I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16708

Firms and Worker Health

Alexander Ahammer
Analisa Packham
Jonathan Smith

JANUARY 2024

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16708

Firms and Worker Health

Alexander Ahammer
Johannes Kepler University Linz and IZA

Analisa Packham
Vanderbilt University, IZA and NBER

Jonathan Smith
Georgia State University and IZA

JANUARY 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Firms and Worker Health*

We estimate the role of firms in worker health care utilization. Using linked administrative data on Austrian workers from 1998–2018, we exploit mobility between firms to estimate how much a firm contributes to worker-level differences in utilization in a setting with non-employer provided universal health care. We find that firms are responsible for nearly 30 percent of the variation in across-worker health care expenditures. Effects are not driven by changes in geography or industry. We then estimate a measure of relative firm-specific utilization and explore existing correlates to help explain these effects.

JEL Classification: H51, I1, J2

Keywords: firms, health care utilization, sick leave

Corresponding author:
Alexander Ahammer
Johannes Kepler University Linz
Altenberger Straße 69
4040 Linz
Austria
E-mail: alexander.ahammer@jku.at

* For helpful discussions and comments we thank Janet Currie, Chloe East, Amy Finkelstein, Emily Lawler, and seminar participants at Georgia State University, Georgia Institute of Technology, Hamburg University, University of Georgia, FAU Nürnberg, and Vanderbilt University.

1. Introduction

There exists considerable variation in individual health care spending, and recent work has focused on what factors determine health care utilization (Newhouse, Garber, Graham, McCoy, Mancher & Kibria 2013). For example, evidence from the RAND health insurance experiment suggests that prices are a key determinant of take-up (Aron-Dine, Einav & Finkelstein 2013). Other recent work attributes some of this variation in health care utilization to providers and geography, showing large variation in spending patterns even after controlling for patient needs and preferences (Ahammer & Schober 2020, Badinski, Finkelstein, Gentzkow & Hull 2023, Finkelstein, Gentzkow & Williams 2016, 2021). Yet, given that people spend so much of their waking hours at work, one understudied aspect of this literature is whether firms play a role in health care utilization. We fill this gap in the literature by estimating how much firms contribute to workers' health care utilization. In particular, we focus on a setting where health insurance is not tied to employment and workers experience little cost sharing, removing the ties between employment and health care affordability.

The workplace may affect a number of important determinants of worker health care utilization, both physical and mental. For example, firms may have different safety standards, working hours and conditions, and/or job requirements. Moreover, peers have the potential to influence a worker's decision-making. Co-workers at firms may be more or less supportive, competitive, or motivated. Peers may pressure each other to engage in riskier behaviors, like smoking or drinking, or encourage a culture of healthier eating and exercise. Lastly, firms directly affect wages and other types of compensation, which can have effects on healthy behaviors. Identifying how much firms contribute to a worker's health care spending, and through which channels, could have important cost-saving policy implications for both firms and government.

To measure the role of the firm in health care utilization we use newly linked labor market and health expenditure data on workers from Upper Austria from 1998 to 2018. We first show that there is substantial variation in average health care expenditures at the firm level and that moving to a new firm along this distribution has implications for worker expenditures. For example, a worker that moves from a firm with high utilization to a firm with low utilization reduces their own health care expenditures by €236.2, or 37 percent, while a symmetric move in the opposite direction increases health care expenditures by nearly double. Those moving to firms with similar average expenditures do not change their health care expenditures. To more directly estimate the contribution of firms to workers' health care expenditures, we use an event-study framework that examines whether workers who move firms have a change in their health care expenditures that approaches that of the average health care expenditure of the destination firms. Unlike in a U.S. context, health insurance status for Austrian workers is unaffected by changes in employment, which provides additional reassurance that we can identify changes in expenditures due to firm changes and not changes in health insurance coverage.

Our main finding is that firms are responsible for 30 percent of the variation in log health care expenditures. These contribution sizes increase over time, consistent with habit formation models (Bronnenberg, Dubé & Gentzkow 2012). We find little heterogeneity by age, occupation, and gender. However, firms appear to be more important for workers with higher baseline health expenditures. In subsequent analyses, we show that these main findings hold for workers who do not move across industries or zip codes, thus providing new evidence that firms, and not just trade- or place-based characteristics, influence health care utilization. We also show that estimates are not driven by changes in health care expenditures due to childbirth at the time of the move.

When we investigate the potential drivers behind the fact that firms are responsible for 30 percent of health care expenditures, we find little evidence of changes in underlying health status in the short run. Instead, we show that this effect is mostly due to increases in physician visits, with smaller effects for prescription and inpatient expenditures, suggesting that health care take-up is largely responsible for our effects. Exploring further, we show that firms contribute to both positive health behaviors, including preventative care, and also negative health behaviors, like alcohol and opioid use. We then test whether these contributions of the firm are a result of peer effects and provide new evidence that co-workers influence both positive and negative behaviors. In further analyses, we ask to what extent the social and physical firm environment can affect health. We show that firms do influence mental health take-up—a proxy for stress—and also show that firms are a key input to injuries and accidents. Together, these findings provide evidence to suggest that changes in health care take-up, health behaviors, peers, and workplace safety most likely explain our effects, while a change in health *status* is less likely.

We then investigate what firm characteristics correlate with firm health to better understand how firms can differentially affect worker health care utilization. To get a measure of whether a firm is a high-utilization or low-utilization firm, we estimate models with additive worker and firm fixed effects, which also nest our movers-focused event-study model. When analyzing which firm characteristics relate to utilization, in particular, we show that larger firms, higher-paying firms, and firms in urban areas tend to have lower health care utilization, on average, while firms in industries with high market concentration and older firms tend to have higher utilization. Manufacturing firms have the highest health care expenditures, while tourism and public administration tend to have the lowest. Finally, we test the extent to which wages relate to our measure of firm health effects. Consistent with the theory of compensating differentials, we show that there is a modest positive correlation between firm wage premiums and firm health care expenditures as well as a positive correlation between accidents rates and wages.

Our findings contribute to and tie together three main strands of literature. First, we complement a literature showing that place-based factors and physicians drive health care utilization for Medicare recipients. In particular, Finkelstein, Gentzkow & Williams (2016) and Finkelstein, Gentzkow & Williams (2021) show that while nearly half of the variation in an individual's health care expenditures is due to geography, differences in physician practice styles make up about one-third of this place-based variation.[1] One major advantage of our study is that we are able to leverage new linked administrative data to look at an understudied input to health: firms. Unlike data used in other related work, we are able to observe the universe of individuals' employment, wages, and health care expenditures over time.

Second, we contribute to a broader literature on occupational health. Much of the recent

[1]Similarly Ahammer & Schober (2020) show that while much of the variation in health care utilization is attributable to patient characteristics, physician practice style is also an important determinant of expenditures.

work in this area focuses on how firms can impose psychic costs that manifest in both mental and physical health conditions. For example, existing evidence from the famous Whitehall studies shows that employment-grade is inversely related to morbidity, with workers in lower status jobs reporting a higher instance of adverse health outcomes, likely due to psycho-social stressors from the workplace hierarchy (Marmot, Bosma, Hemingway, Brunner & Stansfeld 1997, Marmot, Smith, Stansfeld, Patel, North, Head, White, Brunner & Feeney 1991). Similar to this idea, it is well-documented that job insecurity can have health-damaging effects, further indicating that firms matter for worker health. In particular, Caroli & Godard (2016) show that perceived job insecurity can cause headaches and eyestrain, and several papers find that perceived job insecurity negatively affects mental health outcomes (Cottini & Ghinetti 2018, Green 2011, Johnston, Shields & Suziedelyte 2020, Reichert & Tauchmann 2017). Additionally, using administrative data from Austria, Ahammer, Grübl & Winter-Ebmer (2023) show that mass layoffs have persistent effects on mental and physical health for surviving workers, consistent with the idea that the firm can affect health through psychological channels.

Beyond the mental stressors generated by the firm, there exists a body of work showing that physical demands of a job can also impact worker health. For example, dangerous working conditions and strain have also been linked to chronic diseases and poor health status (e.g., Defebvre 2018, Fletcher, Sindelar & Yamaguchi 2011, Gihleb, Giuntella, Stella & Wang 2022, Ose 2005). Moreover, studies from both U.S. and European contexts show that health and mortality vary by occupation, with those employed in more physically demanding jobs experiencing more adverse outcomes later in life (e.g., Case & Deaton 2005, Ravesteijn, van Kippersluis & van Doorslaer 2013, 2018, van Kippersluis, O'Donnell, van Doorslaer & Van Ourti 2010). We build on these studies to analyze the effects beyond industry or occupation to address how firms can affect both physical and mental health. Furthermore, in estimating heterogeneous effects, we determine what types of firms most contribute to worker health to help speak to these uneven distributional consequences.

Third, because we are able to connect data on worker health and wages, we generate new suggestive evidence to contribute to the literature on compensating differentials. Following both the long-standing methods in labor economics, and the idea that firms play an important role in workers' lives, we test whether physically and mentally straining firms compensate their workers accordingly and show that unhealthier firms and those with more workplace accidents do indeed pay higher wage premiums. In doing so, we additionally contribute to a smaller literature regarding how firms compensate workers for unhealthier or stressful environments (Bjerk & Mason 2014, Hersch 2011, Makowsky & Bacon 2023, Nagler, Rincke & Winkler 2023, Rao, Gupta, Lokshin & Jana 2003, Wissmann 2022).[2]

2. Institutional Context

2.1. Health Care and Social Security

Austria has a universal health care system with compulsory insurance financed through social security contributions. Health care access is not tied to employment. Since enrollment to the system is automatic, almost 99.9 percent of Austrian residents are covered by health insurance (Ahammer, Wiesinger & Zocher 2021). Provider reimbursement rates are the same across regions.

Health care provision is two-tiered, with most services being provided publicly and parallel private markets existing for outpatient services and specialized hospitals, such as fertility clinics. Since these private suppliers offer the same types of services as public providers, they are used almost exclusively to avoid waiting lines. There is no formal gatekeeping system, but general practitioners (GPs) are typically the first point of access to the health care system. Cost-sharing is limited to minor co-payments for drug prescriptions (around €5 per script) and overnight hospital stays (€9,97 per day in 2018, for a maximum of 28 days). Top-up private insurance is available but only covers single rooms in hospitals and expenses for private physicians. Apart from health

[2] For example, Wissmann (2022) shows that when restaurants and bars in Germany implemented a smoking ban, workers' wages fell while revenues remained constant due to the changing health risk. Similarly, Bjerk & Mason (2014) shows that drug mules are compensated for sentencing risk. Hersch (2011) shows that female workers receive a compensating wage differential for exposure to the risk of sexual harassment, while Rao et al. (2003) finds that female sex workers receive a compensating wage differential for exposure to sexually transmitted diseases. Nagler et al. (2023) estimate sizable pay premiums for high-pressure jobs and, using a stated-choice experiment, show that workers have a willingness-to-pay to avoid such jobs. Makowsky & Bacon (2023) shows that leniency in federal and state enforcement of safety regulations results in employees being paid higher wage premiums for bearing additional fatality risk.

care, the Austrian social security system provides universal access to accident, pension, disability, and unemployment benefits.

2.2. Labor market

The Austrian labor market is characterized by strong industrial relations with centrally bargained wages and working conditions (Böheim 2017). At the same time, the labor market is highly flexible, with particularly weak job protection and high turnover (OECD 2020).[3] Employment contracts can generally be terminated without a given reason, but unilateral terminations require a notice period be observed. Unemployment rates have historically remained low, ranging, for example, from 4.72 in 1998 to 5.21 in 2018 (OECD 2023). Female labor force participation is particularly low, and almost 50 percent of female workers work part-time.

3. Data

3.1. Data Sources

We combine data from several administrative registers. First, we use employment histories from the *Austrian Social Security Database* (ASSD). The ASSD is an employer-employee panel that covers the universe of Austrian workers from 1972 to 2018. We have daily information on employment status, yearly information on wages up to a social security cap, and data on basic demographics, such as age and gender. A drawback of these data is that they do not contain information on working hours and occupational codes. However, the data do contain information on industry codes and occupational blue-collar/white-collar status.

Second, we use health records from the *Upper Austrian Health Insurance Fund* (UAHIF). Upper Austria is one of the nine states of Austria, containing approximately 1.5 million residents. The UAHIF provides us with individual-level health care claims, including drug prescriptions, sick

[3]For example, in 2018, the last year of our data, job turnover for female workers and male workers was 9.6 percent and 9.3 percent, respectively. In comparison, the European Union averages were 8.6 for female workers and 8.1 for male workers. The OECD employment protection legislation indicator is 1.7 for Austria, which is the fifth-lowest value among OECD countries. The United States rank last with an indicator of 1.3.

leaves, outpatient physician visits and hospital stays. These health care utilization data include the amounts spent and also detailed information about the type of health services. Diagnoses—which are only available for hospital stays and sick leaves—are recorded using ICD-10 codes. Drugs are classified using the ATC system. We do not observe emergency department visits. The UAHIF covers all private-sector workers in Upper Austria, which represent around 75 percent of the population, but does not cover self-employed persons, farmers, and civil servants. Health care claims are available from 1998 to 2018.

3.2. Analytic Sample

To construct our sample, we build a worker-year panel covering all private-sector employees between the ages of 15 and 65 in Upper Austria.[4] For workers with multiple jobs in a given year, we keep only the job that pays the highest wage.[5] After dropping workers with missing wage information, we are left with 9,184,913 observations for 1,237,595 workers. For our movers analysis, we focus on a balanced sample of workers that had been employed at least 4 years at their origin firm and remain employed for at least 4 years post-move at their destination firm, although we relax this assumption for additional sensitivity checks. We also allow for multiple moves if a worker had been employed for 8 years at their origin firm and remains employed 4 years post-move at their destination. Only 1 percent of our mover sample move twice, however, according to this definition. This procedure yields 519,228 observations for 57,696 movers.[6]

For placebo analyses, we draw a sample of workers that are employed for at least 9 consecutive years at the same firm and assign a random move between 5 years after their employment spell start and 5 years before their employment spell end.

[4]We drop those after age 65, the statutory retirement age for men in Austria.

[5]Estimates are not sensitive to this choice and are statistically similar at the 1 percent level when omitting workers with multiple jobs.

[6]Removing this pre- and post-move tenure criterion yields data for 260,173 movers. We show below that estimates are not sensitive to this data restriction.

3.3. Measuring Health Care Utilization

The main outcome we study is the logarithm of total health care expenditures, comprising physician expenses, drug expenses, and hospital expenses. These are expenditures in Euros that providers are reimbursed for by the public health insurance. We take logarithms to give less weight to extreme outliers, which are common in health care claims data (Karlsson et al. 2023), and because it allows us to conveniently describe our results in shares (or percents). Because around 10 percent of observations have no health care expenditures in a given year, we add one to health care expenditures before taking logs. In alternative specifications we also estimate Poisson models, which behave well with zero-inflated non-negative continuous outcomes (Correia et al. 2020).

Table 1 presents the summary statistics for our full worker-year panel and for a balanced panel of movers, i.e., workers that switch firms during our sample period. A majority of workers are male and hold blue-collar occupations. Workers are 37 years old, on average. Movers tend to have more firm tenure and have slightly lower health care expenditures as compared to non-movers. When looking at specific types of health care utilization, including outcomes associated with “good" and “bad" health behaviors, accidents, and mental health take-up, formally defined in Appendix B, movers mirror the main sample of workers.

3.4. Variation in Health Care Expenditures

We first present some descriptive figures to show the substantial variation in health care expenditures across firms. In Figure 1, we show the distribution of firms’ health care expenditures, averaged across workers and over all sample years.[7] The mean average per-worker health care expenditures across firms is €517 per year. However, the standard deviation is about twice as large as the mean, at €1,074, suggesting a considerable amount of variation in firm-level average health care expenditures. There are also quite a few firms with very few expenditures, highlighting the fact that health care in Austria is relatively inexpensive, as compared to the U.S. For example,

[7] For visual purposes, we exclude the long right tail by censoring the average yearly health expenditures at €2,000, which is about the 95th percentile.

approximately 14 percent of firms have between €0 and €50 annual, per-worker health care expenditures. Because health care prices are generally low in Austria, this amounts to roughly one physician visit per worker per year, on average.

4. Movers Analysis

4.1. Empirical Approach

Our goal is to estimate how much a firm can influence worker health care utilization. The main challenge to identification in this setting is that many observed and unobserved factors play a role in affecting a worker's decision-making process. Therefore, we estimate the effects of health care expenditures and how they vary for workers that move between firms. This approach relies on the notion that firm-specific stressors change when a worker switches firms, but person-specific characteristics do not.

Similar to Finkelstein et al. (2016), we start by defining a variable δ_i that represents the change in average health care expenditures between the origin and destination firm for mover i. More formally,

$$\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)}, \tag{1}$$

where $\bar{y}_{d(i)}$ represents the average log health care expenditures in the destination firm d, and $\bar{y}_{o(i)}$ represents the average log health care expenditures in the origin firm, o.

Then, we estimate the following event study:

$$y_{it} = \alpha_i + \sum\nolimits_r \theta_r \cdot \hat{\delta}_i + \tau_t + x_{it}\beta + \varepsilon_{it}, \tag{2}$$

where α_i are worker fixed effects, θ_r are time indicators relative to a firm move (in our case from $r = [-4, 4]$, normalizing $r = -1$ to 0), τ_t are calendar-year fixed effects, and x_{it} are additional controls (in our case: age-year fixed effects, industry sector fixed effects, and a dummy variable for blue-collar workers).

Notably, our primary variables of interest in Equation (2) are θ_r, which reflect the changes in health care expenditures around the move. Parameters in years post-move can be interpreted as the weighted average of the share of variation in health expenditures across firms that can be attributed to firms (Finkelstein et al. 2016). Importantly, in using log expenditures, θ_r will be a value between 0 and 1 and can be interpreted as the firm's contribution to health care expenditures. The larger the effect of δ_i on y_{it} at time $t = 0$, the larger the share of variation in health care expenditures that can be attributed to the firm.

We display the estimate for θ_0 in our main figures to focus mainly on the jump in utilization at the time of the move. In other words, if firms do not affect worker health, we would expect $\hat{\theta}_0$ to be equal to zero, implying that health care utilization is entirely driven by worker preferences and demand. If the firms are the only contributor to medical spending, we would expect $\hat{\theta}_0$ to be equal to one.

Our empirical approach relies on the idea that workers move to new firms with differential levels of health care utilization. In other words, identification comes from the variation in the changes across movers with different origins and destinations. Below, we present evidence that reinforces that the move patterns are also consistent with the relative importance of patients being similar across origin-destination pairs.

Our approach also relies on the idea that timing of the move does not correspond to other simultaneous changes to worker health. Our estimates may be biased, for example, if a worker moves to a high-utilization firm after experiencing a negative health condition. In this case, we would overstate the contributions of the firm.

We account for these possibilities in a number of ways. First, we note that movers and non-movers are similar in terms of observable characteristics, like age, wage, and health behaviors, although movers have longer job tenure and slightly lower health expenditures (see Table 1). Moreover, we show that movers are not systematically moving to low-utilization firms, and we additionally provide evidence that non-movers do not experience a change in the firm contributions to health care utilization when assigned a random move date.

Second, we note that any deteriorating health effects or large health shocks leading up to a move would likely appear as a pre-trend on our event study figures. And, if an acute health shock in $t = 0$ is responsible for a worker switching firms, we would expect to observe a jump at $t = 1$, with effects fading over time. We present evidence against these patterns of worker-firm sorting in our event-study figures, providing additional support for our identification assumption. Specifically, we present a figure showing the variation in worker moves across the firm expenditure distribution and test for health care expenditure event-study pre-trends to show that worker health expenditures do not react to destination firm utilization.

Finally, we note that when workers move firms, they are also potentially moving places, which has been shown to be an important determinant for health care expenditures (Finkelstein et al. 2016). Below we test the extent to which workers that move zip codes at the time of the firm switch and show that workers moving places are not driving our findings. We additionally show that the convergence in health care utilization is not a result of workers changing industries or changing firms after childbirth.

4.2. Variation in Firms' Health Care Expenditures Among Movers

In this section we present descriptive evidence to further motivate our mover event studies, before presenting our main results. In particular, Figure 2 shows the distribution of the difference in log health expenditures between the destination and origin firm, δ_i. It reveals several findings. First, the distribution is centered around zero, indicating that some movers move to firms with higher expenditure firms than their origin firm, while some do the opposite. Second, the distribution is symmetric, which strongly suggests that moves to new firms are not dictated by the expected health care expenditures of the origin or destination firm. Third, the mean difference between destination and origin firm utilization is positive, implying that, if anything, more workers move to higher-expenditure firms than lower-expenditure firms, on average. This suggests that systematic sorting of workers to low-utilization firms is unlikely.

4.3. Changes in Utilization Patterns

We note that this documented variation in firm health care utilization is also positively correlated with the change in the worker's log health care expenditure after a move, and we present two pieces of evidence to support this relationship as a prelude to our event study results. To start, we investigate whether average expenses for workers that move from firms in the top quartile of the firm health expenditure distribution to the bottom quartile converge to their destination firm averages, and vice versa, and present these descriptive trends in Figure 3. Panel (a) displays trends for workers moving away from high-utilization firms, while Panel (b) displays trends for workers moving away from low-utilization firms.

These pictures reveal three facts: (i) workers moving to low- and high-utilization firms have similar spending patterns both in levels and trends prior to the move, (ii) workers moving to destination firms with similar expenditure levels do not change their own health care utilization practices, and (iii) workers moving to firms with starkly different average expenditure levels change their own behavior, in both spending levels and trends, to converge to the new firm. Putting these magnitudes into context, a move from a firm with high utilization to a firm with low utilization reduces a worker's own health care expenditures by €236.2, or 37 percent, while a move from a low utilization firm to a firm with high utilization increases health care expenditures by €543.4, or 190 percent.

When quantifying this relationship more formally, these patterns are again echoed across the distribution. Figure 4 plots the change in the worker's log health care expenditures against the difference in the log health care expenditures between the destination and origin firm. The difference in the destination to origin health care expenditures—the horizontal axis—are split into ventiles and the change in workers' health care expenditures—the vertical axis—are averaged in each ventile.

Figure 4 shows that workers moving to firms with higher (lower) health care expenditures also increase (decrease) their own expenditures. The upward slope of this line indicates that movers' health care expenditures change by 37.4 percent for a 100 percent increase in the difference between the destination and origin average health care expenditure. Motivated by these findings, we present event study estimates from our main models in the next section which account for potential confounders and help us explore potential drivers behind this relationship.

4.4. Main Results

Figure 5 presents the event study estimates for workers that move firms in our sample period. The estimates correspond to Equation (2) for four years prior to and four years after a move. Before the move, workers experience no systematic change in health care expenditures, providing some support for the idea that health conditions are not the cause for moving firms.

If health care expenditures are solely determined by worker preferences, we should see no change in expenditures. On the other hand, if health care expenditures are explained entirely by the firm, the shift at $t = 0$ would be equal to one. We show that, after a move, health care expenditures attributed to the firm converge to 29 percent after just one year. This immediate jump in the event study after a worker switches firms provides the primary piece of evidence to show that firms play a critical role in health care expenditures.

Moreover, estimates in Figure 5 indicate that this change in firm contributions stays above 29 percent and continually increases one year after the move, indicating potential habit formation. After four years, the firm's share of the worker's health care expenditures is 41.7 percent. These findings provide support for the idea that workers do not largely change firms due to health shocks or deteriorating health conditions and that the firm continues to affect worker health care utilization long after the initial move.

In Figure A.1 we test if these estimates differ across subsamples of the population. We find little heterogeneity by occupation, age, and gender. When estimating effects for workers with high baseline health expenditures, we find that firms seem to matter more than if we only sample workers with low baseline expenditures. Firm shares estimates are 34 percent for high-expenditure workers but only 19 percent for low-expenditure workers.

4.5. Alternative Explanations and Robustness Tests

In this section, we examine whether our effects can be explained by changes in worker location or industry and test the sensitivity of our event-study estimates. Recent work suggest that geography plays an important role in health care utilization and the frequency of specific health treatments (Chandra, Cutler & Song 2011, Finkelstein, Gentzkow & Williams 2016). In fact, if all workers moving firms required a relocation, we would not be able to easily distinguish between firm and geography effects on health care expenditures. Fortunately, only 31 percent of movers in Upper Austria relocate to another county, implying that firms, and not geographic location, are likely responsible for any estimated effects. More formally, we test the sensitivity of our main results, using only the subsample of workers who move firms but did not change county of residence. Estimates in the left panel of Figure 6 shows a nearly identical result to our main event study, providing additional reassurance that our findings are not simply a result of changes in geographic location.

Related to the above finding that our results are not primarily driven by individuals that move zip codes, the right panel of Figure 6 shows that results are larger for workers that switch firms but not industries. Only 37 percent of workers switched industries when they moved firms, suggesting that changes in industry are not the main factor behind our results.

We also show that our results are robust when omitting workers that had children during our sample period. Because having children drives up health care spending, a concern is that we wrongly attribute changes in health expenditures to firms if firm moves coincide with childbirth. Results in Figure A.2 suggest, however, that estimates are practically unchanged if we only look at movers that did not have children during the observation window.

Furthermore, as an additional robustness check, we test that our estimates are not sensitive to the minimum number of years a worker has to be employed at the origin and destination firm. See Figure A.3 for event study estimates when we relax this 4-year tenure criterion. Estimates are all statistically similar to our main estimates at the 5 percent level and range between 0.18 to 0.36, indicating that the firm contributes between 18 and 36 percent of worker's health care expenditures.

Even for a 7-year pre- and post-move tenure window, we cannot reject firm contributions up to 27 percent. Importantly, this suggests that our results are not only applicable to more stable firms or workers with longer work histories, but also applies to all workers that stay in a firm for at least a year.

We also note that our results are not sensitive to functional form or covariate choice. In our main specification, we take logs and add 1 to account for workers with zero health care expenditures in a given year. As a robustness check, we show estimates from a Poisson model, similar to Badinski et al. (2023).[8] Poisson has several desirable properties for non-negative zero-inflated continuous data (Correia et al. 2020). The estimated firm share using Poisson is 35 percent, which is similar to our main finding (Figure A.4). In Table A.1, we additionally show that different sets of covariates and fixed effects have little influence on our firm share estimate.

Lastly, we perform a placebo test in which we randomly draw δ_i for movers, akin to randomly assigning origin and destination firms. In Figure 7, we present an event-study plot using our main sample of movers, but randomize δ_i. Just as in our main event study, any jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in health care expenditures attributable to firms. We estimate a statistically insignificant jump for movers, which suggests that any and all changes in worker health care expenditures at the move are due to differences in average firm health. We have also estimated a placebo check using non-movers, i.e., workers that did not change firms for at least 9 consecutive years. When we randomly assign a moving date and simulate a δ_i with the same moments as the actual δ_i in Figure 2, estimates indicate no change in the firm's contribution towards health care expenditures (Figure A.5). This indicates that there are likely no other systematic events unrelated to firm moves that cause discontinuous jumps in worker health care expenditures over time.

[8]The Poisson equivalent of Equation 2 we estimate is

$$E(y_{it}) = \exp\left(\alpha_i + \sum\nolimits_r \theta_r \cdot \hat{\delta}_i + \tau_t + x_{it}\beta + \varepsilon_{it}\right),$$

where the $\hat{\theta}_0$ has a similar interpretation as in our main specification.

4.6. Understanding Potential Drivers

In this section, we analyze potential explanations as to why firms contribute about 30 percent to an individuals' health care expenditures. We first investigate whether the changes in utilization from switching firms is likely to be moreso a result of changes in health, health care take-up, or health behaviors. We then provide evidence on the role of workplace peers and environment on health care expenditures. We note that the evidence for each piece cannot stand alone in explaining the mechanisms behind our findings. But, altogether, our results weave a cohesive narrative.

4.6.1. Health Status and Health Care Take-Up

To start, we analyze whether the change in expenditures after workers move firms is due to changes in actual *health status* (i.e., well-being), or changes in health care *take-up* (i.e., spending for health care services, conditional on health status). Notably, our main event study, Figure 5, helps to inform whether switching firms systematically affects health. In particular, we estimate no gradual change in health care expenditures for workers prior to switching firms. In other words, the observed sharp changes in health expenditures in $t = 0$ (which cannot be a result of changes in health insurance coverage) are more likely measuring changes in utilization rather than health status. Additionally, the change in health care expenditures does not fade out over time, suggesting habit formation, rather than existing pent-up demand.

Given this hypothesis, we explore more direct measures of health care take-up. Two main ideas support the notion that firms motivate workers to change their health care utilization: (i) firms encourage new employees to get screenings or other preventative care as part of a workplace wellness initiative; and/or (ii) the firm allows for more generous time off policies, granting workers the ability to visit a physician at will.

To investigate changes in take-up, we separate expenditures that may reflect real changes in health status versus types of expenditures that reflect demand for health care services. We start by noting that, in Austria, physicians serve as gatekeepers for drug prescriptions and non-acute inpatient care. Therefore, obtaining a prescription drug or receiving more testing or hospitalization services is a two-step process. Individuals that are seeking health care services for both non-acute illness and preventative care will visit a physician. Beyond that, any take-up in prescription drugs or inpatient care likely reflects both utilization, broadly speaking, as well as a need for health care services due to poor health.

We estimate effects for these two types of health care spending separately and present the corresponding event studies in Figure 8. Both event studies appear similar to our main event studies for total expenditures. Estimates indicate that the convergence to firm contributions for physician expenditures is larger than the convergence for drug and inpatient expenditures (35.8 percent versus 19.8 percent).

These findings reveal three conclusions. First, the change in physician expenditure contributions is large and immediate, consistent with the notion that the firm affects changes in health care take-up. Second, the change in drug and inpatient expenditures could partly be driven by changes in underlying health conditions. However, as noted above, seeing a doctor more frequently is highly correlated with receiving prescription drugs and/or hospital services, implying that any changes at move may also be related to health care take-up. Third, the post-move upward trend is stronger for drug and inpatient expenditures (i.e., outcomes that more likely measure underlying health status), supporting the idea that the firm contributes to both health care take-up and health status in the longer run.

To build on the finding that some firms may allow workers the chance to seek health care services, and other firms less so, we test whether firms also contribute to whether workers take off more workdays for illness. In Figure A.6 we present event studies for sick leave take-up. Sick leave in Austria is an entitlement program compensating workers for lost earnings due to disease. Firms compensate workers for 6 to 12 weeks, depending on job tenure.[9] To take sick leave, employees are obligated to notify their employer immediately. Firms may require workers to produce a doctor's note and workers are required to produce one for leaves greater than four days.[10] As shown in the

[9]After this period, workers can receive a replacement rate ranging from 60–80 percent for an additional four weeks.

[10]Physician-provided notes do not contain a diagnosis and it is forbidden for employers to require employees to disclose medical conditions.

figure, firms are responsible for 31.7 percent of sick leave take-up. Therefore, we note that one way in which firms affect health may be the culture surrounding taking time off for illness or having the time to visit a physician during the workday.

4.6.2. Health Behaviors

Next, we explore to what extent a firm contributes to an individual's health behaviors. On one hand, firms may improve worker health by encouraging workers to get vaccines, wash their hands, or engage in other types of preventative health care. On the other hand, firms may also contribute to riskier behaviors, like smoking or drinking.

One limitation of our data is that we cannot see daily behaviors like hygiene practices, drinking frequency, or exercise routines. However, we do observe proxies for healthy and unhealthy behaviors, like preventative health care screenings, prescription drug take-up for smoking cessation or weight loss, sexually transmitted disease diagnoses, and variables for more serious health outcomes related to risky behaviors, like alcohol misuse. For simplicity, we analyze the firm's contributions on two categories of behavior, labeled "good" and "bad" health behaviors. For the full description and inclusion of the diagnosis and prescription codes included in each of these outcomes, see Appendix B.

We present the event studies for good and bad health behaviors in Figure 9 and find that firm shares on these good and bad health behaviors are even larger than the overall shares we previously documented. The firm contribution is 43.7 percent for "good" health behaviors and 59.3 percent for "bad" health behaviors. These findings suggest not only that health behaviors are in important driver of changes in health care utilization, but that firm contributes even moreso to the types of expenditures that are closely related to behavioral changes.

4.6.3. Peer Effects

Given that we find evidence of firms affecting both types of health behaviors, and given the recent evidence that some health behaviors are highly correlated among workers in Austria (Pruckner, Schober & Zocher 2020), we now turn to the question of whether this effect is driven by peers or is instead driven by something inherent in the workplace. In Appendix C, we first show that health care expenditures are strongly correlated within peer groups, as defined by age, gender, and blue/white collar occupation status. In particular, we run regressions of a worker's health care expenditures on average peer-group expenditures. Even after controlling for time-invariant heterogeneity in worker health status, we find a significant correlation. Peers also influence health behaviors. Estimates indicate that peers are much more influential for adverse, or "bad," health behaviors, contributing 61.6 percent. However, peers also affect positive health behaviors, contributing to a worker's "good" behaviors by over 37 percent. Altogether, estimates indicate that peer correlations are much larger for behaviors than for overall health care utilization, suggesting that peers influence certain types of decision-making more than others.

Additionally, we estimate separate event studies for the effects of differences in peer-group and non-peer group (i.e., all other workers in a worker's firm) averages in health care expenditures between the origin and destination firm. This allows us to calculate the weighted average of the share of variation in health expenditures that can be attributed to a worker's destination-firm peers and non-peers. Differences in peer-group averages are much more important in explaining a worker's health care expenditures than differences in non-peer group averages. Together, these results suggest that peer effects are an important factor in determining workers' health care utilization.

4.6.4. Workplace Safety

Firms can also affect worker health expenditures through the dangers presented in the workplace. For example, even within occupation, workers moving to firms that include a higher probability of injury may also experience an increase in health care expenditures. We test this hypothesis directly using data on accidents and injuries, including those that occur at the workplace. We provide the event study in Figure 10. Estimates are similar to those of our main results, albeit larger in magnitude, suggesting that workplace safety is an important input in worker health care utilization.

4.6.5. Workplace Environment

Lastly, we note that workplace culture, or environment, may affect a worker's health care expenditures. For example, stressful work environments may lead to higher health care utilization, and we may expect this relationship to grow over time. Alternatively, workplace amenities or incentive programs may promote healthier behaviors and lead to lower utilization. Indeed, one solution to rising health costs that firms have pointed to in recent years is workplace wellness initiatives. However, recent evidence shows that employer-sponsored programs in the U.S. have been relatively unsuccessful, due to positive selection of participants, and do not change health spending or self-reported health status (Jones, Molitor & Reif 2019). This evidence suggests that the firm affects health more systematically through workplace environment than through healthy behavior nudges. We investigate this relationship in greater detail below.

We note that one limitation of our data is that we cannot look directly at workplace amenities or wellness programs, nor can we analyze stress directly. However, we are able to analyze effects on mental health outcomes, which may be highly related to stress experienced in the workplace. In particular, we perform the same baseline analysis described in Equation (2) to estimate the contribution of the firm on mental health care take-up. This outcome variable includes take-up of mental health drugs, like antidepressants and anti-anxiety medication, as well as visits to therapists other mental health professionals. In doing so, we can provide weak evidence on one such channel–stress–that may explain why firms contribute to worker health care expenditures.

We present event study estimates on mental health care take-up in Figure 11. Estimates indicate that the firm plays an important role in mental health expenditures. Together with our other results, this implies that firms not only contribute to a worker's health care utilization through peers and safety, but also through the demands of the job and/or management style in practice.

5. What's Behind Firm-Specific Health Care Expenditures?

The previous section establishes that there is a wide distribution of average per-worker health care expenditures across firms and that the average firm contributes to nearly one-third the amount of workers' health care expenditures. We also present evidence to suggest these effects are explained by a combination in both good and bad health behaviors, peer effects, and workplace environment. To better understand how our estimates may vary by industry or types of firms, we now introduce a new measure for *firm-specific* contributions to health care expenditures. In particular, we estimate models with additive worker and firm fixed effects, which allow us to recover an estimate for each firm's contribution to health care expenditures, conditional on characteristics of its workforce.

These firm-specific estimates of health care expenditures allow us to explore several lines of inquiry. For example, using this approach, we can examine correlates with the firm-specific impacts on health care expenditures. Due to the rich nature of the data, we are able to test whether firms with higher levels of expenditures have particular characteristics related to age, size, industry, or family friendliness, allowing us to observe what types of firms may have healthier workplaces, on average. We also use data on workplace accidents by industry, which should directly affect health care expenditures.

Moreover, we analyze how the firm-specific impacts on health care expenditures relate to the firm-specific impacts on wages. We note that how wages vary with working conditions speaks to an old and unsettled literature on compensating differentials. The theory predicts that workers should be compensated for undesirable working conditions. Some fraction or subset of our health care expenditures are certainly undesirable and may arise from the firm itself. We link individual-level data on health expenditures, firms, and wages to directly answer this question and supplement our analysis with data on workplace accidents to better speak to the effects of the firm on worker health.

We begin below by describing the estimation strategy. Then we present the firm-specific estimates and explore some of the described relationships.

5.1. Additive Model of Health Care Expenditures

First, we disentangle the factors of our health care expenditure variable attributable to worker-specific and firm-specific heterogeneity by fitting models for log health care expenditures that account for unobserved worker and firm characteristics and worker age. Our goal is to estimate a model that allows us to capture the components attributable to firms, holding worker characteristics constant. Following Abowd et al. (1999), we estimate the following models with additive worker and firm fixed effects:

$$\log y_{it} = \alpha_i + \theta_j + x_{it}\beta + \varepsilon_{it}, \tag{3}$$

where α_i represents worker fixed effects, and θ_j represents firm fixed effects. We additionally control for worker-specific observed characteristics; x_{it} contains a dummy variable for blue-collar worker status as well as variables for age and work experience.

Our main outcome of interest, y_{it}, represents health care expenditures. Similar to our movers design, we use a log expenditure model to maintain the implication that worker and firm characteristics affect the level of utilization multiplicatively. Thus, the model implicitly assumes that the utilization of workers who are sick or prefer intensive care will vary more across firms than that of workers who are healthy or rarely seek care.

Importantly, θ_j can be interpreted as the firm contributions to log health care expenditures. Our additive fixed effects imply that θ_j is orthogonal to worker characteristics ($\alpha_i + x_{it}\beta$). This implies that any estimates of θ_j are not a result of worker demographics such as age, or behavioral factors, like poor diet or smoking. Moreover, estimates of both worker effects ($\alpha_i + x_{it}\beta$) and firm fixed effects (θ_j) allow us to calculate an additive decomposition of log health care expenditures between high- and low-expenditure firms to identify how workers and firms separately contribute to log utilization.

In subsequent analyses, we then explore the correlates of these firm-specific health care expenditures by estimating how firm characteristics correlate with θ_j. In other words, we estimate the following model:

$$\hat{\theta}_j = x_j \lambda + \varepsilon_j, \tag{4}$$

where x_j represents firm characteristics, including firm age and size, measures for industry concentration and unionization, leadership, and measures of family friendliness. These correlations inform what types of firms have the potential to drive health care expenditures for workers and in which direction.

5.2. Firm-Specific Impacts on Health Care Expenditures

Figure 12 shows the distribution of estimated firm fixed effects for health care expenditures from Equation (3). By construction, it is centered around zero and it also has a standard deviation of 0.60. The figure shows that there is variation in firms being classified as “high-expenditure" or “low-expenditure" firms. Moreover, the long tails imply that moving from the left to right tails of the distribution is a very big change in the type of firm, but that moves for most workers will be less consequential.[11]

Additionally, Table 2 presents the additive decomposition of log health care expenditures. To display information on how firms and workers contribute across the health care expenditure distribution, we separately present the differences in average log expenditures for firms above and below the median log expenditures (Column 1), for firms in the top and bottom quartile of expenditures (Column 2) and for firms in the top and bottom decile of expenditures (Column 3). We present the difference in the average of the above estimated effects for workers ($\hat{\alpha}_i + x_{it}\hat{\beta}$) and firms ($\hat{\theta}_j$) in the bottom two rows, respectively. We find that the difference in average log health care expenditures is primarily driven by workers, with firms also largely contributing to this effect. Similar to our event study results, we find that firms make up 36 percent of the difference in average health care expenditures across all firms, with this share ranging between 39–45 percent for the

[11]Showing this more directly, Table A.2 shows each firm health care expenditure fixed effect decile, while Column 2 presents the average difference, relative to decile 1. The lowest decile firm has an average health care expenditure of about €315 and the second decile jumps 61 percent to €508. Ultimately, the tenth decile is 131 percent the average expenditures as the first decile.

firms that comprise the tails of the expenditure distribution.

5.3. Firm Health Care Expenditure Heterogeneity

5.3.1. Firm Characteristics

The results described above indicate that firm expenditure levels can affect worker health care utilization, on average, but may mask important heterogeneity. Given that firms vary along many dimensions, we then ask to what extent these effects change across firm types. In Figure 13 we plot coefficients from a regression of the estimated health fixed effect, $\hat{\theta}_j$, from Equation (4), on the listed firm characteristics. In particular, we analyze whether firm characteristics including age, size, location, industry concentration and median wages explain whether a firm is likelier to have lower or higher health care expenditures. Moreover, we consider whether the firm has a female CEO, the share of female workers, and the share of workers on parental leave—all potential measures of "family friendliness". We additionally include the share of blue-collar workers and share of unionized workers, to reflect worker protections.

Overall, we find that firms that are larger, younger, more urban, have higher wages, and have a female CEO are more likely to have lower health care utilization. Firms with more blue-collar workers and unionized workers are also lower-expenditure firms. In comparison, firms that are in more highly concentrated industries and are older have higher average health care expenditures in our context. A potential explanation is that incumbent firms with monopsony power, where workers have fewer outside options, have less incentive to provide a healthy workplace.

When analyzing effects by industry, we find that sectors including manufacturing and construction contain relatively high-utilization firms, while public administration firms maintain lower overall health care utilization (Figure A.7).

5.3.2. Health Care Expenditures and Wages

Since firms directly affect wages, we additionally consider the extent to which health care utilization and wages may be related. First, in Figure 14, we present distributions for worker health and wage fixed effects. While worker health fixed effects are symmetric and centered around zero, with a standard deviation of 1.84, the distribution for wage fixed effects is more tightly centered around zero, with a standard deviation of only 0.43.

Theory predicts that physically and mentally straining firms should compensate their workers accordingly. Given that we find that individuals moving to firms with higher average health care expenditures also increase their own expenditures, we test whether there is a correlation between firm wage premiums and our estimated firm health fixed effects. In Figure 15 we present evidence that there is indeed a positive correlation, suggesting that higher-utilization firms also offer higher wage premiums.

A natural next question is whether firms are compensating for safety on the job, tying into the evidence on work environment, presented in Section 4.6. We investigate this in Figure 16. The left and right panels of Figure 16 display the average firm health fixed effects and wage fixed effects, respectively, based on the industry accident rate (i.e., the number of accidents per 1,000 workers). Both plots show a modest positive relationship. In other words, estimates indicate that as the accident rate increases, firm health expenditures also increase, suggesting that firm accidents necessitate immediate care. However, we also find that as accidents increase, firm wage fixed effects increase. These results fit into a large literature showing that firms compensate workers for job risk and/or poor working conditions (Lavetti 2023, Rosen 1986, Viscusi & Aldy 2003). Our results also expand on work using similar methods that shows that firms account for between 5 and 25 percent of the variation in workers' wages (Bonhomme, Holzheu, Lamadon, Manresa, Mogstad & Setzler 2023, Card, Heining & Kline 2013).

6. Conclusion

In this paper, we provide new evidence that firms play a major role in workers' health care utilization. We use individual-level data linked with health outcomes for Upper Austrian workers and leverage migration of workers to estimate a model that allows us to account for differences across worker characteristics. Our estimates indicate that firms are responsible for nearly 30 percent of workers' health care utilization. These effects are not driven by changes in health insurance, changes in firm location, or industry switching. We show that these effects are a consequence of some combination of peer effects, workplace safety, and/or firm-specific job stressors. In particular, we find that peer utilization influences worker's own utilization, and show that peers in destination firms largely contribute to both positive and adverse health behaviors. Firms also contribute to mental health expenditures, providing suggestive evidence that workplace environment can affect worker health through psychosocial channels. We provide little evidence that firm moves are correlated with changes in health diagnoses nor that firms themselves contribute to changes in health status.

We then test what firm characteristics are more likely to explain higher average expenditures and estimate an additive fixed effects model to establish a measure of firm utilization. We find that younger firms, larger firms, and firms with higher wages have lower health care expenditures, on average. Building on a literature on the relationship between wages and health, we find that firms with higher health care expenditures and more workplace accidents pay higher wages, consistent with a theory of compensating differentials.

Overall, our findings contribute to a growing literature showing that physicians and place-based determinants drive decision-making for workers' health care take-up. Using more granular data, we are able to speak to an important determinant of work behavior: firms. Our findings thus have important policy implications, especially given the evidence that workplace wellness programs in the U.S. have been relatively unsuccessful (Jones et al. 2019). Since many lawmakers and non-profit organizations maintain targets for making workplaces safer and workers physically healthier, we note that achieving these goals could be one avenue to improve total social welfare.

References

Abowd, J. M., Kramarz, F. & Margolis, D. N. (1999), 'High Wage Workers and High Wage Firms', *Econometrica* **67**(2), 251–333.

Ahammer, A., Grübl, D. & Winter-Ebmer, R. (2023), 'The Health Effects of Downsizing Survival', *Review of Economics and Statistics* **forthcoming**.

Ahammer, A. & Schober, T. (2020), 'Exploring variations in health-care expenditures—What is the role of practice styles?', *Health Economics* **29**(6), 683–699.

Ahammer, A., Wiesinger, R. & Zocher, K. (2021), The Austrian Healthcare System: Changes and Challenges, *in* B. H. Baltagi & F. Moscone, eds, 'The Sustainability of Health Care Systems in Europe', Vol. 295 of *Contributions to Economic Analysis*, Emerald Publishing Limited, pp. 153–166.

Aron-Dine, A., Einav, L. & Finkelstein, A. (2013), 'The RAND Health Insurance Experiment, Three Decades Later', *Journal of Economic Perspectives* **27**(1), 197–222.

Badinski, I., Finkelstein, A., Gentzkow, M. & Hull, P. (2023), 'Geographic Variation in Healthcare Utilization: The Role of Physicians'.

Bjerk, D. & Mason, C. (2014), 'The market for mules: Risk and compensation of cross-border drug couriers', *International Review of Law and Economics* **39**, 58–72.

Böheim, R. (2017), 'The labor market in Austria, 2000–2016', *IZA World of Labor* **408**.

Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M. & Setzler, B. (2023), 'How Much Should We Trust Estimates of Firm Effects and Worker Sorting?', *Journal of Labor Economics* **41**(2), 291–322.

Bronnenberg, B. J., Dubé, J.-P. H. & Gentzkow, M. (2012), 'The Evolution of Brand Preferences: Evidence from Consumer Migration', *American Economic Review* **102**(6), 2472–2508.

Card, D., Heining, J. & Kline, P. (2013), 'Workplace Heterogeneity and the Rise of West German Wage Inequality', *Quarterly Journal of Economics* **128**(3), 967–1015.

Caroli, E. & Godard, M. (2016), 'Does job insecurity deteriorate health?', *Health Economics* **25**(2), 131–147.

Case, A. & Deaton, A. S. (2005), Broken Down by Work and Sex: How Our Health Declines, *in* D. A. Wise, ed., 'Analyses in the Economics of Aging', University of Chicago Press, pp. 185–212.

Chandra, A., Cutler, D. & Song, Z. (2011), Who Ordered That? The Economics of Treatment Choices in Medical Care, *in* M. V. Pauly, T. G. Mcguire & P. P. Barros, eds, 'Handbook of Health Economics', Vol. 2 of *Handbook of Health Economics*, Elsevier, pp. 397–432.

Correia, S., Guimarães, P. & Zylkin, T. (2020), 'Fast Poisson estimation with high-dimensional fixed effects', *Stata Journal* **20**(1), 95–115.

Cottini, E. & Ghinetti, P. (2018), 'Employment insecurity and employees' health in Denmark', *Health Economics* **27**(2), 426–439.

Defebvre, É. (2018), 'Harder, better, faster ... Yet stronger? Working conditions and self-declaration of chronic diseases', *Health Economics* **27**(3), e59–e76.

Finkelstein, A., Gentzkow, M. & Williams, H. (2016), 'Sources of Geographic Variation in Health Care: Evidence From Patient Migration', *Quarterly Journal of Economics* **131**(4), 1681–1726.

Finkelstein, A., Gentzkow, M. & Williams, H. (2021), 'Place-based drivers of mortality: Evidence from migration', *American Economic Review* **111**(8), 2697–2735.

Fletcher, J. M., Sindelar, J. L. & Yamaguchi, S. (2011), 'Cumulative effects of job characteristics on health', *Health Economics* **20**(5), 553–570.

Gihleb, R., Giuntella, O., Stella, L. & Wang, T. (2022), 'Industrial robots, Workers' safety, and health', *Labour Economics* **78**, 102205.

Green, F. (2011), 'Unpacking the misery multiplier: How employability modifies the impacts of unemployment and job insecurity on life satisfaction and mental health', *Journal of Health Economics* **30**(2), 265–276.

Hersch, J. (2011), 'Compensating Differentials for Sexual Harassment', *American Economic Review* **101**(3), 630–634.

Johnston, D. W., Shields, M. A. & Suziedelyte, A. (2020), 'Macroeconomic Shocks, Job Security, and Health: Evidence from the Mining Industry', *American Journal of Health Economics* **6**(3), 348–371.

Jones, D., Molitor, D. & Reif, J. (2019), 'What do Workplace Wellness Programs do? Evidence from the Illinois Workplace Wellness Study', *Quarterly Journal of Economics* **134**(4), 1747–1791.

Karlsson, M., Wang, Y. & Ziebarth, N. R. (2023), Getting the Right Tail Right: Modeling Tails of Health Expenditure Distributions, Working Paper 31444, National Bureau of Economic Research.

Lavetti, K. (2023), 'Compensating Wage Differentials in Labor Markets: Empirical Challenges and Applications', *Journal of Economic Perspectives* **37**(3), 189–212.

Makowsky, M. D. & Bacon, K. R. (2023), The wages of irregular tasks: Workers' compensation benefits and occupational misclassification, Working paper.

Marmot, M., Bosma, H., Hemingway, H., Brunner, E. & Stansfeld, S. (1997), 'Contribution of job control and other risk factors to social variations in coronary heart disease incidence', *Lancet* **350**(9073), 235–239.

Marmot, M. G., Smith, G., Stansfeld, S., Patel, C., North, F., Head, J., White, I., Brunner, E. & Feeney, A. (1991), 'Health inequalities among British civil servants: the Whitehall II study', *Lancet* **8**, 1387–1393.

Nagler, M., Rincke, J. & Winkler, E. (2023), 'High-Pressure, High-Paying Jobs?', *Review of Economics and Statistics* **forthcoming**.

Newhouse, J. P., Garber, A. M., Graham, R. P., McCoy, M. A., Mancher, M. & Kibria, A. (2013), *Variation in Health Care Spending: Target Decision Making, Not Geography*, National Academies Press, Washington, D.C.

OECD (2020), Employment Outlook 2020, Technical report, Organisation for Economic Cooperation and Development.

OECD (2023), Unemployment rate, OECD Data, accessed December 21, 2023.

Ose, S. O. (2005), 'Working conditions, compensation and absenteeism', *Journal of Health Economics* **24**(1), 161–188.

Pruckner, G. J., Schober, T. & Zocher, K. (2020), 'The company you keep: Health behavior among work peers', *European Journal of Health Economics* **21**, 251–259.

Rao, V., Gupta, I., Lokshin, M. & Jana, S. (2003), 'Sex workers and the cost of safe sex: The compensating differential for condom use among Calcutta prostitutes', *Journal of Development Economics* **71**(2), 585–603.

Ravesteijn, B., van Kippersluis, H. & van Doorslaer, E. (2013), The Contribution of Occupation to Health Inequality, *in* O. O'Donnell & P. Rosa Dias, eds, 'Health and Inequality', Vol. 21 of *Research on Economic Inequality*, Emerald Group Publishing Limited, pp. 311–332.

Ravesteijn, B., van Kippersluis, H. & van Doorslaer, E. (2018), 'The wear and tear on health: What is the role of occupation?', *Health Economics* **27**(2).

Reichert, A. R. & Tauchmann, H. (2017), 'Workforce reduction, subjective job insecurity, and mental health', *Journal of Economic Behavior & Organization* **133**, 187–212.

Rosen, S. (1986), The theory of equalizing differences, *in* O. C. Ashenfelter & R. Layard, eds, 'Handbook of Labor Economics', Vol. 1, Elsevier, pp. 641–692.

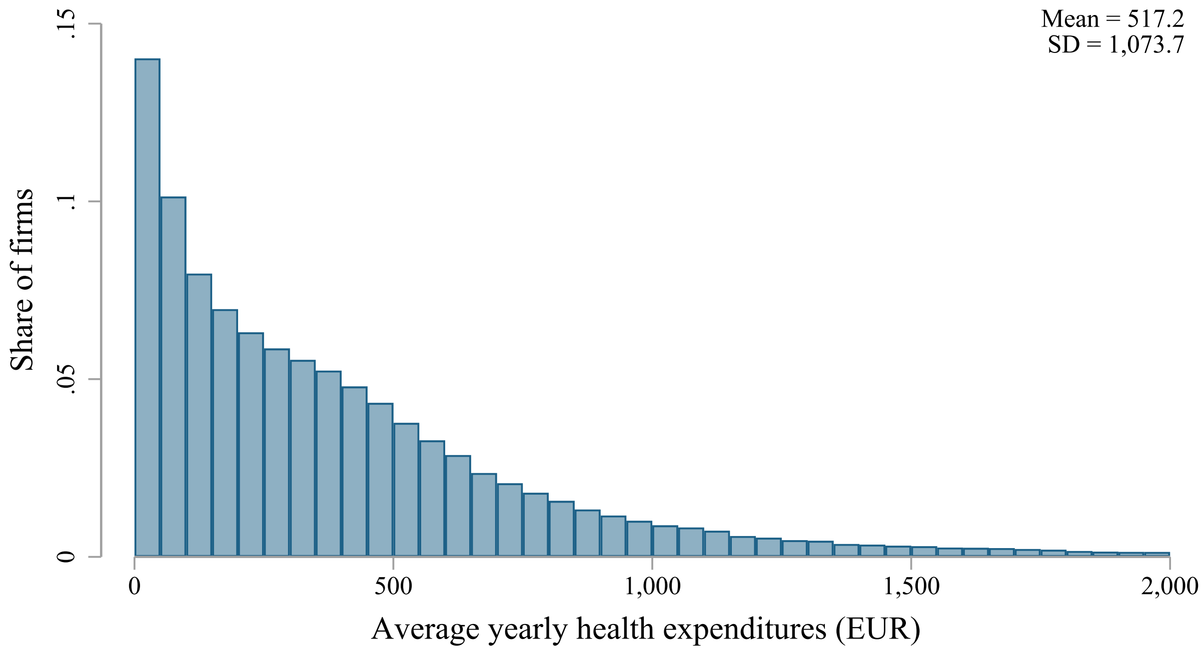
van Kippersluis, H., O'Donnell, O., van Doorslaer, E. & Van Ourti, T. (2010), 'Socioeconomic differences in health over the life cycle in an Egalitarian country', *Social Science & Medicine* **70**(3), 428–438.

Viscusi, K. W. & Aldy, J. (2003), 'The value of a statistical life: A critical review of market estimates throughout the world', *Journal of Risk and Uncertainty* **27**, 5–76.

Wissmann, D. (2022), 'Finally a Smoking Gun? Compensating Differentials and the Introduction of Smoking Bans', *American Economic Journal: Applied Economics* **14**(1), 75–106.

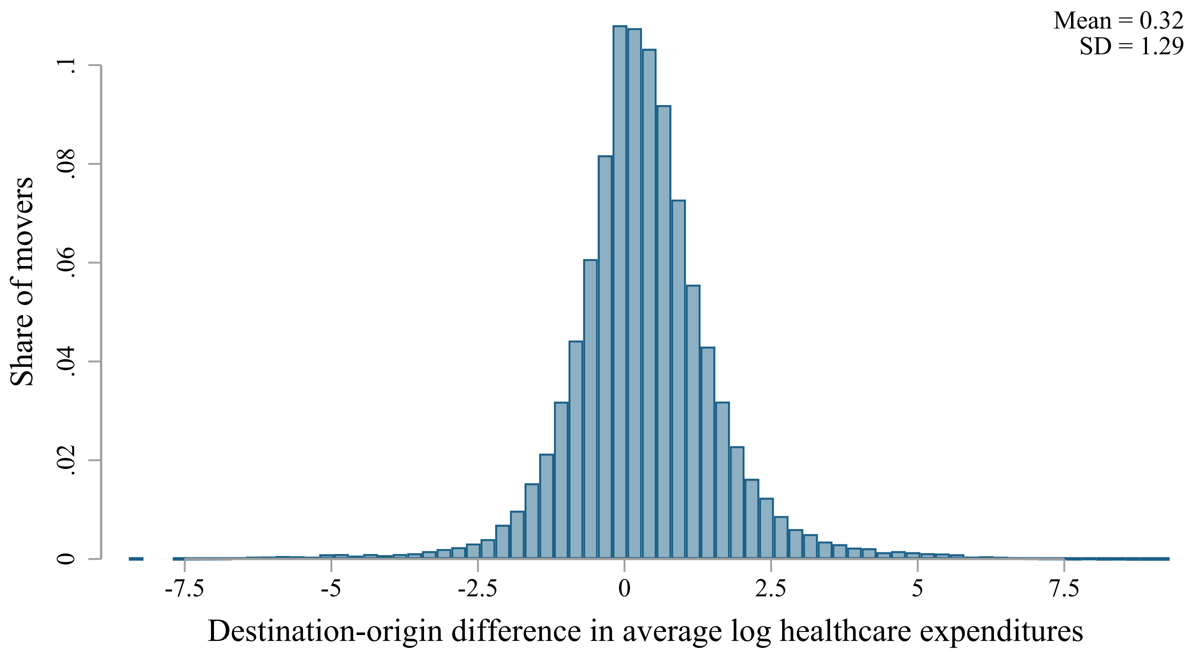
Tables and figures

Figure 1 — Distribution of average per-worker health expenditures across firms



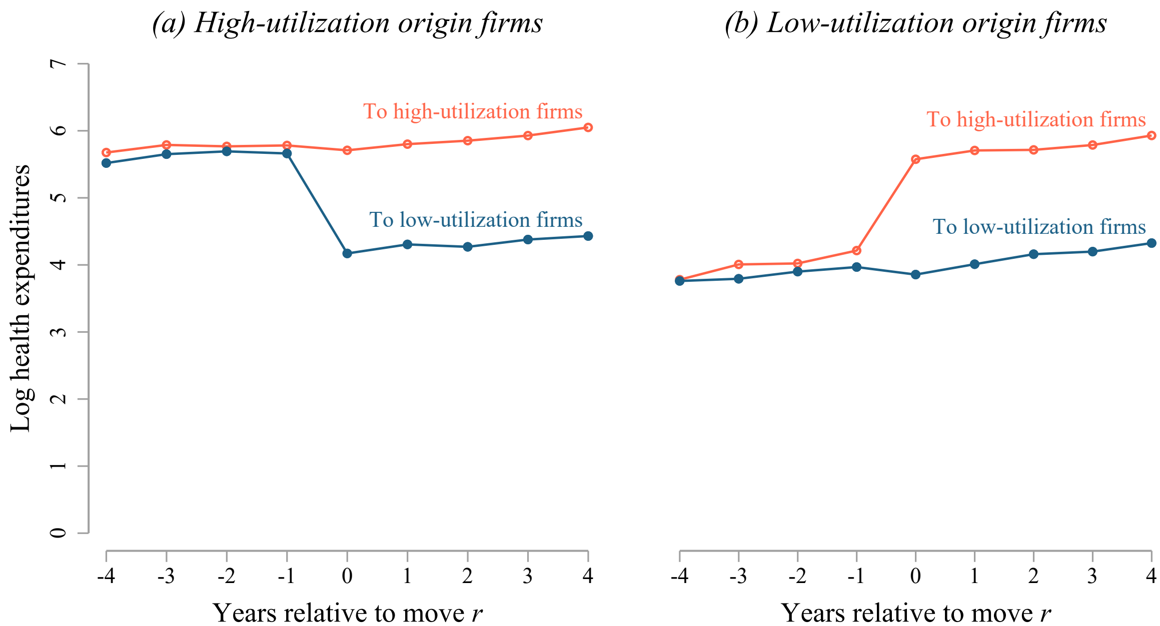
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure displays the distribution of average per-worker health expenditures across firms, within a given firm-year, using a bin size of €50. We omit firms with zero average health expenditures and those with per-worker health expenditures above €2,000, i.e., the 95th percentile of the distribution rounded to the next €1,000. Averages are based on the full worker-by-year panel. N = 9,184,913

FIGURE 2 — Distribution of destination-origin difference in log health expenditures



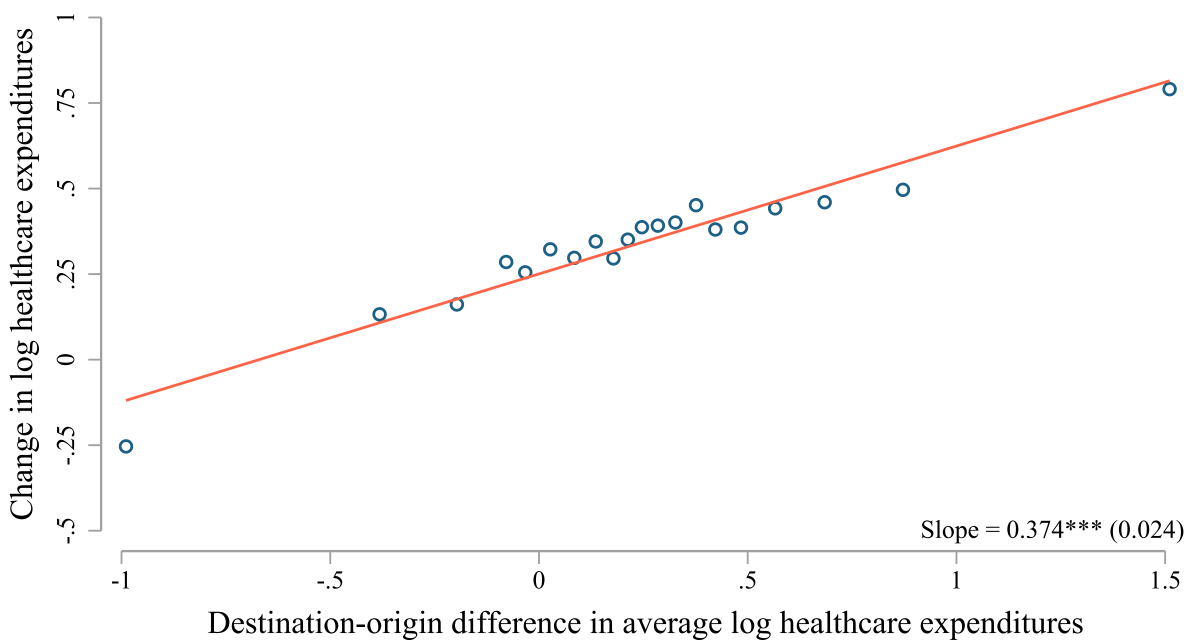
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the distribution of the difference in average log health care expenditures between destination and origin firms across movers. For each mover, we consider average expenditures over the immediate 4 pre-move years and 4 post-move years. Averages are based on a balanced mover sample. N = 519,228

FIGURE 3 — Changes in utilization by origin and destination firm utilization



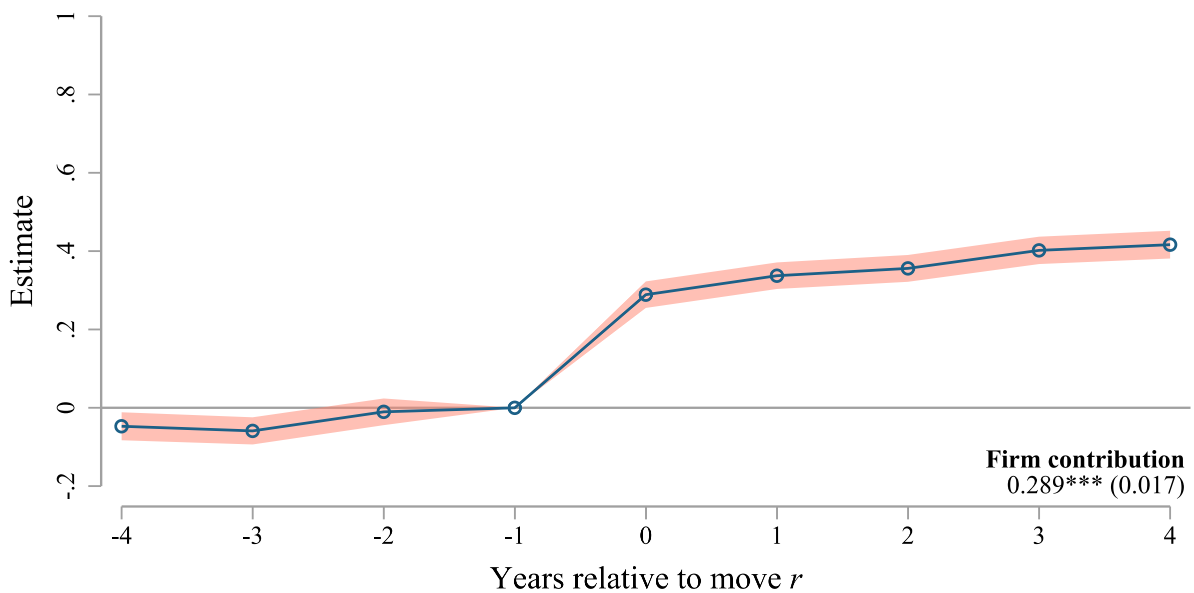
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. For this figure, we define "high-utilization" firms as firms in the top quartile of the per-worker per-year health care expenditure distribution, while "low-utilization" firms are classified as those in the lower quartile of the expenditure distribution. Panel (a) plots the raw means of log health care expenditures for workers moving away from high-utilization firms. Panel (b) plots the raw means of the log health care expenditures for workers moving away from low-utilization firms. In each panel, the top line shows the mean log expenditure for the workers with a high-utilization destination firm, while the bottom line presents the mean log expenditure for the workers with a low-utilization destination firm. Averages are based on a balanced mover sample. N = 519,228

FIGURE 4 — Change in log health care expenditures by destination-origin difference



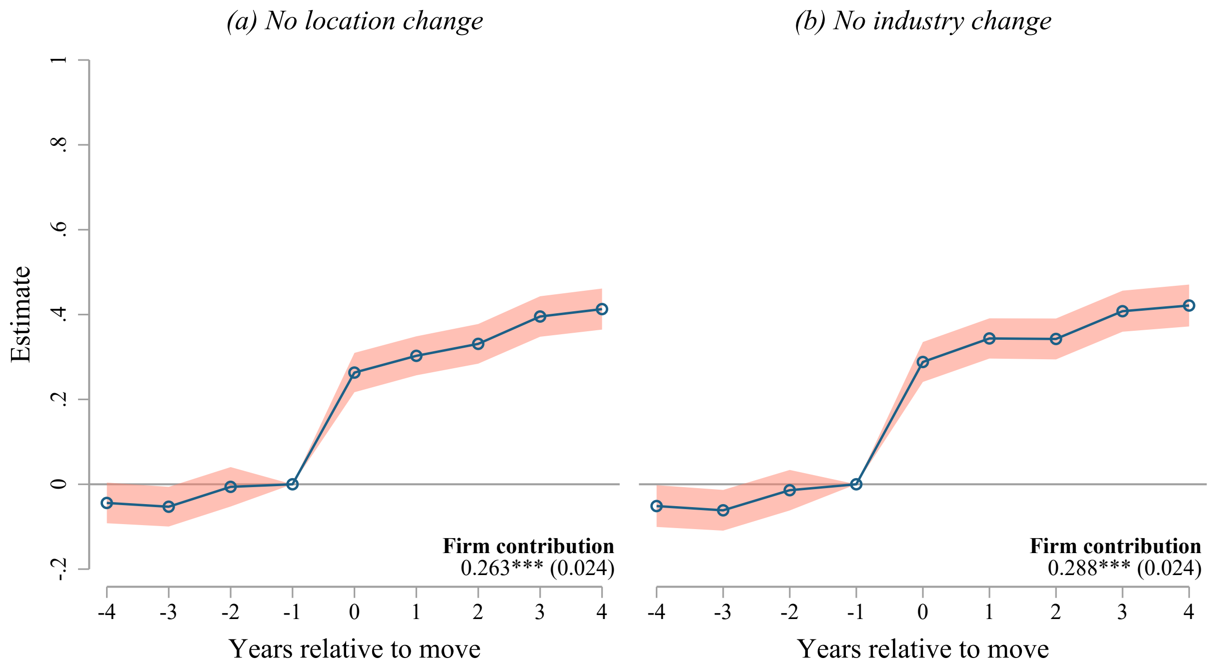
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the change in log health care expenditures against the difference in average per-worker log health care expenditures between the destination and the origin firm (δ_i). For each mover, we calculate the difference in average per-worker log health care utilization between the origin and destination firm and group these differences into 20 quantiles, the horizontal axis plots average log expenditures within these quantiles. The vertical axis shows, for each quantile, average log expenditures 4 years pre-move minus average log expenditures 4 years post-move. Estimates are based on a balanced mover sample. N = 519,228

Figure 5 — Event study for log health care expenditures



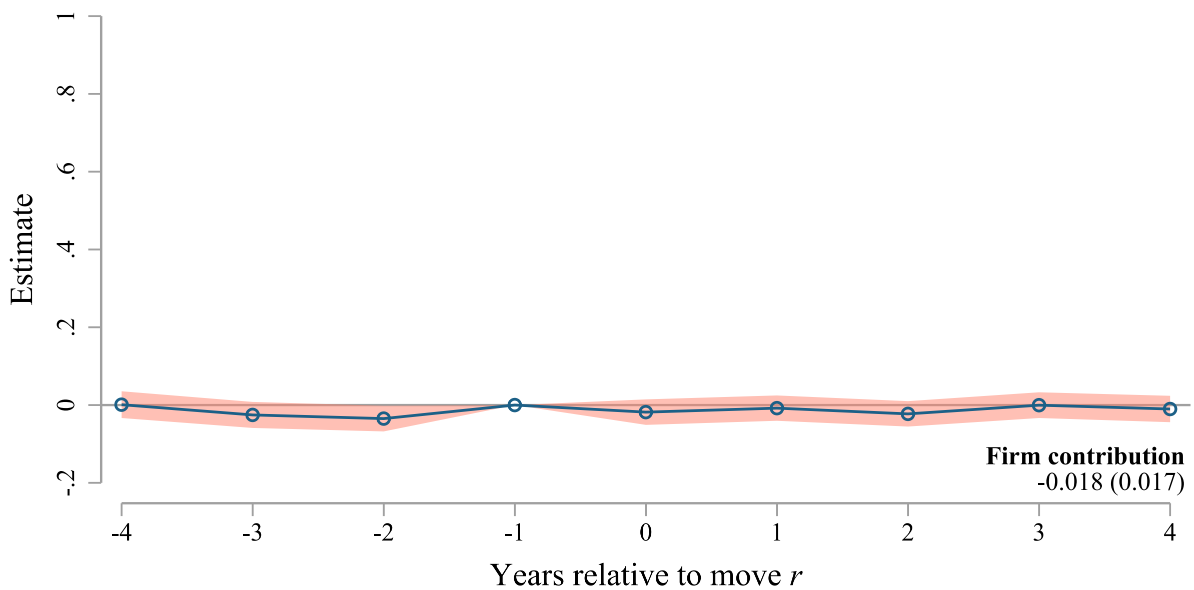
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from Equation (2) and their respective 95 percent confidence intervals. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in health care expenditures across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. $N = 519{,}228$

Figure 6 — Event study for log health care expenditures, movers with no area or industry change



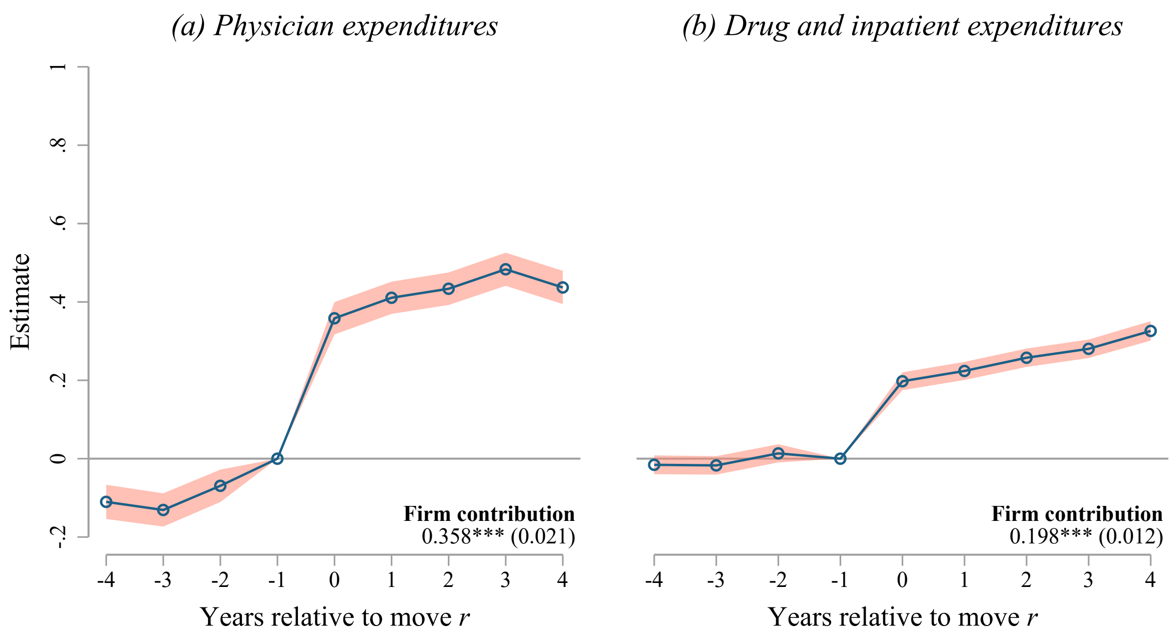
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from Equation (2) for the sample of movers that do not change geographic location (left panel) or industries (right panel). Locations are defined based on the first two digits of the Austrian zip code, which coincide approximately with county borders. Industries are defined based on the first letter of firms' NACE08 code. N = 519,228

Figure 7 — Placebo test



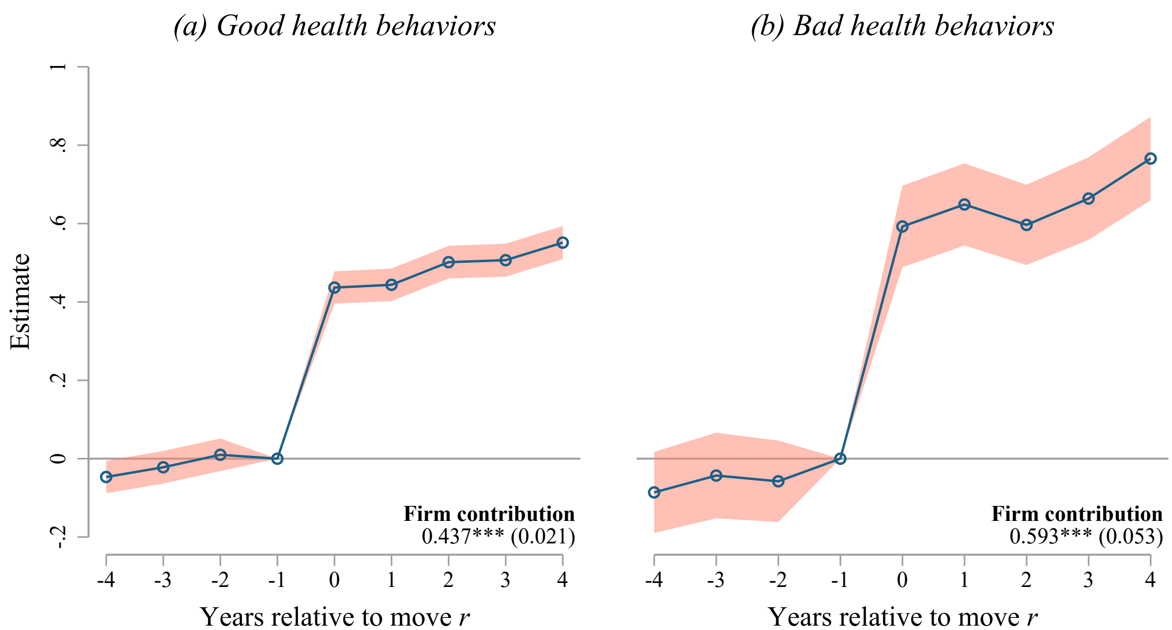
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ and their respective 95% confidence intervals from Equation (2) for the sample of movers, but instead of using the actual $\hat{\delta}$, we simulate a δ by drawing from a normal distribution that has the same moments as $\hat{\delta}$ in the balanced mover sample. The dependent variable is log health care expenditures. Estimates are based on a balanced mover sample. N = 519,228

Figure 8 — Event studies for physician expenses vs. drug and inpatient expenses



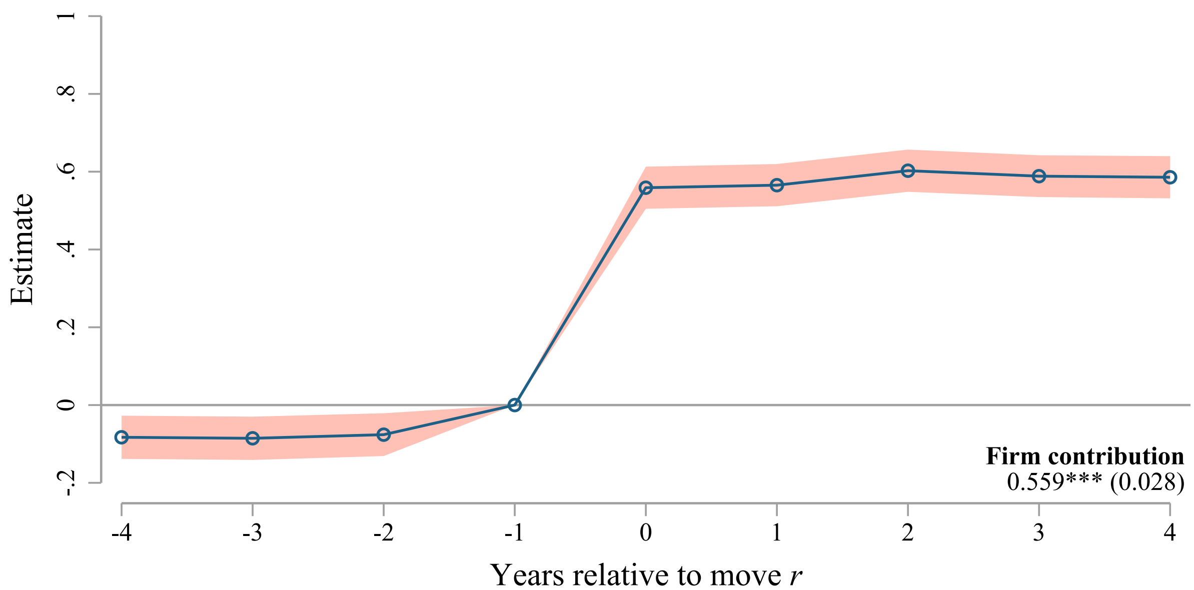
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ and their respective 95% confidence intervals from Equation (2) separately for physician expenses (left panel) and drug and inpatient expenses (right panel). The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in physician, drug, and inpatient expenditures across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. $N = 519{,}228$

Figure 9 — Event studies for good and bad health behaviors



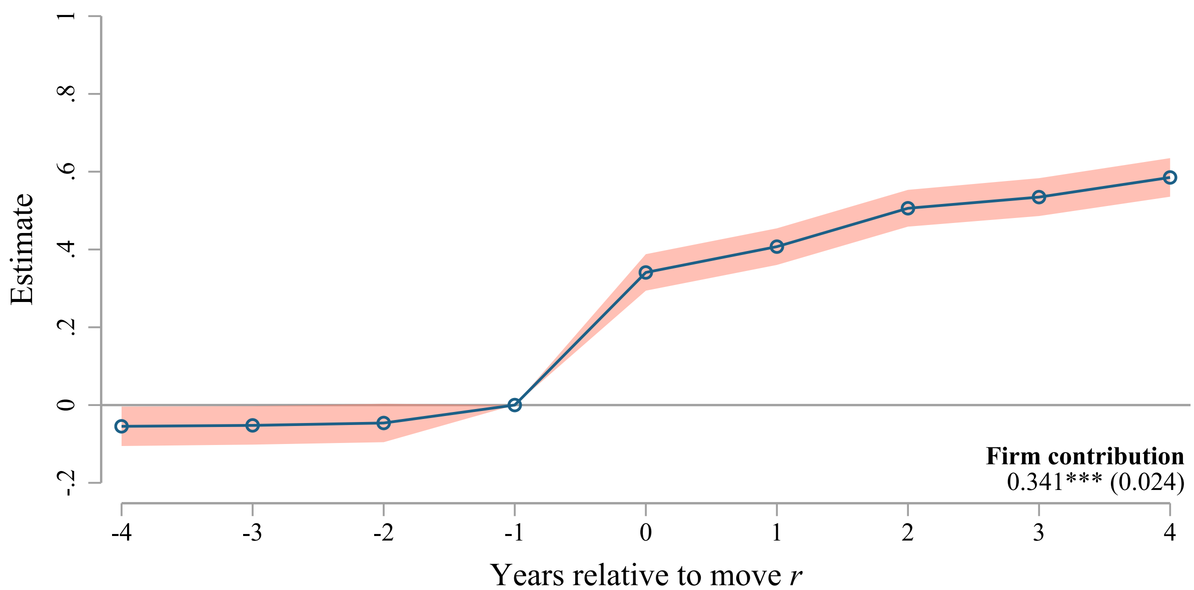
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ and their respective 95% confidence intervals from Equation (2) separately for good health behaviors (left panel) and bad health behaviors (right panel). Appendix section B discusses how these outcomes are defined. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in good and bad health behaviors across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. $N = 519{,}228$

Figure 10 — Event study for accidents and injuries



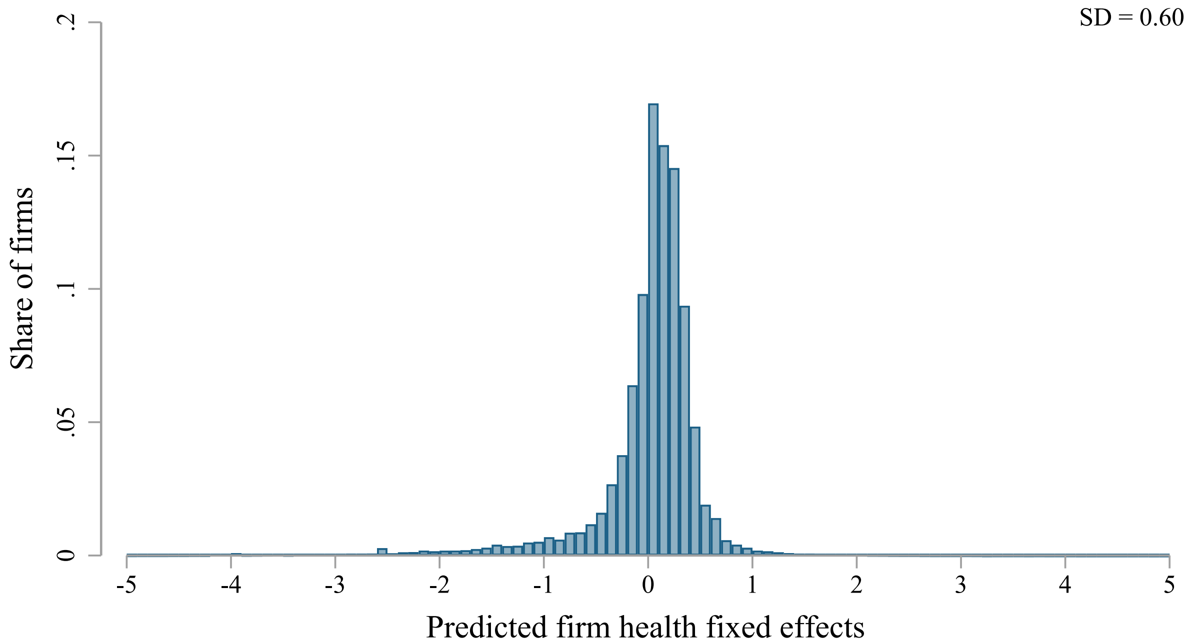
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ and their respective 95% confidence intervals from Equation (2) for accidents and injuries, including those occurring at the workplace. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in accidents and injuries across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. N = 519,228

Figure 11 — Event studies for mental health care



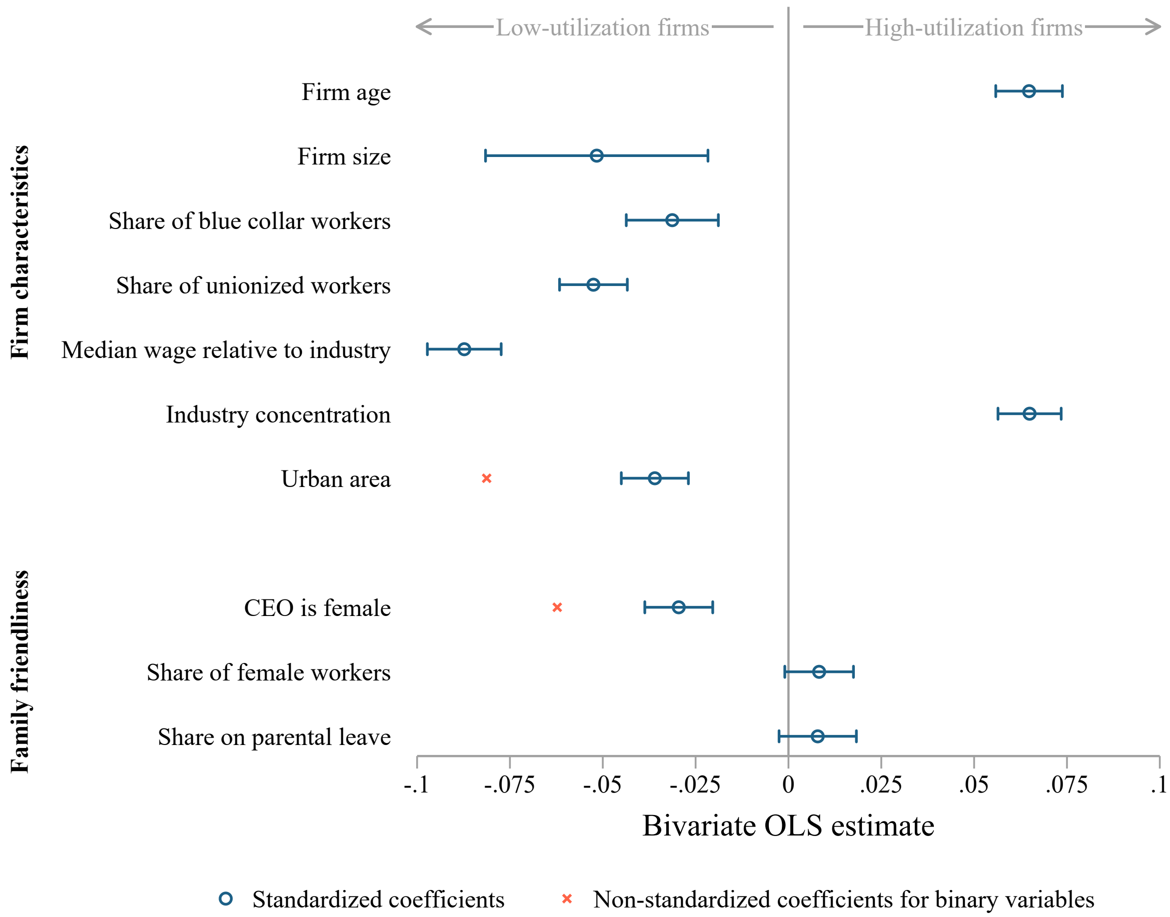
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ and their respective 95% confidence intervals from Equation (2) for mental health care. Appendix section B discusses how these outcomes are defined. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in mental health care take-up across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. N = 519,228

Figure 12 — Firm health fixed effects distribution



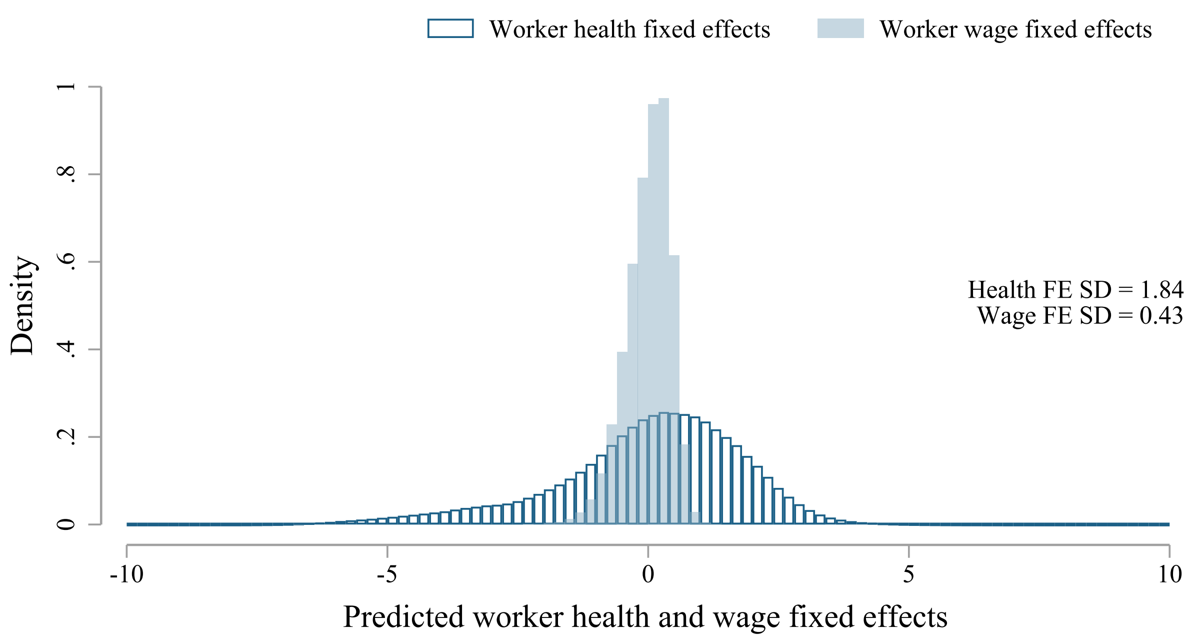
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure displays estimated firm health fixed effects $\hat{\theta}_{j(it)}$, centered around zero. We plot the interval $[-5, 5]$, excluding the 0.1% of observations with very low firm health fixed effects. Estimates are based on the full worker-by-year panel. N = 9,184,913

FIGURE 13 — Explaining firm health fixed effects



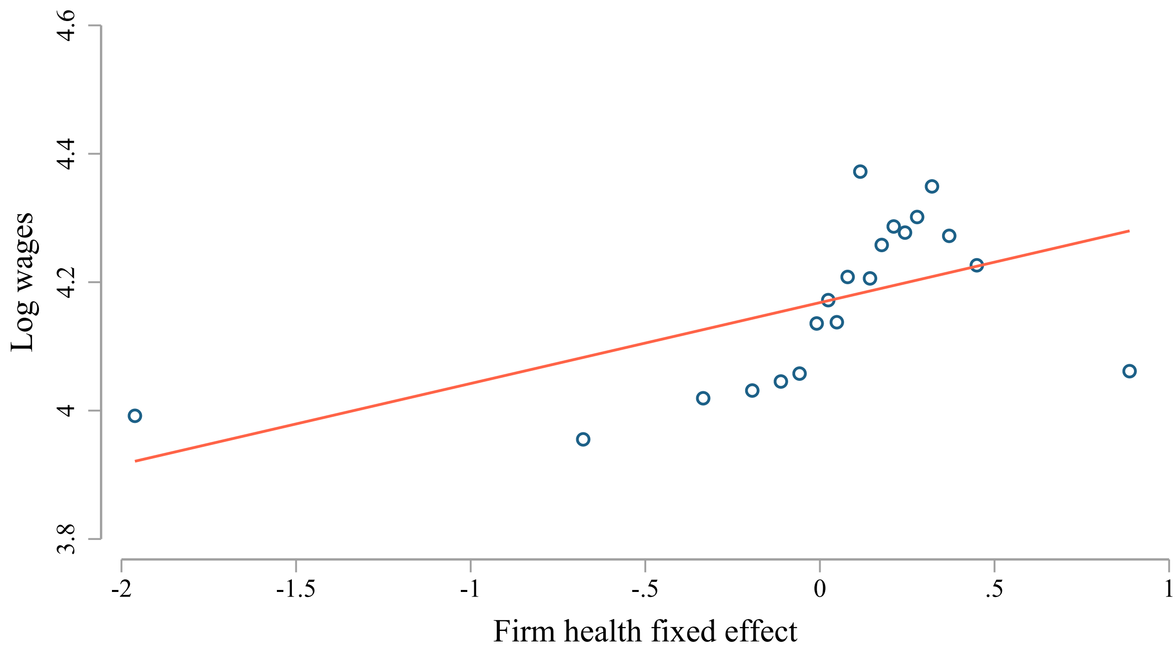
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure displays coefficients from simple bivariate regressions of the estimated firm health fixed effect, $\hat{\theta}_j$, on a firm characteristic x_j, as detailed in Equation (4). The coefficients can be interpreted as standard deviation changes in the health fixed effect in response to a one standard deviation increase in the firm characteristic. For binary variables, we plot both standardized and non-standardized coefficients. Estimates are based on the full worker-by-year panel. N = 9,184,913

Figure 14 — Worker health and wage fixed effects distributions



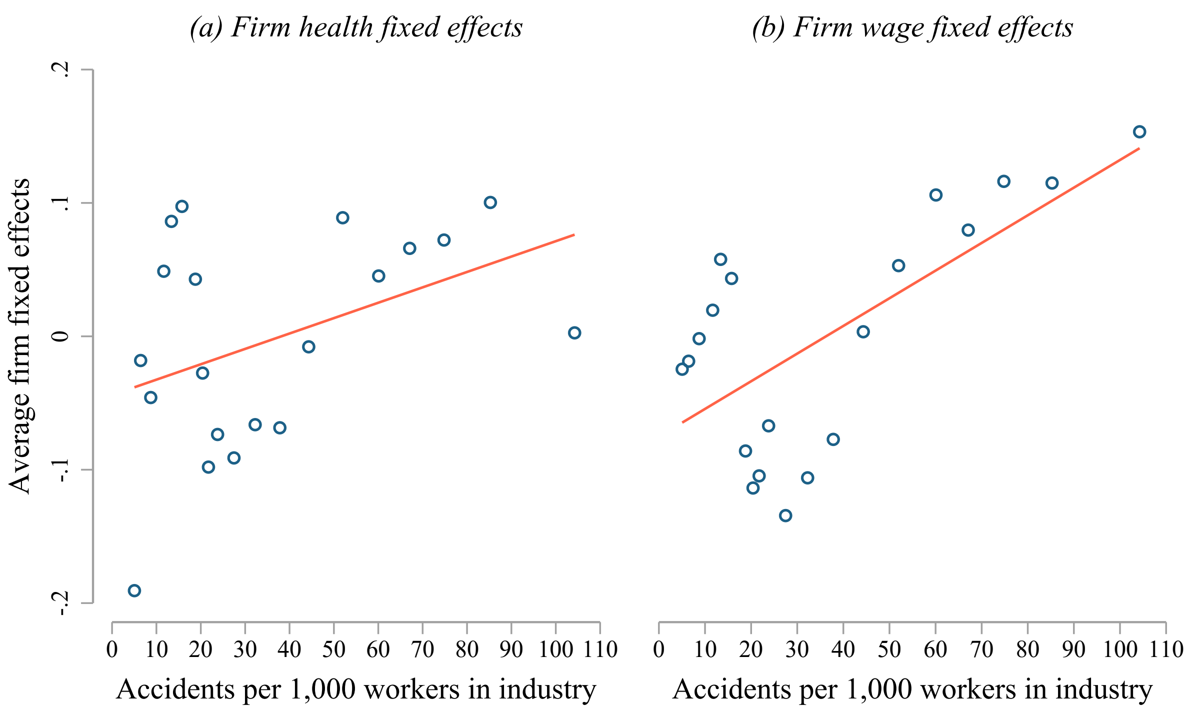
Notes: Data on workers and wages is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure displays estimated worker fixed effects, $\hat{\alpha}_i$, with log total health expenditures and log wages as outcomes, both centered around zero. We plot the interval $[-10, 10]$, excluding the 0.01% of observations with very low worker health fixed effects. Estimates are based on the full worker-by-year panel. N = 9,184,913

Figure 15 — Correlation between log wages and firm health fixed effects



Notes: Data on workers and wages is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure shows average log wages by firm health fixed effects. We divide estimated firm health fixed effects into 20 quantiles and plot average fixed effects within these quantiles on the horizontal axis. On the vertical axis we show, for each quantile, average log wages. Estimates are based on the full worker-by-year panel. N = 9,184,913

Figure 16 — Correlations between firm fixed effects and work accidents



Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. Scatters represent average firm health and wage fixed effects against industry work accidents. For each NACE08 2-digit industry, we calculate the number of accidents per 1,000 workers between 2000 and 2017 by blue-collar status and group accidents into 20 quantiles. The horizontal axis plots average accidents within these quantiles. The vertical axis shows, for each quantile, the average firm health fixed effects (panel a) and wage fixed effects across firms (panel b). Estimates are based on the full worker-by-year panel. The sample period is restricted to 2000–2017, due to workplace accidents data availability. N = 8,018,551

Table 1 — Summary statistics

	All workers (1)	Mover sample (2)
Female (share)	0.44	0.39
Age (years)	36.11	37.70
Blue-collar (share)	0.53	0.51
Daily wage (€)	72.09	73.72
Tenure (years)	5.13	7.65
Health care expenditures (€)	592.72	429.42
Share with zero health care expenditures	0.15	0.10
Types of health care expenses		
Physician expenses (€)	223.47	202.22
Drug and inpatient expenses (€)	369.24	227.20
Health behaviors		
Good (share)	0.21	0.21
Bad (share)	0.02	0.02
Accidents and injuries (share)	0.12	0.13
Mental health care utilization (share)	0.08	0.06
Worker × year observations	9,184,913	519,228

Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998 to 2018. Column (1) presents yearly means for the full sample of workers, while Column (2) presents means for workers that switch firms during our sample period, considering only the pre-move period.

Table 2 — Additive decomposition of log health care expenditures

	Above/ below median	Top & bottom 25%	Top & bottom 10%
Difference in average log expenditures			
Overall	2.31	5.04	6.35
Due to firms	0.83	1.95	2.87
Due to workers	1.48	3.09	3.48
Share of difference due to			
Firms	0.36	0.39	0.45
	(0.002)	(0.002)	(0.003)
Workers	0.64	0.61	0.55

Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. Each column in this table defines a set of firms R and R', based on percentiles of average health care utilization. The first row shows differences in average log utilization between the two sets, the second row shows the difference that is due to firms, and the third row shows the difference that is due to workers. The fourth row reports the share of the difference in average utilization between the two sets of firms due to firms, which is the ratio of the third and the first row, along with standard errors for this ratio. The last row represents the share that is due to workers, which is the ratio of the second and the first row.

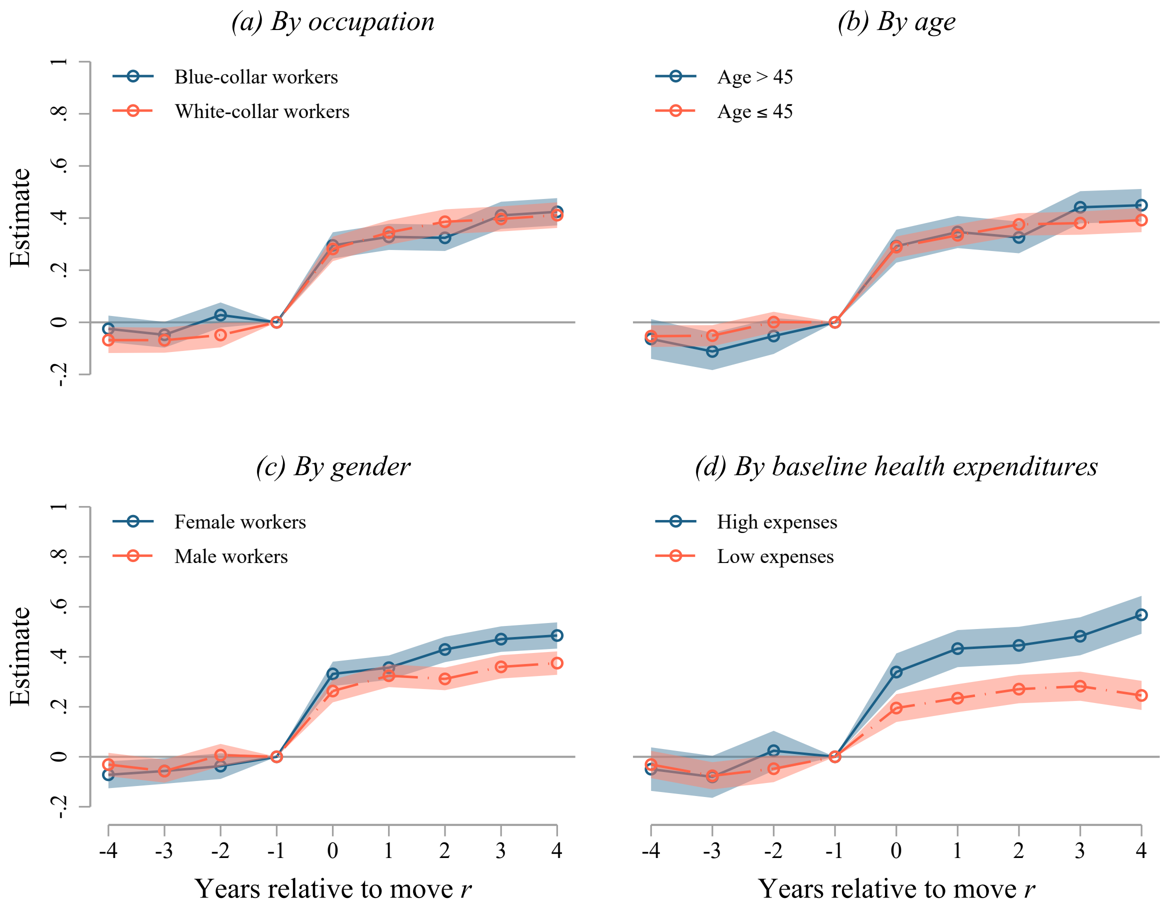
Web appendix

This web appendix contains additional material for the paper *"Firms and Worker Health"* by Alexander Ahammer, Analisa Packham, and Jonathan Smith.

Contents

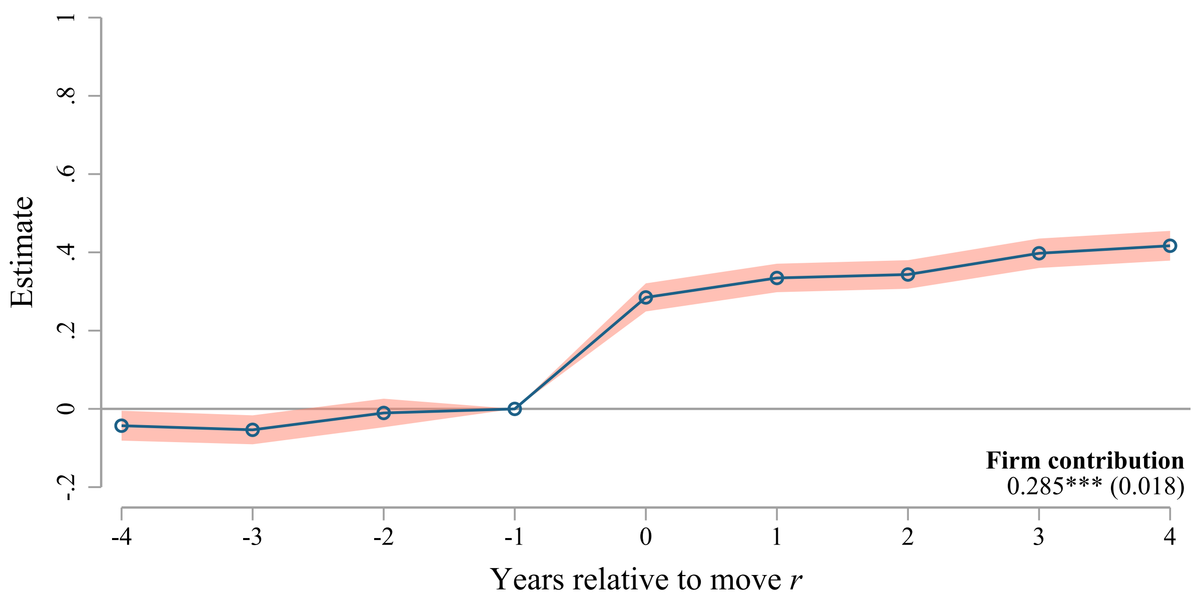
A. Additional tables and figures

Figure A.1 — Heterogeneity analyses



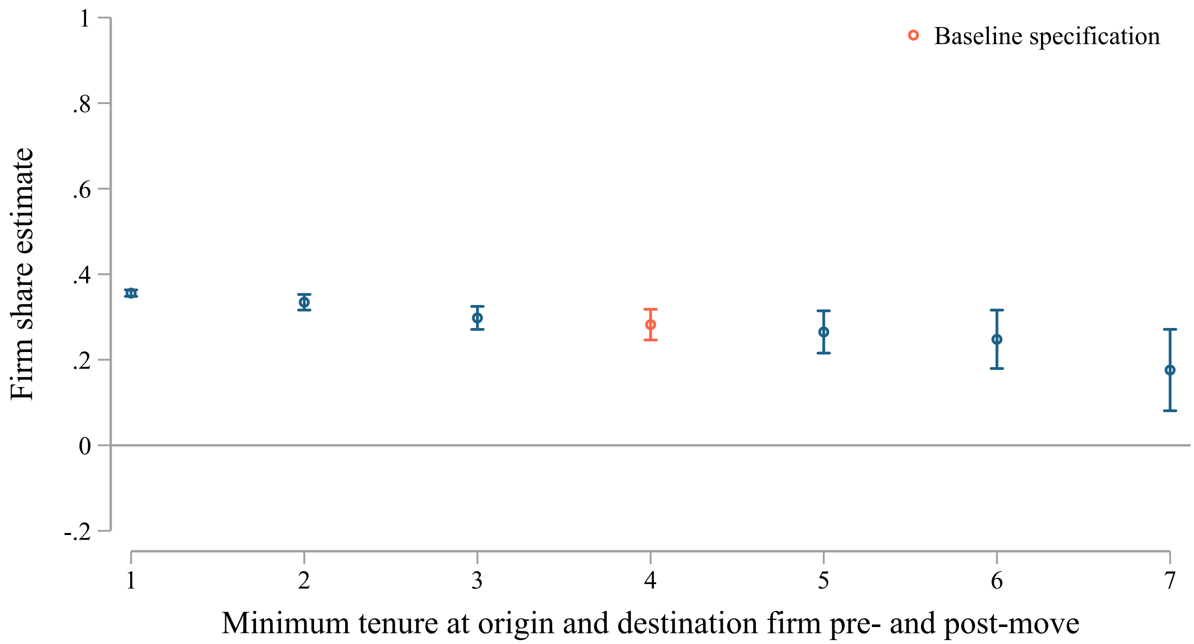
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from Equation (2) for different subsets of the population. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in health care expenditures across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. N = 519,228

FIGURE A.2 — Event study for log health care expenditures, omitting workers that had children



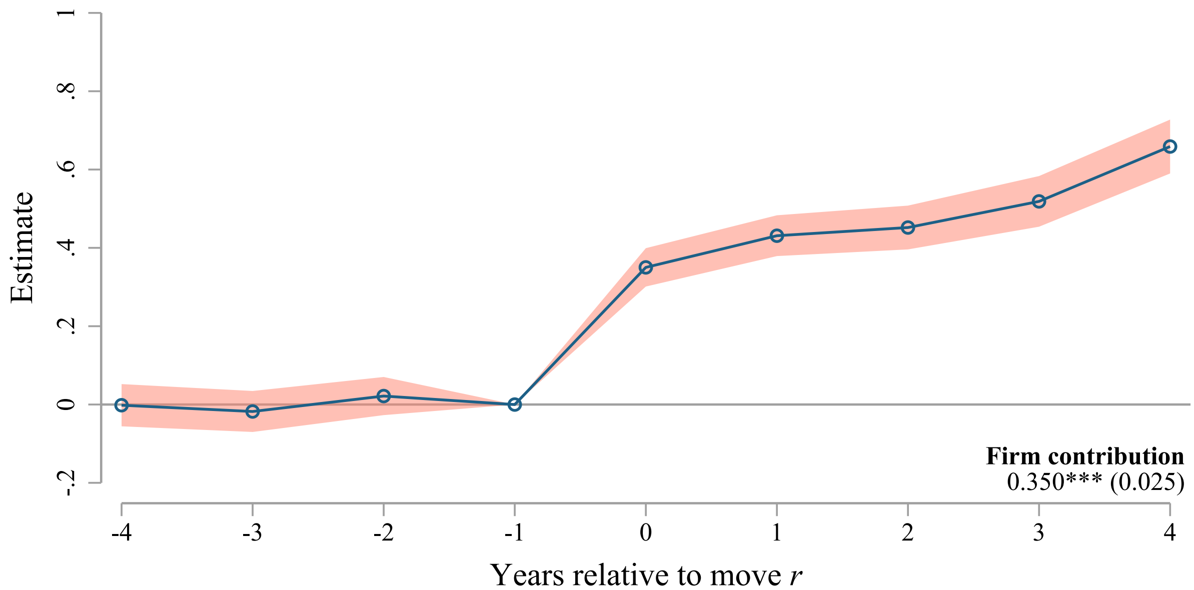
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from Equation (2) omitting 13 percent of observations for movers that had children at some point during the observation period. N = 449,262

Figure A.3 — Event-study estimates for log health care expenditures, relaxing the tenure criterion



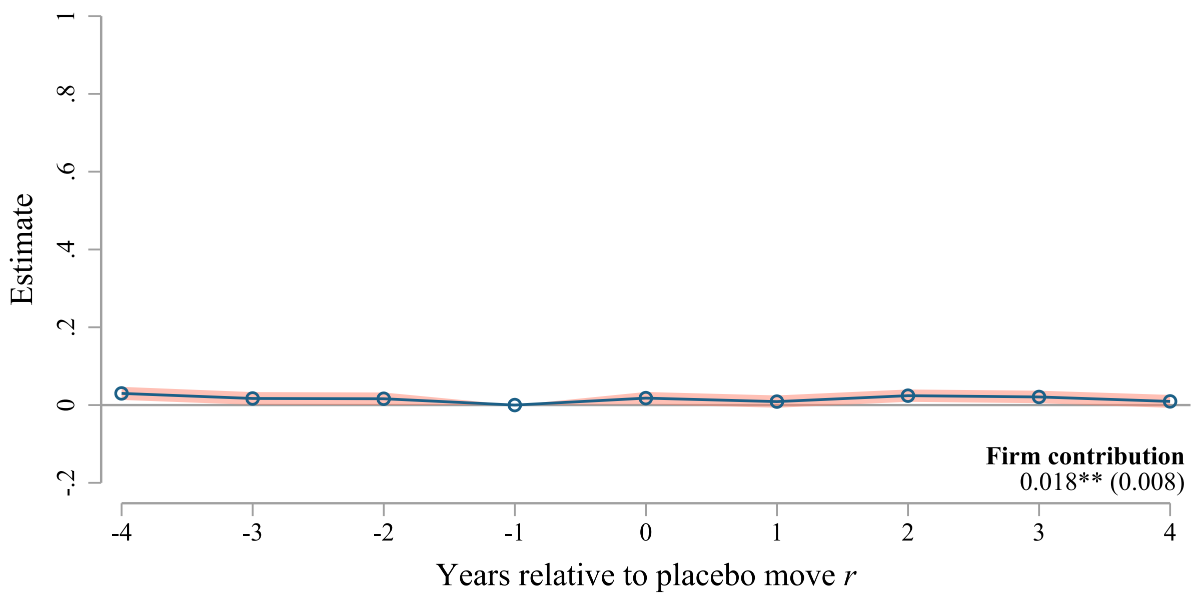
Notes: See Figure 5. For each estimate, we relax the 4-year tenure requirement, allowing for workers that have remained at the origin firm for $j = 1, 2, ..., 7$ years prior to a move and will remain at the destination firm for $j = 1, 2, ..., 7$ years after a move. Estimates of θ_r for $t = 0$ are shown from balanced panels using panel data for j years before and after the first move per worker as listed on the x-axis.

Figure A.4 — Event study for log health care expenditures, Poisson



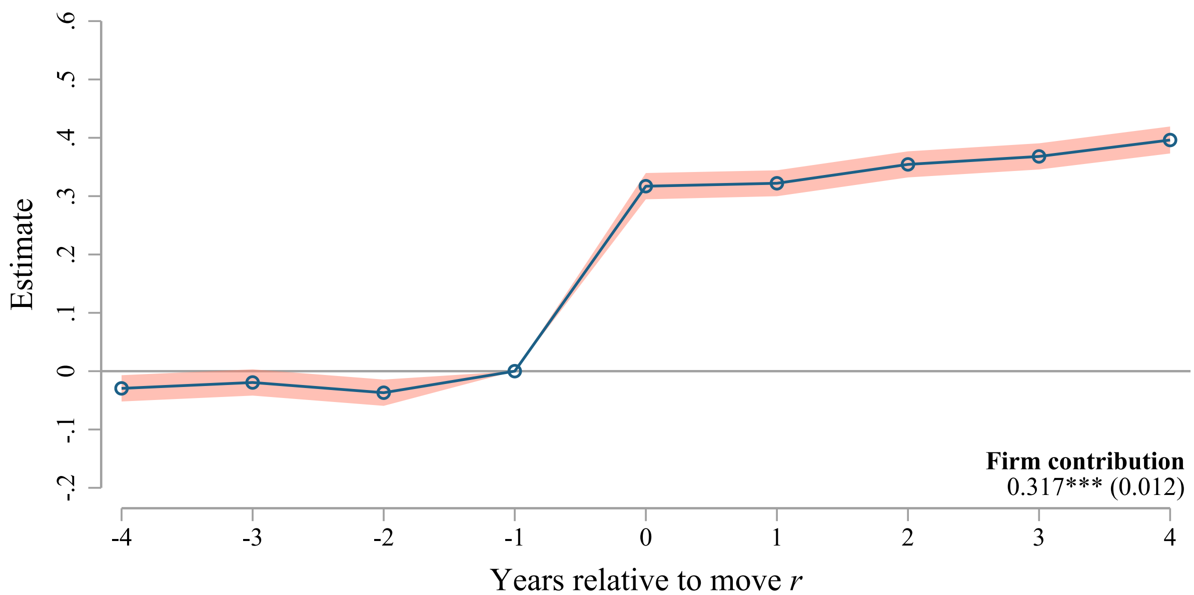
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from a Poisson model analogue of Equation (2). The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in health care expenditures across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. $N = 519{,}228$

Figure A.5 — Placebo test: non-movers



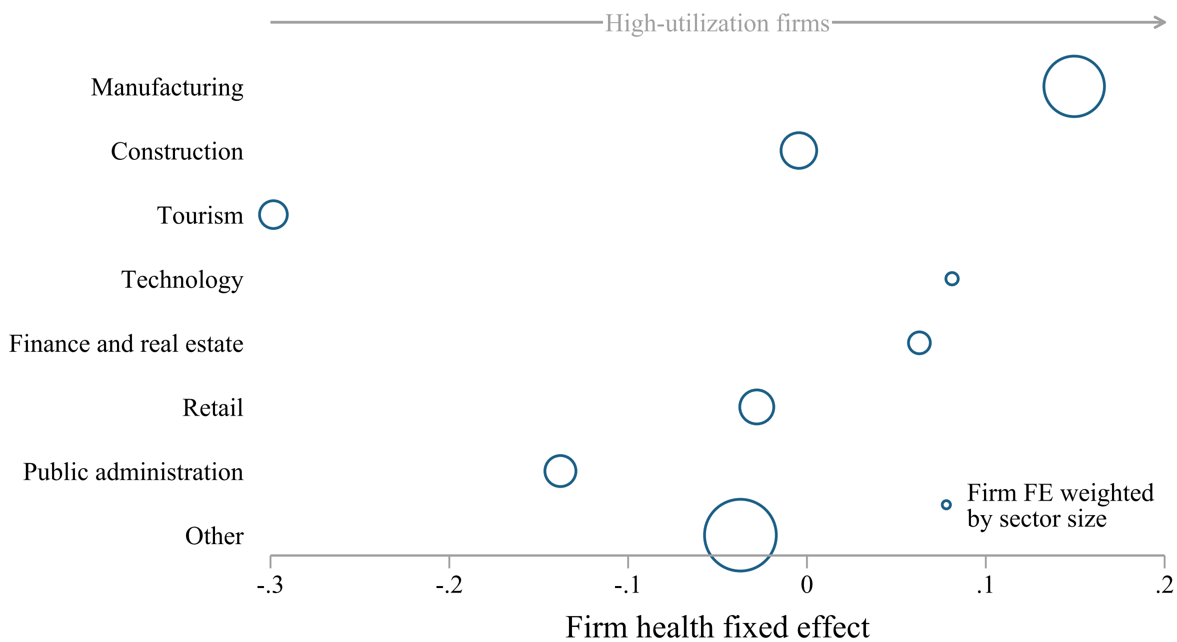
Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from Equation (2) for a sample of non-movers. Similar to Figure (7), we simulate δ for non-movers by drawing from a normal distribution that has the same moments as $\hat{\delta}$ in the balanced mover sample. The dependent variable is log health care expenses y_{it}. The red-shaded area is a 95 percent confidence interval. The jumps between $r = 0$ and $r = 1$ can be interpreted as the share of variation in health care expenditures across firms attributable to firms, the rest is explained by worker characteristics. Estimates are based on a balanced non-mover sample. $N = 2{,}121{,}202$

Figure A.6 — Event study for sick leave take-up



Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients $\hat{\theta}_r$ from Equation (2) and their respective 95 percent confidence intervals. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in sick leave take-up across firms attributable to firms; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. $N = 519{,}228$

Figure A.7 — Firm health fixed effects, by sector



Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure displays averages of estimated firm health fixed effects $\hat{\theta}_{j(it)}$ from equation (3) averaged over NACE08 industry sectors. Bubble size represents the number of workers in each sector. Estimates are based on the full worker-by-year panel. $N = 9{,}184{,}913$

TABLE A.1 — Firm share estimates with different covariate sets

	(1)	(2)	(3)	(4)	(5)
$\hat{\theta}_0$	0.288***	0.288***	0.287***	0.288***	0.289***
	(0.030)	(0.017)	(0.017)	(0.017)	(0.017)
Worker FEs	No	Yes	Yes	Yes	Yes
Age FEs	No	No	Yes	Yes	Yes
Year FEs	No	No	No	Yes	Yes
Sector FEs	No	No	No	No	Yes
Blue-collar	No	No	No	No	Yes

Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This table summarizes estimates for $\hat{\theta}_0$ from Equation (2) for different sets of covariates. In column (1), we do not use any covariates and no worker fixed effects. In column (2), we add worker fixed effects. In column (3), we add age fixed effects. In column (4), we add year fixed effects. In column (5), we add sector fixed effects and a blue-collar dummy. Estimates are based on a balanced mover sample, $N = 519{,}228$. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2 — Average health care expenditures and wages by firm fixed effect decile

Decile	Health		Wages	
	Average	% difference	Average	% difference
	(1)	(2)	(3)	(4)
1	315.3		40.4	
2	507.9	0.61	49.5	0.23
3	580.7	0.84	57.9	0.43
4	610.8	0.94	65.6	0.62
5	624.0	0.98	71.3	0.76
6	631.8	1.00	76.3	0.89
7	626.2	0.99	80.1	0.98
8	649.6	1.06	84.7	1.10
9	666.1	1.11	92.9	1.30
10	726.8	1.31	103.8	1.57

Notes: Data on workers and wages is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This table reports average health care utilization, in Euros, for each firm health fixed effect decile (Column 1) and wages (in Euros) for each firm wage fixed effect decile (Column 3). Columns (2) and (4) present the percentage differences for the listed decile, relative to decile 1.

B. Outcome definitions

Good health behaviors: Mammograms, well visits, prostate-specific antigen tests, vitamins (ATC A11), mineral supplements (ATC A12), antihypertensives (ATC C02), statins (ATC C10), antithrombotic drugs (ATC B01), osteoporosis drugs (ATC M05), smoking cessation drugs (ATC N07BA), alcohol cessation drugs (ATC N07BB), opioid substitution therapy (ATC N07BC), weight loss drugs (ATC A08).

Bad health behaviors: Smoking diagnoses (ICD-10 F17), alcohol diagnoses, including alcohol dependence, alcohol poisonings and alcoholic liver disease (ICD-10 F10, T51, K70, G72.1, Z50.2, K85.2), obesity diagnosis (ICD-10 E66), sexually transmittable disease (ICD-10 Z11.3–Z11.5, Z11.8, Z11.9, Z12.4, Z12.7, Z20.6, Z20.8, Z20.9, Z71.8, Z72.5, A5, A60, A63, A64, B20), prescription opioids (ATC N01AH and N02A).

Accidents and injuries: ICD-10 categories S and T.

Mental health take-up: Mental health diagnoses (ICD-10 F), psycholeptics, including benzodiazepines (ATC N05), psychoanaleptics, including antidepressants (N06), psychiatrist visits, psychologist visits.

C. Estimating peer effects

We start with a descriptive analysis of peer effects in the workplace. First, for every worker i in the full worker-by-year panel, define a peer group of workers $J(i)$, $i \notin J(i)$, based on the worker's firm, 10-year age bracket (15–24, 25–34, 35–44, 45–54, 55–65), gender, and occupation (blue-collar/white-collar). Second, for every outcome y, calculate coworker averages in every year t within the peer group, $\bar{y}_{J(i,t)}$. We then estimate

$$y_{it} = \beta \bar{y}_{J(i,t)} + \theta_i + \varepsilon_{it}, \tag{C.1}$$

where θ_i is a worker fixed effect that accounts for unobserved baseline differences in health status across workers. If peer effects are present, we expect $\hat{\beta}$ to be significantly different from zero.

Results are presented in Table C.1. We find that the estimates for β are positive and significant across outcomes, indicating that worker health care utilization and health behaviors correlate positively with peer-group averages. For example, if the share of peers engaging in good health behaviors switches from 0 to 100 percent, the worker is 7.7 percentage points or 37.4 percent more likely to engage in good behaviors themselves. This correlation is strongest for bad health behaviors. For accidents and injuries, we do find descriptive evidence of peer effects too.

In a second step, we compare event study estimates when the treatment variable is either differences in peer-group averages and differences in averages of other workers not in i's peer group between the origin and destination firm:

$$\begin{aligned} y_{it} &= \alpha_i + \sum\nolimits_r \theta_r^{\text{peers}} \cdot \phi_i^{\text{peers}} + \tau_t + x_{it}\beta + \varepsilon_{it} \\ y_{it} &= \alpha_i + \sum\nolimits_r \theta_r^{\text{non-peers}} \cdot \phi_i^{\text{non-peers}} + \tau_t + x_{it}\beta + \varepsilon_{it}, \end{aligned} \tag{C.2}$$

with

$$\begin{aligned} \phi_i^{\text{peers}} &= \bar{y}_{J(d(i,t))} - \bar{y}_{J(o(i,t))} \\ \phi_i^{\text{non-peers}} &= \bar{y}_{-J(d(i,t))} - \bar{y}_{-J(o(i,t))}, \end{aligned} \tag{C.3}$$

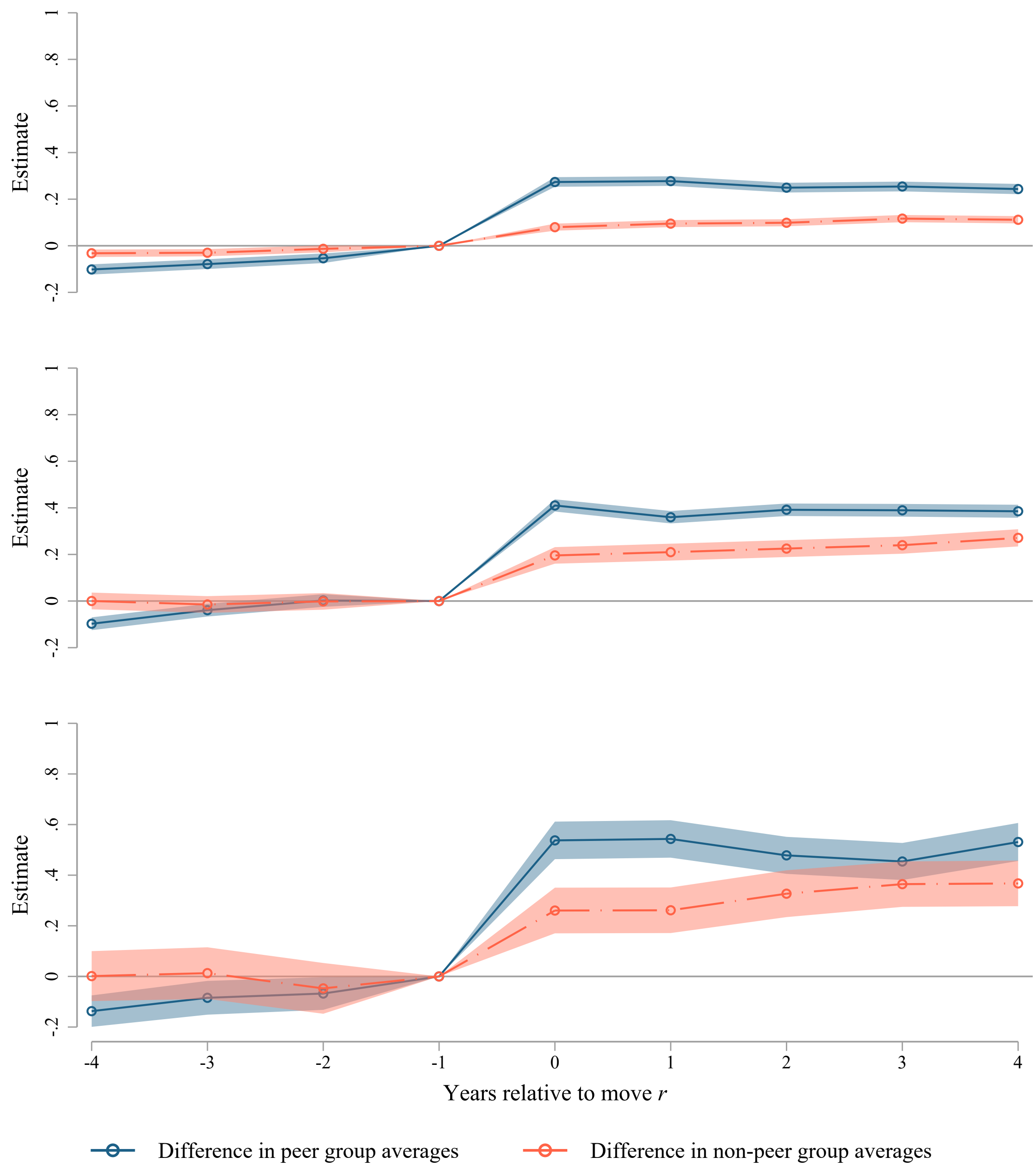
where $\bar{y}_{J(d(i,t))}$ and $\bar{y}_{J(o(i,t))}$ is average utilization in the worker i's destination and origin firm peer group, respectively, while $\bar{y}_{-J(d(i,t))}$ and $\bar{y}_{-J(o(i,t))}$ is average utilization among all other workers in i's the destination and origin firm. We present these event study estimates in Figure C.1. Across outcomes, peer group contributions are much larger than non-peer group contributions. This suggests that peer effects are important in explaining our effects.

TABLE C.1 — Peer effects: Descriptive analysis

	Log expenditures	Health behaviors	
		Good	Bad
	(1)	(2)	(3)
$\bar{y}_{J(i),t}$	0.201***	0.077***	0.014***
	(0.004)	(0.001)	(0.001)
	[4.2]	[37.4]	[61.6]
Mean	4.76	0.20	0.02

Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. Estimates from Equation (C.2) are based on the full worker-by-year panel. Column (1) presents the relationship between worker log health care expenditures and peer log health care expenditures. Columns (2) and (3) present estimates for “good" and “bad" health behaviors, as defined in Appendix B. Percentage effects are in square brackets. Standard errors are presented in round brackets and are clustered at the peer group level. N = 9,184,913
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.1 — Reaction to differences in peer-group and non-peer-group health care utilization and health behaviors



Notes: Data on workers is from the Austrian Social Security Database. Data on health expenditures is from the Upper Austrian Health Insurance Fund and spans from 1998–2018. This figure plots the coefficients θ_r^{peers} and $\theta_r^{\text{non-peers}}$ from Equation (C.2) and their respective 95 percent confidence intervals. The jump between $r = 0$ and $r = 1$ can be interpreted as the share of variation in health care expenditures across firms attributable to within-firm peers; the rest is explained by worker characteristics. Estimates are based on a balanced mover sample. N = 519,228