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Anikó Bíró and Peter Elek

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Anikó Bíró* and Péter Elek†

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**Abstract**

We provide evidence on the impact of firm productivity on the health maintenance of employees. Using linked employer-employee administrative panel data supplemented with healthcare records 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 suggest that more productive firms have a beneficial effect on the detection of previously undiagnosed chronic illnesses and on the mental health of their employees. Plausible mechanisms include the higher quality of occupational health check-ups and less stressful job conditions.

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

*HUN-REN Centre for Economic and Regional Studies, Hungary. Email: biro.aniko@krtk.hun-ren.hu.

†HUN-REN Centre for Economic and Regional Studies, Hungary, and Corvinus University of Budapest, Hungary. Email: elek.peter@krtk.hun-ren.hu.

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# 1 Introduction

Firms have important non-pay characteristics that workers value (Sorkin, 2018). Workers may be willing to accept jobs that pay less but offer better amenities, and conversely, they may be paid more in jobs with disamenities. Health-related (dis)amenities include workplace hazards or access to health insurance, among others (Lavetti, 2023). The presence of such (dis)amenities may explain part of the variation of worker-level healthcare utilization across firms that is documented in the literature (e.g., 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 as firm productivity – on various aspects of healthcare utilization of employees. As a motivating descriptive analysis displayed in Figure 1, simple cross-sectional regressions from the administrative data show that prescription drug use for major physical and mental health conditions as well as diagnostic and inpatient care use are less common among workers of 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 to 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 reduce 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 in age group $30-79$ was 32% for women and 34% for men, of whom only 59% of women and 49% of men 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 (NCD Risk Factor Collaboration, 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). The actual treatment rate of lipid modifying agents (predominantly statins) for high blood cholesterol is more difficult to assess because of different treatment guidelines (Mortensen et al., 2022). The fourth examined drug category, psychoanaleptics, mostly covers antidepressants in the $30 - 55$ years old population that we examine. Antidepressants are mainly prescribed for major depressive disorders and anxiety disorders, hence their usage rate is an indicator of the mental health of the population.

In this paper 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 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 the deterioration of physical health. Finally, we find that the consumption of psychoanaleptics (including 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-specific average wage premium as an alternative measure of firm quality. Also, the effect of firm productivity remains significant if firm size and individual wage are included as additional control variables.

Overall, taking into account the high rate of undiagnosed hypertension and diabetes in the population, and the chronic nature of the examined conditions, our results suggest that more productive firms have a beneficial effect on the detection of previously undiagnosed chronic illnesses and on the mental health of the employees. Plausible mechanisms include the higher quality of occupational health check-ups and less stressful job conditions.

Our paper contributes to the following strands of the literature.

First, 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. 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.

Second, our work contributes to understanding the relationship between firm characteristics and employee health (or healthcare utilization). Simple correlations between these variables are misleading because of selection decisions both on the firms' and the employees' sides (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. Connected to this, the results show how firm-specific factors shape health inequalities (Ravesteijn et al., 2013 examined the role of occupations in this context).

Third, 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, hence 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 across-worker healthcare expenditure. We replicate their main result in Appendix B and find that the firm-specific share of variation is also slightly less than 30% in our sample in Hungary, but in this paper we focus specifically on the effects of firm productivity instead of the decomposition of the variation in healthcare use. Also, we examine relatively healthy employees, and most of our outcome variables correspond to health maintenance, hence our estimated effects may differ from those implied by Ahammer et al. (2023).

Fourth, our work contributes to the literature on the potential 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.

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 psychoanaleptics) 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.[1] Larger

[1]Occupational medicine is regulated by the 89/1995. (VII. 14.) Government Decree and by the 33/1998. (VI. 24.) Decree of the Ministry for National Economy.

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).

Key elements of the employee health screening include eye test, audiometry test and blood pressure measurement, but, depending on the agreement between the firm and the occupational physician, the check-up may include further elements. 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.

# 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 $2009 - 2017$.[2]

**Demographic and labor force variables.** We observe gender, 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 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). We regress the logarithm of value added (gross revenue minus the cost

[2]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.

of goods sold) on year effects, the logarithm of firm size (variable input) and the logarithm of subscribed capital (state variable), while using material and service costs as proxies for unobserved productivity. The TFP is the residual estimated from this regression. Finally, we take the firm-specific average of the TFP indicator.

We also 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). That is, we regress log wages on individual and firm fixed effects, controlling for year effects, age squared, age cubed (in line with Card et al., 2013 and Card et al., 2018). We take the estimated firm fixed effects and call them "(log) AKM firm FE".[3]

**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: antidiabetics (A10, including insulin and oral medications), antihypertensives (C02-C09), lipid modifying agents (C10, predominantly statins), and psychoanaleptics (N06, mostly containing antidepressants in the age group of our interest).[4] The data cover purchases of prescription drugs in pharmacies, but do not contain non-prescription drugs, or medications received during inpatient stays.

**O*NET indicators of job characteristics.** Using the four-digit occupation codes of employees, we merge the 2011 February version of the O*NET data set to our administrative data.[5] The O*NET indicators contain numeric descriptions of knowledge, skills, and abilities needed in each occupation. We use the following three indicators, ranging from 1 (not important) to 5 (extremely important), each defined as the average of the components listed below:

1. Physically demanding jobs: abilities that influence strength, endurance, flexibility, balance and coordination (O*NET item 1.A.3).
2. Hazardous jobs: extreme environmental conditions the worker is placed in as part of the job; hazardous conditions the worker could be exposed to as part of the job (O*NET items 4.C.2.b.1, 4.C.2.c.1).

[3]When estimating the TFP and AKM firm FE indicators, we use the entire linked employer-employee administrative data set for years 2003-2017.

[4]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.

[5]First we use the O*NET to ISCO08 conversion of Hardy et al. (2018) and then the lists provided by the Hungarian Central Statistical Office to convert the ISCO08 codes to the Hungarian coding.

3. Stressful jobs: achievement orientation, stress tolerance, time pressure, consequence of error, level of competition (O*NET items 1.C.1.a, 1.C.4.b, 4.C.3.d.1, 4.C.3.a.1, 4.C.3.c.1).

For all three indicators, we define binary variables denoting whether a specific job is above the median value of the O*NET indicator in our analysis sample.

# 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).[6] 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, hence we consider event 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 include only those persons (1) who were private sector employees throughout the whole event time window at firms with at least 50 workers;[7] (2) and moved between firms only once.

We make some further sample restrictions. We examine individuals aged $30-55$ at the time of the move, 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"). 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.

[6] 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). This method can be reliably applied for firms with at least 10 workers (corresponding, on average, to 5 observed workers in our 50% sample).

[7] 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 A3.

## 4.2 Empirical Specifications

We analyze the heterogeneity in the time pattern of health-related outcomes by the change in the TFP of the employer around the move. We estimate the following model:

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

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, $\tau_t$ denotes calendar year fixed effects (measured at the first month in the event time period), $\mu_i$ denotes individual fixed effects, $X_{it}$ includes gender-specific quadratic functions of age, one-digit industry dummies, and two-digit occupation dummies. $\Delta_i$ is the difference between log TFP in the post- vs. pre-move firm. The coefficients of interest are the $\beta_j$, 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 $\Delta_i$ 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, irrespective of the true effects of the firms on healthcare use. We provide two pieces of 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 $\Delta_i$ 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.

Next, we estimate the average change in the health-related outcomes after vs. before the move between firms, allowing the change to vary with the change in the TFP, the AKM firm FE, the size of the employer, or the wage of the worker:

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

where we use the same notation as in equation (1), $E_{it}$ is a binary indicator that 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), and $\tilde{\boldsymbol{\Delta}}_i$ is a vector denoting a subset of four indicators in different regression specifications: (1) the difference of log TFP in the post- vs. pre-move firm; (2) difference of (log) AKM firm FE in the post- vs. pre-move firm; (3) difference of the log size in the post- vs. pre-move firm (measured at event times 1 and $-1$); (4) difference of log individual wage at event time 1 (at the post-move firm) vs. event time $-1$ (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.

Also, to analyze heterogeneity in the relationship between healthcare use and firm quality, we estimate event studies (1) and difference-in-differences type equations (2) separately on subgroups defined by age group, gender, location of residence and pre-move occupation and firm characteristics.

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.[8] 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 its 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.[9]

Figure 2 displays the time patterns of the healthcare use variables around the move by four categories according to the TFP of the origin and the destination firm being below or above the median. The figure suggests that the trends before the moves are roughly parallel. According to the figure, the use of lipid modifying agents and 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 of psychoanaleptics use (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.

Importantly, in our empirical analysis, we include individual fixed effect 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.

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

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

## 5.2 Baseline Results

We turn to the $\beta_j$ 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 3, and separately for age groups $30-42$ and $43-55$ at the time of the transition between firms in Appendix Figure A2.[10] The parameter estimates are summarized in single difference-in-differences type results in the first panel 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 TFP. The difference-in-differences type estimates for the two age groups are shown in the top of each panel in Figure 5.

**Prescription drug consumption.** Panel (a) of Figure 3 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 3 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 heterogeneity by firm productivity in the use of antidiabetics and psychoanaleptics.

Looking at the two age groups separately, Figures 5 and A2 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 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 4 show the estimated $\beta_j$ 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

[10]Appendix Figure A3 shows results for the sample of firms with at least 20 workers (instead of at least 50 workers in the baseline sample).

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 4 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 3 show the estimated $\beta_j$ from equation (1) for non-diagnostic and diagnostic outpatient care use (the difference-in-differences 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 A2).

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 health maintenance (via prescription of drugs and diagnosis of diseases), 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 3), suggesting a cyclical pattern in the screening and care of chronic diseases.

Among outpatient care specialties, the increasing use of physiotherapy and rheumatology with higher TFP also suggests the positive role of firm productivity in health maintenance. 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 3 and Appendix Figure A2, 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.

## 5.3 Heterogeneities in the Relation Between Firm Productivity and Healthcare Use

Now, we estimate equation (2) with the difference between the log TFP in the post- vs. pre-move firm in $\tilde{\mathbf{\Delta}}_i$, and analyze if the relation between healthcare use and firm productivity differs across worker sub-groups. Figure 5 shows the estimation results on our sample split by age category, gender, living area (county seat vs. not), broad industry groups, and occupation categories (blue- vs. white-collar, physically demanding nature, hazard level and stress level).[11]

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 gender 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), for more hazardous and for less stressful jobs (for the latter, the same applies in the case of lipid modifying agents). The negative relation between firm productivity and the the use of psychoanaleptics is stronger for people working in more stressful jobs, where the relative effect of working conditions on mental health may be larger. Finally, heterogeneities by settlement type and industry are mixed or non-existent.

## 5.4 Firm Quality Measures, Firm Size, and Wages

In this section, we analyze the robustness of our results to using the AKM firm FE instead of firm TFP as an indicator of firm quality, and investigate if heterogeneities by firm productivity remain significant after controlling for firm size (with higher TFP firms being larger on average) or for individual wage (with higher TFP firms paying more on average). We estimate equation (2) with various choices for $\tilde{\boldsymbol{\Delta}}_i$.

The top half of Table 2 shows that the use of antihypertensives, lipid modifying agents and diagnostic visits increase significantly at least at the 10% level with firm quality irrespective of the choice of the quality indicator, while neither quality indicator has a significant relation with the use of antidiabetics and, more importantly, with hospital days. For psychoanaleptics and outpatient visits, the parameters have the same sign but different level of significance depending on the quality indicator.

According to the lower half of Table 2, the relation between the analyzed healthcare use indicators and TFP is robust to the inclusion of firm size and individual wage, suggesting that firm productivity influences prescription drug use and physician visits beyond the impact of these variables. Note finally that the relation between the use of psychoanaleptics and firm quality is statistically significant for the whole sample in both robustness checks, not just for the relatively older, more responsive subgroup as in the baseline specification reported in Figure 5.

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

# 6 Discussion and 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 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.

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 AKM wage premium as a firm quality indicator, and to netting out the influence of firm size or, more importantly, 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. This result is based on an institutional setting with universal health insurance coverage provided by the social security system, hence our findings are not affected by incentives inherent in employer-based health insurance.

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) 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.

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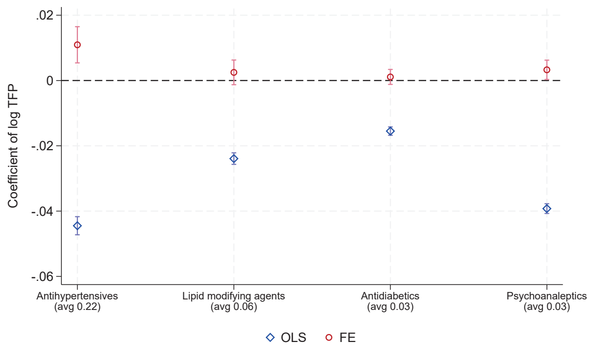
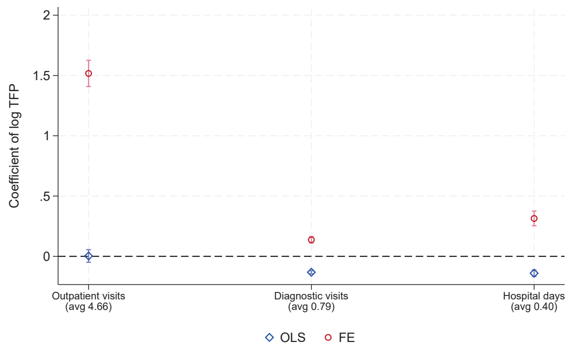
# Figures and Tables

Figure 1: Relation between firm productivity and healthcare use

(a) Prescription drugs

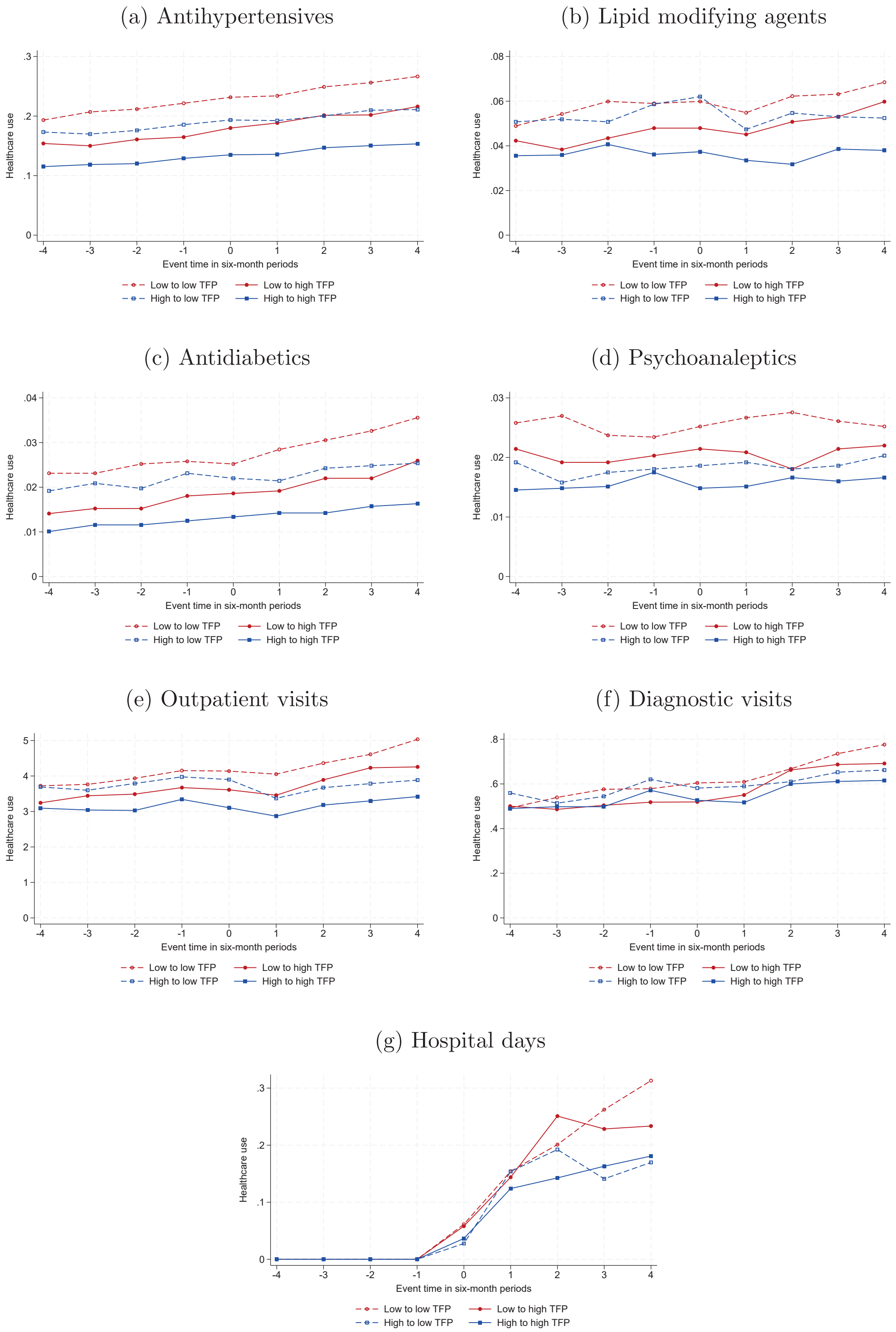



(b) Outpatient and inpatient care




*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.

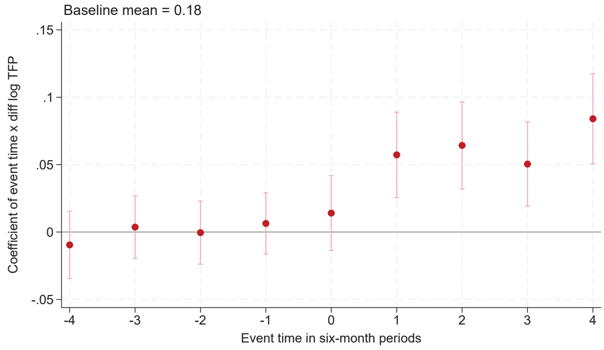
Figure 2: Healthcare use around job-to-job transition by TFP change



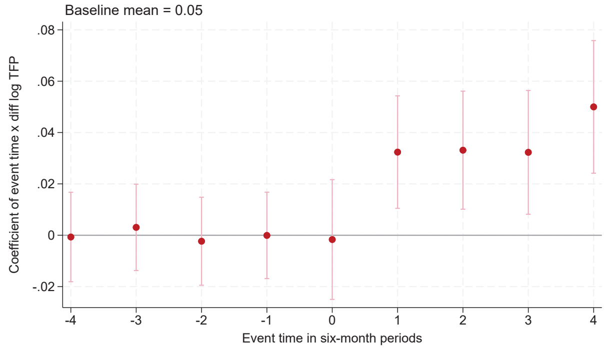

*Notes:* Figure shows the evolution of six-monthly healthcare use indicators split by the origin and destination TFP being below or above its median (low vs. high TFP). Sample is as described in Section 4.1. Event time 0 corresponds to the month of the move between firms, the two months after, and the three months before. Number of individuals: 10,291 (low to low TFP 3,373; low to high TFP 1,773; high to low TFP 1,773; high to high TFP 3,372).

Figure 3: Event studies for healthcare use, heterogeneity by TFP

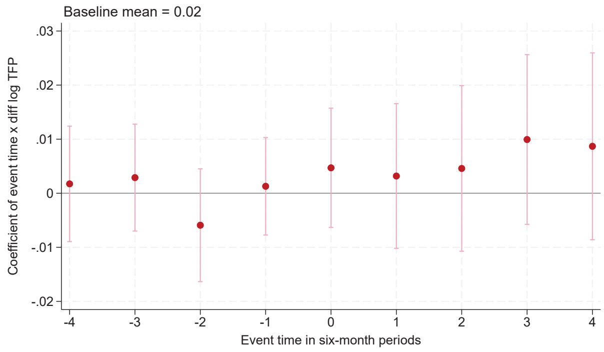
(a) Antihypertensives



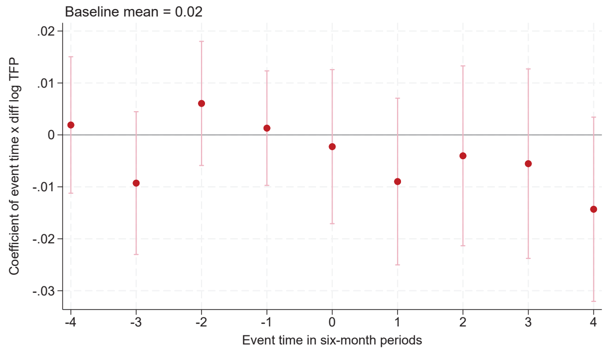

(b) Lipid modifying agents



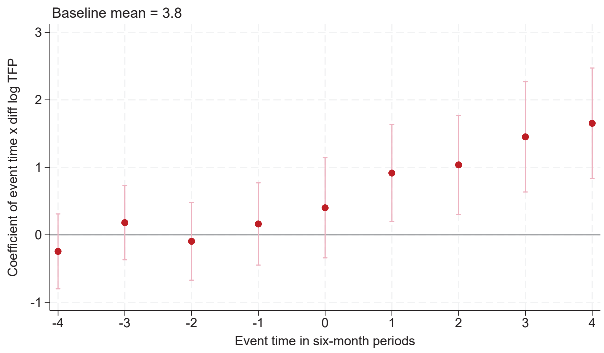

(c) Antidiabetics



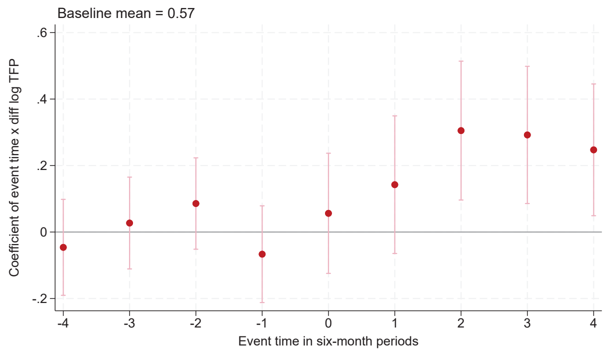

(d) Psychoanaleptics



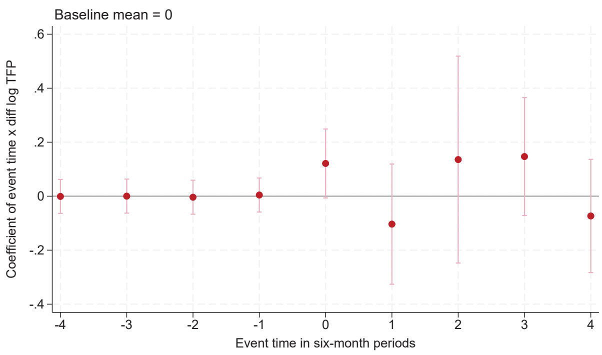

(e) Outpatient visits




(f) Diagnostic visits



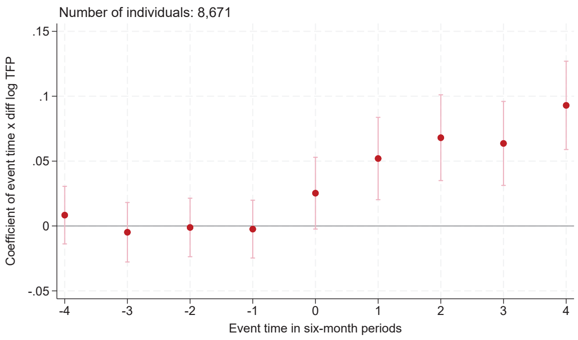

(g) Hospital days



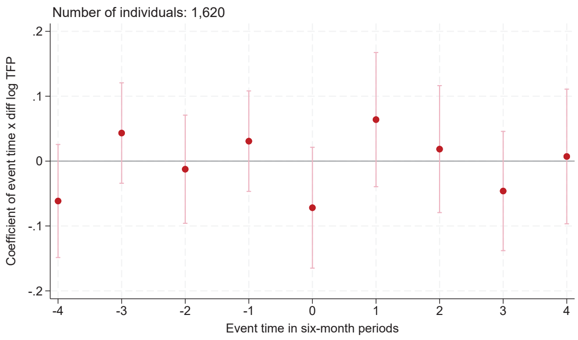

*Notes:* Figure shows estimated $\beta_j$ parameters (coefficients of event time $\times$ difference between post- vs. pre-move log TFP) with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. Sample is as described in Section 4.1. Event time 0 corresponds to the 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 4: Event studies for initiation and continuation of prescription drug consumption, heterogeneity by TFP

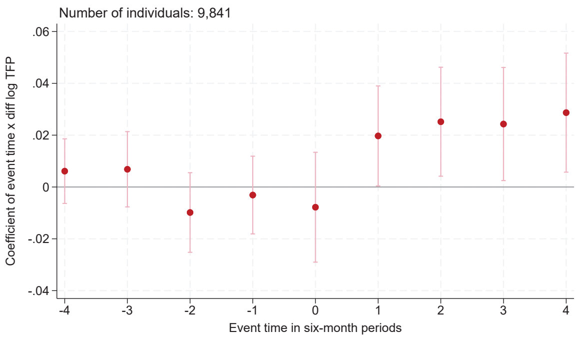
(a) Antihypertensives, not used at event time $-4$



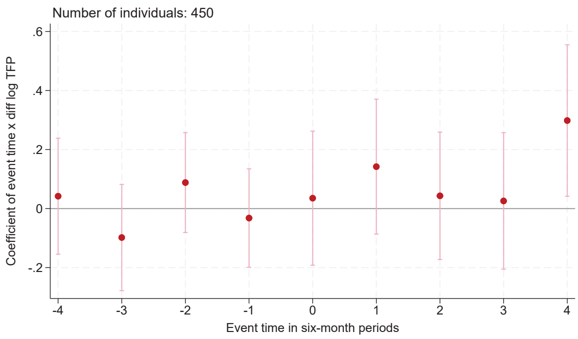

(b) Antihypertensives, used at event time $-4$



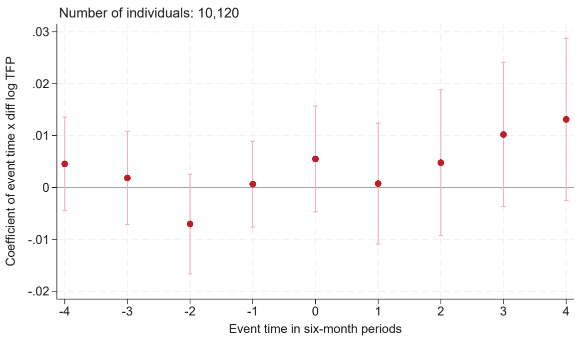

(c) Lipid mod. agents, not used at event time $-4$



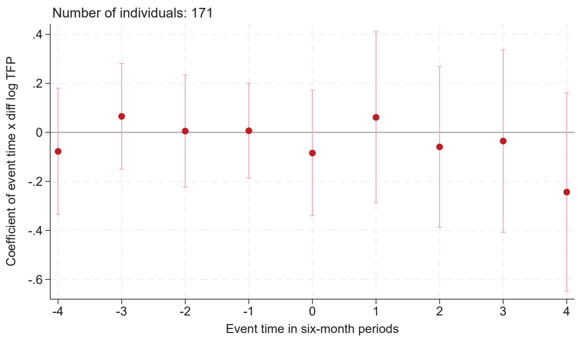

(d) Lipid mod. agents, used at event time $-4$



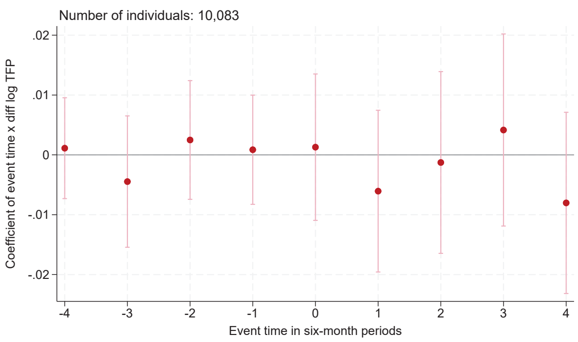

(e) Antidiabetics, not used at event time $-4$



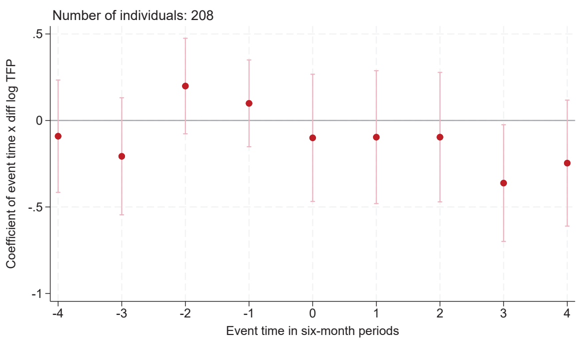

(f) Antidiabetics, used at event time $-4$




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

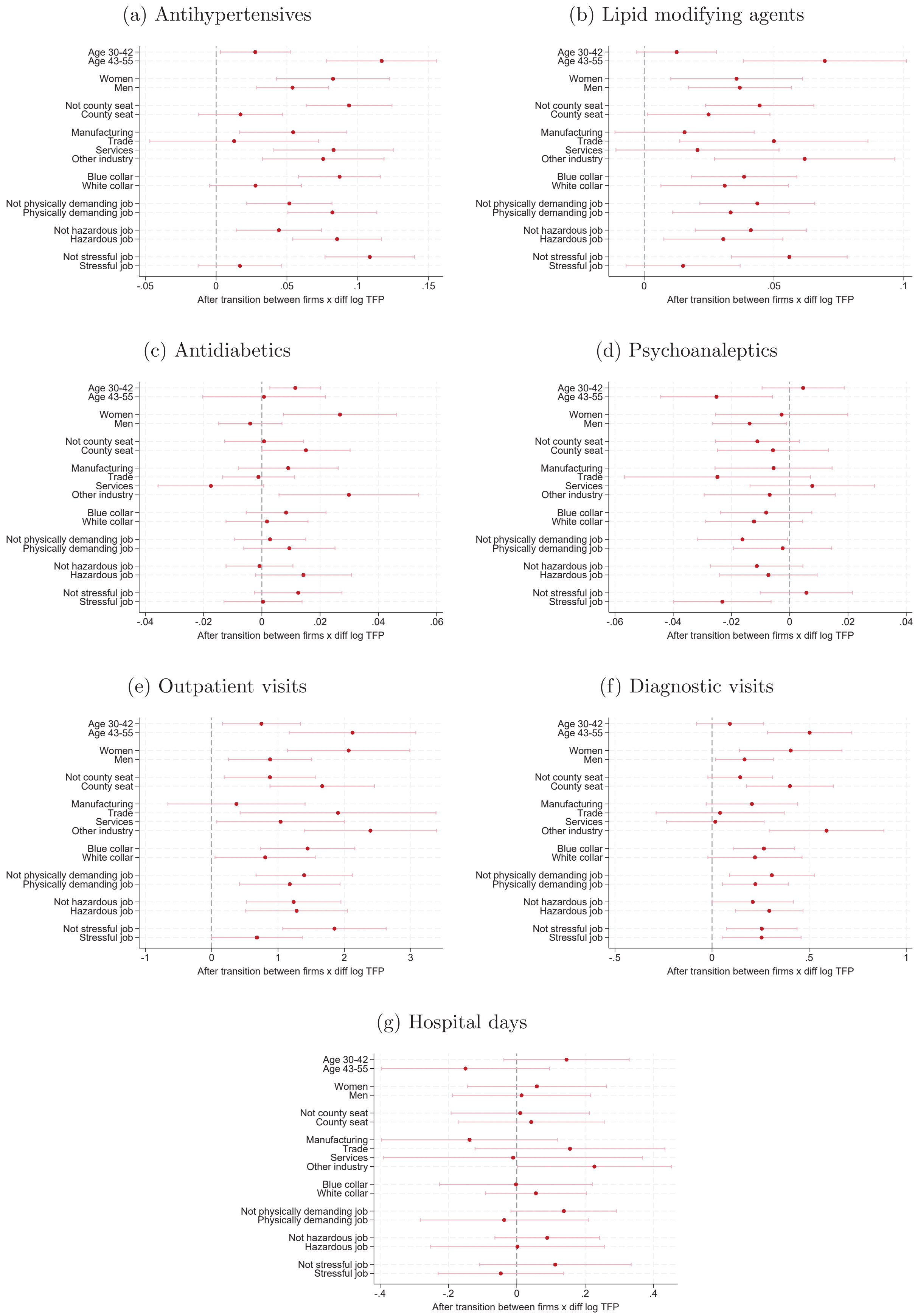



(h) Psychoanaleptics, used at event time $-4$




*Notes:* Figure shows estimated $\beta_j$ 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 5: Heterogeneity in healthcare use by TFP, results by sub-samples




*Notes:* Figure shows estimated $\beta$ 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

| | 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 |
| *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 wage | 12.388 | 0.605 | 12.217 | 0.545 | 12.303 | 0.582 |
| (Log) AKM firm FE | 0.181 | 0.203 | 0.085 | 0.199 | 0.133 | 0.207 |
| Firm size | 3579 | 6076 | 967 | 2366 | 2273 | 4792 |
| *Job characteristics* | | | | | | |
| White-collar worker | 0.459 | 0.498 | 0.389 | 0.488 | 0.424 | 0.494 |
| Physically demanding job (1 to 5) | 1.716 | 0.506 | 1.814 | 0.500 | 1.765 | 0.505 |
| Hazardous job (1 to 5) | 2.069 | 0.595 | 2.185 | 0.615 | 2.127 | 0.608 |
| Stressful job (1 to 5) | 3.492 | 0.249 | 3.482 | 0.254 | 3.487 | 0.251 |
| *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.

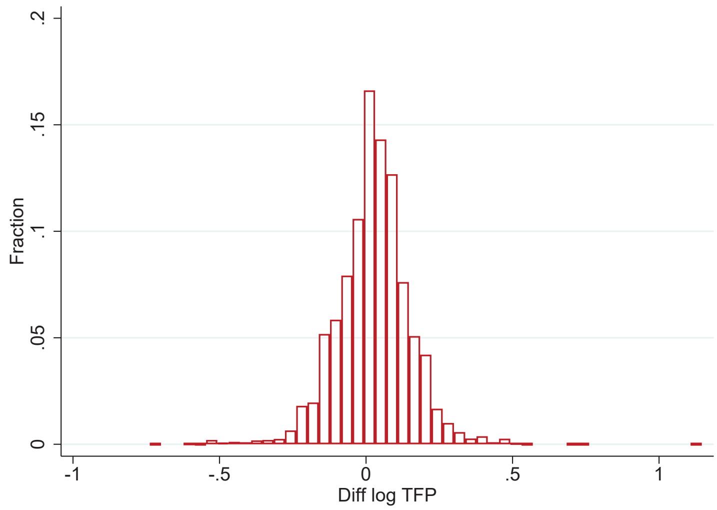
Table 2: Heterogeneity in healthcare use by firm characteristics

| Heterogeneity indicator | Anti-hypertens. | Lipid mod. agents | Anti-diabetics | Psycho-analeptics | Outpatient visits | Diagnostic visits | Hosp. days |
|---|---|---|---|---|---|---|---|
| *Robustness to quality indicator* | | | | | | | |
| Diff log TFP | 0.063*** | 0.037*** | 0.007 | -0.008 | 1.260*** | 0.251*** | 0.032 |
| | (0.011) | (0.008) | (0.005) | (0.006) | (0.265) | (0.068) | (0.076) |
| Observations | 82,327 | 82,327 | 82,327 | 82,327 | 82,327 | 82,327 | 82,327 |
| Individuals | 10,291 | 10,291 | 10,291 | 10,291 | 10,291 | 10,291 | 10,291 |
| | | | | | | | |
| Diff AKM firm FE | 0.030*** | 0.008* | 0.003 | -0.007** | 0.225 | 0.074* | 0.001 |
| | (0.006) | (0.005) | (0.002) | (0.003) | (0.159) | (0.039) | (0.035) |
| Observations | 82,319 | 82,319 | 82,319 | 82,319 | 82,319 | 82,319 | 82,319 |
| Individuals | 10,290 | 10,290 | 10,290 | 10,290 | 10,290 | 10,290 | 10,290 |
| | | | | | | | |
| *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 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) |
| Observations | 82,215 | 82,215 | 82,215 | 82,215 | 82,215 | 82,215 | 82,215 |
| Individuals | 10,277 | 10,277 | 10,277 | 10,277 | 10,277 | 10,277 | 10,277 |
| | | | | | | | |
| Mean outcome at event time $-1$ | 0.175 | 0.050 | 0.020 | 0.020 | 3.773 | 0.573 | 0.000 |

*Notes:* Table shows estimated $\beta$ 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. *** p<0.01, ** p<0.05, * p<0.1.

# A Appendix: Additional Figures and Tables

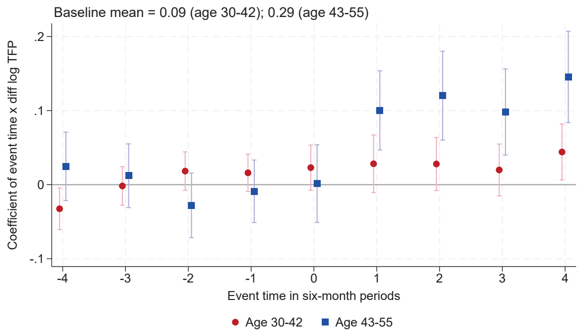
Appendix Figure A1: Distribution of the change in log TFP upon transition



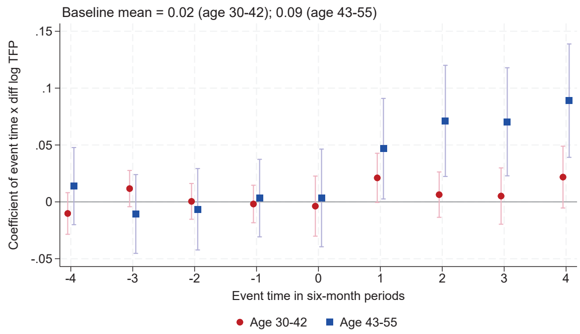

*Notes:* Figure shows the distribution of the difference between log TFP in the post- vs. pre-move firm.

Appendix Figure A2: Event studies for healthcare use, heterogeneity by TFP, in age groups 30-42 and 43-55 at the time of the move

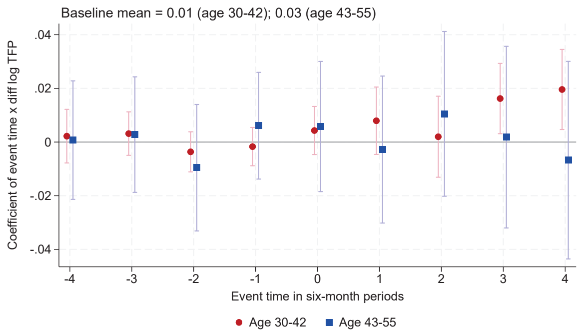
(a) Antihypertensives



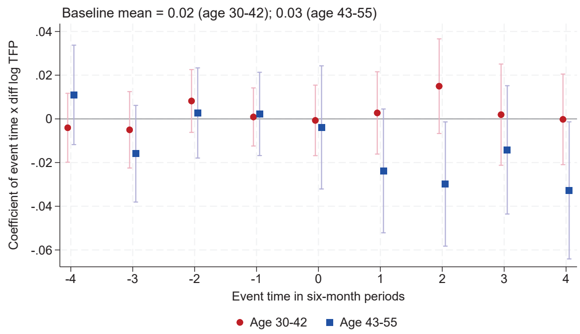

(b) Lipid modifying agents



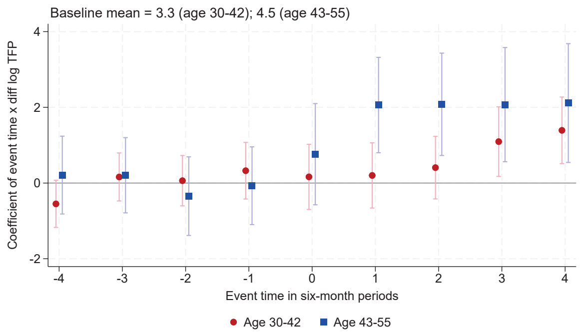

(c) Antidiabetics



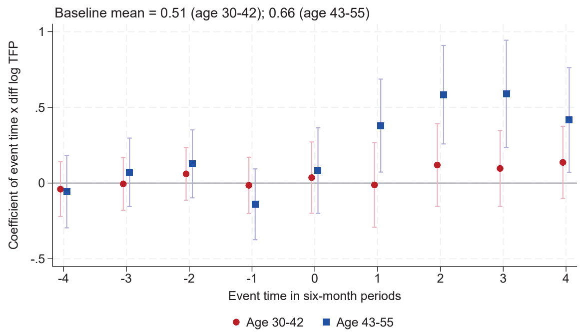

(d) Psychoanaleptics



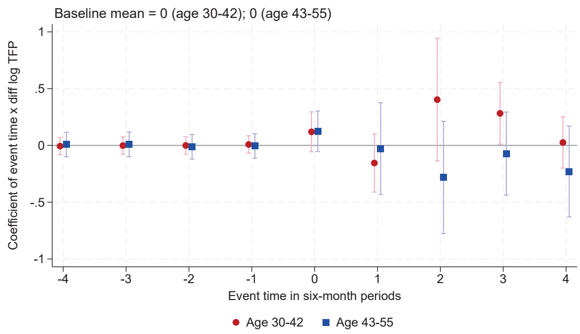

(e) Outpatient visits




(f) Diagnostic visits



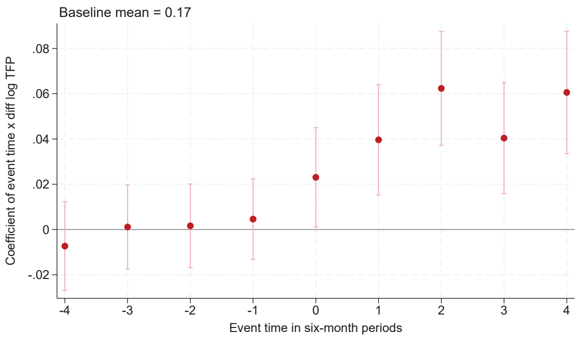

(g) Hospital days



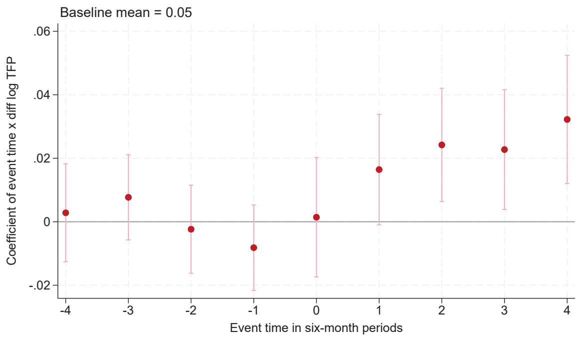

*Notes:* Figure shows estimated $\beta_j$ parameters with 95% confidence intervals from equation (1). Normalization: $\sum_{j=-4}^{-1} \beta_j = 0$. The sample is as described in Section 4.1, split to individuals aged 30-42 vs. 43-55 at the time of the move between firms. Event time 0 corresponds to 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 A3: Event studies for healthcare use, heterogeneity by TFP, including smaller firms in sample

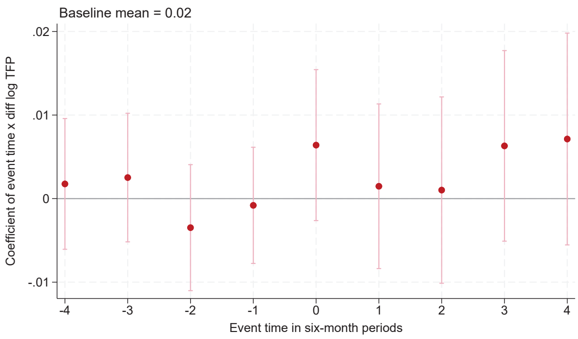
(a) Antihypertensives



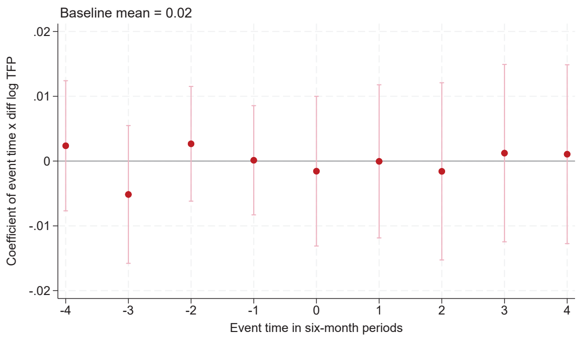

(b) Lipid modifying agents



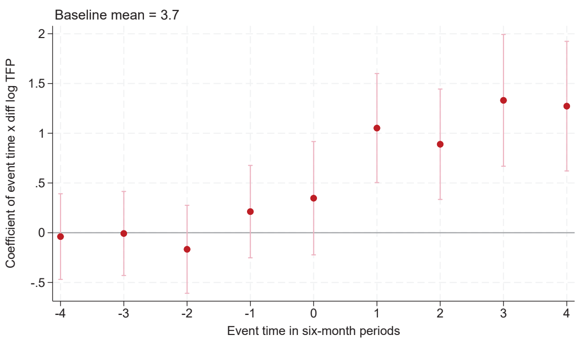

(c) Antidiabetics



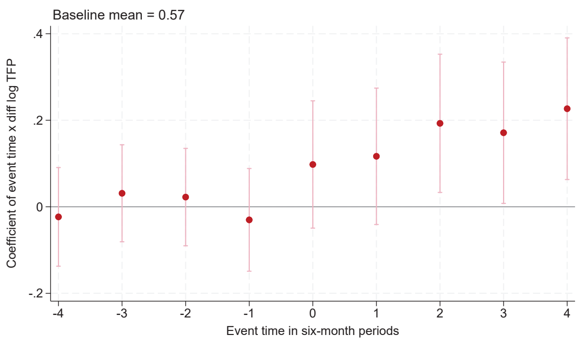

(d) Psychoanaleptics



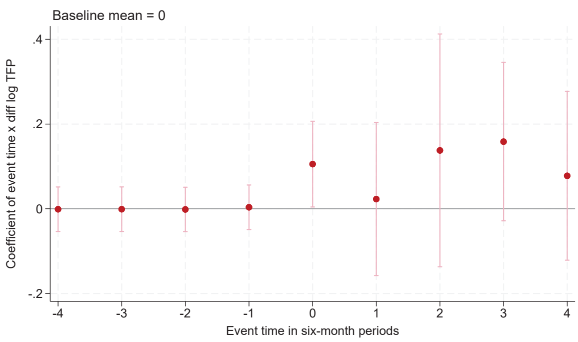

(e) Outpatient visits




(f) Diagnostic visits




(g) Hospital days




*Notes:* Figure shows estimated $\beta_j$ 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 Table A1: Heterogeneity of outpatient and diagnostic visit categories by TFP

| | After × diff log TFP Coeff. | SE | Mean value at 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 $\beta$ 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 observations: 82,327. Number of individuals: 10,291. *** p<0.01, ** p<0.05, * p<0.1.

# 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.

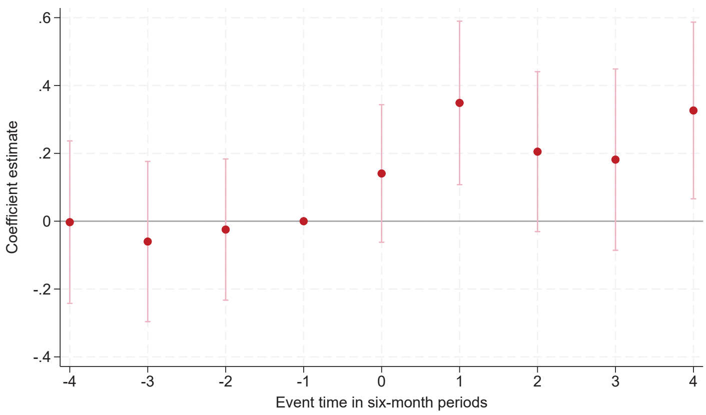
More specifically, we estimate the following model:

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

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 gender-specific quadratic function of age, and $\delta_i$ is the difference of average healthcare spending in the post- vs. pre-move firm. The coefficients of interest are $\theta_j$.

Appendix Figure A4 shows that, according to this calculation, the contribution of firms to the variation in worker-level healthcare spending is slightly less than 30%.[12]

Appendix Figure A4: Role of firms in the variaton 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 ($\theta_j$ 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.

[12]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).