Health Shocks, Social Insurance, and Firms*

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Abstract

We study the role that firms play in social insurance benefit uptake after their workers experience health shocks. Social insurance in our setting, Hungary, is universal and comprehensive, thus allowing us to quantify the impact of firms on benefit uptake and labor market outcomes on top of the social safety net. Using matched employer-employee administrative data linked to individual-level health records, we find that firm responses to worker health shocks are heterogeneous: workers hit by a health shock at high-quality firms are less likely to take up disability insurance or exit the labor force than those at low-quality firms.

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1 Introduction

Beyond higher wages, "good" firms and "good" jobs may offer different amenities than "bad" firms and "bad" jobs. Workers may be willing to accept jobs that pay less but offer amenities that they value (Rosen, 1986; Sorkin, 2018). Amenities typically considered in the literature include safety (Lavetti, 2020), flexibility (Mas and Pallais, 2017), paid time off (Maestas, Mullen, Powell, von Wachter, and Wenger, 2023), family leave (Bana, Bedard, Rossin-Slater, and Stearns, 2023), or more recently the ability to work from home (Barrero, Bloom, Davis, Meyer, and Mihaylov, 2022). The distribution of amenities across jobs with different wage levels also influences inequality. Most of the literature finds that jobs with higher wages offer better amenities, which implies that inequality accounting for amenities is larger than wage inequality.

In this paper, we study the distribution of one potentially valuable amenity: job security after health shocks. Using matched employer-employee administrative data from Hungary linked to individual-level health records, we estimate the consequences of major health shocks for employment and disability insurance uptake and examine how these consequences vary along the firm quality distribution.

We find that health shocks have a larger impact on employment for workers in lower-quality firms. While in the bottom two tertiles of the firm quality distribution employment decreases by about 10 percentage points three years after the health shock, in the top tertile of firms this impact is only about 8 percentage points. Looking at employment without the concurrent receipt of disability benefit (which is possible and prevalent in Hungary), we find that employment decreases by about 14 percentage points in the bottom two tertiles of the firm quality distribution three years after the health shock, whereas this impact is less than 10 percentage points in the top tertile of firms. At the same time, disability benefit receipt increases by about 14 percentage points among workers of lower-quality firms but only by about 9 percentage points among workers of high-quality firms. We show evidence that these heterogeneity patterns are not driven by the frequency or type of health shocks experienced by workers of different firms, by differences in pre-shock health level (proxied by healthcare use), by the sorting of workers across firms along the quality distribution, or by the lower replacement rate of disability benefits for high-wage workers.

We provide a conceptual framework to interpret our results. In our framework, a highly productive worker is more valuable in expectation to a highly productive firm, even after recovering from a health shock, than the typical new draw from the worker distribution. This leads to the prediction that matches between high-productivity workers and firms are less likely to dissolve as health shocks hit, consistent with our empirical results.

Our results suggest that firms play an important role in mediating the consequences of health shocks for their workers. Conditional on suffering a health shock, a worker's likelihood of dropping out of employment and taking up disability insurance benefits is significantly impacted by where they work. This implies that policies that are targeted at firms to reduce disability insurance benefit takeup, such as experience rating, may be useful. Their incidence will, however, fall on lower-quality firms that have more workers take up benefits. Our findings also imply that beyond paying higher wages, high-quality firms also offer better protection against the consequences of health shocks. Therefore, earnings inequality understates overall inequality in worker welfare.

Our work contributes to multiple strands of the literature. We most directly contribute to the literature that has considered the role of firms in disability insurance (DI) takeup. This literature so far is inconclusive: while Kyyrä and Paukkeri (2018) show no major effect of experience rating on the inflow to sickness and disability benefits, Hawkins and Simola (2020) and Prinz and Ravesteijn (2020) provide evidence for significant impacts of experience rating on disability inflow. Our results suggest that after a major health shock, even in the absence of experience rating, the inflow to DI varies substantially with firm quality. This means that experience rating the DI system may address heterogeneous responses to health shocks and thus incentivize the retention of workers following these shocks. This implies that firm-side policies—part of many policy proposals (Autor and Duggan, 2010; Autor, 2011; Burkhauser and Daly, 2011; Liebman, 2015)—could play an important role in disability insurance.

More broadly, we contribute to a recent strand of the literature that has examined the relationship between firm characteristics and the takeup of various social insurance programs. Considering temporary benefits, the use of which is generally considered a positive outcome, Bana, Bedard, Rossin-Slater, and Stearns (2023) show that temporary DI and paid family leave program takeup is substantially higher at firms with high earnings premiums. Aizawa, Mommaerts, and Rennane (2022) show that firm characteristics explain a substantial part of variation in the takeup of disability accommodations. Lachowska, Sorkin, and Woodbury (2022) focus on unemployment insurance (UI) claims and provide evidence for important employer effects. They argue that some of the incomplete UI claiming is due to experience rating of the UI payroll tax. We contribute to this literature by focusing on labor market and social security outcomes after a major health shock, and analyzing the interplay of individual and firm quality in these outcomes. We perform this analysis in a setting where social insurance is universal and comprehensive.

Our paper is also related to the literature on the impact of health shocks on individuals' labor market outcomes (e.g., Dobkin, Finkelstein, Kluender, and Notowidigdo, 2018; Fadlon and Nielsen, 2021; Parro and Pohl, 2021).[1] This literature generally estimates negative effects of health shocks on employment and earnings, although the estimates vary. We are not familiar with studies that provide evidence on heterogeneities in the labor market consequences of major health shocks by firm quality.[2]

The rest of the paper is structured as follows. Section 2 provides background on the healthcare system and disability insurance system in Hungary and introduces our data and methods. Section 3 presents the results. Section 4 provides a conceptual framework to interpret our empirical findings. Section 5 concludes.

[1]For an overview of this literature, see Section 3.4 of Prinz, Chernew, Cutler, and Frakt (2018).

[2]In recent work, Ahammer, Packham, and Smith (2023) show that firms are responsible for nearly 30 percent of the variation in across-worker healthcare expenditures but they do not analyze the consequences of health shocks across firm types.

2 Background, Data, and Methods

Institutional background. In Hungary, the health insurance coverage rate of the population is close to 100 percent (Gaál, Szigeti, Csere, Gaskins, and Panteli, 2011) in the unified public social health insurance scheme which is funded from payroll taxes. Public inpatient and outpatient care services are available to the insured population free of charge. Medications are also provided free of charge for hospital patients, but co-payment is needed for medications bought in pharmacies.

Employees who are not able to work due to health reasons are entitled to 15 days of sick leave per year, during which they receive 70 percent of their salary from their employer. Afterwards, they are entitled to sickness benefit (50–60 percent of the salary) for up to one year, paid by social security. While workers are on sick leave or sickness benefit, the employer is not allowed to lay them off.

People with health damage of at least 40 percent can apply for disability insurance (DI), the amount of which depends on the severity of the health problem and previous earnings. During the period we study, individuals were allowed to work while receiving DI benefits, subject to an earnings limit of 150 percent of the minimum wage. Recipients of the rehabilitation allowance for beneficiaries with less health damage were allowed to work 20 hours per week. Benefits are financed from social security contributions that are not experience-rated, that is, they do not depend on the share of employees of a firm claiming benefits.

People with at least 20 years of work history are entitled to old-age pension benefits upon reaching the statutory retirement age. Over our analyzed period, the statutory retirement age increased from 62 to 63.5 both for men and women. However, women could retire earlier with 40 years of work credit, regardless of age.

Linked employer-employee-health data. We use linked employer-employee administrative data covering years 2003–2017 on a random 50 percent sample of the 2003 population. Our sample is drawn from the whole population, and not just those who have a job. Health records in the data cover years 2009–2017, and DI and old-age pension status are observed in 2003–2016.

The database consists of linked data sets at the monthly frequency of the pension, tax and health care authorities and contains detailed individual-level information on employment and earnings history, use of the health care system, pension and other social benefits, and firm-level indicators. Importantly, it also contains information on the type and amount of different disability benefits and old-age pensions received. Two important limitations of the data are that the employment status of DI recipients cannot be observed until April 2007 and we do not observe the health condition based on which the disability benefit is received.

An individual is defined to be employed in a given month if he is employed on the 15th of the month, and the employment is not under the public works scheme. We also observe in the data the employer of the worker (or self-employment). For employers with double-entry bookkeeping we also observe balance sheet information from the tax authority.

We restrict the sample to men, to make sure that the health shocks we analyze are not related to pregnancy or childbirth. However, we show that our main results also hold for women. We further restrict the sample to ages 18–60, thus workers close to or above the statutory retirement age are excluded.

Health shocks. We define health shocks as the first month of hospitalization for a previously unhospitalized individual. Specifically, we generate the binary indicator of a health shock by first flag 12-month periods with at least 10 days of hospital stay. In such 12-month periods, we identify the first month of hospitalization. We set the health shock indicator to one for the first month of hospitalization, conditional on no hospitalization during the preceding 24 months. We set the health shock indicator to zero if there was no hospitalization either during the current and next 11 months or the preceding 24 months. We apply the 10-day cut-off in the length of hospital stay to ensure that we focus on major health problems that potentially lead to the DI uptake.

In the following, we work with annual data, using from each year the calendar month of hospitalization. For each individual we consider only the first health shock event. For individuals without any health shocks, the observation month is generated randomly. Since health-related data is available only from 2009 in the administrative data we use, the health shock indicator is defined only for years 2011–2017 to have at least 2 years of pre-shock observations. For women, we define health shocks the same way as for men, but do not consider birth-related hospitalizations as health shocks.[3]

Note, that while we use the term "health shock" to indicate hospitalization without prior hospitalization, these events may be expected (or planned) based on existing health problems. Nevertheless, our health shock indicator captures a major health event (prolonged hospital stay).

Worker and firm fixed effects. We perform an Abowd, Kramarz, Margolis (AKM) style decomposition of wages (Abowd, Kramarz, and Margolis, 1999) and compute worker and firm wage premia (fixed effects, FE). That is, we regress wages on individual and firm fixed effects, controlling for year fixed effects, age squared, age cubed,[4] (firm-specific) tenure, tenure squared and firm size. We also include a large set of occupation dummies to account for wage heterogeneity by occupations, similarly as in Boza (2021). For individuals who experience a health shock, we split their wage observations into a healthy and an unhealthy set (before and after the shock) in order to avoid the negative effect of health shocks on wages entering the worker effects. We estimate the following wage regression:

$$\ln w_{ijt} = \mathbf{X}_{ijt}\beta + \theta_{ih(it)} + \psi_{j(it)} + \lambda_{k(it)} + \delta_t + \varepsilon_{ijt}, \tag{1}$$

[3] Due to measurement errors in the diagnosis codes and the possible use of private healthcare (which is not included in our data), we do not observe perfectly if a women is pregnant or has given birth. Therefore, we do not include women in our main analysis sample.

[4] We follow Card, Cardoso, Heining, and Kline (2018) and assume that the wage profile is flat at the age of 41.

where i is an individual, j is a firm, t indicates time, k represents occupations, and h refers to the health status of an individual (healthy or not). In our main analysis we use the person effect related to the healthy period of all individuals.[5] When estimating the worker and firm wage premia, we include all sample years of the linked employer-employee administrative data and also include both men and women in the sample. For most of our analyses, we divide firms into three tertiles (low, middle, and high FE firms).[6]

Since we measure firm quality by the AKM firm fixed effect, it is important to reflect on what these fixed effects effectively capture. On top of pure firm-specific productivity, the literature has identified several drivers of firm wage premia, ranging from labor market power (Berger, Herkenhoff, and Mongey, 2022; Lamadon, Mogstad, and Setzler, 2022) to product market power (De Loecker, Eeckhout, and Unger, 2020; Edmond, Midrigan, and Xu, 2023) to non-wage amenities (Wong, 2024). All of these mechanisms result in a wedge between wages and the marginal revenue product of workers. We capture these labor wedges by a simplified rent-sharing rule in our conceptual framework in Section 4, and show how assortative matching between workers and firms drives higher-paying firms to retain their workers at higher rates than low-paying firms.

Labor market outcomes and DI. We define the following four mutually exclusive categories of labor market outcomes and DI status, where employment always includes self-employment but excludes public work: (1) DI without employment; (2) employment without DI; (3) employment with DI; (4) other (i.e., no employment and no DI). We also analyze total DI (1+3) and total employment (2+3).

Our monthly wage measure includes all the income that forms the basis of social security contributions. We focus on the wages of full-time workers (working weekly 40 hours, which holds for 87 percent of the working population in our analysis sample), and deflate the wages to 2015 using the CPI. To ensure that the wage patterns are not driven by lower wage during sickness absence, we adjust the wage for sickness benefit receipt. We also adjust the wage for sick leave (first 15 days of sickness absence in a given calendar year), assuming that the 15 days of sick leave are used in the month preceding the first month of sickness absence, or in January, if the worker already has sickness absence in January. Because of likely measurement errors in the adjusted monthly wage, we use the average of non-zero wages in a given calendar year as our preferred wage measure.

Raw data patterns. We present several pieces of evidence that workers do not select into firms based on their health status. Appendix Figure A1 shows the probability of suffering a health shock by calendar year and month. This probability is similar across all years and months,

[5] The worker premium estimated for the unhealthy period of a given individual is on average 78.5 percent of that of the healthy period of the same individual, with a strong correlation of 0.81.

[6] Limited mobility bias, a common issue in the AKM framework, is not a concern in our setting. This bias would cause some firms to be incorrectly classified into to wrong tertile—if anything, this would shrink the difference in firm group-level outcomes. Even so, we exclude low-mobility firms—those with less than two mobility events per year, either inflow or outflow—to mitigate this issue.

the exceptions are January and December—the probability is higher in January and by the same magnitude lower in December, suggesting a reallocation of hospitalizations from December of a year to January of the next year. Appendix Figure A2 indicates that the majority of individuals who suffered a health shock spent less than 20 days in hospital and were absent from work for less than two month in the corresponding 12-month period. These distributions are similar across all three firm quality categories. Appendix Figure A3 shows that the probability of suffering a health shock is between 1.0–1.4 percent in each firm quality category. Netting out the impact of individual age, age squared, two-digit occupation codes, and calendar year, the difference in the conditional probability of a health shock across the firm quality categories is less than 0.02 percentage points.

Table 1 shows descriptive statistics for men with and without a health shock. Those suffering a health shock are on average 6.5 years older and earn about 11 percent less. Firm quality and the occupation and industry distributions are similar for men with and without a health shock. Table 2 displays the prevalence of major disease categories at the onset of the health shock. The most prevalent categories are cardiovascular, digestive, and musculoskeletal diseases and accidents, and the distribution of disease categories is essentially the same across firm quality.

Figure 1 shows descriptive plots of labor market status over time by firm quality categories. It is apparent that after a health shock, DI entry increases and employment rate decreases the most at the lowest-quality firms.

Appendix Table A1 illustrates the magnitude of sorting of individuals across firms by quality, with individual quality referring to the pre-health shock period. We see evidence for sorting, with similar patterns among those with and without a health shock. Still, more than 10 percent of the population are in the low firm–high individual FE or high firm–low individual FE cells.

Estimating the impact of health shocks. To quantify the impact of the health shock on labor market outcomes, we estimate the following regression:

$$Y_{it} = \sum_{\substack{j=-3 \\ j \neq -1}}^{3} \alpha_j \mathbb{1}[E_{it} = j] + \sum_{\substack{j=-3 \\ j \neq -1}}^{3} \beta_j \mathbb{1}[E_{it} = j] \cdot S_i + \theta age_{it}^2 + \mu_i + \delta_t + u_{it}, \tag{2}$$

where i indexes individuals, t indexes calendar year, E_{it} indicates event time (in years), which is the time to the health shock or to the random event for the control group (individuals never experiencing a health shock). Y_{it} is a labor market outcome indicator, μ_i captures individual fixed effects, δ_t captures calendar year effects, and S_i is a binary indicator for ever experiencing a health shock. Event time for men who do not experience a health shock is defined by assigning a random health shock year and month. The coefficients of interest are the β's which capture the differential evolution of labor market outcomes for individuals who suffer a health shock (treatment group) relative to individuals who do not experience a health shock (control group).

We restrict the estimation sample to individuals employed full time (40 hours per week) in the private sector at event time zero. To analyze the heterogeneity in outcomes by firm quality, we allow the β parameters to vary with the tertiles of AKM firm FE at event time zero (we denote this indicator with F_i ranging from 1 to 3) and control for AKM firm FE tertile at event time zero:

$$Y_{it} = \sum_{\substack{j=-3 \\ j\neq-1}}^{3} \alpha_j \mathbb{1}[E_{it} = j] + \sum_{l=1}^{3} \sum_{\substack{j=-3 \\ j\neq-1}}^{3} \beta_j^l \mathbb{1}[F_i = l] \cdot \mathbb{1}[E_{it} = j] \cdot S_i + \theta age_{it}^2 + \mu_i + \delta_t + u_{it}. \quad (3)$$

3 Results

Figure 2 shows our main result, the estimated β parameters of Equation (3) for labor market status. As a result of a health shock, the probability of DI without employment increases by almost 10 percentage points two and three years after the shock in the bottom two firm quality tertiles, while this increase is only around 6–7 percentage points in the highest firm quality tertile. The probability of DI with concurrent employment also increases more (by about two percentage points) at the lowest-quality firms than at the highest-quality firms as a consequence of a health shock. The negative impact of a health shock on employment probability without the concurrent receipt of DI is 4–5 percentage points stronger (around 14 percentage points) at the bottom two firm quality tertiles than at the top quality tertile.[7] While the negative impact on employment without the concurrent receipt of DI is similar one to three years after the health shock, the positive impact on DI without employment probability is more than twice as large two to three years after the health shock than one year after.[8]

Robustness

Treatment effect heterogeneity. A potential concern with the validity of our estimates is that they may be biased due to treatment effect heterogeneity. Appendix Figure A5 dispels this concern, showing that our results are robust to implementing the estimator of Sun and Abraham (2021) which allows for the presence of treatment effect heterogeneity across treatment cohorts. Note that we report these estimates only for the DI outcomes because we cannot apply the estimator for the employment outcomes. The reason is that the Sun and Abraham (2021) estimator uses the control group to identify the time trend without attaching an event time; however, our control group for the employment outcomes must be employed at event time -1 which would be undefined here.

Worker productivity. A possible explanation for the heterogeneous impact of a health shock across firm quality categories is that different quality firms employ different types of workers, who respond differently to a health shock. While we cannot categorically rule out this mechanism—as sorting of better workers to better firms is inherent in the labor market—,

[7] Our results change very little if we restrict the control group to those who worked at firms at event time 0 that had at least one worker who suffered a health shock between 2011 and 2017 (86.4 percent of our baseline sample).

[8] Appendix Figure A4 shows the estimated β parameters of Equation (3) by firm quality quintiles, one, two, and three years after shock.

Appendix Figures A6 and A7 provide evidence that even within the same individual AKM FE tertile (Appendix Figure A6) and within the same broad occupation category (Appendix Figure A7) the effect of a health shock on employment and DI entry is stronger at lower-quality firms. That is, holding worker productivity fixed, the effect is decreasing in firm quality.

DI benefit replacement rate. Another potential mechanism behind the firm heterogeneity in DI entry after a health shock may be that the DI benefit replacement rate is lower for high wage earners, who typically work at higher-quality firms. To analyze the relevance of this mechanism, we first plot the DI replacement rates by deciles of relative wage, where replacement rate is the ratio of DI benefit when first receiving benefit and the average wage 1–3 years before entering DI. Relative wage is defined as the nominal wage divided by the minimum wage. Panel (a) of Appendix Figure A8 shows that the DI replacement rate decreases from 66 percent in the bottom relative wage decile to 22 percent in the top relative wage decile, although the replacement rate is close to flat up to the 7th relative wage decile. Panel (b) of the figure confirms this pattern, where we net out also the impact of calendar year, age, and age squared.

Since the DI replacement rate decreases little up to the top part of the wage distribution relative to the minimum wage, we re-estimate the baseline regressions (using Equation (2)) on the sample of men whose wage at event time -1 relative to the minimum wage was in the bottom half (deciles 1–5) of the relative wage distribution. We present the results estimated on this restricted sample in Appendix Figure A9. Although some of the confidence intervals are relatively large, the results still clearly show that even among those men for whom the DI benefit replacement rate was similar, the health shock is less likely to lead to DI entry and has weaker negative employment effect for those employed at the top tertile quality firms at event time zero.

Health indicators. A further potential explanation for the heterogeneous impact of a health shock across firm quality categories may be that health shocks differ across firm types. We provide two pieces of evidence against this mechanism.

First, we estimate the average effect of the health shock 1–3 years after the shock by major disease categories. Here, we define disease-specific health shock indicators which equal one if the baseline health shock indicator equals one and the given disease category is diagnosed in the first month of the health shock. We report the estimated average effects in Appendix Table A2. It can be seen that cancer and cardiovascular diseases have the strongest negative employment effects. Importantly, the firm heterogeneity of the impact of the health shock generally holds for all disease categories, although the heterogeneity is weak and the heterogeneity pattern is not so clear in the case of accidents, musculoskeletal, and urogenital diseases.

Second, we check if the effect of the health shock on healthcare use varies across firm quality categories. The results reported in Appendix Figure A10 indicate that there is little heterogeneity by firm quality. Both the descriptive plots (left panels) and the estimation results of Equation (3) (right panels) show a major increase in the average number of sickness benefit days, GP visits, specialist visits, and prescription drug spending at the onset of the health shock, and these indicators are still higher than their pre-shock values three years after the shock. At the same time, there is little variation in the effect of the health shock on these outcomes across the three quality tertiles. The pre-shock levels of healthcare use are also similar across the three quality tertiles.

Alternative firm quality indicators. Focusing on the outcome DI without employment, in Appendix Figure A11 we estimate the heterogeneous impact of the health shock by three other firm quality indicators: foreign ownership being above 50 percent, total factor productivity (TFP) of the firm split at its median,[9] and firm size categories. Panel (a) of the figure indicates that 2–3 years after the shock, the effect of the shock on DI probability is two percentage points lower for workers who worked at a foreign owned firm at the time of the shock. Similar heterogeneity is observed by TFP (Panel (b)). Panel (c) of the same figure indicates that three years after the shock, the impact of the shock on DI probability is two percentage points lower at large firms (with at least 250 workers) than at smaller firms. Altogether, these results suggest that the heterogeneous effect of health shock on DI entry by firm quality is robust to the choice of quality indicator.

Heterogeneity

Women. Although we exclude women from our baseline sample to ensure that the health shock is not related to childbirth or pregnancy, we report the baseline results for women in Appendix Figure A12. The estimated effects of the health shock on DI benefit uptake and employment, and their heterogeneity by firm quality are similar to the results for men.

Age. Appendix Figure A13 shows the estimated impact of the health shock for two age groups: 18–39 vs. 40–60. Men aged 40–60 are at least twice as likely to enter DI as a consequence of a health shock than men aged 18–39. Consequently, the negative employment impact of a health shock is about twice as large in the older age group. The age-heterogeneity is present in all three firm quality categories.

Geographical location. Appendix Figure A14 shows that the negative labor market consequences of a health shock are more severe outside the capital city, where, in general, the labor market is less thick. The heterogeneity in the effects of the health shock on DI entry by living area is stronger among men who worked at firms in the bottom two quality tertiles.

Firm heterogeneity within industries. Appendix Figure A15 provides evidence that the heterogeneous effect of health shock on DI entry is not driven by a specific industry. We re-estimate equation (3) with adding a further heterogeneity indicator in addition to the firm quality measure, capturing the three largest industry groups of Hungary (manufacturing, trade,

[9] We calculate the value added-based TFP. When doing so, we apply the estimation procedure of Wooldridge (2009) and use the `prodest` Stata package by Rovigatti and Mollisi (2020).

services) and a remainder industry category. Both the industry and the firm quality refer to the employer at event time zero. In all four industry groups, the effect of the health shock on DI probability is at least two percentage points lower at the highest quality tertile firms than at the bottom two quality tertiles.

Firm size. A potential concern is that our results are driven by firm size. It might be possible that larger firms are better able to redistribute the tasks of an employee who suffered a health shock while smaller firms have no choice but to replace them. Appendix Figure A16 dismisses this concern: the firm quality gradient of our results remains present within firm size categories. The effect of a health shock on DI probability is 2–5 percentage points lower at high-quality firms than the bottom two tertiles for all firm size categories.

Further outcomes

Wages and income. Figure 3 shows a descriptive plot of log wage over time by firm quality categories (Panel (a)), and the estimated β parameters of Equation (3) for log wage (Panel (b)). Compared to the wage trajectories of men who did not suffer a health shock, log wage lags behind more at the highest-quality firms after a health shock. Looking at the estimated effect on wage, the negative impact of the health shock is weaker at the bottom quality tertile firms (around -1 percent effect) than at the top two quality tertile firms (around -3 to -5 percent effect two and three years after the shock). However, at higher (lower) quality firms, log wage starts to decrease (increase) already before the health shock (relative to the income of individuals in the control group), therefore the impact of the health shock on log wage cannot be clearly established based on these results.

In Appendix Figure A17 we present the estimated effect of the health shock on income (wages plus DI benefit, without restricting the wages to full-time workers). The figure shows that 3 years after the health shock, the estimated effect of the shock on income is around -2 percent at the top quality firms and around $+2$ percent at the bottom quality firms (firm quality measured at event time zero). Similarly to the wage results, the impact of the health shock on log income cannot be clearly established due to the differential trends observed before the health shock.

Job switching. Appendix Figure A18 shows how health shocks affect the probability of working at a different firm than a year before, conditional on employment.[10] Panel (a) indicates that this probability is generally higher at lower quality firms, without clear heterogeneity in the consequences of health shocks. Panel (b) shows that health shocks increase the probability of employment at a new firm by one to three percentage points three years after the shock, more so for those who were employed at firms in the top tertile of the quality distribution at event time zero, although the results are statistically uncertain and we also observe some pre-trends.

[10]Note that this is not equivalent to the separation rate. The figure only shows the propensity of E2E switches.

These results provide weak evidence that if an individual remains employed after a health shock at a low-quality firm then he is also more likely to remain at the same firm.

Hours. Appendix Figure A19 shows descriptive statistics and estimated effect of a health shock on weekly working hours, conditional on employment. Working hours three years after the health shock decrease more at the bottom tertile-quality firms (0.8 hour per week decrease) than at the top two tertile quality firms (0.3–0.4 hour per week decrease).

4 Conceptual Framework

We now provide a stylized framework that aids the interpretation of our results from a theoretical perspective. Consider an economy populated by workers and firms. Both are heterogeneous with respect to their productivity: workers are endowed with productivity $x \sim X$, firms are endowed with productivity $y \sim Y$. Time is discrete and discounted by ρ. Workers and firms match on a frictionless labor market, produce a final good using the technology $f(x, y)$ with $\partial f/\partial x > 0$ and $\partial f/\partial y > 0$, and share rents according to a $(1-\beta)$—β division rule, with β fraction of the rent going to the firms. At rate δ, workers are hit by a health shock and their productivity level drops to γx, $\gamma \in [0, 1]$. When a health shock hits, workers and firms both decide whether to keep the match or dissolve it. If a match dissolves, workers exit to unemployment and collect benefits according to the benefit schedule $b_s(\gamma, x, y)$ which depends on the duration of being on benefit s, the previous wage (pinned down by x and y), and the severity of the shock γ.[11] Unemployed workers can re-enter the labor force by matching with a new firm, drawn from the firm distribution Y. If a match dissolves, the firm draws another worker from the worker distribution X.

The value of a match for a firm is

$$\begin{aligned} V_t^F(x, y) = \beta f(x, y) + \rho\big((1-\delta)V_{t+1}^F(x, y) \\ + \delta\big\{\mathbb{1}(\text{keep}) \cdot V_{t+1}^F(\gamma x, y) + (1 - \mathbb{1}(\text{keep})) \cdot \mathbb{E}_{\tilde{x}}[V_{t+1}^F(\tilde{x}, y)]\big\}\big) \end{aligned} \tag{4}$$

where $\mathbb{1}(\text{keep})$ indicates whether the match is kept after the health shock, as defined below. The value of a match for a worker is

$$\begin{aligned} V_t^W(x, y) = (1-\beta)f(x, y) + \rho\big((1-\delta)V_{t+1}^W(x, y) \\ + \delta\big\{\mathbb{1}(\text{keep}) \cdot V_{t+1}^W(\gamma x, y) + (1 - \mathbb{1}(\text{keep})) \cdot V_1^U(\gamma, x, y)\big\}\big). \end{aligned} \tag{5}$$

The value for an unemployed worker s periods after being hit by a shock is

$$V_s^U(\gamma, x, y) = b_s(\gamma, x, y) + \rho \max\big\{V_{s+1}^U(\gamma, x, y), \mathbb{E}_{\tilde{y}}[V_1^W(\gamma x, \tilde{y})\big\}. \tag{6}$$

[11] A typical benefit schedule is $b_s(\gamma, x, y) = b(x, y)/\gamma$ if $s \leq \bar{s}, 0$ if $s > \bar{s}$ for a pre-specified duration cutoff $\bar{s}$.

The indicator for keeping the match is

$$\mathbb{1}(\text{keep}) = \left[V^F_{t+1}(\gamma x, y) \geq \mathbb{E}_{\tilde{x}}[V^F_{t+1}(\tilde{x}, y)]\right] \cdot \left[V^W_{t+1}(\gamma x, y) \geq V^U_1(\gamma, x, y)\right]. \quad (7)$$

That is, the match is kept if keeping it is more valuable for both the worker and the firm in expectation than dissolving it.

This stylized model implies the following predictions:

Worker productivity. A higher x implies that the value of the match after the health shock is higher, making it more likely that the value of the match after the shock remains higher than the expected value of a match with a randomly drawn worker, and than the value of unemployment. Therefore, the match is more likely to remain for more productive workers. Our results in Appendix Figure A6 align with this model prediction.

Firm productivity. Higher y implies that both the continuation value of the match for the firm ($V^F_{t+1}(\gamma x, y)$) and the expected value of a new match ($\mathbb{E}_{\tilde{x}}[V^F_{t+1}(\tilde{x}, y)]$) are higher. Similarly, both the continuation value of the match for the worker and the value of unemployment are higher. If there is positive assortative matching between workers and firms then high-productivity firms are more likely to employ high-productivity workers, for whom a health shock is less likely to lead to separation. Our main result in Figure 2 is in line with this prediction.

Impact of the health shock on worker productivity. If the health shock has a smaller negative impact on the productivity of worker (i.e., γ is closer to 1) then it is more likely that the match remains. This is more likely the case in white-collar jobs where the deterioration of health is less likely to affect the capacity to work. If the production technology at high-quality firms is such that the health of the worker has a smaller impact on productivity then it is more likely that the match remains at high quality firms after a health shock. We see both of these model predictions play out in Appendix Figure A7.

Social security benefits. Higher social security benefits make the separation after the health shock more likely. Also, if social security benefits are relatively small, compared to the continuation value of the match then separation is less likely—which is the case, e.g., if benefits are capped. We do not have sufficient policy variation during the sampling period of our data to corroborate this model prediction.

5 Conclusion

This paper studies the labor market and benefit uptake consequences of major health shocks and investigates how these outcomes vary with the quality of the employer at the time of the shock. We show that workers hit by a health shock at a high-quality firm are more likely to remain employed and less likely to take up disability insurance benefits. We provide evidence that these heterogeneity patterns are not primarily driven by the sorting of high-quality workers to high-quality firms, by differences in the type of health shocks by firm quality, or by the lower replacement rate of disability benefits for high-wage workers.

These results suggest that firms play an important role in mediating the consequences of health shocks for their workers. This in turn implies that social insurance policies should take into account firm heterogeneity. For example, disability insurance experience rating policies that would collect higher premiums from firms that have more workers take up benefits could be an effective approach, though their incidence would initially be on lower-quality firms. Furthermore, the findings in this paper imply that inequality in worker welfare is higher than wage inequality due to the unequal distribution of the amenity of protection from the consequences of health shocks. Workers in higher-quality firms make more and are also more likely to remain employed if they are hit by a shock, exacerbating inequality.

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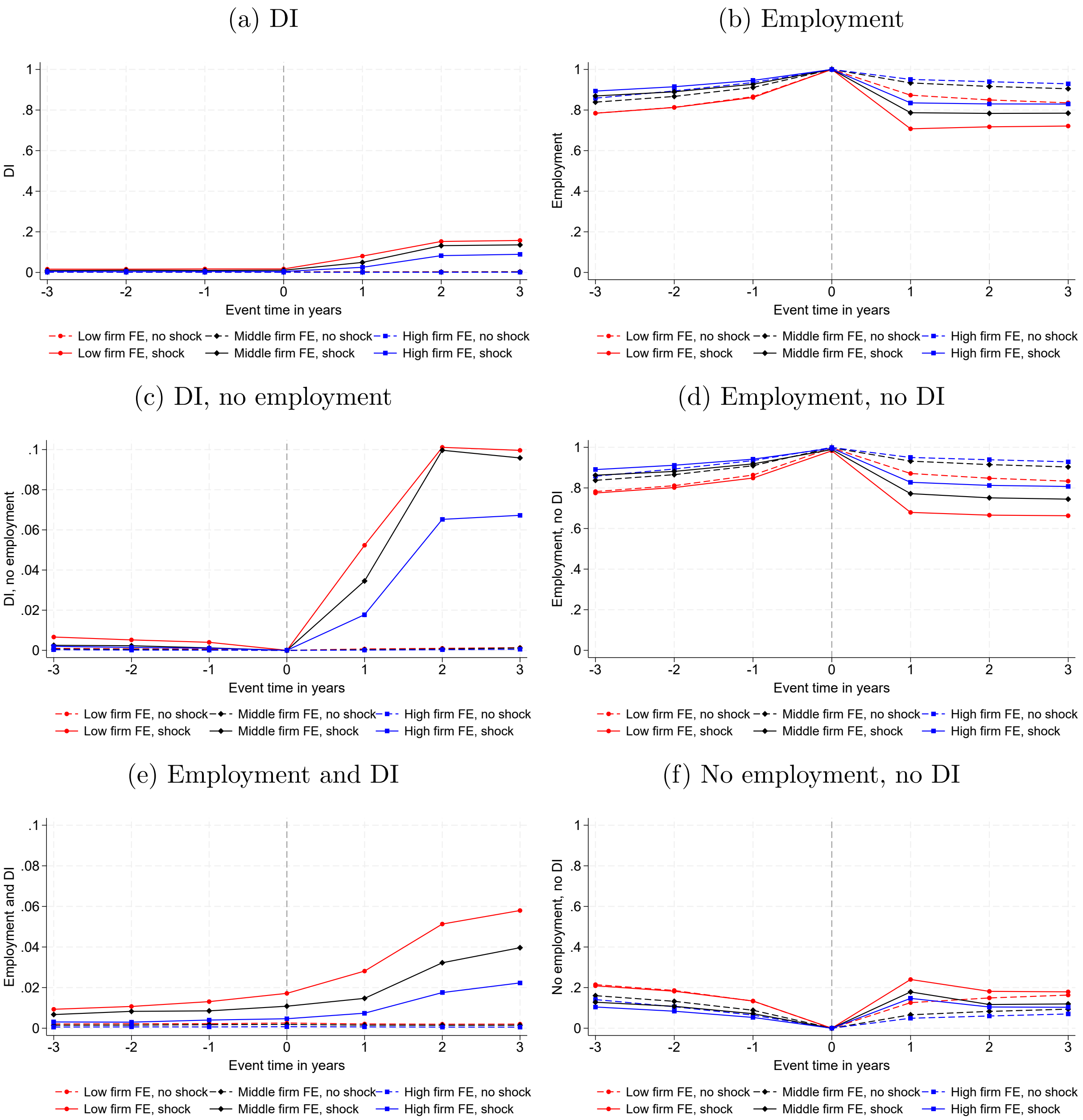
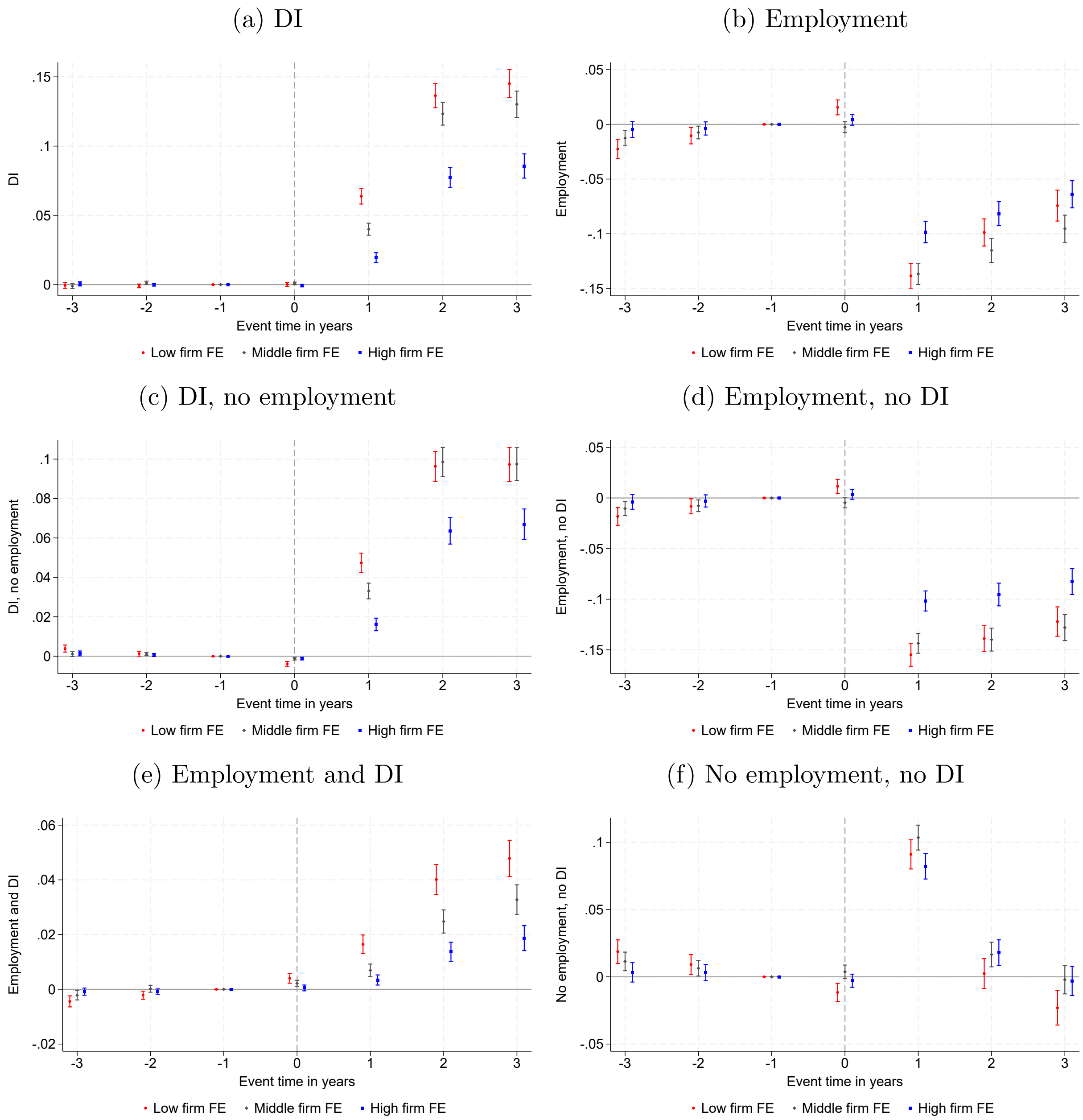
Figures and Tables

Figure 1: Labor Market Outcomes Over Time by Health Shock and Firm Quality



Note: Figure shows time patterns of labor market outcomes for individuals suffering a health shock (treated group) and individuals who never suffered a health shock (control group). For the control group, event time zero is set randomly. Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

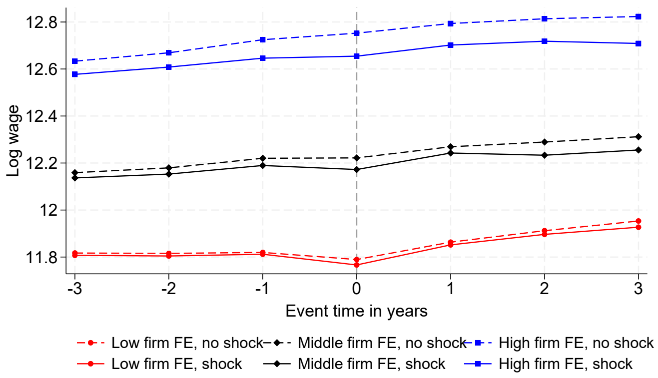
Figure 2: Impact of Health Shock Over Time



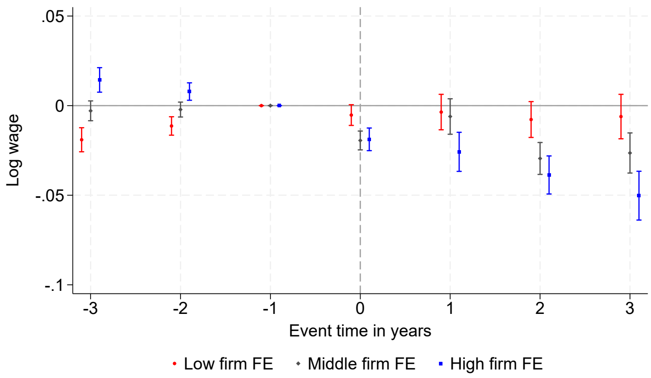
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Figure 3: Wages Over Time by Health Shock and Firm Quality

(a) Descriptives



(b) Impact of health shock



Note: Panel (a) shows time patterns of wages for individuals suffering a health shock (treated group) and individuals who never suffered a health shock (control group). For the control group, event time zero is set randomly. Panel (b) shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed full-time. Firm quality categories refer to the employer at event time zero. Wage is the annual average monthly wage, adjusted for sickness absence. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Table 1: Descriptive Statistics

	Health Shock				No Shock			
	Mean	Std.Dev.	p(10)	p(90)	Mean	Std.Dev.	p(10)	p(90)
Age	46.2	9.9	31.0	57.0	39.4	10.2	26.0	54.0
AKM firm FE	0.06	0.24	-0.26	0.37	0.07	0.25	-0.27	0.39
Monthly wage (HUF)	243,602	241,759	111,979	431,081	272,836	360,501	113,172	512,410
Lives in Budapest	0.13				0.14			
Occupation								
Manager	0.07				0.08			
Professional	0.07				0.12			
Other white collar	0.11				0.14			
Skilled blue collar	0.35				0.31			
Assembler, machine op.	0.27				0.24			
Unskilled laborer	0.12				0.11			
Industry								
Agriculture	0.001				0.001			
Manufacturing	0.33				0.35			
Construction	0.07				0.07			
Trade	0.10				0.12			
Accommodation, food	0.02				0.02			
Transportation, storage	0.16				0.14			
Services	0.16				0.18			
Other or missing	0.16				0.12			

Note: Table shows descriptive statistics 12 months before the health shock (first four columns) or 12 months before the health shock indicator is set to zero (i.e., for individuals with zero days of hospitalization in the current and preceding two years – second four columns). The sample is restricted to men employed in the private sector, for whom the occupation code is not missing. The number of observations is 25,289 in the health shock, and 303,085 in the no shock sample.

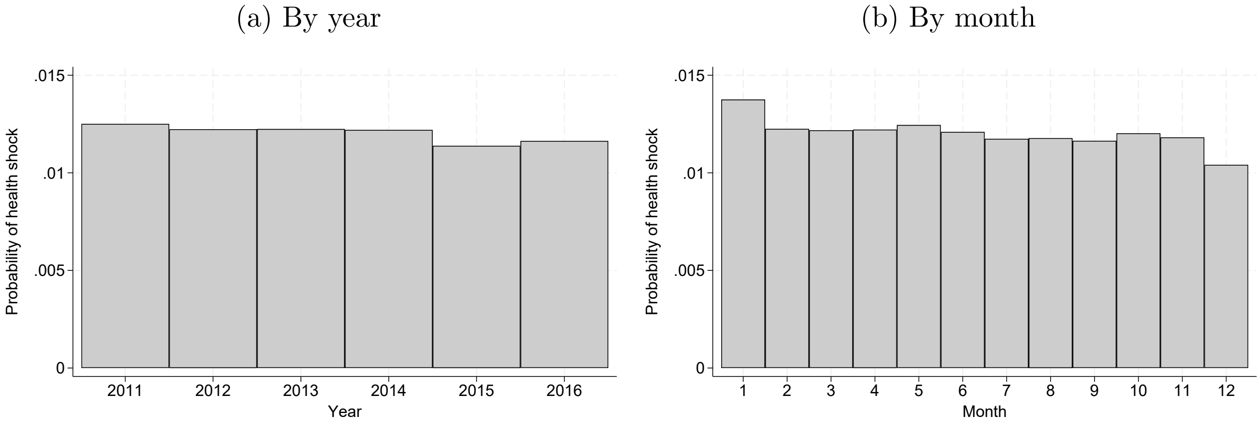
Table 2: Prevalence of Major Disease Groups at the Onset of Health Shock

	Firm FE tertile		
	Low	Middle	High
Accident	0.14	0.12	0.13
Cancer	0.09	0.10	0.10
Cardiovascular	0.23	0.23	0.22
Digestive	0.11	0.11	0.11
Mental	0.08	0.08	0.07
Musculoskeletal	0.11	0.13	0.13
Respiratory	0.07	0.07	0.07
Urogenital	0.04	0.04	0.04

Note: Table shows share of major categories of inpatient diagnosis codes (ICD-10 codes) in the first month of the health shock. The health shock definition is provided in Section 2. Sample is restricted to people employed at the onset of the shock. We split the table by firm FE tertiles – we measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix: Additional Figures and Tables

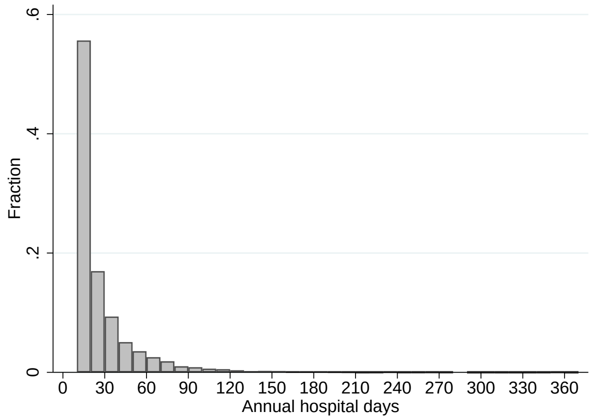
Appendix Figure A1: Monthly Probability of a Health Shock by Year and Month



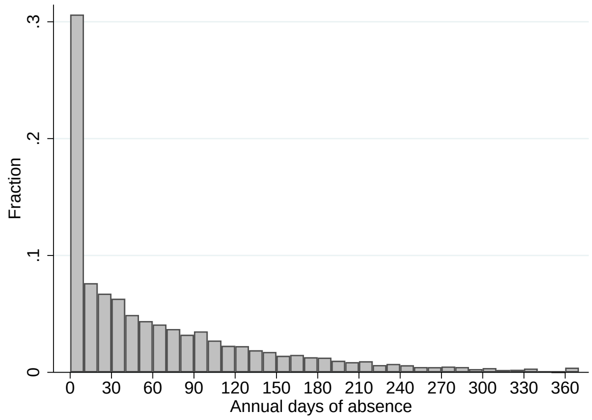
Note: Figure shows the probability of suffering a health shock by calendar year and month over 2011-2016. The health shock definition is provided in Section 2. Sample is restricted to employed men.

Appendix Figure A2: Hospital Days and Days of Absence from Work in the 12-month Period Following a Health Shock

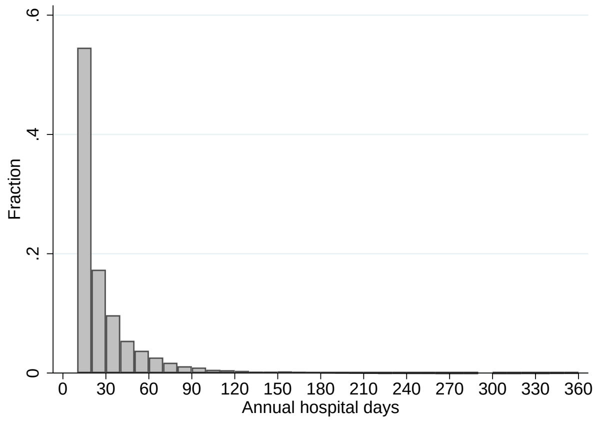
(a) Hospital days, low firm FE



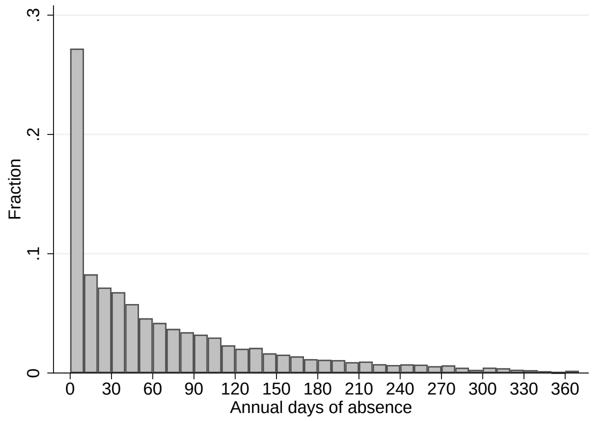
(b) Days of absence, low firm FE



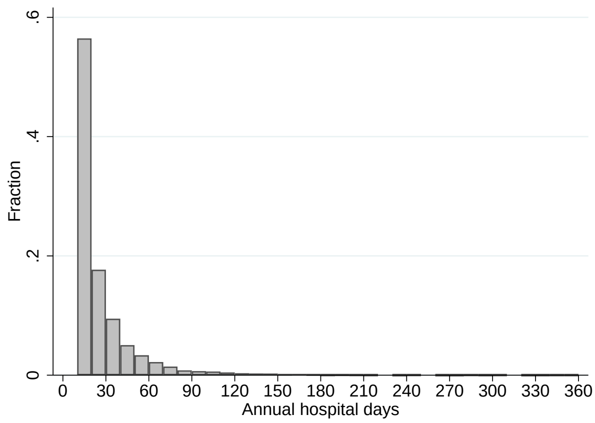
(c) Hospital days, middle firm FE



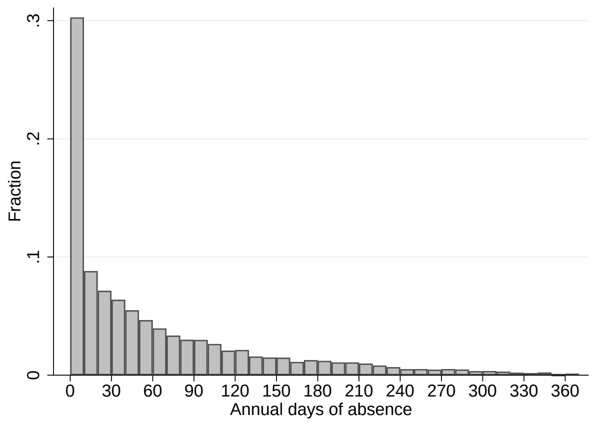
(d) Days of absence, middle firm FE



(e) Hospital days, high firm FE



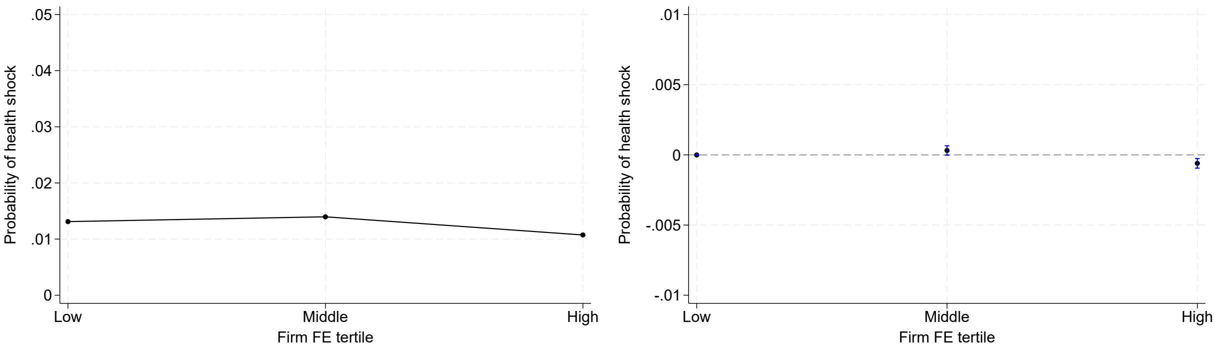
(f) Days of absence, high firm FE



Note: Figure shows the distribution of hospital days (left panels) and days of absence (right panel) over the 12-month period following the health shock, by firm quality. Sample is restricted to men suffering a health shock, who were employed at the onset of the shock. The days of absence do not include the (unobserved) sick leave days, which are at most 15 days per calendar year. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

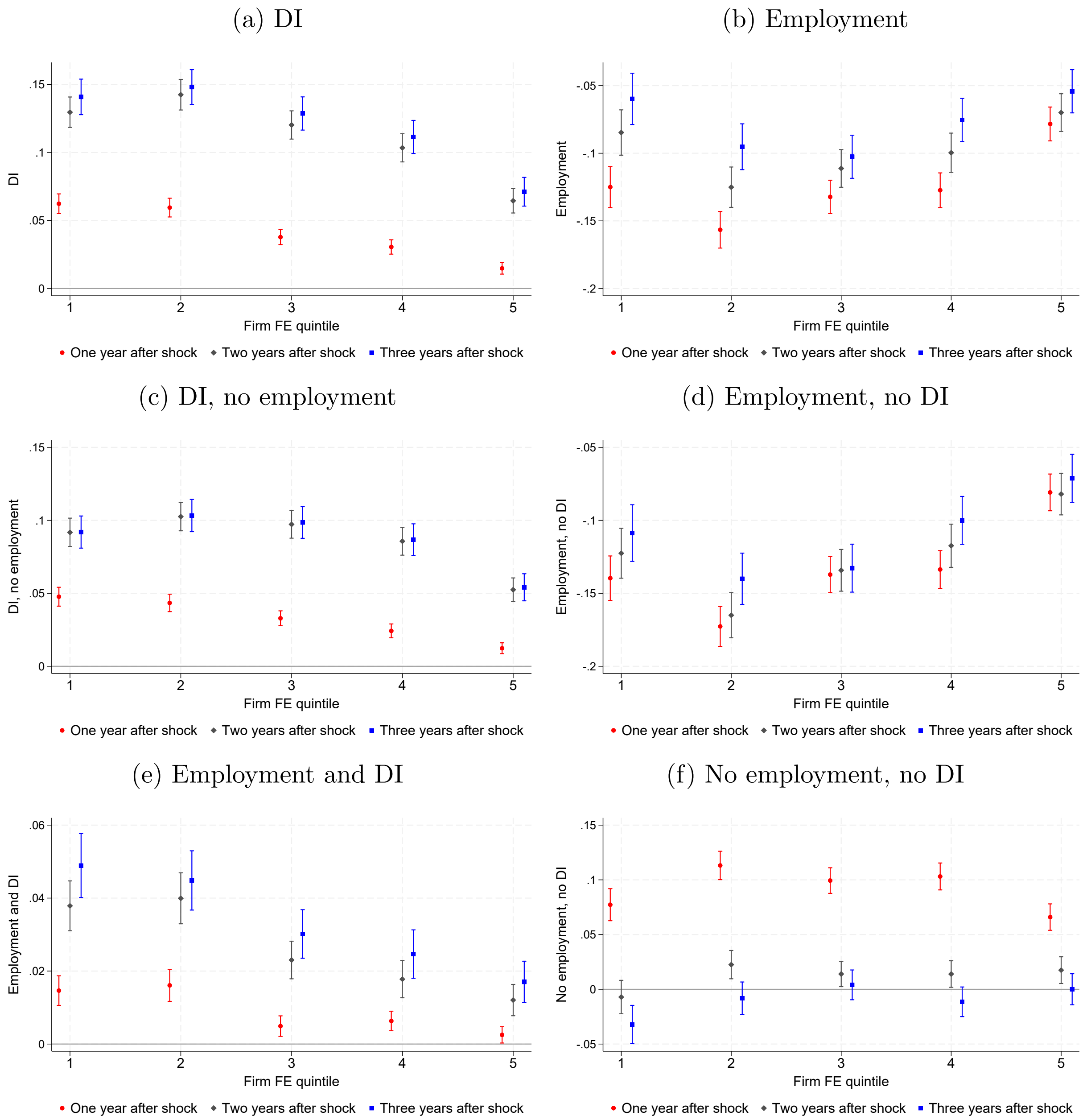
Appendix Figure A3: Health Shock Probability by Firm Quality

(a) Averages (b) Net of individual characteristics



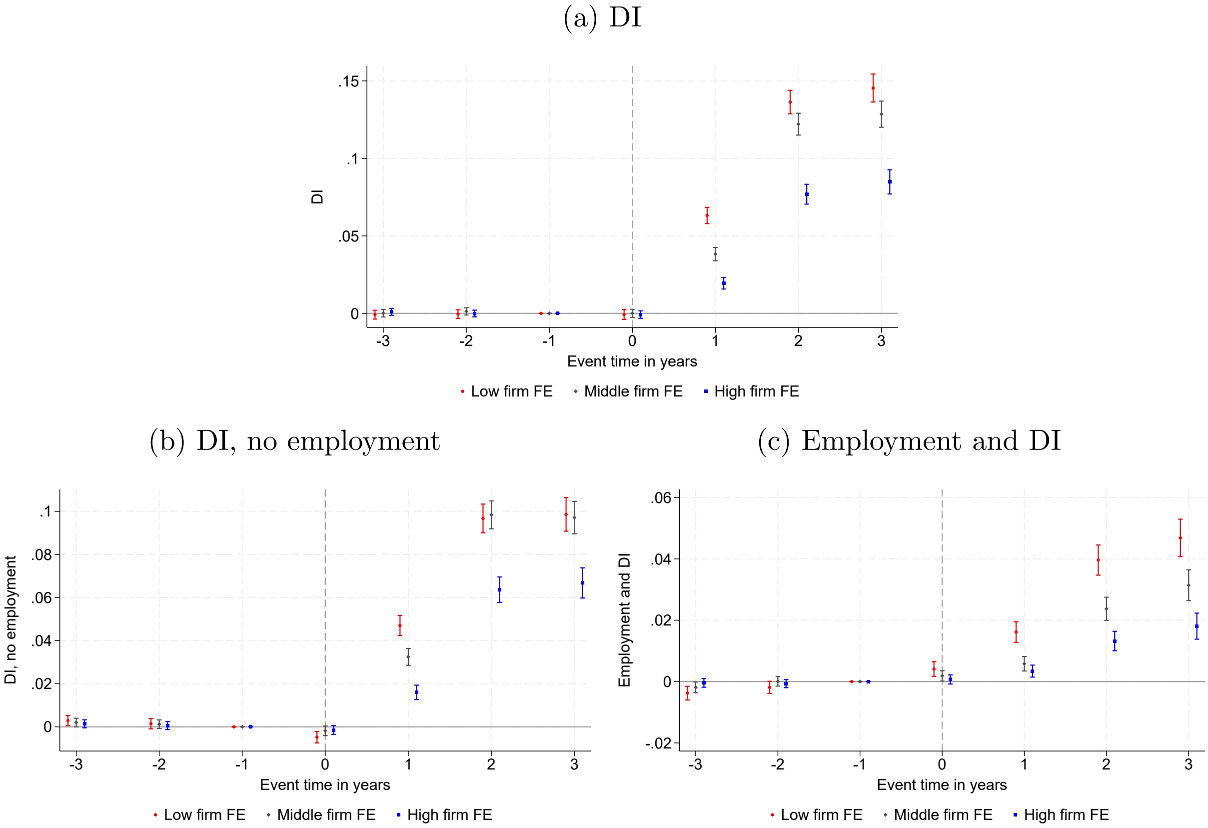
Note: Figure shows the probability of suffering a health shock by firm quality over 2011-2016. Panel (a) shows sample averages, Panel (b) shows regression estimates. Control variables in Panel (b) are: age, age squared, 2-digit occupation code dummies, year dummies. 95% CI is displayed. Sample is restricted to employed men. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A4: Impact of Health Shock by Firm FE Quintiles



Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to quintiles.

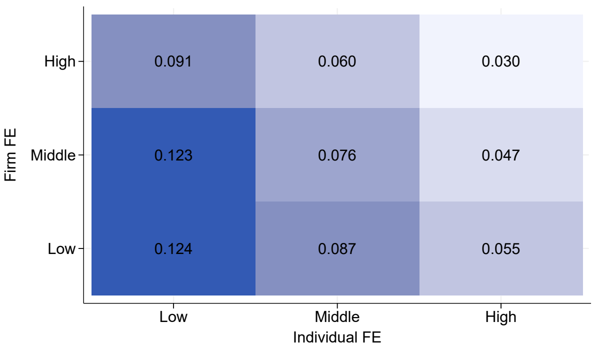
Appendix Figure A5: Impact of Health Shock Over Time–Estimation Allowing for Treatment Effect Heterogeneity



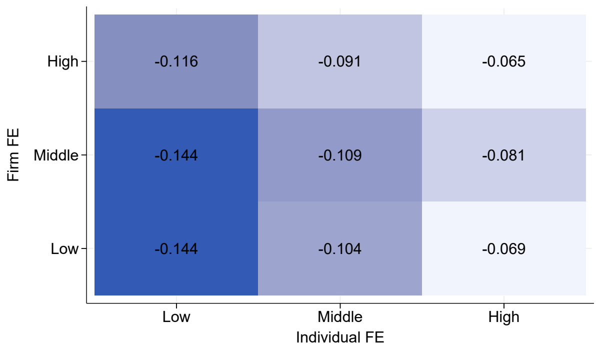
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). We use the estimator of Sun and Abraham (2021), implemented with Stata package Sun (2021). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A6: Average Effect of Health Shock by Firm Quality and Individual Quality

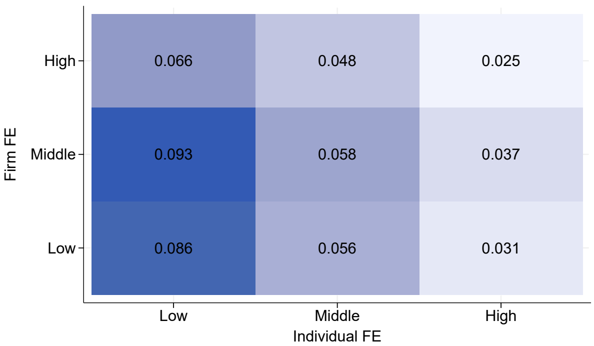
(a) DI



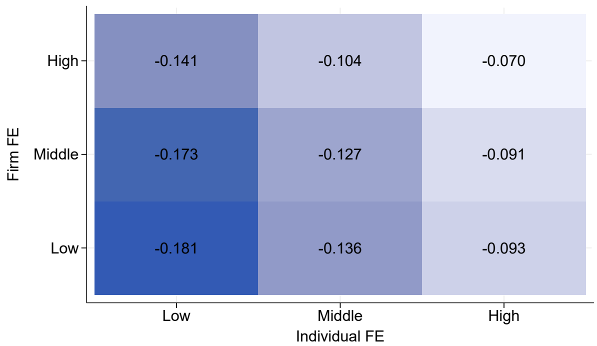
(b) Employment



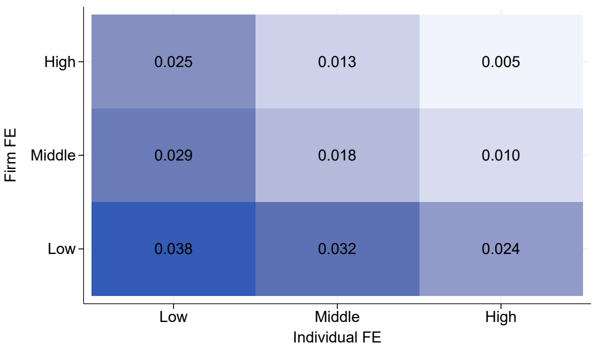
(c) DI, no employment



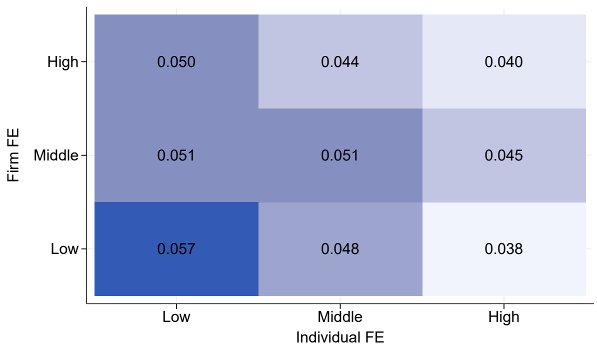
(d) Employment, no DI



(e) Employment and DI

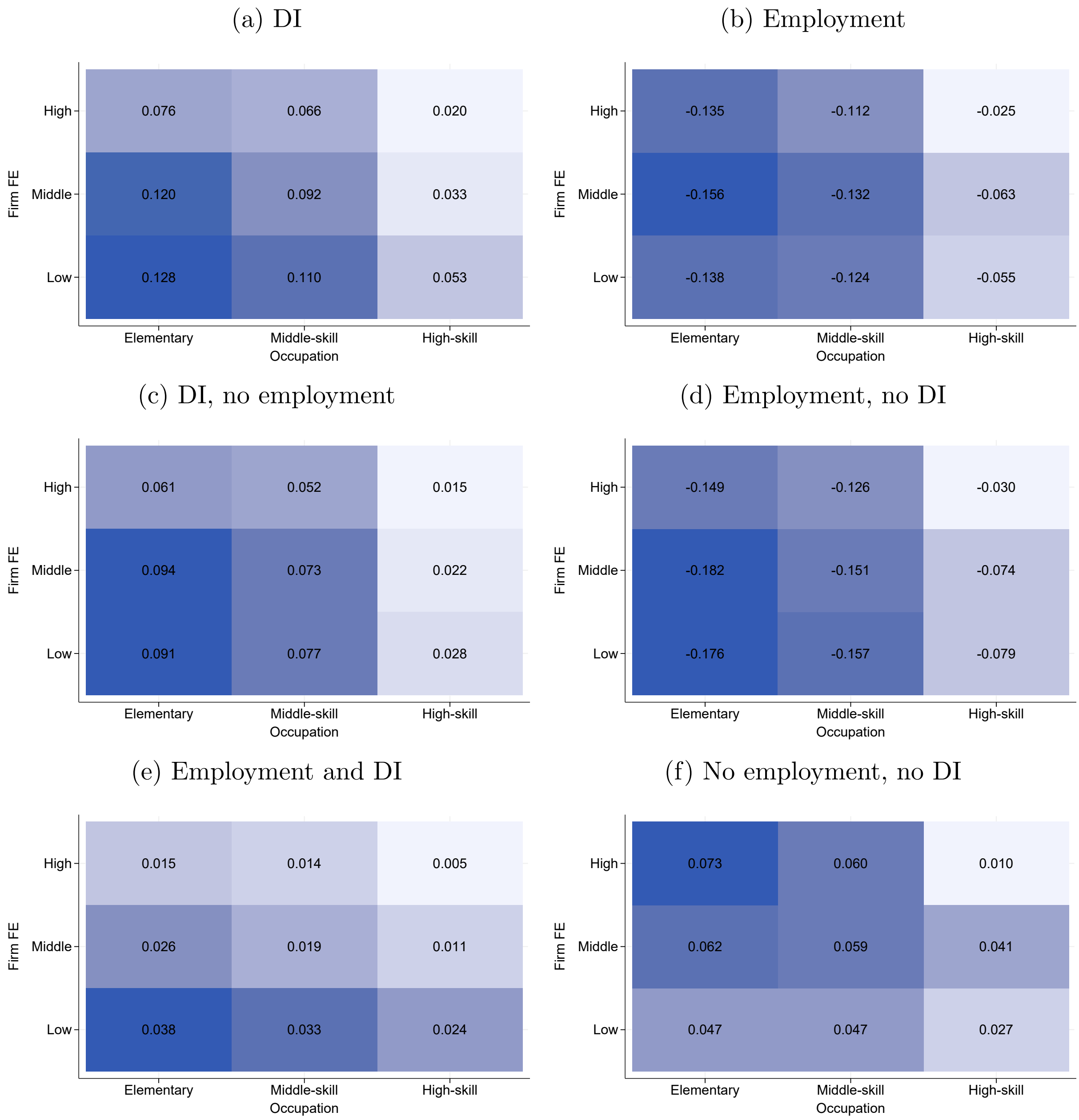


(f) No employment, no DI



Note: Figure shows estimated β parameters of a modified version of Equation (2), in which the event time categories are replaced by a binary indicator that equals zero 1-3 years before the shock and equals one 1-3 years after the shock (the year of the event is omitted). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time 0. Individual quality categories refer to the individual at event time -1. We measure individual and firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated individual and firm fixed effects to tertiles.

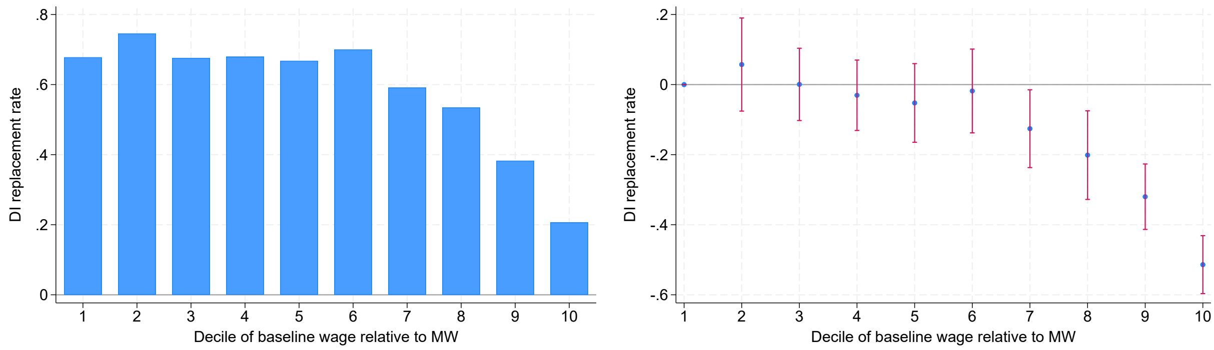
Appendix Figure A7: Average Effect of Health Shock by Firm Quality and Occupation Category



Note: Figure shows estimated β parameters of a modified version of Equation (2), in which the event time categories are replaced by a binary indicator that equals zero 1-3 years before the shock and equals one 1-3 years after the shock (the year of the event is omitted). Sample is restricted to men employed at event time zero. Firm quality and occupation categories refer to the employer at event time 0. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A8: DI Wage Replacement Rate

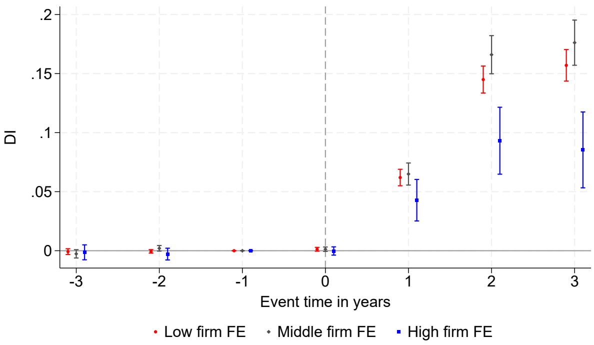
(a) Average replacement rate (b) Regression estimates



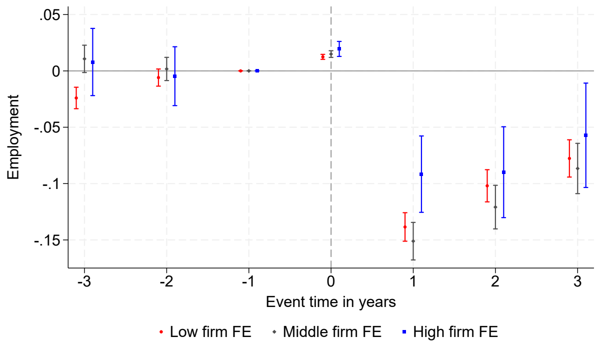
Note: Figure shows DI replacement rate by deciles of average of relative wage (relative to the minimum wage) 1-3 years before entering DI. To calculate the replacement rate, in the nominator we have the DI benefit measured at the first year of DI recipiency, in the denominator we have the average wage income 1-3 years before entering DI. Panel (b) shows point estimates with 95% confidence interval (based on robust standard errors). Control variables in Panel (b): calendar year, age and age squared.

Appendix Figure A9: Impact of Health Shock Over Time, Low Wage Earners

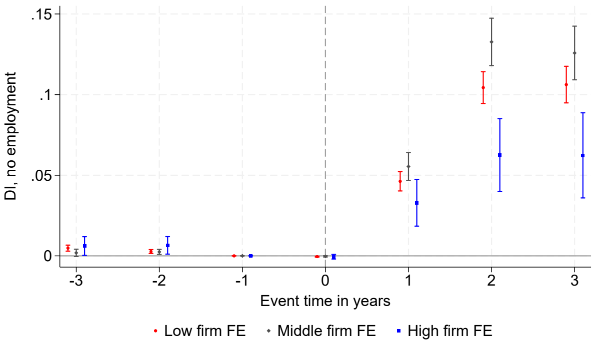
(a) DI



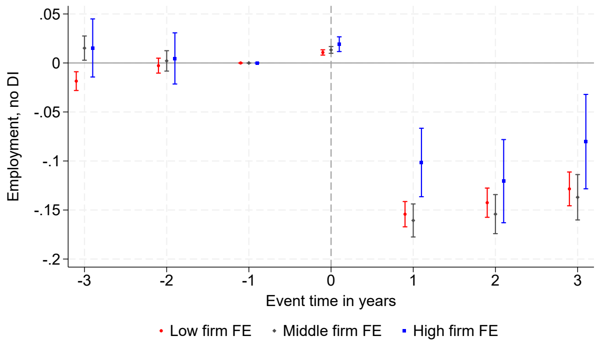
(b) Employment



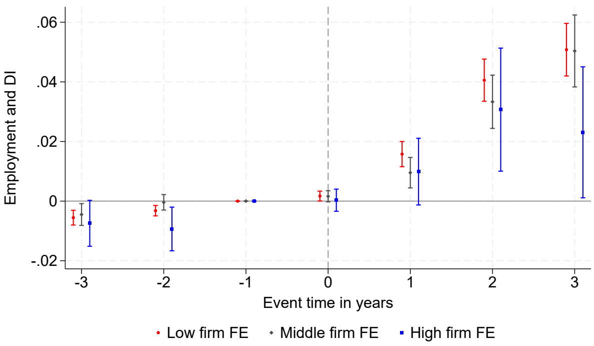
(c) DI, no employment



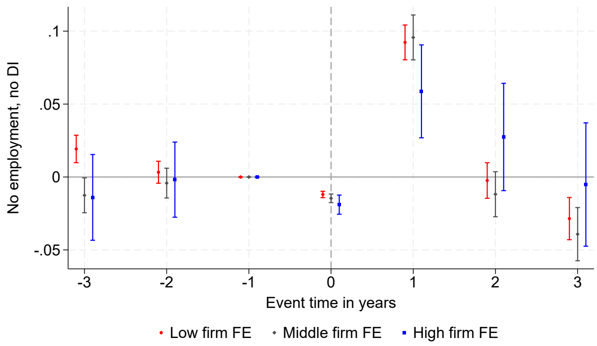
(d) Employment, no DI



(e) Employment and DI



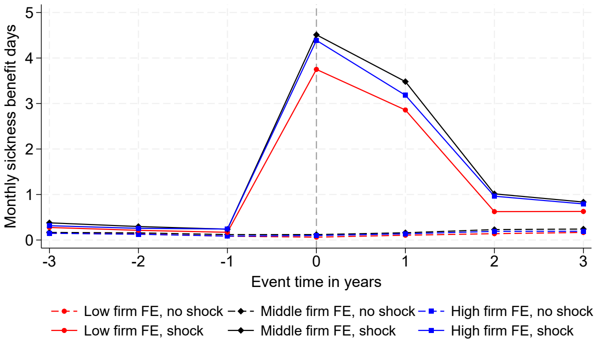
(f) No employment, no DI



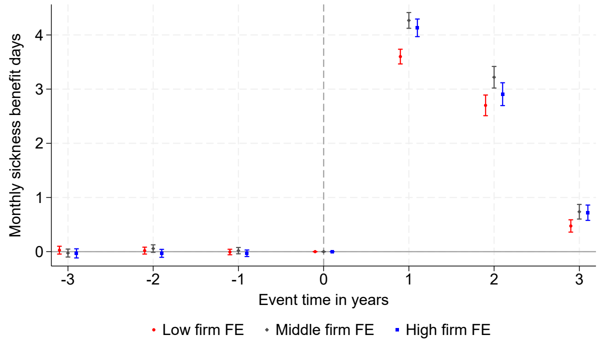
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed at event time zero and 12 months before, whose wage relative to the minimum wage at event time -1 was in decile 1-5. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A10: Healthcare Use Over Time

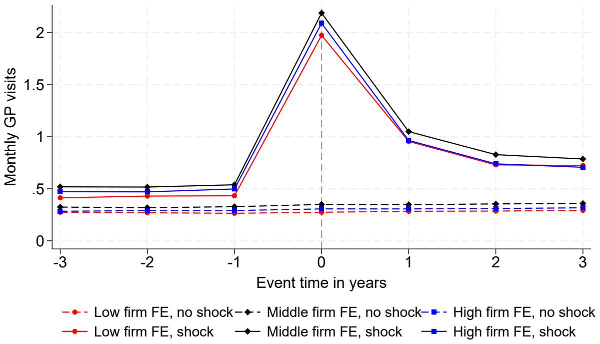
(a) Sickness benefit days



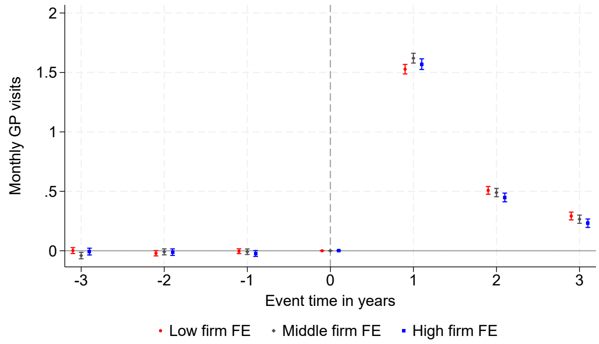
(b) Sickness benefit days



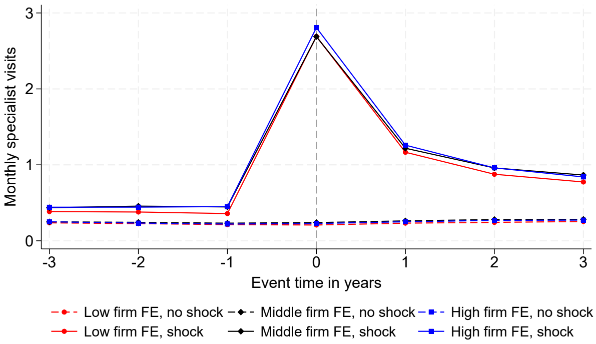
(c) GP visits



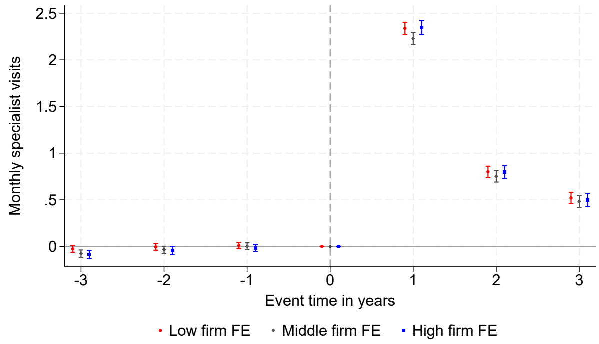
(d) GP visits



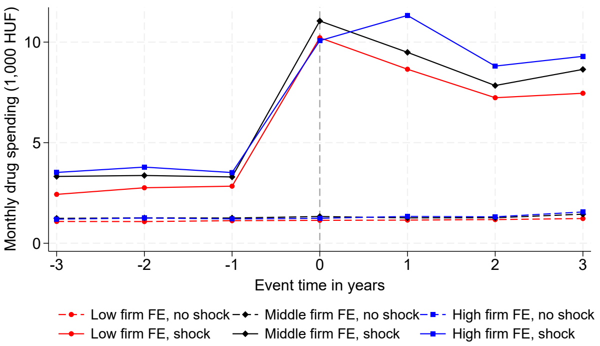
(e) Specialist visits



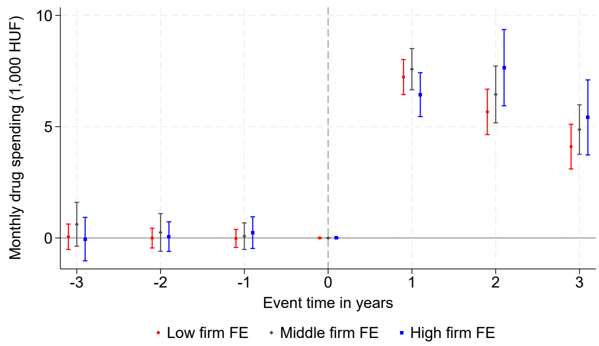
(f) Specialist visits



(g) Prescription drug spending



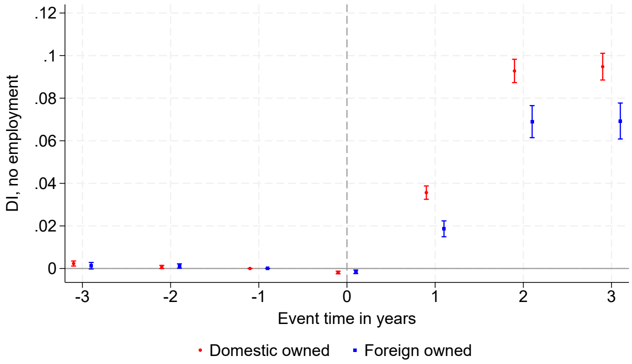
(h) Prescription drug spending



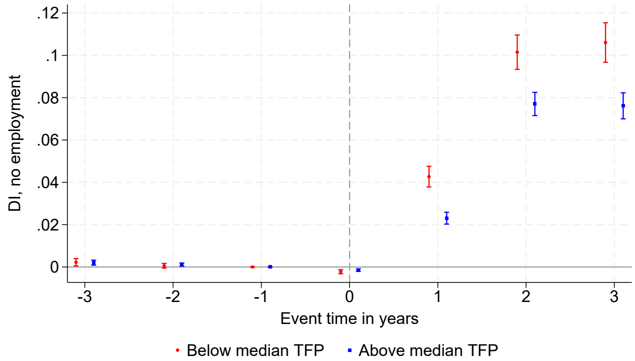
Note: Figure shows the time pattern of monthly healthcare use indicators. Left panels show means of healthcare use indicators, right panels show estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A11: Impact of Health Shock on DI Without Employment by Ownership Type, TFP and Firm Size

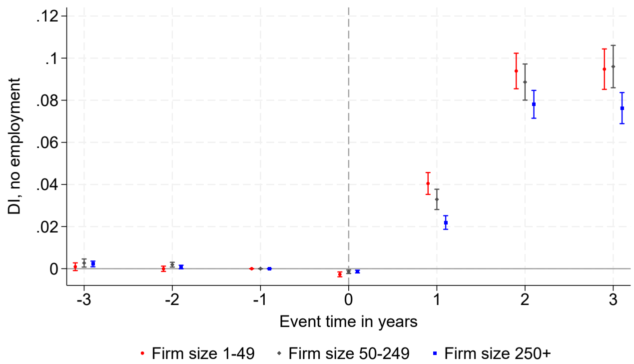
(a) By ownership



(b) By TFP

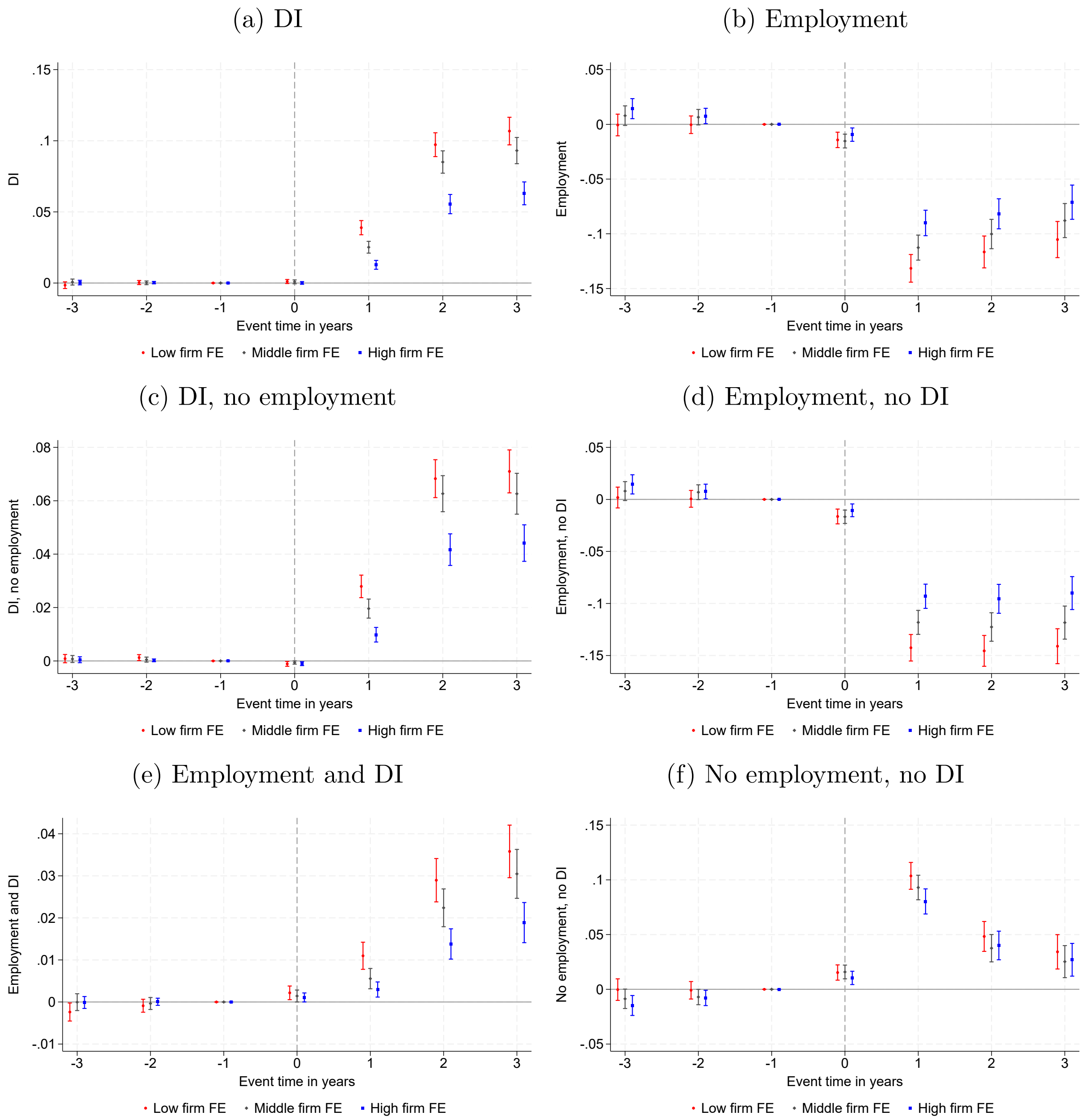


(c) By firm size



Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). The heterogeneity indicator is firm ownership (Panel (a)), total factor productivity (TFP) (Panel (b)) and firm size (Panel (c)), each referring to the employer at event time zero. Sample is restricted to men employed at event time zero.

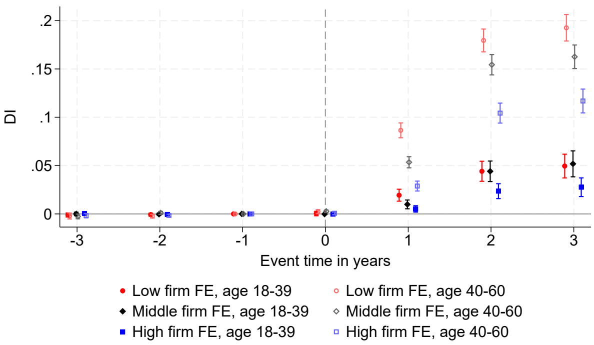
Appendix Figure A12: Impact of Health Shock Over Time Among Women



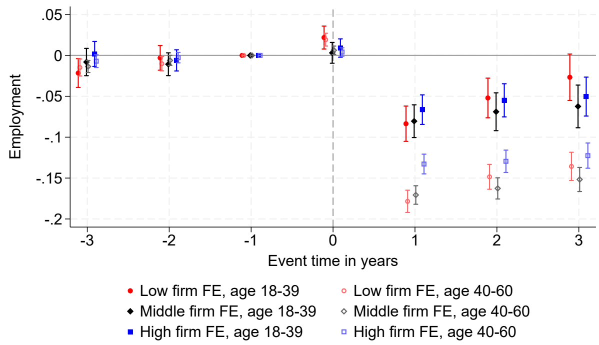
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to women employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A13: Impact of Health Shock Over Time by Age of Worker

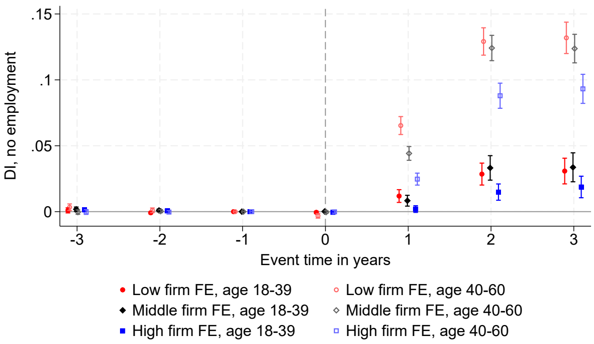
(a) DI



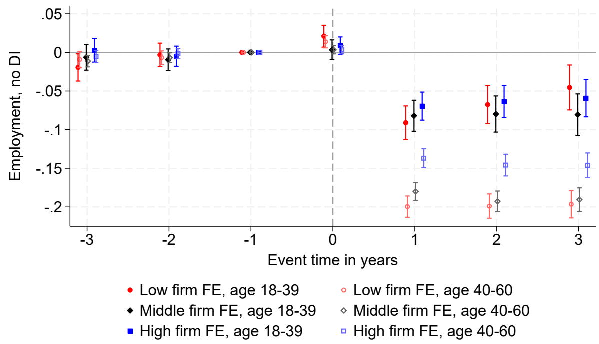
(b) Employment



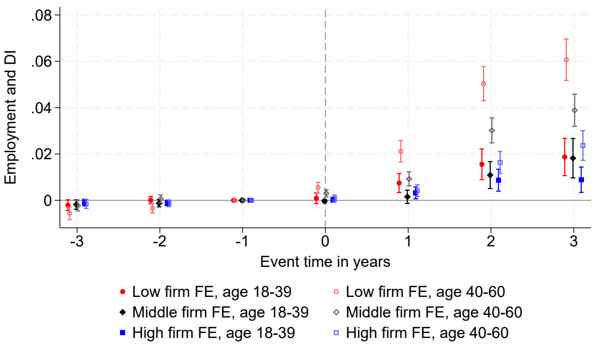
(c) DI, no employment



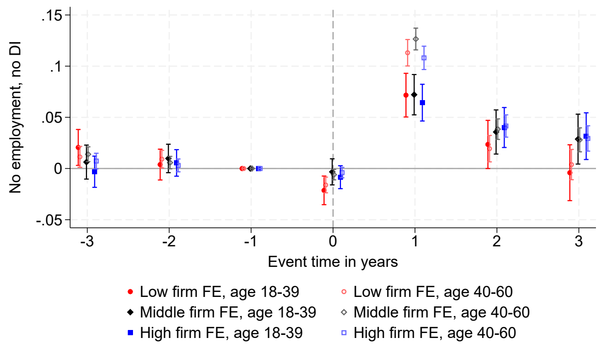
(d) Employment, no DI



(e) Employment and DI



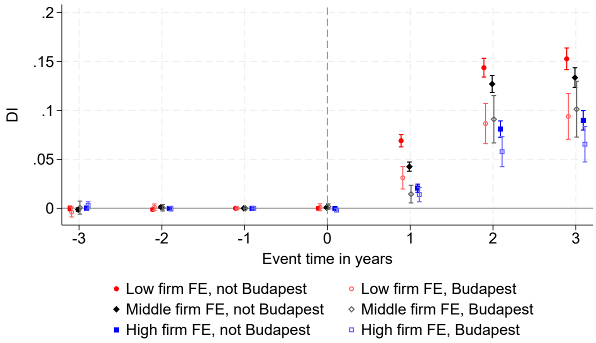
(f) No employment, no DI



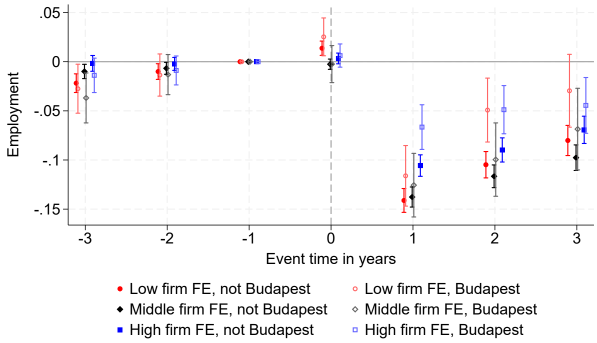
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is split by age ($18-39$ vs. $40-60$). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A14: Impact of Health Shock Over Time by Living Area

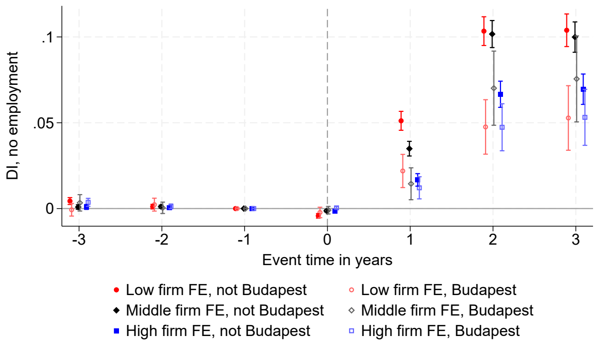
(a) DI



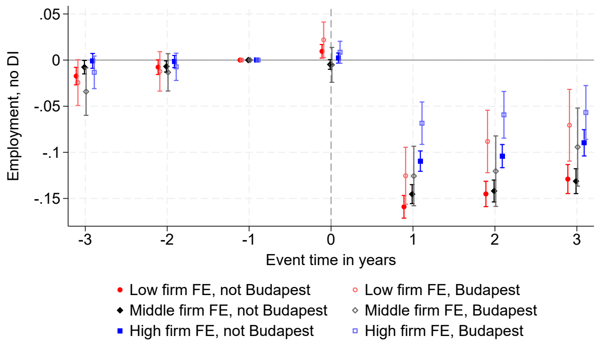
(b) Employment



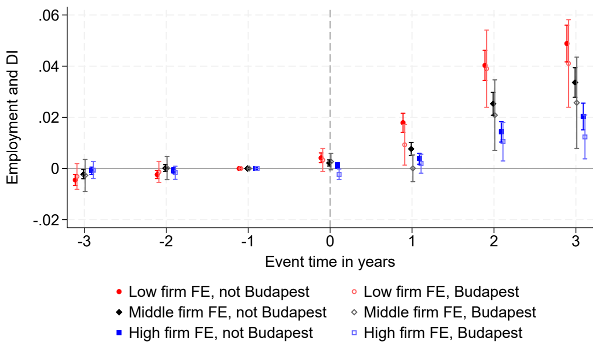
(c) DI, no employment



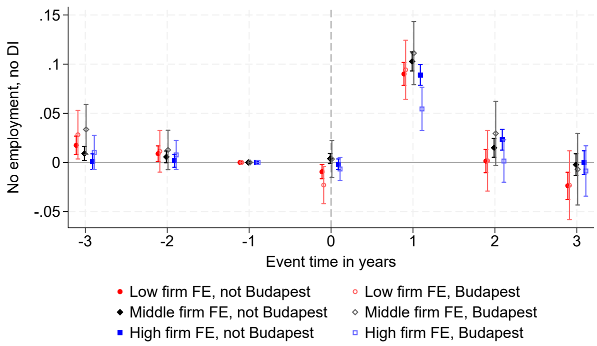
(d) Employment, no DI



(e) Employment and DI



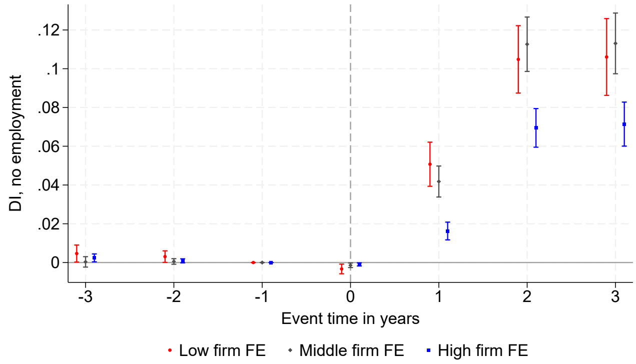
(f) No employment, no DI



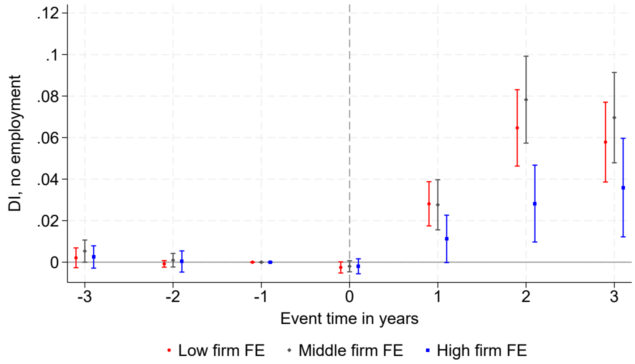
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is split by living area (Budapest or outside Budapest). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A15: Impact of Health Shock on DI Without Employment by Industry Groups and AKM Firm FE Categories

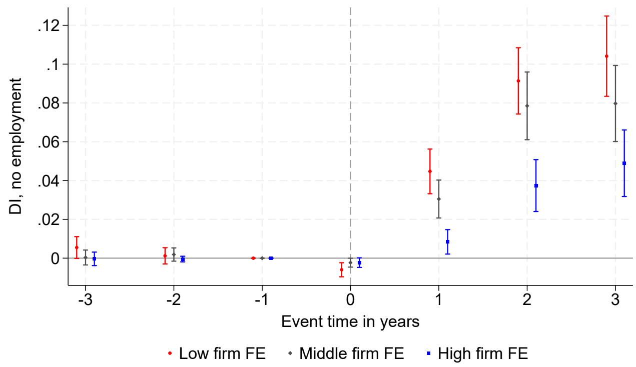
(a) Manufacturing



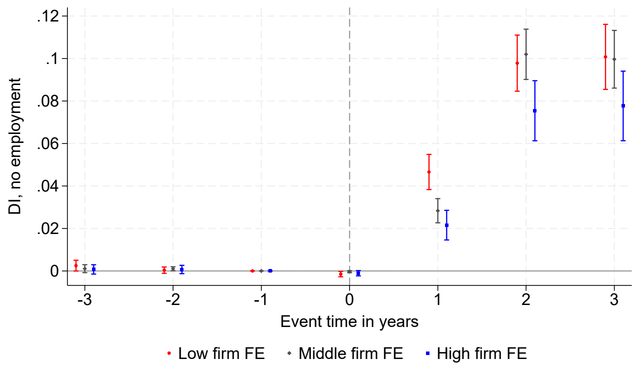
(b) Trade



(c) Services



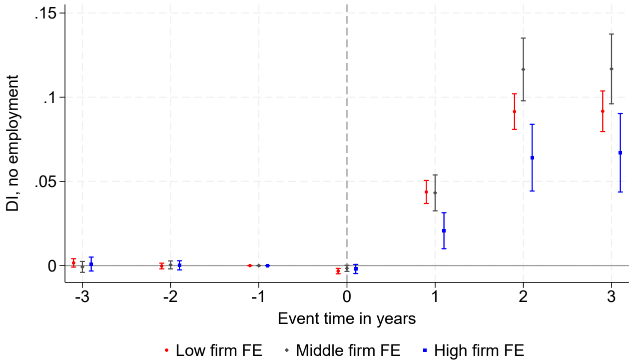
(d) Other industries



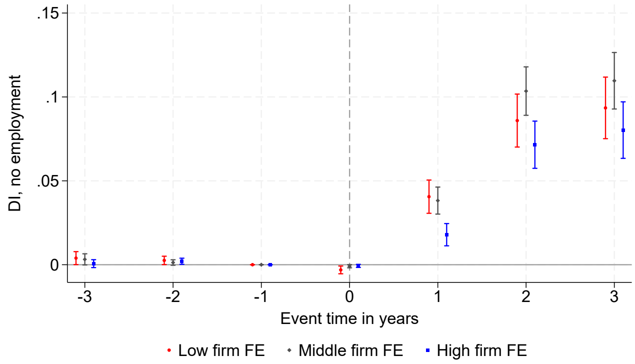
Note: Figure shows estimated parameters of the interaction term between the treatment indicator, event time, firm quality (AKM firm FE tertiles), and industry categories in an extended version of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed at event time zero. Industry and firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A16: Impact of Health Shock on DI Without Employment by Firm Size and AKM Firm FE Categories

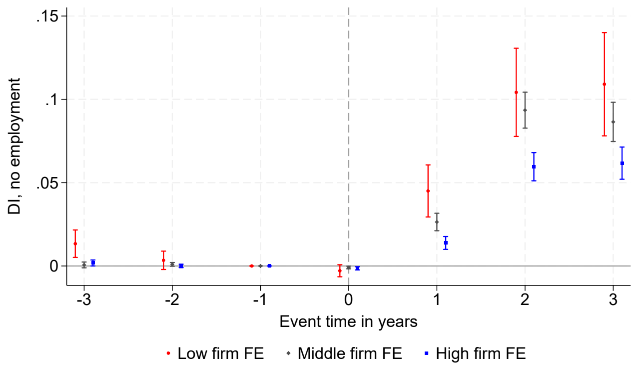
(a) Small firms (1–49)



(b) Medium firms (50–249)

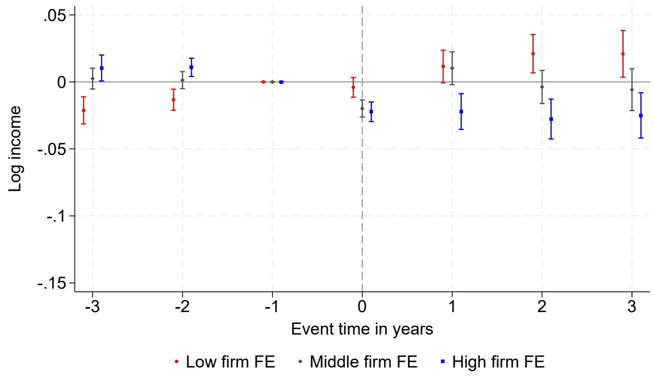


(c) Large firms (250+)



Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval, splitting the sample by firm size category. Sample is restricted to men employed at event time zero. Firm size and quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

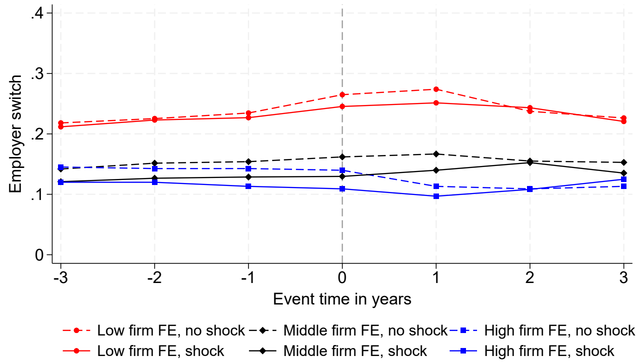
Appendix Figure A17: Impact of Health Shock on Income Over Time



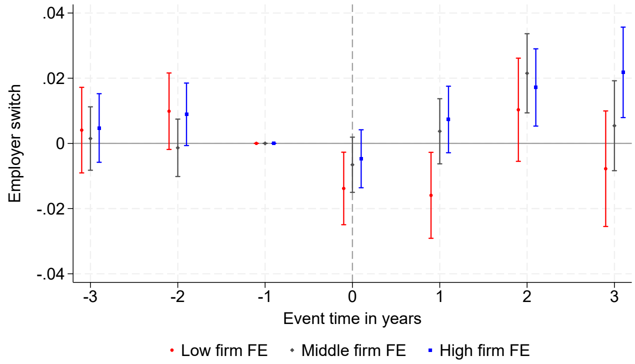
Note: Figure shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. Income is the sum of the annual average monthly wage and DI benefit. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A18: Impact of Health Shock on Switching Employer, Conditional on Employment

(a) Descriptives

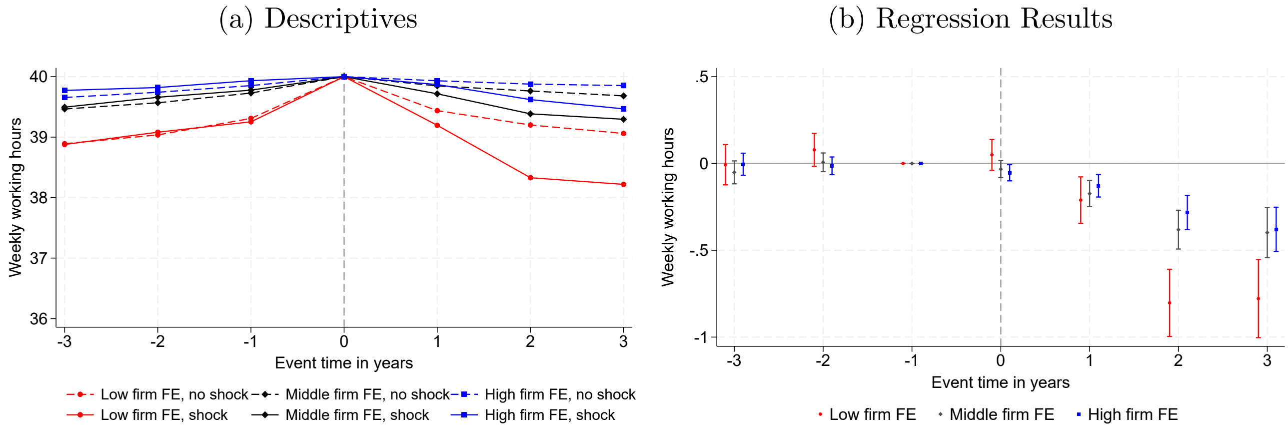


(b) Regression Results



Note: Figure shows the time pattern of the probability of moving between employers. The binary indicator of switching employer is defined on the sample of men employed currently and 12 months before. It equals one if the current employer and the employer 12 months before are different. Panel (a) shows averages of employer switches for individuals suffering a health shock (treated group) and individuals who never suffered a health shock (control group). Panel (b) shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to employed men. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Figure A19: Impact of Health Shock on Weekly Working Hours, Conditional on Employment



Note: Panel (a) shows averages of weekly working hours for individuals suffering a health shock (treated group) and individuals who never suffered a health shock (control group). Panel (b) shows estimated β parameters of Equation (3) with 95% confidence interval (based on robust standard errors). Sample is restricted to employed men. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles.

Appendix Table A1: Sorting of Individuals Across Firm Types

No health shock		Firm FE tertile				
		Low	Middle	High	Total	
	Low	13%	12%	6%	31%	
Individual FE tertile	Middle	12%	12%	10%	33%	
	High	5%	10%	20%	36%	
	Total	31%	33%	36%	100%	N=242,024
With health shock		Firm FE tertile				
		Low	Middle	High	Total	
	Low	15%	16%	7%	38%	
Individual FE tertile	Middle	11%	12%	9%	31%	
	High	6%	10%	15%	30%	
	Total	32%	37%	31%	100%	N=22,788

Note: Table shows the distribution of workers across individual and firm FE tertiles. Firm FE and individual FE are measured one year before the health shock or before the random event for the no health shock group. We measure individual and firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated individual and firm fixed effects to tertiles.

Appendix Table A2: Average Effect of Health Shock by Disease Categories

	DI	Employment	DI, no emp.	Emp. & DI	Emp., no DI	No emp., no DI
Accident						
Low firm FE	0.040***	-0.053***	0.024***	0.017***	-0.070***	0.030**
	(0.006)	(0.012)	(0.005)	(0.005)	(0.012)	(0.012)
Middle firm FE	0.035***	-0.098***	0.031***	0.004	-0.102***	0.067***
	(0.006)	(0.011)	(0.005)	(0.003)	(0.011)	(0.010)
High firm FE	0.021***	-0.079***	0.016***	0.005**	-0.084***	0.063***
	(0.005)	(0.010)	(0.004)	(0.003)	(0.010)	(0.010)
Cancer						
Low firm FE	0.263***	-0.245***	0.200***	0.063***	-0.308***	0.045***
	(0.017)	(0.020)	(0.015)	(0.011)	(0.021)	(0.017)
Middle firm FE	0.205***	-0.268***	0.169***	0.035***	-0.303***	0.099***
	(0.014)	(0.016)	(0.013)	(0.007)	(0.017)	(0.013)
High firm FE	0.114***	-0.178***	0.091***	0.023***	-0.201***	0.087***
	(0.012)	(0.016)	(0.011)	(0.006)	(0.016)	(0.013)
Cardiovascular						
Low firm FE	0.174***	-0.151***	0.124***	0.049***	-0.200***	0.027***
	(0.008)	(0.010)	(0.007)	(0.005)	(0.010)	(0.009)
Middle firm FE	0.141***	-0.148***	0.109***	0.032***	-0.181***	0.039***
	(0.007)	(0.008)	(0.006)	(0.004)	(0.009)	(0.007)
High firm FE	0.099***	-0.116***	0.082***	0.017***	-0.133***	0.034***
	(0.007)	(0.009)	(0.006)	(0.003)	(0.009)	(0.007)
Digestive						
Low firm FE	0.050***	-0.051***	0.028***	0.022***	-0.073***	0.023*
	(0.008)	(0.015)	(0.006)	(0.006)	(0.015)	(0.014)
Middle firm FE	0.033***	-0.065***	0.026***	0.007**	-0.073***	0.039***
	(0.006)	(0.012)	(0.005)	(0.003)	(0.013)	(0.011)
High firm FE	0.024***	-0.025**	0.021***	0.003	-0.028**	0.004
	(0.006)	(0.012)	(0.005)	(0.003)	(0.013)	(0.011)
Mental						
Low firm FE	0.049***	-0.128***	0.028***	0.021***	-0.150***	0.101***
	(0.009)	(0.017)	(0.007)	(0.005)	(0.017)	(0.016)
Middle firm FE	0.036***	-0.140***	0.024***	0.011***	-0.151***	0.116***
	(0.008)	(0.017)	(0.006)	(0.004)	(0.017)	(0.016)
High firm FE	0.033***	-0.144***	0.022***	0.011**	-0.155***	0.122***
	(0.006)	(0.017)	(0.005)	(0.005)	(0.017)	(0.016)
Musculoskeletal						
Low firm FE	0.064***	-0.053***	0.033***	0.031***	-0.084***	0.020*
	(0.008)	(0.013)	(0.005)	(0.006)	(0.014)	(0.012)
Middle firm FE	0.045***	-0.049***	0.023***	0.022***	-0.071***	0.025***
	(0.007)	(0.010)	(0.005)	(0.005)	(0.011)	(0.009)
High firm FE	0.030***	-0.054***	0.026***	0.005	-0.059***	0.028***
	(0.006)	(0.011)	(0.005)	(0.003)	(0.011)	(0.009)
Respiratory						
Low firm FE	0.083***	-0.063***	0.056***	0.027***	-0.090***	0.008
	(0.011)	(0.018)	(0.007)	(0.008)	(0.019)	(0.016)
Middle firm FE	0.077***	-0.125***	0.073***	0.005	-0.129***	0.052***
	(0.011)	(0.018)	(0.010)	(0.005)	(0.018)	(0.015)
High firm FE	0.036***	-0.050***	0.028***	0.008**	-0.059***	0.022
	(0.008)	(0.016)	(0.007)	(0.004)	(0.016)	(0.014)
Urogenital						
Low firm FE	0.063***	-0.111***	0.036***	0.027***	-0.139***	0.075***
	(0.015)	(0.021)	(0.009)	(0.010)	(0.022)	(0.019)
Middle firm FE	0.070***	-0.076***	0.062***	0.007	-0.083***	0.013
	(0.013)	(0.021)	(0.012)	(0.007)	(0.022)	(0.017)
High firm FE	0.020**	-0.051**	0.018**	0.002	-0.053**	0.033*
	(0.009)	(0.021)	(0.008)	(0.004)	(0.021)	(0.020)

Note: Table shows estimated β parameters of a modified version of Equation (3), in which the event time categories are replaced by a binary indicator that equals zero 1-3 years before the shock and equals one 1-3 years after the shock (the year of the event is omitted). Sample is restricted to men employed at event time zero. Firm quality categories refer to the employer at event time zero. We measure firm quality with an AKM-type fixed effect (Equation (1)) and divide the estimated firm fixed effects to tertiles. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.