The role of firms in the wage penalty for chronic health conditions

Márta Bisztray[1], Balázs Muraközy[1,2]*and Rita Pető[1]

[1] Hun-Ren Centre for Economic and Regional Studies, Budapest, Hungary
[2] University of Liverpool Management School

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Abstract

More than one-third of people in the EU report having a chronic health condition (CHC), and their share in the workforce is expected to rise. Using unique linked employer-employee administrative data from Hungary—combining detailed healthcare utilization with wage records—we identify workers with CHCs and analyze their labor market outcomes with a focus on the role of firms. Men and women with CHCs are 7 and 14 percentage points less likely to be employed, respectively. Among the employed, we find wage penalties of 5.8% for men and 13.9% for women. Differences in firm-specific pay premiums account for 12% of the penalty for men and 23% for women. Event-study models with worker fixed effects show persistent wage losses following CHC onset—4% for men and 1.5% for women—of which 0.2–0.5 percentage points are due to moving to lower-paying firms, with the rest likely reflecting missed promotions and raises. We then look at the role of firm ownership, foreign ownership being a strong proxy for technology, and find that 20% of the penalty is accounted for by this firm characteristic, 60-70% of which results from worker sorting and the remaining from CHC workers benefiting less from the higher wage premium of foreign-owned firms. These numbers imply that the fall in wages between the ages 40 and 60 would be 10-20% lower had there been no CHC penalty, about 20% of which is attributable to the presence of foreign-owned firms.[1]

Keywords: Chronic health conditions, firm heterogeneity, wage inequality, foreign-owned firms

JEL-codes: J14, J31, M52, F23

*Corresponding Author

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1 Introduction

More than a third of people in the EU reported having a chronic health condition (or CHC).[2] With population aging and longer working lives, the labor market implications of such conditions will be even more important in the future. Inequality in health capital in the form of chronic conditions also translates into inequality both within age groups and along the life cycle.[3] At the same time, recent research has documented the large role firms play in the inequality of labor market outcomes both in terms of overall inequality (Song et al., 2019) and inequality along key demographics, for example gender (Card et al., 2016) and race (Kline et al., 2022). Firm heterogeneity in terms of technology, management and culture can potentially play a large role in CHC-related inequality both because of the different demand of firms for health capital and the effect of these on the amenities of workers suffering from such conditions.

Motivated by these observations, this paper examines the magnitude of the labor market penalty associated with CHCs and investigates the role that firms play in shaping it. In order to address this question, we use rich linked administrative data from Hungary that has information on employment, wages and detailed health care usage, and also provides information on characteristics of the employers. To measure chronic health conditions, we follow the approach developed by Danesh et al. (2024), who construct a Chronic Disease Index (CDI) based on similar data on medicine use and socioeconomic conditions. This approach starts from identifying the set of conditions each person suffers from and then calculates an index from them, in which the weights are based on how the different conditions and their interactions predict long hospitalization and death later in life.[4] A great advantage of this method is that it is data-driven and works consistently for people of different ages. We consider people to suffer from CHC if they are in the top decile of the index distribution, using alternative definitions as robustness checks.

We quantify the role of firms in the wage gap with two approaches. First, we look at how the firm-specific wage premium, estimated from Abowd et al. (1999)-type (AKM) regressions, differ between workers with CHCs and other workers. Second, we look at different firm-level observables to investigate the role of such firm characteristics in the wage penalty. In terms of observables, we mainly focus on comparing foreign-owned firms with those owned by domestic private owners. Foreign-owned firms are expected to be more productive (see Helpman et al., 2004), and foreign ownership is a strong proxy for many positive firm and worker outcomes, especially in a Central-Eastern European setting. Foreign-owned firms are typically high up in the job ladder, paying 60% more. They also play a large role in many economies, including Hungary, where they employ around 30% of all workers, have on average about 70% higher labor productivity and use more immaterial assets in their production process compared to domestic-owned firms. At the same time, the higher productivity of foreign-owned firms is also associated with different performance requirements,

[2]Based on self-reported health statistics, see https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Self-perceived_health_statistics. In the US, in 2018, more than half of people had at least one chronic health condition, with 27.2% reporting multiple such conditions (https://pmc.ncbi.nlm.nih.gov/articles/PMC7553211/.) In Hungary, the country we study, 46% of people older than 16 reported at least one chronic condition in 2023, see https://www.portfolio.hu/gazdasag/20240715/megdobbento-hirek-erkeztek-a-magyarok-egeszsegi-allapotarol-698629.

[3]As Case et al. (2002) and Danesh et al. (2024) also show, poor health status can largely be explained by the presence of chronic health conditions, both in older and younger ages.

[4]We differ from Danesh et al. (2024) by also considering long hospitalization beyond mortality, given that it also indicates a severe health condition relevant for employers and is more frequent than mortality, making our predictive model more robust.

stronger monitoring and incentives (Bloom et al., 2012), reflected by the larger role of flexible wage elements and wage dispersion within the firm (see Table 1), which can impact CHC workers differently. Moreover, foreign-owned firms have also become central to policy discussions on inequality, particularly as economies grow increasingly integrated into the global marketplace.[5] In addition to foreign ownership, we also report results with other firm observables reflecting firm quality, such as labor productivity and the average wage of the firm.

We find that both men and women with CHC are less likely to work: the difference is 7 percentage points for men and 14 percentage points for women. Differences still remain but are about halved if we focus on people who work at least in one year in our sample and control for their worker fixed effect from an AKM model or run event-study-type regressions. The event studies show a quick fall in the probability of working around the onset of CHC.

Conditional on working, we find a wage penalty of 5.8 percent for men and 13.9 percent for women when controlling for year, age and industry. From this gap, differences in firm-specific pay premiums explain 0.7 percentage points for men and 3.2 percentage points for women. Event study wage regressions including worker fixed effects show a fall in wages after the onset of CHCs: in the long term, the wage penalty in these specifications increases to about 4 percent for men and 1.5 percent for women, from which about 0.2 (men) and 0.5 (women) percentage points are due to moving to lower-paying firms. The remaining part is likely to reflect missed promotions and raises.

Looking at foreign ownership, we find that men with CHC are 1.6 percentage points less likely to work at a foreign firm compared to their healthy peers, while this difference is 6 percentage points for women. This difference mainly results from the lower probability of joining such firms, though the separation rate from foreign-owned firms is also higher for workers with CHC. Turning to wages, we show that people with CHC benefit less from the higher wage premium of foreign firms: the CHC penalty for workers in foreign firms is 1.9 percentage points higher for men and 3.3 percentage points higher for women compared to workers in domestic-owned firms. Put together, a Card et al. (2016)-type decomposition implies that the difference between foreign and domestic firms explains about 20 percent of the CHC penalty, 60-70 percent of which results from CHC workers sorting into domestic-owned firms, and the remaining part from such workers benefiting less from the higher wage premium of foreign firms (a bargaining component).

These patterns are not specific to foreign-owned firms. We find a very similar relationship when we define "high-quality" firms in different ways: based on productivity, average wage, or AKM fixed effect. We find that workers with CHC are less likely to work at the "high-quality" firms, and the within-group wage penalty is larger in that group of firms.

We also consistently find that women experience larger employment and wage penalties compared to men and a larger proportion of this penalty is explained by firm heterogeneity both when looking at firm-specific wage premiums and firm observables. Working conditions in firms offering higher wage premiums, being foreign-owned or other "high-quality" firms, may weight especially heavily on women with CHC and they may value a work environment which involves more flexibility – including part-time work – more, especially if they are not the primary earners in the family.

[5] Reflecting this trend, global FDI flows totaled USD 802 billion in the first half of 2024 (OECD, 2024).

Finally, we show that CHC penalties contribute significantly to the concavity of he age-wage relationship, thus raising inequality along the life cycle. In particular, in our data wages fall by 15 percent on average between the ages of 40, which would be 1.5 (men) and 3 (women) percentage points smaller were there no CHC penalties. 20 percent of this counterfactual difference results from the heterogeneity between foreign- and domestic-owned firms.

We show that our results are not restricted to older workers or blue-collar workers. In fact, white collar workers seem to face a similarly large penalty both in terms of sorting and within-firm wage differences as the whole population. The results are also not driven by disability benefits: even workers not receiving disability benefits face a wage penalty similar in magnitude to other CHC workers.

We contribute to four main strands of literature. The first is the literature that has documented that CHCs tend to be associated with lower participation and wages either by using cross-country comparisons (Rodriguez-Alvarez and Rodriguez-Gutierrez, 2018), or surveys (Pelkowski and Berger, 2004; Gignac et al., 2014; Halima and Rococo, 2014; Luo et al., 2023; Polanco et al., 2024). Relatively few papers use administrative health care data on chronic illnesses (Dixon, 2015; Danesh et al., 2024).[6] This literature also highlights that not only does lower health lead to lower wages, but lower-income people are also more likely to become ill (e.g. de Oliveira et al., 2023; Danesh et al., 2024). We contribute to this literature by documenting labor market inequalities along CHC status from rich administrative data that covers 50% of workers in Hungary. In addition to that, the main novelty of our paper is documenting the role of firms in this inequality by quantifying the importance of firm-specific wage premium, and also documenting that foreign-owned and higher productivity firms are less likely to employ workers with CHC, and they also apply a larger within-firm wage penalty.

Second, we also contribute to the literature on the role of firm heterogeneity in wage inequality. Recent papers have documented that firms play a large role in wage inequality in general (Song et al., 2019; Card et al., 2018; Kline et al., 2019) and in inequality along important observable dimensions, such as along gender (see e.g. Card et al., 2016) or race (see e.g. Kline et al., 2022). Our investigation extends previous work on firm effects related to gender and race by highlighting how CHC status interacts with firm heterogeneity to shape labor market outcomes. In addition, we link these dynamics to age-related inequality, showing how firm heterogeneity contributes not just to cross-sectional wage gaps but also to life-cycle inequality.

Third, we contribute to the large literature on gender gaps in the labor market (Goldin, 2014; Blau and Kahn, 2017; Card et al., 2016). A growing strand of that literature has looked at gender differences in labor market outcomes among workers with CHCs. While previous studies have shown that women with health limitations often face larger employment and earnings penalties than men (e.g., Carmichael and Charles, 2003; Gignac et al., 2014), evidence has typically relied on survey data and focused on specific conditions. We advance this literature by using rich administrative employer-employee data covering a broad range of chronic conditions and linking it to detailed firm characteristics. Our results show that the gender gap in CHC-related wage penalties is closely tied to firm heterogeneity: women with CHCs are particularly

[6] Chronic illnesses are also associated with worse financial outcomes in general, partly reflecting lower earnings but also higher medical costs, see e.g. Becker et al. (2022).

underrepresented in high-paying firms and face steeper wage penalties within them. This highlights how firm-level sorting and treatment do not merely add up gender and health-based disparities, but interact in ways that multiply disadvantage.

Finally, with our focus on foreign-owned firms, we also contribute to the literature on the impact of FDI on inequality. Recent surveys of this literature (see Huang et al., 2020; Cruz et al., 2023) found that in general FDI is associated with increased inequality in less developed countries, while the results for more developed countries are less consistent. A large literature has documented that foreign-owned firms tend to be more productive and pay higher wages (Aitken et al., 1996; Conyon et al., 2002; Sjöholm and Lipsey, 2006; Girma and Görg, 2007; Arnold and Javorcik, 2009; Broniatowska and Strawiński, 2021; Hijzen, 2007; Earle et al., 2018; Setzler and Tintelnot, 2021; Alfaro-Ureña et al., 2021). In this paper, we establish a novel channel behind this relationship by showing that the presence of foreign-owned firms contributes to inequality along CHC status in several ways. Such workers are less likely to work in these high-wage firms, and foreign-owned firms apply a larger penalty for workers with CHC. Given that older workers are more likely to suffer from CHCs, this also implies that the presence of foreign-owned firms reduces the wages of older workers relative to younger ones.

These findings have important implications for labor market policy. Current subsidies for hiring workers with chronic health conditions (CHCs) could be restructured to encourage their employment in "high-quality firms", not just in lower-wage segments. In addition, anti-discrimination and workplace regulation could better address how performance management systems affect CHC workers, and support firms in adopting more inclusive practices—such as offering flexible or remote work options. Since the penalties are especially large for women with CHCs, targeted policy attention at the intersection of gender and health is particularly warranted.

In what follows, Section 2 describes the Hungarian institutional background and presents a simple theoretical framework to motivate our empirical approach, Section 3 presents the data, Section 4 discusses the measurement of chronic health conditions. Section 5 shows our main empirical results, with a robustness analysis in Section 6, and Section 7 concludes.

2 Institutional setup and Theoretical framework

2.1 Institutional setup

Labor market institutions: The Hungarian labor market is flexible, with institutions more similar to those of liberal Anglo-American labor markets than to those of continental Europe. It is relatively easy to dismiss workers (Tonin et al., 2009) and wage bargaining takes place mostly at the individual level. Collective wage bargaining is based on firm-level agreements with unions. Union membership was 10.2% percent in 2014, one of the lowest in the OECD.[7] Less than 4% of firms are covered by collective agreements and this share does not differ much between domestic-owned and foreign-owned firms in our dataset (see

[7] OECD Employment and Labor Market Statistics.

Table 1).[8]

In Hungary, employees who become ill are entitled to payed sick leave, which is regulated by the Labor Code and the Social Security Act.[9] If the illness becomes long-term and results in a significant loss of work capacity, individuals may undergo an assessment to qualify for rehabilitation or disability benefits under the national system (European Commission, 2022).[10]

Health care provision: The Hungarian health system is highly centralised, with the National Institute of Health Insurance Fund Management (NEAK) administering a single health insurance fund that ensures nearly universal coverage. Despite relatively high out-of-pocket (OOP) spending—amounting to 25% of total health expenditures in 2021, compared to the EU average of 15%—unmet medical needs are rare, with only 1.4% of the population reporting issues in 2022 due to cost, distance, or waiting times. In this paper, we use administrative data on medicine use from the NEAK. Prescription medicines — covering nearly all treatments for chronic conditions — are only available with a physician's prescription, whether issued by public or private providers, so our data should include all such prescriptions.[11]

2.2 Theoretical framework

CHCs may reduce a worker's productivity either directly—through fatigue, pain, or the need for medical leave—or indirectly, by making them appear less reliable or promotable. Even when not severely debilitating, CHCs can lead to more frequent absences and reduced capacity during work hours (presenteeism), which lowers both actual and perceived performance.[12] Employers often respond to these declines by adjusting employment terms: reducing wages (Bubonya et al., 2017), limiting promotion opportunities (McGregor and Poot, 2016), or terminating contracts (Bertrand et al., 2017). At the same time, workers

[8] Apart from firm-level bargaining, industry-level agreements are rare and set only weak requirements. Unions participate in the country-level bargaining forum called National Interest Reconciliation Council, which makes only non-binding recommendations (Rigó, 2012).

[9] During the first 15 days of sick leave within a calendar year, the employer covers a sick pay amounting to 70% of the employee's average daily wage. After this period, if the illness continues, the employee may receive a sickness benefit ("táppénz") from the National Health Insurance Fund (NEAK), typically covering 60% of their average earnings, up to a maximum limit, and paid for a maximum of one year. Eligibility for this benefit requires a minimum of 365 days of social security coverage within the two years preceding the illness. While on sick leave or receiving sickness benefits, employees have legal protection from dismissal, meaning their employment cannot be terminated during this period.

[10] Since 2012, Hungary's disability benefit system has distinguished between individuals with some work capacity (eligible for rehabilitation benefits) and those without (eligible for disability benefits). Recipients are classified through a comprehensive medical and labor-market assessment. Employers receive financial incentives to hire people with reduced work capacity and face a mandatory 5% employment quota for firms with over 25 employees. However, enforcement appears weak, and most firms fall short of this requirement without facing substantial penalties (Krekó and Scharle, 2021; Krekó and Telegdy, 2025). See more details in Appendix C.6.

[11] Such medicines are accessible for most people. The first step in accessing these medicines is a consultation with a physician, which in Hungary is widely accessible due to nearly universal health coverage and the absence of user fees for most medical visits. As a result, individuals with chronic conditions are generally able to obtain the necessary prescriptions without significant barriers. The second step—obtaining the medicine once prescribed—is also relatively accessible. If the medicine is administered in secondary or tertiary care (e.g., hospitals), it is provided free of charge. If it is purchased at a pharmacy, many medicines for chronic conditions benefit from reduced co-payments, with the state often covering up to 100% of the cost. Additionally, since 2005, patients with chronic illnesses in vulnerable socioeconomic situations have been eligible for monthly subsidies to help cover out-of-pocket expenses for recurrent health needs (European Observatory on Health Systems and Policies, 2024).

[12] See Collins et al. (2005) and Zhang et al. (2016) for evidence on absenteeism and presenteeism linked to chronic illness.

with chronic health problems may themselves adjust their labor supply in response to the new demands on their time, energy, and attention and the resulting increased cost of working (Autor and Duggan, 2003).

The consequences of chronic health conditions can affect worker outcomes differently depending on firm characteristics—particularly in foreign-owned or high-productivity firms, which often set up different performance requirements and use distinct incentives. These systems, while productivity-enhancing, may disadvantage workers with chronic conditions, who are more likely to experience intermittent productivity loss, fatigue, or reduced reliability compared to their peers (Gignac et al., 2014; Nepal et al., 2021). One possible channel is that these firms tend to use more intensive people-management strategies that emphasize close performance monitoring and stronger performance incentives.[13] In line with this idea, in our database the share of workers receiving flexible wage elements (such as bonus or payment for overtime) is 40 percentage points higher in foreign-owned firms compared to their domestic-owned counterparts and wage dispersion is also 50% larger (see Table 1). Another difference is that domestic firms may be more likely to offer amenities important for CHC workers, such as part-time work. Indeed, 17.5% of people work in a part-time position in domestic-owned firms compared to 6.1% in foreign-owned firms. Importantly, the share of firms covered by collective agreements is low and similar for the two groups of firms, suggesting that it is unlikely that differences in centralized wage setting would drive any differences we find (Table 1).

Women with CHCs are more likely than men to adjust their labor supply or career trajectories in response to CHC, through several distinct channels. First, exit from the labor market is more common among women with CHCs, partly due to intra-household optimization when women are secondary earners. When health constraints arise, women may reduce paid work to prioritize home production or caregiving, particularly if their partner remains employed full time (Lundberg and Pollak, 1996; Sandi and Westerlund, 2017; Smith and Kington, 2018; Johnson and McGill, 2020).[14] Even if they don't exit the labor market completely, many women with CHCs may shift to lower-wage firms or firms offering part-time employment (for example domestic-owned firms), often trading income for flexibility to manage health and care responsibilities (Blau and Kahn, 2017; Carmichael and Charles, 2003; Smith and Kington, 2018). Discrimination can also contribute to gender differences in this respect.[15]

[13]For example, Bloom et al. (2012) show that US multinational affiliates "tend to be more aggressive in promoting and rewarding high-performing workers and removing underperforming workers." These management practices are often linked to greater IT adoption and complementary technologies, which require substantial firm-specific human capital investment from employees. Indeed, in Hungary both the share of intangible assets in non-current assets and the amount of intangible assets per worker are higher in foreign-owned firms (Table 1). Bloom et al. (2012); Bartel et al. (2007); Bloom et al. (2017) show that IT and productivity gains are amplified in firms with lower turnover and better management. However, these returns depend on worker continuity and firm-specific learning, which may be more challenging for workers suffering from CHCs.

[14]This choice can partly reflect a utility-maximizing response to constraints: women, in particular, often bear additional household and caregiving responsibilities (Carmichael and Charles, 2003; Heitmueller and Inglis, 2007), which magnify the value of flexible hours, predictable routines, or proximity to home — attributes more frequently found in domestic-owned firms (Berniell and Sánchez-Páramo, 2011; Fortin, 2015).

[15]There is a growing body of evidence that workers with health limitations face employer discrimination, and gender can amplify this penalty. For example, Gignac et al. (2014) find that employees with chronic conditions report lower workplace support, reduced promotion prospects, and stigma around reliability. Kruse and Schur (2003) document persistent gaps in employment rates and earnings for workers with disabilities even after controlling for productivity proxies, consistent with discrimination. Qualitative research further suggests that women face more negative assumptions regarding their long-term availability and caregiving burden (Carmichael and Charles, 2003). Employers may therefore be more reluctant to invest in

3 Data, Sample and Measurement Issues

3.1 Dataset

We use the Linked Administrative Data (Admin3) database, provided by the Databank of the HUN-REN Centre for Economic and Regional Studies (HUN-REN KRTK).[16] The data source contains linked administrative data provided by the National Health Insurance Fund Administration, the Hungarian State Treasury, the National Tax and Customs Administration, the Ministry of Finance, and the Educational Authority. The main body of the data is a linked employer-employee data that is a 50 percent random sample of the population in 2003 and follows people up until 2017 on a monthly basis.[17] These data contain basic demographic information (such as age and gender) and labor market information (such as wage, working hours, 4-digit occupation codes, etc.) about the individual's main job. The data set contains unique identifiers for employees and employers, indicating the start and end dates of employment contracts. The unique identifier allows us to supplement the core data with additional modules, such as balance sheet data on the firm level and health care-related information on the individual level.

The firm-level data contains the corporate income tax returns for the universe of double-entry bookkeeping firms collected by the National Tax and Customs Administration. This includes balance sheet and income statement information of firms at the yearly level as well as the number of employees and the NACE industry code of the firm. We link this dataset to ownership information provided by the Central European University MicroData, which includes both direct and indirect ownership links.[18]

In the dataset, information on individuals' employers is available for every month. Given that our chronic health condition measure is calculated at the annual level, we also use employer information at the same level of aggregation. In particular, we consider the firm where worker i worked as a main job in the May of year t as the worker's employer in year t.

A module containing individual healthcare utilization can be linked to the core dataset between 2009 and 2017, based on information on state-funded healthcare, provided by the National Health Insurance Fund Administration (NAIK). For each individual, the database contains monthly information on buying prescription medicines, outpatient services, and hospitalizations by different health conditions. In this paper, we focus on information about medicine prescriptions. Medicines are classified by the Anatomical Therapeutic Chemical (ATC) code at the ATC2 digit level. As Section 2.1 explains, these data are likely to capture most medicines used for chronic conditions.

female employees with chronic health issues, fearing reduced future commitment or performance. These dynamics may result in exclusion from fast-track roles or underutilization, even when the individual remains capable and willing to work.

[16] The linked administrative data collection (Admin3) is the property of the data owners and their legal successors: NEAK, MÁK, NAV, ITM, and OH. The data used was processed by the KRTK Data Bank.

[17] This sample includes children in 2003, the youngest of whom are 14 years old in 2017, the last year of our estimation sample – so we observe the new cohorts entering the labor market each year.

[18] HUN-REN KRTK (distributor). 2024. "Mérleg LTS [data set]" Published by Opten Zrt, Budapest. Contributions by CEU MicroData. Data usage is subject to a licensing agreement with Opten Kft. To process the data, CEU MicroData received funding from the National Research, Development and Innovation Office (Forefront Research Excellence Program contract number 144193).

The two datasets were merged using a probabilistic matching method based on Card et al. (2016). More details about the dataset and the matching process can be found in Pető and Reizer (2025).

3.2 Variable definitions

3.2.1 Chronic conditions

To measure chronic health conditions, we follow the approach developed by Danesh et al. (2024), who construct a Chronic Disease Index (CDI) based on similar data on medicine use and socioeconomic conditions. A key innovation of this measure is its comparability across the life course. Rather than counting conditions equally or weighting them arbitrarily, the index anchors chronic illness to its long-term consequences by modeling the relationship between chronic conditions observed at a certain age (64-65 years in our case) and subsequent five-year mortality (or severe hospitalization)[19] outcomes. By estimating this relationship using a flexible, data-driven prediction model—including multiple lags and interaction terms—the CDI captures not only the independent effects of each condition but also their combined impact. This is crucial because many individuals suffer from co-morbidities, and the health burden of having multiple conditions often exceeds the sum of their individual effects. The estimation procedure, based on Double-Lasso regression (Belloni et al., 2014b), also accounts for a rich set of socio-economic controls to isolate the health consequences of chronic illness from other mortality risks. Importantly, the procedure has been extensively verified by Danesh et al. (2024) on data from the Netherlands.

In particular, the procedure follows three steps. First, we use the mapping provided by Danesh et al. (2024) between ATC medicine codes and 19 chronic conditions to identify which conditions each individual suffers from in each year. In particular, if individual i buys medicine belonging to chronic illness n in at least two months in year t, we consider individual i to suffer from condition n in year t. This procedure yields a separate indicator variable for each of the 19 conditions. Appendix Table A.2 presents the proportion of individuals diagnosed with a chronic condition disaggregated by gender, while Appendix Figure A.1 shows the five most prevalent conditions. Cardiovascular disease emerges as the most prevalent condition for both men and women. While notable similarities exist across genders in several disease categories—such as acid-related disorders, diabetes, and hyperlipidemia—distinct gender-specific patterns are also evident.

In the second step, we consider individuals of 64-65 years old and predict whether they die or are hospitalized for a long period in the following 5 years based on the indicators for chronic conditions they have, considering both current and lagged values from years $t-1$ and $t-2$, interactions between the different indicators and the different lags, and specific socioeconomic variables as controls.[20] We conduct these prediction separately by gender, using a Double-Lasso regression (Belloni et al., 2014b).

As a third step, the coefficients from the above regression allow us to calculate an index – the probability of death or long hospitalization for each individual of any age in each year – , based on the indicator variables, their interactions and the socioeconomic variables. Note that these calculations require two lagged values of the health care utilization variables, so we can only calculate the index from 2011 onward.

[19]Given that we look at 5-6 year younger individuals than Danesh et al. (2024), we also include the somewhat less sever but still highly indicative outcome of a hospitalization event of at least 3 days.

[20]In particular, we include the following variables: occupation at 2-digit level held in 2003, the location at NUTS 4-level where the person lives, dummy indicating whether the individual receive pension in 2003 and the type of the pension received (old-age pension, pre-retirement pension, disability pension), age dummies, and dummies indicating the decile in which the person falls according to the 2003 income distribution. As opposed to Danesh et al. (2024), we do not have any information at the household level.

Appendix Section A.1 provides further details about the construction of the index.

In our main exercise, we transform this index into an indicator variable in two steps. First, we classify individual i in year t as having a chronic health condition (CHC) if their index value falls within the highest 10 percent of the person-year level CHC index distribution in the 20-60 age population. Second, for each individual we change the CHC variable to one in every year after their index exceeds this threshold for the first time – i.e. we assume that they cannot recover from this status to correct for the possibility that they don't take medicines every year after the onset of the condition. The share of such individuals by age is presented in Figure 1. Note that the overall share is above 10% because of our second step. The differences in health outcomes – indicating the explanatory power of the model – are illustrated by Figure A.2 in the Appendix.

This method is conservative in the sense that it classifies people as suffering from CHC if they actually take medicine for conditions with strong health implications. Therefore, it is likely that people identified as having CHC are, indeed, suffering from these conditions. At the same time, some people actually suffering from CHCs may not be classified as such if they do not take medicine, so the control group may involve some treated people. Related to this, it is likely that we can only identify the onset of conditions with some lag. This results from several factors. It takes time to diagnose the condition, the patient may only start taking medicine with a lag, and our model, which relies on both contemporary and lagged information on medicine might capture this with a further lag. One consequence of this is that person fixed effects specifications are likely to be biased toward zero as some years in the pre-period may actually be treated. Therefore, to understand dynamics better, we also run event-study-type regressions.

To further support our main results, we provide a number of robustness checks with alternative CHC measures in Section 6.

3.2.2 Firm quality indicators

Our primary focus in the main analysis is foreign ownership, a key dimension of firm heterogeneity both in Hungary and in many other countries. We define a firm to be foreign-owned if the share of directly or indirectly held foreign capital is above 50 percent.

However, to demonstrate that our findings are not specific to ownership structure but apply more broadly to high-productivity, high-paying firms, we also report results using alternative measures of firm quality. First, we classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. Second, we define high-wage firms as those in the top quartile of the average wage distribution. Finally, we identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Appendix Section A.2.

3.2.3 Wage variable

Our wage measure is the average daily wage, calculated using the total compensation variable in the dataset, which includes all income components subject to social security contributions. Since this variable is reported monthly, we aggregate it to the annual level by summing the non-zero monthly earnings for the employee's main job in that year (as defined in Section 3.1). We then divide this annual total by the number of days with earned income to obtain this average daily wage. We adjust this variable in two ways when we define our wage measure. First, we correct it with sickness benefit receipts to ensure that the wage patterns are not driven by lower wages during sickness absence.[21] Second, we transform the variable to full time equivalent (FTE) wages.[22] Unless otherwise noted, throughout the analysis, "daily wage" or simply "wage" refers to the adjusted average daily wage as defined above.

3.2.4 Worker productivity

In wage regressions, time-invariant worker productivity can be captured by including worker fixed effects besides firm fixed effects as in Abowd et al. (1999). When we run regressions for other outcomes, such as employment status or separation,[23] we apply a two-step procedure instead. First, we run an Abowd et al. (1999)-type two-way fixed effects model. Second, we use the estimated worker fixed effect ($\hat{\eta}_i$) as an explanatory variable in the main regression. We can only estimate this measure for those individuals who appear at least once in our "Regression sample". For more details, see Appendix Section A.2. We also save firm fixed effects from this equation to study the role of firm-specific wage premiums in wage dynamics.

3.3 Regression Sample

We construct a sample called "General Population" for our descriptive analysis and for regressions that examine the probability of working, we limit our sample to the period of 2011-2017, corresponding to the years for which our chronic condition indicator can be defined, and to individuals aged between 20 to 60 to exclude age groups with significant retirement.[24]

For all other analysis, the sample is further restricted to individuals employed under labor contracts at firms that had at least 10 employees at any point during the observation period – we call this the "Regression Sample". Given our focus, we restrict the sample to Manufacturing and non-financial market services (NACE B-D, F-J, M-N and S) and exclude firms which were publicly owned at any point in our

[21] In Hungary, sick leave consists of two distinct phases (see Section 2.1). In our dataset, we can directly observe the number of days covered by state-paid sickness benefits, allowing us to adjust for income loss during these periods. However, the initial phase—the employer-paid sick leave—is not directly observed in the data. To account for income loss during this unobserved period, we assume that any employee who received at least one day of sickness benefit had previously utilized the full 15 days of employer-paid sick leave, during which they received 70% of their wage. We further assume that these 15 days were taken with an even distribution over the months preceding the first month in which the sickness benefit was recorded. A similar approach is used by Bíró et al. (2024).

[22] The FTE wage was obtained by dividing the average daily wage by the number of hours worked per day and then multiplying the result by 8, corresponding to a standard full-time workday. This adjustment allowed for a standardized wage measure that accounts for part-time employment by converting it into a full-time equivalent basis. Earnings data include both regular earnings and variable wage elements such as bonuses. In addition, they may also include severance payments – therefore, we have a robustness check in which we exclude the last year of work spells.

[23] An alternative would be to add worker fixed effects into these regressions as well. This, however, would have a conceptually less clear interpretation than the time-invariant worker productivity in the Abowd et al. (1999) wage regressions. In addition, these regressions involve binary dependent variables observed only few times per worker, making within-worker identification hard (Arellano and Carrasco, 2003).

[24] During the study period, Hungary's official retirement age was above 62. However, since 2011, women with at least 40 years of service have been eligible for early retirement with a reduced pension.

sample period. In addition, we exclude person-year observations with missing wage or occupation data and also those cases in which the person retires in the subsequent year. Furthermore, we restrict the sample to the largest connected set, so that we can calculate worker- and firm-fixed effects as in Abowd et al. (1999).

3.4 Descriptive statistics

The "Regression sample" contains 1,468,476 female and 2,095,170 male worker-year observations. 129,892 (293,393) of the female (male) worker-year observations are classified as suffering from CHC in our sample. Appendix Table B.4 and B.5 show descriptive statistics for the workers in our sample. In general, foreign firms have a younger workforce but with longer tenure and higher wages. Workers with CHC are older and have longer tenure than their healthy counterparts, both at domestic and at foreign firms (see Appendix Table B.4). The raw wage gap by health status is around 4 percent for men and 14 percent for women.

Table 1 and Appendix Table B.6 presents descriptive statistics for the firms included in our sample, comprising 67,750 domestic firm-year observations and 20,932 foreign firm-year observations. As we have already described, foreign-owned firms are larger, export more, more productive and use more capital, especially intangible capital. They also provide fewer part-time positions and require more overtime work and use stronger performance incentives in terms of flexible wage elements and larger wage dispersion. Additionally, foreign firms employ a higher proportion of female workers. In terms of workforce health, foreign firms appear to have a healthier employee base, with only 10.5 percent of workers having CHC, compared to 12.3 percent among domestic firms.

Figure 1 compares the prevalence of chronic health conditions by age and gender in the general population and our regression sample. The x-axis represents age, and the y-axis shows the proportion of individuals with CHC in the general population (orange) and our regression sample (red). The prevalence of chronic health conditions increases strongly with age: for men, the prevalence is around 8% at the age of 30, which increases to more than 40% at the age of 60. The levels are somewhat lower for women, but the increase is similar, from 5% at the age of 30 to nearly 30% at the age of 60. As a result of restricting our sample to workers with an employment contract and excluding very small firms, chronic health conditions are less prevalent in our sample than in the general population, a pattern observed for both men and women.

3.5 Empirical approach

Our main question is the relationship between labor market outcomes and having chronic health conditions.

To look at the extensive margin, we run linear probability models looking at whether individual i is working in year t on the "General Population" sample:

$$Works_{it} = \alpha \times CHC_{it} + age_{it} + \tau_t + \beta \times \hat{\eta}_i + \epsilon_{it} \tag{1}$$

where CHC_{it} is the dummy showing whether worker i had a chronic health condition (CHC) in year t, age_{it} is a set of age category dummies for each 5 years age group, τ_t is a set of calendar year dummies and $\hat{\eta_i}$ is our proxy for the productivity of the worker, that we measure by the worker-specific premium estimated form an AKM model described in Section 3.2.4. Standard errors are clustered at the firm level in all regressions if not otherwise stated.

To investigate wage effects, we estimate the following equation:

$$\ln(wage_{it}) = \alpha \times CHC_{it} + X'_{it}\beta + s_{j(it)} + \tau_t + \eta_i + [\nu_{j(it)}] + \epsilon_{it} \tag{2}$$

where $\ln(wage_{it})$ is the daily wage of worker i in year t. $s_{j(it)}$ is the 1-digit industry of firm j in which worker i works in year t, X represents time-varying worker level characteristics, such as a set of age category dummies, tenure, and its square. τ_t is a set of calendar year dummies, while η_i denotes worker fixed effects. In some specifications, we include firm fixed effects, represented by $\nu_{j(it)}$, in the model.[25]

In order to understand the role of firm-specific wage premiums in the wage differences, we also re-estimate Equation 2 by replacing the left hand-side variable with estimated firm fixed effects from an AKM decomposition, as explained 3.2.4.

Note that when including worker fixed effects, we identify α only from the change in the worker's health status.[26] This within-worker identification strategy is likely to underestimate the impact of suffering from CHC, because the onset of the condition is likely to be measured with a lag and the some of the mechanisms involved – e.g. missed promotions, job switching – may take time to materialize (see more details in Section 3.2.1).

To investigate the dynamic effect more precisely, we also estimate an event-study regression:

$$\ln(wage_{it}) = \sum_{k \neq -1} \alpha_k \cdot \mathbf{1}\{event\_time_{it} = k\} + X'_{it}\beta + s_{j(it)} + \tau_t + \eta_i + \epsilon_{it} \tag{3}$$

where $\mathbf{1}\{event\_time_{it} = k\}$ is a dummy taking the value of one in event time k, with event time specified as zero in the last year before the worker is identified as suffering from CHC for the first time. α_k shows the wage difference between event year t and the year just before the onset of conditions. We exclude always treated workers (for whom $CHC_{it} = 1$ already in the first year we observe them in the sample). Therefore, the control group consists of never treated (never CHC) workers and not-yet treated workers, conditional on worker fixed effects. Given the staggered setup, we use the Sun and Abraham (2021) estimator.

As discussed in Section 3.2.1, due to the two-period lag in our predictive model—in addition to potential delays in diagnosis and prescription—the exact timing of CHC onset is uncertain. In practice, the CHC indicator may switch to 1 with a delay of one to two periods after the actual onset of symptoms. To account for this, we treat the interval between $k = -2$ and $k = 0$ as the likely window for the onset of CHC.

[25] We don't control for occupation in the main specification as one channel of interest may be that people with CHC are not promoted to different occupations, and, therefore, it can be a bad control. In addition, high-quality firms may use a different occupational structure. In any case, we show that our results are robust to controlling for occupation in Appendix Section C.7.

[26] Recall that we classify the worker are having CHC in all years after their CDI crosses the threshold, so the CHC dummy can't "switch back". As a result, the within-worker identification strategy implies a before-after comparison.

In a parallel way, we again use the Sun and Abraham (2021) estimator to estimate an event study equation for the probability of working, which takes the following form on the "General Population" sample:

$$Works_{it} = \sum_{k \neq -1} \alpha_k \cdot \mathbf{1}\{event\_time_{it} = k\} + \beta \times everCHC_i + age_{it} + \tau_t + \epsilon_{it} \tag{4}$$

where $everCHC_i$ is a dummy that equals 1 if the worker had CHC status in any year, and zero otherwise to control for treated status, as no worker fixed effects are included.[27]

4 People with chronic conditions in the labor market

4.1 Employment

Figure 2 illustrates the share of individuals who are employed – including self-employed and public workers – (y-axis) by age (x-axis) and health status, with the red line representing those with CHC and the orange line representing those without. Figure 2a shows the results for men. Across all age groups, employment rates are consistently higher among those without CHC. The difference is relatively stable across different ages. For women (Figure 2b), employment rates of people without CHC are also always higher, but the difference between the two groups is much larger above 40 compared to younger women, suggesting that many more women stop working when facing chronic diseases than men.

Table 2 provides further evidence for these patterns by estimating separate regressions with employment as the dependent variable (Equation (1)). Men with a CHC are approximately 7 percentage points, while women 14 percentage points less likely to be employed than their counterparts without a CHC (column (1)). The results are similar when we control for age (column (2)). Next, we include the estimated person fixed effects from the Abowd et al. (1999)-type specification (as explained in Section 3.2.4) to handle unobserved worker heterogeneity. First, we re-run the regression from column (2) on the sample where these person fixed effects are available, i.e. workers who were observed in our regression sample (column (3)). The estimates on this sample are about half of those in column (2), showing that people who never work during the period we study are more likely to suffer from CHC. Accounting for worker productivity leaves the results essentially unchanged (column (4)): 3 percentage points for men and 6 percentage points for women, both highly significant.

Figure 3 shows the results of estimating an event study specification (Equation (4)) when controlling for calendar year and age. The x-axis shows event time relative to the onset of chronic illness, where $event\_time = 0$ marks the period when the CHC indicator switches to 1. As discussed in Section 3.5, due to the use of two lags in constructing the CHC indicator and potential delays in diagnosis or treatment, the exact timing of onset is uncertain. The shaded area, spanning from $event\_time = -2$ to $event\_time = 0$,

[27] We don't include the worker quality proxy, as it is available only for people who worked at least in one year, potentially introducing a selection into the sample. Including that variable leads to event studies with an even stronger fall in the probability of working around the offset of CHCs.

represents the likely window in which the condition began. The y-axis represents the difference in the probability of working relative to $event\_time = -1$. The figure shows a quick fall in the probability of working during the onset of CHC, followed by a slight declining trend for men, with a slight evidence for pre-trend. The estimated long term effects are around 4 percentage points for men and 6 percentage points for women, which is consistent with the results in columns (4) in Table 2. The results are robust to use the traditional two-way fixed effects estimator (see Appendix Figure B.2).

Appendix Figure B.1 further details the distribution of workers across different employment types by age and gender. It reinforces the large differences in terms of being employed, especially for women above 40. But it also shows that the composition of workers in terms of employment types, conditional on working, does not differ substantially between people with and without CHC within the same gender-age bracket - our findings are unlikely to be driven by large shifts of CHC workers to self-employment or to the public sector.

CHC workers also reduce the hours they work, as we show in Appendix Section B.1: men with CHC are 5 percentage points, women 15 percentage more likely to work part-time, even when we control for AKM worker fixed effects.

4.2 Wages

As a next step, Figure 4 represents the age–wage profiles—average daily wages by age—for workers with CHC (red line) and without CHC (orange line). A wage gap is evident across both genders, becoming more pronounced after age 25. However, the gap is substantially larger among women than among men. The wage differential does not appear to increase systematically with age; rather, both younger and older workers with a CHC experience a relatively stable wage penalty across the age distribution.

Regressions reported in Table 3 investigate the wage gap further by estimating Equation (2) separately for men and women. The first specifications include year- and industry-specific fixed effects and a set of age dummies, followed by a model that additionally controls for tenure. In column (3), we include worker-specific effects; in column (4), firm-specific fixed effects, and the final specification incorporates both.

Among male workers (Panel A), those with CHC earn approximately 5-6 percent less than their healthy counterparts. When including worker fixed effects, the estimated wage penalty falls to 1.3%, which is also highly significant. This lower estimate is likely to be the consequence of our measure capturing the onset of chronic conditions with a lag, as discussed in Section 3.2.1. The significant point estimate is in line with the idea that the estimated wage penalty is not only a consequence of worker composition. Column (4) includes firm fixed effects but no person fixed effects. The point estimate for the CHC penalty is 3.2, about 60% of the estimate in column (2). This suggests that about 40% of the original wage penalty results from CHC workers working at lower wage firms and the remaining 60% is a within-firm component. Finally, column (5) includes both worker and firm fixed effects, and yields very similar estimates to the worker fixed effects specification. Panel B of Table 3 shows similar results for women. The overall wage penalty is between 12-14%, half of which is explained by firm fixed effects and half by within-firm wage differences (column (3)). The results with worker fixed effects are between 0.5-0.7 percent.

To understand better the role of firm-specific wage premiums, in Table 4 we re-run Equation 2 but replace the dependent variable with firm fixed effects estimated from an AKM specification. We find that both men and women with CHC work at lower paying firms on average compared to other workers. This differences is 0.7% for men, which is 12% of the total wage penalty reported in column (1) of Table 3. For women, the difference in firm specific premia is 3.2%, or 23% of the cross sectional wage penalty. The larger role of sorting for women can be partly explained by their stronger preference for part-time work (Appendix Section B.1), which is more available at lower-paying firms.

To look at wage dynamics, Figure 5 shows event study results from estimating Equation (3) with the Sun and Abraham (2021) estimator. We use the same control variables as in Column (3) of Table 3, i.e. we include year, industry and age dummies, and further control for tenure (and is square) and worker-specific fixed effects. The results show little pre-trend before the onset of CHCs, followed by a trend break from $event\_time = -2$. The presence of a trend break, rather than a jump, in wages is in line with the hypothesis that the wage penalty results from the lack of promotions or raises. The estimated long-term effect is about 4 percent for men and 2 percent for women, substantially larger than the corresponding estimates in column (3) of Table 3, which is in line with the trend break in the figure. Appendix Figure B.3 panels (a) and (b) show the results by using the traditional two-way fixed effects model rather than the Sun and Abraham (2021) estimator as in our main specification, which yields very similar results.

To investigate the role of firm-specific wage premiums in wage dynamics, Figure 6 and Appendix Figure B.4 re-estimates Equation (3) with the AKM firm fixed effect as the dependent variable, rather than the wage. We find no change in the firm-specific wage premiums during the onset, but there is a significant fall afterwards, in line with some workers switching to lower-paying firms. This effect is about 0.3 percent for men and 0.5 percent for women, explaining 6% of the fall in wage for men and 25% for women.

5 Workers with Chronic Conditions and Firm Types

The previous results show that sorting of worker across firms explains about half of the CHC penalty. In this section we look at how much of this is attributable to the main observable firm characteristics. We first compare foreign- and domestically-owned firms, and demonstrate in Section 5.2 that similar patterns emerge when firms are classified by productivity or wage levels.

5.1 Foreign-owned firms

5.1.1 Differences in Employment

Figure 7 shows the share of workers in our sample employed at foreign-owned firms by age, separately for men and women. For male workers, the share employed at foreign firms increases in the early stages of their careers, peaking at nearly 60 percent around age 30 before gradually declining. Across all age groups, the share of workers with CHC employed at foreign firms is slightly lower than that of their healthier counterparts, with the gap being most pronounced among older workers. A similar trend is observed for female workers, though the difference between those with and without CHC is more pronounced. The largest gap appears among older women, reaching 10 percentage points in their late 50s.

To investigate employment effects, we run linear probability models – similar to Equation (1) – looking at whether individual i is working at a foreign-owned firm in year t conditional on working:

$$Foreign_{j(it)t} = \alpha \times CHC_{it} + X'_{it}\gamma + \tau_t + \beta \times \hat{\eta}_i + \epsilon_{it} \tag{5}$$

where X'_{it} includes individual controls such as a set of age dummies, tenure and its square.

Table 5 presents the results. The employment gap is 1.6 percentage points for men and 6.0 percentage points for women (column (1)). This gap does not change much as we control for tenure (column (2)). When our worker productivity proxy is included in the regression, the gap shrinks to 0.3 percentage point for men and 3.6 percentage points for women (column (3)).

Appendix Section B.2 looks at worker flows to identify how hiring and separation contributes to these differences. We find a difference between CHC and non-CHC workers along both margins. The penalty is similar for men and women in terms separation (about 1.5 percentage points) but the penalty is much higher for women in terms of joining foreign firms (5-6 percent vs 1.1-1.4 percent for men).

5.1.2 Differences in wages

Figure 8 shows the evolution of wages during a person's life path from the age of 20 to the age of 60 by ownership. Employees at foreign firms earn higher wages than those at domestic firms at all stages of their lives, with an especially steep rise for early-career workers. There is a CHC wage penalty within both groups of firms, and this gap is larger for women.

To understand wage effects better, we slightly modify Equation (2) estimating

$$\begin{aligned} \ln(wage_{it}) = {} & \alpha_0 \times CHC_{it} + \alpha_1 \times Foreign_{j(i,t)t} + \alpha_3 \times CHC_{it} \times Foreign_{j(i,t)t} \\ & + X'\beta + s_{j(it)} + \tau_t + \eta_i + \nu_{j(it)} + \epsilon_{it} \end{aligned} \tag{6}$$

where the main coefficient of interest is α_3 showing the difference between domestic and foreign firms in terms of the wage penalty for workers with CHC.

The results are presented in Table 6. Foreign firms pay a significant wage premium: nearly 50% for men and 35% for women (columns (1)-(2)). This partly reflects worker composition, but even when controlling for worker fixed effects, the foreign wage premium remains 18% for men and 13% for women (column (3)).[28] The CHC penalty is larger by 1-2 percentage points in foreign firms for men, and by 0.5-3 percentage points for women, with lower estimates when worker fixed effects are included.

[28] There are few firms switching between foreign/domestic ownership, which makes the foreign premium estimated with firm fixed effect specifications less meaningful.

5.2 Alternative firm quality measures

In the previous analysis, we defined high-quality firms as those under foreign ownership. To assess the robustness of our results, we consider alternative definitions of firm quality based on (i) firm-specific wage premiums, (ii) labor productivity, and (iii) average firm-level wages. Further details regarding the construction of these measures are provided in Section 3.2.2.

To see the CHC-gap in the probability of working for "high-quality" firms, we re-estimate Equation (5) using alternative definitions of firm quality, and report the estimated CHC gap in Figure 9a, in which we control for year and industry fixed effects, along with a set of age dummies. Figure 9b also includes controls for worker productivity, proxied by worker-specific fixed effects. In each figure, red markers correspond to the estimates from the main specification based on ownership status, while estimates based on alternative firm quality measures are depicted in other colors. Across all specifications, the results are highly consistent: parameter estimates are similar in magnitude and not statistically distinguishable across different firm quality definitions.

These results show that, indeed, CHC workers are less likely to work in "higher-quality" firms, independently of its exact definition. We also find similar differences both in hiring and separation (Appendix Figure B.6).

Finally, we examine differences in wages by re-estimating Equation (6) using alternative firm quality definitions. Figure B.5 and B.5b show the wage premium at "high-quality" firms. The results for the interaction term – the difference between the CHC penalties applied by "high-quality" and "low-quality" firms – are presented in Figure 10a and 10b. Red markers again depict estimates from the main analysis based on firm ownership, while other colors reflect alternative firm quality measures. Across all specifications, "high-quality" firms pay a significant wage premium. The wage differences by health status remain stable – with somewhat weaker results for high-productivity firms – and parameter estimates do not vary significantly by the firm quality definition employed.

5.3 Quantitative importance

5.3.1 Decomposing the CHC penalty

The previous results have shown that CHC workers are less likely to work for high-wage firms and they earn less compared to other workers in that group. To quantify the importance of these channels, we can apply the following decomposition, in which F denotes foreign and D domestic firms (or "firm groups" in general), C workers with CHC and N workers with no CHC:

$$
\begin{aligned}
&E(\ln w|C) - E(\ln w|N) = \\
&= \underbrace{(P(F|C) - P(F|N))\,(E(\ln w|N,F) - E(\ln w|N,D))}_{\text{between group}} + \\
&+ \underbrace{P(F|C)\,(E(\ln w|C,F) - E(\ln w|N,F)) + (1 - P(F|C))\,(E(\ln w|C,D) - E(\ln w|N,D))}_{\text{within-group}}.
\end{aligned}
$$

The between term represents sorting, i.e. CHC workers being more likely to work for domestic-owned in general. We can further decompose the within-term in the following way:

$$
\begin{aligned}
\text{Within} = &\underbrace{(E(\ln w|C,D) - E(\ln w|N,D))}_{\text{Domestic CHC gap}} + \\
+ &\underbrace{P(F|C)\,[(E(\ln w|C,F) - E(\ln w|N,F)) - (E(\ln w|C,D) - E(\ln w|N,D))]}_{\text{Difference between foreign/domestic CHC gap}}
\end{aligned}
$$

The 'domestic CHC gap' shows the CHC penalty in domestic firms, while the second term in analogous to the bargaining term in Card et al. (2016). The decomposition allows us to isolate how the presence of foreign firms contribute to the overall penalty. In particular, the contribution of foreign firms consists of sorting into them (the between term) and the bargaining term (the difference between foreign/domestic CHC gap).

We can use the estimated parameters to decompose the wage difference, which we conduct for the case when industry and year fixed effects are included in our model. In particular, the first component $(P(F|C) - P(F|N))$ is the CHC coefficient from Equation (5) (Table 5, column (1)). The wage differences are all derived from Equation (6) (Table 6, column (1)), and $P(F|C)$ is calculated from the data.

The results of the decomposition are presented in Table 7 for the different types of firms. For men, the total CHC penalty (with industry and year fixed effects) is 5.8%. The between (sorting) term – the lower probability of working at foreign firms which pay a higher wage – explains 0.8 percentage points, the penalty applied by domestic firms explains 4.5 percentage points, while the larger penalty applied by foreign firms (bargaining term) accounts for 0.6 percentage points. This mean that the contribution of foreign-owned firms to the CHC penalty is 25%, from which 14 percentage points result from sorting and 11 from bargaining. The relative role of the between (sorting) term is somewhat larger when high-productivity or high-wage firms are considered (25 percentage points for high-wage firms).

The total penalty is larger, 14%, for women, but the relative role of the different terms is similar to that of men: the between term captures 2.2 percentage points, the domestic penalty 10.7 percentage points and the difference in penalties across firm groups 1 percentage points.

5.3.2 How does the CHC penalty affect the age-wage relationship?

Since older people are more likely to suffer from CHC (see Figure 7), the expected wage of older people would be higher in the absence of the CHC penalty, leading to a less concave age-wage curve under such a counterfactual. In addition, given the role of firm heterogeneity in the CHC penalty, an alternative counterfactual could assume that foreign-owned firms behave similarly to domestic ones.

To quantify how the age-wage curve would change under these circumstances, we conduct the following counterfactual exercises and present their results in Figure 11, which shows the difference between the counterfactual and the actual age-wage curve (the contribution of the CHC penalty). The increasingly negative values in the figure show that the actual age-wage curve is more concave than the counterfactual one.

Counterfactual 1: No CHC penalty. In this exercise, we assume that there is no CHC penalty at all. To calculate the difference between the counterfactual and the actual wage for each age group, we multiply the share of CHC people in each age group with the estimated total CHC penalty in Table 7. The red line in Figure 11 shows the results. Actual wages are substantially lower than counterfactual ones: according to our estimates, the average wage of 60 year old men (women) would be 2 percent (4 percent) higher under the counterfactual. The difference is quickly increasing with age, suggesting that the CHC penalty makes the age-wage curve more concave. To illustrate the quantitative importance of this, consider the wage difference between 60 and 40 year old people, which is about 15 percent for both genders. According to Figure 11, this difference would be 1.5 (men) and 3 (women) percentage points smaller in the absence of CHC penalties.

Counterfactual 2: No foreign firms. In this exercise, we assume that foreign firms behave similarly to domestic firms in terms of employing CHC workers. This means that they would employ CHC workers to the same extent as domestic firms and that they also apply the same CHC penalty to domestic firms. In terms of the decomposition in Table 7, this means that the 'between' and the 'difference in CHC gap' terms are zero. Therefore, the difference between the counterfactual and actual wage for each wage group is the share of CHC workers in the group multiplied by these two terms. The results are presented in orange line in Figure 11, while the other lines show a similar counterfactual for the other type of firms. While the differences are smaller in this case compared to the first counterfactual, the different behavior of "high-quality" firms – especially of high-wage firms – regarding CHC workers also contributes to the concavity of the age-wage curve.

6 Robustness and Heterogeneity analysis

We present three types of robustness checks, some of which also provide evidence on the (lack of) heteroegenity. First, we show that the results are robust to different definitions of the CHC status. Second, by using sample restrictions, we show that the results are not restricted to younger or older workers, blue-collar workers or workers receiving disability benefits. Finally, we show that controlling for occupation – which is not included in our main specification as it can be a "bad control" does not change the main findings.

Alternative measure of the chronic disease index (CDI) As we have described in Section 3.2.1, in our main specification we follow Danesh et al. (2024) in using a lasso regression that includes nonlinear functions of the 19 chronic condition dummies and socioeconomic variables to build the continuous CDI variable. To check whether the results are robust to a simpler and more transparent definition, we simply use a linear probability model with the 19 dummies to predict negative health outcomes. Otherwise we follow the main specification. Appendix Section C.1 explains this exercise in more detail. The results are very similar when we use this alternative measure rather than the mean measure (Section C.1) suggesting that the main results are not driven by the non-linear functions or the inclusion of the socioeconomic variables.

Alternative thresholds for the CHC status As described in Section 3.2, we construct a continuous measure of chronic health conditions and individuals are classified as having a CHC if their index value falls within the top 10 percent of the distribution. Recognizing that the choice of the 10 percent cutoff is inherently arbitrary, we assess the robustness of our findings by applying three alternative classification thresholds: i) Top 10 Percent within Gender; ii) 1.5 $\times$ Median, iii) 2 $\times$ Median. The details and results are reported in Appendix Section C.2.

We find that the qualitative patterns are very similar across these definitions: people with CHC are less likely to work (Figure C.2), earn lower wages (Figure C.3), sort to lower paying firm (Figure C.4), are less likely to work in foreign firms (Figure C.5) and face a larger penalty in foreign firms (Figure C.7). Women face larger penalties, similarly to our main results. We find that the median-based definitions are stricter than our preferred definition – less then 5 percent of people are considered to be sick according to these definitions – and the penalties are larger both in terms of wages and the probability of working or working at higher quality firms.

White-collar workers Potentially the CHC penalty could be driven solely or mainly by blue-collar workers. Because their jobs are more physically demanding, chronic health conditions can have a greater impact on their productivity. Additionally, absenteeism may be more problematic for blue-collar workers, as their tasks are generally less flexible and cannot be performed remotely. To address this issue, we restrict our sample to white-collar workers. First, we re-run Equation (1) on the subsample of workers that had white-collar job for at least once during the period of 2011-2017 and were observed in our regression sample, thus worker fixed effects are available for them. Appendix Table C.6 presents the results. Male workers with CHC work with 1.5-2 percentage point lower probability than their healthy counterparts. The CHC penalty in the likelihood of working is larger among female workers, reaching 4 percentage points. As a next step, we re-run Equation (2) on the subsample of white-collar workers. Appendix Table C.7, the CHC wage penalty is comparable in size and significant for both gender across all specification to our main findings. In Table C.8, we re-estimating Equation (2) using firm fixed effects derived from the AKM specification as the dependent variable on the subsample of white-collar workers. On average, both men and women with CHC are employed at firms that offer lower firm specific premium compared to those without CHC. However, among white-collar workers, this sorting effect is more pronounced for men. The average difference the firm fixed effect is 1.1% for men and 1.8% for women with CHC, corresponding to 20% and 17% of the overall wage penalty reported in column (1) of Table C.7, respectively. These results confirms, that our main findings are not driven by physical workers, but holds for all job types.

Splitting the sample by age Another potential concern is that people of different ages may suffer from different conditions and those may impact their work differently. Therefore, we split the sample by age, looking at workers below and above the age of 40. The results are described in Appendix Section C.4. In general we find very similar patterns for the two age groups, confirming that CHCs affect negatively younger as well as older workers. The main difference is that older workers with CHC are more likely to exit the labor market, but the wage penalties and selection to higher wage/foreign firms are very similar across the two groups.

Severance payments A potential concern with our estimates is that the payments received by the worker in the last year of their job may include severance payments, which may also differ by firm type (see Section 3.2.3). To handle this issue, we re-run the wage regressions by excluding the last year of the worker's spell. Appendix Table C.17 reports the main wage specification (similar to Table 3) and Appendix Table C.18 the results for the domestic-foreign gap (similar to Table 6). The results are very similar to the main specification.

Disability benefits Another concern is that firms' and workers' incentives are affected disability benefit policies (Section 2.1), which may drive differences in wages and employment. As applying for disability benefit itself is a decision to a large extent, we don't take this into account in our main specifications. At the same time, we investigate how results change when we restrict our attention to workers who don't receive disability benefits, and, therefore firms don't receive subsidies for applying these workers. The results are presented in Appendix Section C.6.

When restricting the sample to workers who don't receive disability benefits, we estimate similar overall CHC wage penalties compared to the main sample when we control for worker fixed effects (Table C.19). At the same time, worker sorting is much weaker both overall and between domestic- and foreign-owned firms, especially for men (see Table C.21), suggesting that sorting is stronger for men with disability benefits. This is in line with domestic firms valuing the incentives for employing these workers more, but can also result from people with CHC in these firms being more likely to apply for a disabled status. While sorting is weaker on this sample, the difference in the CHC penalty between foreign and domestic firms is somewhat larger (Table C.22). The estimated difference in the penalty is 4 percentage points for men and 6 for women when worker fixed effects are not included and 1-1.5 with worker fixed effects.

Controlling for occupation In the main analysis, we do not control for the occupation held by the worker, as occupational choice may itself be a key part of the mechanism under investigation. Specifically, individuals with CHC may self-select into occupations with lower physical demands or reduced stress. Even more importantly, firms may not promote CHC workers into managerial positions, which is part of the main mechanism in our theoretical framework (Section 2.2). Still, it is important to see whether our results mainly reflect differences in occupation among workers or firms or we still have a CHC wage penalty even when controlling for occupation. The details and results of this investigation are reported in Appendix Section C.7.

We re-estimate the main specifications while controlling for 2-digit ISCO occupation codes (Appendix Table C.23). Consistent with our primary findings, workers with CHCs remain significantly less likely to be employed at foreign-owned firms than their healthy counterparts, even after accounting for occupational differences (Appendix Table C.23). Turning to wage outcomes, we find that controlling for occupation tend to yield smaller wage penalties compared to the main specification, showing that CHC workers tend to work in lower-payed occupations, but the estimates remain significant and negative (Appendix Table C.24). The estimates are essentially unchanged when worker fixed effects are included, suggesting that the within-person wage effect is not a result of occupational changes either in the treated or the control group. Among male workers, the ownership-specific wage penalty seems to be fully explained by occupational differences in specifications that do not account for worker selectivity, but it remains significant for female workers (Appendix Table C.26).

7 Conclusion

This paper has shown that workers suffering from CHCs face a substantial penalty in their labor market outcomes, both in terms of the extensive margin, the type of firms they work for as well as the within-firm wage penalty. We also found that women face a larger CHC penalty along all these margins.

Our results are in line with the hypothesis that foreign-owned and other "high-quality" firms, while more productive, apply production and management methods which impact workers with CHC in a more negative way, reducing their wage and pushing them to work in firms with a less demanding work environment and more flexibility in terms of part time positions.

Our findings document a specific channel, different behavior regarding CHC workers, through which the presence of foreign-owned and other high-quality firms contributes to wage inequality both within and across cohorts. In the absence of such firms wage differences between CHC and other workers would be smaller and the age-wage relationship would be less concave.

These findings can be important for policymaking. Subsidies for employing CHC workers could be re-designed in a way that promote employment in high-quality firms rather than only in lower quality firms. Anti-discrimination and other rules could pay more attention on how CHC workers are affected by management systems and nudge firms to support their CHC workers better, by, for example, offering part-time or remote work options. Given the higher penalties women with CHCs face, policy should pay a particular attention to this group, and focus on the intersection of health and gender in designing support programs.

References

Abowd, J.M., Kramarz, F., Margolis, D.N., 1999. High wage workers and high wage firms. Econometrica 67, 251–333.

Aitken, B., Harrison, A., Lipsey, R.E., 1996. Wages and foreign ownership a comparative study of mexico, venezuela, and the united states. Journal of international Economics 40, 345–371.

Alfaro-Ureña, A., Manelici, I., Vasquez, J.P., 2021. The effects of multinationals on workers: Evidence from Costa Rican microdata. Technical Report. Working paper.

Arellano, M., Carrasco, R., 2003. Binary choice panel data models with predetermined variables. Journal of econometrics 115, 125–157.

Arnold, J.M., Javorcik, B.S., 2009. Gifted kids or pushy parents? foreign direct investment and plant productivity in indonesia. Journal of International Economics 79, 42–53.

Autor, D.H., Duggan, M.G., 2003. The rise in the disability rolls and the decline in unemployment. Quarterly Journal of Economics 118, 157–205. doi:10.1162/00335530360535162.

Bartel, A., Ichniowski, C., Shaw, K., 2007. How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. The quarterly journal of Economics 122, 1721–1758.

Becker, N.V., Scott, J.W., Moniz, M.H., Carlton, E.F., Ayanian, J.Z., 2022. Association of chronic disease with patient financial outcomes among commercially insured adults. JAMA Internal Medicine 182, 1044–1051.

Belloni, A., Chernozhukov, V., Hansen, C., 2014a. High-dimensional methods and inference on structural and treatment effects. Journal of Economic Perspectives 28, 29–50.

Belloni, A., Chernozhukov, V., Hansen, C., 2014b. Inference on treatment effects after selection among high-dimensional controls. Review of Economic Studies 81, 608–650.

Berniell, I., Sánchez-Páramo, C., 2011. Overview of Time Use Data Used for the Analysis of Gender Differences in Time Use Patterns. Technical Report 5785. World Bank Policy Research Working Paper. URL: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/182121468281337664/overview-of-time-use-data-used-for-the-analysis-of-gender-differences-in-time-use-patterns.

Bertrand, M., et al., 2017. Disability, wages, and labor market participation: Evidence from a field experiment. American Economic Review 107, 252–256.

Bíró, A., Boza, I., Gyetvai, A., Prinz, D., 2024. Health Shocks, Social Insurance, and Firms. Technical Report. IZA Discussion Papers.

Blau, F.D., Kahn, L.M., 2017. The gender wage gap: Extent, trends, and explanations. Journal of Economic Literature 55, 789–865. doi:10.1257/jel.20160995.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R.S., Patnaik, M., Saporta-Eksten, I., Van Reenen, J., 2017. What drives differences in management? Technical Report. National Bureau of Economic Research.

Bloom, N., Sadun, R., Reenen, J.V., 2012. Americans do it better: Us multinationals and the productivity miracle. American Economic Review 102, 167–201.

Broniatowska, P., Strawiński, P., 2021. Foreign-and domestic firm ownership and its impact on wages. evidence from poland. European Journal of Industrial Relations 27, 445–466.

Bubonya, M., Cobb-Clark, D.A., Wooden, M., 2017. Health and labour market participation: Evidence from australian panel data. Labour Economics 48, 188–200.

Card, D., Cardoso, A.R., Heining, J., Kline, P., 2018. Firms and labor market inequality: Evidence and some theory. Journal of Labor Economics 36, S13–S70.

Card, D., Cardoso, A.R., Kline, P., 2016. Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. The Quarterly journal of economics 131, 633–686.

Carmichael, F., Charles, S., 2003. The opportunity costs of informal care: Does gender matter? Journal of Health Economics 22, 781–803. doi:10.1016/S0167-6296(03)00044-4.

Case, A., Lubotsky, D., Paxson, C., 2002. Economic status and health in childhood: The origins of the gradient. American economic review 92, 1308–1334.

Collins, J.J., Baase, C.M., Sharda, C.E., Ozminkowski, R.J., Nicholson, S., Billotti, G.M., Turpin, R.S., Olson, M., Berger, M.L., 2005. The assessment of chronic health conditions on work performance, absence, and total economic impact for employers. Journal of occupational and environmental medicine 47, 547–557.

Conyon, M.J., Girma, S., Thompson, S., Wright, P.W., 2002. The productivity and wage effects of foreign acquisition in the united kingdom. The Journal of Industrial Economics 50, 85–102.

Cruz, M., Nayyar, G., Toews, G., Vézina, P.L., 2023. Fdi and wage inequality. Handbook of Labor, Human Resources and Population Economics , 1–25.

Danesh, K., Kolstad, J.T., Spinnewijn, J., Parker, W.D., 2024. The chronic disease index: Analyzing health inequalities over the lifecycle. Technical Report. National Bureau of Economic Research.

Dixon, S., 2015. The employment and income effects of eight chronic and acute health conditions. 15/15, New Zealand Treasury working paper.

Earle, J.S., Telegdy, Á., Antal, G., 2018. Foreign ownership and wages: evidence from hungary, 1986–2008. ILR Review 71, 458–491.

European Commission, 2022. Your social security rights in hungary. https://ec.europa.eu/social/BlobServlet?docId=13766&langId=en. Accessed: 2025-05-22.

European Observatory on Health Systems and Policies, 2024. Hungary: Pharmaceutical care. https://eurohealthobservatory.who.int/monitors/health-systems-monitor/countries-hspm/hspm/hungary-2011/provision-of-services/pharmaceutical-care. Accessed: 2025-05-22.

Fortin, N.M., 2015. Gender role attitudes and labor market outcomes: A cross-country perspective. IZA Journal of Labor Economics 4, 1–19.

Gignac, M.A.M., Cao, X., McAlpine, D., Badley, E.M., 2014. Perceived productivity, stigma, and workplace support among employed people with arthritis. Journal of Occupational Rehabilitation 24, 73–84. doi:10.1007/s10926-013-9446-x.

Girma, S., Görg, H., 2007. Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. Journal of International Economics 72, 97–112.

Goldin, C., 2014. A grand gender convergence: Its last chapter. American Economic Review 104, 1091–1119. doi:10.1257/aer.104.4.1091.

Halima, M.A.B., Rococo, E., 2014. Wage differences according to health status in france. Social Science & Medicine 120, 260–268.

Heitmueller, A., Inglis, K., 2007. The earnings of informal carers: Wage differentials and opportunity costs. Journal of Health Economics 26, 821–841. doi:10.1016/j.jhealeco.2006.12.001.

Helpman, E., Melitz, M.J., Yeaple, S.R., 2004. Export versus fdi with heterogeneous firms. American economic review 94, 300–316.

Hijzen, A., 2007. International outsourcing, technological change, and wage inequality. Review of International Economics 15, 188–205.

Huang, K., Sim, N., Zhao, H., 2020. Does fdi actually affect income inequality? insights from 25 years of research. Journal of Economic Surveys 34, 630–659.

Johnson, R.W., McGill, B., 2020. Gender, chronic illness, and labor market outcomes: Evidence from longitudinal data. Labour Economics 64, 101826.

Kline, P., Petkova, N., Williams, H., Zidar, O., 2019. Who profits from patents? rent-sharing at innovative firms. The quarterly journal of economics 134, 1343–1404.

Kline, P., Rose, E.K., Walters, C.R., 2022. Systemic discrimination among large us employers. The Quarterly Journal of Economics 137, 1963–2036.

Krekó, J., Scharle, Á., 2021. Changes in disability benefits and their impacts .

Krekó, J., Telegdy, Á., 2025. The effects of a disability employment quota when compliance is cheaper than defiance. Economica 92, 614–643.

Kruse, D., Schur, L., 2003. Employment of people with disabilities following the ada. Industrial Relations: A Journal of Economy and Society 42, 31–66. doi:10.1111/1468-232X.00275.

Lundberg, S., Pollak, R.A., 1996. Bargaining and distribution in marriage. Journal of Economic Perspectives 10, 139–158. doi:10.1257/jep.10.4.139.

Luo, F., Chapel, G., Ye, Z., Jackson, S.L., Roy, K., 2023. Labor income losses associated with heart disease and stroke from the 2019 panel study of income dynamics. JAMA Network Open 6, e232658–e232658.

McGregor, A., Poot, J., 2016. Health, productivity, and labor market outcomes: Evidence from a population-based panel. Health Economics 25, 884–903.

Nepal, B., Brown, L., Mohanty, I., 2021. Chronic illness and job strain among australian workers: An intersectional analysis. Health Sociology Review 30, 28–46. doi:10.1080/14461242.2021.1878750.

OECD, 2024. Fdi in figures - october 2024. URL: https://www.oecd.org/en/publications/fdi-in-figures-october-2024_fcdc2fb2-en.html.

de Oliveira, C., Iwajomo, T., Kurdyak, P., 2023. Mental health care use among children and adolescents with high health care costs in ontario, canada. JAMA Network Open 6, e2313172–e2313172.

Pelkowski, J.M., Berger, M.C., 2004. The impact of health on employment, wages, and hours worked over the life cycle. The Quarterly Review of Economics and Finance 44, 102–121.

Pető, R., Reizer, B., 2025. FDI, technological progress and inequality: A task-based approach. Technical Report.

Polanco, B., Oña, A., Sabariego, C., Barzallo, D.P., 2024. Chronic health conditions and their impact on the labor market. a cross-country comparison in europe. SSM-Population Health 26, 101666.

Rigó, M., 2012. Estimating union-non-union wage differential in hungary. Unpublished PhD dissertation chapter. Central European University .

Rodriguez-Alvarez, A., Rodriguez-Gutierrez, C., 2018. The impact of health on wages: evidence for europe. The European Journal of Health Economics 19, 1173–1187.

Sandi, M., Westerlund, H., 2017. Does health impact labor market outcomes equally for men and women? European Journal of Public Health 27, 1047–1051. doi:10.1093/eurpub/ckx112.

Setzler, B., Tintelnot, F., 2021. The effects of foreign multinationals on workers and firms in the united states. The Quarterly Journal of Economics 136, 1943–1991.

Sjöholm, F., Lipsey, R.E., 2006. Foreign firms and indonesian manufacturing wages: An analysis with panel data. Economic Development and Cultural Change 55, 201–221.

Smith, J.A., Kington, R., 2018. Gender differences in workplace accommodations for chronic health conditions. Journal of Health Economics 62, 123–135.

Song, J., Price, D.J., Guvenen, F., Bloom, N., Von Wachter, T., 2019. Firming up inequality. The Quarterly journal of economics 134, 1–50.

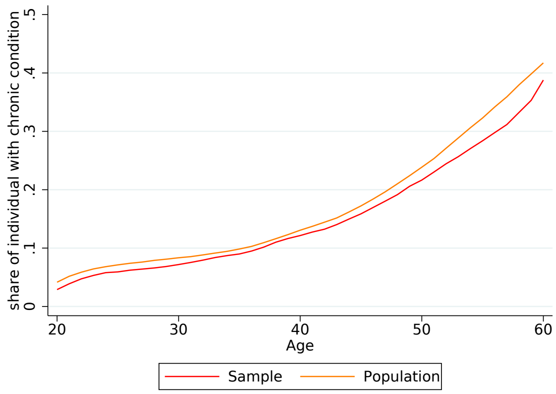
Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of econometrics 225, 175–199.

Tonin, M., et al., 2009. Employment protection legislation in central and east european countries. SEER-South-East Europe Review for Labour and Social Affairs , 477–491.

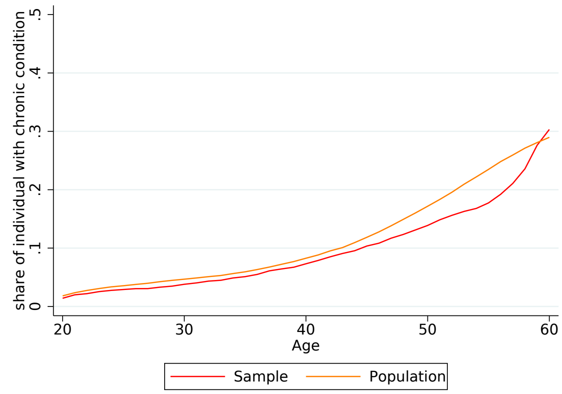
Zhang, W., McLeod, C., Koehoorn, M., 2016. The relationship between chronic conditions and absenteeism and associated costs in canada. Scandinavian Journal of Work, Environment & Health , 413–422.

Figures

Figure 1: Share of people with chronic health conditions (CHC) by age in the population and in our regression sample



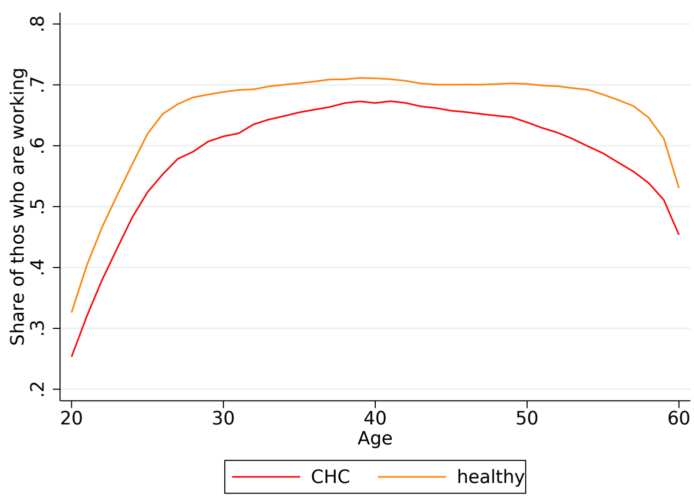
(a) Male



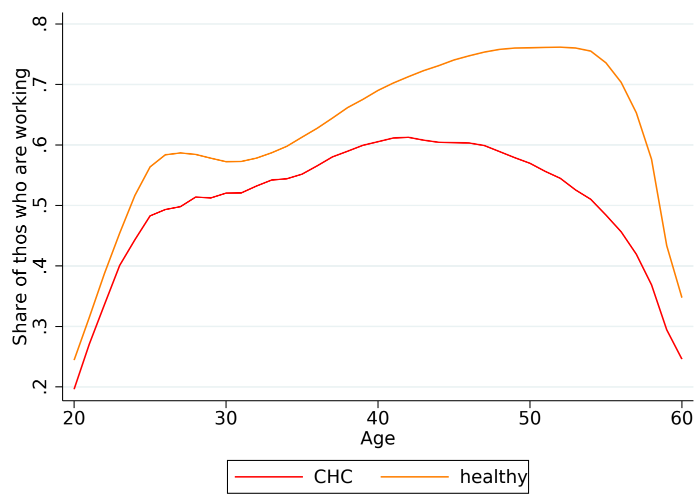
(b) Female

Note: The figure shows the share of individuals with CHC in the 20–60-year-old population (i.e., all observations in the dataset, including those who never worked) and in our regression sample by gender. CHC is a dummy, and is defined based on health care utilization information, as explained in Section 3.2.1.

Figure 2: Employment rate by gender, age, and CHC status



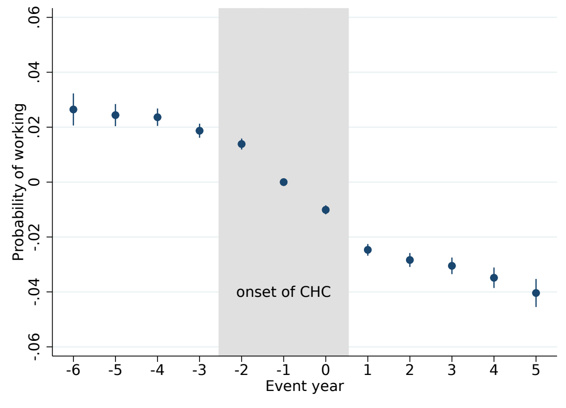
(a) Male



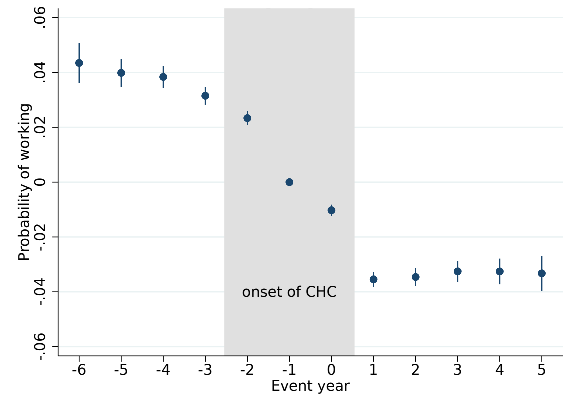
(b) Female

Note: The figure shows the share of individuals who are working – including self-employed and public workers for each age group by CHC status. For the purpose of this analysis, we use all observations in our population sample aged between 20-60, including those that never worked.

Figure 3: Probability of working: Event study



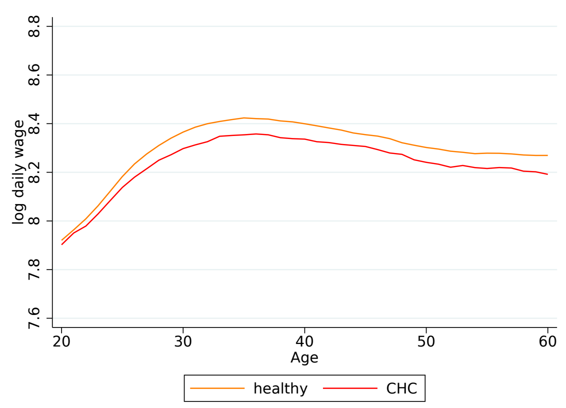
(a) Male



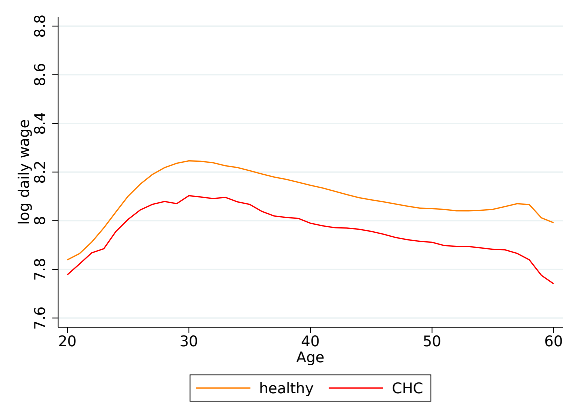
(b) Female

Note: The figure shows the parameter estimates of event study Equation (4) by using the Sun and Abraham (2021) estimator. The dependent variable is a dummy showing whether the person works and event years capture the time relative to the onset of CHC. We use the same control variables as in Column (2) of Table 2: year and age dummies. The figure shows the difference in the probability of working for an individual with CHC relative to the last healthy year. The bars show 95% confidence intervals and standard errors are clustered at the individual level.

Figure 4: The average wage of workers by age, gender, and CHC status



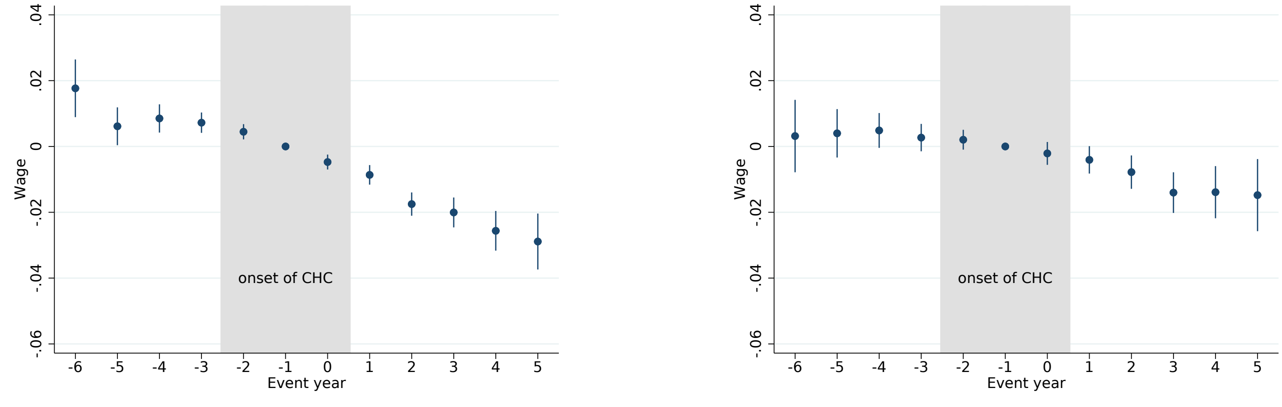
(a) Male



(b) Female

Note: The Figure represents the age-wage profiles – average wages by age – for workers with and without CHC. It shows the estimated age dummies from a regression in which the dependent variable is the logarithm of the daily wage and the independent variables are calendar year dummies and age dummies interacted with with the two values of the CHC dummy. We estimate the model separately by gender.

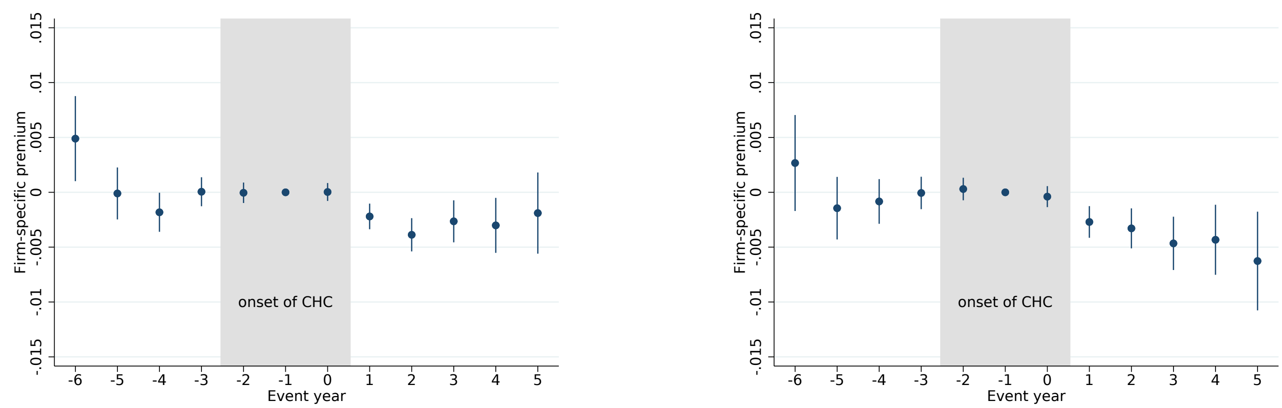
Figure 5: CHC wage penalty: Event study



(a) Male (b) Female

Note: The figure shows the parameter estimates of the event-study type Equation (3) by using the Sun and Abraham (2021) estimator. The dependent variable is log daily wage and event time capture the time in years relative to the onset of CHC. We use the same control variables as in Column (3) of Table 3: calendar year, industry, and age dummies, and further control for tenure (and its square) and worker-specific fixed effects. The figure shows the difference in the CHC wage penalty relative to the last healthy year. The bars show 95% confidence intervals, and standard errors are clustered at the firm level.

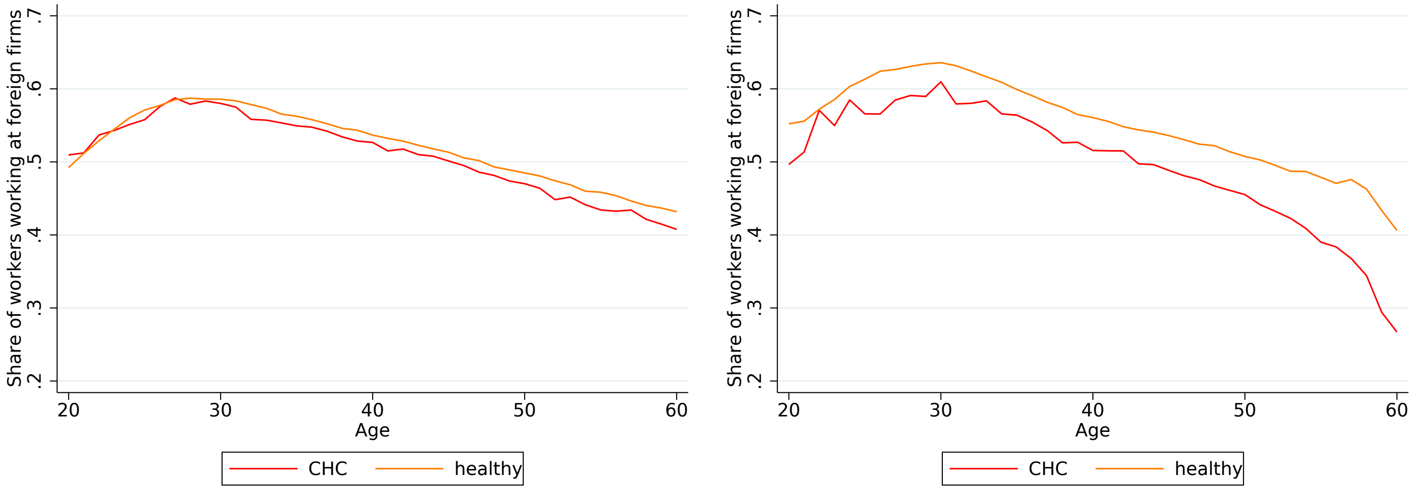
Figure 6: CHC penalty in firm-specific premium: Event study



(a) Male (b) Female

Note: The figure shows the parameter estimates of the event-study type Equation (3) by using the Sun and Abraham (2021) estimator. The dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. We use the same control variables as in Column (3) of Table 3: calendar year, industry, and age dummies, and further control for tenure (and its square) and worker-specific fixed effects. The figure shows the difference in the CHC penalty in firm-specific wage premium relative to the last healthy year. The bars show 95% confidence intervals, and standard errors are clustered at the firm level.

Figure 7: The share of workers working at foreign-owned firms by CHC status and gender

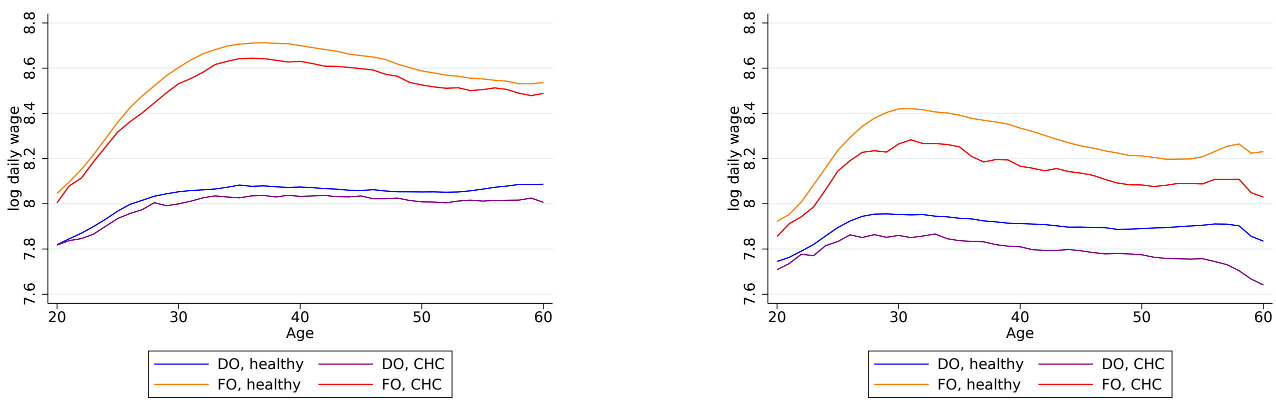


(a) Male workers

(b) Female workers

Note: The figure shows the share of workers in our sample employed at foreign-owned firms (y-axis) by age (x-axis), separately for individuals with (red line) and without (orange line) CHC. Firms are classified as foreign-owned if the share of directly and indirectly owned foreign capital is at least 50%.

Figure 8: Age-wage curve by the ownership type of the firm

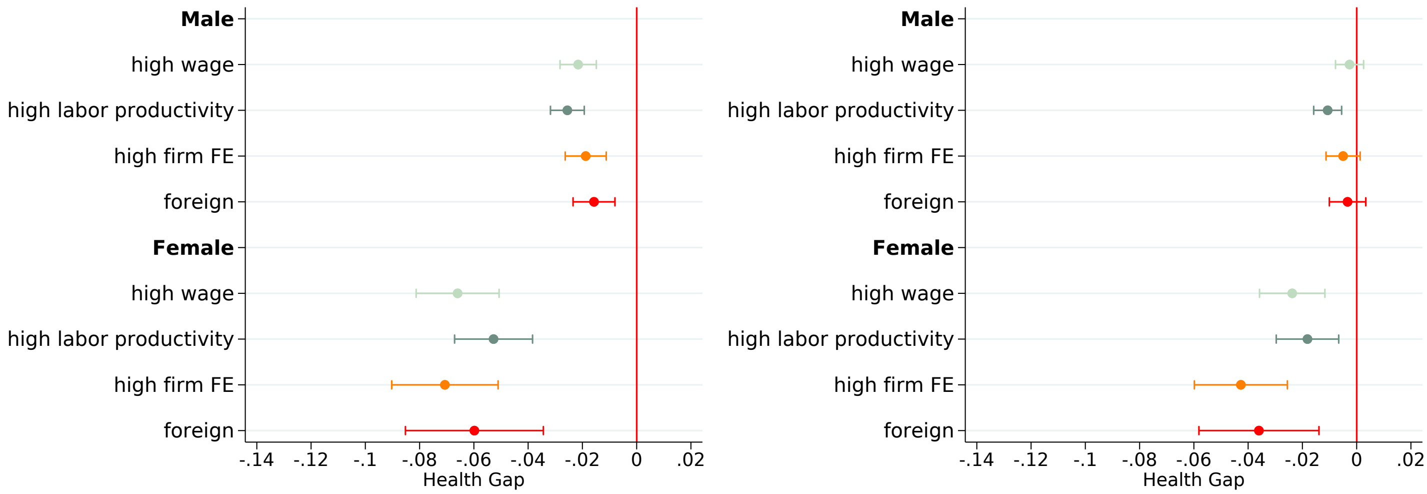


(a) Male - by health status

(b) Female

Note: The figure shows the average wage for each age separately for foreign (FO) and domestic (DO) companies by the CHC-status of the worker. The figure shows the estimated coefficients from gender-CHC status-specific regressions in which we regress log wage on age x ownership interactions.

Figure 9: CHC penalty in the probability of working in high-quality firms – using different proxies for firm quality

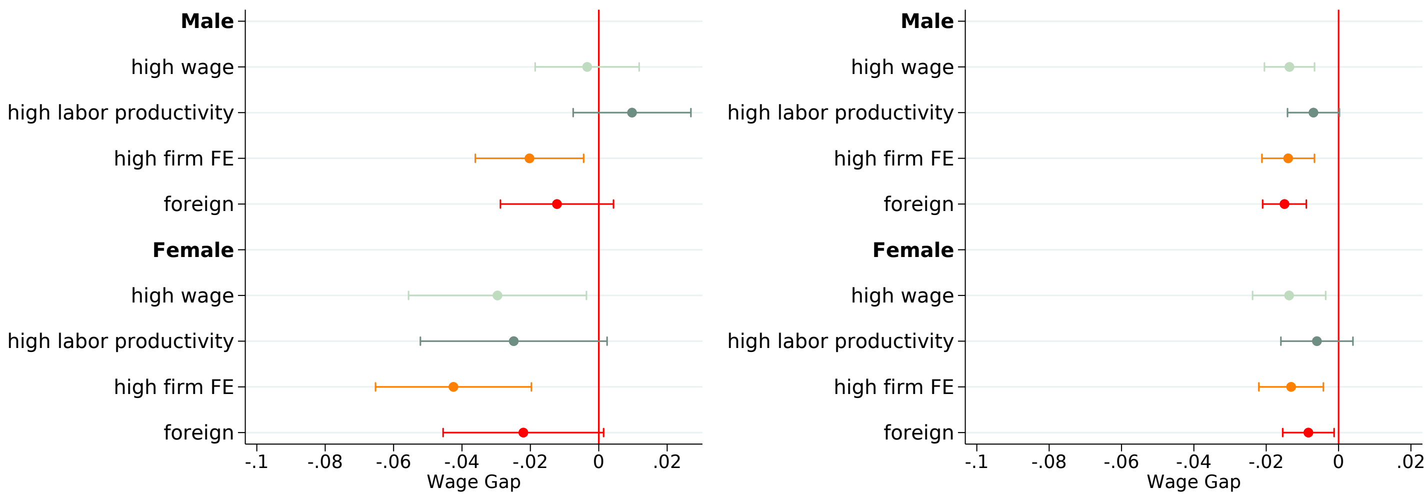


(a) Probability of working at high-quality firm - unconditional

(b) Probability of working at high-quality firm - conditional on worker productivity

Note: This Figure shows the conditional difference in the probability of working for high-quality firms between CHC and other workers – when different proxies are used to identify high-quality firms. We re-estimate Equation (5) by using alternative firm quality measures. In Panel (a), we control for year-specific and industry-specific fixed effects, and a set of age dummies. In Panel (b), we further control for the productivity of the workers (proxied by worker-specific premium estimated from an AKM model). These results mimic columns (1) and (3) of Table 5. Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2. The bars show 95% confidence intervals and standard errors are clustered at the firm level.

Figure 10: Difference in the CHC wage penalty between high- and low-quality firms – using different measures for high-quality firms

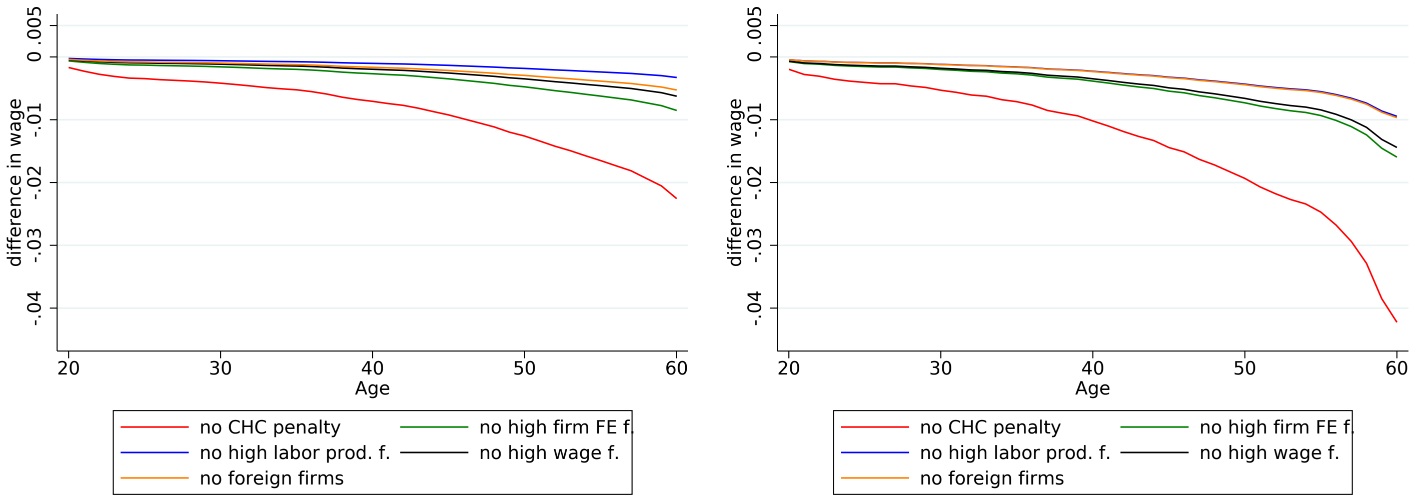


(a) Difference in CHC penalty - unconditional

(b) Difference in CHC penalty - conditional

Note: This Figure shows the difference in CHC wage penalty –the conditional difference between the wages of CHC and other workers – between "high-quality" and other firms, by using different definitions for high quality firms. In particular, we re-estimate Equation 6 by using alternative firm quality measures and we report the coefficient of the foreign x CHC interaction in the figure. In Panel (a), we control for a set of year, industry, and age dummies, while in Panel (b), we further control for tenure and its square, and we add worker-specific fixed effects to the model. Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2. The bars show 95% confidence intervals and standard errors are clustered at the firm level.

Figure 11: Difference between the actual and counterfactual age-wage curves



(a) Male

(b) Female

Note: This figure shows the difference between the actual and different counterfactual age-wage curves, i.e. shows the contribution of the CHC penalty to the level and concavity to the age-wage curve we observe. We conduct two types of counterfactual analysis. Counterfactual 1: Under the "no CHC penalty" scenario, we assume that there is no CHC penalty at all. To calculate the difference between the counterfactual and the actual wage for each age group, we multiply the share of CHC people in the age group with the estimated total CHC penalty in Table 7. The red line in Figure 11 shows the results, which shows the difference between the counterfactual and the actual age-wage curve (the contribution of the CHC penalty). Counterfactual 2: Under the "no foreign firms" scenario, we assume that foreign firms behave similarly to domestic firms in terms of employing CHC workers. This means that they would employ CHC workers to the same extent as domestic firms and that they also apply the same CHC penalty to domestic firms. In terms of the decomposition in Table 7, this means that the between and the difference in CHC gap terms are zero. Therefore, the difference between the counterfactual and actual wage for each wage group is the share of CHC workers in the group multiplied by these two terms. The results are presented in orange line, again, the difference between the counterfactual and the actual age-wage curve. Other lines show a similar counterfactual for the other type of firms.

Tables

Table 1: Descriptive statistics of foreign and domestic-owned firms in 2014

	Domestic	Foreign
Share of part-time workers[a]	17.5%	6.1%
Share of workers with at least a college degree[a]	16.1%	29.7%
Share of workers covered by collective agreement[a]	3.4%	3.9%
Average hours of overtime per week[a]	1.2	3.4
Share of workers that worked overtime[a]	7.9%	21.1%
Share of workers receiving flexible payment[ac]	35.1%	72.9%
Share of flexible payment in total wage[ad]	13.6%	17.1%
Log daily wage[b]	8.1	8.6
Within-firm standard deviation of the log daily wage[b]	0.21	0.37
Share of female workers[b]	35.6%	40.6%
Share of workers with CHC[b]	12.6%	10.9%
Share of export revenue in sales revenue[b]	11.3%	41.5%
Share of intangible assets in total assets[b]	5.5%	7.9%
Logarithm of intangible asset per worker[b]	3.6	4.0
Logarithm of labor productivity[b]	8.3	9.0
Number of employees[b]	54	196

Notes: This Table shows the average values of different variables for domestic- and foreign-owned firms in 2014. A firm is considered to be foreign-owned if the share of direct and indirect ownership is above 50% in it.

[a] The source of information is the Hungarian Structure of Earnings Survey(HSES) from year 2014, there is 6,455 domestic and 1,351 foreign-owned firms in the dataset. The Hungarian Structure of Earnings Survey is a property of the NAV, NMH. The data were processed by the KRTK Databank.

[b] Calculated from our main regression sample from the year of 2014 based on the Linked Administrative Data (Admin3) database (see more in Section 3.1)

[c] A worker is considered to receive flexible payments if she receives either monthly or occasional bonuses, premia, allowances, or additional payments for overtime hours or for weekend and night shifts.

[d] Calculated only for those workers that received any flexible payment

Table 2: Difference in the probability of working by chronic health condition (CHC)

(a) Panel A: Men

	(1)	(2)	(3)	(4)
CHC=1	-0.069***	-0.075***	-0.033***	-0.027***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	10021891	10021891	3329429	3329429
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)
CHC=1	-0.141***	-0.160***	-0.068***	-0.058***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	9989253	9989253	2592729	2592729
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

Notes: The Table presents the estimated parameters of Equation (1) in which we regress a dummy showing whether an individual is working (including self-employed and public workers) on whether they suffer from a Chronic Health Condition (CHC=1). For the purpose of this analysis, we use all observations in the dataset aged between 20-60, including those who never worked. The CHC status is identified from health care use data, as explained in Section 3.2.1. In column (1), we include a set of year dummies, in column (2), we add a set of age dummies to the control variables. In column (3), we re-run the regression from column (2) on the sample where we could estimate Abowd et al. (1999)-type worker fixed effects in a previous step, i.e. workers who were observed in our wage regression sample (see more details in Section 3.2.4). In column (4), we control for worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. Standard errors are clustered at the worker level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: CHC wage penalty

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.058***	-0.053***	-0.013***	-0.032***	-0.012***
	(0.005)	(0.005)	(0.001)	(0.002)	(0.001)
Observations	2095170	2095170	2095170	2095170	2095170
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.139***	-0.122***	-0.007***	-0.058***	-0.005***
	(0.009)	(0.008)	(0.002)	(0.002)	(0.002)
Observations	1468476	1468476	1468476	1468476	1468476
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: This Table shows the conditional wage gap between workers having CHC and those without such conditions. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4) firm fixed effects, while in column (5) we have both worker and firm fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: CHC penalty in firm-specific wage premium

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.007***	-0.005***	-0.001**
	(0.002)	(0.002)	(0.001)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.032***	-0.029***	-0.002***
	(0.005)	(0.005)	(0.001)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

Notes: This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: CHC penalty in the probability of working at a foreign-owned firm

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.016***	-0.014***	-0.003
	(0.004)	(0.004)	(0.003)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.060***	-0.052***	-0.036***
	(0.013)	(0.013)	(0.011)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table shows the conditional gap in the probability of working at a foreign-owned firm between workers with CHC and other workers, conditional on working. In particular, the table shows parameter estimates of Equation (5). The dependent variable is a dummy showing whether worker i is working at a foreign-owned firm in time t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Foreign-Domestic difference in the CHC wage penalty

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.045***	-0.037***	-0.004**	-0.022***	-0.007***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Foreign=1	0.482***	0.465***	0.178***	0.019**	0.015**
	(0.020)	(0.019)	(0.010)	(0.009)	(0.007)
CHC=1 × Foreign=1	-0.012	-0.019**	-0.015***	-0.019***	-0.009***
	(0.008)	(0.008)	(0.003)	(0.004)	(0.003)
Observations	2095170	2095170	2095170	2095170	2095170
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.107***	-0.088***	-0.002	-0.044***	-0.003
	(0.010)	(0.009)	(0.003)	(0.003)	(0.002)
Foreign=1	0.362***	0.348***	0.132***	0.015**	0.010
	(0.023)	(0.023)	(0.008)	(0.006)	(0.007)
CHC=1 × Foreign=1	-0.022*	-0.033***	-0.008**	-0.027***	-0.004
	(0.012)	(0.011)	(0.004)	(0.005)	(0.003)
Observations	1468476	1468476	1468476	1468476	1468476
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: The Table shows conditional wage differences between CHC and other workers in foreign-owned and domestic-owned firms. In particular, it presents coefficient estimates from Equation (6), in which the dependent variable is the daily wage of worker i in year t and the variables of interest are the CHC status of the worker, whether the firm was foreign-owned, and their interaction. Of special interest is the coefficient of the interaction, which shows the difference in the CHC penalty between foreign- and domestic-owned firms. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5) both worker and firm fixed effects are included. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Decomposition of the CHC wage penalty

(a) Panel A: Men

	Between	Domestic CHC penalty	Fo-Do difference	Total CHC penalty
Foreign firm	-0.008	-0.045	-0.006	-0.058
High firm FE	-0.012	-0.036	-0.010	-0.058
High labor productivity	-0.012	-0.050	0.004	-0.058
High average wage	-0.015	-0.042	-0.001	-0.058

(b) Panel B: Women

	Between	Domestic CHC penalty	Fo-Do difference	Total CHC penalty
Foreign firm	-0.022	-0.107	-0.010	-0.139
High firm FE	-0.037	-0.087	-0.016	-0.139
High labor productivity	-0.025	-0.108	-0.006	-0.139
High average wage	-0.039	-0.092	-0.008	-0.139

Note: The table presents the results from decomposing the average (total) CHC penalty into its different components (i) between firm components, resulting from CHC workers being more likely to work in firms which pay lower wages even for non CHC-workers, (ii) the CHC penalty applied by domestic-owned firms, and (iii) the higher penalty applied by foreign-owned firms (see Section 5.3.1). We use the estimated parameters to conduct the decomposition of the wage difference for the case when industry and year fixed effects are included in our model. The "Between" effect is the results of the multiplication of the CHC coefficient from Equation (5) (Table 5, column (1)) with the foreign wage premium derived from Equation (6) (Table 6, column (1)). The "Domestic CHC penalty" is the parameter estimates of CHC from from Equation (6) (Table 6, column (1)). To calculate the "foreign-domestic difference the wage differences are all derived from Equation (6) (Table 6, column (1)), and $P(F|C)$ is calculated from the data.

Appendix

A Variable construction

A.1 Measuring chronic health conditions (CHC) at the Individual-Year Level

A key variable in our analysis is the measure identifying people suffering from chronic health conditions. Section 3.2.1 explains the procedure, and we provide more details in this Appendix. We follow Danesh et al. (2024) in constructing a measure of chronic conditions at the individual-year level by leveraging detailed historical health data

Defining Chronic Conditions. As a starting point, we identify 19 chronic conditions based on prescription data, adopting the mapping provided by Danesh et al. (2024) (see Appendix Table A.1). While Danesh et al. (2024) mapped prescription data at the ATC3 (Anatomical Therapeutic Chemical Classification System) level, our data availability is limited to ATC2. In most cases, we could follow their mapping precisely, with a few exceptions noted in Table A.1. Due to this constraint, we merged two categories—"pain" with "migraine" and "dementia" with "other psychological disorders". Since only an extremely small proportion of individuals in the observed population suffered from tuberculosis during the studied period, this information was not made available to us by the data provider to prevent potential violations of personal privacy. Consequently, this categorical variable was not included in the analysis. These modifications resulted in 19 chronic conditions instead of the 22 defined by Danesh et al. (2024).

An individual is classified as having a specific chronic condition if she has bought medication for that condition at least twice in a given year. This restriction helps us exclude short-term medication use while ensuring that chronic patients remain included. In Hungary, prescription regulations allow for a maximum of three-month supply at a time, necessitating multiple purchases per year for ongoing treatment. Appendix Table A.2 shows the share of individuals suffering from a chronic condition in the population and in our main sample, separately by gender. The leading chronic condition is cardiovascular disease for both genders. While there are similarities between men and women across most disease groups—for instance, a substantial share of both genders are affected by conditions like acid-related disorders, diabetes, and hyperlipidemia —certain gender-specific differences also emerge. More than 4% of women are affected by thyroid-related disorders, compared to less than 1% among men. In contrast, gout is more prevalent among men, with over 2% affected, whereas the prevalence remains below 1% among women. Appendix Figure A.1 shows the five most common chronic conditions in the sample and in our population by age groups.

We follow Danesh et al. (2024) in constructing a summary measure of chronic conditions (Chronic Disease Index, CDI) in two steps. First, we estimate the predictive relationship between chronic illness and later-life mortality or long hospitalization, controlling for relevant covariates. Second, we use these estimates to assign weights to our 19 chronic conditions at any age, generating a summary Chronic Disease Index (CDI). We do this separately for men and women.

As acknowledged by Danesh et al. (2024), it is important to note that this methodology—including our version—captures only chronic conditions actively managed with medication. Consequently, undiagnosed or untreated conditions are not accounted for. As noted in Section 2.1, in Hungary, where healthcare is universally and freely accessible, this limitation is mitigated to some extent, though likely not entirely eliminated. Medical consultations are easily accessible thanks to universal coverage, and no fees apply for most visits. Hospital-provided medications are free, while pharmacy purchases often come with reduced co-payments, with the state covering up to 100% of costs for certain chronic conditions. Since 2005, monthly subsidies have helped low-income patients with chronic illnesses manage recurring healthcare expenses. During the observation period, patients paid in total less than 25%[29] of the price of medications covered by the national social security, with the remaining costs financed through public and social security subsidies.

Step 1: Estimating the relationship between specific conditions and negative outcomes: In the first step, we restrict our analysis to individuals aged 64–66 in 2012 to estimate the parameters of a model predicting their likelihood of long hospitalization[30] or death within the subsequent five years (i.e., by the end of 2017). If either of these happens with individual i, $M_{i,2013-2017} = 1$, otherwise $M_{i,2013-2017} = 0$. Long hospitalization is defined as spending at least three days in inpatient care across two consecutive months, with a minimum of two consecutive days within that period.[31]

Our main equation is a linear probability model to predict the probability of dying or being hospitalized.

$$M_{i,2013-2017} = X_i^{*\prime}\beta_x + f(CC_{i,2012})^{*\prime}\beta_{CC} + \xi_i, \tag{A.1}$$

In this model $X_i^{*\prime}$ is a set of socio-economic variables (fixed for each worker) and $f(CC_{i,2012})^{*\prime}$ is the potential interaction terms between the 19 chronic condition dummies and their lags. We randomly choose the 20 percent of the 64-66 years old population for the prediction and we conduct this whole process separately for men and women.

Given the possibility of overfitting resulting from the large number of explanatory variables, we follow Danesh et al. (2024) and Belloni et al. (2014a), and employ a variable selection process to identify variables with significant predictive power. Specifically, we run the following lasso regressions to select the relevant socio-economic variables:

- Lasso estimation to identify the socioeconomic variables[32] most relevant to predicting mortality or long hospitalization (1 regression).

[29]Source: Hungarian Statistical Office, https://www.ksh.hu/stadat_files/ege/hu/ege0022.html, downloaded: 22.05.2025.

[30]As opposed to Danesh et al. (2024), we also include longer hospitalization events as bad outcomes, since we look at somewhat younger individuals with lower mortality rates, and we aim for capturing a broader scale of negative health outcomes, not only fatal ones.

[31]With this definition we rule out such non-severe cases like routine surgery requiring one night spent at the hospital.

[32]We include the following set of socio-economic variables: the location at NUTS 4-level where the individual lives in 2012. In addition, we consider variables that capture individuals' work histories. In our observation year (2012), all individuals in the estimation sample were already retired (aged 64–66). Therefore, we use their work characteristics from nine years earlier (2003), when they were 56–57. Since 2003 is the earliest available year in the database, no prior information is accessible. We use this data to account for the occupation (2-digit code) in which individuals worked in 2003 (if applicable), whether they received any pension or disability benefits, and their position in the wage distribution at that time (measured by income deciles).

$$M_{i,2013-2017} = X_i'\theta_m + \xi_i, \tag{A.2}$$

- Lasso estimation for each 19 chronic conditions to detect the most relevant socioeconomic variables in predicting each of the chronic conditions (19 regressions).

$$c^k_{i,2012} = X_i'\theta^k_c + v^k_{i,2012} \quad \forall \quad k = 1,..,19, \tag{A.3}$$

After running these regressions, we select all socio-economic variables which were selected by at least one of the lasso regressions above and include them into the $X_i^{*\prime}$ vector in Regression Equation (A.1).

Next, we select the chronic conditions variables and interactions which have predictive power by estimating the following equation:

- Lasso estimation to identify the relevant interactions between different types of chronic conditions and their lagged effect

$$M_{i,2103-2017} = f(CC_{i,2012})'\theta_v + \epsilon_{i,2012},, \tag{A.4}$$

where $f(CC_{i,2012})$ shows the potential interaction terms between each chronic condition dummies, as well as between the different lags. It includes three-years lags of chronic conditions (thus chronic conditions of 2012, 2011, and 2010), within-chronic-condition interactions across different lags ($c^k_{2012} * c^k_{2011}$, $c^k_{2012} * c^k_{2010}$, $c^k_{2011} * c^k_{2010} \quad \forall \quad k = 1,..,19$) and across condition interaction for the most recent year ($c^i_{2012} * c^j_{2012} \quad \forall \quad i = 1,..,19, j = 1,..,19$).

We include the variables selected by the lasso estimator into the $f(CC_{i,2012})^{*\prime}$ vector in regression Equation (A.1).

After this, we estimate regression Equation (A.1) itself with a linear probability model.

Step 2: Constructing Chronic Disease Index (CDI) : Next, we calculate the Chronic Disease Index (CDI) for each individual i in each year t in the general population sample (2011-2017) by using the estimated parameters as follows:

$$CDI_{i,t} = \overline{X_i}^{*\prime}\hat{\beta} + f(CC_{i,t})^{*\prime}\hat{\beta}_{CC},, \tag{A.5}$$

where the intercept captures the mean socioeconomic effects. Note that this can be only done from 2011, as $f(CC_{i,t})^{*\prime}$ includes up to two lags.

By the end of the process, we obtain an estimated CDI_{it} for each individual and every year, independently of the age of the individual.

Step 3: Constructing the Chronic Health Condition (CHC) indicator variable:

We construct an indicator variable from this continuous index in two steps.

First, using this continuous CDI_{it} measure, we classify individual i in year t as having a Chronic Health Condition (CHC_{it}) if their CDI_{it} value falls within the highest 10 percent in the "General Population" sample.

Second, if someone was classified as having CHC in year t, we replace the CHC index to 1 in all years afterwards, i.e. we assume their condition remains unchanged and do not allow for recovery in our analysis. Our main motivation is that people may stop taking medicine a few years after being diagnosed with a condition even if the condition persists.

To evaluate the fit of our measure, Figure A.2 shows the number of days spent in inpatient care and drug expenditure for individuals with and without CHC by gender. People identified as suffering from CHC face a substantially higher probability of all these outcomes for both genders.

Table A.1: Chronic condition and ATC code mapping

chronic condition	ATC	name
Acid related disorders	A02	Drugs for acid related disorders
Bone diseases (osteoporosis)	M05	Drugs for treatment of bone diseases
Cancer	L01	Antineoplastic agents
Cardiovascular diseases (inc. hypertension)	B01, C01, C04, C02, C07, C08, C09	Antithrombotic agents, cardiac therapy, peripheral vasodilators, antihypertensives, beta blocking agents, calcium channel blockers, agents acting on the renin-angiotensin system
Dementia and other Psychological disorders[a]	N06	Psychoanaleptics
Diabetes (mellitus)	A10	Insulins and analogues, Blood glucose lowering drugs (excl. insulins), other drugs used in diabetes
Epilepsy	N03	Antiepileptics
Glaucoma[b]	S01	Ophthalmologicals
Gout (Hyperuricemia)	M04	Antigout preparations
HIV	J05	Direct acting antiviral drugs
Hyperlipidemia	C10	Lipid modifying agents
Intestinal (inflammatory) diseases[c]	A07	Antidiarrheals, intestinal anti-inflammatory/anti-infective agents
(Iron deficiency) anemia[d]	B03	Iron preparations
Migraines, Pain[e]	N02	Antimigraine preparations,Opioids, other analgesics and antipyretics
Parkinson's disease[f]	N04	Anti-parkinson drugs
Psychoses[f]	N05	Psycholeptics
Respiratory illnesses	R03	Drugs for obstructive airway diseases
Rheumatological conditions	L04	Immunosuppressants
Thyroid disorders	H03	Thyroid therapy

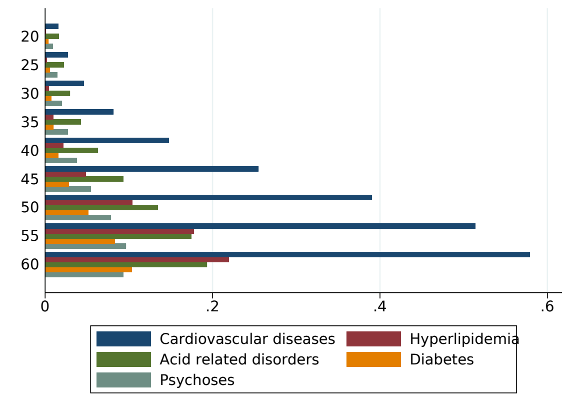
Note: [a]while Danesh et al. (2024) distinguished between Dementia (N06D Anti-dementia drugs) and Psychological disorders (N06 Antidepressants), we are unable to do so due to data limitations and merge the two categories
[b]while Danesh et al. (2024) used S01E Antiglaucoma preparations and miotics, we use S01 Ophthalmologicals, that includes: S01A Antiinfectives, S01B Antiinflammatory agents, S01C Antiinflammatory agents and antiinfectives in combination, S01E Antiglaucoma preparations and miotics, S01F Mydriatics and cycloplegics, S01G Decongestants and antiallergics, S01H Local anesthetics, S01J Diagnostic agents, S01K Surgical aids, S01L Ocular vascular disorder agents, S01X Other ophthalmologicals
[c]while Danesh et al. (2024) used A07E Intestinal antiinflammatory agents, we use A07 Antidiarrheals, intestinal anti-inflammatory/anti-infective agents, that includes: A07A Intestinal anti-infectives, A07B Intestinal adsorbents, A07C Electrolytes with carbohydrates, A07D Antipropulsives, A07E Intestinal anti-inflammatory agents, A07F Antidiarrheal micro-organisms, A07X Other antidiarrheals
[d]while Danesh et al. (2024) used B03A Iron preparations, we use B03 Antianemic preparations, intestinal anti-inflammatory/anti-infective agents, that includes: B03A Iron preparations, B03B Vitamin B12 and folic acid, B03X Other antianemic preparations
[e]while Danesh et al. (2024) distinguished between Migraines (N02C Antimigraine preparations) and Pain (N02A, N02B Opioids, other analgesics and antipyretics), we are not able to distinguish the two, thus we merged these two chronic conditions into a single one.
[f]while Danesh et al. (2024) considered Parkinson's disease as N04 Anti-parkinson drugs, N05B and N05C, and Psychoses as N05A, due to data limitation we regrouped them and used N04 Anti-parkinson drugs as drugs related to Parkinson's disease and N05 Psycholeptics as those related to Psychoses.

Table A.2: Share of individuals suffering from chronic condition

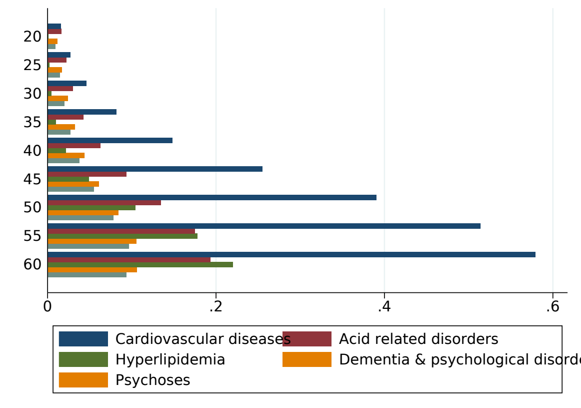
	Regression Sample		Population Sample	
	Female	Male	Female	Male
Acid related disorders	6.6%	4.8%	7.8%	5.9%
Bone diseases (osteoporosis)	0.3%	0.1%	0.6%	0.1%
Cancer	0.1%	0.1%	0.1%	0.1%
Cardiovascular diseases	18.6%	18.8%	20.3%	18.8%
Dementia and other Psychological disorders	3.8%	1.7%	5.1%	2.5%
Diabetes	2.1%	3.0%	2.9%	3.7%
Epilepsy	1.8%	1.1%	2.9%	2.3%
Glaucoma	1.2%	1.0%	1.5%	1.1%
Gout (Hyperuricemia)	0.8%	2.2%	1.1%	2.5%
HIV	0.3%	0.2%	0.3%	0.2%
Hyperlipidemia	3.8%	5.5%	5.3%	6.2%
Intestinal	0.5%	0.5%	0.6%	0.5%
(Iron deficiency) anemia	2.3%	0.3%	2.3%	0.4%
Migraines, Pain	1.7%	0.8%	3.1%	2.0%
Parkinson's disease	0.1%	0.0%	0.2%	0.2%
Psychoses	2.6%	1.1%	4.5%	2.8%
Respiratory illnesses	2.5%	1.8%	3.0%	2.1%
Rheumatological conditions	0.2%	0.2%	0.3%	0.2%
Thyroid disorders	4.1%	0.6%	4.1%	0.5%

Note: An individual is classified as having a chronic condition if she has bought medication for that condition at least twice in a given year. This restriction helps us exclude short-term medication use while ensuring that chronic patients remain included. In Hungary, prescription regulations allow for a maximum of three-month supply at a time, necessitating multiple purchases per year for ongoing treatment.

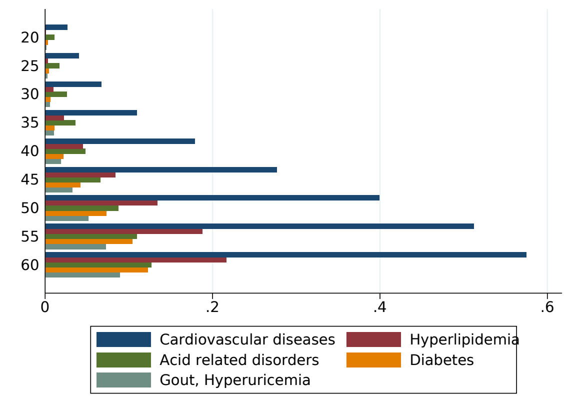
Figure A.1: The five most common chronic conditions by age and gender in the population and regression sample



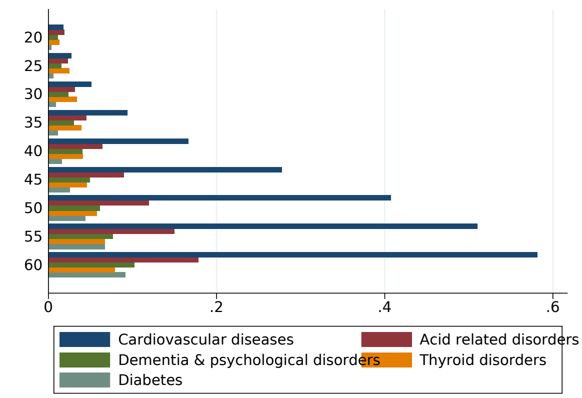
(a) In the population sample, Male



(b) In the population sample, Female



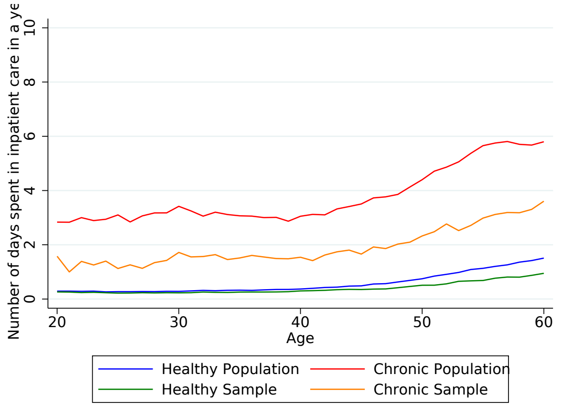
(c) In the regression sample, Male



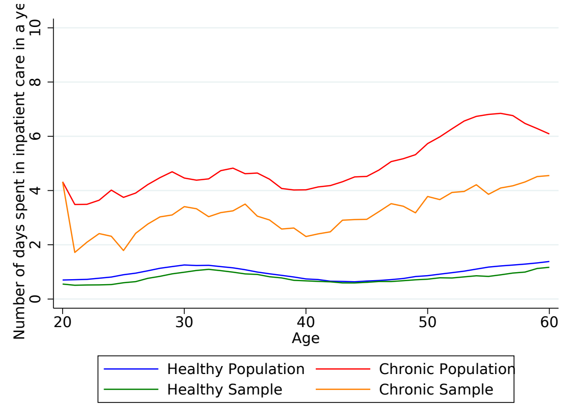
(d) In the regression sample, Female

Note: An individual is classified as having a chronic condition if she has bought medication for that condition at least twice in a given year.

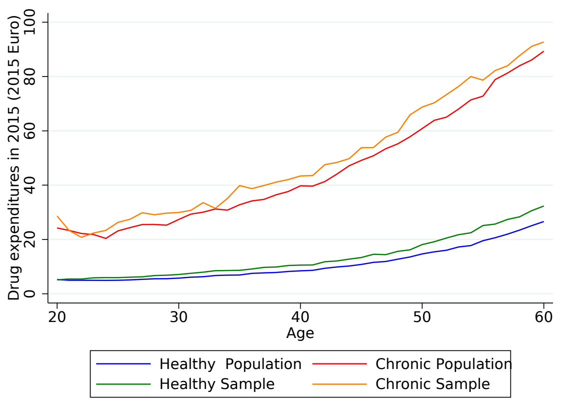
Figure A.2: Number of days spent in inpatient care and drug expenditure and sick leave for individuals with and without CHC by gender



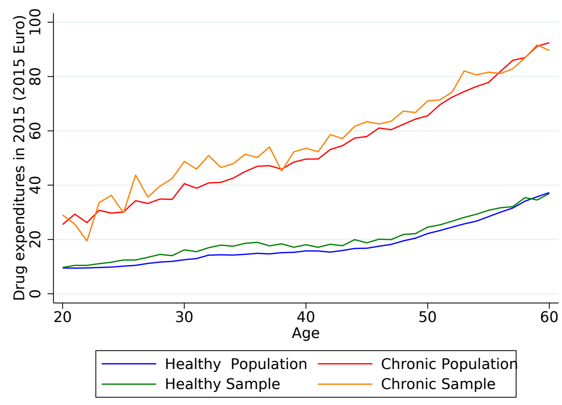
(a) Inpatient care, Male



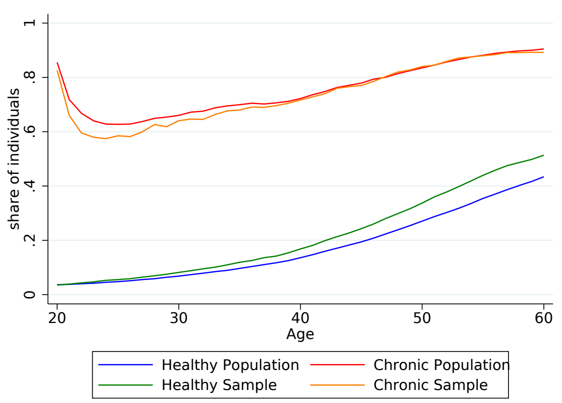
(b) Inpatient care, Female



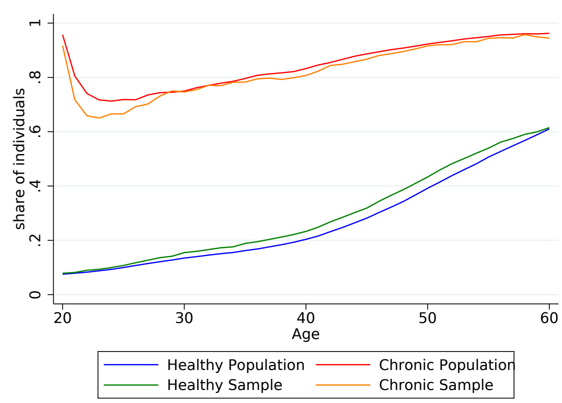
(c) Drug expenditure, Male



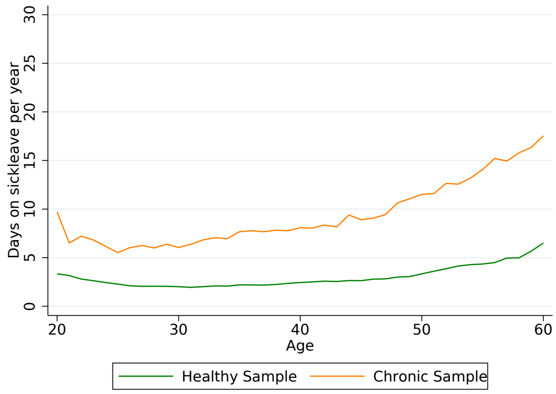
(d) Drug expenditure, Female



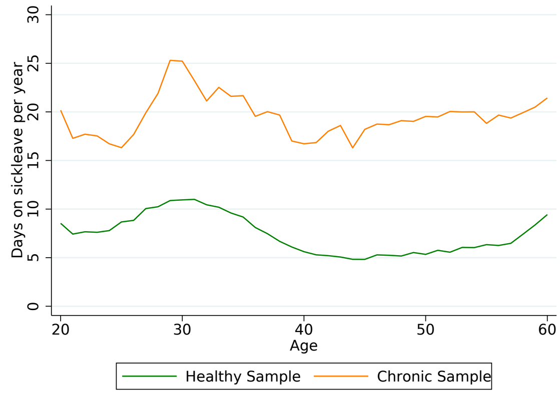
(e) Medicine for chronic cond., Male



(f) Medicine for chronic cond., Female



(g) Sick leave, Male



(h) Sick leave, Female

A.2 Worker productivity measure

As we discuss in Section 3.2.4, we control for worker productivity in our extensive margin regressions by running a preliminary Abowd et al. (1999)-type wage regression and then including worker fixed effects from this regression as proxies for worker productivity into the extensive margin regression. This Appendix explains the procedure in detail.

When running the Abowd et al. (1999)-type regression, we regress the wages on individual and firm fixed effects, while controlling for age square and cube of the age (the age is normalized at 40). We further include a control variable for having CHC to account for the negative effect of sickness on wages. We restrict the sample to the largest connected set. We estimate the following equation:

$$\ln(wage_{it}) = \alpha_0 \times CHC_{it} + X'_{it}\beta + \tau_t + \eta_i + \nu_{j(it)} + \epsilon_{it} \tag{A.6}$$

where $ln(wage_{it})$ denotes the logarithm of daily wage of worker i working at firm j in year t. CHC_{it} is a dummy indicating that worker i has chronic condition in year t. X represents time-varying worker-level characteristics, such as age square and cube of the age (the age is normalized at 40). τ_t is a set of year dummies. η_i is worker-specific, and $\nu_{j(it)}$ is firm-specific fixed effects. We include both men and women in the sample when estimating worker and firm wage premia. We use the estimated worker fixed effects ($\hat{\eta}_i$) as a measure of worker productivity. In addition, we use the estimated firm fixed effects as an alternative firm quality measure in Section 6 as a proxy for firm quality.

B Additional Results

B.1 Probability of Working Part-Time

One motivation for CHC workers to move to domestic or less productive firms could be to work part-time. To investigate the importance of this factor, we re-run equation 1 but replace the dependent variable with an indicator showing whether the worker works part-time and restrict our sample to the regression sample to look only workers who are working and for whom the hours information is available. Table B.1 shows the results. We find that suffering from CHCs raise the probability of working part-time by 5 percentage points for men and 15 points for women even when controlling for estimated worker fixed effects from an AKM regression.

Table B.1: The probability of working part-time for workers with and without CHC

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	0.053***	0.052***	0.050***
	(0.005)	(0.005)	(0.005)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	0.160***	0.154***	0.145***
	(0.017)	(0.016)	(0.015)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table presents the estimated parameters of Equation (1) in which we regress a dummy showing whether an individual is working at part-time on whether they suffer from a Chronic Health Condition (CHC=1). For the purpose of this analysis, we use our "Regression Sample" described in Section 3.3 in more details. In column (1), we include a set of year, industry and age dummies, in column (2), we add tenure and its square to the model. In column (4), we also control for worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. Standard errors are clustered at the worker level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Foreign-Owned Firms: Separation and Entry

In Section 5.1.1 we have shows that people with CHC are more likely to work at foreign-owned firms. This Appendix Section looks at worker flows, separation and entry, to see how these margins contribute to the differences in the stock of workers.

B.2.1 Definitions

We define these events in the following way.

Separation. We consider workers to experience separation in year t if they had worked at the same firm both in years $t-1$ and t but not in year $t+1$. Their comparison group consists of workers who worked at the same firm in all three years. In other cases, the variable is not defined.[33] As we have no information about the type of the separation, our separation indicator refers to leaving a firm, regardless of whether it was voluntary or involuntary, and independent of the worker's future employment status. While the definition does not explicitly exclude old-age retirement, since we restrict the analysis to workers under 60, old-age retirements are rare in our sample.

New entry. New entrants are employees who work for the firm in the current year (t) but did not do so in the previous year ($t-1$). These workers may be entering the labor market for the first time, transferring from other firms, or returning after a temporary absence.[34]

B.2.2 Regression Specifications and results

Separation To understand what drives the differences in the share of workers, we look at the flows, starting with separation. We estimate the following worker-level regression, similar to Equation (1), restricted to workers who worked for the same firm both in t and $t-1$. Workers who already had CHC in 2011 or joined a firm after 2011 but with CHC are excluded from the sample.

$$Separation_{it} = \alpha_0 \times CHC_{it} + \alpha_1 \times Foreign_{j(i,t)t} + \alpha_3 \times CHC_{it} \times Foreign_{j(i,t)t} + X_{it}'\gamma + \tau_t + \beta \times \hat{\eta}_i + \epsilon_{it} \quad \text{(B.7)}$$

where $Separation_{it}$ is a dummy indicating that the worker leaves the firm in $t+1$ (see more on the definition in Section B.2.1), and α_3 shows the difference in the CHC penalty between foreign- and domestic-owned firms.

Table B.2 shows the results. Workers – especially women – suffering from CHC are more likely to separate from domestic-owned firms, and foreign-owned firms keep their non-CHC workers longer. The gap in the separation rate between workers with and without CHC is substantially larger at foreign-owned firms than at domestic-owned firms, and it is significant both for men and women.

[33] We do not define this variable for workers who pass away the following year ($t+1$). Similarly, it is not defined for worker-year observations where the employee did not remain at the same firm in the current (t) and previous years ($t-1$). Also, if a worker's primary job becomes their secondary job, it is not considered a separation.

[34] We do not consider entry if a worker's secondary job becomes their primary job.

Newcomers Next, we look at entry flows. The workers in our sample are now restricted to the new entrants' subsample. We keep those workers in our sample who worked in t at a given firm but did not work there in $t-1$, either because they worked at another firm or because they did not work at all (see more on the definition in Section B.2.1).

We estimate the following model for workers who move to new firms in year t

$$Foreign_{j(it)t} = \alpha_1 * CHC_{it-1} + \alpha_2 * X_{it} + \tau_t + s_{j(it-1)} + o_{it-1} + \epsilon_{ijt}, , \tag{B.8}$$

where $Foreign_{j(it)}$ is a dummy indicating whether the firm the worker joint at year t is a foreign company. In this specification we lag the explanatory variables (industry and occupation[35], denoted with $s_{j(it-1)}$ and o_{it-1}, respectively), so that they refer to the worker's previous workplace.[36] We also control for the number of months worked in the previous 3 years and the square of this variable. The main coefficient of interest is α_1, showing the difference between those with and without CHC in the probability of starting their job at a foreign company.

The results are presented in Table B.3. Workers with CHC enter foreign firms with a lower probability, and this pattern is particularly pronounced among women. Male (female) workers with CHC enter a foreign firm with a 6 (12) percentage points lower probability than their healthy counterparts. The CHC gaps shrink to 1.4 (5.8) percentage points as we control for the age of the workers. Controlling for the fact that individuals with and without chronic conditions can have different work histories does not further alter the results (columns (3)-(4)).

[35] While in general we consider worker occupation as a bad control – as it can both depend on the type of firm the worker works for and CHC – lag occupation in this specification is unlikely to suffer from this issue and allows us to compare more similar workers. In any case, we provide robustness checks when controlling for occupation in our main results in Section C.7.

[36] In this case, workers who did not have a job in the previous year are treated as if no industry (no occupation) were a separate category.

Table B.2: Foreign-domestic gap in the probability of separation for those with and without CHC

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.006*	0.006*	0.005
	(0.003)	(0.003)	(0.003)
Foreign=1	-0.031***	-0.025***	-0.016***
	(0.005)	(0.005)	(0.005)
CHC=1 × Foreign=1	0.018***	0.017***	0.016***
	(0.005)	(0.005)	(0.005)
Observations	1251032	1251032	1251032
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	0.012**	0.020***	0.018***
	(0.005)	(0.005)	(0.005)
Foreign=1	-0.031***	-0.025***	-0.022***
	(0.006)	(0.005)	(0.005)
CHC=1 × Foreign=1	0.018***	0.017***	0.016***
	(0.006)	(0.006)	(0.006)
Observations	889292	889292	889292
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table shows the conditional difference in the probability of separation between CHC workers and other workers. The sample includes only workers who worked at the same firm in years $t-1$ and t, and the worker experiences separation if they work at a different firm or don't work in year $t+1$. The main explanatory variables show whether the worker suffered from CHC in year t and whether the firm in which the worker worked in year t was foreign-owned. In particular, the table presents the estimated parameters from Equation (B.7). In column (1), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: CHC penalty in the probability of joining a foreign-owned firm

(a) Panel A: Men

	(1)	(2)	(3)	(4)
Lag CHC=1	-0.058***	-0.014***	-0.011**	-0.011**
	(0.006)	(0.005)	(0.004)	(0.004)
Observations	403108	403108	403108	403108
Year	YES	YES	YES	YES
Lag Industry	NO	NO	YES	YES
Lag Occupation	NO	NO	YES	YES
Age	NO	YES	YES	YES
Work histrory	NO	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)
Lag CHC=1	-0.118***	-0.058***	-0.053***	-0.052***
	(0.014)	(0.010)	(0.010)	(0.010)
Observations	307270	307270	307270	307270
Year	YES	YES	YES	YES
Lag Industry	NO	NO	YES	YES
Lag Occupation	NO	NO	YES	YES
Age	NO	YES	YES	YES
Work histrory	NO	NO	NO	YES

Notes: The Table presents the gap in the probability of joining a foreign-owned firm (rather than a domestic-owned one) between workers suffering from CHCs and other workers. The workers in our sample are restricted to the new entrants' subsample. That is, we keep those workers in our sample who worked in t at a given firm but did not work there in $t-1$, either because they worked at another firm or because they did not work at all (see more on the definition in Section B.2.1). The dependent variable shows whether the firm they joined was foreign-owned in t and the variable of interest is (Lag CHC=1) shows the workers' CHC status in $t-1$. In particular, the table shows the parameter estimates of Equation (B.8). In column (1), we include a set of year dummies in the regression. In column (2), we add a set of age dummies to the model. In column (3), we also include industry and occupation dummies. We lag these explanatory variables in this specification so that they refer to the worker's previous workplace. In column (4), we also control for the number of months worked by the worker in the previous 3 years and the square of this variable. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Additional Descriptive Statistics

In this Appendix section, we provide additional descriptive statistics to characterize our data in more detail.

Tables B.4 and B.5 provide worker-year-level averages of key variables, while Table B.6 shows statistics at the firm-year level. Table 1 provides a more detailed comparison of domestic- and foreign-owned firms, but as that table builds on multiple data sources there we focus on one year (2014) rather than the average across years.

Figure B.1 provides detailed information on labor market status by age, gender, and CHC status. It distinguishes between workers who work in private firms with labor contract (only these workers are included in our main regression sample), those working in the public sector, self-employed, other working (including workers in public works program, and casual workers) and those that do not work. In line with Figure 2, it confirms the gap in the share of employed people between CHC and non-CHC individuals, but the composition of the different types of employment is quite similar conditional on working – the difference in unlikely to be driven by CHC people moving to the public sector or self-employment.

Table B.4: Descriptive Statistics of Male Workers

	Healthy	Chronic	Healthy	Chronic
	Domestic		Foreign	
Age	39.0	46.3	37.5	44.2
	(10.5)	(10.1)	(10.0)	(10.3)
Tenure	4.9	5.5	5.6	6.6
	(3.9)	(4.2)	(4.0)	(4.4)
Log daily wage in 2017	8.42	8.38	8.91	8.87
	(0.46)	(0.45)	(0.52)	(0.52)
Observation	839,043	149,498	962,734	143,895
	Low firm-specific premium		High firm-specific premium	
Age	38.9	46.2	37.6	44.4
	(10.5)	(10.2)	(10.0)	(10.3)
Tenure	4.9	5.5	5.6	6.6
	(3.9)	(4.2)	(4.1)	(4.4)
Log daily wage in 2017	8.33	8.29	8.96	8.92
	(0.39)	(0.39)	(0.49)	(0.50)
Observation	840,403	147,921	961,374	145,472
	Low labor productivity		High labor productivity	
Age	38.3	45.7	38.1	44.7
	(10.6)	(10.4)	(9.8)	(10.1)
Tenure	4.9	5.6	5.7	6.7
	(3.9)	(4.2)	(4.0)	(4.4)
Log daily wage in 2017	8.43	8.39	8.97	8.92
	(0.43)	(0.43)	(0.53)	(0.54)
Observation	996,929	173,391	804,848	120,002
	Low wage		High wage	
Age	38.4	45.8	38	44.6
	(10.6)	(10.3)	(9.8)	(10.2)
Tenure	4.8	5.4	5.8	6.9
	(3.9)	(4.2)	(4.1)	(4.4)
Log daily wage in 2017	8.34	8.30	9.02	8.98
	(0.37)	(0.37)	(0.48)	(0.49)
Observation	946,165	164,450	855,612	128,943

Notes: This Table shows descriptive statistics of the male workforce at different types of firms by CHC status. Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2.

Table B.5: Descriptive Statistics of Female Workers

	Healthy	Chronic	Healthy	Chronic
	Domestic		Foreign	
Age	40.2	47.4	38.3	44.7
	(10.3)	(9.1)	(10.0)	(9.4)
Tenure	4.7	4.7	5.2	5.9
	(3.7)	(3.8)	(3.8)	(4.2)
Log daily wage in 2017	8.29	8.15	8.65	8.51
	(0.39)	(0.35)	(0.48)	(0.45)
Observation	586,105	69,640	752,479	60,252
	Low firm-specific premium		High firm-specific premium	
Age	40.0	47.2	38.1	44.5
	(10.3)	(9.1)	(10.0)	(9.5)
Tenure	4.9	5.0	5.1	5.7
	(3.8)	(3.9)	(3.8)	(4.2)
Log daily wage in 2017	8.24	8.13	8.75	8.60
	(0.32)	(0.30)	(0.47)	(0.46)
Observation	713,468	81,999	625,116	47,893
	Low labor productivity		High labor productivity	
Age	39.5	46.7	38.4	44.6
	(10.3)	(9.3)	(9.8)	(9.4)
Tenure	4.8	5.0	5.3	6.0
	(3.8)	(3.9)	(3.8)	(4.1)
Log daily wage in 2017	8.32	8.19	8.81	8.66
	(0.36)	(0.33)	(0.50)	(0.49)
Observation	884,857	96,655	453,727	33,237
	Low wage		High wage	
Age	39.7	46.8	38.2	44.4
	(10.4)	(9.2)	(9.8)	(9.5)
Tenure	4.8	4.9	5.3	6.1
	(3.7)	(3.9)	(3.8)	(4.2)
Log daily wage in 2017	8.26	8,16	8.83	8.71
	(0.31)	(0.30)	(0.47)	(0.48)
Observation	841,002	94,463	497,582	35,429

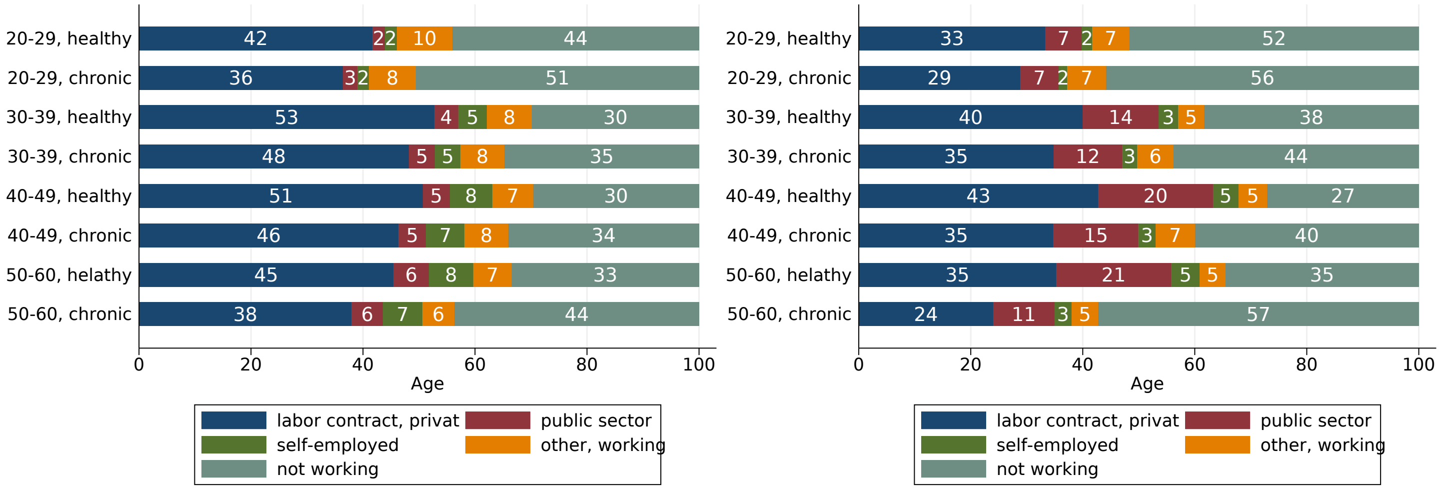
Notes: This Table shows descriptive statistics of the female workforce at different types of firms by CHC status. Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2.

Table B.6: Descriptive Statistics of Firms in our Sample

	Domestic	Foreign
Log employment	3.5	4.3
	(0.9)	(1.2)
Log wage bill	11.2	12.7
	(1.1)	(1.4)
Log sales	13.2	14.7
	(1.3)	(1.7)
Share of workers with CHC	12.3%	10.5%
Share of female workers	35.6%	40.8%
Observations	67,750	20,932
	Low firm-specific premium	High firm-specific premium
Log employment	3.6	4.2
	(0.9)	(1.2)
Log wage bill	11.2	12.7
	(1.1)	(1.3)
Log sales	13.2	14.7
	(1.3)	(1.7)
Share of workers with CHC	12.2%	11.1%
Share of female workers	37.5%	35.1%
Observations	66,169	22,513
	Low labor productivity	High labor productivity
Log employment	3.6	4.0
	(0.9)	(1.2)
Log wage bill	11.3	12.4
	(1.2)	(1.4)
Log sales	13.2	14.8
	(1.4)	(1.5)
Share of workers with CHC	12.3%	10.8%
Share of female workers	38.5%	32.0%
Observations	66,509	22,173
	Low wage	High wage
Log employment	3.6	4.1
	(0.9)	(1.2)
Log wage bill	11.2	12.6
	(1.1)	(1.3)
Log sales	13.2	14.7
	(1.3)	(1.6)
Share of workers with CHC	12.3%	10.8%
Share of female workers	38.0%	33.7%
Observations	65,846	22,836

Notes: This Table shows descriptive statistics of the firms included in our regression sample by firm types. Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2.

Figure B.1: Labor market status by gender, age, and health status



(a) Male

(b) Female

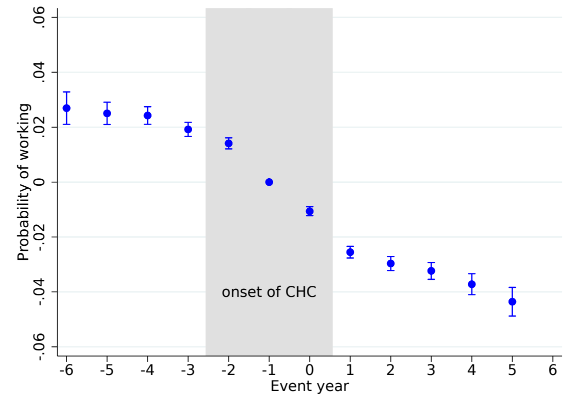
Note: The Table provides detailed information on labor market status by age, gender, and CHC status. It distinguishes between workers who work in private firms with labor contract (only these workers are included in our main regression sample), those working in the public sector, self-employed, other working (including workers in public works program, and casual workers) and those that do not work.

B.4 Additional Results

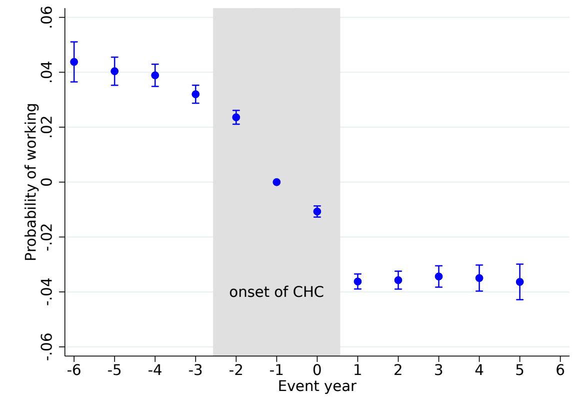
In this Appendix, we provide some additional results to complement our main results.

The event study regressions in our main text (Figure 3, Figure 5 and Figure 6) provide estimates by using the Sun and Abraham (2021) estimator to handle the staggered nature of the treatment. Figures B.2, B.3 and Figure B.4 provides robustness checks for these. These figures repeat the main event study regression, but they use the simple two-way fixed effects estimator rather than the Sun and Abraham (2021) estimator. The figures remain very similar with this more traditional estimator.

Figure B.2: Probability of working: Event study - using the standard 2-way fixed effect estimator



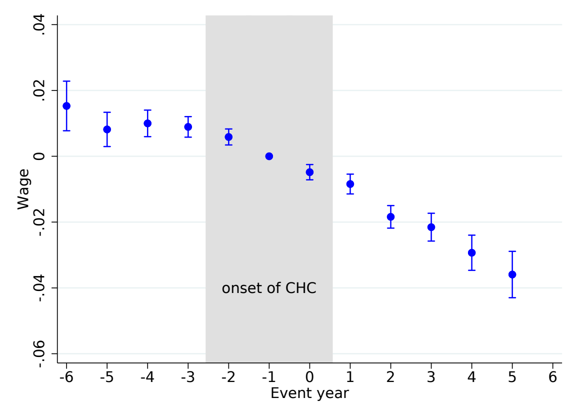
(a) Male, 2WFE



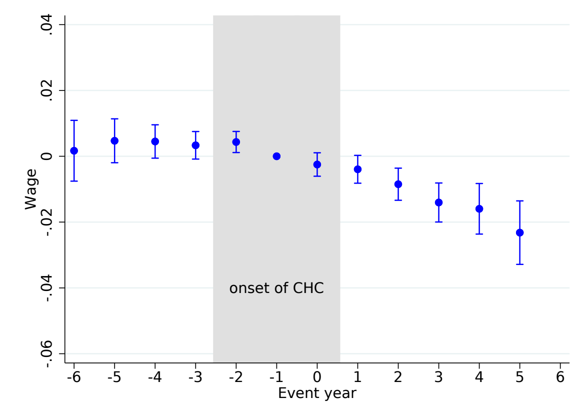
(b) Female, 2WFE

Note: The figure shows robustness checks for the results presented in Figure 3. In particular, it present results from a standard 2-way fixed effects estimator rather than the Sun and Abraham (2021) estimator used for our main results. The dependent variable is a dummy showing whether the person works and event years capture the time relative to the onset of CHC. We use the same control variables as in Column (2) of Table 2:year and age dummies. The figure shows the difference in the probability of working for an individual with CHC relative to the last healthy year. The bars show 95% confidence intervals and standard errors are clustered at the individual level.

Figure B.3: CHC wage penalty: Event study - using the standard 2-way fixed effect estimator



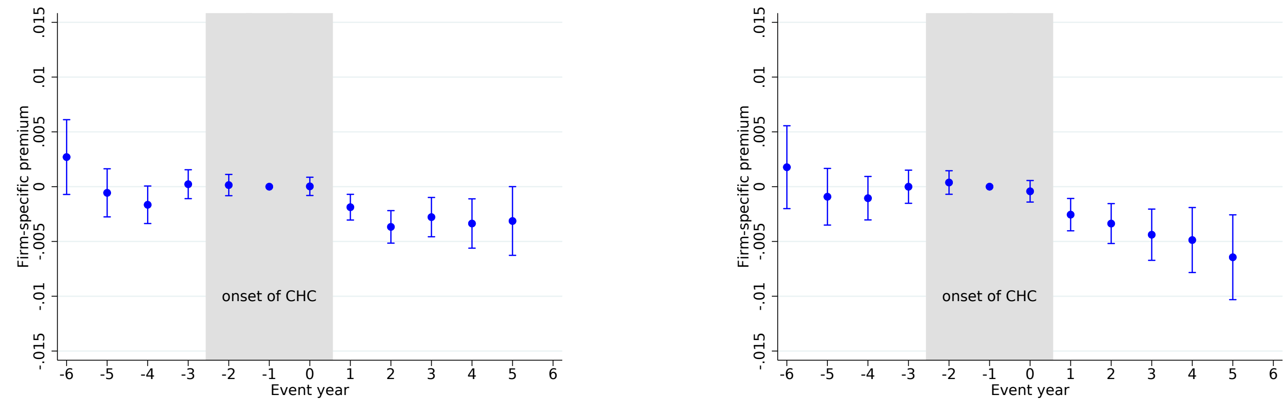
(a) Male, 2WFE



(b) Female, 2WFE

Note: The figure shows robustness checks for the results presented in Figure 5. The Figure present results from a standard 2-way fixed effects estimator rather than the Sun and Abraham (2021) estimator used for our main results. The dependent variable is log daily wage and event time capture the time in years relative to the onset of CHC. We use the same control variables as in Column (3) of Table 3: calendar year, industry, and age dummies, and further control for tenure (and its square) and worker-specific fixed effects. The figure shows the difference in the CHC wage penalty relative to the last healthy year. The bars show 95% confidence intervals, and standard errors are clustered at the firm level.

Figure B.4: CHC penalty in firm-specific wage premium: Event study - using the standard 2-way fixed effect estimator

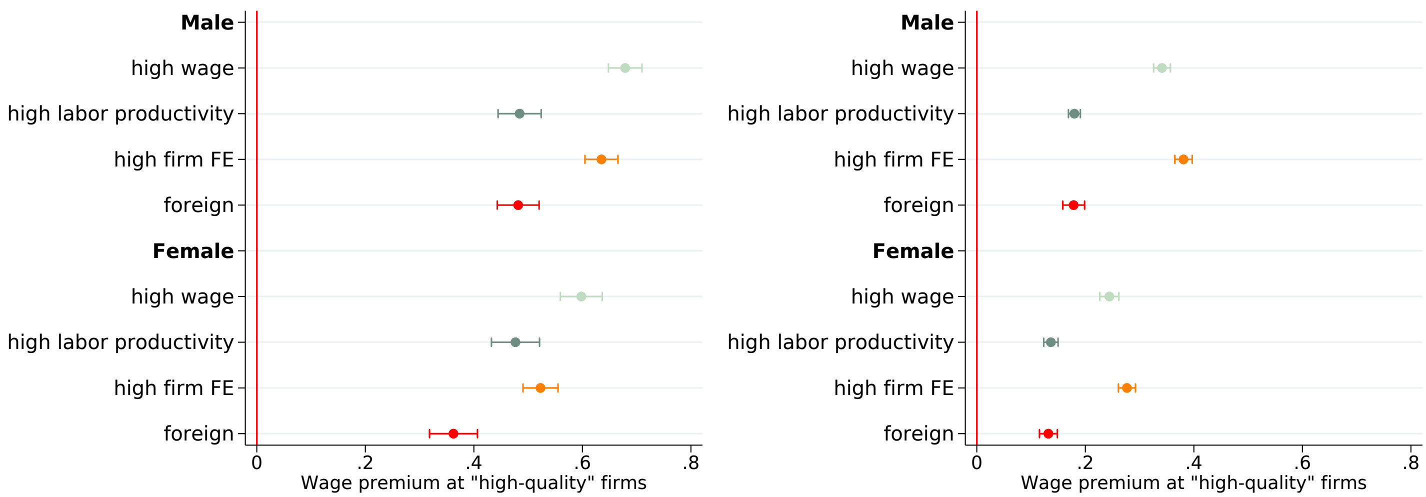


(a) Male, 2WFE

(b) Female, 2WFE

Note: The figure shows robustness checks for the results presented in Figure 6. The Figure present results from a standard 2-way fixed effects estimator rather than the Sun and Abraham (2021) estimator used for our main results. he dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. We use the same control variables as in Column (3) of Table 3: calendar year, industry, and age dummies, and further control for tenure (and its square) and worker-specific fixed effects. The figure shows the difference in the CHC penalty in firm-specific wage premium relative to the last healthy year. The bars show 95% confidence intervals, and standard errors are clustered at the firm level.

Figure B.5: Wage premium at high-quality firms – using different measures for high-quality firms

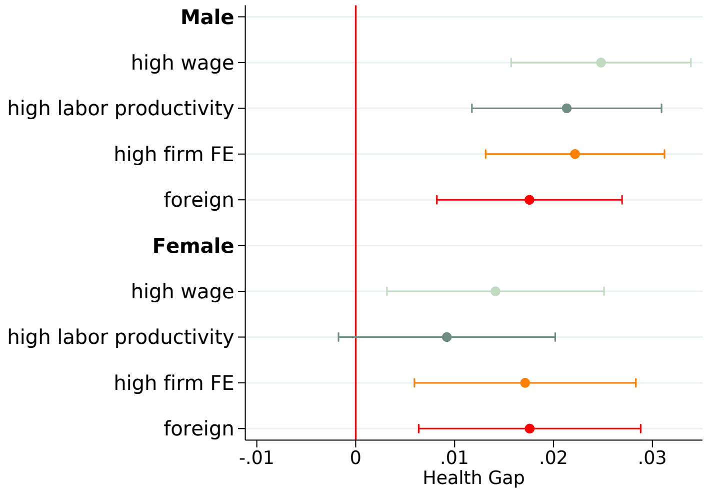


(a) "high-quality" firm wage premium - unconditional

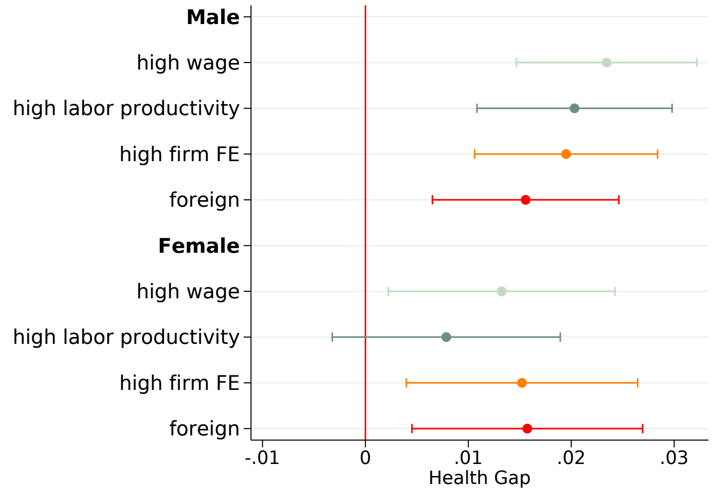
(b) "high-quality" firm wage premium - conditional

Note: This Figure shows the wage premium at "high-quality" firms by using different definitions for high quality firms. In particular, we re-estimate Equation 6 by using alternative firm quality measures and we report the coefficient of the foreign x CHC interaction in the figure. In Panel (a), we control for a set of year, industry, and age dummies, while in Panel (b), we further control for tenure and its square, and we add worker-specific fixed effects to the model. Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2. The bars show 95% confidence intervals and standard errors are clustered at the firm level.

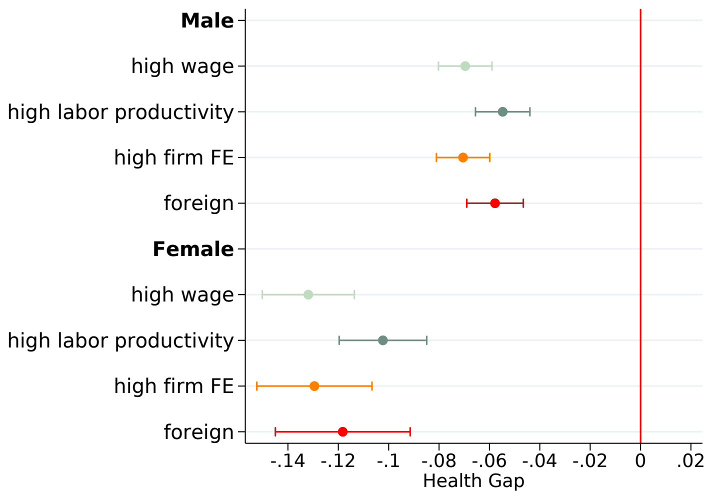
Figure B.6: CHC gap in Probability of moving to or separating from high-quality firms, different quality measures



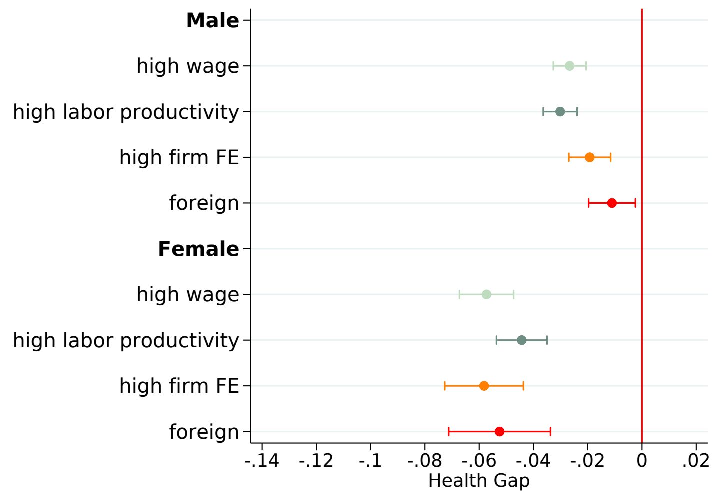
(a) Likelihood of separation - unconditional



(b) Likelihood of separation - conditional



(c) Likelihood of joining a specific firm - unconditional



(d) Likelihood of joining a specific firm - conditional

Note: In Panels (a) and (b) presents the conditional difference in the probability of separation between CHC workers and other workers. In particular, the figure presents the estimated parameters from Equation (B.7). In panel (a), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In panel (b), we add tenure and its square, and our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). These results mimic columns (1) and (3) of Table B.2.
Panels (c) and (d) presents the gap in the probability of joining a "high-quality" firm between workers suffering from CHCs and other workers. In particular the figure shows the parameter estimates of Equation (B.8). In panel (c), we include a set of year dummies in the regression. In column (d), we add a set of age dummies, industry, occupation dummies to the model. We lag these explanatory variables in this specification so that they refer to the worker's previous workplace. We also control for the number of months worked by the worker in the previous 3 years and the square of this variable. These results mimic columns (1) and (4) of Table B.3.
Firms are classified as foreign-owned if the share of directly or indirectly owned foreign capital is at least 50%. We classify high-productivity firms as those in the top quartile of the labor productivity distribution, measured by value added per worker. We define high-wage firms as those in the top quartile of the average wage distribution. We identify high wage-premium firms as those in the top quartile of the distribution of the Abowd et al. (1999) firm fixed effects distribution. Further methodological details are provided in Section 3.2.2.

C Robustness and Heterogeneity

This Appendix provides more details and presents the results described in Section 6.

C.1 Alternative measure of the chronic condition index

As we have described in Section 3.2.1, in our main specification we follow Danesh et al. (2024) in using a lasso regression that includes nonlinear functions of the 19 chronic condition dummies and socioeconomic variables to build the continuous CDI variable. To check whether the results are robust to a simpler and more transparent definition, we simply use a linear probability model with the 19 dummies to predict negative health outcomes. Otherwise we follow the main specification. Section C.1 explains this exercise in more detail. The results are very similar when we use this alternative measure rather than the mean measure (Section C.1) suggesting that the main results are not driven by the non-linear functions or the inclusion of the socioeconomic variables.

In more detail, to construct the index, we use the same 19 chronic condition dummies described in Section A.1. To construct the summary index, we follow the following steps. First, we restrict our analysis to individuals aged 64–66 in 2012 to predict their likelihood of hospitalization or death within the subsequent five years (i.e., by the end of 2017). We define hospitalization in the same way as described in Section A.1. We run a simple linear probability model on this subsample, where the dependent variable is one if the individual dies or gets hospitalized between 2012 and 2017. We do not include additional control variables into the model, but we estimate the model separately by gender. In the second step, we use these estimates to assign weights to chronic conditions at any age, generating the summary index. We define an individual to have CHC if this index falls in the top 10 percent of the general population.

To evaluate the robustness of our main results, we re-estimate our models by using this alternative measure of CHC. Similarly to our main results, we find that individuals with CHC work with a lower probability (Table C.1). Conditional on working, workers with CHC are less likely to sort to foreign owned firms (Table C.4). Turning to the wage penalty, we find a positive wage penalty for workers with CHC (Table C.2) which is partly explained by sorting of CHC workers to firms with lower firm specific premium (Table C.3). The penalty is significantly larger at foreign owned firms (Table C.5).

Table C.1: Difference in the probability of working by chronic health condition (CHC) - by using an alternative measure for the Chronic Disease Index

(a) Panel A: Men

	(1)	(2)	(3)	(4)
CHC=1	-0.049***	-0.056***	-0.022***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	10021891	10021891	3329429	3329429
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)
CHC=1	-0.151***	-0.172***	-0.073***	-0.062***
	(0.001)	(0.001)	(0.002)	(0.001)
Observations	9989253	9989253	2592729	2592729
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

Notes: The Table presents the estimated parameters of Equation (1) in which we regress a dummy showing whether an individual is working (including self-employed and public workers) on whether they suffer from a Chronic Health Condition (CHC=1). For the purpose of this analysis, we use all observations in the dataset aged between 20-60, including those who never worked. For the purpose of this robustness analysis we use an alternative measure of CHC status, as explained in Section C.1. In column (1), we include a set of year dummies, in column (2), we add a set of age dummies to the control variables. In column (3), we re-run the regression from column (2) on the sample where we could estimate Abowd et al. (1999)-type worker fixed effects in a previous step, i.e. workers who were observed in our wage regression sample (see more details in Section 3.2.4). In column (4), we control for worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. Standard errors are clustered at the worker level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: CHC wage penalty - by using an alternative measure for the Chronic Disease Index

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.050***	-0.046***	-0.010***	-0.027***	-0.009***
	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)
Observations	2095170	2095170	2095170	2095170	2095170
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.143***	-0.125***	-0.008***	-0.059***	-0.005***
	(0.010)	(0.009)	(0.002)	(0.003)	(0.002)
Observations	1468476	1468476	1468476	1468476	1468476
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: This Table shows the conditional wage gap between workers having CHC and those without such conditions by using an alternative measure of Chronic Condition Index. In particular, it presents the estimated parameters from Equation (2), in which The dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4) firm fixed effects, while in column (5) we have both worker and firm fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: CHC penalty in firm-specific wage premium - by using an alternative measure for the Chronic Disease Index

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.005***	-0.004**	-0.000
	(0.002)	(0.002)	(0.001)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.034***	-0.030***	-0.002***
	(0.006)	(0.005)	(0.001)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

Notes: This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions by using an alternative measure of Chronic Condition Index.. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: CHC penalty in the probability of working at a foreign-owned firm - by using an alternative measure for the Chronic Disease Index

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.012***	-0.011***	-0.002
	(0.004)	(0.004)	(0.003)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.063***	-0.055***	-0.039***
	(0.014)	(0.013)	(0.012)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table shows the conditional gap in the probability of working at a foreign-owned firms between workers with CHC and other workers, conditional on working by using an alterantive measure of CHC. In particular, the table shows parameter estimates of Equation (5). The dependent variable is a dummy showing whether worker i is working at a foreign owned firm in time t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Foreign-Domestic difference in the CHC wage penalty - by using an alternative measure for the chronic condition index

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.038***	-0.032***	-0.002	-0.018***	-0.005***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)
Foreign=1	0.482***	0.465***	0.179***	0.019**	0.015**
	(0.020)	(0.019)	(0.010)	(0.009)	(0.007)
CHC=1 × Foreign=1	-0.011	-0.017**	-0.014***	-0.017***	-0.008***
	(0.008)	(0.007)	(0.003)	(0.004)	(0.003)
Observations	2095170	2095170	2095170	2095170	2095170
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.111***	-0.091***	-0.004	-0.046***	-0.004
	(0.011)	(0.010)	(0.003)	(0.003)	(0.003)
Foreign=1	0.362***	0.348***	0.132***	0.014**	0.010
	(0.023)	(0.023)	(0.008)	(0.006)	(0.007)
CHC=1 × Foreign=1	-0.021*	-0.032***	-0.006	-0.027***	-0.003
	(0.012)	(0.011)	(0.004)	(0.005)	(0.004)
Observations	1468476	1468476	1468476	1468476	1468476
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: The Table shows conditional wage differences between CHC and other workers in foreign-owned and domestic-owned firms by using alternative measure of CHC. In particular, it presents coefficient estimates from Equation (6), in which The dependent variable is the daily wage of worker i in year t and the variables of interest are the CHC status of the worker, whether the firm was foreign-owned and their interaction. Of especial interest in the coefficient of the interaction, which shows the difference in the CHC penalty between foreign- and domestic-owned firms. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5) both worker and firm fixed effects are included. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Alternative thresholds for CHC status

As Section 6 explains, our main CHC measure is based on a continuous measure of chronic health conditions and individuals are classified as having a CHC if their index value falls within the top 10 percent of the distribution. Recognizing that the choice of the 10 percent cutoff is inherently arbitrary, we assess the robustness of our findings by applying three alternative classification thresholds.

- **Top 10 Percent within Gender**: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups.
- **1.5 × Median**: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill.
- **2 × Median**: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median.

As in the baseline approach, individuals identified as chronically ill under any alternative definition are assumed to remain in that state permanently. Figure C.1 illustrates the share of workers classified as having a chronic condition under each alternative threshold. The two median-based thresholds provide a stricter definition, with less than 5 percent of people being identified as suffering from CHC.

To evaluate the robustness of our main results, first we re-estimate Equation (1) by using alternative definitions of CHC (Figure C.2). In Panel (a), we control for year-specific fixed effects. Panel (b) we further adds a set of age dummies and the productivity of the workers (proxied by worker-specific premium estimated from an AKM model) to the list of control variables. The red points represent the baseline definition, i.e. the results from columns (1) and (4) from Table 2. People with CHC are less likely to work independently of the definition, but the differences are much larger when we consider the median-based definitions.

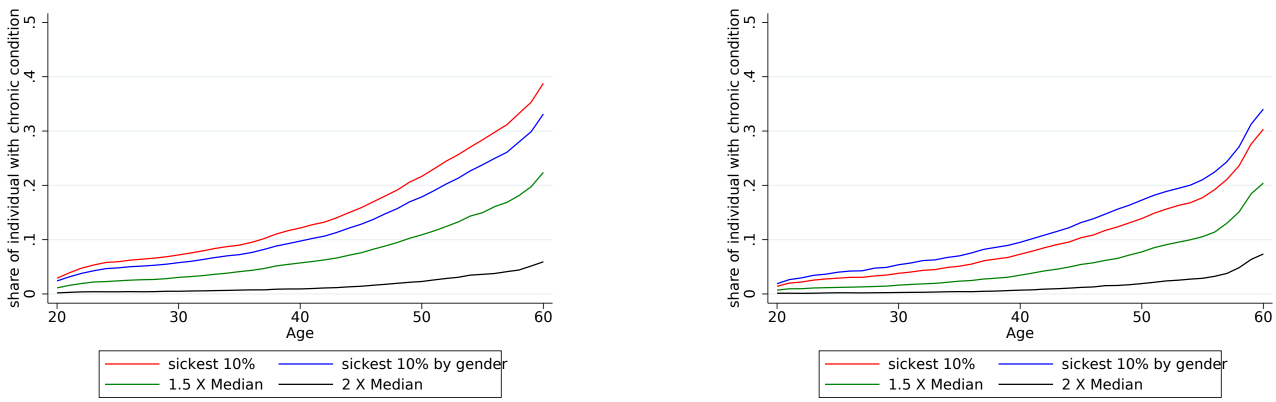
Next we turn to the CHC wage penalty and re-estimate Equation (2) by using alternative definitions for chronic condition (Figure C.3). We find that the wage penalty is much larger for the median based definitions when controlling only for age, industry and year fixed effects (Panel A, similar to column (1), Table 3) than the one we find for our main measure, reflecting that these definitions tend to capture more serious conditions. The estimates are more similar across definitions when worker fixed effects are included (Panel B similar to column (4), Table 3).

In parallel to the wage estimates, we also re-run Equation (2) but replace the dependent variable with firm fixed effects estimated from an AKM specification and use the alternative definitions for chronic condition. Our results that both men and women with CHC work at lower paying firms on average is robust to this modification (Figure C.4).

We also show that workers with CHC are less likely to work at foreign firms (Figure C.5a), have a lower probability of joining such firms, while also the separation rate from such firms is higher for them (Figure C.6) irrespectively of the CHC definitions used – the difference increasing in the restrictiveness of the CHC definition.

Finally, we examine the difference between the CHC penalty applied by foreign and domestic-owned firms by re-estimating Equation 6 using alternative definitions of chronic conditions. The estimates for the coefficient of the foreign x CHC interaction are presented in Figure C.7, where red markers indicate estimates based on our baseline CHC definition and the other colors correspond to alternative classifications. Panel A and Panel B corresponds to columns (1) and (3) of Table 6, respectively. The findings remain robust across all specifications: even when stricter thresholds for identifying chronic illness are applied, the estimated effects on wages exhibit no significant variation. Within each specification, parameter estimates remain stable regardless of the specific definition of the chronic health condition employed.

Figure C.1: Share of people with CHC by age in our regression sample, using alternative thresholds for CHC status

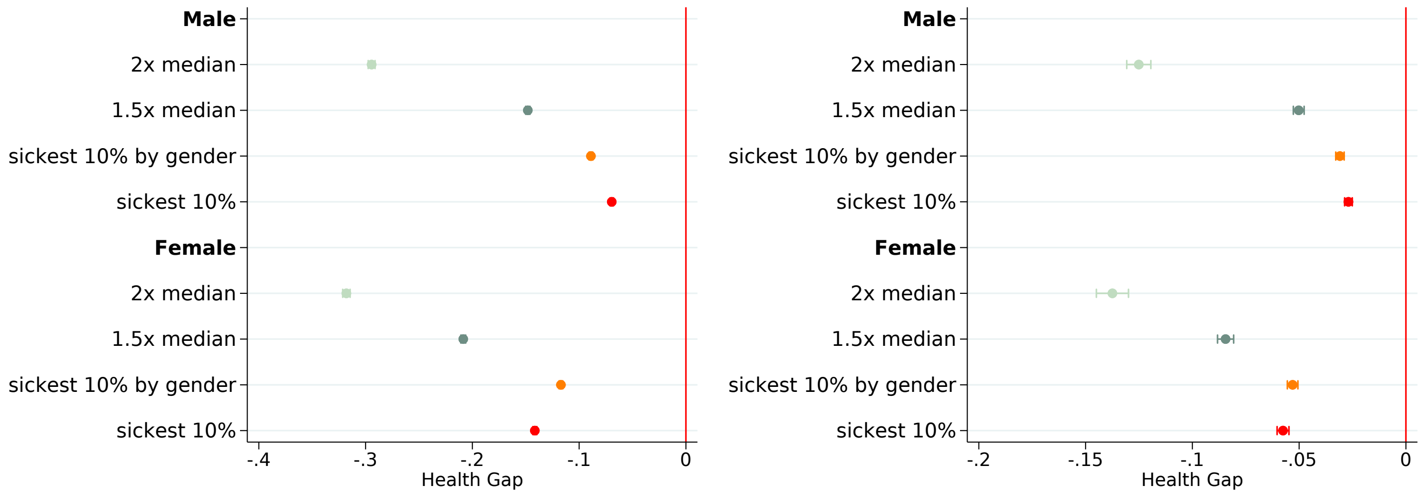


(a) Male

(b) Female

Note: The figure shows the share of workers in our sample with CHC (y-axis) by age (x-axis), separately for different thresholds for CHC status. The red line corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to our alternative definitions. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median.

Figure C.2: Difference in the probability of working by chronic health condition (CHC) – using alternative thresholds for CHC status

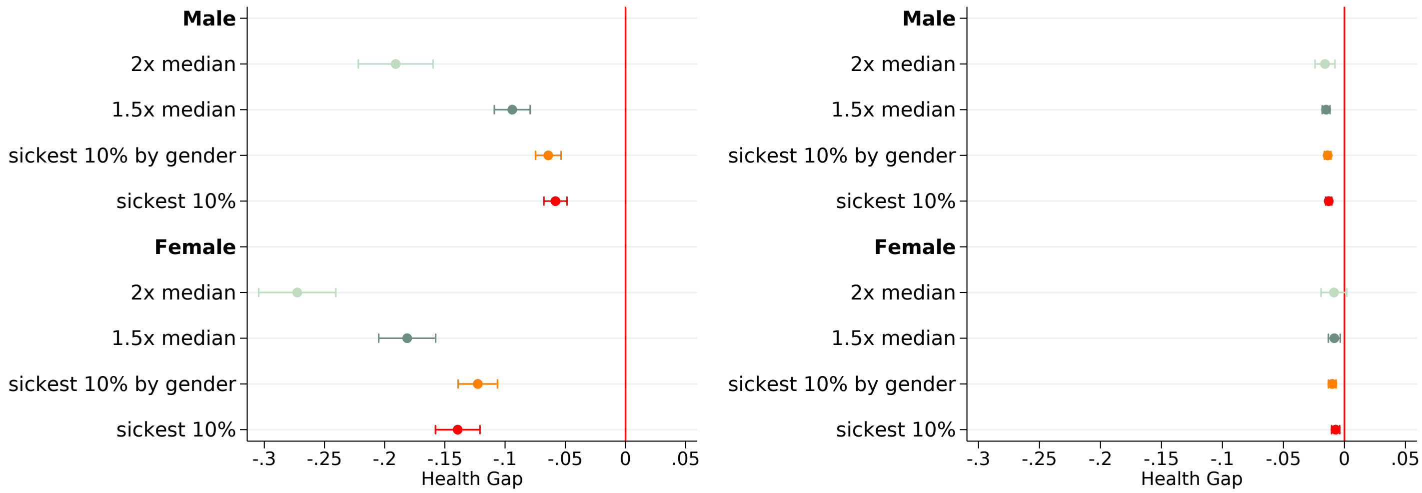


(a) Probability of working - unconditional

(b) Probability of working - conditional

Note: The Figure presents the estimated parameters of Equation (1) in which we regress a dummy showing whether an individual is working (including self-employed and public workers) on whether they suffer from a Chronic Health Condition (CHC=1) by using alternative thresholds for CHC status. For the purpose of this analysis, we use all observations in the dataset aged between 20-60, including those who never worked. In panel (a), we include a set of year dummies. In column (b), we also control for a set of age dummies and worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. These results mimic columns (1) and (4) of Table 2. The red mark corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to the alternative thresholds used to define CHC status. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median. The figure show 95% confidence intervals and standard errors are clustered at the individual level.

Figure C.3: CHC wage penalty by using alternative thresholds for CHC

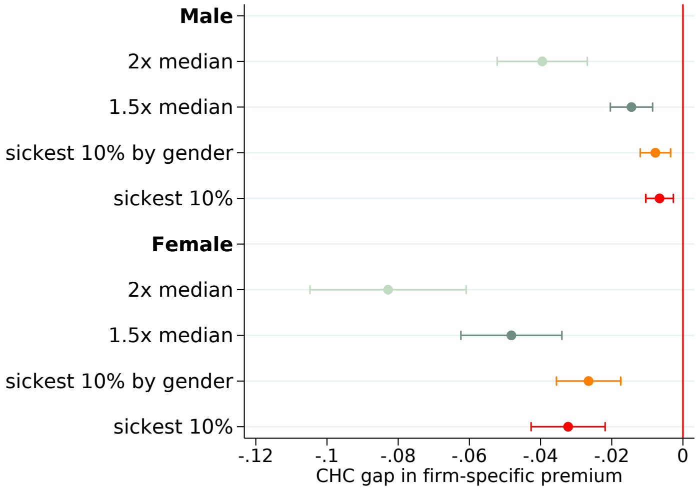


(a) CHC penalty - unconditional

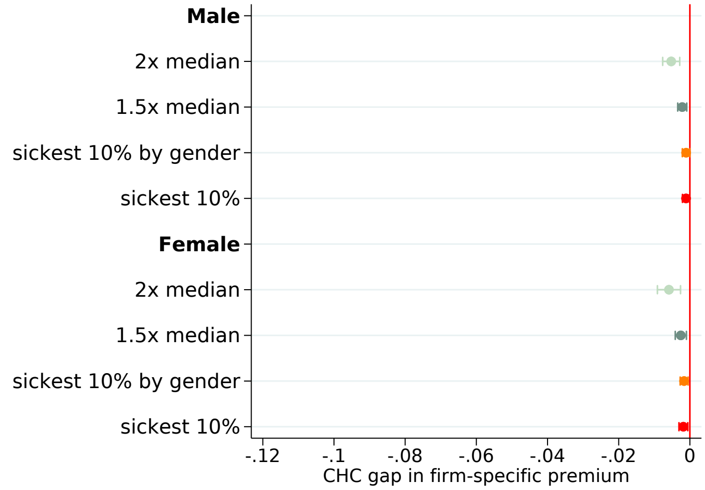
(b) CHC penalty - conditional

Note: This Figure shows the conditional wage gap between workers having CHC and those without such conditions by using alternative thresholds for CHC. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In panel (a), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (b), we also add tenure and its square and worker fixed effects to the model. The red mark corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to the alternative thresholds used to define CHC status. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median. The figure show 95% confidence intervals and standard errors are clustered at the firm level.

Figure C.4: CHC penalty in firm-specific wage premium by using alternative thresholds for CHC



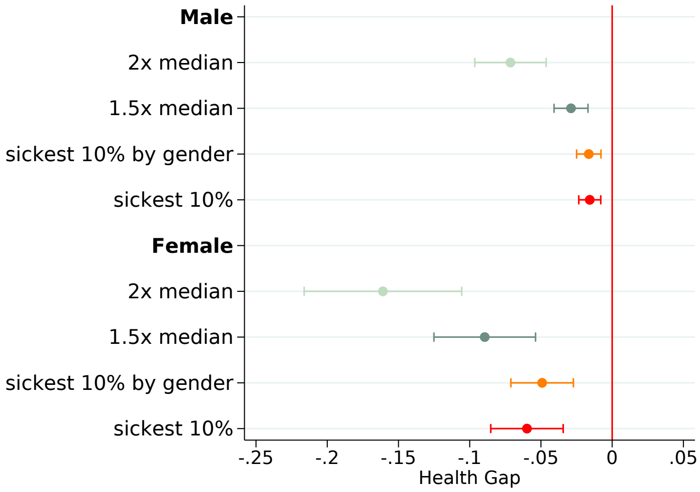
(a) CHC penalty - unconditional



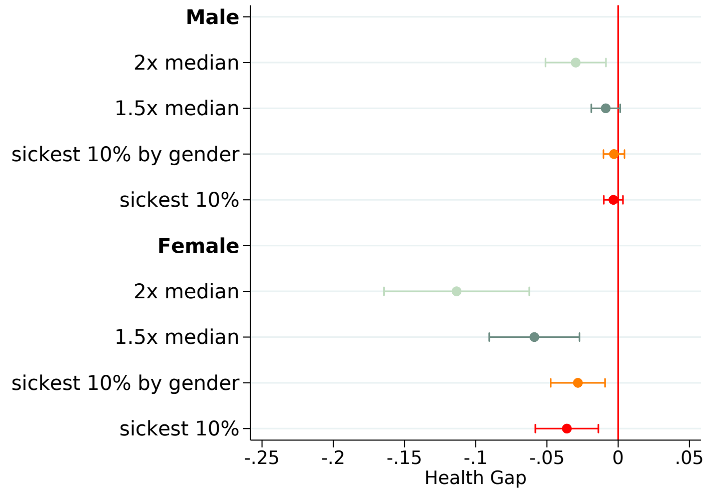
(b) CHC penalty - conditional

Note:
This Figure shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions by using alternative thresholds for CHC. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In panel (a), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (b), we also add tenure and its square and worker fixed effects to the model. The red mark corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to the alternative thresholds used to define CHC status. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median. The figure show 95% confidence intervals and standard errors are clustered at the firm level.

Figure C.5: CHC penalty in the probability of working at a foreign-owned firm - by using alternative thresholds for CHC status



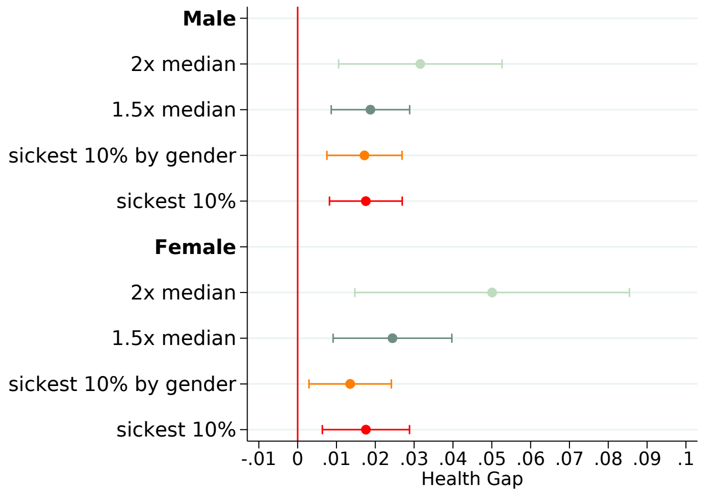
(a) Probability of working at a foreign firm - unconditional



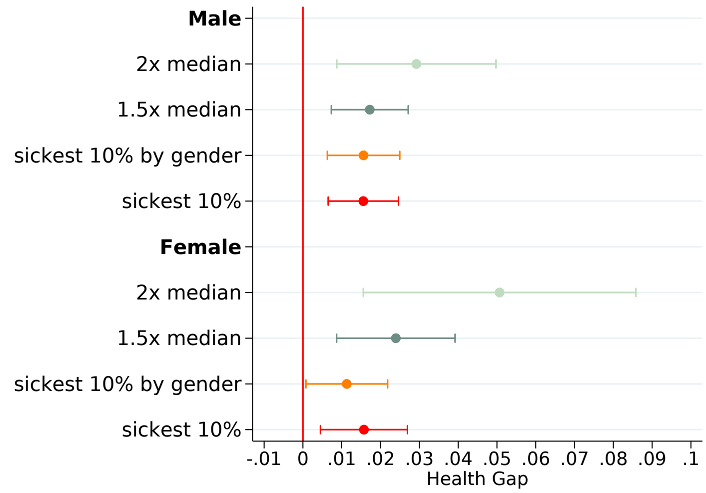
(b) Probability of working at a foreign firm - conditional

Note: This Figure shows the conditional gap in the probability of working at a foreign-owned firms between workers with CHC and other workers, conditional on working. In particular, the Figure shows parameter estimates of Equation (5). The dependent variable is a dummy showing whether worker i is working at a foreign owned firm in time t and the main explanatory variable is the CHC status of the worker. In panel (a), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In panel (b), we add tenure and its square and our proxy for worker productivity to the model. These results mimic columns (1) and (3) of Table 5. The red mark corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to the alternative thresholds used to define CHC status. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median. The figure show 95% confidence intervals and standard errors are clustered at the firm level.

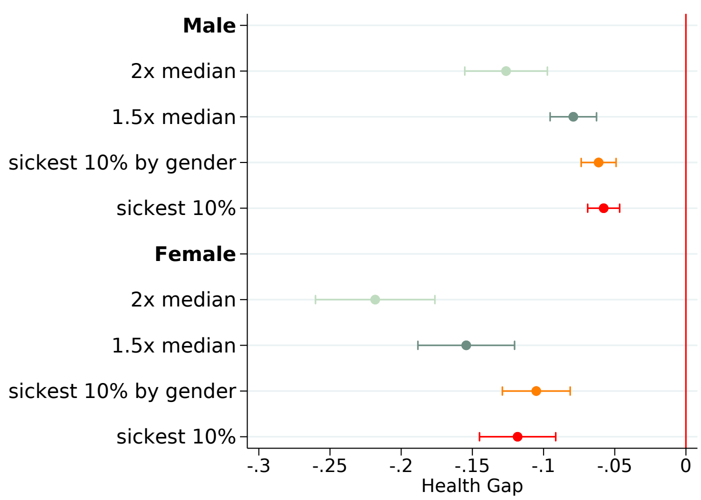
Figure C.6: Selection on chronic illness using alternative thresholds for CHC status - Flows of workers



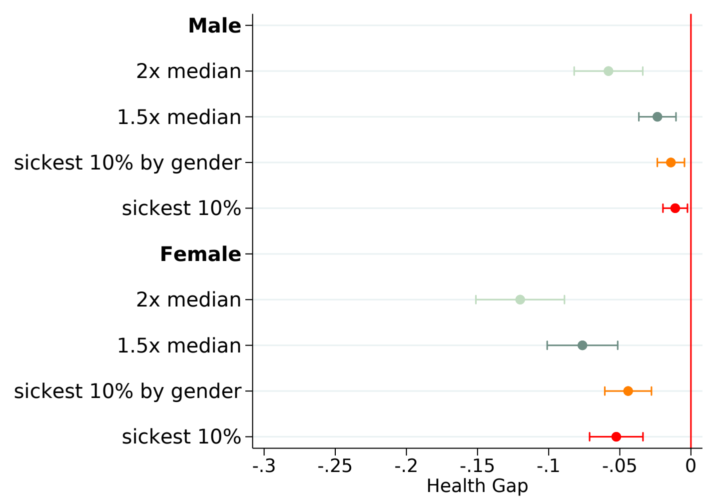
(a) Likelihood of separation - unconditional



(b) Likelihood of separation - conditional



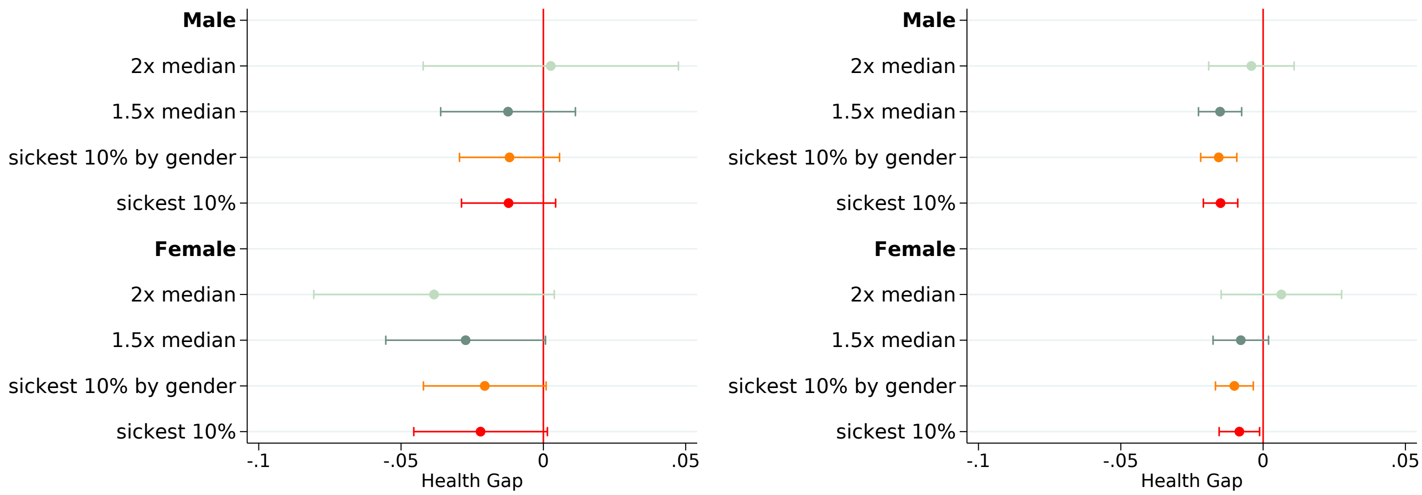
(c) Likelihood of joining a foreign firm - unconditional



(d) Likelihood of joining a foreign firm - conditional

Note: In Panels (a) and (b) present the conditional difference in the probability of separation between CHC workers and other workers. In particular, the figure presents the estimated parameters from Equation (B.7). In panel (a), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In panel (b), we add tenure and its square, and our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). These results mimic columns (1) and (3) of Table B.2. Panels (c) and (d) present the gap in the probability of joining a "high-quality" firm between workers suffering from CHCs and other workers. In particular the figure shows the parameter estimates of Equation (B.8). In panel (c), we include a set of year dummies in the regression. In column (d), we add a set of age dummies, industry, occupation dummies to the model. We lag these explanatory variables in this specification so that they refer to the worker's previous workplace. We also control for the number of months worked by the worker in the previous 3 years and the square of this variable. These results mimic columns (1) and (4) of Table B.3. The red mark corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to the alternative thresholds used to define CHC status. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median. The figure show 95% confidence intervals and standard errors are clustered at the firm level.

Figure C.7: Foreign-domestic difference in the wage penalty by using alternative threshold for CHC status



(a) Difference in CHC penalty - unconditional

(b) Difference in CHC penalty - conditional

Note: This Figure shows the difference in CHC wage penalty –the conditional difference between the wages of CHC and other workers – between foreign and domestic firms, by using different thresholds for CHC status. In particular, we re-estimate Equation 6 by using different thresholds for CHC status and we report the coefficient of the foreign x CHC interaction in the figure. In Panel (a), we control for a set of year, industry, and age dummies, while in Panel (b), we further control for tenure and its square, and we add worker-specific fixed effects to the model. The red mark corresponds to our main definition of CHC status using the 10 percent threshold. The other color corresponds to the alternative thresholds used to define CHC status. Top 10 Percent within Gender: Individuals are classified as chronically ill if they fall within the top 10 percent of the index distribution within their respective gender groups. 1.5 × Median: Individuals whose index value exceeds 1.5 times the median are classified as chronically ill. 2 × Median: A stricter threshold, whereby individuals are classified as chronically ill if their index value exceeds twice the median. The figure show 95% confidence intervals and standard errors are clustered at the firm level.

C.3 White-collar workers

The CHC penalty could potentially be driven solely or mainly by blue-collar workers. Because their jobs are more physically demanding, chronic health conditions can have a greater impact on their productivity. Additionally, absenteeism may be more problematic for blue-collar workers, as their tasks are generally less flexible and cannot be performed remotely. To address this issue, this Appendix shows how the results change when we restrict our sample to white-collar workers.

First, we re-run Equation (1) on the subsample of workers that had a white-collar job for at least once between 2011 and 2017 and were observed in our regression sample, thus worker fixed effects are available for them. Appendix Table C.6 presents the results. Male workers with CHC work with 1.5-2 percentage point lower probability than their healthy counterparts. The CHC penalty in the likelihood of working is larger among female workers, reaching 4 percentage points. As a next step, we re-run Equation (2) on the subsample of white-collar workers.Table C.7, the CHC wage penalty is comparable in size and significant for both genders across all specifications to our main findings. Table C.8 replicates Table 4 on the subsample of white-collar workers by the re-estimation of Equation (2) having firm fixed effects estimated from an AKM specification as dependent variables. Both men and women with CHC work at lower-paying firms on average compared to workers without CHC, but among white-collar workers, this sorting channel is larger for male workers. For men (women), the difference in firm specific premia is 1.1% (1.8%), which is 20% (17%) of the total wage penalty reported in column (1) of Table C.7. These results confirm that our main findings are not driven by physical workers, but hold for all job types.

Table C.6: Difference in the probability of working by chronic health condition (CHC) for white-collar workers.

(a) Panel A: Men

	(1)	(2)
CHC=1	-0.018***	-0.015***
	(0.001)	(0.001)
Observations	1200573	1200573
Year	YES	YES
Age	YES	YES
Worker FE proxy	NO	YES

(b) Panel B: Women

	(1)	(2)
CHC=1	-0.041***	-0.036***
	(0.002)	(0.002)
Observations	1181662	1181662
Year	YES	YES
Age	YES	YES
Worker FE proxy	NO	YES

Notes: The Table presents the estimated parameters of Equation (1) on the subsample of workers that had at a white-collar job for at least once between 2011-2017 and person fixed effects are available, i.e. workers who were observed in our regression sample (see more details in Section 3.2.4). We regress a dummy showing whether an individual is working (including self-employed and public workers) on whether they suffer from a Chronic Health Condition (CHC=1).In column (1), we control for a set of year and age dummies. In column (2), we control for worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. Standard errors are clustered at the worker level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: CHC wage penalty for white-collar workers.

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
Chronic=1	-0.057***	-0.055***	-0.015***	-0.030***	-0.013***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)
Observations	657795	657795	657795	657795	657795
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.104***	-0.098***	-0.011***	-0.063***	-0.008**
	(0.007)	(0.007)	(0.003)	(0.005)	(0.003)
Observations	565502	565502	565502	565502	565502
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: This Table shows the conditional wage gap between workers having CHC and those without such conditions for white-collar workers. In particular, it presents the estimated parameters from Equation (2) on the subsample of white-collar workers, in which the dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4) firm fixed effects, while in column (5) we have both worker and firm fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: CHC penalty in firm-specific wage premium among white-collar workers.

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.011***	-0.011***	-0.001
	(0.002)	(0.002)	(0.001)
Observations	657795	657795	657795
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.018***	-0.016***	-0.002*
	(0.003)	(0.003)	(0.001)
Observations	565502	565502	565502
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

Notes:
This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions for white-collar workers. In particular, it presents the estimated parameters from Equation (2) on the subsample of white-collar workers. The dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Splitting the sample by age

This Appendix reproduces the main results on the subsamples of workers younger/older than 40 to see whether the results are only driven by older/younger workers.

Consistent with our primary findings for both younger and older workers, CHCs remain significantly less likely to work in general than their healthy counterparts (Tables C.9 and C.10) and also less likely to work at foreign firms (Tables C.16 and C.15). While the difference in the probability of working is larger for the older age group, the gap in terms of working for foreign-owned firms is similar.

Turning to wage outcomes, we find that workers with CHC receive significantly lower wages than those without CHC for both age groups (Appendix Tables C.11 and C.12), with no fundamental differences in the wage penalties. Selection in terms of firm-specific wage premia is also similar for the two groups (Appendix Tables C.14 and C.13).

Table C.9: Probability of working for individuals under 40 with and without chronic conditions

(a) Panel A: Men

	(1)	(2)	(3)	(4)
CHC=1	-0.043***	-0.065***	-0.025***	-0.019***
	(0.001)	(0.001)	(0.002)	(0.001)
Observations	5118448	5118448	2007095	2007095
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)
CHC=1	-0.041***	-0.071***	-0.043***	-0.032***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	4912995	4912995	1503459	1503459
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

Notes: This Table shows the conditional probability of working for workers under age 40 by CHS status. It presents the estimated parameters of Equation (1) in which we regress a dummy showing whether an individual is working (including self-employed and public workers) on whether they suffer from a Chronic Health Condition (CHC=1). For the purpose of this analysis, we use all observations in the dataset aged between 20-40, including those who never worked. The CHC status is identified from health care use data, as explained in Section 3.2.1. In column (1), we include a set of year dummies, in column (2), we add a set of age dummies to the control variables. In column (3), we re-run the regression from column (2) on the sample where we could estimate Abowd et al. (1999)-type worker fixed effects in a previous step, i.e. workers who were observed in our wage regression sample (see more details in Section 3.2.4). In column (4), we control for worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. Standard errors are clustered at the worker level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.10: Probability of working for individuals above age 40 with and without chronic conditions

(a) Panel A: Men

	(1)	(2)	(3)	(4)
CHC=1	-0.096***	-0.081***	-0.037***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4903443	4903443	1322334	1322334
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)
CHC=1	-0.219***	-0.189***	-0.078***	-0.068***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	5076258	5076258	1089270	1089270
Year	YES	YES	YES	YES
Age	NO	YES	YES	YES
Worker FE proxy	NO	NO	NO	YES

Notes: This Table shows the conditional probability of working for workers above age 40 by CHS status. It presents the estimated parameters of Equation (1) in which we regress a dummy showing whether an individual is working (including self-employed and public workers) on whether they suffer from a Chronic Health Condition (CHC=1). For the purpose of this analysis, we use all observations in the dataset aged between 41-60, including those who never worked. The CHC status is identified from health care use data, as explained in Section 3.2.1. In column (1), we include a set of year dummies, in column (2), we add a set of age dummies to the control variables. In column (3), we re-run the regression from column (2) on the sample where we could estimate Abowd et al. (1999)-type worker fixed effects in a previous step, i.e. workers who were observed in our wage regression sample (see more details in Section 3.2.4). In column (4), we control for worker productivity proxied by the Abowd et al. (1999)-type person fixed effects estimated in a previous regression. Standard errors are clustered at the worker level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.11: Wage Gap between workers under age 40 with and without chronic conditions

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.060***	-0.056***	-0.015***	-0.035***	-0.015***
	(0.005)	(0.005)	(0.002)	(0.003)	(0.002)
Observations	1190214	1190214	1190214	1190214	1190214
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.123***	-0.114***	-0.015***	-0.060***	-0.012***
	(0.006)	(0.006)	(0.003)	(0.004)	(0.003)
Observations	779191	779191	779191	779191	779191
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: The Table presents the estimated parameters from Equation 6 on the sub-sample of workers under age 40. The dependent variable is the daily wage of worker i in year t. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5) worker and firm fixed effects to the model. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.12: Wage Gap between workers above age 40 with and without chronic conditions

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.056***	-0.048***	-0.003*	-0.028***	-0.001
	(0.006)	(0.005)	(0.002)	(0.002)	(0.001)
Observations	904956	904956	904956	904956	904956
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.142***	-0.120***	0.001	-0.054***	0.002
	(0.011)	(0.009)	(0.002)	(0.002)	(0.002)
Observations	689285	689285	689285	689285	689285
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: The Table presents the estimated parameters from Equation 6 on the subsample of workers above age 40. The dependent variable is the daily wage of worker i in year t. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5) worker and firm fixed effects to the model. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.13: CHC penalty in firm-specific wage premium for workers above age 40

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.006***	-0.004*	-0.000
	(0.002)	(0.002)	(0.001)
Observations	904956	904956	904956
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.035***	-0.030***	-0.001
	(0.007)	(0.006)	(0.001)
Observations	689285	689285	689285
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

Notes:This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions for workers above age 40. In particular, it presents the estimated parameters from Equation (2) on the subsample of workers above age 40. The dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.14: CHC penalty in firm-specific wage premium for workers under age 40 with and without chronic conditions

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.006***	-0.005**	-0.000
	(0.002)	(0.002)	(0.001)
Observations	1190214	1190214	1190214
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.022***	-0.021***	-0.003*
	(0.003)	(0.003)	(0.001)
Observations	779191	779191	779191
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

Notes: This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions for workers under age 40. In particular, it presents the estimated parameters from Equation (2) on the subsample of workers under age 40. The dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.15: Probability of working at a foreign firm for workers above age 40

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.017***	-0.015***	-0.006
	(0.004)	(0.004)	(0.004)
Observations	904956	904956	904956
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.068***	-0.059***	-0.047***
	(0.016)	(0.015)	(0.014)
Observations	689285	689285	689285
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table shows the parameter estimates of Equation 5 by restricting the sample to workers older than 40 years. The dependent variable is a dummy showing whether worker i is working at a foreign owned firm in time t. In column (1), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.16: Probability of working at a foreign firm for workers under age 40

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.013***	-0.011***	0.001
	(0.004)	(0.004)	(0.004)
Observations	1190214	1190214	1190214
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.041***	-0.036***	-0.017**
	(0.008)	(0.008)	(0.007)
Observations	779191	779191	779191
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table shows the parameter estimates of Equation 5 by restricting the sample to workers under 40 years. The dependent variable is a dummy showing whether worker i is working at a foreign owned firm in time t. In column (1), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.5 Severance payments

A potential concern with our estimates is that the payments received by the worker in the last year of their job may include severance payments, which may also differ by firm type (see Section 3.2.3), potentially introducing a bias in the estimated CHC penalty. To handle this issue, we re-run the wage regressions by excluding the last year of the worker's spell.

Appendix Table C.17 reports the main wage specification (similar to Table 3) and Appendix Table C.18 the results for the domestic-foreign gap (similar to Table 6). The results are very similar to the main specification.

Table C.17: CHC wage penalty on the subsample of incumbent workers

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.056***	-0.052***	-0.017***	-0.032***	-0.016***
	(0.005)	(0.005)	(0.001)	(0.002)	(0.001)
Observations	1385359	1385359	1385359	1385359	1385359
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.143***	-0.128***	-0.013***	-0.063***	-0.010***
	(0.011)	(0.009)	(0.002)	(0.003)	(0.002)
Observations	934730	934730	934730	934730	934730
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: This Table shows the conditional wage gap between workers having CHC and those without such conditions on the subsample of incumbent workers. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4) firm fixed effects, while in column (5) we have both worker and firm fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.18: Foreign-Domestic difference in the CHC wage penalty on the subsample of incumbent workers

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.040***	-0.034***	-0.010***	-0.021***	-0.011***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Foreign=1	0.501***	0.489***	0.137***	0.016*	0.014**
	(0.021)	(0.020)	(0.019)	(0.009)	(0.006)
CHC=1 × Foreign=1	-0.015	-0.021**	-0.012***	-0.021***	-0.008**
	(0.009)	(0.009)	(0.004)	(0.005)	(0.004)
Observations	1385359	1385359	1385359	1385359	1385359
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.108***	-0.091***	-0.008***	-0.045***	-0.006**
	(0.012)	(0.010)	(0.003)	(0.004)	(0.003)
Foreign=1	0.369***	0.358***	0.092***	0.011	0.009
	(0.025)	(0.025)	(0.012)	(0.007)	(0.008)
CHC=1 × Foreign=1	-0.024*	-0.035***	-0.008*	-0.034***	-0.007
	(0.014)	(0.012)	(0.004)	(0.006)	(0.005)
Observations	934730	934730	934730	934730	934730
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: The Table shows conditional wage differences between CHC and other workers in foreign-owned and domestic-owned firms among incumbent workers. In particular, it presents coefficient estimates from Equation (6) on the subsample of incumbent workers, in which the dependent variable is the daily wage of worker i in year t and the variables of interest are the CHC status of the worker, whether the firm was foreign-owned, and their interaction. Of special interest is the coefficient of the interaction, which shows the difference in the CHC penalty between foreign- and domestic-owned firms. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5) both worker and firm fixed effects are included. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.6 People with disability benefits

Hungary operates a disability benefit system that provides both payment for disabled workers and incentives for firms to employ such workers (see Section 2.1). As disabled status is a choice variable to some extent, we ignore it in the main analyses. In this Appendix Section, we present some descriptive statistics about disability status and and we also re-estimate our main regressions when excluding such workers from the sample.

As a first step, we identify workers who receive disability benefits, rehabilitation benefits or disability-related pensions and define anyone receiving any of these benefits as having a disabled status.

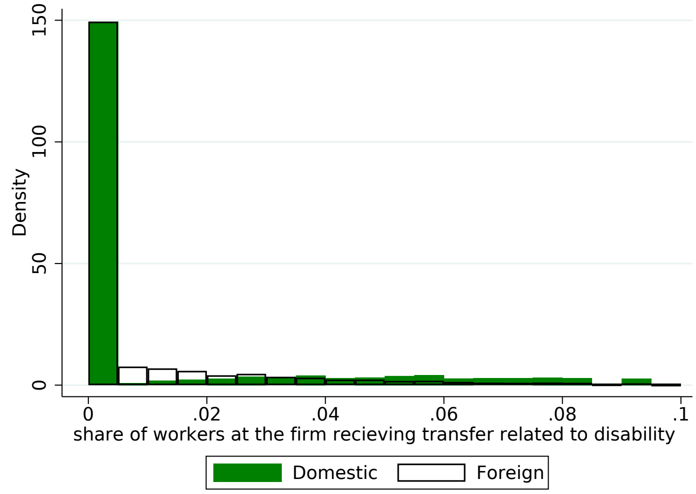
Figure C.8 shows the distribution of the share of such workers in the labor force across firms. A large share of firms do not employ such workers ar all, and few firms employ more than 10%. Similarly to people with CHC in general, foreign firms tend to employ a lower share of such workers. Also, importantly, there is no bunching around the 5% threshold under which firms need to pay "rehabilitation contribution" (see Section 2.1). This is in line with the findings of Krekó and Telegdy (2025) who show that firms do not prioritize meeting this quota.

Figure C.9 shows the distribution of workers across four categories: i) working, not disabled; ii) working, disabled; iii) not working, not disabled; iv) not working, disabled. The Figure provides a number of conclusions. First, there is a strong correlation between disabled and CHC status, but it is far from perfect: many people we identify to suffer from CHC are not considered to be disabled and vice versa. Second, most people with a disabled status do not work: in most age groups, only around 20% of disabled people work.

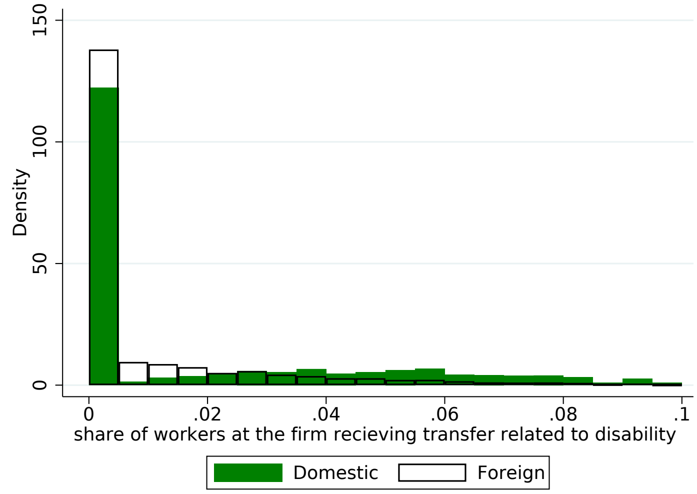
Table C.19 repeats Table 3 on the subsample of non-disabled status workers. The wage penalty when not controlling for worker fixed effects is substantially smaller compared to the main sample, but still large and significant. The worker fixed effects regressions yield similar results to the main regression. Including firm fixed effects shows that there is no sorting for men, but that sorting is significant for women, explaining about 40% of the CHC penalty. In line with no sorting for men, there is no gap in the probability of working for foreign firm in this subsample (see Table C.21, similar to Table 5), suggesting that sorting is stronger for men with disability benefits. This is in line with domestic firms appreciating the incentives for employing these men more, but can also imply that people with CHC in these firms are more likely to apply for a disabled status. For women, there is a 1 percentage point gap in the share of working at foreign firms, again substantially smaller compared to the main results.

While sorting is weaker in this sample, the difference in the CHC penalty between foreign and domestic firms is somewhat larger (Table C.22, similar structure to Table 6). The estimated difference in the penalty is 4 percentage points for men and 6 percentage points for women when worker fixed effects are not included and 1-1.5 with worker fixed effects.

Figure C.8: Share of workers receiving disability benefits by the ownership status of the firm



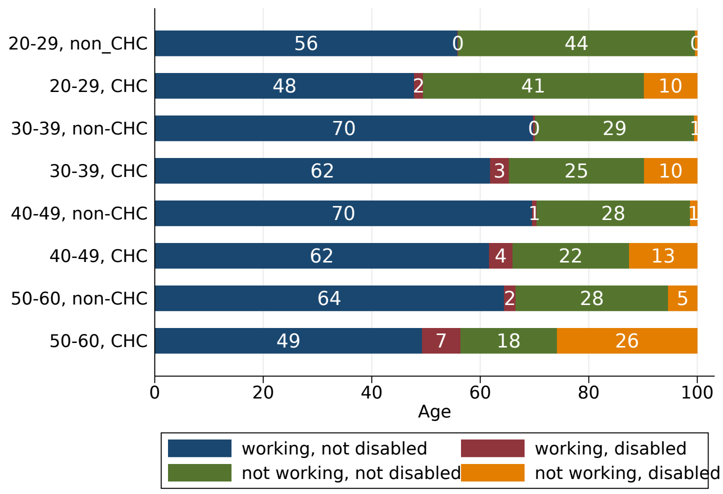
(a) All firms



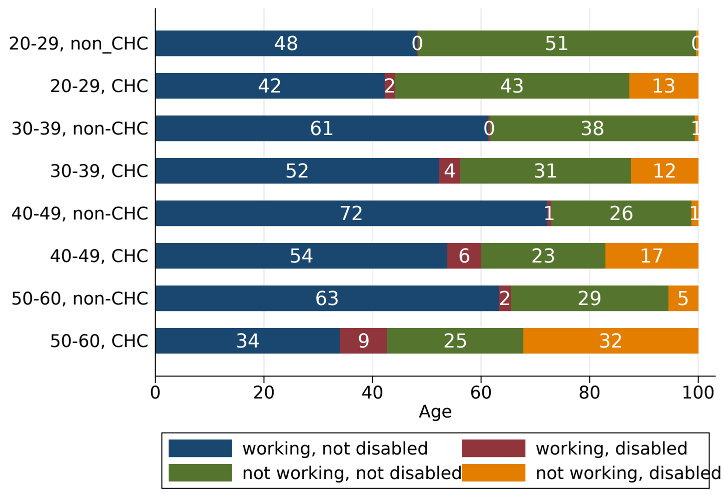
(b) Firms with more than 25 employees

Note:

Figure C.9: Labor market status by gender, age and disability benefits status for those with and without CHC



(a) Male



(b) Female

Note: This Figure shows the share of individuals who are working – including self-employed and public workers for each age group by CHC status and disability benefit status. For the purpose of this analysis, we use all observations in our population sample aged between 20-60, including those that never worked.

Table C.19: CHC wage penalty - excluding those receiving disability benefits

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.023***	-0.022***	-0.012***	-0.021***	-0.011***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)
Observations	2050758	2050758	2050758	2050758	2050758
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.078***	-0.070***	-0.005***	-0.043***	-0.004**
	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)
Observations	1419363	1419363	1419363	1419363	1419363
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: This Table shows the conditional wage gap between workers having CHC and those without such conditions for workers who do not receive disability related benefits. In particular, it presents the estimated parameters from Equation (2) on the subsample of workers who do not receive and kind of disability related benefits, in which the dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4) firm fixed effects, while in column (5) we have both worker and firm fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.20: CHC penalty in firm-specific wage premium - excluding those receiving disability benefits

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	0.003**	0.003***	-0.001
	(0.001)	(0.001)	(0.001)
Observations	2050758	2050758	2050758
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.010***	-0.008***	-0.001
	(0.002)	(0.002)	(0.001)
Observations	1419363	1419363	1419363
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES

Notes: This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions for workers who do not receive disability related benefits. In particular, it presents the estimated parameters from Equation (2) on the sub-sample of workers who do not receive and kind of disability related benefits. The dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.21: CHC penalty in the probability of working at a foreign-owned firm - excluding workers receiving disability benefits

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	0.001	0.001	0.006**
	(0.002)	(0.002)	(0.002)
Observations	2050758	2050758	2050758
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.012**	-0.009*	0.002
	(0.005)	(0.005)	(0.004)
Observations	1419363	1419363	1419363
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES

Notes: The Table shows the conditional gap in the probability of working at a foreign-owned firm between workers with CHC and other workers, conditional on working for workers who do not receive disability benefits. In particular, the table shows parameter estimates of Equation (5) on the subsample of workers who do not receive any kind of disability related benefits. The dependent variable is a dummy showing whether worker i is working at a foreign-owned firm in time t, and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, and a set of age dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.22: Foreign-Domestic difference in the CHC wage penalty - excluding workers receiving disability benefits

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.004	-0.002	-0.004	-0.009***	-0.007***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Foreign=1	0.479***	0.463***	0.179***	0.019**	0.014*
	(0.019)	(0.019)	(0.010)	(0.009)	(0.008)
CHC=1 × Foreign=1	-0.036***	-0.039***	-0.015***	-0.023***	-0.008***
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)
Observations	2050758	2050758	2050758	2050758	2050758
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.045***	-0.036***	0.001	-0.026***	-0.002
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Foreign=1	0.360***	0.346***	0.132***	0.013**	0.010
	(0.022)	(0.022)	(0.008)	(0.007)	(0.007)
CHC=1 × Foreign=1	-0.054***	-0.059***	-0.010***	-0.031***	-0.003
	(0.007)	(0.006)	(0.004)	(0.004)	(0.003)
Observations	1419363	1419363	1419363	1419363	1419363
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES

Notes: The Table shows conditional wage differences between CHC and other workers in foreign-owned and domestic-owned firms for those who do not receive disability workers. In particular, it presents coefficient estimates from Equation (6) on the subsample of workers do not receiving disability related benefits, in which the dependent variable is the daily wage of worker i in year t and the variables of interest are the CHC status of the worker, whether the firm was foreign-owned, and their interaction. Of special interest is the coefficient of the interaction, which shows the difference in the CHC penalty between foreign- and domestic-owned firms. In column (1), we control for a set of year dummies, 1-digit industry dummies, and age category dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5) both worker and firm fixed effects are included. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.7 Controlling for occupation

This section investigates how robust results are when controlling for occupation. In the main specification, we don't control for the worker's occupation because it may be a bad control – i.e. affected by CHC status, and different types of firms may use different occupation structures. At the same time, wages differ across occupations, therefore, it may also be a confounder.

To assess the robustness of our results to this, we re-estimate the main specifications while controlling for 2-digit ISCO occupation codes (Appendix Table C.23). Consistent with our primary findings, workers with CHCs remain significantly less likely to be employed at foreign-owned firms than their healthy counterparts, even after accounting for occupational differences (Appendix Table C.23).

Turning to wage outcomes, we find that workers with CHCs receive significantly lower wages than those without CHCs, even within the same occupational category (Appendix Table C.24). Among male workers, the ownership-specific wage penalty disappears in specifications that do not account for worker selectivity. As highlighted in the main analysis, much of the observed ownership differential in wage penalties appears to be driven by worker-level selection (Appendix Table C.26).

Table C.23: CHC penalty in the probability of working at a foreign-owned firm by taking into account occupational differences

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.011***	-0.009***	-0.003
	(0.004)	(0.004)	(0.003)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES
Occupation	YES	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.051***	-0.045***	-0.034***
	(0.011)	(0.011)	(0.010)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE proxy	NO	NO	YES
Occupation	YES	YES	YES

Notes: The Table shows the conditional gap in the probability of working at a foreign-owned firm between workers with CHC and other workers, conditional on working. In particular, the table shows parameter estimates of Equation (5) by controlling for occupation. The dependent variable is a dummy showing whether worker i is working at a foreign-owned firm in time t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, a set of age dummies, and 2-digit occupation dummies. In column (2), we add tenure and its square to the list of control variables. In column (3), we also add our proxy for worker productivity, the worker-specific premium estimated from an AKM model in a previous regression (see more details in Section 3.2.4). Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.24: CHC wage penalty by taking into account occupational differences

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.035***	-0.032***	-0.012***	-0.021***	-0.011***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Observations	2095170	2095170	2095170	2095170	2095170
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES
Occupation	YES	YES	YES	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.074***	-0.067***	-0.006***	-0.032***	-0.004**
	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Observations	1468476	1468476	1468476	1468476	1468476
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES
Occupation	YES	YES	YES	YES	YES

Notes: This Table shows the conditional wage gap between workers having CHC and those without such conditions by taking into account occupational differences. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the log daily wage of worker i in year t and the main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, age category dummies, and 2-digit occupation dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4) firm fixed effects, while in column (5) we have both worker and firm fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.25: CHC penalty in firm-specific wage premium by taking into account occupational differences

(a) Panel A: Men

	(1)	(2)	(3)
CHC=1	-0.003	-0.002	-0.001**
	(0.002)	(0.002)	(0.001)
Observations	2095170	2095170	2095170
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES
Occupation	YES	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)
CHC=1	-0.021***	-0.019***	-0.002***
	(0.004)	(0.004)	(0.001)
Observations	1468476	1468476	1468476
Year	YES	YES	YES
Industry	YES	YES	YES
Age	YES	YES	YES
Tenure	NO	YES	YES
Worker FE	NO	NO	YES
Occupation	YES	YES	YES

Notes: This Table shows the conditional gap in firm-specific premium between workers having CHC and those without such conditions by taking into account occupational differences. In particular, it presents the estimated parameters from Equation (2), in which the dependent variable is the firm specific fixed effect estimated form an Abowd et al. (1999) AKM model described in Section A.2. The main explanatory variable is the CHC status of the worker. In column (1), we control for a set of year dummies, 1-digit industry dummies, age category dummies, and 2-digit occupation dummies.. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.26: Foreign-Domestic difference in the CHC wage penalty by taking into account occupational differences

(a) Panel A: Men

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.034***	-0.029***	-0.003	-0.021***	-0.006***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Foreign=1	0.400***	0.391***	0.174***	0.018**	0.015**
	(0.015)	(0.015)	(0.010)	(0.008)	(0.007)
CHC=1 × Foreign=1	0.006	0.002	-0.015***	-0.001	-0.009***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Observations	2095170	2095170	2095170	2095170	2095170
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES
Occupation	YES	YES	YES	YES	YES

(b) Panel B: Women

	(1)	(2)	(3)	(4)	(5)
CHC=1	-0.045***	-0.037***	-0.001	-0.021***	-0.002
	(0.007)	(0.007)	(0.002)	(0.003)	(0.002)
Foreign=1	0.324***	0.317***	0.128***	0.018***	0.010
	(0.017)	(0.018)	(0.008)	(0.007)	(0.007)
CHC=1 × Foreign=1	-0.028***	-0.032***	-0.008**	-0.022***	-0.004
	(0.009)	(0.008)	(0.004)	(0.004)	(0.003)
Observations	1468476	1468476	1468476	1468476	1468476
Year	YES	YES	YES	YES	YES
Industry	YES	YES	YES	NO	NO
Age	YES	YES	YES	YES	YES
Tenure	NO	YES	YES	YES	YES
Worker FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	YES
Occupation	YES	YES	YES	YES	YES

Notes: The Table shows conditional wage differences between CHC and other workers in foreign-owned and domestic-owned firms by taking into account occupational differences. In particular, it presents coefficient estimates from Equation (6), in which the dependent variable is the daily wage of worker i in year t and the variables of interest are the CHC status of the worker, whether the firm was foreign-owned, and their interaction. Of special interest is the coefficient of the interaction, which shows the difference in the CHC penalty between foreign- and domestic-owned firms. In column (1), we control for a set of year dummies, 1-digit industry dummies, age category dummies and 2-digit occupation dummies. In column (2), we also add tenure and its square to the model. In column (3), we add worker fixed effects, in column (4), firm fixed effects, while in column (5), both worker and firm fixed effects are included. Standard errors are clustered at the firm level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.