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Firm quality and health maintenance

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Abstract

We estimate the impact of firm quality – primarily measured by firm productivity – on the health maintenance of employees. Using linked employer-employee administrative panel data from Hungary, we analyze the dynamics of healthcare use before and after moving to a new firm. We show that moving to a more productive firm leads to higher consumption of drugs for cardiovascular conditions and more physician visits, without evidence of deteriorating physical health, and, among older workers, to lower consumption of medications for mental health conditions. The results are robust to using alternative firm quality indicators based on firm-level wages and worker flows, and to controlling for firm size, individual wage and possible peer effects. The results suggest that more productive firms have a beneficial effect on the detection of previously undiagnosed chronic physical illnesses and on mental health. Plausible mechanisms include higher quality occupational health check-ups and less stressful working conditions.

Keywords: firm productivity; healthcare use; mover identification; preventive care
JEL Codes: I10, J32, J62

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1 Introduction

Firms may affect mental and physical health of their employees via various channels such as work intensity or working conditions. Also, they may indirectly influence health through employer-provided healthcare services and occupational health screenings. Indeed, regular health screening of workers is common practice in many countries (Steel et al., 2022), such as in the US, where the Occupational Safety and Health Administration (OSHA) requires medical surveillance for numerous hazardous substances,[1] or in the European Union, where workers' participation in health surveillance is mandatory in most member states (Colosio et al., 2017). According to the EU-OSHA's 2014 European Survey of Enterprises on New and Emerging Risks,[2] 77% of establishments (and 97% of large firms) in the EU arrange regular medical examinations to monitor the health of employees. Hence, health maintenance at the workplace may be one of the important non-pay characteristics (amenities) that workers value (Sorkin, 2018; Sockin, 2022). In total, the above mechanisms may be the reason why firms explain a large share of the variation in healthcare utilization at the worker level that is documented in the literature (Ahammer et al., 2023).

In this paper, we use linked employer-employee administrative panel data supplemented with detailed healthcare records from Hungary to analyze the effect of firm quality – primarily measured by firm productivity – on various aspects of healthcare utilization of employees.

As a motivating descriptive analysis shown in Figure 1, simple cross-sectional regressions from Hungarian administrative data suggest that prescription drug use for major physical and mental health conditions, as well as diagnostic and inpatient care use, are less common among workers in higher productivity firms, presumably due to differences in individual health status. However, if we net out the influence of time-constant individual characteristics with individual fixed effects (and thus rely on workers who move between firms), we find positive associations between firm productivity and most of the healthcare categories. This positive relationship may be driven by (1) the sorting of workers into firms according to changing health status, (2) a direct effect of firms on worker health, or (3) the influence of firms on healthcare use, supporting health maintenance, a major determinant of worker well-being. In this paper, we argue that, at least in a relatively healthy sample we examine, the latter mechanism plays the dominant role.

Beyond looking at main indicators of outpatient and inpatient care, we focus on four prescription drug categories: antihypertensive drugs, lipid modifying agents, antidiabetics and psychoanaleptics. It is well known that appropriate treatment of hypertension (high blood pressure), high blood cholesterol and diabetes substantially reduces the number of deaths from cardiovascular disease, the leading cause of morbidity and mortality worldwide (Arnett et al., 2019). However, although these chronic conditions are highly prevalent, they are notoriously underdiagnosed. In 2019, the global age-standardized prevalence of hypertension

[1] https://www.osha.gov/medical-surveillance

[2] https://osha.europa.eu/en/facts-and-figures/esener

in age group 30–79 was around 33%, of whom only slightly more than half were diagnosed, and 47% of women and 38% of men were treated. In Hungary, the corresponding hypertension prevalence was substantially higher (41% for women and 56% for men), with treatment rates of 60% for women and 46% for men (Zhou et al., 2021). Similarly, the worldwide prevalence of diabetes was 8.8% in age group 20–79 in 2019 (IDF, 2017) with comparable rates in Hungary (Kempler et al., 2016), and around half of the cases worldwide (and 39% of cases in Europe) were undiagnosed (IDF, 2017). Also, although the use of lipid modifying agents (predominantly statins) for high blood cholesterol is more controversial due to different treatment guidelines (Mortensen et al., 2022), there is evidence for undertreatment in Central and Eastern Europe, including Hungary (Vrablik et al., 2021). The fourth examined drug category, psychoanaleptics, mainly covers antidepressants in the working age population that we analyze.[3] Antidepressants are mainly prescribed for major depressive disorders and anxiety disorders, thus their usage rate is an indicator of the mental health of the population. In Hungary, depression is more often untreated than in Europe on average because its prevalence is higher (Arias-de la Torre et al., 2021) but antidepressant consumption is lower, less than half of the OECD average (OECD, 2019).

We estimate event study models to analyze the dynamics of healthcare use before and after moving to a new firm. We focus on a relatively healthy population and show that moving to a more productive firm, compared to a less productive one, leads almost immediately to a persistently higher consumption of drugs for cardiovascular conditions (antihypertensives and lipid modifying agents) and a larger number of outpatient and diagnostic visits. We provide evidence that these patterns are unlikely to be driven by deterioration of physical health. Finally, we find that the consumption of psychoanaleptics (mainly antidepressants) decreases among relatively older workers after moving to a more productive firm compared to a less productive one. Our estimates are robust to using the firm-level mean wage, the firm-specific average wage premium and the poaching index as alternative measures of firm quality. The effect of firm productivity remains significant if we control for firm size, individual wage or a measure of peer effects.

Overall, taking into account the high rate of latency and the chronic nature of the examined cardiovascular conditions, our results suggest that more productive firms have a beneficial effect on the detection of previously undiagnosed chronic physical illnesses and are associated with better access to (preventive) care. At the same time, the decreased use of psychoanaleptics suggests a positive effect of firm productivity on the mental health of the employees. Plausible mechanisms include higher quality occupational health check-ups and less stressful job conditions.

Our paper contributes to the following strands of the literature.

First, our work contributes to understanding the relationship between firm characteristics and employee health (or healthcare utilization). Simple correlations between these variables

[3]The aggregation level of drug categories in our data does not allow us to analyze antidepressants separately.

are misleading due to selection decisions both by the firms and the employees (Rettl et al., 2024). Similar issues arise in the analysis of the health effects of occupation: e.g., Ravesteijn et al. (2018) find that while selection into occupations explains an important part of the correlation between occupation and health, occupations themselves have causal health effects. With our analysis, we contribute to the scarce literature on the health effects of firms, controlling for occupation. Since working conditions influence mental health even within the same occupation (Belloni et al., 2022), our estimated mental health effect of firms may be a consequence of different working conditions.

Second, we contribute to the recent literature that decomposes the individual-level variation of healthcare utilization into place-, provider- and patient-specific components by exploiting moves of patients between regions or providers (see Finkelstein et al., 2016 for the origins of this literature and Bíró et al., 2024 for a recent review). Instead, we use mobility of employees between firms, therefore, our work is closely related to the recent paper by Ahammer et al. (2023). Based on administrative data from Austria, Ahammer et al. (2023) show in a mover-identification setting that firms are responsible for nearly 30% of the variation of worker-level healthcare expenditure. We replicate their main result in Appendix B and obtain similar-sized estimates, but otherwise the results of the two papers are not directly comparable because in the main analysis we focus on relatively healthy employees and on outcome variables related to health maintenance.

Third, our work contributes to the literature on the role of health screening at the workplace. A statement of the American Heart Association claims that "conducting health screenings in the workplace is a promising strategy for early detection of established risk factors" (Arena et al., 2014). Also, there is evidence in the literature that workplace screening programs help identify undiagnosed hypertension and diabetes among employees (Legorreta et al., 2015; Bali et al., 2018). We extend this literature with suggestive evidence on the firm-dependent role of employee health screening in health maintenance based on large-scale administrative linked employer-employee data in the Hungarian context where such screening is mandatory. Importantly, the mandatory nature of the screening avoids self-selection issues such as shown by Jones et al. (2019) in an experimental employer-sponsored wellness program in the US. Nevertheless, our findings (an immediate and persistent level shift in cardiovascular drug consumption) are consistent with the habit-formation patterns seen in that US-based program (Jones et al., 2024).

Fourth, we relate to the literature of non-pay characteristics of firms. As Rodrik and Sabel (2022) highlight, "good jobs" may be described by a broad range of characteristics, which are reflected in wage differentials (Lavetti, 2023). Such health-related job characteristics include the level of workplace hazards (Lavetti, 2020), job stress (French and Dunlap, 1998; Nagler et al., 2023) or access to health insurance (Gruber, 1994; Qin and Chernew, 2014). The maintenance of good health of workers may be a key characteristic of a "good job", and we provide evidence on the important and heterogeneous role of firms in this.

The rest of this paper proceeds as follows. In Section 2 we provide background on the healthcare system and workplace health check-ups in Hungary. We present our data in Section 3, our analysis sample and empirical methods in Section 4, and our results in Section 5. In Section 6 we discuss our findings and make conclusions.

2 Institutional Background

The following overview of the Hungarian healthcare system is based on Gaál et al. (2011). In the country, the health insurance coverage rate of the population is close to 100%. Public inpatient and outpatient care services are available free of charge. Each insured person is registered at a primary care physician, who is generally the first point of contact in case of a health problem, although some specialist care services can be accessed without the referral of a primary care physician. Both primary care physicians and specialists can prescribe medications, although the former can make some prescriptions (e.g., of antidepressants) only based on a recommendation of a specialist. On average, there is a slightly larger than 50% copayment on prescribed medications.

In Hungary, employers are responsible for financing occupational health services.[4] Larger employers maintain and run their own services, while smaller employers can contract with occupational health care providers on a private basis. The employer should ensure the services of one occupational physician and one nurse per 1,000–2,000 workers, depending on the occupational hazards at the workplace. The main roles of occupational physicians are health prevention, and the monitoring of health hazards at the workplace.

When taking up a job at a firm, each new worker has to undergo and pass a health evaluation provided by the occupational physician as a prerequisite for starting to work. In addition, occupational physicians provide regular as well as exceptional health check-ups. By law, regular health screening is only compulsory for certain groups of employees based on age and occupational hazard, but in practice firms often make annual health screening compulsory for all workers. In 2017, 2.2 million employees were served by 2,543 occupational physicians, who performed 2.2 million health evaluations (of which 610,000 for new workers and 1.35 million regular evaluations) (Hungarian Central Statistical Office, 2024). The failure rate during these evaluations was less than 1% (Nagy et al., 2022).

Employee health screening is comprised of an eye test, audiometry test and blood pressure measurement, but, depending on the agreement between the firm and the occupational physician, may include further elements as well. As the main role of occupational physicians is prevention, if they detect a health problem, they may contact the primary care physician of the patient, and may provide health advice. However, occupational physicians cannot put a worker on sick leave, which remains the responsibility of primary care physicians and specialists.

[4]Occupational medicine is regulated by the Act XCIII of 1993 on Occupational Safety, 89/1995. (VII. 14.) Government Decree and by the 33/1998. (VI. 24.) Decree of the Ministry for National Economy.

Based on EU-OSHA's 2014 European Survey of Enterprises on New and Emerging Risks, Figure 2 displays statistics on occupation and health management in Hungary and the EU-28. Panel (a) indicates that the share of firms using an occupational health doctor increases with firm size both in Hungary and the EU. The share is above 90% in each firm size category in Hungary and exceeds 85% in firms with at most 50 employees in the EU. Panel (b) shows that the share of firms performing regular risk assessment also increases with firm size, and these shares are very similar in Hungary and the EU. These heterogeneities by firm size suggest that firm characteristics are related to the role of workplace health screening.

3 Data

We use linked employer-employee administrative data, complemented with health-related information, for a 50% random sample of the entire population of Hungary on the monthly level for years 2009–2017.[5]

Demographic and labor force variables. We observe sex, age, living area (district), employment status, employment type (private sector employee, public sector employee, self-employed) for each person in each month. For employees, we observe their wage, occupation (International Classification of Occupations, ISCO codes), firm and industry.

Firm quality indicators. For double-bookkeeping firms, we have yearly data on firm size, revenue, costs, and value of capital from the tax records of the firm. We define firm quality indicators in the following way.

We estimate the value added-based total factor productivity (TFP) of firms using the *prodest* Stata module of Rovigatti and Mollisi (2020) and applying the estimation procedure of Wooldridge (2009). In a system GMM (generalized method of moments) framework, we regress the logarithm of value added (gross revenue minus the cost of goods sold) on year effects, the logarithm of firm size (variable input) and the logarithm of subscribed capital (state variable). Unobserved productivity is assumed to be a function of the state variable and proxy variables (material and service costs), and follows a first-order Markov-chain. The TFP is the residual estimated from this regression. Finally, we take the firm-specific average of the TFP measure.

As a simple wage-related firm quality indicator, we use firm-specific logarithmic mean wage. Furthermore, we perform an Abowd-Kramarz-Margolis (AKM) style decomposition of logarithmic wages (Abowd et al., 1999) and compute worker and firm wage premia (fixed effects, FE) by exploiting moves between firms. That is, on the largest connected set of the employers and employees, we regress log wages on individual and firm fixed effects,

[5]The sample was drawn in 2003 and the same people were followed until 2017. The health-related variables are available only from 2009. The administrative database used in this paper is owned by the National Health Insurance Fund Administration, the Central Administration of National Pension Insurance, the National Tax and Customs Administration, the National Employment Service and the Educational Authority of Hungary. The data was processed by the Databank of the HUN-REN Centre for Economic and Regional Studies.

controlling for year effects, age squared, age cubed (in line with, e.g., Card et al., 2013). We take the estimated firm fixed effects and call them "AKM firm FE".

Following Bagger and Lentz (2019), we also calculate the poaching index (PI), the share of new hires coming from other firms (and not from unemployment). We define this index based on all hires between 2009–2017 for each firm that had at least 10 hires in our sample in this period.

Healthcare use indicators. The data covers a wide array of healthcare use indicators on the monthly level. In our empirical analysis, we aggregate the variables by six-month periods, because some categories of regular healthcare use (such as prescription drug purchases) might take place only once in every couple of months. Our definition of outpatient visits includes the sum of the number of primary care visits and specialist outpatient visits, excluding diagnostic visits. The number of diagnostic visits is the sum of (outpatient) laboratory, X-ray and ultrasound visits. Inpatient care use is measured with the number of days spent in hospital. We also create binary indicators of consumption of four major prescription drug categories, defined by Anatomical Therapeutic Chemical (ATC) codes at the level of aggregation available in our data: antihypertensives (C02-C09), lipid modifying agents (C10, predominantly statins), antidiabetics (A10, including insulin and oral medications) and psychoanaleptics (N06, mostly containing antidepressants in the age group of our interest).[6] As an additional indicator, we also look at the six-monthly number of sick pay days.

Data on outpatient and inpatient care cover public healthcare only. Data on prescription drugs cover prescriptions provided in public and private outpatient care as well, but do not contain non-prescription drugs, or medications received during inpatient stays. A limitation of our data is that we do not observe medical procedures such as cancer screening or vaccination.

4 Methods

4.1 Analysis Sample

Throughout the analysis, we focus on private sector employees who move between firms. For each employee we identify the first month in the period 2011–2015 when the employee works at a different firm than in the month before (if such a month exists).[7] We focus on 2011–2015 to ensure that at least two pre-transition and post-transition years are observed in the data. The month of the move, the three preceding months and the two subsequent months are defined as the six-monthly event time 0. We make this choice because healthcare use a few months before the move might be affected by the foreseen move, therefore, we consider event

[6] Within ATC N06, antidepressants (N06A) and "psychostimulants, agents used for ADHD and nootropics" (N06B) are the two substantial categories. The latter mainly covers vinpocetine, a drug used in the treatment of dementia and some other neurological disorders, hence is rarely prescribed in the age group of our interest.

[7] To make sure that a change of the firm identifier does not lead to a false move we apply the worker-flow method of detecting firm identifier changes as in Saygin et al. (2021).

time 0 as the transition period. We follow employees through six-monthly event time -4 to 4, i.e., for a period spanning four and a half years, which we call the *event time window*.

We examine individuals aged 30–55 at the time of the move (sample size: 208,301 individuals), as we focus on ages when healthcare use becomes more frequent but retirement is still distant (the majority of individuals retired after age 60 in this period). We exclude employees who were hospitalized at least once within the two-year period before the move, as our aim is to analyze a relatively healthy population without major pre-move health deterioration to ensure that the transition between firms is not driven by health problems. We also exclude from the sample those women who ever had (in the 2009–2017 period) an inpatient or outpatient diagnosis code referring to pregnancy, childbirth and the puerperium (ICD10 [International Classification of Diseases] "O") (sample size: 152,666 individuals).

We include only those persons who were private sector employees throughout the whole event time window at firms with at least 50 workers (reducing the sample to 15,382 individuals),[8] and moved between firms only once (sample size: 11,288 individuals). Finally, we exclude employees whose district of residence changed during the event time window (Hungary is divided into 197 districts, with an average population of about 50,000 inhabitants per district).

After the sample restrictions, we have $10,291$ individuals in our analysis sample. 91% of them remain in the same broad occupation category (white-collar or blue-collar) after the move; 62% of them remain in the same one-digit industry category.[9]

We define as a comparison group the sample of workers who remain occupied at the same firm with at least 50 employees for a period spanning four and a half years around a randomly selected event date. For this non-mover comparison group, we also require the no-hospitalization condition before the pseudo event, and the condition of no change in the district of residence (129,636 individuals).

4.2 Empirical Specifications

We analyze the effect of moving to a firm with a different TFP on health-related outcomes by estimating the following event study model:

$$H_{it} = \sum_{j=-4}^{4} \beta_j \mathbb{1}[e_{it} = j]\Delta_i + \sum_{j=-4}^{4} \alpha_j \mathbb{1}[e_{it} = j] + X_{it}\gamma + \tau_t + \mu_i + \varepsilon_{it}, \tag{1}$$

where i indexes individuals, t indexes calendar time, H_{it} is a health-related dependent variable, e_{it} indicates event time in six-month periods, $\mathbb{1}[e_{it} = j]$ is the event time dummy for event time j, τ_t denotes calendar year fixed effects (measured at the first month in the

[8]We make the firm size restriction because the estimated TFP is noisy for smaller firms. A robustness check including firms with at least 20 workers is shown in Appendix Figure A4.

[9]In the analysis sample, 19% of the moves between firms occur after a mass lay-off at the original firm, defined as a reduction in the workforce by at least 50% based on annual average workforce size.

event time period), μ_i denotes individual fixed effects, X_{it} includes sex-specific quadratic functions of age, one-digit industry dummies, and two-digit occupation dummies. Δ_i is the difference between log TFP in the post- vs. pre-move firm. The coefficients of interest are the β_j, capturing the effect of the post-move firm's productivity relative to the pre-move firm's productivity on the health-related outcome over time. We make the normalization $\sum_{j=-4}^{-1} \beta_j = 0$.

The identification of the effect hinges on the assumption that Δ_i is not related to changes in the health of workers. If, for example, workers with deteriorating health were more likely to move to lower-TFP than to higher-TFP firms, then we would observe higher healthcare use at lower-TFP than at higher-TFP firms after the move, irrespective of the true effects of the firms on healthcare use. We provide three pieces of indirect evidence that the difference between the TFP in the post- vs. pre-move firm is not related to changes in worker health: (1) the relation between healthcare use and Δ_i is flat preceding the move between firms (i.e., parallel trend holds before the move); (2) capturing health status with hospitalization, we do not see evidence that the difference in firm productivity would be related to major changes in worker health; (3) moving to a higher-TFP firm and moving to a lower-TFP firm both influence health outcomes in a roughly symmetric manner.

Next, we estimate the effect of the change of firm- and individual-level indicators on health-related outcomes in a difference-in-differences (DiD) type specification:

$$H_{it} = \tilde{\boldsymbol{\beta}} E_{it} \tilde{\boldsymbol{\Delta}}_i + \alpha E_{it} + X_{it}\gamma + \tau_t + \mu_i + \varepsilon_{it}, \tag{2}$$

where we use the same notation as in equation (1), and E_{it} is a binary indicator of the post-move period, i.e., it equals one for event times 1 to 4 and zero for event times -1 to -4 (omitting the six-month transition period, event time 0, from the model). In various specifications $\tilde{\boldsymbol{\Delta}}_i$ denotes the difference of a single firm quality measure (log TFP, log mean wage, AKM firm FE or the poaching index) in the post- vs. pre-move firm or a vector of differenced indicators (such as the difference of log TFP, log firm size and log individual wage in the same model). We measure time-varying firm characteristics and individual wage at event times 1 (at the post-move firm) and -1 (at the pre-move firm). The parameter (vector) of interest is $\tilde{\boldsymbol{\beta}}$, which shows the effect of the change in firm-level parameters or log individual wage on healthcare use.

On the methodological side, when estimating versions of equation (2), we directly regress individual-level healthcare use on the change in firm quality measures while controlling for the change in other firm characteristics such as industry or firm size. As discussed in Agha et al. (2019) in a mover-based setting, this is equivalent to first decomposing healthcare use into worker and firm effects and then regressing the estimated firm fixed effects on firm-level indicators as done in Ahammer et al. (2023), similarly to most of the mover-based literature. However, our aim here is not to examine in detail the correlates of the firm effects but to show that taking into account other firm characteristics does not cancel the estimated effects of the firm quality measures.

To analyze heterogeneity in the relationship between healthcare use and firm quality, we estimate event studies (1) and DiD-type equations (2) separately on subgroups defined by age group, sex, location of residence and pre-move industry and occupation category.[10] In all regressions, we display standard errors clustered at the individual level.

5 Results

5.1 Descriptive Analysis

Table 1 displays descriptive statistics at event time −1, i.e., in the six-month period before moving between firms, separately for individuals whose change in the employer's TFP is below vs. above its median.[11] The share of males is around 65%, and average age is around 40 years in both groups. Individuals for whom the change in TFP is above the median have a higher average wage, are more likely to work at smaller firms, in the services, in blue-collar, physically demanding and hazardous jobs, and are less likely to work in manufacturing before the transition. According to Table 1, the six-monthly indicators of healthcare use are similar in the two groups, although movers with below-median TFP change use slightly more antihypertensives than those with above-median TFP change.[12]

Figure 3 displays the time patterns of healthcare variables of movers from below-median to above-median TFP firms and from above-median to below-median TFP firms, as well as of the non-mover (stayer) comparison group with placebo event times. We weight the sample of stayers to match the age and sex composition of movers. The figure suggests that the trends before the moves are roughly parallel and the mean healthcare use of stayers is close to that of movers. According to the figure, the use of lipid modifying agents and the number of outpatient visits (panels (b) and (e)) decrease slightly just after a move from an above-median to a below-median productivity firm. The patterns suggest that for some healthcare services, the transition between firms may imply a disruption in care. More importantly for our analysis, the use of antihypertensives, lipid modifying agents, antidiabetics, outpatient visits and diagnostic visits (panels (a) to (c), (e) and (f)) increase more among workers moving from a below-median to an above-median productivity firm than after a move in the opposite direction. There is no clear evidence for changing levels or trends in the use of psychoanaleptics (panel (d)). The increase in hospital days (panel (g)) stems from the construction of our sample, i.e., no hospital stays in the two-year period before transition.

[10] The industry and occupation categories refer to the first month of event time −1, i.e., the six-month period before the move between firms.

[11] Appendix Figure A1 shows that the change in log TFP upon the move has a roughly symmetric distribution with a slightly positive mean.

[12] Here we regard a difference as substantial if the standardized mean difference is greater than 0.1 in absolute value.

Importantly, in our empirical analysis, we include individual fixed effects to ensure that any differential time patterns in healthcare use are not driven by time-constant differences between individuals moving to more or less productive firms, and we also control for the (possibly time varying) occupation and industry categories.

In Appendix Figure A2 we show binned scatter plots that relate the difference between log TFP in the post- vs. pre-move firm to the difference between the person-specific mean healthcare use in the post- vs. pre-move firm. These plots also reinforce the positive relationship of TFP with the use of antihypertensives, lipid modifying agents, outpatient visits and diagnostic visits.

5.2 Baseline Results

We turn to the β_j event study parameters estimated from equation (1), showing the dynamic effect of the difference of the post- vs. pre-move TFP on healthcare use. We display the results for the entire estimation sample in Figure 4, and separately for age groups 30–42 and 43–55 at the time of the transition between firms in Appendix Figure A3.[13] The parameter estimates are summarized in single difference-in-differences type results in the top row of Table 2, which shows the estimated $\tilde{\boldsymbol{\beta}}$ parameter of equation (2) when $\tilde{\boldsymbol{\Delta}}_i$ only contains the difference of the post- vs. pre-move log TFP. The DiD-type estimates for the two age groups are shown in the top of each panel in Figure 6.

Prescription drug consumption. Panel (a) of Figure 4 and the first column of Table 2 indicate that a 10% higher TFP (i.e., a 0.1, roughly one standard deviation, higher log TFP) implies an around 0.6 %point higher (half-yearly) probability of antihypertensive use after the transition, which is about 4% of the average rate of antihypertensive use in our sample. TFP is also positively related to the use of lipid modifying agents (panel (b) of Figure 4 and second column of Table 2), with a 10% higher TFP implying a 0.4 %point higher (in relative terms, 7% higher) probability of consumption. On average, we do not see an effect of firm productivity on the use of antidiabetics and psychoanaleptics.

Looking at the two age groups separately, Figure 6 and Appendix Figure A3 indicate that the effects on the use of antihypertensive medications and lipid modifying agents are larger for relatively older than for younger workers. The probability of the use of psychoanaleptics significantly decreases with TFP among the 43–55 years old employees: a 10% higher TFP implies an around 0.3 %point reduction, which roughly equals 8% of the average consumption ratio in this age group.

Initiation and continuation of prescription drug consumption. To better understand the dynamics of prescription drug consumption around the transition between firms, for each analyzed prescription drug category, we split the sample by whether the individual used the specific drug at event time -4 (i.e., around two years before the move between

[13]Appendix Figure A4 shows results for the sample of firms with at least 20 workers (instead of at least 50 workers in the baseline sample).

firms). For each subsample, we estimate equation (1). These specifications can provide indicative evidence on new diagnoses (subsamples with no drug use at event time −4), and on continuation of treatment (subsamples with drug use at event time −4).

The left-hand side panels of Figure 5 show the estimated β_j parameters from equation (1) on the initiation of drug use. According to panels (a) and (c), for antihypertensives there is a 0.5–1 %point increase and for lipid modifying agents there is a 0.2–0.3 %point increase in the six-monthly probability of new prescriptions if someone moves to a 10% more productive firm (and the corresponding drug category was not consumed in the six-monthly period two years before the move). These results are in line with the hypothesis that health screening upon entering a new firm and regular screening afterwards have a larger role in the diagnosis of hypertension and high blood cholesterol at more productive than at less productive firms. The event study estimates for the initiation of antidiabetics and psychoanaleptics are noisier.

The right-hand side panels of Figure 5 indicate that the relation between firm productivity and the continued use of the analyzed categories of drugs is mostly around zero and statistically insignificant. However, panel (h) of the same figure suggests that around two years after the move, there is a 2–3 %point decrease in the six-monthly probability of prescription of psychoanaleptics if someone, who consumed psychoanaleptics two years before the transition, moves to a 10% more productive firm.

Outpatient and inpatient care use. Panels (e) and (f) of Figure 4 show the estimated β_j from equation (1) for non-diagnostic and diagnostic outpatient care use (the DiD-type results are shown in Table 2). According to the estimates, a 10% higher TFP is associated with 0.13 more six-monthly outpatient (non-diagnostic) and 0.03 more diagnostic visits (both about 3–4% in relative terms). These relations are stronger among older workers (Appendix Figure A3).

Looking at outpatient care categories separately, Appendix Table A1 shows that the effect of TFP is positive and statistically significant for primary care, physiotherapy, rheumatology, infectology, pulmonology and all three groups of diagnostics services (laboratory, X-ray and ultrasound diagnostics). As primary care physicians have a key role in general health maintenance (via prescription of drugs and diagnosis of diseases), physiotherapy and rheumatology directly contribute to the maintenance of musculosceletal health, and the three types of diagnostic care serve the detection of health problems, these results suggest more effective health maintenance at more productive firms. Diagnostic visits become especially frequent one year after the transition to a more productive firm (panel (f) of Figure 4), suggesting a cyclical pattern in the screening and care of chronic diseases. Remarkably, the use of psychiatric services seems to increase (at least does not decrease), suggesting that the decreased use of psychoanaleptics is not driven by a deterioration of access to mental health care.

Importantly, the results in panel (h) of Figure 4 and Appendix Figure A3, and the last column of Table 2 reveal that higher firm productivity does not imply a higher number of hospital days, therefore, it is not likely that the higher use of antihypertensives, lipid modifying agents and outpatient care services are due to the worsening health of individuals moving to more productive firms.[14]

According to Appendix Figure A6, the baseline results are robust to including the non-mover comparison group (with placebo event dates) in the estimation.

5.3 Heterogeneities

Subgroup Analysis. Now, we estimate equation (2) across worker subgroups, where $\tilde{\boldsymbol{\Delta}}_i$ is defined again as the difference between the log TFP in the post- vs. pre-move firm. Figure 6 shows the estimation results on our sample split by age category, sex, living area (county seat vs. not), pre-move broad industry group and occupation category (blue- vs. white-collar).

As already discussed, the positive relation between firm productivity and the use of antihypertensives, lipid modifying agents, outpatient visits and diagnostic visits, and the negative relation between firm productivity and the use of psychoanaleptics is stronger (or only present) for the relatively older workers, whose baseline usage rates and chronic disease latency rates are already larger, than for the younger workers. Regarding sex differences, the positive relations are significantly larger for women than for men in the case of antidiabetics and outpatient care. Looking at occupations, the positive relation between firm productivity and the use of antihypertensives is stronger for blue-collar workers who may be less health-conscious and may have less access to healthcare outside occupational health. Finally, heterogeneities by settlement type and industry are mixed or non-existent.

Moving to Higher- or Lower-TFP Firms. Next, we check if moving to more productive or to less productive firms drives our estimation results. In Table 3 we report estimated coefficients from a modified version of equation (2), in which we replace the continuous indicator of TFP change with binary indicators of low-to-high and high-to-low moves in terms of TFP, the baselines being the low-to-low and high-to-high moves. These results indicate that moving to a higher (respectively, lower) TFP firm has an increasing (respectively, decreasing) effect on healthcare use in cases where the effect is statistically significant, and the two effects are similar in absolute value (and do not differ significantly at the 5% level).

5.4 Alternative Firm Quality Measures

To examine the robustness of our results to using the firm-specific mean wage, the AKM firm FE and the poaching index instead of firm TFP as an indicator of firm quality, we estimate equation (2) with these choices for $\tilde{\boldsymbol{\Delta}}_i$. Table 2 shows that the use of antihypertensives, lipid

[14]We report descriptive trends and event study results for sickness absence days in Appendix Figure A5. These estimates suggest that two years after the move, there is a 0.2 day increase in the six-monthly number of sick pay days if someone moves to a 10% more productive firm. The interpretation of this result is not straightforward as the increase is also consistent with a more permissive sick leave policy (i.e., with a higher probability of sickness absence given the same health status), not just with a deterioration in health.

modifying agents and diagnostic visits increase with firm quality statistically significantly at least at the 10% level irrespective of the firm quality measure used, while, reassuringly, none of the quality indicators has a significant relation with hospital days. For antidiabetics, psychoanaleptics and outpatient visits, the parameters have the same sign but different level of significance depending on the choice of the quality indicator. In a sense, the stability of the results is not surprising because high-TFP firms are consistently better than low-TFP firms in these other aspects, too, as shown in Appendix Table A2.

5.5 Possible Mechanisms

To investigate potential mechanisms that can explain the relationship between firm productivity and healthcare use, we estimate equation (2) with including different control variables in $\tilde{\boldsymbol{\Delta}}_i$ beyond the difference of post- vs. pre-move log TFP.

Firm Size and Individual Wage. First we investigate if heterogeneities by firm productivity remain significant after controlling for firm size (with higher TFP firms being larger on average) and for individual wage (with higher TFP firms paying more on average). According to the top panel of Table 4, the relation between the analyzed healthcare use indicators and TFP is robust to the inclusion of these variables in the model, suggesting that firm productivity influences prescription drug use and physician visits beyond the impact of firm size and wage. Note, that under this extended specification, the relation between the use of psychoanaleptics and firm quality is statistically significant for the whole sample, not just for the relatively older, more responsive subgroup as in the baseline specification reported in Figure 6.

Despite the 50% average co-payment for prescription drugs, individual wages do not affect drug consumption significantly, therefore wage effects seem not to play a key role in the relation between firm productivity and prescription drug use. A likely explanation for this finding is that the analyzed drugs are relatively cheap. The average six-monthly total (social security plus out-of-pocket) cost of the analyzed four drug categories, conditional on non-zero spending, was 22–24 euros for antihypertensives, lipid modifying agents and psychoanaleptics, and 57 euros for antidiabetics, which are not substantial compared to the median gross six-monthly wage of 4,498 euros (corresponding to 1.259 million Hungarian forint) and the median net six-monthly wage of 2,991 euros in our sample.

Peer Effects. In principle, the relation between firm productivity and healthcare use may be driven by peer effects, if, for example, co-workers are more health conscientious at more productive firms and they influence their peers' healthcare use (Pruckner et al., 2020). As an indicative test of this mechanism, we estimate equation (2) with, in addition to the TFP indicator, including the difference in the mean of the 5-year age group – sex – one digit occupation specific healthcare use of peers at the post- vs. pre-move firm. If peer effects were important, we would expect a positive coefficient for this indicator (β parameter of equation (2)). Note, however, that our estimation is subject to the well-known reflection problem

(Manski, 1993), therefore, our focus is not on peer effects themselves but on the sensitivity of the estimated relation between healthcare use and TFP. According to the middle panel of Table 4, the estimated relation between healthcare use and TFP is qualitatively robust to the addition of the mean healthcare use by narrow worker groups at the firm, therefore, is unlikely to be driven by peer effects.

Role of Industry-Specific Risk Categories. Based on occupational health risks, regulations in Hungary define occupational health categories which determine the minimal frequency of occupational health check-ups and the minimal ratio of occupational physicians per employee. This categorization applies mainly to blue-collar workers[15] and is determined by the two-digit industry code of the employer. We check in the bottom panel of Table 4 whether moving to an employer in a different risk category has an effect on healthcare use after controlling for firm productivity. Here, risk level is coded as zero for the low-risk and one for the high-risk industry-specific risk categories, and we take the difference of this risk level in the destination versus origin firm.[16] The estimated effect of this variable is essentially zero and the TFP-parameters for the relevant outcome variables remain significant, which suggests that the impact of TFP is not driven by the peculiarities of the Hungarian occupational health regulations.

Further Mechanisms. Although we do not observe occupational medicine in our data, we know that by law, each worker entering a new firm has to undergo a health check-up, provided by the new employer. The result that new treatment of cardiovascular diseases is more likely to commence after arriving at a more productive firm can be explained by multiple possible mechanisms: (1) more productive firms take the health check-up upon hiring a new worker more seriously (they contract with the occupational physician to provide more thorough health check-up); (2) more productive firms can afford (or are more willing) to provide regular health check-ups via the occupational physician to their workers – this mechanism is suggested by the increasing difference by firm quality over time in some healthcare use categories; (3) occupational physicians at more productive firms can devote more time to their (sick) patients as workers are on average in better health and therefore have lower healthcare needs; (4) people moving to more productive firms take the recommendations of the occupational physician more seriously, partly because they are more motivated to maintain their capacity to work. The understanding of the exact mechanism behind our results remains to future research, which necessitates detailed data on occupational medicine.

[15]White-collar workers employed in similar environment in most of their working hours are also covered but we cannot define them in the administrative data.

[16]Before the move, 36% of the blue-collar workers in our sample work at a high-risk industry. The mean difference in the risk level indicator in the destination vs. origin firm is 0.01 with standard deviation 0.51.

6 Conclusion

Using workers' transitions between firms, we analyzed how firm productivity is related to healthcare use. We focused on a population without hospitalization before moving to a different firm, to ensure that the transition is not driven by health deterioration. We found no evidence for major changes in health status after the move between firms. However, moving to a more productive firm implies almost immediately a persistently higher use of antihypertensives, lipid modifying agents, non-diagnostic and diagnostic outpatient care. At the same time, the consumption of psychoanaleptics of workers aged 43–55 decreases with firm productivity.

The decline in the use of drugs for mental health conditions is unlikely to be the consequence of reduced access to care, as outpatient care use increases simultaneously (and the use of specialist psychiatric services does not decrease). We therefore conclude that mental health tends to improve with firm productivity among relatively older workers, and this may be driven by better working conditions. If mental illnesses are better diagnosed at more productive firms (implying a positive effect on the use of drugs for mental health conditions) then our results may underestimate the beneficial effects of firm productivity on mental health.

Our main results suggest that moving to a more productive firm is accompanied by a higher awareness of diagnostic services and a higher probability of the diagnosis and treatment of existing cardiovascular diseases such as hypertension and high blood cholesterol, which have a large latency rate. The estimates are robust to using the firm-level average wage, the firm-level AKM wage premium and the poaching index as a firm quality indicator, and to netting out the influence of peer effects, changes in the industry-specific formal risk category, firm size and individual wages. The latter robustness check implies that income effects are unlikely to drive the results. Although people moving to more productive firms may achieve higher wage growth, this does not have a major role because most outpatient and inpatient services are free of charge and the analyzed drug categories have low out-of-pocket costs.

In sum, we conclude that more productive firms contribute to the maintenance of the health of their workers through the prevention channel if there is health screening at the workplace. This result is based on an institutional setting with universal health insurance coverage provided by the social security system, therefore our findings are not affected by incentives inherent in employer-based health insurance. Our results are relevant to other institutional settings with some employee health screening, such as in the European Union (based on the Directive 89/391/EEC), and in the US (based on the Occupational Safety and Health Act).

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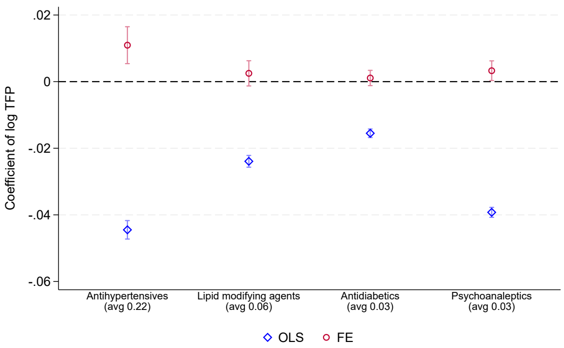
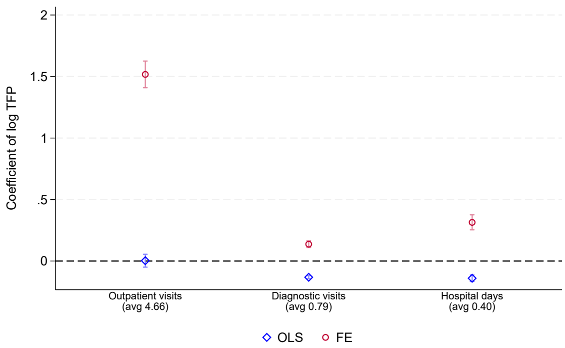
Figures and Tables

Figure 1: Relation between firm productivity and healthcare use

(a) Prescription drugs



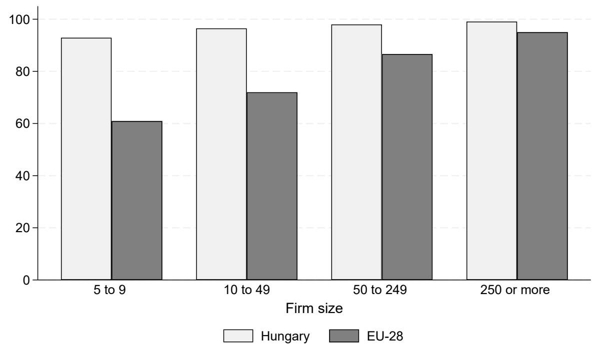
(b) Outpatient and inpatient care



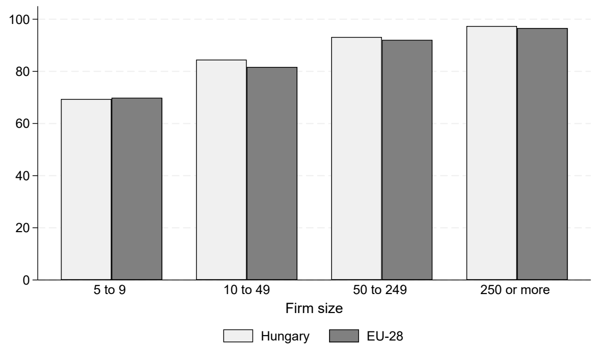
Notes: Figure shows regression estimates with 95% confidence intervals for binary indicators of six-monthly use of prescription drug categories, and six-monthly indicators of outpatient and inpatient care use, with log TFP as the main explanatory variable. Sample is private sector workers aged 30–55 in the entire administrative data set over 2009–2017 (the averages indicated on the x-axis labels also refer to this sample). Control variables: age effects, logarithmic wage, six-monthly date for the OLS results and additionally individual fixed effects for the FE results. Number of observations: 6,504,125; number of individuals: 779,339.

Figure 2: Occupation safety and health management statistics in Hungary and the EU

(a) Share of firms using an occupational health doctor

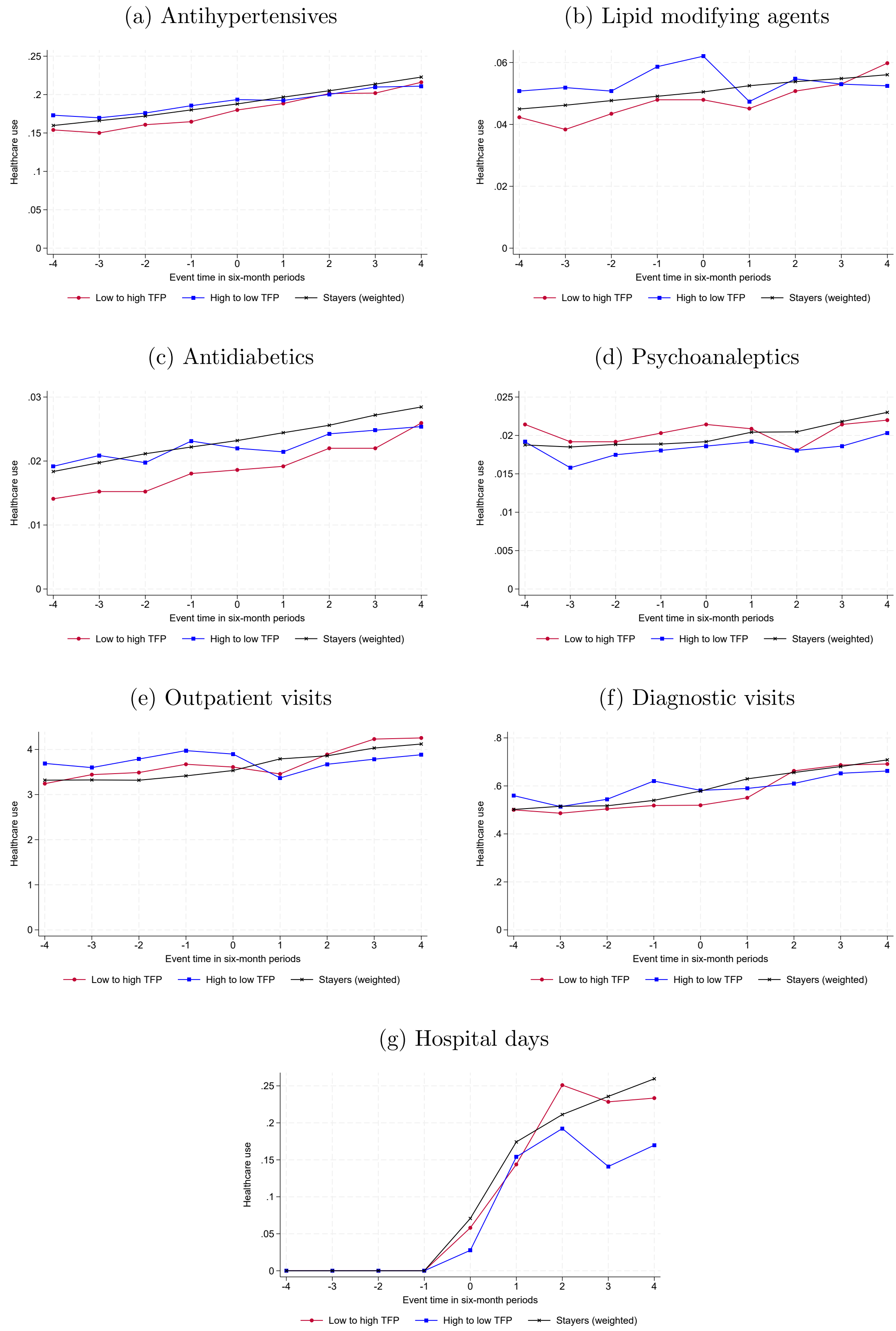


(b) Share of firms performing regular risk assessment



Notes: Figure shows statistics from the 2014 EU-OSHA's European Survey of Enterprises on New and Emerging Risks (ESENER) (https://osha.europa.eu/en/facts-and-figures/esener) by firm size. Panel (a) shows the share of firms using an occupational health doctor either in-house or contracted externally. Panel (b) shows the share of firms carrying out workplace risk assessments on a regular basis. .

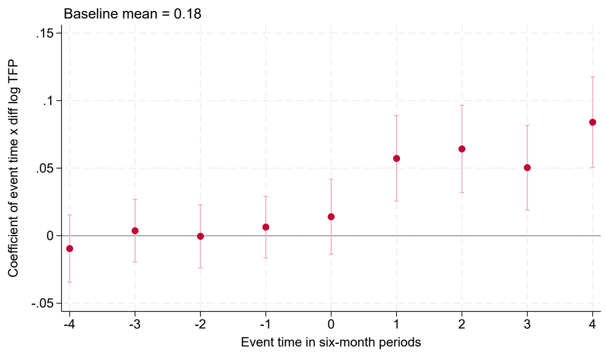
Figure 3: Healthcare use around job-to-job transition by TFP change



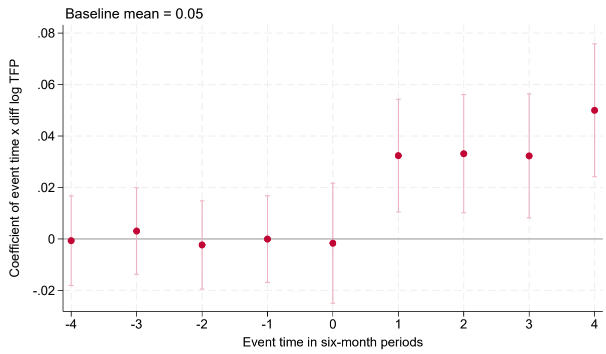
Notes: Figure shows the evolution of six-monthly healthcare use indicators split by the origin and destination TFP being below or above its median (low vs. high TFP). Low-to-high and high-to-low moves are displayed. Sample is as described in Section 4.1, extended with workers not moving between firms. The sample of individuals not moving between firms ("stayers") is weighted to match the age and sex composition of the mover sample. Event time 0 corresponds to the month of the move between firms (or a random event date for those who do not move), the two months after, and the three months before. Number of individuals: low-to-high TFP 1,773; high-to-low TFP 1,773; 129,636 stayers.

Figure 4: Event studies for healthcare use, effect of TFP

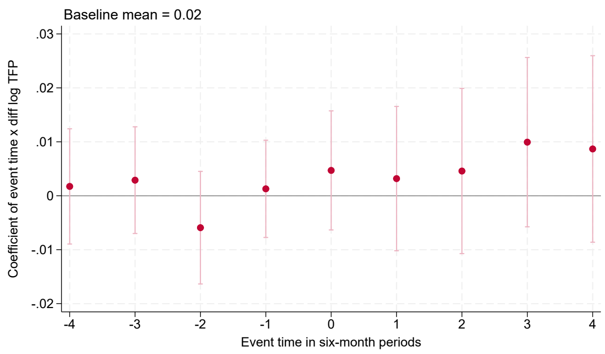
(a) Antihypertensives



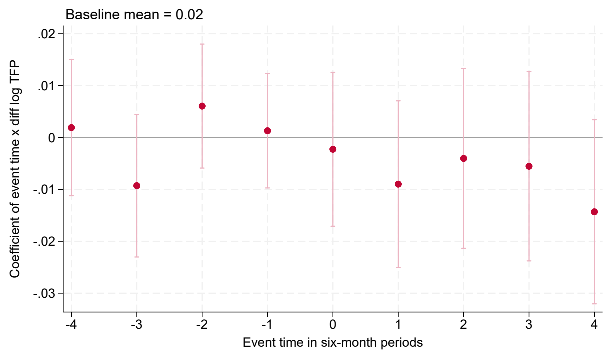
(b) Lipid modifying agents



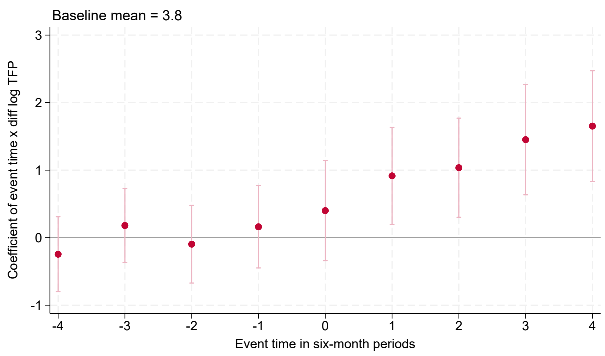
(c) Antidiabetics



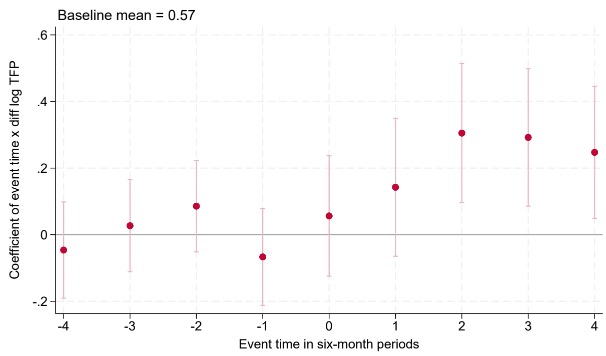
(d) Psychoanaleptics



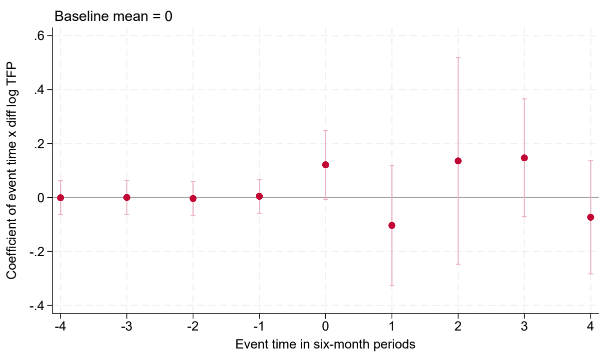
(e) Outpatient visits



(f) Diagnostic visits



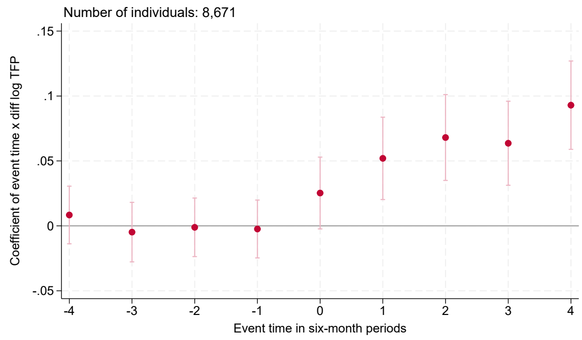
(g) Hospital days



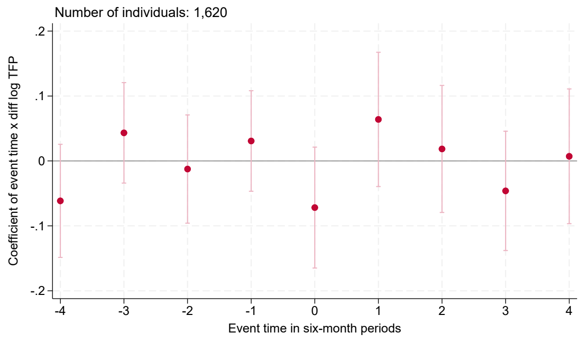
Notes: Figure shows estimated β_j parameters (coefficients of event time $\times$ difference between post- vs. pre-move log TFP) with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. Sample is as described in Section 4.1. Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. The mean outcome measured at event time -1 is displayed at the top of each panel. Number of individuals: 10,291.

Figure 5: Event studies for initiation and continuation of prescription drug consumption, effect of TFP

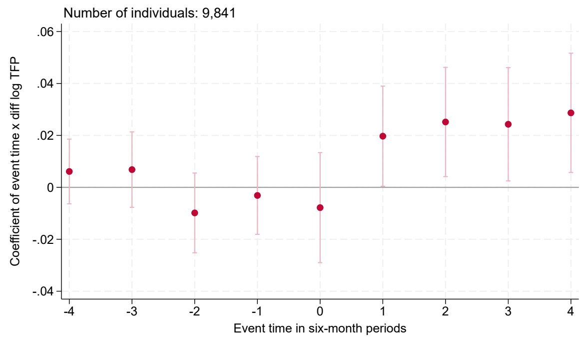
(a) Antihypertensives, not used at event time -4



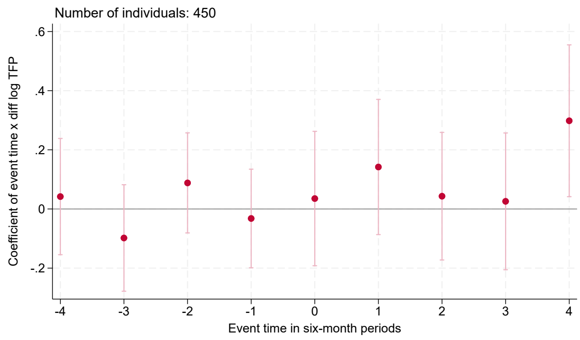
(b) Antihypertensives, used at event time -4



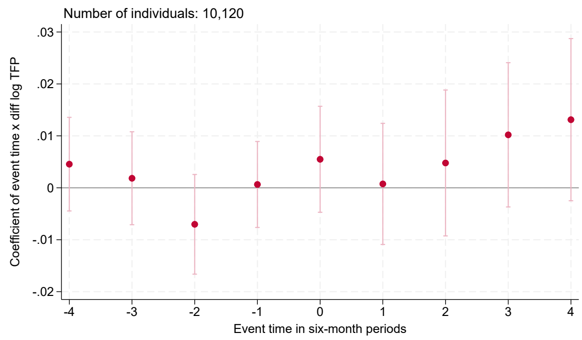
(c) Lipid mod. agents, not used at event time -4



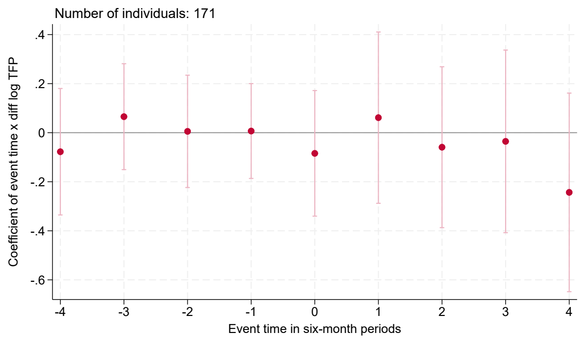
(d) Lipid mod. agents, used at event time -4



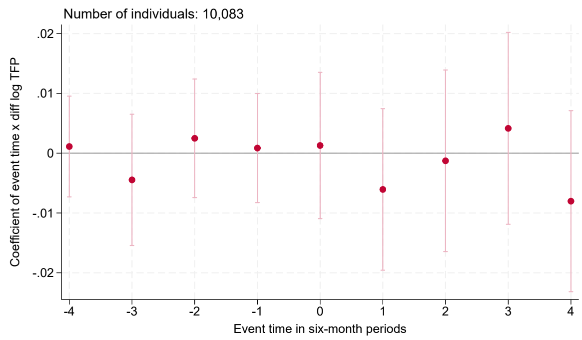
(e) Antidiabetics, not used at event time -4



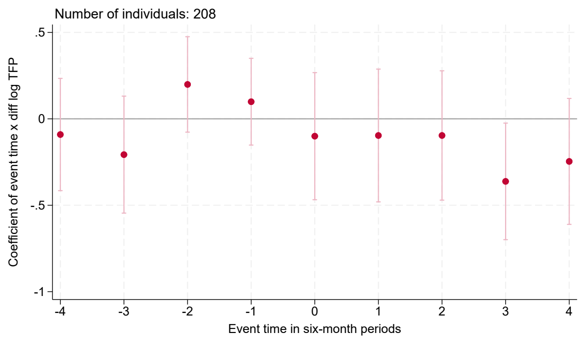
(f) Antidiabetics, used at event time -4



(g) Psychoanaleptics, not used at event time -4



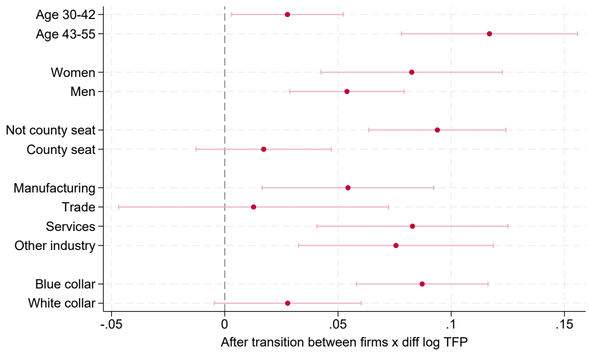
(h) Psychoanaleptics, used at event time -4



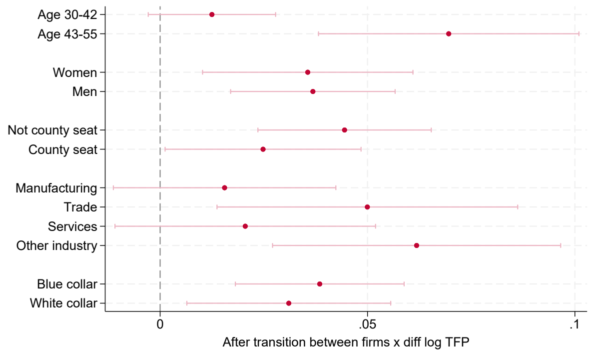
Notes: Figure shows estimated β_j parameters with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. Sample is as described in Section 4.1, split by having used the specific drug category at event time -4. Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. Number of individuals is indicated at the top of each panel.

Figure 6: Effect of TFP on healthcare use, results by sub-samples

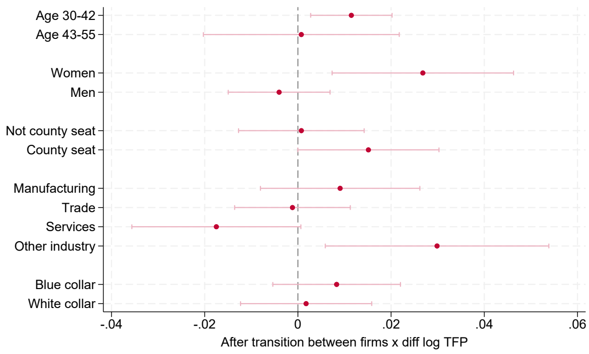
(a) Antihypertensives



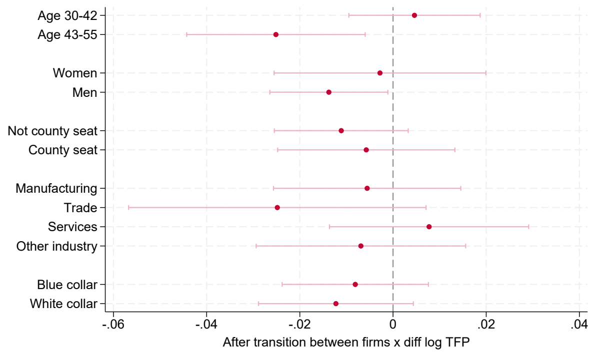
(b) Lipid modifying agents



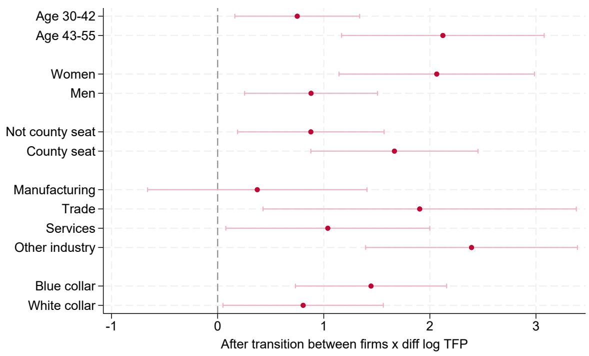
(c) Antidiabetics



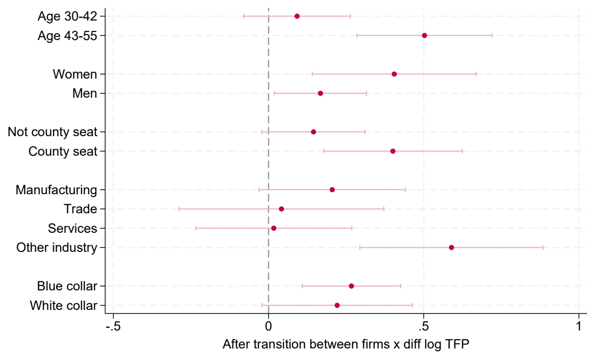
(d) Psychoanaleptics



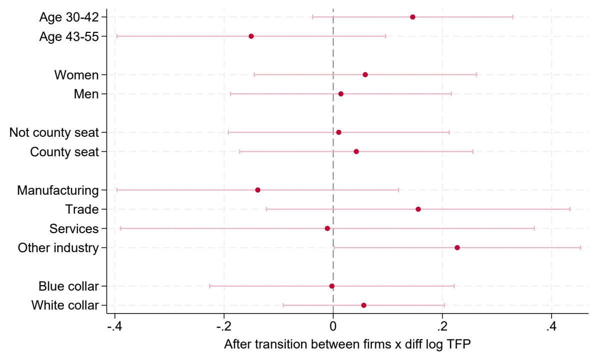
(e) Outpatient visits



(f) Diagnostic visits



(g) Hospital days



Notes: Figure shows estimated β parameters with 95% confidence intervals from equation (2), using the difference between post- vs. pre-move log TFP as the main explanatory variable. Sample is as described in Section 4.1. Number of individuals: 10,291.

Table 1: Descriptive statistics by the change of TFP

	TFP change below median		TFP change above median		Total	
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Male	0.657	0.475	0.647	0.478	0.652	0.476
Age	40.365	7.278	40.234	7.218	40.299	7.248
County seat (incl. Budapest)	0.430	0.495	0.399	0.490	0.414	0.493
Log individual wage	12.388	0.605	12.217	0.545	12.303	0.582
White-collar worker	0.459	0.498	0.389	0.488	0.424	0.494
Healthcare use (six-monthly)						
Antihypertensives (binary)	0.179	0.384	0.171	0.377	0.175	0.380
Lipid mod. agents (binary)	0.054	0.226	0.045	0.208	0.050	0.217
Antidiabetics (binary)	0.020	0.141	0.019	0.136	0.020	0.139
Psychoanaleptics (binary)	0.019	0.137	0.021	0.143	0.020	0.140
Outpatient visits	3.872	6.628	3.674	5.054	3.773	5.894
Diagnostic visits	0.607	1.333	0.539	1.222	0.573	1.279
Hospital days	0.000	0.000	0.000	0.000	0.000	0.000
Employer characteristics						
Log TFP	2.411	0.101	2.312	0.097	2.361	0.110
Change in log TFP	-0.068	0.088	0.117	0.081	0.024	0.125
Log mean wage	12.497	0.475	12.229	0.434	12.363	0.475
Change in log mean wage	-0.044	0.393	0.305	0.406	0.130	0.436
AKM firm FE	0.181	0.203	0.085	0.199	0.133	0.207
Change in AKM firm FE	-0.021	0.190	0.114	0.196	0.047	0.204
Poaching index	0.419	0.188	0.379	0.175	0.399	0.183
Change in poaching index	0.106	0.263	0.161	0.223	0.133	0.245
Firm size	3579	6076	967	2366	2273	4792
Industry						
Manufacturing	0.323	0.468	0.284	0.451	0.303	0.460
Trade	0.142	0.350	0.127	0.333	0.135	0.341
Services	0.184	0.387	0.321	0.467	0.252	0.434
Other	0.351	0.477	0.268	0.443	0.310	0.462
Individuals	5,146		5,145		10,291	

Notes: Table displays mean values measured in the six-month period before moving between firms. Sample is as described in Section 4.1, split at the median change of the log TFP (0.026) upon transition between firms.

Table 2: Effect of various firm quality measures on healthcare use

Indicator	Anti-hypertens.	Lipid mod. agents	Anti-diabetics	Psycho-analeptics	Outpatient visits	Diagnostic visits	Hosp. days
Separate model for each firm characteristic							
Diff log TFP	0.063***	0.037***	0.007	-0.008	1.260***	0.251***	0.032
{Std.dev. 0.125}	(0.011)	(0.008)	(0.005)	(0.006)	(0.265)	(0.068)	(0.076)
Diff log mean wage	0.013***	0.005**	0.002*	-0.004***	0.207***	0.064***	-0.001
{Std.dev. 0.436}	(0.003)	(0.002)	(0.001)	(0.001)	(0.075)	(0.019)	(0.017)
Diff AKM firm FE	0.030***	0.008*	0.003	-0.007**	0.225	0.074*	0.001
{Std.dev. 0.204}	(0.006)	(0.005)	(0.002)	(0.003)	(0.159)	(0.039)	(0.035)
Diff poaching index	0.033***	0.012***	0.006***	-0.004	0.842***	0.153***	0.033
{Std.dev. 0.245}	(0.006)	(0.004)	(0.002)	(0.003)	(0.135)	(0.035)	(0.036)
Mean outcome at event time -1	0.175	0.050	0.020	0.020	3.773	0.573	0.000

Notes: Table shows estimated β parameters and robust standard errors (in brackets) from equation (2), using the variables indicated in the first column of the table in separate models. Sample standard deviations of the differenced variables are also shown. Sample is as described in Section 4.1. Number of individuals: 10,290 (10,260 when using the poaching index as quality indicator). *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of positive and negative firm productivity change on healthcare use

Indicators	Anti-hypertens.	Lipid mod. agents	Anti-diabetics	Psycho-analeptics	Outpatient visits	Diagnostic visits	Hosp. days
Baseline: low-to-low or high-to-high TFP move							
Low-to-high move	0.012***	0.006**	0.001	-0.001	0.177**	0.030	0.029
	(0.004)	(0.002)	(0.001)	(0.002)	(0.086)	(0.021)	(0.023)
High-to-low move	-0.008**	-0.004	-0.003**	0.001	-0.401***	-0.038*	-0.035
	(0.003)	(0.002)	(0.001)	(0.002)	(0.084)	(0.021)	(0.021)
p-value for equal abs. value of coeffs	0.501	0.485	0.262	0.956	0.086	0.814	0.866
Mean outcome at event time -1	0.175	0.050	0.020	0.020	3.773	0.573	0.000

Notes: Table shows estimated β parameters and robust standard errors (in brackets) from equation (2), using the variables indicated in the first column of the table as heterogeneity indicators. P-values for the equality of the absolute value of the low-to-high and high-to-low TFP coefficients are also shown. Sample is as described in Section 4.1. Number of individuals: 10,291. *** p<0.01, ** p<0.05, * p<0.1.

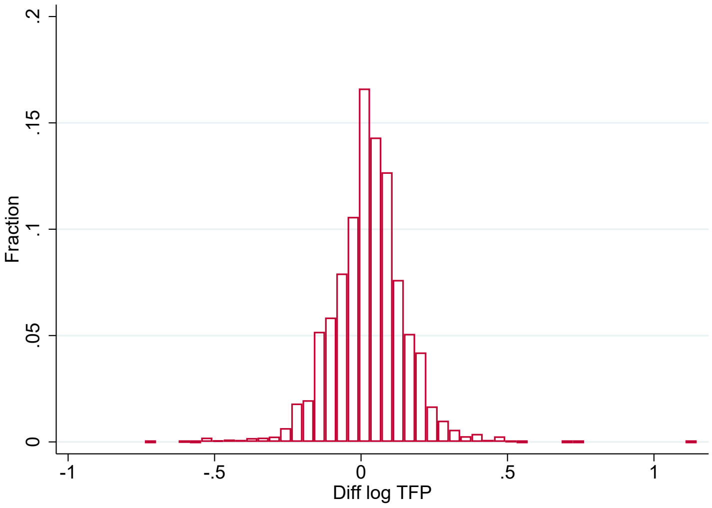
Table 4: Effect of firm TFP on healthcare use, controlling for other firm characteristics

Indicators	Anti-hypertens.	Lipid mod. agents	Anti-diabetics	Psycho-analeptics	Outpatient visits	Diagnostic visits	Hosp. days
Panel A: TFP, firm size, and individual wage in same model							
Diff log TFP	0.064***	0.046***	0.001	-0.014**	1.048***	0.321***	-0.017
	(0.013)	(0.010)	(0.006)	(0.007)	(0.317)	(0.085)	(0.079)
Diff log size	0.00001	-0.001**	0.001**	0.001*	0.059***	-0.005	0.007
	(0.001)	(0.0006)	(0.0003)	(0.0004)	(0.021)	(0.005)	(0.005)
Diff log ind. wage	-0.002	0.005	0.0002	-0.001	-0.508***	-0.053**	-0.038
	(0.004)	(0.003)	(0.001)	(0.002)	(0.103)	(0.025)	(0.024)
Panel B: TFP and peer effects in same model							
Diff log TFP	0.068***	0.033***	0.008*	-0.005	1.349***	0.261***	0.034
	(0.011)	(0.008)	(0.005)	(0.006)	(0.273)	(0.070)	(0.078)
Diff peer's use	0.162***	0.286***	0.150***	0.268***	2.351***	1.672***	3.599***
	(0.011)	(0.024)	(0.028)	(0.038)	(0.204)	(0.151)	(0.553)
Panel C: TFP and change in risk level of industry in same model							
Diff log TFP	0.106***	0.038***	0.008	-0.007	1.519***	0.245***	-0.011
	(0.016)	(0.011)	(0.008)	(0.009)	(0.405)	(0.089)	(0.124)
Diff risk level	0.000	0.005	0.000	-0.000	0.040	-0.016	0.001
	(0.005)	(0.003)	(0.002)	(0.002)	(0.106)	(0.025)	(0.035)
Mean outcome at event time -1,							
Panels A & B	0.175	0.050	0.020	0.020	3.773	0.573	0.000
Panel C	0.215	0.058	0.024	0.020	4.207	0.557	0.000

Notes: Table shows estimated β parameters and robust standard errors (in brackets) from equation (2), using the variables indicated in the first column of the table as heterogeneity indicators. Sample is as described in Section 4.1. In Panel C the sample is restricted to blue-collar workers. In Panel B, peer's use refers to healthcare use in the same 5-year age group – sex – one-digit occupation category. In Panel C, risk level is coded as zero for the low-risk and one for the high-risk industry-specific risk categories. Number of individuals: 10,290 (5,475 in Panel C). *** p<0.01, ** p<0.05, * p<0.1.

A Appendix: Additional Figures and Tables

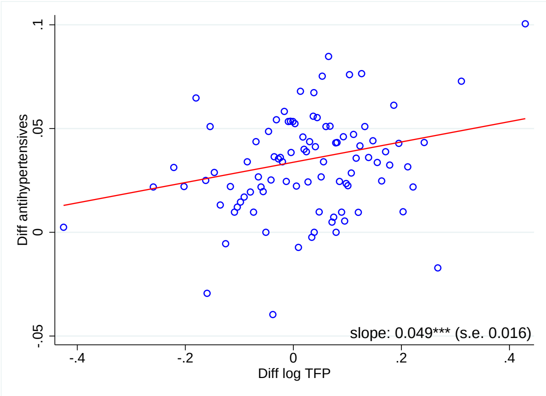
Appendix Figure A1: Distribution of the change in log TFP upon transition



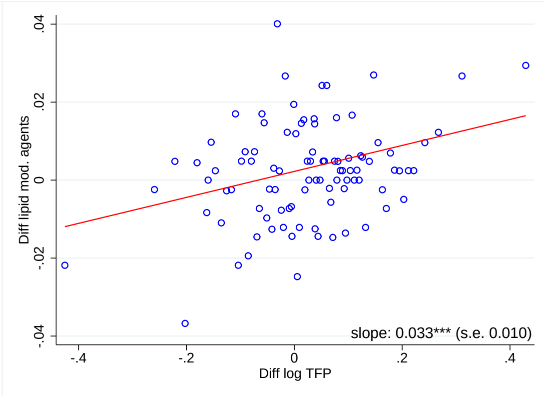
Notes: Figure shows the distribution of the difference between log TFP in the post- vs. pre-move firm.

Appendix Figure A2: Relation between change in log TFP and log healthcare use

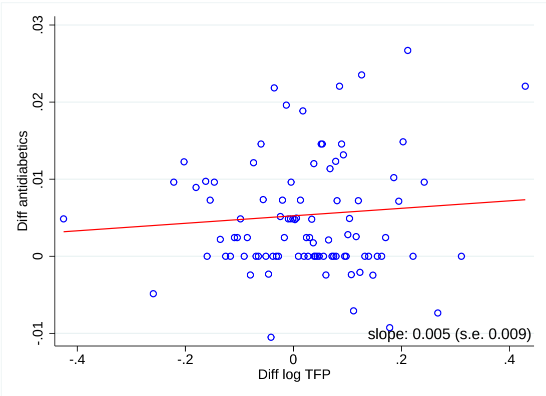
(a) Antihypertensives



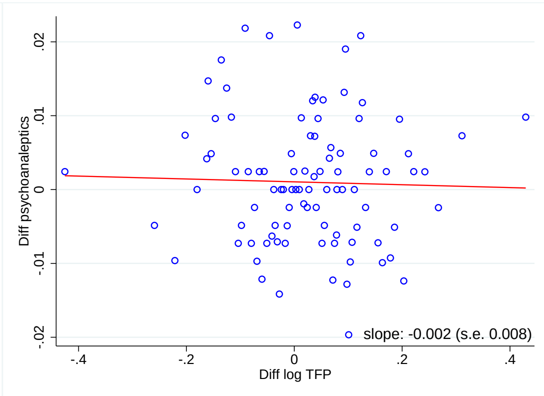
(b) Lipid modifying agents



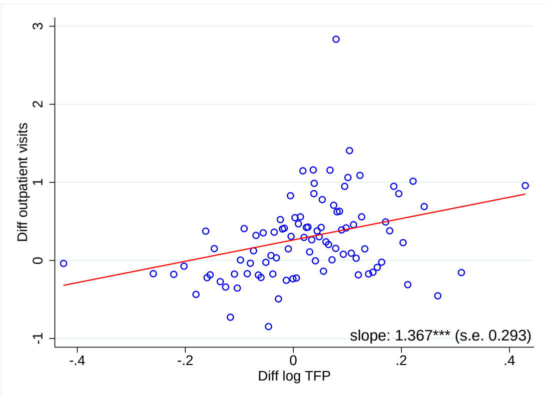
(c) Antidiabetics



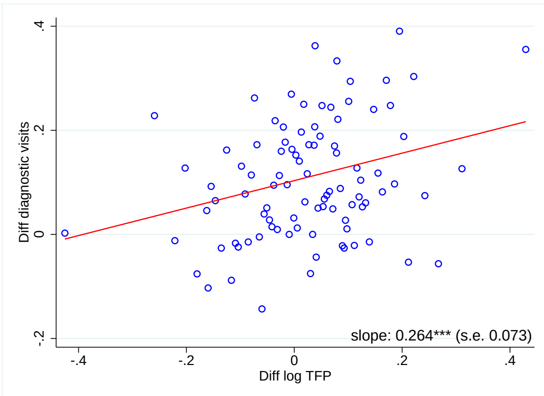
(d) Psychoanaleptics



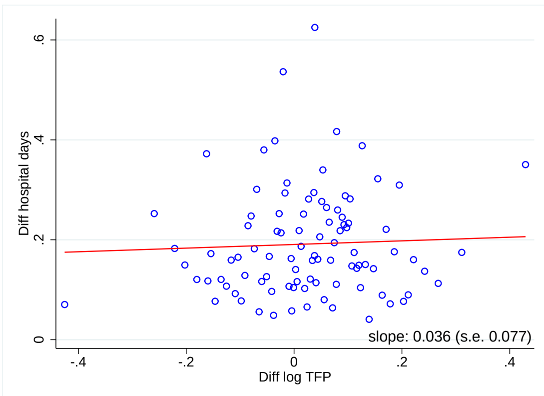
(e) Outpatient visits



(f) Diagnostic visits



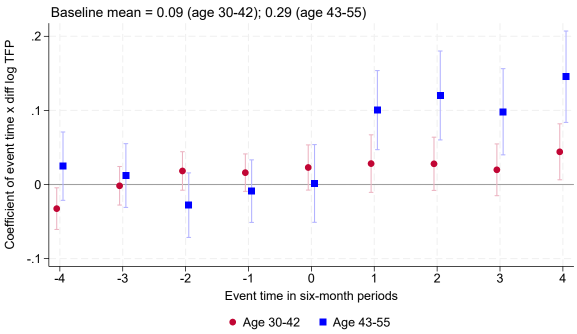
(g) Hospital days



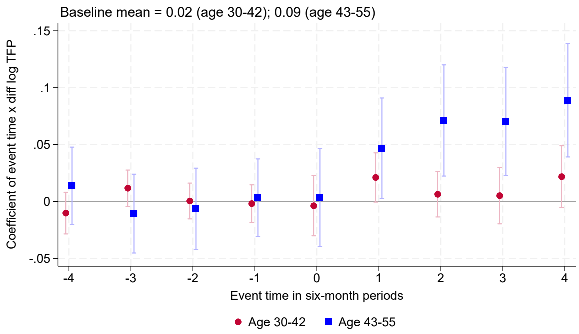
Notes: Figure shows binned scatter plots for the relation of the difference between log TFP in the post- vs. pre-move firm to the difference between the person-specific mean healthcare use in the post- vs. pre-move firm. The distribution of differenced log TFP is split to 100 equally sized bins.

Appendix Figure A3: Event studies for healthcare use, effect of TFP, in age groups 30–42 and 43–55 at the time of the move

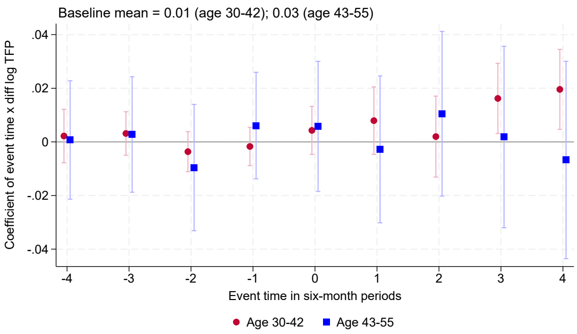
(a) Antihypertensives



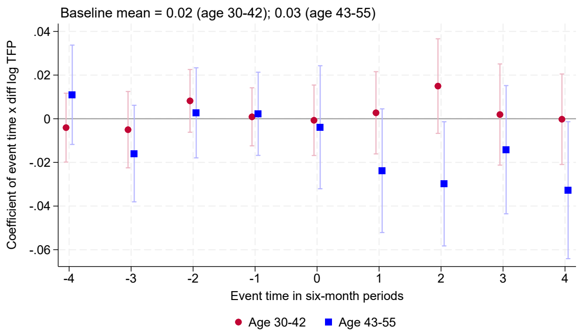
(b) Lipid modifying agents



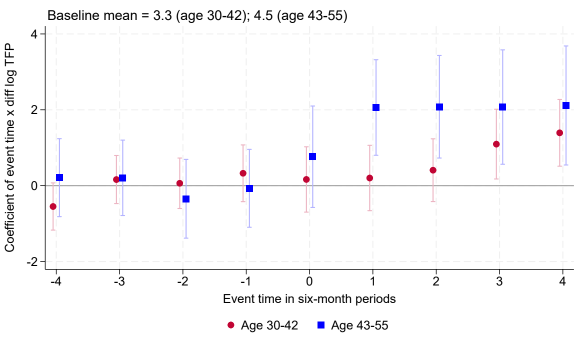
(c) Antidiabetics



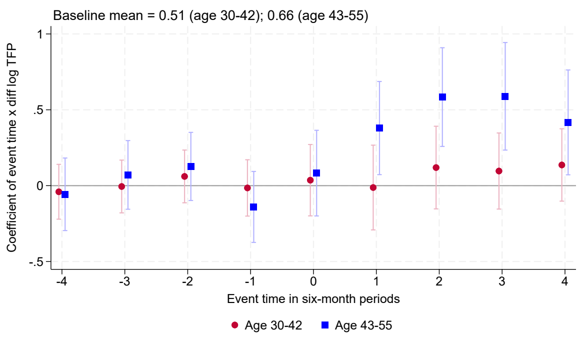
(d) Psychoanaleptics



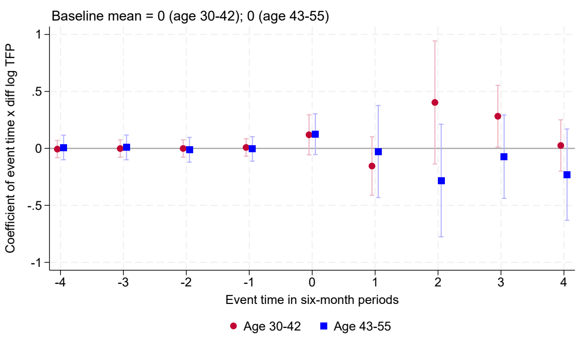
(e) Outpatient visits



(f) Diagnostic visits



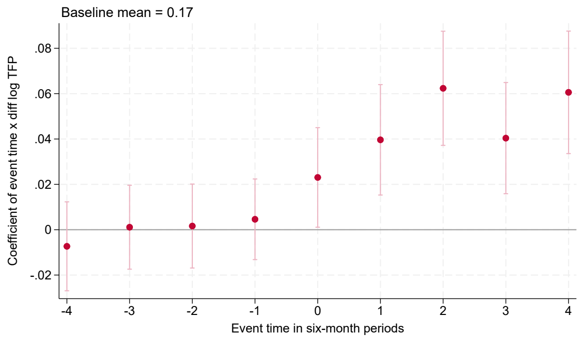
(g) Hospital days



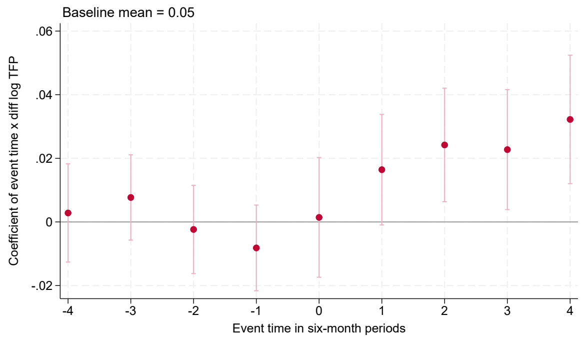
Notes: Figure shows estimated β_j parameters with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. The sample is as described in Section 4.1, split to individuals aged 30–42 vs. 43–55 at the time of the move between firms. Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. The mean outcome measured at event time -1 is displayed at the top of each panel. Number of individuals: 6,053 (aged 30–42 at the move); 4,238 (aged 43–55 at the move).

Appendix Figure A4: Event studies for healthcare use, effect of TFP, including smaller firms in sample

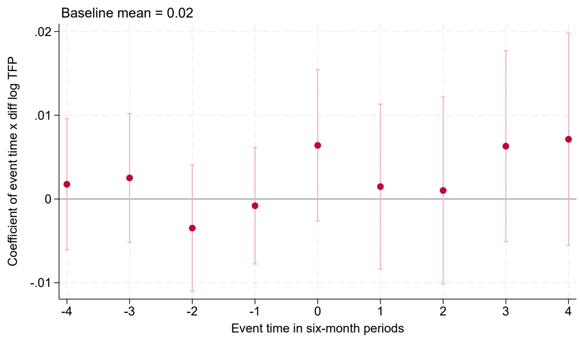
(a) Antihypertensives



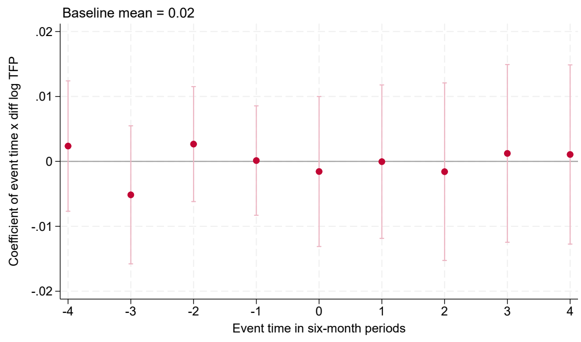
(b) Lipid modifying agents



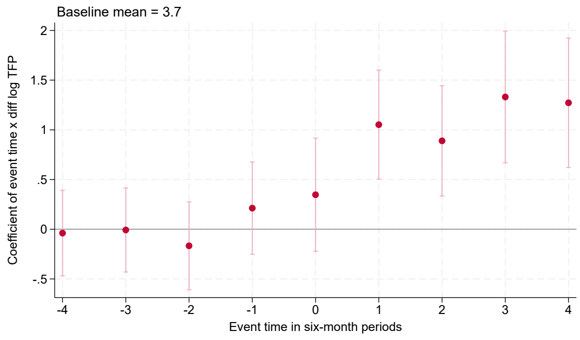
(c) Antidiabetics



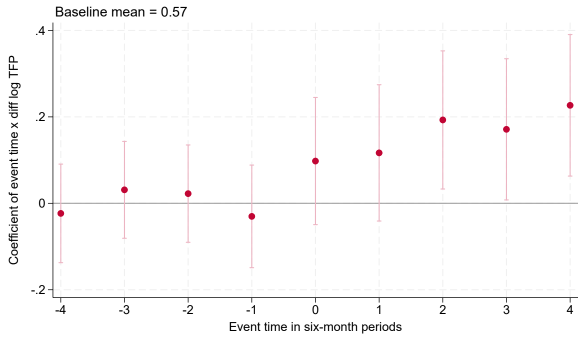
(d) Psychoanaleptics



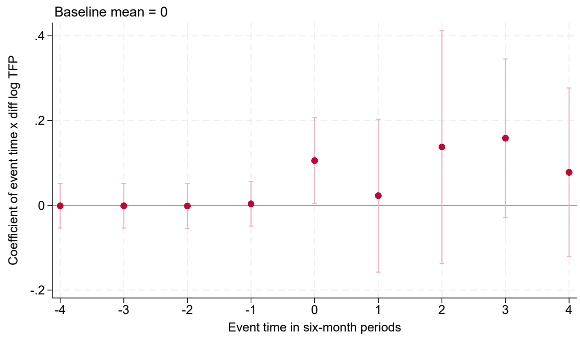
(e) Outpatient visits



(f) Diagnostic visits



(g) Hospital days

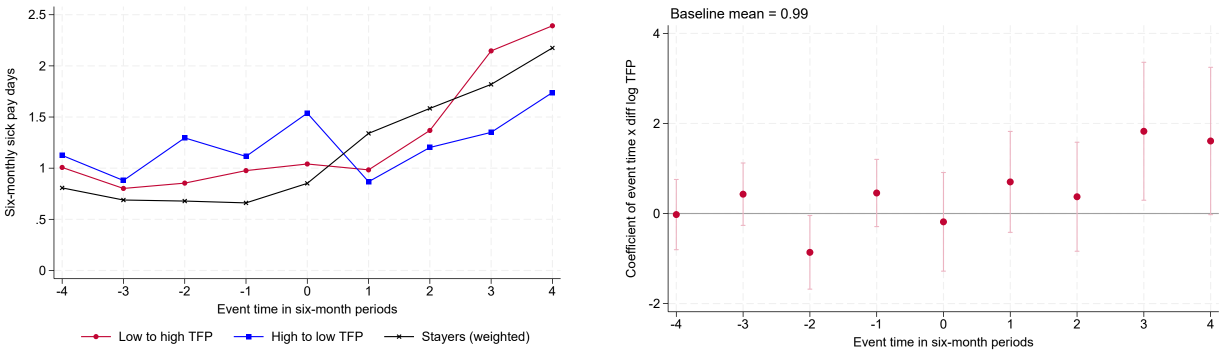


Notes: Figure shows estimated β_j parameters with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. Sample is as described in Section 4.1, extended to individuals working at firms with at least 20 workers (instead of the baseline sample of at least 50 workers). Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. The mean outcome measured at event time -1 is displayed at the top of each panel. Number of individuals: 13,707.

Appendix Figure A5: Sickness absence around job-to-job transition

(a) Six-monthly averages

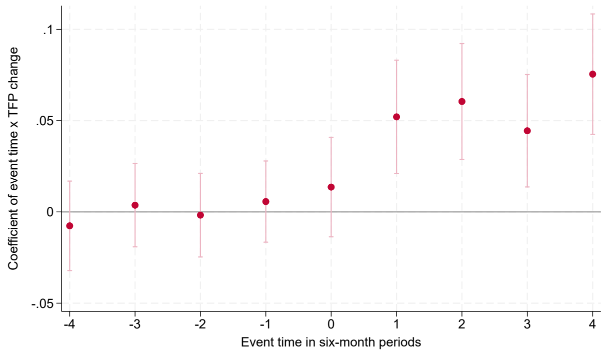
(b) Event study estimates



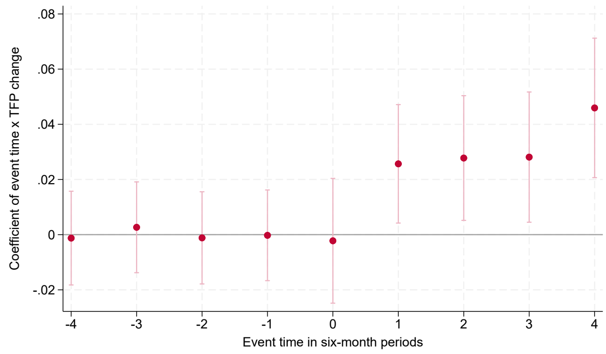
Notes: Left panel shows the evolution of six-monthly days on sick pay, split by the origin and destination TFP being below or above its median (low vs. high TFP). Low-to-high and high-to-low moves are diplayed. Sample is as described in Section 4.1, extended with workers not moving between firms. The sample of individuals not moving between firms ("stayers") is weighted to match the age and sex composition of the mover sample. Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. Number of individuals: low-to-high TFP 1,773; high-to-low TFP 1,773; 129,636 stayers. Right panel shows estimated β_j parameters (coefficients of event time $\times$ difference between post- vs. pre-move log TFP) with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. Sample is as described in Section 4.1. The mean outcome measured at event time -1 is displayed at the top of the panel. Number of individuals: 10,291.

Appendix Figure A6: Event studies for healthcare use, effect of TFP, including stayers in the sample

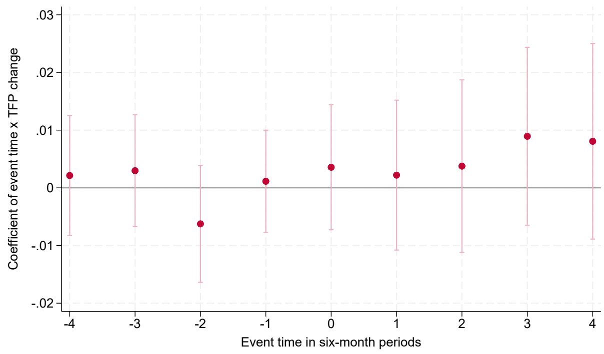
(a) Antihypertensives



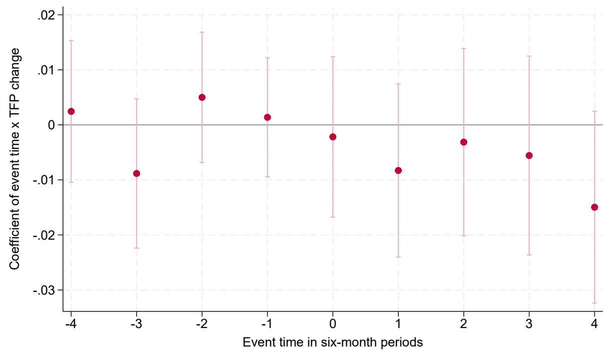
(b) Lipid modifying agents



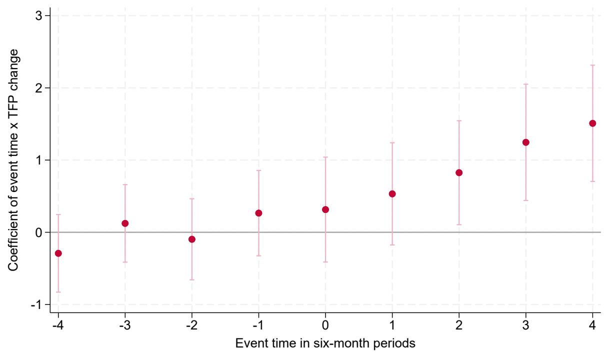
(c) Antidiabetics



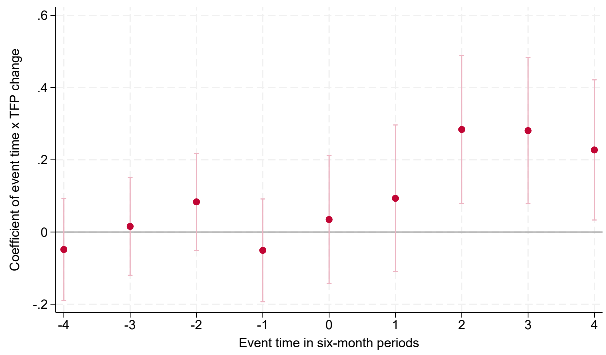
(d) Psychoanaleptics



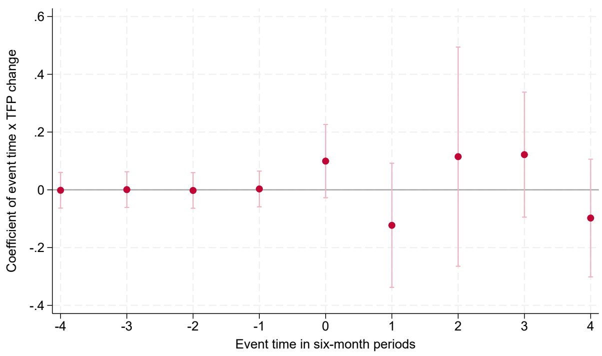
(e) Outpatient visits



(f) Diagnostic visits



(g) Hospital days



Notes: Figure shows estimated β_j parameters (coefficients of event time $\times$ difference between post- vs. pre-move log TFP) with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. Sample is as described in Section 4.1, extended with workers not moving between firms. The sample of individuals not moving between firms is weighted to match the age and sex composition of the mover sample. Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. Number of individuals: 129,636 stayers and 10,291 movers.

Appendix Table A1: Effect of TFP on outpatient and diagnostic visit categories

	After × diff log TFP		Mean value at
	Coeff.	SE	event time −1
Primary care visits	0.549***	0.124	2.349
Specialist care visits			
Internal medicine	0.041	0.026	0.108
Surgery	0.050	0.038	0.088
Traumatology	-0.009	0.036	0.068
Gynaecology	0.029	0.023	0.084
Otolaryngology	-0.041	0.028	0.093
Ophtalmology	-0.015	0.020	0.069
Dermatology	0.052	0.032	0.077
Neurology	0.011	0.014	0.032
Orthopaedics	0.007	0.013	0.021
Urology	0.018	0.020	0.043
Oncology	-0.001	0.014	0.015
Physiotherapy, rheumatology	0.391**	0.155	0.385
Intensive care	0.013	0.009	0.002
Infectology	0.009**	0.004	0.004
Psychiatry	0.027	0.019	0.036
Pulmonology	0.057**	0.022	0.158
Rehabilitation	0.022	0.022	0.014
Cardiology	0.013	0.016	0.036
Diagnostic visits			
Laboratory	0.162***	0.053	0.373
X-ray	0.046*	0.027	0.141
Ultrasound	0.042***	0.015	0.059

Notes: Table shows estimated β parameters with robust standard errors from equation (2), using the difference between post- vs. pre-move log TFP as the main explanatory variable. Outcome variables are six-monthly numbers of visits in categories of outpatient care. Sample is as described in Section 4.1. Number of individuals: 10,291. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A2: Descriptive statistics of firms by level of TFP

	TFP below median		TFP above median		Total	
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Log TFP	2.278	0.071	2.445	0.073	2.361	0.110
Log mean wage	12.104	0.322	12.623	0.461	12.363	0.475
AKM firm FE	0.023	0.157	0.243	0.192	0.133	0.207
Poaching index	0.327	0.150	0.470	0.184	0.399	0.183
Firm size	528	538	4119	6365	2323	4860
Industry						
Manufacturing	0.292	0.455	0.314	0.464	0.303	0.459
Trade	0.142	0.349	0.127	0.332	0.134	0.341
Services	0.204	0.403	0.302	0.459	0.253	0.435
Other	0.362	0.481	0.257	0.437	0.310	0.462
Individuals	5,146		5,145		10,291	

Notes: Table displays mean values measured in the six-month period before moving between firms. Sample is as described in Section 4.1, split at the median of TFP.

B Appendix: Decomposition of the Variation in Healthcare Spending

In this Appendix, we replicate equation (2) of Ahammer et al. (2023), estimating the firms' contribution to healthcare spending. We restrict the sample to individuals aged $30-55$ when moving between firms, who had no hospital stay in the two years before the move, live in the same district, are continuously employed, and change firms only once (at event time 0) in the analyzed interval (+/− two years). Here we allow the TFP indicator to be missing, and only require that the destination and origin firms have at least 50 workers immediately before and after the move, therefore the sample size is larger than in the baseline analysis.

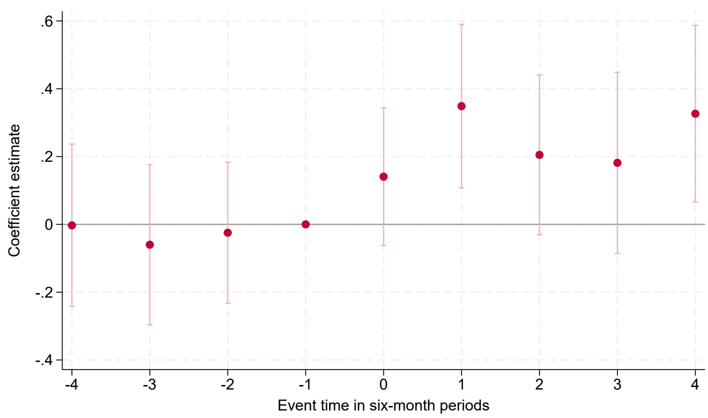
More specifically, we estimate the following model:

$$H_{it} = \sum_{j=-4}^{4} \alpha_j \mathbb{1}[e_{it} = j] + \sum_{j=-4}^{4} \theta_j \mathbb{1}[e_{it} = j]\Gamma_i + \tilde{X}_{it}\gamma + \tau_t + \mu_i + \varepsilon_{it}, \tag{3}$$

where, beyond using the notations of equation (1) in this paper, H_{it} is now total healthcare spending (sum of prescription drug, inpatient and, outpatient spending, including diagnostic care spending, the sum trimmed at the top 99% of its distribution), $\tilde{X}_{it}$ includes sex-specific quadratic function of age, and Γ_i is the difference of average healthcare spending in the post- vs. pre-move firm. The coefficients of interest are θ_j.

Appendix Figure A7 shows that, according to this calculation, the contribution of firms to the variation in worker-level healthcare spending is slightly less than 30%.[17]

Appendix Figure A7: Role of firms in the variation of healthcare spending – event study coefficients



Notes: Figure shows the coefficients of the interaction term between event time and the difference in average healthcare spending in the post- vs. pre-move firm (θ_j parameters) from equation (3). Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. Number of observations: 152,535; number of individuals: 17,113.

[17]Note that the specification slightly differs from that of Ahammer et al. (2023) due to the different sample and the different outcome variable (level instead of logarithm of healthcare spending).