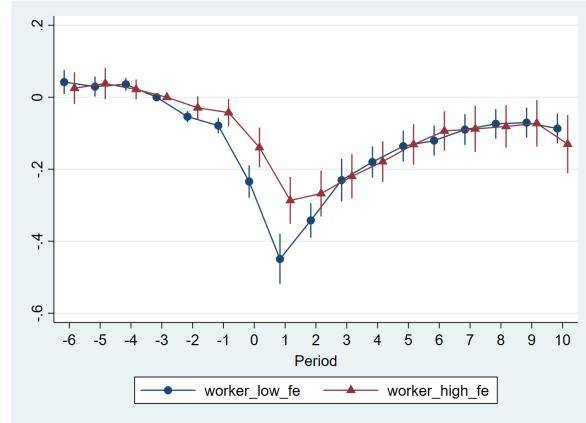
(a) The effect of displacement on the firm FE



(b) By pre-displacement firm FE

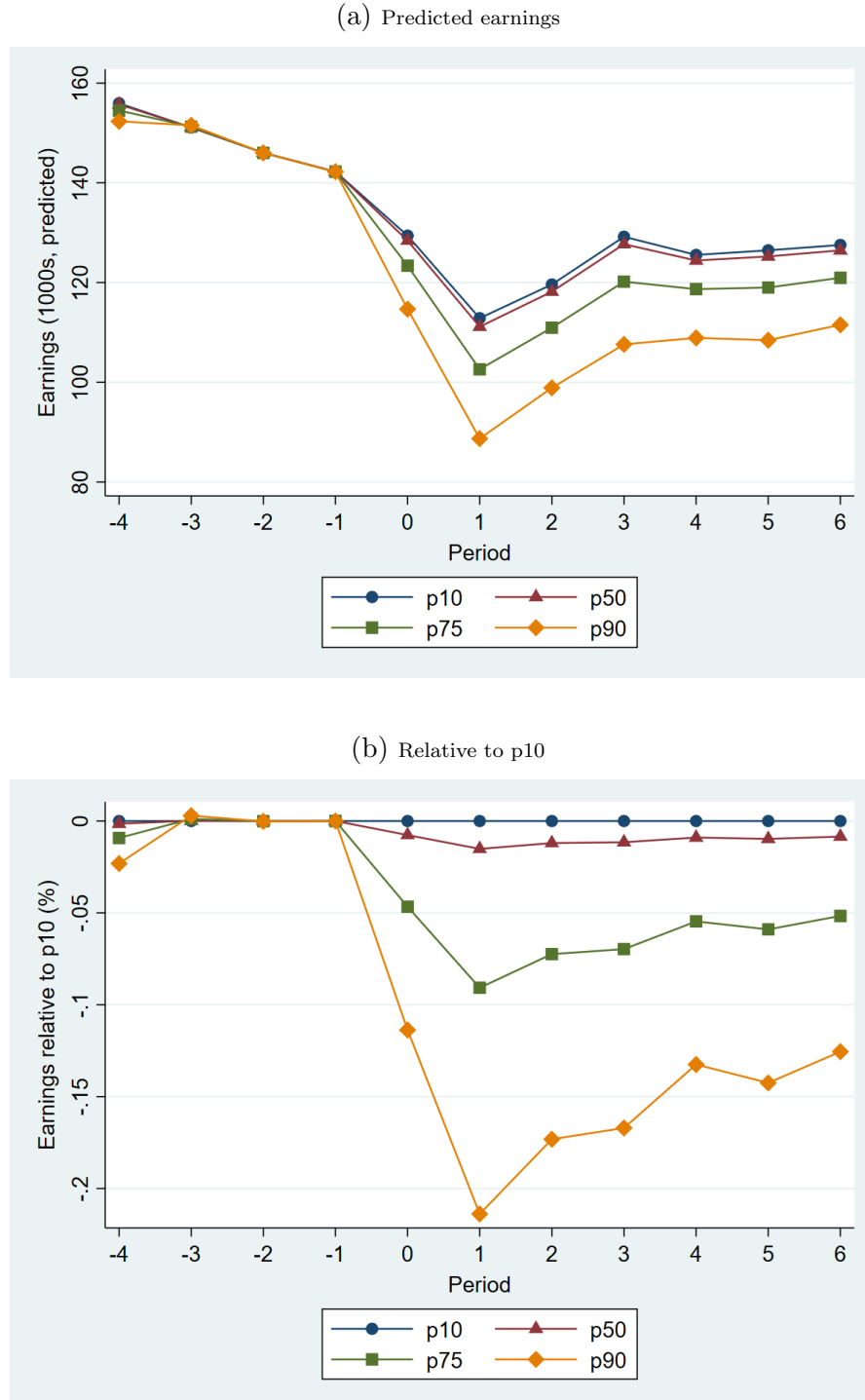


(c) By pre-displacement worker FE



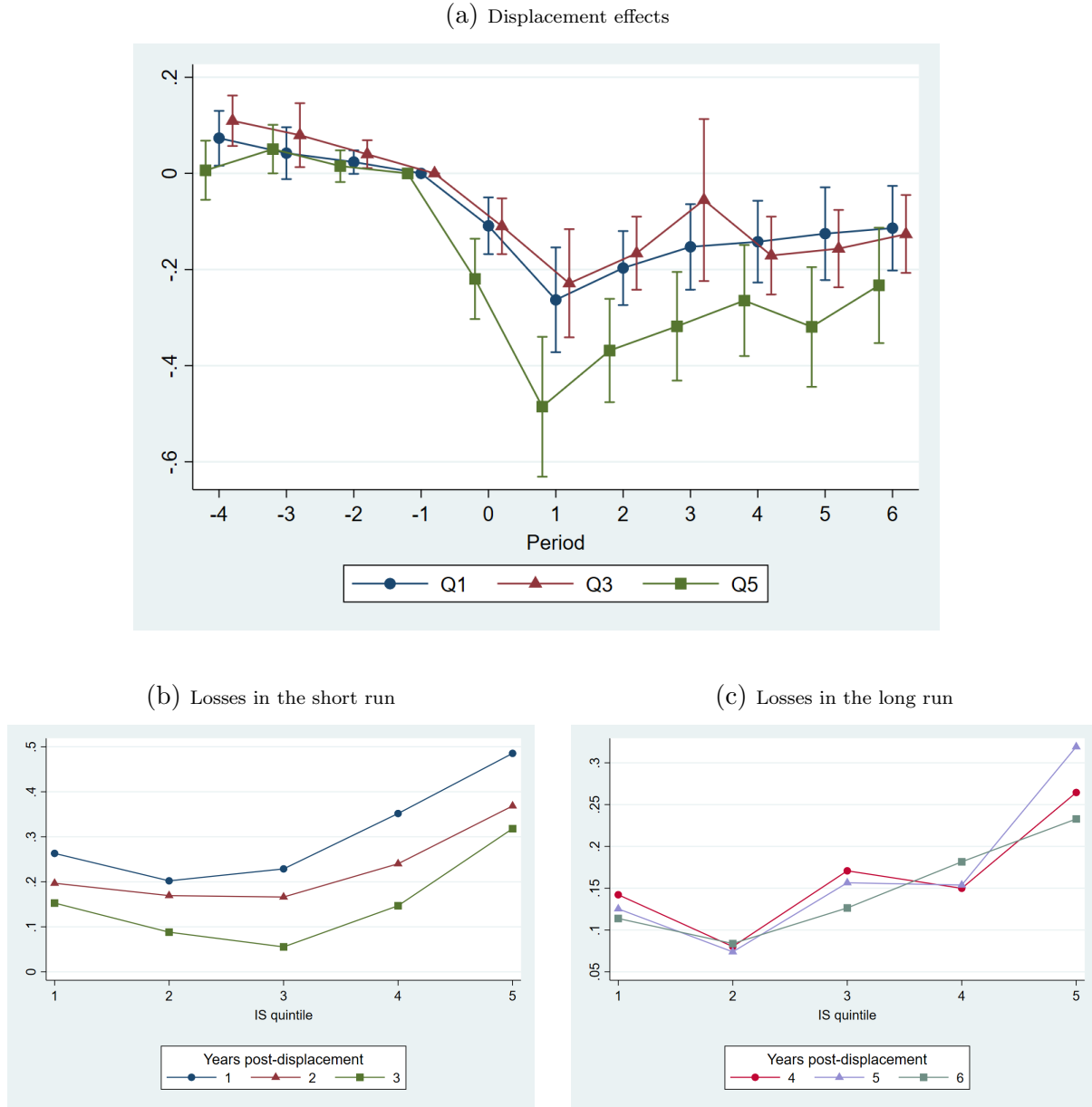
Note: All panels plot estimates of  $\beta_p$  from Eq. 1. In Panel (a) the dependent variable is the firm FE of the current employer. In Panels (b) and (c) the dependent variable is earnings. In Panel (b) the coefficients are estimated separately for workers displaced from firms with an estimated firm FE above the median (*firm\_high\_fe*) and below the median (*firm\_low\_fe*). In Panel (c), similarly, the coefficients are estimated separately for workers with an estimated worker FE above and below the median level. The firm FE and worker FE are estimated as described in Appendix C.1.1. The sample is the General Sample defined in Appendix B.1.1. Standard errors are clustered at the pre-displacement firm level.

Figure C.4: Heterogeneity in the effect of IS in shrinking industries



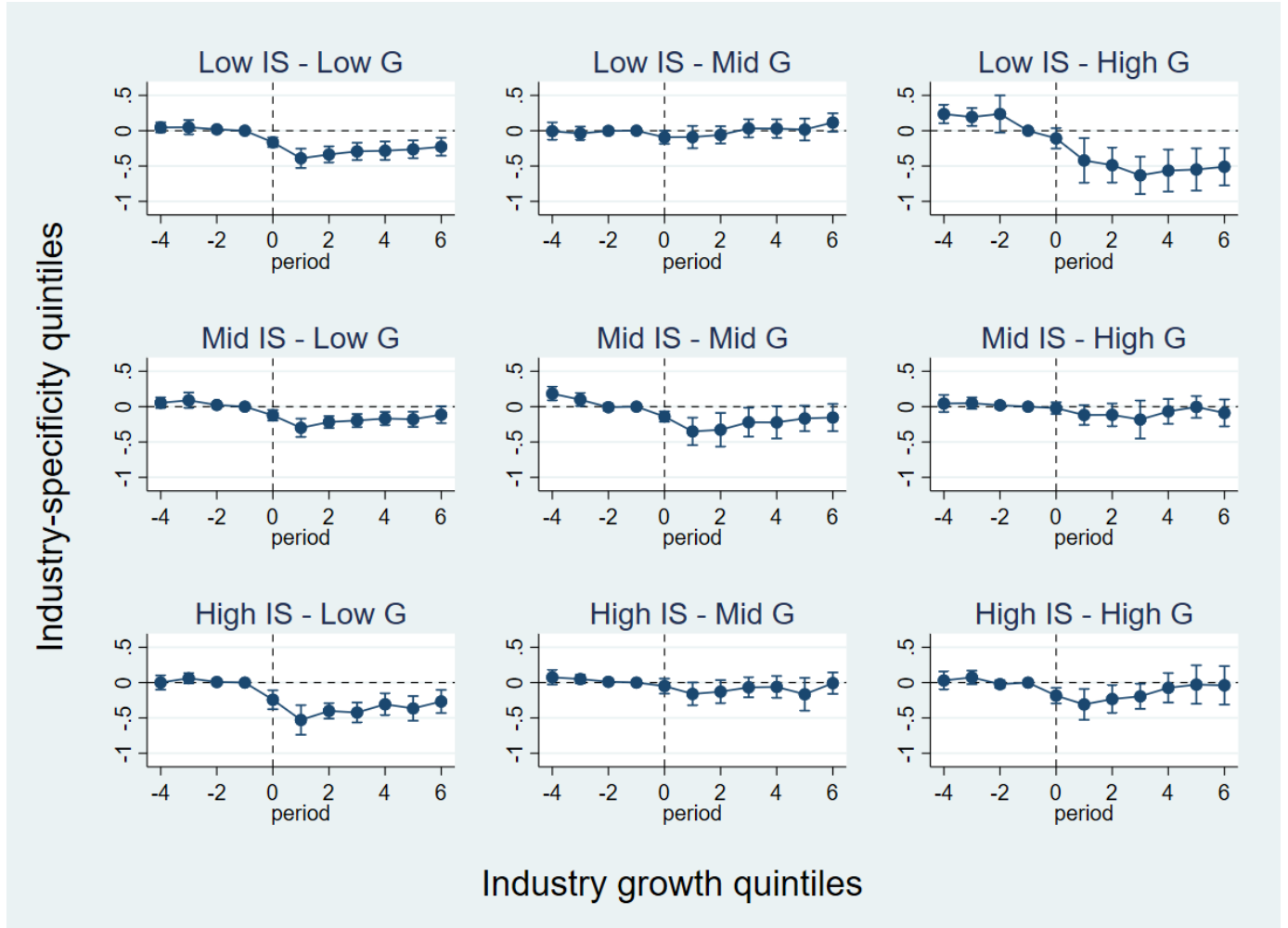
Note: This figure reports predicted values of earnings for treated workers at different levels of IS, following an estimation of Eq. 3 for shrinking industries, as defined in Section 5.2. The sample is the Occupation Sample defined in Appendix B.1.2. Panel (a) depicts the adjusted means. Panel (b) reports the adjusted means in relative terms, using the predicted values at p10 as the baseline.

Figure C.5: The effect of IS in shrinking industries, by IS quintiles



Note: Panel (a) plots estimates of  $\beta_p$  from Eq. 1, estimated separately for each quintile of the IS measure, using shrinking industries, as defined in Section 5.2. Panels (b) and (c) reports the same coefficients, in absolute values, where each curve represents a different period. The sample is the Occupation Sample defined in Appendix B.1.2. The dependent variable is earnings. Standard errors are clustered at the pre-displacement firm level.

Figure C.6: Heterogeneity - by IS and G quintiles

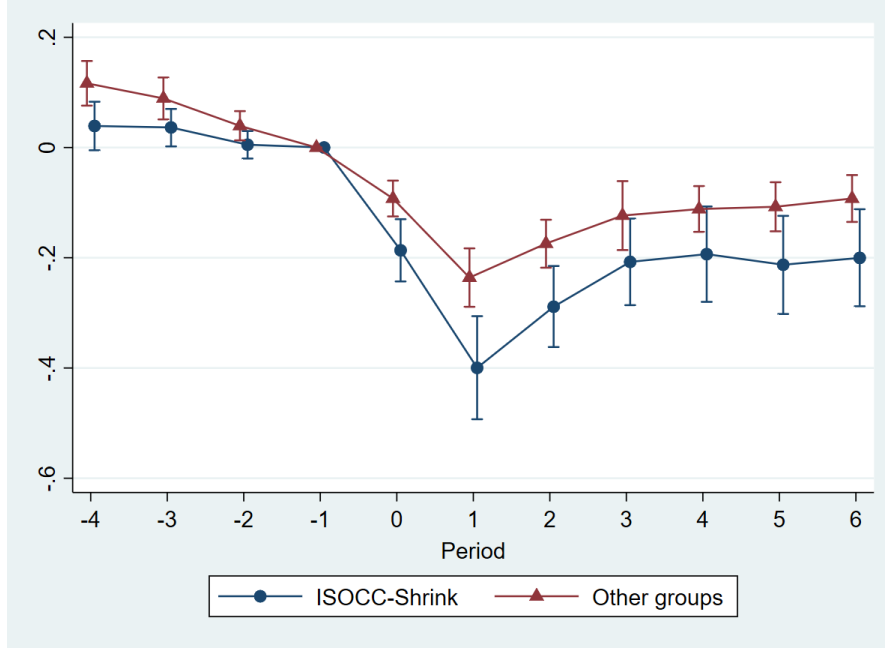


Note: This figure plots estimates of  $\beta_p$  from Eq. 1, estimated separately for different intersections of industry-specificity quintiles and of industry growth quintiles. Low IS (G), Mid IS (G), and High IS (G), refer to the bottom, middle, and top quintile of IS (industry growth), respectively. The sample is the Occupation Sample defined in Appendix B.1.2. The dependent variable is earnings. Standard errors are clustered at the pre-displacement firm level.

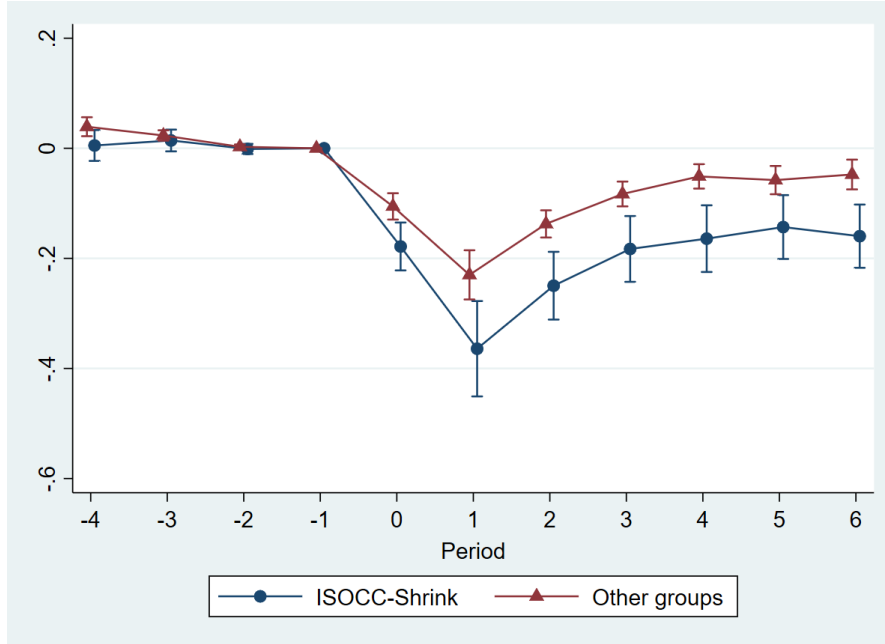


Figure C.7: Displacement effects – the ISOCC-Shrinking group

(a) Earnings



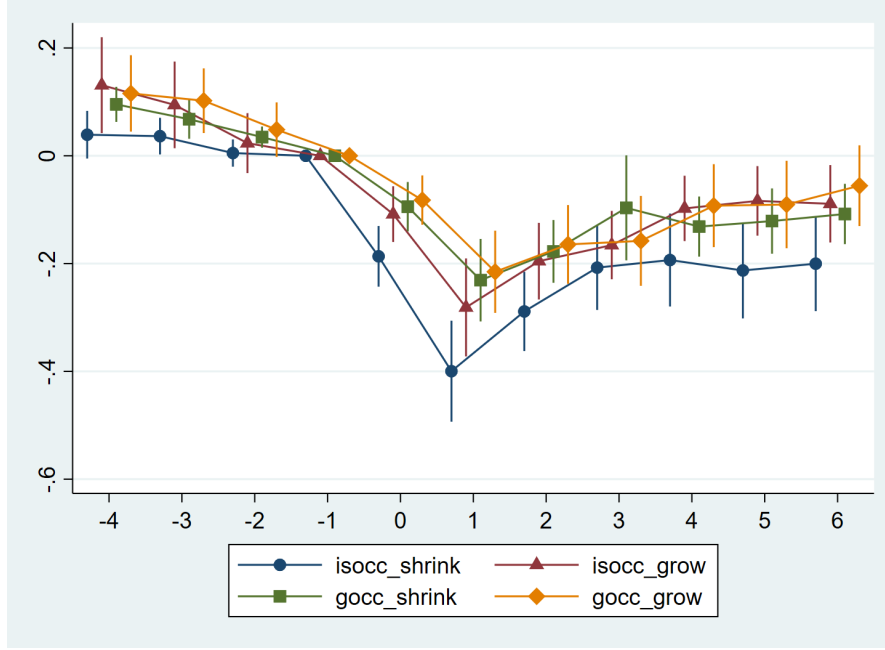
(b) Employment months



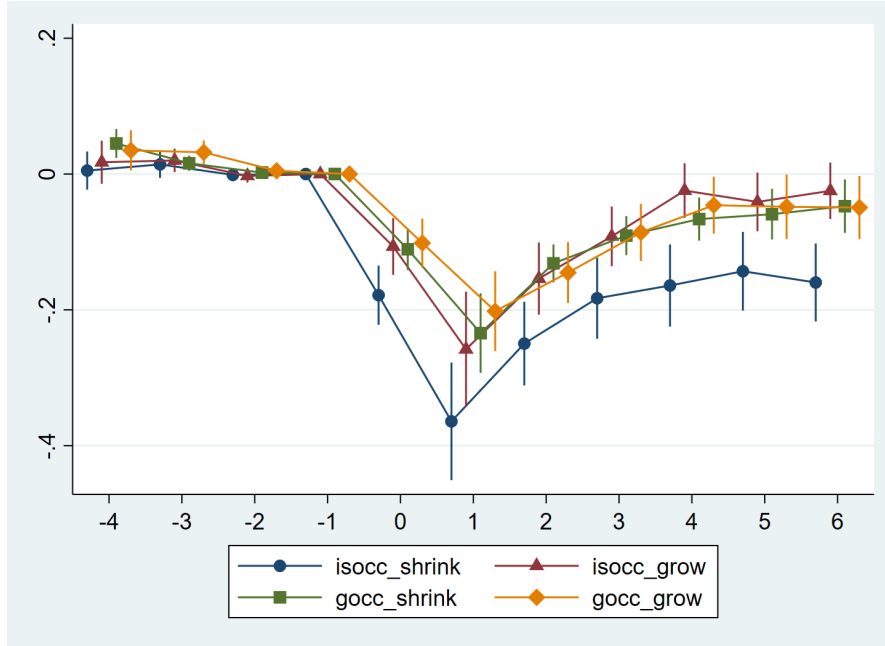
Note: This figure shows estimates of  $\beta_p$  from Eq. 1. The blue curves are the results for the ISOCC-Shrinking group, as defined in Section 5.2. The red curves depict the displacement effects for the rest of the groups, combined. In Panel (a), the dependent variable is earnings. In Panel (b), the dependent variable is employment months. The sample is the Occupation Sample defined in Appendix B.1.2. Standard errors are clustered at the pre-displacement firm level.

Figure C.8: Displacement effects, by ISHC groups

(a) Earnings

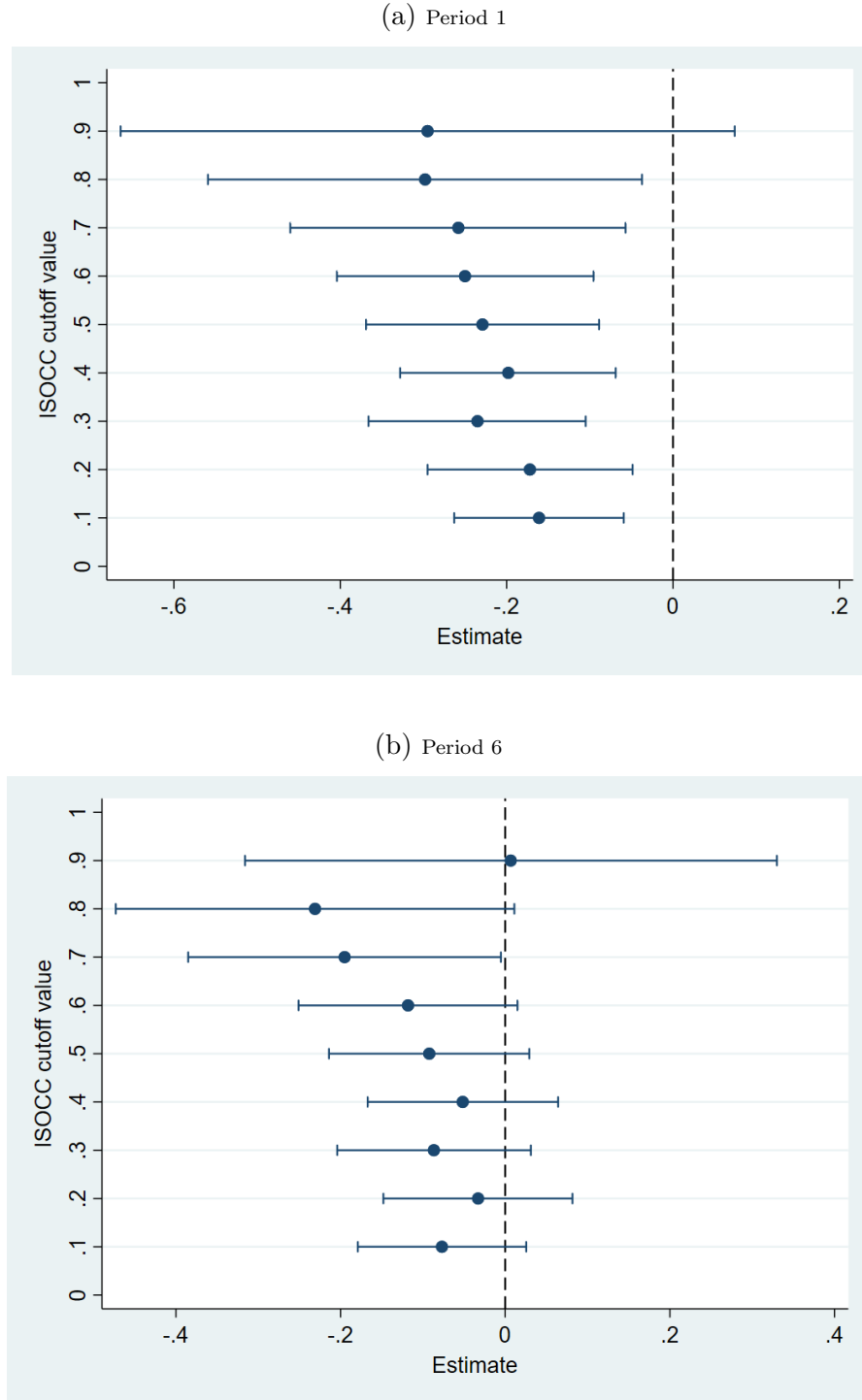


(b) Employment months



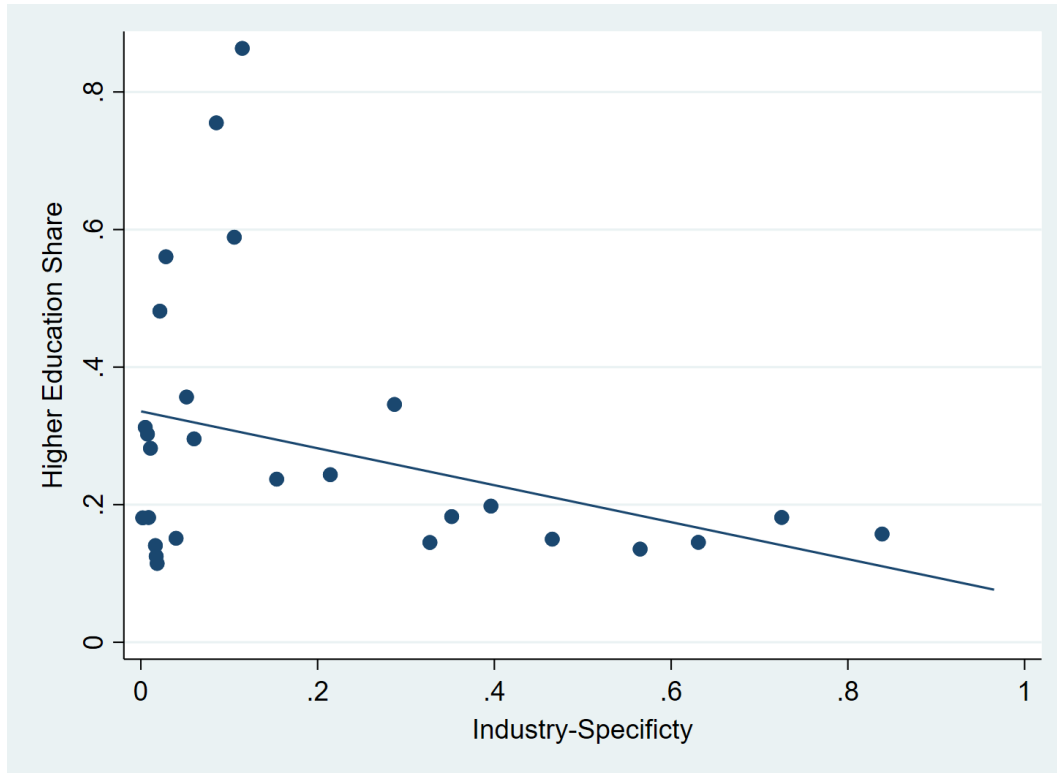
Note: This figure shows estimates of  $\beta_p$  from Eq. 1, run separately for the four ISHC groups defined in Section 5.2. The sample is the Occupation Sample defined in Appendix B.1.2. In Panel (a), the dependent variable is earnings. In Panel (b), the dependent variable is employment months. Standard errors are clustered at the pre-displacement firm level.

Figure C.9: The effect of ISOCC in shrinking industries, by cutoff value



Note: This figure shows estimates of  $\eta_p$  from Eq. 3, where the continuous IS variable is replaced with the binary ISOCC variable. Each estimate in the plot represents the coefficient from the regression where ISOCC is defined using a different cutoff level. The sample is the Occupation Sample defined in Appendix B.1.2, using only mass layoffs occurring in shrinking industries, as defined in Section 5.2. Standard errors are clustered at the pre-displacement firm level.

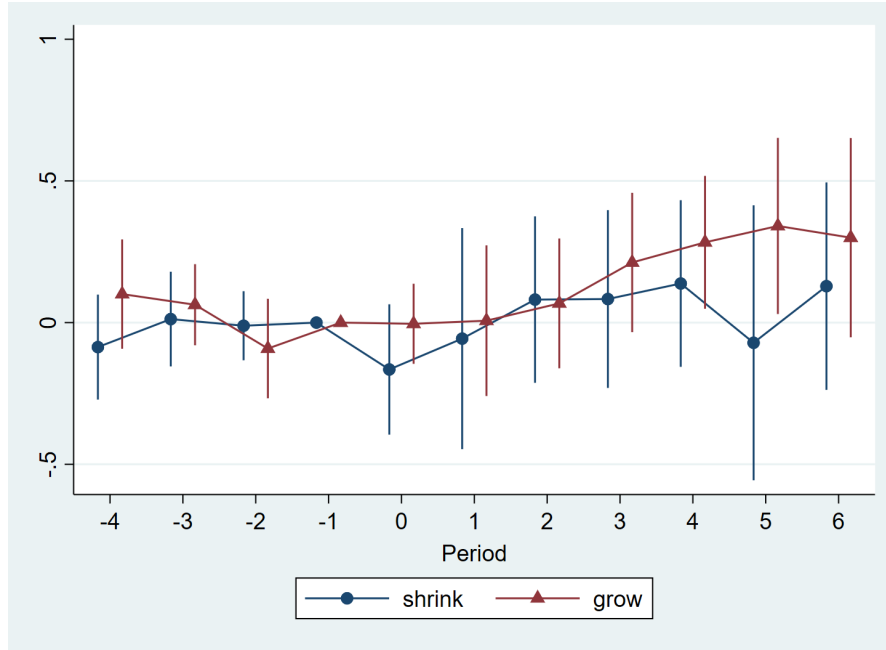
Figure C.10: The Industry-Specificity measure and education levels



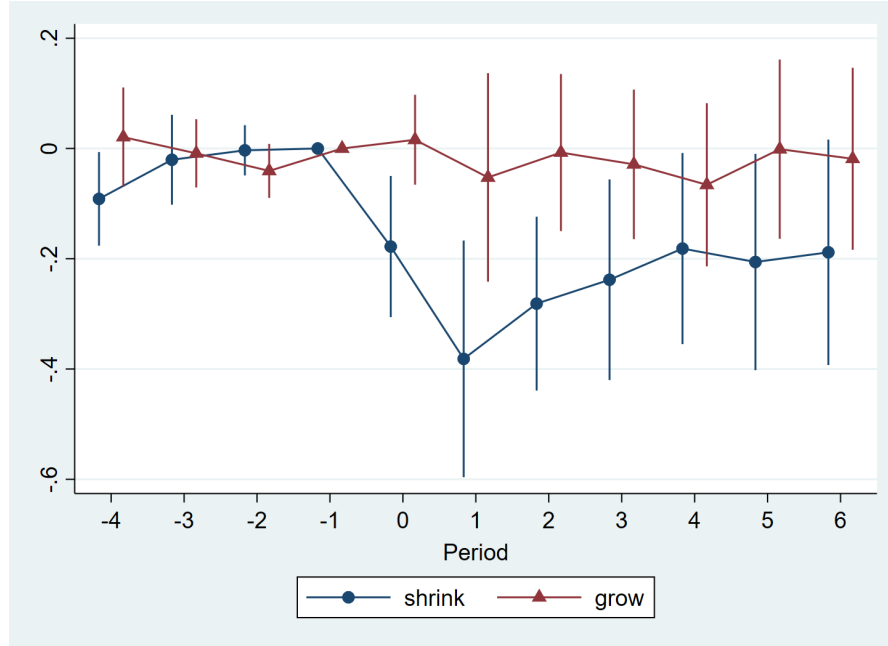
Note: This is a binned scatter plot, applying a bin-scatter least squares estimation using the Stata package *binsreg* (Cattaneo et al. 2019). Workers are grouped into 30 equal-sized bins, according to their occupations' industry-specificity level. The y-axis reports the share of workers in each bin with higher education (college degree or above). The sample is the Occupation Sample defined in Appendix B.1.2.

Figure C.11: The effect of IS, by industry growth and education level

(a) Higher Education



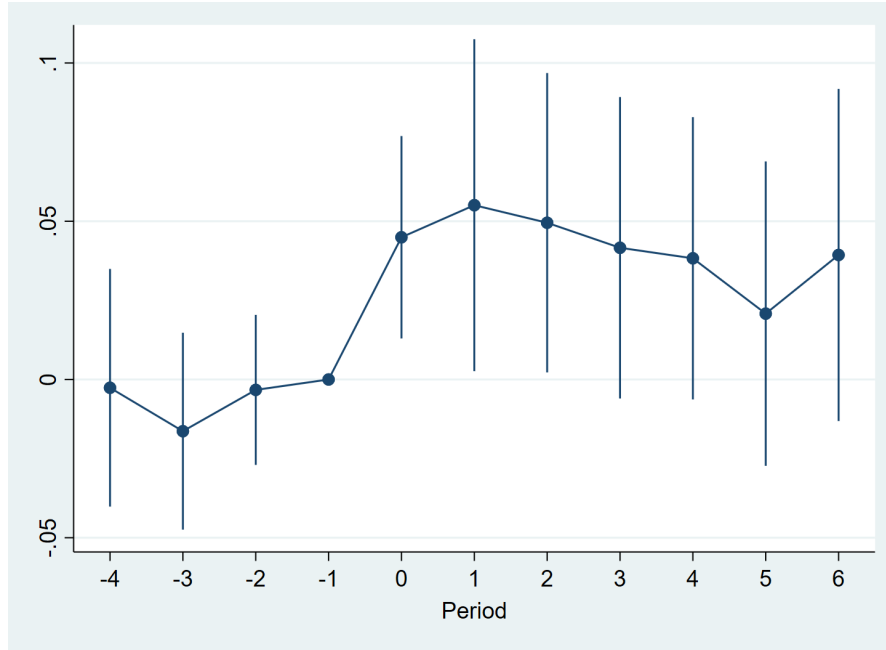
(b) Lower Education



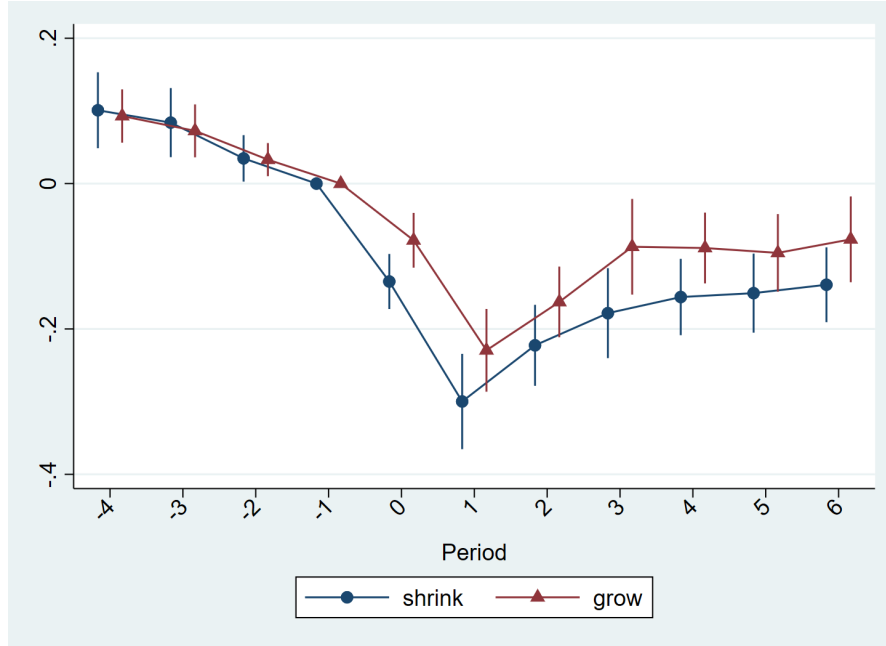
Note: These figures show estimates of  $\eta_p$  from Eq. 3, estimated separately for growing and shrinking industries, as defined in Section 5.2. The sample is the Occupation Sample defined in Appendix B.1.2. Panel (a) restricts the analysis to workers with higher education (defined as college degree or above), and Panel (b) to workers without higher education. The dependent variable is earnings. Standard errors are clustered at the pre-displacement firm level.

Figure C.12: Effects by growth of occupation

(a) Treated X Occupation growth



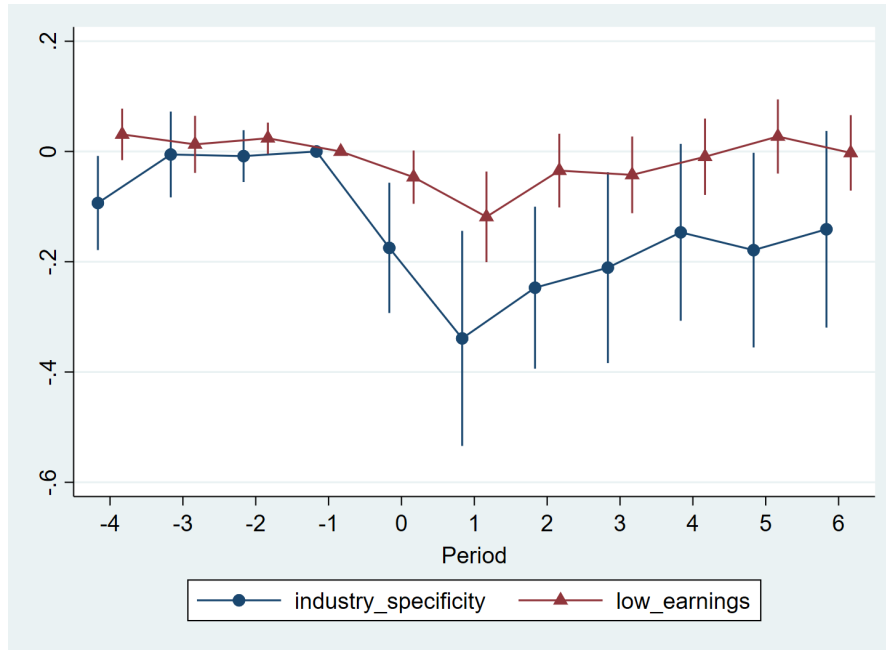
(b) By occupation growth



Note: Panel (a) plots a estimates of of  $\eta_p$  from modified versions of Eq. 3, where the IS variable is replaced with the occupation grow rate over the period 1995-2008. Panel (b) shows estimates of  $\beta_p$  from Eq. 1, run separately for growing and shrinking occupations, where the cutoff is set to the median occupation growth rate. The sample used is the Occupation Sample, defined in Appendix B.1.2. Standard errors are clustered at the displacing-firm level.

Figure C.13: Additional robustness

(a) Low-earnings



(b) Tenure

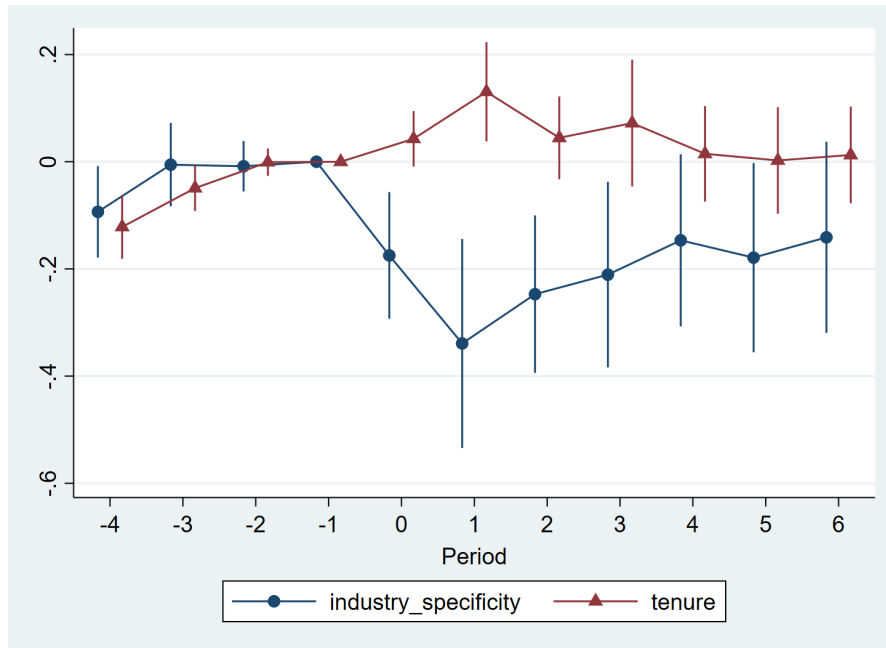
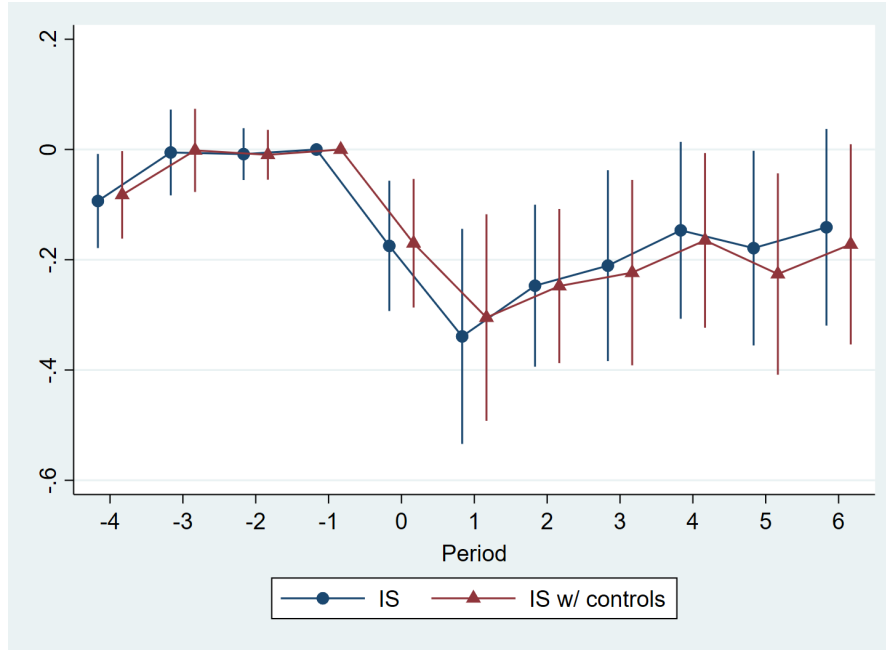


Figure C.13: Additional robustness - Cont.

(c) Additional controls

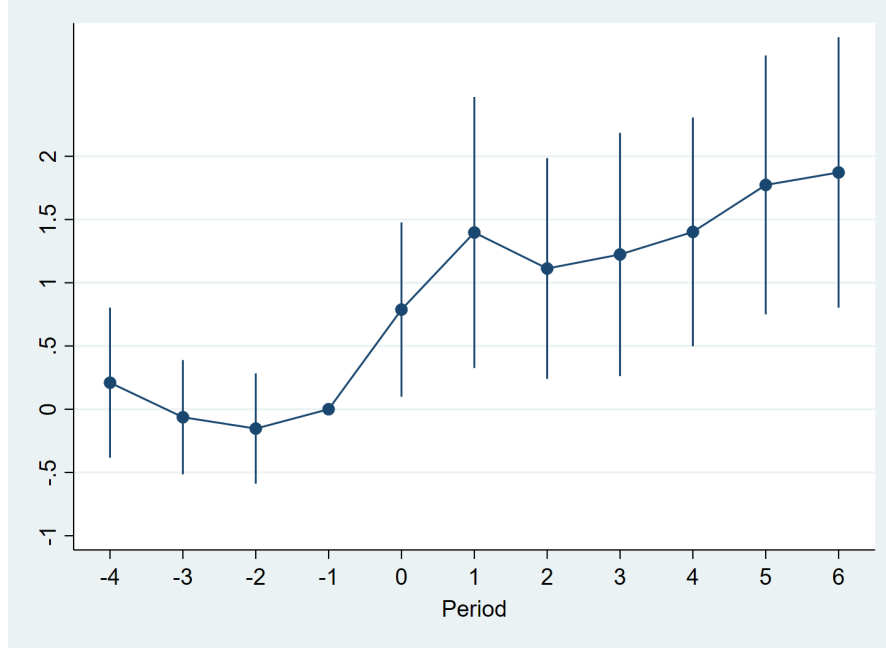


Note: This figure plots estimates of  $\eta_p$  from modified versions of Eq. 3, estimated for shrinking industries. For the red triangles in Panel (a), the IS variable is replaced with the inverse to the log of earnings in period -2. For the red triangles in Panel (b), the IS variable is replaced with the log of firm-tenure at the time of displacement. For the red triangles in Panel (c), the regression includes additional controls: pre-earnings, tenure, age and education. The sample used is the Occupation Sample, defined in Appendix B.1.2. Standard errors are clustered at the displacing-firm level.

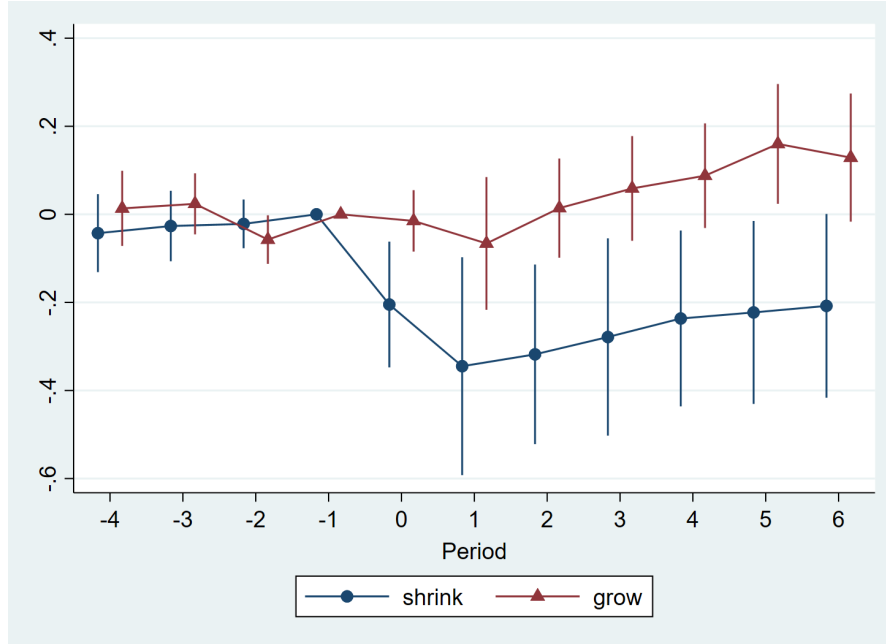


Figure C.14: Robustness: Alternative measure of industry growth

(a) The effect of  $IS \times Growth$  on earnings



(b) The effect of IS on earnings, by industry growth



Note: Panel (a) shows estimates of  $\phi_p$  from Eq. 2. Panel (b) shows estimates of  $\eta_p$  from Eq. 3, estimated separately for growing and shrinking industries. For both panels: Industry growth is defined as the change in employment in the three years prior to displacement, see Appendix C.3.3; the sample is the Occupation Sample defined in Appendix B.1.2; the dependent variable is earnings; and the standard errors are clustered at the pre-displacement firm level.