Health Shocks, Human Capital, and Labor Market Outcomes*

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Abstract

Health, human capital, and labor market outcomes are linked through complex connections that are not fully understood. We explore these links by estimating a flexible yet tractable dynamic model of human capital accumulation in the presence of health shocks using administrative data from Chile. We find that (i) human capital mitigates the negative labor market effects of health events, (ii) these alleviating effects operate through channels involving occupational choice, the frequency of exposure to health events, and access to health care, and (iii) the effect of health shocks on labor market outcomes is heterogeneous across industries and types of diagnoses.

Keywords: health shocks, hospitalizations, labor market outcomes, earnings, human capital, education.

JEL codes: I10, I26, J22, J24.

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1 Introduction

Ample evidence documents a positive correlation between human capital, health status, and labor market outcomes. One strand of literature shows the positive effects of education on earnings and other labor market outcomes (see Card, 1999, for a review). A second set of studies supports positive effects of health on earnings and labor market attachment (see Currie and Madrian, 1999, for a review). Furthermore, Cutler et al. (2010) and Lleras-Muney (2005), among others, document the links between health and education. The complex relationships between health, human capital, and labor market outcomes are, however, not fully understood. Specifically, how human capital interacts with the potential negative labor market effects of adverse health events is a fundamental question that remains open. That is, human capital could contribute not only to raising the earnings and employment possibilities of workers but also to decreasing the adverse effects of health events. Our paper contributes to disentangling the interaction between health, human capital, and labor market outcomes.

We provide new evidence showing how higher levels of education may mitigate the negative consequences of health events for labor market outcomes. To this end, we develop and estimate a model that can capture these complex interactions in a unified and tractable framework. We use administrative earnings and hospital data from Chile to estimate the model, which allows us to overcome several of the biases arising from the use of survey data. We show that (i) human capital plays an attenuating role in the negative labor market effects of health events, (ii) these alleviating effects operate through channels involving occupational choice, the frequency of exposure to health events, and access to health care, and (iii) the health shock impact on labor market outcomes is heterogeneous across industries and types of diagnoses.

To interpret the connection between human capital, health status, and labor market outcomes, we provide a theoretical model that links these three variables in a dynamic framework. Specifically, monthly earnings are a function of a worker's human capital, which in turn depends on his employment history and past and present health shocks. Negative health events affect human capital depending on the type of health shock experienced, the type of job currently held, and the level of health care that the worker can access. This flexible yet tractable framework allows us to account for several pathways through which human capital and health shocks may affect earnings. This framework can potentially be applied to other data sources and types of health measures, thereby facilitating a comparison of our results with those from other settings.

We estimate this model using monthly earnings data for approximately 100,000 male Chilean workers that span almost 10 years matched with the universe of hospital discharge records, allowing us to identify sudden changes in workers' health status ("health shocks"). We include a rich set of interactions between health shocks, educational attainment, job type, and health insurance coverage to model these relationships flexibly.

Using health events that require hospitalization as a proxy for changes in health status yields a direct indicator of a relevant change in the health status of an individual. Many existing studies only observe (self-reported) measures of health status, treating changes in health in a somewhat arbitrary way. Moreover, health events may be endogenous to labor market outcomes. To deal with potentially endogenous changes in health, we combine three strategies. First, we only include individuals in the treatment group who were hospitalized but were not hospitalized in the preceding year. In that way, we increase the probability of health shocks not being anticipated by workers, which is important to ensure that they did not change their labor supply before the occurrence of the shock. Second, we use propensity score weighting to equalize the pre-shock employment trends between the treatment and the control group. Third, we account for time-invariant unobservable differences between individuals with and without health shocks by using the difference-in-differences and fixed-effect strategies. Hence, we are able to analyze the labor market effects of a diverse range of health shocks while ensuring that our results are not biased by observable and unobservable heterogeneity.

Our paper relates to the literature exploring (i) the effects of human capital on earnings, (ii) the effects of education on health, and (iii) the impact of health on labor market outcomes. In general, those three issues have been studied in separate frameworks. We contribute to these strands of literature by providing empirical evidence on how education, health, and labor market outcomes interact in a unified framework: concretely, the extent to which education mitigates the labor market effects of health shocks and the possible pathways that explain this relationship.

Human capital affects the existence and frequency of adverse health events – such as accidents, heart attacks, or cancer diagnoses – through three main channels. First, better-educated individuals tend to engage in fewer unhealthy behaviors, such as smoking (e.g., Jürges, Reinhold, and Salm, 2011) and behaviors leading to obesity (e.g., Brunello, Fabbri, and Fort, 2013).[1] Second, individuals with higher levels of education are more likely to work in white-collar occupations (e.g., Autor and Handel, 2013; Speer, 2017), which are less intensive in manual tasks and thus less likely to cause workplace accidents or exposure to unsafe conditions (e.g., Guardado and Ziebarth, 2016).[2] Finally, better-educated individuals may have better access to health care or be more efficient producers of health (e.g., Lange, 2011; Jeon and Pohl, 2017).

Conditional on education, health also affects labor market outcomes. While the effects of education on health and of health on labor market outcomes are well documented, evidence concerning the way in which education mitigates the negative consequences of health shocks for employment and earnings is limited. Closest to our paper, Lundborg, Nilsson, and Vikström (2015) investigate how the labor market effects of adverse health events vary by education in Sweden in a purely empirical analysis. Our paper therefore contributes to the understanding of how education and health interact in their effects on labor market outcomes and digs deeper into the underlying factors behind these relationships.

[1] See Cutler and Lleras-Muney (2010) for an overview of the possible pathways between education and health behaviors.

[2] Workplace-related stress may also contribute to lower health status. While stress may not necessarily be associated with blue-collar occupations, Johnson et al. (2005) find that stress is overall more prevalent in occupations that require lower levels of education.

By using administrative data, we avoid the common problems in the use of survey data to estimate the effect of health status on labor market outcomes, such as non-random measurement error, reverse causality, and justification bias, which can lead to endogenous health measures (e.g., Bound, 1991; Crossley and Kennedy, 2002; Baker, Stabile, and Deri, 2004).[3] Another issue that arises when using survey data relates to the timing of changes in health status and labor market outcomes, that is, the difficulties involved in measuring which change occurred first. This problem persists even with panel data due to the existence of a recall bias.

To address the endogeneity problem arising from the health measures, several methodologies are explored in the literature. Bound, Stinebrickner, and Waidmann (2010), French (2005), and Gallipoli and Turner (2009) impose an exogenous structure on the relationship between health and labor market outcomes, which allows them to estimate causal effects. At the other end of the spectrum, Mohanan (2013) and Thomas et al. (2006) use experimental and quasi-experimental variation in treatment (iron supplements) and health shocks (bus accidents), respectively, to estimate a reduced-form effect of health on the labor supply and household finances. **?** use an event study framework to investigate the economic effects of hospitalizations.

The difficulty in establishing causal pathways from health to labor market outcomes persists even when using administrative data. For instance, Dano (2005), Jeon (2017), and Lundborg, Nilsson, and Vikström (2015) use annual earnings reported on tax returns as a measure of the intensive labor supply margin. This type of data complicates the assessment of the timing of events, since lower earnings in a given year may result from a labor market shock that precedes a change in health status; thus, reverse causality cannot be ruled out. In contrast, our paper is the first to use monthly earnings data in this context. Therefore, we are able to rule out most cases of reverse causality, since in our data set we can identify the exact date when a health shock occurred.

Our paper is among the first to estimate the effect of health shocks on economic outcomes in an emerging or developing economy. The only exception is Mohanan (2013), who uses a small sample from one Indian village. Like many similar countries, Chile provides an interesting setting for studying the effect of health and education on labor market outcomes for two reasons. First, a substantial fraction of the workforce is employed in jobs that involve mostly manual tasks. The effect of disabling health events is therefore more pronounced than in a setting in which most workers have desk jobs. Second, the education levels are low, with half the workforce not having a high school degree. Therefore, the potential gains from increasing education are large if better-educated individuals can cope more easily with health shocks.

Our results are policy relevant. They highlight that education not only improves the labor market outcomes of workers but also allows them to mitigate the harmful effects of health shocks. Policies that aim to increase education levels therefore have the added potential benefit of positively affecting labor market outcomes through the health channel. At the same time, other factors, such

[3] Justification bias refers to the bias introduced when respondents list their health as the reason for labor market outcomes such as early retirement. While some individuals retire for health reasons, it is also a socially acceptable reason and may therefore be over-reported in surveys, as first noted by Bazzoli (1985).

as occupational choice and health care, also play an important role that policy makers should take into account when designing education policies.

The rest of this paper is organized as follows. In Section 2, we provide a brief background on the Chilean education system, labor market, health care system, and social safety net. We then describe the data used for the empirical analyses in Section 3 and discuss our empirical methodology, including propensity weighting, in Section 4, in which we also provide some initial graphical evidence on the effect of health shocks on labor market outcomes and the way in which these effects are influenced by educational attainment. Section 5 contains our model, which relates health shocks to human capital accumulation and the latter to labor market outcomes, and the estimation results based on this model are presented in Section 6. We conclude in Section 7.

2 The Institutional Background

In this section, we briefly describe the features of the Chilean education system, labor market, health care system, and social safety net that are relevant to our analysis.

2.1 The Chilean Education System and Labor Market

The Chilean primary and secondary education system consists of public schools financed by government subsidies, free and fee-charging voucher schools, and private schools financed exclusively by parents. Overall, public schools, voucher private schools, and private schools have represented 36 percent, 55 percent, and 9 percent, respectively, of the total enrollment in primary and secondary education in recent years. The higher education system is composed by three types of institutions: universities, professional institutes, and technical schooling centers. Universities are divided between "traditional" universities (public and private), which belong to the Universities of the Rectors' Council, and purely private institutions. Professional institutes are private institutions offering professional degrees that are not offered by universities. Technical schooling centers are also private institutions offering technical degrees only. Enrollment in universities represents 57 percent of the total number of students who attend higher education, whereas enrollment in professional institutes and technical schooling centers is 32 percent and 11 percent, respectively.

Labor relations in the formal sector are ruled by two types of contracts: written contracts (86 percent) and verbal contractual agreements (14 percent). Regarding the duration of the contractual relationship between workers and employers, 73 percent of the contracts have an indefinite term, whereas 27 percent are fixed-term contracts. Informality represents around 30 percent of the total employment. A large share of the workers in the informal sector (70 percent) does not make contributions to the social security system. Informality is mainly concentrated among domestic service personnel, 45.5 percent of whom operate under a verbal contractual agreement with their employer. The share of part-time work in the Chilean labor market is relatively small. However, part-time work rose from 4.7 percent in 2000 to 16.8 percent in 2015. On the other hand, the share of workers who usually work 60 hours or more weekly reached 8.6 percent, well above the OECD average. The hourly earnings in Chile are the third lowest in the OECD, and a substantial share (14.8 percent) of working-age individuals live in poor households. Lastly, female labor force participation is relatively low compared with that in the OECD countries, although a closing gap is observed; in 1996, the female employment rate was about 31 percent, whereas it was about 45 percent by the end of 2016 .

2.2 The Chilean Health Care System

Chile has a dual health care system. The *Fondo Nacional de Salud* (FONASA) is the public health insurance plan run by the Ministry of Health. In addition, there are several *Instituciones de Salud Previsional* (ISAPREs), which are private plans that act as alternatives to the FONASA.[4] Employees are enrolled in the public FONASA system by default but can opt out and join an ISAPRE. In 2009, about 74 percent of the members of the Chilean population were enrolled in the FONASA and about 16 percent were members of an ISAPRE.

FONASA beneficiaries are classified into four groups. Group A beneficiaries are individuals who lack resources or formal employment, individuals who receive welfare or government pensions, pregnant women, and children under six years of age. Group A beneficiaries obtain free health care from all the providers in the public network. They do not have to pay a premium for enrollment or make any copayments to public providers. About 36 percent of FONASA beneficiaries are classified into group A. The remaining 64 percent are employees who contribute 7 percent of their salary to the insurer, up to a monthly salary ceiling. They are classified into groups B, C, and D according to their monthly income. FONASA members pay copayments for health care services that vary between 0 and 20 percent depending on their earnings relative to the minimum wage and their number of dependents. Beneficiaries can only obtain health care in public facilities or private facilities that have an agreement with the FONASA at these copayment levels.

Individuals who opt out of the FONASA can choose among 13 ISAPRE plans that are run by private insurance providers. Each plan offers different levels of coverage and different treatment options with different premiums. ISAPRE plans are more expensive than FONASA plans but provide access to better health care. ISAPREs collect the mandatory contribution of 7 percent, but members can pay an additional premium amounting to 2.2 percent of their income on average. ISAPRE beneficiaries almost exclusively use private providers for two main reasons. First, by law, most public hospitals do not make hospital beds available to non-FONASA beneficiaries. Second, ISAPRE beneficiaries avoid using public providers, because they can obtain better-quality and more timely care through their regular coverage. Overall, ISAPRE plans are more expensive than FONASA plans but provide access to better health care with shorter waiting times. In our analysis, we therefore use ISAPRE membership as a proxy for better access to and higher quality of health care.

[4] As a third option, some workers are enrolled in plans that are sponsored by firms or other special groups.

2.3 Disability Benefits

Chilean workers who are temporarily or permanently unable to work due to a health shock may be eligible for disability benefits. Permanently disabled workers receive benefits depending on the decrease in their earnings-generating capacity, as determined by a medical committee.[5] In addition, workers who are enrolled in the social security system are insured against temporary disability through the *Subsidio de Incapacidad Laboral* (SIL).[6]

Labor incapability is defined by the Chilean law as the impossibility for the worker to offer her services as a consequence of medically prescribed leave. The SIL covers illnesses and injuries that are work related and due to other issues. In the case of non-work-related illnesses, employees receive 100 percent of their wage up to about 2,000 dollars. The benefits for workplace accidents and occupational illnesses equal 100 percent of the average monthly wage received in the 3 calendar months before the leave and are paid for 52 weeks at most but can be extended to 104 weeks.

In our data, we do not observe whether workers receive any disability benefits after a health shock, but, since they are enrolled in the social security system, they are eligible. Our analysis focuses on market earnings and, thus, it is possible that we overestimate the negative effect of health shocks on the total income of incapacitated workers. However, the latter issue does not apply to the extensive labor supply margin, that is, the employment status, which we also consider in our empirical analysis.

3 Data and Summary Statistics

3.1 Data Sources

We combine administrative data on monthly earnings and hospital stays from two sources. The earnings data come from the Chilean unemployment insurance system, *Seguro de Cesantía* (SC). The Chilean government enacted the SC as an addition to the existing social protection net in 2002. Participation in SC is mandatory for all workers who have begun a new employment relationship since October 2002. The monthly contributions amount to 3 percent of the employee's salary. Firms therefore report their employees' salaries to the SC administration on a monthly basis. Our data consist of monthly observations of individual earnings, employment status (defined by non-zero earnings), and the employer's industry. In addition, the SC records employees' educational attainment, sex, year and month of birth, and the date when they became affiliated with the SC. Our data set includes the universe of SC records from October 2002 to December 2011. Monthly

[5] If a worker suffers a reduction of 15 to 40 percent in her earnings-generating capacity, she receives a one-time indemnity. If the reduction in the earning capacity is between 40 and 70 percent, the injured worker receives a monthly pension amounting to 35 percent of her base salary. Lastly, a worker who becomes totally disabled is entitled to a monthly pension of 70 percent of her base wage.

[6] Employers contribute 0.95 percent of the worker's wage, and employees contribute up to 3.4 percent of their wage depending on the riskiness of their activity.

earnings are deflated with 2009 as the base year and expressed in 1,000 Chilean pesos (CLP).[7] There are about 4.2 million men in this data set.[8]

To measure health shocks, we use the universe of Chilean hospital discharge records for the years 2004 to 2007. For each hospital stay, we observe the ICD-10 diagnosis code, the patients health insurance provider, and the exact dates of admission and discharge. The Ministry of Health of Chile collects these records from all the hospitals in the country. We classify a hospital stay by major type of diagnosis according to the first letter of the ICD-10 code.[9] For estimation purposes, we select the ten most frequent types of diagnosis and lump the remaining ones into an "other" category. There are about 1.4 million men in this data set.

Both data sets contain individuals' *Rol Único Tributario* (RUT), which acts as a unique identifier for tax and other official purposes in Chile. We match individuals' monthly employment records with the hospital records on RUT and sex.[10] We restrict the sample to men born between 1950 and 1980 and exclude men who became affiliated with the SC after December 2003 to ensure that we can observe a sufficiently long employment history before the health shock. In addition, we drop men who were employed for fewer than 24 months between 2002 and 2011 to eliminate individuals with weak ties to the formal labor market. Men who had a hospital stay in 2004 are dropped from the sample. This restriction implies that hospitalization is a true health shock in the sense that an individual experienced no severe health events in the previous year.

To make the estimation more manageable, we draw a random 10 percent sample from the potential control group, that is, men without a hospital stay. The final estimation sample consists of 46,485 men with a hospital stay and 55,089 control group members. To compare treatment and control group individuals before and after a health shock in our event study framework in Section 4, we have to assign a placebo health shock month to members of the control group. We do so by randomly assigning a number between 1 and 36 to each man without a hospital stay, which corresponds to the months between January 2005 and December 2007. We can then compare the labor market outcomes of men who experienced a health shock in a given calendar month with control group members who were randomly assigned to the same month.

3.2 Summary Statistics

We now describe the data that we use for estimation. Columns (1) and (2) of Table 1 show the summary statistics for individual characteristics by treatment status. The two groups are roughly similar, with the treatment group being slightly older and less educated. As in other emerging economies, the average levels of education of the workforce during the last decades are low in Chile,

[7] 1,000 CLP equals roughly 2 US dollars.

[8] Since the earnings data stem from SC records, only employees in the formal workforce are included. There are about 5.6 million men aged 15 to 64 in Chile, so we capture the majority of this population.

[9] See http://www.icd10data.com/ICD10CM/Codes for a list of all the ICD-10 codes.

[10] The data sets were merged on a secure server of the Chilean Ministry of Finance, and only deidentified data were made available to the authors. This project was granted IRB approval by the General Research Ethics Board of Queen's University.

with over half of the sample not having a high school degree. The labor market status in the month before the health shock ($t = -1$) does not differ substantially between the treatment and the control group either. In addition to employment in $t = -1$, we categorize employees by "blue collar" and "white collar" industry and within-industry earnings tercile. We observe no significant differences in these dimensions between individuals in the treatment and control groups.[11]

To document the relationship between health shocks, education, and labor market outcomes, we first summarize the health shock frequencies and characteristics by education. Panel A in Table 2 shows the fraction of men with different levels of educational attainment who were hospitalized between 2005 and 2007, both overall and by the industry in which they were employed in the month before the health shock. We observe a gradient across individuals' education, with 8.2 percent of men without a high school degree, 7.5 percent of high school graduates, and 6.9 percent of those with post-secondary education experiencing a health shock between 2005 and 2007, respectively. This gradient mostly persists when conditioning on industry, although its magnitude varies across industries.

Panel B in Table 2 displays the distribution of health shock characteristics by education.[12] We observe that external health shocks, such as car and workplace accidents, are more frequent among less educated workers. On the other hand, those with a post-secondary education are more likely to suffer from diseases related to the digestive system. The severity of hospital stays, measured in days spent in the hospital, is higher for men with lower educational attainment. Specifically, the proportion of men staying for more than two weeks is double that of men without a high school degree compared with the post-secondary education group. This pattern applies to the initial hospital stay and to the sum of days spent in the hospital for the same diagnosis within one year of the initial health shock. Lastly, panel B of Table 2 reports the fraction of men with a health shock who are enrolled in the FONASA and an ISAPRE. While most men without a high school degree are enrolled in FONASA A or B due to their low income, almost half of those with post-secondary education are covered by an ISAPRE. Hence, there is a strong positive correlation between education and the quality of health insurance coverage.

Overall, Table 2 shows that higher education levels are associated both with fewer and with less severe health shocks. Hence, this descriptive evidence suggests that education lowers the propensity for health shocks, particularly more severe shocks. Moreover, the relationship between education and private insurance coverage suggests a possible pathway between human capital and labor market outcomes, as modeled in Section 5. We formally investigate in Section 6 whether higher educational attainment also has a protective effect in the sense that it leads to better labor market outcomes following a health shock independently of other factors.

[11] We assign each employee to an industry that tends to have more blue-collar or white-collar jobs as a proxy for occupation, which we do not observe directly. In addition, we use the earnings tercile within the two industry categories to capture different types of occupations.

[12] In the summary statistics displayed in panel B, we only include men who experienced at least one health shock.

Next, we describe the outcome variables to provide a sense of their magnitudes and some preliminary evidence regarding the effect of health shocks. We are interested in the effects of health shocks on both the extensive and the intensive labor supply margins. To measure the extensive margin, we use an indicator for whether an individual was employed in a given month. Since the data do not contain the hours worked, we use monthly earnings to capture the intensive margin. Lastly, we investigate the aggregate effect of health shocks on the individual's financial situation. To do so, we sum up the monthly earnings during the one or two years before and after the health shock, respectively, and divide them by the average monthly earnings of the corresponding group. Formally, we define

$$W_i^{S+} = \frac{\sum_{s=1}^{S} W_{i,s}}{\bar{W}^C_{g(i),0}} \quad \text{and} \quad W_i^{S-} = \frac{\sum_{s=-S}^{-1} W_{i,s}}{\bar{W}^C_{g(i),0}}, \tag{1}$$

where $W_{i,s}$ represents the monthly earnings of person i in month s, $s = -1$ denotes the month before the health shock, and $s = 1$ denotes the month after the health shock. In addition, $\bar{W}^C_{g(i),0}$ is the average monthly earnings in the month of the placebo health shock for control individuals belonging to group $g(i)$, the same group as person i (with $S = \{12, 24\}$). The groups are defined by age, education, and industry. Hence, we interpret W_i^{S+} and W_i^{S-} as the number of months' worth of earnings within one or two years compared with the average person in the group.[13]

Table 3 shows the average employment and earnings for the treatment and control groups before and after the health shock. We observe that between 70 and 75 percent of men are employed in any given month, with average monthly earnings around 240,000 and 340,000 pesos. We can also construct an unconditional DID estimate using this information. The last column in Table 3 shows that the effect of a health shock on employment equals about -3.1 percentage points, whereas the effect on monthly earnings equals $-19{,}300$ pesos or about 40 US dollars. These estimates do not account for any other factors but are suggestive of the potential negative effect of health shocks on employment and earnings. The preliminary inspection of the average earnings measure defined in equation (1) also suggests financial losses as a consequence of health shocks. Specifically, the average health shock leads to a loss of 0.39 average monthly earnings during the first year after the health shock and about 0.81 average monthly earnings during the 2 years following the health shock.

4 Empirical Strategy and Preliminary Evidence

In this section, we describe our empirical strategy and in particular the propensity score weighting method used for all the remaining empirical analyses. Then, we generate plots of the weighted labor market outcomes and provide the event study results to shed some light on the relationship between health shocks, education, and labor market outcomes and to motivate the theoretical model.

[13] For example, $W_i^{12^+} = 10$ would indicate that this person earns 10 months' worth of average monthly earnings in the group during the year following a health shock.

4.1 Overall Empirical Strategy

Estimating the effect of health shocks on labor market outcomes is challenging, because the health shocks may be endogenous. To mitigate this issue, we combine three strategies. First, we account for the fact that workers who experience health shocks may be observably different from their healthier peers. To control for selection on observables, we use propensity score weighting, which we describe in more detail in the following subsection. Second, some workers may be more likely to suffer a health shock than others due to unobserved factors. Assuming that these characteristics do not vary over time, we include worker fixed effects to control for unobserved heterogeneity.

Finally, similarly to **?**, we exploit the hospital data to construct measures for changes in health status that are likely to be unexpected by individuals and therefore constitute true health shocks. Since our hospital data encompass the universe of hospital admissions from 2004 to 2007, we can identify workers who were admitted to a hospital for the first time within a 12-month period. Specifically, we drop individuals with hospital admissions in 2004 and only use data from 2005 to 2007 (see Section 3.1). While it is possible that a worker's health deteriorates before being admitted to a hospital, a sudden decline in health that requires a hospital visit constitutes a change in his information set. Conditional on propensity score weighting and individual fixed effects, we can therefore view these unexpected health shocks as being close to randomly assigned.

4.2 Propensity Score Weighting

Here we describe our weighting procedure using the propensity score. The goal is to balance observed covariates that are predetermined at the time of the (placebo) health shock between the treatment group and the control group. Using monthly earnings data, we can account flexibly for labor market outcomes before the health shock. Hence, in addition to individual characteristics, such as age and education, we include employment, earnings, and industry up to one year before the health shock in the propensity score covariates.

Imbens (2015) stresses the importance of the design stage and in particular of the overlap in the support of the covariates included to build the propensity score. Following this insight, we check the overlap in the support of the covariates between the treatment group and the control group using normalized differences.[14] Column (3) in Table 1 shows the normalized differences for selected covariates, including the labor market status in the month preceding the health shock. They are all below 0.1 and hence well below the rule-of-thumb value of 0.25 suggested by Imbens and Wooldridge (2009). Therefore, the overlap between the treatment and the control group is satisfactory; individuals with and without health shocks do not appear to be very different even before weighting, including their pre-treatment outcomes. This similarity between the treatment

[14]The use of normalized differences to check the overlap is preferred to the use of t-statistics, because the former is independent of the sample size. The normalized difference for the covariate Z_k is defined as $\left(\bar{Z}_k^T - \bar{Z}_k^C\right) / \left[0.5\left(S^2_{Z_k^T} + S^2_{Z_k^C}\right)\right]^{1/2}$, where $\bar{Z}_k^T$ and $\bar{Z}_k^C$ are the sample mean of Z_k in the treatment and the control group, respectively, and $S^2_{Z_k^T}$ and $S^2_{Z_k^C}$ are the corresponding sample variances.

and the control group implies that we do not have to rely solely on propensity score weighting to equalize the observables between the two groups. Moreover, it lends support to the common trend requirement needed to implement a DID strategy. To estimate the propensity score of a health shock, we use a logit regression that includes the set of covariates shown in Table 1 and, in addition, the employment status for 12 months before the health shock and the industry of occupation in the month preceding the health shock.

After estimating the propensity score, we also check the overlap between the treatment and the control group by examining the distribution of the estimated propensity scores by treatment status. Figure 1, which displays kernel density estimates of the propensity score distribution, shows that the overlap is very good. In other words, the distribution of the estimated propensity of a health shock conditional on observables is almost identical in the treatment and control groups. The good overlap is further illustrated when we trim the sample to exclude treated individuals whose propensity score is below the minimum or above the maximum propensity score in the control group and vice versa. We only exclude 18 individuals out of over 100,000 due to this restriction.

While there are many possibilities to match treatment and control group members based on the propensity score, Busso, DiNardo, and McCrary (2014) show that using inverse propensity score weights (IPSW) leads to a relatively small bias if the overlap between the treatment and the control group is good. We therefore use the estimated propensity score to calculate the IPSW as follows:

$$\hat{w}_i^{ATET} = T_i + (1 - T_i)\frac{\hat{p}(Z_i)}{1 - \hat{p}(Z_i)}, \tag{2}$$

where $\hat{p}(Z_i)$ is the estimated propensity score conditional on covariates Z_i and $T_i = \{0, 1\}$ is the treatment indicator for having any health shock. We use the IPSW in equation (2) in all the regressions and other empirical analyses in the remainder of this paper.

4.3 Graphical Evidence

Using the propensity weights described in the previous subsection, we now provide graphical evidence showing how the effect of health shocks on labor market outcomes varies by educational attainment. Specifically, Figure 2 plots the monthly employment rates relative to the month of the (placebo) health shock for the treatment and control groups. The employment data are weighted by the IPSW as defined in equation (2), so we can interpret the vertical difference between the employment rates of the treatment and control groups as the time-varying ATET of a health shock.[15] First, we note that the propensity score weighting works very well, so the pre-treatment employment rates of the treatment and the control group are almost identical for each education category. Second, we find that health shocks have an immediate and substantial effect on the employment

[15] Here we aggregate all the types of diagnoses. However, the model-based regression results in Section 6 also explore specifications that treat health shocks as heterogeneous based on diagnosis.

rates. This negative effect decreases a little over time, but, even four years after the health shock, men in the treatment group are substantially less likely to be employed.

Finally, we can provide the first evidence regarding the role of education in the relationship between health shocks and labor market outcomes. Specifically, the employment rate of men without a high school degree falls by about 6 percentage points immediately after the health shock, while that of high school graduates and those with post-secondary education experience declines by 4 and 2 percentage points, respectively. Hence, this evidence is suggestive regarding the alleviating effect that education exerts on the employment effects of health shocks. In the next section, we explore the extent to which this education differential can be explained by other factors, such as an individual's health shock characteristics and industry.

In Figure 3, we plot the monthly log-earnings by treatment status and educational attainment. Hence, these graphs show the effect of health shocks on the intensive labor supply margin conditional on employment. In contrast to the extensive margin effects exhibited in Figure 2, the effect for all education groups is much smaller. Earnings fall by about 20 percent in the month of the health shock for men without a high school degree; however, in the months following the health shocks, the earnings of the treatment group catch up with the earnings of the control group. Overall, the evidence does not unveil a large long-term effect of a health shock on earnings conditional on employment. Instead, it seems that the medium- and long-term effects of a health shock occur at the extensive margin. In the case of individuals with a high school degree or post-secondary education, the initial drop in earnings is even smaller.[16]

Two important preliminary conclusions can be drawn from the evidence presented in Figures 2 and 3. First, the adjustment in men's labor supply in response to a health shock is mostly observed at the extensive margin. This finding suggests either that they stop working completely after hospitalization and return to work very slowly or that men who remain employed or only stop working for one month do not experience a long-term decline in earnings. In the regressions below, we investigate whether this pattern persists when we control for health shock characteristics and an additional set of covariates. Second, we find strong evidence for a mitigating effect of education. In other words, the negative effect of health shocks on the labor supply is mitigated in individuals with higher educational attainment. Notice that this protective effect of education can be triggered through a variety of indirect channels, for instance through the choice of a better-quality health insurance provider or through different types of jobs. The model introduced in the following section formalizes these channels, and the regression analysis performed in Section 6 allows us to disentangle some of the channels through which education creates the mitigating effect that we have documented in this section.

[16] The pre-treatment earnings of men with post-secondary education are not perfectly matched between the treatment and the control group due to the fact that we do not include earnings but only employment in the propensity score. The common trends assumption is still satisfied, however.

5 The Model

In this section, we develop a flexible yet tractable dynamic model that relates workers' human capital and health events to their earnings and employment. Specifically, we start out with a familiar Mincerian earnings equation. In this model, current earnings are determined by accumulated human capital. The latter evolves as a function of past worker-firm matches as well as health shocks and health care inputs. We also substitute employment status for earnings to capture the extensive labor supply margin. We add heterogeneity to the model by allowing the effect of health shocks to vary with the type of job, past health shocks, and access to health care.

5.1 The Model Set-Up

Consider an economy populated by N heterogenous workers and N heterogenous firms, each of which employs exactly one worker.[17] We denote by $i \in \mathcal{I}$ the index for workers and by $j \in \mathcal{J}$ the index for firms. Workers are endowed with an initial stock of human capital (or skills), $E_{i,0}$, and the human capital evolves over time, as specified below. Firms differ in the complexity of the service that they produce, which we denote by c_j.[18] Service complexity is fixed over time. Each period, workers are assigned to firms according to an exogenously given matching function: $c_j = s_t\left(E_{i,0}\right)$; therefore, at time t, workers with an initial stock of human capital of $E_{i,0}$ produce services of complexity c_j.[19] To simplify the notation, hereafter, we denote the matching function as $i = s_t^{-1}(j)$.

In addition, we denote by ω_i the unit price of skill i and by v_t the aggregate state of the economy at time t. We express the earnings of worker i at time t as a function of the unit price of her skill (ω_i), her stock of human capital ($E_{i,t}$), the state of the economy (v_t), and the equilibrium sorting (s_t):[20]

$$w_{i,t} = f\left(\omega_i, s_t^{-1}(j), v_t, E_{i,t}\right). \tag{3}$$

We assume that workers continue to build their skills during their working life according to the following linear technology:

$$E_{i,t} = E_{i,t-1} + g_{i,j,t} - \delta_{i,j,t}, \tag{4}$$

where $g_{i,j,t}$ is learning or the amount of skills that a worker of type i accumulates in firm j at time t, and $\delta_{i,j,t}$ is the loss of human capital that worker i experiences in firm j at time t. In addition,

[17] Without loss of generality, we assume that the numbers of workers and firms are the same, so there are no unemployment and no vacancies.

[18] When estimating the model, we use data without firm identifiers, so we replace firms with industries.

[19] We can interpret this sorting function as workers having an initial endowment of specific human capital $E_{i,0}$, which determines the type of firm in which they work and develop their professional path. However, as we state below, workers can increase the stock of this specific human capital over their working life.

[20] The latter element captures the fact that a mismatch between workers and firms could lead a worker to earn a low wage in the labor market, even though her stock of human capital is high.

human capital losses have both a deterministic and a stochastic element:

$$\delta_{i,j,t} = \overline{\delta}_{i,j,t} + \widetilde{\delta}_{i,j,t}, \tag{5}$$

where $\overline{\delta}_{i,j,t}$ and $\widetilde{\delta}_{i,j,t}$ are the deterministic and stochastic components of human capital losses, respectively. Notice that we can simply denote by $\overline{g}_{i,j,t} = g_{i,j,t} - \overline{\delta}_{i,j,t}$ the deterministic net-of-depreciation learning of worker i in firm j at time t.

We relate the stochastic human capital accumulation component $\widetilde{\delta}_{i,j,t}$ to health shocks, which undermine the human capital of a worker. We assume that there exists a finite set of shock types $\mathcal{T} = \{\tau_0, \tau_1, ..., \tau_S\}$. For instance, the set $\mathcal{T}$ could contain a stroke, a bone fracture, and flu, among other health events. We denote by $\theta_{\tau_s,i,t}$ the indicator for a shock of type $\tau_s \in \mathcal{T}$ experienced by individual $i \in \mathcal{I}$ at time t.

We model the effect of a health shock on human capital as depending on four factors: (i) the specific skills of the worker (indexed by i), (ii) any health care received by the injured or sick worker, which we hereafter denote by $e(i)$, (iii) the set of health events that a worker i has suffered in the past, and (iv) the type of job j performed by the worker. We motive this modeling choice as follows. First, the human capital impact of a given health shock could vary across types of skills. For instance, a bone fracture significantly undermines physical capabilities but not cognitive skills. In addition, the utilization of health care, such as medical treatment or first aid, affects the impact that a health shock could have on human capital. Moreover, past health shocks may alleviate or aggravate the negative effects of a current health shock. For instance, a worker who has suffered several health events could learn how to deal with a specific change in her health status. Therefore, the pre-existing medical history could shape the effect of a health shock on a worker's human capital. Finally, the effect of a health event can also be dependent on the job characteristics performed by the worker. For example, a broken leg could reduce the specific human capital of production workers involved in manual tasks significantly but the human capital of workers performing white-collar jobs to a lesser degree.

To model all the relationships discussed previously, we denote by $\Omega^S_{i,t}$ a proxy variable for the pre-existing medical history of worker i at time t. Then, we can summarize the impact that a health shock type τ_s has on human capital as a function of $\alpha_{\tau_s,t}\left(i, j, e_i, \Omega^S_{i,t}\right)$. We model the function $\alpha(\cdot)$ as being dependent on t, since different health shocks could also exhibit heterogeneous degrees of persistence over time. Therefore, we can express the stochastic component of human capital losses as:

$$\widetilde{\delta}_{i,j,t} = \sum_{s=1}^{S} \theta_{\tau_s,i,t} \times \alpha_{\tau_s,t}\left(i, j, e_i, \Omega^S_{i,t}\right). \tag{6}$$

5.2 The Earnings Equation

Using equations (4) to (6), we can express the stock of human capital of worker i at time t as

$$E_{i,t} = E_{i,0} + \sum_{m=1}^{t} \overline{g}_{i,j,m} + \sum_{m=1}^{t}\sum_{s=1}^{S} \theta_{\tau_s,i,m} \times \alpha_{\tau_s,m}(i,j,e_i,\Omega_{i,m}^S). \tag{7}$$

Together, equations (3) and (7) provide a general model of how health shocks affect earnings through the human capital channel. We next work on the general formulation provided by equations (3) and (7) to obtain a linear reduced-form equation that allows us to estimate the effects of health shocks on labor market outcomes and some of the channels through which these effects are triggered. Accordingly, we assume functional forms for the elements contained in (3) and (7).

First, we use a traditional Mincerian functional form for labor market earnings:

$$\log w_{i,t} = \beta_0\omega_i + \beta_1 s(j) + \beta_2 v_t + \beta_3 E_{i,t}, \tag{8}$$

That is, log-earnings are a linear function of the worker's skills, the firm or industry in which he works, the aggregate state of the economy, and her human capital. In the empirical analyses in Section 6, we also substitute employment status for log-earnings on the right-hand side of equation (8) to capture the extensive labor supply margin.

Next, we model the learning-net-of-depreciation function $\overline{g}$ as depending on the labor market attachment of each worker and the specific firm in which that worker has worked. In this way, we capture the fact that learning is faster when individuals are more active on the labor market. Moreover, the learning curves could be heterogeneous across firms. We summarize those elements with the following linear functional form for the deterministic period-by-period net accumulation of human capital:

$$\overline{g}_{i,j,t} = \kappa_0 + \kappa_1 D_{i,t} + \kappa_2 \left(D_{i,t} \times j\right), \tag{9}$$

where $D_{i,t}$ is an indicator that equals one if worker i is employed in time period t and j indexes firms.[21] Past labor market experience plays an important role, because health shocks may reduce the labor supply at the extensive margin. Hence, the human capital accumulation of workers who suffer health shocks may be slower than that among healthy peers, which introduces dynamic health effects.

Regarding the stochastic component of human capital accumulation, we assume a linear functional relationship between the effects of specific health shocks and (i) the type of skills of a worker, (ii) his job characteristics, (iii) the medical history of the worker, and (iv) the actions that a worker takes to alleviate the effects of health event:

$$\alpha_{\tau_s,t}\left(i,j,e_i,\Omega_{i,t}^S\right) = \alpha_{0,\tau_s,t} + \alpha_{1,\tau_s,t}E_{i,0} + \alpha_{2,\tau_s,t} \times j + \alpha_{3,\tau_s,t}\Omega_{i,t}^S + \alpha_{4,\tau_s,t}e_i. \tag{10}$$

[21] In our empirical analyses, j indexes industries.

Substituting equations (7), (9), and (10) into (8), and adding an error term $\varepsilon_{i,t}$, we obtain the earnings equation that can take the data to estimate the model parameters:

$$
\begin{aligned}
\log w_{i,t} \quad = \quad & \beta_0 \omega_i + \beta_1 s(j) + \beta_2 v_t + \beta_3 E_{i,0} + \beta_3 \kappa_0 t + \beta_3 \kappa_1 \sum_{m=1}^{t} D_{i,m} \\
& + \beta_3 \kappa_2 \sum_{m=1}^{t} (D_{i,m} \times j) + \sum_{m=1}^{t} \sum_{s=1}^{S} \beta_3 \alpha_{0,\tau_s,m} \theta_{\tau_s,i,m} \\
& + \sum_{m=1}^{t} \sum_{s=1}^{S} \beta_3 \alpha_{1,\tau_s,m} \left(E_{i,0} \times \theta_{\tau_s,i,m}\right) + \sum_{m=1}^{t} \sum_{s=1}^{S} \beta_3 \alpha_{2,\tau_s,m} \left(j \times \theta_{\tau_s,i,m}\right) \\
& + \sum_{m=1}^{t} \sum_{s=1}^{S} \beta_3 \alpha_{3,\tau_s,m} \left(\Omega_{i,m}^{S} \times \theta_{\tau_s,i,m}\right) + \sum_{m=1}^{t} \sum_{s=1}^{S} \beta_3 \alpha_{4,\tau_s,m} \left(e_i \times \theta_{\tau_s,i,m}\right) + \varepsilon_{i,t}.
\end{aligned}
\tag{11}
$$

5.3 Identification

Our identification strategy relies on reduced-form regressions and thus on the linearity of the functional forms that relate different variables of the model. In this section, we discuss how our data set, which we described in detail in Section 3, permits the identification of the parameters in equation (11).

First, our panel data allow us to include worker and industry fixed effects. By doing so, we can identify the parameters $\beta_0 + \beta_3$ and β_1; that is, the joint effect of skill prices and educational attainment on earnings $\beta_0 + \beta_3$, and the effect of the equilibrium sorting, β_1. Next, using data on (i) workers' age as a proxy for t, (ii) the past labor market attachment of workers, and (iii) the industry in which the worker is employed, we can identify $\beta_3\kappa_0$, $\beta_3\kappa_1$, and $\beta_3\kappa_2$, that is, how labor market participation affects wages through learning and how that effect differs across industries.

In addition, our data set contains information on current and past health events experienced by workers and the health insurance provider for workers with a health event. The former information allows us to construct proxies for $\theta_{\tau_s,i,t}$ and $\Omega_{i,t}^{S}$, and the latter piece of information serves as a proxy variable for e_i. Hence, these data and the information on the educational attainment and industry of the worker enable us to identify the set of parameters $\beta_3\alpha_{0,\tau_s,m}$, $\beta_3\alpha_{1,\tau_s,m}$, $\beta_3\alpha_{2,\tau_s,m}$, $\beta_3\alpha_{3,\tau_s,m}$, and $\beta_3\alpha_{4,\tau_s,m}$, for all $\tau_s \in \mathcal{T}$ and $m \leqslant t$. In turn, those parameters identify the effect of current and past health shocks on earnings and the gradient of those effects across individuals with different educational attainment levels, different health insurance providers, and different medical histories and across industries.

6 Model Estimation Results

In this section, we present the estimates of the human capital model developed in the previous section. We estimate models with the worker fixed effect in which the dependent variable is the monthly log-earnings and the included covariates follow the earnings model in equation (11). Specifically, we include a quadratic in age as a proxy for t, individual fixed effects to control for skill prices ω_i and educational attainment $E_{i,0}$, industry dummies as proxies for $s(j)$, time fixed effects (v_t), the employment history $(\sum_{m=0}^{t} D_{i,m})$, a proxy for the health shock $(\theta_{i,t})$, past health events $(\Omega_{i,t}^S)$, the insurance provider (as a proxy for access to health care e_i) of each worker, as well as all the interaction terms between these variables that we model in Section 5. We only simplify model (11) in one direction. We assume that all the lags of the α parameters, which refer to the interaction with past health shocks, are equal to zero. This assumption is necessary due to the likely high collinearity between the lagged health shock variable and the variable capturing the past health events $(\Omega_{i,t}^S)$. We still include the main effect of past health shocks $\Omega_{i,t}^S$. We also estimate the same model using an employment indicator as the labor market outcome measure. The latter specification allows us to assess the impact of health shocks on the extensive labor supply margin.

We first estimate models that treat the health shock variable, $\theta_{i,t}$, as an aggregate indicator that takes the value of $\theta_{i,t} = 1$ if worker i experienced a health event in month t. In the regression result tables below, we present five columns denoted by (1), (2), (3), (4), and (5), in which we proceed from the least to the most flexible model. Then, as additional results, we exploit the disaggregate information regarding the type of diagnosis experienced by the worker in each health event. In that case, the health shock variable takes the value $\theta_{\tau_s,i,t} = 1$ if the diagnosis was of type τ_s for worker i at time t.[22] In both models, we define $\Omega_{i,t}^S$ as a dummy variable that is equal to one if individual i had any health event before time t.

In all the specifications, time t is measured in calendar months, and we include month and industry fixed effects in all the regressions. Due to the size of the data set, we draw a random 10 percent sample of workers who did not experience any health shocks but keep all the individuals with at least 1 hospital stay. We include weights in the regressions to account for this sampling; see Section 3.1.

6.1 Aggregate Health Shock

In this section, we present estimates of the model that includes the aggregate measure for health shocks ("Health shock"). The results are shown in Table 4. All the regressions include a quadratic in the age, and industry and month fixed effects. In addition, regression (1) only includes the health shock indicator and its interaction with educational attainment. Regressions (2) to (5) add interactions between the employment history and the current industry. Regressions (3) to (5) also add interactions between the health shock indicator and industry. Regressions (4) and (5) further include the interaction between a current and any past health shocks, and finally regression (5) also contains interactions between health shocks and health insurance indicators.

We observe in Table 4 that the effect of a health shock on earnings is negative and statistically significant at the conventional levels in all the specifications. In particular, a health shock reduces contemporaneous monthly earnings by between 22 and 39 percent, depending on the specification.

[22] We define the diagnosis type based on the first letter of the ICD-10 code; see Table 2.

We note that including additional variables increases the estimated health shock coefficient in absolute values. This suggests that omitting these variables biases the health shock effect towards zero. Hence, it is important to account for the human capital channels that we model here to capture the accurate effect of health shocks on earnings.

Moreover, we observe that the negative effect of health shocks is attenuated for individuals with higher educational attainment. Workers with a high school degree lose between 3.2 and 0.6 percent less earnings in the month of a health shock (relative to the least educated workers), and those with post-secondary education between 17.3 and 3.3 percent. Hence, there is a strong protective effect of human capital on earnings losses due to a health event. However, as we add interactions to specifications (3) to (5), the palliative effect of education declines. This result suggests that pathways operating through the type of job and health care matter. Even in the most flexible specification (5), the protective effect of education persists, which implies that human capital leads to a direct reduction in the negative effect of health shocks on earnings. We also find that a longer employment history contributes to higher earnings, and this effect remains unchanged across specifications.

In addition, we find a heterogeneous health shock effect on earnings across industries in columns (3) to (5) of Table 4. Moreover, almost all the interactions between the industry effect and the health shock are positive and statistically significant at the 1 percent level. The excluded industry is agriculture and fishing, so our results imply that workers who are employed in almost all other industries are better protected against earnings losses due to a health shock.

Interestingly, we observe in columns (4) and (5) of Table 4 that the interaction effect between the presence of any past health shock and the contemporaneous health shock is positive and significant at conventional levels. This result suggests that individuals who have experienced a past health shock are better able to adjust to another health shock. However, we cannot rule out the possibility that selection leads to this finding. Specifically, individuals who have experienced a past health shock are more likely to drop out of the labor force completely. Therefore, those who remain in the workforce may have experienced relatively minor health shocks. Nevertheless, it is unlikely that this type of selection can fully explain the significantly positive effect of the interaction with past health shocks.

Finally, we also observe that the impact of a health shock on earnings is mitigated for workers who have private health insurance (ISAPRE) or insurance coverage other than the most common FONASA or ISAPRE plans. These estimates suggest that individuals who have access to high-quality health care are better able to contain the negative effects of health shocks on their earnings. Private insurance coverage is correlated with education and the industry in which an individual works with more highly educated workers, and those employed in white-collar industries are more likely to be enrolled in an ISAPRE plan. In regression (5), we control for both characteristics, however. Comparing the estimates in columns (4) and (5), we find that the protective effects of education and most typical white-collar industries diminish when including health insurance interactions. Our model therefore allows us to disentangle these effects flexibly.

Next, we use an employment indicator as the measure of the labor market outcome. Table 5 presents the results. We find that the main conclusions for the intensive labor supply margin from Table 4 hold. First, we observe that the effect of a health shock on employment is negative and statistically significant at the conventional levels in specifications (1) to (4). However, the effect becomes larger in absolute values as we add more interactions. Hence, the bias is in the opposite direction compared with the earnings results, and neglecting to account for possible pathways leads to an underestimation of the employment effects of a health event. Second, we also observe a protective effect of education on the negative impact of health shocks on employment. The attenuating effect of education is, however, more convex on employment than on earnings. We observe in columns (1) to (4) that workers with a post-secondary education lose between 3.2 and 1.8 percent less in the employment rate with respect to workers with no education. On the other hand, the negative effect of health shocks on employment for workers with a high school degree is statistically similar to that for workers with no formal education under most of the specifications presented in Table 5. Third, we also find a heterogeneous health shock impact on the extensive labor supply margin across industries.

However, in contrast to the earnings results in Table 4, we observe that the impact of a health shock on employment is not significant at the conventional levels, and the protective effect of education also disappears when adding the health insurance interactions in column (5). This finding suggests that the health shock impact on employment and the attenuating effect of education are jointly accounted for by the sectoral choice of workers, the variation in the exposure to health events, and the quality of the health insurance. Another difference that we find for the extensive labor supply margin compared with the intensive margin concerns the influence of past health events on the health shock impact. We observe in column (4) that the interaction effect between the presence of any past health shock and the contemporaneous health shock is negative and significant at the conventional levels. That is, individuals who have experienced a past health shock have more difficulties in adjusting their labor supply to another health shock. The results of Table 4 show that, conditional on employment, individuals with a medical history suffer a smaller decline in their earnings when they face an additional health event. The results of Table 5 suggest, however, that the negative impact of a health shock on the employment rate of these individuals is more pronounced.

Overall, this first set of results using aggregate information for health events shows that health shocks undermine both the earnings and the employment possibilities of injured workers. This result is in line with the literature reviewed by Currie and Madrian (1999). However, in addition, we show that the negative effect of health shocks on these labor market outcomes is mitigated for workers with higher educational attainment, similar to the findings of Lundborg, Nilsson, and Vikström (2015) for Swedish workers. In the case of earnings, this mitigating effect of human capital persists when controlling for the possible pathways that operate through health insurance quality, industry type, and any past health event. Therefore, our findings suggest that the attenuating role of human capital on the earnings effects of health shocks extend beyond the fact that more educated workers are matched with safer jobs, buy better-quality health insurance, or have a different degree of exposure to shock events. On the other hand, when the employment dimension is evaluated, we find that the sectoral choice of workers, the variation in the exposure to health events, and health insurance quality account for the entire interaction effect between the health shock and the human capital. Lastly, the results in Table 4 and Table 5 are also informative about the magnitude and direction of the protective effects on labor market outcomes that are due to variables other than human capital.

6.2 Additional Results: Heterogenous Health Shocks

In this section, we present the results of the model that exploits the disaggregate information on the health shock types. That is, instead of an aggregate health shock indicator, as in Tables 4 and 5, we use a set of indicator variables as proxies for $\theta_{\tau_s,i,t}$, in which each indicator equals one if individual i experienced a health shock of type τ_s at time t. For each interaction with the health shock dummy, we now include a set of ten interactions with diagnosis indicators for hospitalization due to external causes, the digestive system, the circulatory system, the genitourinary system, neoplasms, the musculoskeletal system, the respiratory system, mental disorders, endocrine/nutritional/metabolic problems, and skin and subcutaneous tissue. The remaining structure of the empirical model remains the same as the one described by Table 4 (log-earnings) and Table 5 (employment).

Considering log-earnings as the first labor market outcome in Table 6, we observe that all the health events have a negative and statistically significant coefficient.[23] In the most restrictive specification in column (1), the earnings decrease ranges between 8.4 percent for musculoskeletal system diagnoses and 28 percent for endocrine/nutritional/metabolic diagnoses. These effects therefore exhibit a substantial amount of heterogeneity compared with the overall effect of health shocks reported in Table 4, which equals −22 percent. The strong effect of mental disorder health shocks on earnings, which is observed across all the specifications of Table 6, is particularly interesting. For instance, in the most flexible specification in column (4), we observe that the earnings decrease after a mental health diagnosis is about 44 percent. This result is in line with the recent literature that highlights the importance of mental health for different labor market outcomes (Frijters, Johnston, and Shields, 2014). Regarding the effect of the education interactions, we observe that the negative effect of a specific diagnosis on earnings is not always mitigated by higher levels of education. However, despite this heterogeneity, the overall picture still supports the existence of a protective effect of human capital.

[23]In Tables 6 and 7, we omit the regression results that correspond to column (5) in Tables 4 and 5, because we do not have enough power to include the large number of interactions when considering individual diagnoses.

Next, we consider the interactions between specific diagnoses and industries reported in columns (3) to (4) of Table 6. We observe significant heterogeneity across industries and diagnosis types in the effect of health shocks on earnings. For instance, working in the mining industry is protective for workers diagnosed with genitourinary system diseases, but the same does not apply to workers in the construction and transportation industry. An analogous analysis can be carried out for the remaining diagnosisindustry combinations.

We also find that having had a previous health shock mitigates the earnings loss after an additional health event; see regression (4) in Table 6. However, we observe significant differences in this protective effect depending on the type of contemporaneous health diagnosis. For instance, having experienced a previous health shock lowers the negative effect of a neoplasm diagnosis but has no effect among individuals with a mental disorder diagnosis.[24]

Table 7 presents the results for the same models as Table 6 but uses the employment indicator as the labor market outcome. We find a negative impact of health shocks on employment in columns (1) through (4), which is especially relevant to the case of a mental disorder diagnosis. The protective effect of human capital on the employment effect of health shocks is also observed for some types of diagnoses, such as those involving the digestive system and the musculoskeletal system. Heterogeneity across the diagnosisindustry interaction is also observed; for instance, working in sectors like retail seems to be more protective than working in the agricultural sector when the health shock is due to external causes.

Lastly, consistent with the aggregate results presented in Table 6, we observe the interaction effect between the presence of any past health shock and the fact that the contemporaneous health shock is negative and significant for some types of diagnoses, for instance those related to the digestive system, circulatory system, and genitourinary system. However, we reach the opposite conclusion for a mental disorder diagnosis. Specifically, individuals who have experienced a past health shock seem to face fewer difficulties in adjusting their labor supply when they experience a mental disorder. Overall, this second set of results exploiting disaggregated information on health shock types highlights that the protective effect of human capital on the labor market impact of health shocks is heterogeneous across diagnoses.

7 Conclusion

In this paper, we investigate the mitigating effects of education on the labor market impact of negative health events. Using administrative data on earnings and hospital admissions from Chile, we estimate a model of human capital accumulation and find that health shocks reduce earnings, in line with the results reported in the literature exploring the relationship between health and labor market outcomes. However, in addition, we find that men with higher levels of education exhibit

[24]It would be interesting to split past health shocks into different diagnoses and interact these measures with diagnosis-specific current health shocks, but we lack the power to carry out this analysis.

a smaller fall in earnings and employment after a health event. This result suggests that human capital plays a protective role in the negative labor market effect of health shocks.

Moreover, at the intensive labor supply margin, we find that these mitigating effects of human capital extend beyond the channels arising from the fact that more educated workers work in safer occupations, buy better-quality health insurance, or are exposed to less frequent and less severe health events. In other words, human capital plays a residual role that cannot be explained by these factors. Lastly, we provide evidence suggesting that the protective effect of education is heterogeneous across industries and types of diagnoses. We also find that hospital admissions due to mental health diagnoses have a particularly strong negative effect on labor market outcomes.

Our findings are policy relevant. They illustrate the potential gains that can be realized in an emerging economy such as Chile when education levels are increased. Education not only raises the labor market earnings of workers but also enables them to deal with health shocks more easily. This protective effect operates through various channels. Highly educated individuals qualify for jobs that expose them to fewer unsafe working conditions, thereby lowering the frequency and severity of health shocks. Moreover, they can afford better health care should a health shock occur. Finally, they possess the general human capital that enables them to switch jobs if necessary after a health shock.

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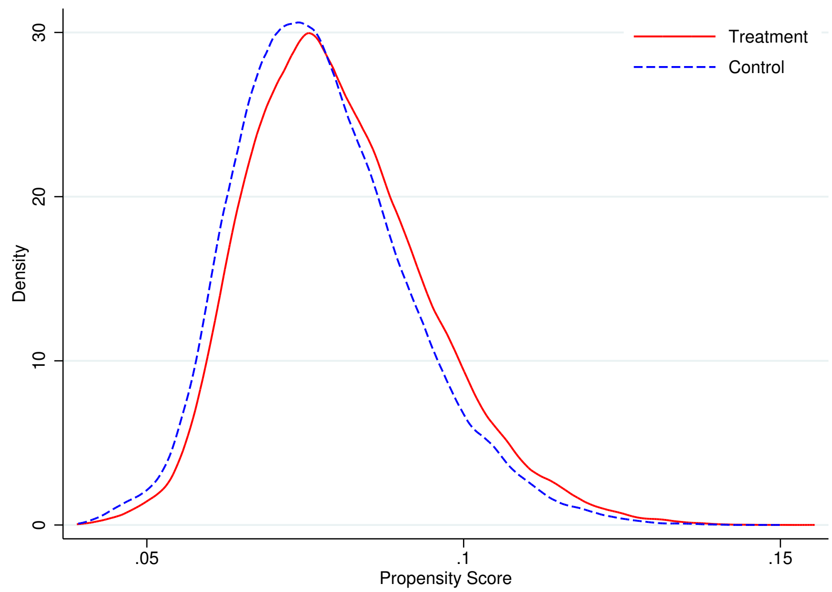

Figure 1: Density Plots of the Propensity Score Distribution For Treatment and Control Groups

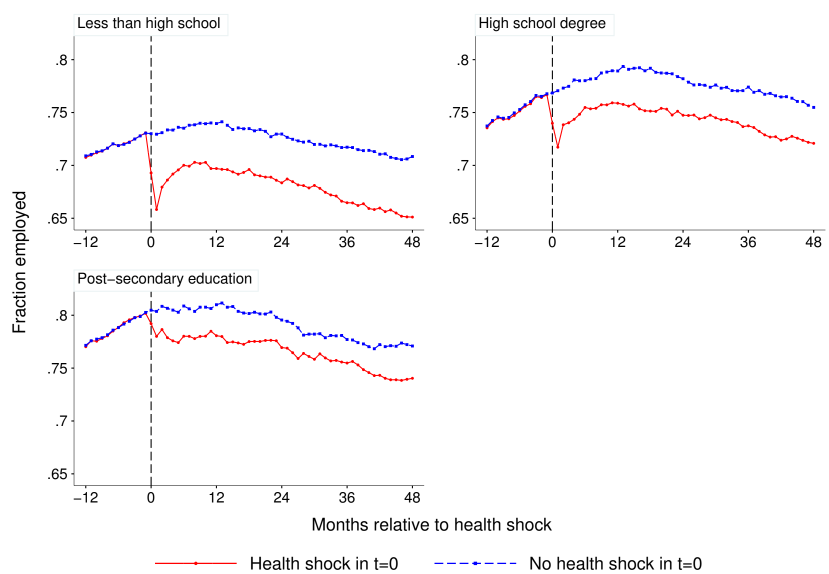

Figure 2: Average Employment over Time Relative to Health Shock by Treatment Status and Education – Weighted by ATET Inverse Propensity Score Weight

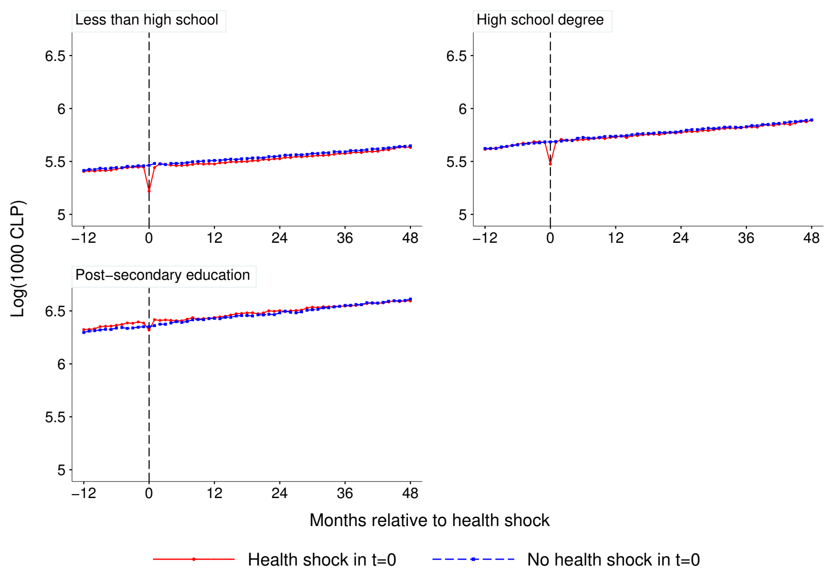

Figure 3: Average Monthly Log-Earnings over Time Relative to Health Shock by Treatment Status and Education – Weighted by ATET Inverse Propensity Score Weight

Table 1: Unweighted and Weighted Means and Normalized Differences of Select Propensity Score Covariates

	(1)	(2)	(3)	(4)	(5)
	Unweighted		Normalized	ATET-weighted	
	Treat.	Control	difference	Treat.	Control
Age at health shock	38.72	37.95	0.0969	37.99	38.01
	(8.088)	(7.861)		(7.878)	(7.881)
Less than high school	0.571	0.541	0.0616	0.544	0.543
	(0.495)	(0.498)		(0.498)	(0.498)
High school degree	0.312	0.325	−0.0287	0.324	0.324
	(0.463)	(0.468)		(0.468)	(0.468)
Post-secondary education	0.117	0.134	−0.0521	0.132	0.133
	(0.321)	(0.341)		(0.338)	(0.339)
Not employed in $t = -1$	0.255	0.247	0.0186	0.248	0.248
	(0.436)	(0.431)		(0.432)	(0.432)
Blue collar, earn. terc. 1 in $t = -1$	0.135	0.128	0.0202	0.130	0.129
	(0.342)	(0.335)		(0.336)	(0.335)
Blue collar, earn. terc. 2 in $t = -1$	0.123	0.129	−0.0170	0.128	0.128
	(0.329)	(0.335)		(0.335)	(0.334)
Blue collar, earn. terc. 3 in $t = -1$	0.119	0.125	−0.0170	0.124	0.124
	(0.324)	(0.331)		(0.329)	(0.330)
White collar, earn. terc. 1 in $t = -1$	0.129	0.117	0.0361	0.118	0.118
	(0.335)	(0.322)		(0.323)	(0.323)
White collar, earn. terc. 2 in $t = -1$	0.108	0.121	−0.0435	0.120	0.120
	(0.310)	(0.327)		(0.325)	(0.325)
White collar, earn. terc. 3 in $t = -1$	0.110	0.111	−0.00376	0.110	0.111
	(0.313)	(0.314)		(0.313)	(0.314)
Fraction of months employed up to $t = -1$	0.721	0.728	−0.0285	0.727	0.728
	(0.264)	(0.262)		(0.262)	(0.263)
Observations	46,485	55,099	101,584	46,485	55,089

Table 2: Health Shock Frequencies and Characteristics by Educational Attainment

	No high school	High school degree	Post-secondary
A. Fraction of men with health shock			
Total	0.0818	0.0748	0.0685
By industry in t = -1			
Not employed	0.0875	0.0736	0.0580
Agriculture, fishing	0.0868	0.0830	0.0782
Mining	0.105	0.101	0.0890
Manufacturing	0.0771	0.0744	0.0715
Construction, transportation	0.0772	0.0725	0.0674
Wholesale, retail, restaurants	0.0713	0.0698	0.0688
Finance, real estate	0.0774	0.0730	0.0715
Education, health	0.0948	0.0915	0.0732
Not employed	0.0875	0.0736	0.0580
By tercile in t =-1			
Blue collar, earn. terc. 1	0.0844	0.0744	0.0736
Blue collar, earn. terc. 2	0.0762	0.0735	0.0601
Blue collar, earn. terc. 3	0.0757	0.0744	0.0731
White collar, earn. terc. 1	0.0864	0.0848	0.0749
White collar, earn. terc. 2	0.0731	0.0678	0.0612
White collar, earn. terc. 3	0.0798	0.0784	0.0737
Observations	56,344	32,399	12,841
B. Health shock characteteristics			
Diagnosis			
External causes	0.289	0.249	0.176
Digestive system	0.243	0.266	0.250
Circulatory system	0.0711	0.0787	0.0850
Genitourinary system	0.0562	0.0644	0.0850
Neoplasms	0.0275	0.0306	0.0462
Musculoskeletal system	0.0606	0.0753	0.0923
Respiratory system	0.0553	0.0523	0.0614
Mental/behavioural	0.0381	0.0340	0.0289
Endocrine/metabolic	0.0127	0.0113	0.0151
Skin/subcutaneous	0.0326	0.0276	0.0259
Other	0.114	0.111	0.134
Length of stay of first hospitalization			
1 day	0.300	0.351	0.441
2 to 7 days	0.529	0.504	0.473
8 to 14 days	0.112	0.0978	0.0570
15+ days	0.0584	0.0476	0.0289
Length of stay of all hospitalizations for same diagnosis within one year			
1 day	0.263	0.316	0.405
2 to 7 days	0.529	0.503	0.483
8 to 14 days	0.126	0.113	0.0717
15+ days	0.0819	0.0680	0.0406
Health insurance provider			
FONASA A	0.279	0.204	0.0928
FONASA B	0.342	0.275	0.129
FONASA C	0.157	0.183	0.101
FONASA D	0.179	0.232	0.192
ISAPRE	0.0434	0.106	0.486
Observations	26,555	14,489	5,441

Notes: Panel A. shows the fraction of men who had at least one hospitalization between 2005 and 2007 (the treatment group) by education attainment overall and the same fraction separately for each industry, in which they were employed in the month prior to the health shock. Panel B. shows the distribution of health shock characteristics along several dimensions for men who had at least one hospitalization, by educational attainment.

Table 3: Labor Market Outcomes by Treatment and Control Group Before and After the Health Shock

	(1)	(2)	(3)	(4)	(5)
	Treatment		Control		Diff-in-diff
	Before	After	Before	After	
Employed	0.719	0.701	0.735	0.747	-0.0311^{***}
	(0.449)	(0.458)	(0.442)	(0.435)	(0.00108)
Monthly earnings	278.9	336.7	241.8	318.8	-19.32^{***}
	(346.5)	(399.2)	(312.2)	(417.4)	(0.913)
Average earnings months ± 1 year	10.91	11.51	10.65	11.64	-0.385^{**}
	(8.142)	(8.821)	(7.759)	(8.256)	(0.159)
Average earnings months ± 2 years	20.24	22.81	19.99	23.36	-0.806^{**}
	(15.15)	(17.48)	(14.51)	(16.57)	(0.316)
Observations	1,817,999	3,122,527	4,149,831	3,663,176	

Notes: Columns (1) to (4): standard deviations in parentheses, column (5): standard error in parentheses (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$). Months worth of earnings are defined in equation (1) in the text.

Table 4: Models of Health: Using aggregate health shock as proxy for θ, dependent variable: log-earnings

	(1)	(2)	(3)	(4)	(5)
Age	0.0603***	0.0634***	0.0634***	0.0634***	0.0634***
	(0.00196)	(0.00194)	(0.00194)	(0.00194)	(0.00194)
Age-sq	-0.000787***	-0.000828***	-0.000828***	-0.000828***	-0.000828***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Health shock=1	-0.223***	-0.225***	-0.288***	-0.298***	-0.385***
	(0.00514)	(0.00514)	(0.01183)	(0.01193)	(0.12341)
High school degree x Health shock=1	0.0289***	0.0315***	0.0207**	0.0211**	0.00567
	(0.00864)	(0.00864)	(0.00868)	(0.00867)	(0.00863)
Post-secondary educ. x Health shock=1	0.169***	0.173***	0.146***	0.147***	0.0330***
	(0.01060)	(0.01060)	(0.01090)	(0.01090)	(0.01224)
Labor experience		0.00400***	0.00400***	0.00400***	0.00400***
		(0.00015)	(0.00015)	(0.00015)	(0.00015)
Mining x Labor experience		0.00183***	0.00183***	0.00183***	0.00183***
		(0.00020)	(0.00019)	(0.00019)	(0.00019)
Manufacturing x Labor experience		0.000518***	0.000523***	0.000523***	0.000525***
		(0.00012)	(0.00012)	(0.00012)	(0.00012)
Construction/transportation x Labor experience		0.00111***	0.00111***	0.00111***	0.00111***
		(0.00009)	(0.00009)	(0.00009)	(0.00009)
Wholesale/retail/restaurants x Labor experience		0.000287**	0.000290**	0.000290**	0.000292**
		(0.00011)	(0.00011)	(0.00011)	(0.00011)
Finance/real estate x Labor experience		0.00104***	0.00106***	0.00106***	0.00106***
		(0.00011)	(0.00011)	(0.00011)	(0.00011)
Education/health x Labor experience		0.000402***	0.000421***	0.000421***	0.000422***
		(0.00013)	(0.00013)	(0.00013)	(0.00013)
Mining x Health shock=1			0.0384	0.0339	-0.0442
			(0.04100)	(0.04103)	(0.04078)
Manufacturing x Health shock=1			0.0679***	0.0671***	0.0485***
			(0.01666)	(0.01662)	(0.01652)
Construction/transportation x Health shock=1			0.0232*	0.0233*	0.0185
			(0.01357)	(0.01356)	(0.01351)
Wholesale/retail/restaurants x Health shock=1			0.0531***	0.0518***	0.0341**
			(0.01601)	(0.01598)	(0.01590)
Finance/real estate x Health shock=1			0.155***	0.153***	0.113***
			(0.01470)	(0.01467)	(0.01462)

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Table 4 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
Education/health x Health shock=1			0.152***	0.146***	0.146***
			(0.01554)	(0.01551)	(0.01548)
Any past shock=1 x Health shock=1				0.0842***	0.0829***
				(0.01159)	(0.01247)
FONASA x Health shock=1					0.0812
					(0.12296)
ISAPRE x Health shock=1					0.361***
					(0.12319)
Other HI x Health shock=1					0.193
					(0.12417)
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Within R^2	0.0826	0.0857	0.0858	0.0858	0.0861
Number of individuals	101,574	101,574	101,574	101,574	101,574
Observations	7,829,210	7,829,210	7,829,210	7,829,210	7,829,210

Note: Standard errors clustered on individual workers in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Models of Health: Using aggregate health shock as proxy for θ, dependent variable: employment

	(1)	(2)	(3)	(4)	(5)
Age	0.0297***	0.0303***	0.0303***	0.0304***	0.0304***
	(0.00143)	(0.00139)	(0.00139)	(0.00139)	(0.00139)
Age-sq	-0.000384***	-0.000392***	-0.000392***	-0.000392***	-0.000392***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Health shock=1	-0.0175***	-0.0217***	-0.0471***	-0.0572***	0.00792
	(0.00242)	(0.00240)	(0.00517)	(0.00523)	(0.05520)
High school degree x Health shock=1	0.00257	0.00717*	0.00200	0.00187	-0.00217
	(0.00407)	(0.00405)	(0.00408)	(0.00408)	(0.00409)
Post-secondary educ. x Health shock=1	0.0268***	0.0319***	0.0184***	0.0192***	-0.0117*
	(0.00573)	(0.00567)	(0.00580)	(0.00580)	(0.00638)
Labor experience		0.00587***	0.00587***	0.00586***	0.00586***
		(0.00009)	(0.00009)	(0.00009)	(0.00009)
Mining x Labor experience		-0.00170***	-0.00170***	-0.00170***	-0.00170***
		(0.00014)	(0.00014)	(0.00014)	(0.00014)
Manufacturing x Labor experience		-0.000944***	-0.000942***	-0.000942***	-0.000941***
		(0.00009)	(0.00009)	(0.00009)	(0.00009)
Construction/transportation x Labor experience		-0.000232***	-0.000233***	-0.000231***	-0.000231***
		(0.00007)	(0.00007)	(0.00007)	(0.00007)
Wholesale/retail/restaurants x Labor experience		-0.000895***	-0.000892***	-0.000894***	-0.000894***
		(0.00009)	(0.00009)	(0.00009)	(0.00009)
Finance/real estate x Labor experience		-0.00110***	-0.00109***	-0.00110***	-0.00110***
		(0.00008)	(0.00008)	(0.00008)	(0.00008)
Education/health x Labor experience		-0.00166***	-0.00165***	-0.00165***	-0.00165***
		(0.00010)	(0.00010)	(0.00010)	(0.00010)
Mining x Health shock=1			0.0200	0.0201	-0.00245
			(0.01236)	(0.01238)	(0.01253)
Manufacturing x Health shock=1			0.0267***	0.0266***	0.0218***
			(0.00751)	(0.00751)	(0.00750)
Construction/transportation x Health shock=1			0.00368	0.00347	0.00210
			(0.00604)	(0.00604)	(0.00602)
Wholesale/retail/restaurants x Health shock=1			0.0324***	0.0325***	0.0281***
			(0.00726)	(0.00726)	(0.00725)
Finance/real estate x Health shock=1			0.0563***	0.0563***	0.0459***
			(0.00674)	(0.00674)	(0.00678)

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Table 5 – continued from previous page

	(1)	(2)	(3)	(4)	(5)
Education/health			0.0916***	0.0922***	0.0919***
x Health shock=1			(0.00724)	(0.00724)	(0.00723)
Any past shock=1				-0.0207***	-0.0290***
x Health shock=1				(0.00548)	(0.00575)
FONASA x Health					-0.0663
shock=1					(0.05497)
ISAPRE x Health					0.0130
shock=1					(0.05513)
Other HI x					0.0222
Health shock=1					(0.05586)
Worker fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Within R^2	0.0103	0.0226	0.0227	0.0229	0.0230
Number of individuals	101,574	101,574	101,574	101,574	101,574
Observations	10,757,300	10,757,300	10,757,300	10,757,300	10,757,300

Note: Standard errors clustered on individual workers in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Models of Health: Using the specific diagnoses as proxies for θ, dependent variable: log-earnings

	(1)	(2)	(3)	(4)
Age	0.0602***	0.0634***	0.0634***	0.0634***
	(0.00196)	(0.00194)	(0.00194)	(0.00194)
Age squared	-0.000787***	-0.000828***	-0.000827***	-0.000827***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
External causes	-0.267***	-0.270***	-0.301***	-0.312***
	(0.01067)	(0.01067)	(0.02132)	(0.02146)
Digestive system	-0.264***	-0.265***	-0.336***	-0.340***
	(0.01035)	(0.01035)	(0.02358)	(0.02370)
Circulatory system	-0.193***	-0.195***	-0.296***	-0.302***
	(0.01702)	(0.01701)	(0.04310)	(0.04371)
Genitourinary system	-0.179***	-0.180***	-0.265***	-0.270***
	(0.01835)	(0.01834)	(0.04113)	(0.04125)
Neoplasms	-0.196***	-0.198***	-0.319***	-0.361***
	(0.03136)	(0.03142)	(0.07134)	(0.07159)
Musculoskeletal system	-0.0837***	-0.0861***	-0.176**	-0.184***
	(0.02083)	(0.02083)	(0.07011)	(0.07043))
Respiratory system	-0.223***	-0.225***	-0.267***	-0.273***
	(0.02141)	(0.02142)	(0.05442)	(0.05472)
Mental disorders	-0.253***	-0.260***	-0.432***	-0.440***
	(0.03401)	(0.03391)	(0.08266)	(0.08417)
Endocrine/nutritional/metabolic	-0.280***	-0.280***	-0.368***	-0.394***
	(0.04427)	(0.04429)	(0.10213)	(0.10379)
Skin and subcutaneous tissue	-0.197***	-0.199***	-0.261***	-0.264***
	(0.02363)	(0.02367)	(0.05012)	(0.05012)
High school degree x External causes	0.0266	0.0295*	0.0226	0.0220
	(0.01779)	(0.01778)	(0.01792)	(0.01789)
High school degree x Digestive system	0.0191	0.0216	0.00950	0.0100
	(0.01714)	(0.01713)	(0.01718)	(0.01718)
High school degree x Circulatory system	0.000210	0.00217	-0.00554	-0.00463
	(0.02954)	(0.02954)	(0.02942)	(0.02977)
High school degree x Genitourinary system	0.0770***	0.0786***	0.0648**	0.0652**
	(0.02784)	(0.02783)	(0.02786)	(0.02781)

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
High school degree x Neoplasms	0.0569 (0.05069)	0.0609 (0.05079)	0.0249 (0.05135)	0.0186 (0.05068)
High school degree x Musculoskeletal system	-0.0184 (0.03180)	-0.0165 (0.03182)	-0.0265 (0.03125)	-0.0271 (0.03123)
High school degree x Respiratory system	0.0320 (0.03472)	0.0353 (0.03473)	0.0283 (0.03754)	0.0294 (0.03748)
High school degree x Mental disorders	0.0324 (0.05932)	0.0352 (0.05923)	0.00619 (0.05939)	0.00604 (0.05932)
High school degree x Endocrine/nutritional/metabolic	0.0934 (0.07055)	0.0932 (0.07056)	0.0842 (0.07122)	0.0837 (0.07080)
High school degree x Skin and subcutaneous tissue	0.0230 (0.04237)	0.0270 (0.04238)	0.0202 (0.04230)	0.0205 (0.04216)
Post-secondary educ. x External causes	0.198*** (0.02586)	0.204*** (0.02589)	0.178*** (0.02648)	0.178*** (0.02641)
Post-secondary educ. x Digestive system	0.177*** (0.02189)	0.181*** (0.02189)	0.147*** (0.02239)	0.148*** (0.02238)
Post-secondary educ. x Circulatory system	0.192*** (0.03076)	0.197*** (0.03067)	0.184*** (0.03153)	0.185*** (0.03153)
Post-secondary educ. x Genitourinary system	0.139*** (0.03243)	0.145*** (0.03243)	0.123*** (0.03273)	0.124*** (0.03278)
Post-secondary educ. x Neoplasms	0.112** (0.05263)	0.115** (0.05274)	0.0768 (0.05344)	0.0853 (0.05306)
Post-secondary educ. x Musculoskeletal system	0.0814** (0.03337)	0.0867*** (0.03331)	0.0652* (0.03351)	0.0639* (0.03350)
Post-secondary educ. x Respiratory system	0.189*** (0.04242)	0.194*** (0.04250)	0.169*** (0.04430)	0.171*** (0.04449)
Post-secondary educ. x Mental disorders	0.145** (0.07271)	0.147** (0.07265)	0.0740 (0.07617)	0.0738 (0.07634)
Post-secondary educ. x Endocrine/nutritional/metabolic	0.232*** (0.08380)	0.233*** (0.08419)	0.182** (0.08447)	0.185** (0.08484)
Post-secondary educ. x Skin and subcutaneous tissue	0.0324 (0.05787)	0.0395 (0.05777)	0.0313 (0.05859)	0.0316 (0.05838)
Labor experience		0.00400*** (0.00015)	0.00400*** (0.00015)	0.00400*** (0.00015)
Mining x Labor experience		0.00183*** (0.00020)	0.00183*** (0.00019)	0.00183*** (0.00019)

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
Manufacturing x Labor experience		0.000518***	0.000523***	0.000523***
		(0.00012)	(0.00012)	(0.00012)
Construction/transportation x Labor experience		0.00111***	0.00111***	0.00111***
		(0.00009)	(0.00009)	(0.00009)
Wholesale/retail/restaurants x Labor experience		0.000287**	0.000290**	0.000290**
		(0.00011)	(0.00011)	(0.00011)
Finance/real estate x Labor experience		0.00104***	0.00106***	0.00106***
		(0.00011)	(0.00011)	(0.00011)
Education/health x Labor experience		0.000403***	0.000421***	0.000420***
		(0.00013)	(0.00013)	(0.00013)
Mining x External causes			-0.0258	-0.0291
			(0.06496)	(0.06474)
Mining x Digestive system			0.0927	0.0912
			(0.09755)	(0.09758)
Mining x Circulatory system			-0.162	-0.164
			(0.27114)	(0.27065)
Mining x Genitourinary system			0.227***	0.226***
			(0.07376)	(0.07371)
Mining x Neoplasms			0.0613	0.0688
			(0.14645)	(0.14842)
Mining x Musculoskeletal system			0.0895	0.0838
			(0.09939)	(0.09971)
Mining x Respiratory system			0.161*	0.156
			(0.09734)	(0.09746)
Mining x Mental disorders			0.129	0.124
			(0.20287)	(0.20323)
Mining x Endocrine/nutritional/metabolic			0.151	0.148
			(0.14337)	(0.14486)
Mining x Skin and subcutaneous tissue			0.0639	0.0614
			(0.11349)	(0.11395)
Manufacturing x External causes			0.0274	0.0272
			(0.03281)	(0.03274)
Manufacturing x Digestive system			0.0612*	0.0607*
			(0.03494)	(0.03492)

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
Manufacturing x Circulatory system			0.0994* (0.05443)	0.0990* (0.05444)
Manufacturing x Genitourinary system			0.136** (0.05489)	0.134** (0.05497)
Manufacturing x Neoplasms			0.233*** (0.08992)	0.230** (0.08929)
Manufacturing x Musculoskeletal system			0.0530 (0.08294)	0.0538 (0.08290)
Manufacturing x Respiratory system			0.0543 (0.07500)	0.0540 (0.07494)
Manufacturing x Mental disorders			0.152 (0.10876)	0.154 (0.10883)
Manufacturing x Endocrine/nutritional/metabolic			0.0421 (0.13001)	0.0455 (0.12956)
Manufacturing x Skin and subcutaneous tissue			0.120 (0.07340)	0.118 (0.07382)
Construction/transportation x External causes			-0.0111 (0.02565)	-0.0120 (0.02560)
Construction/transportation x Digestive system			0.0307 (0.02686)	0.0307 (0.02686)
Construction/transportation x Circulatory system			0.0855* (0.04804)	0.0857* (0.04804)
Construction/transportation x Genitourinary system			0.0647 (0.04620)	0.0637 (0.04624)
Construction/transportation x Neoplasms			0.0395 (0.08533)	0.0297 (0.08424)
Construction/transportation x Musculoskeletal system			0.0435 (0.07318)	0.0443 (0.07315)
Construction/transportation x Respiratory system			0.00828 (0.06456)	0.00763 (0.06452)
Construction/transportation x Mental disorders			0.0549 (0.09793)	0.0556 (0.09806)
Construction/transportation x Endocrine/nutritional/metabolic			0.0325 (0.11666)	0.0328 (0.11626)
Construction/transportation x Skin and subcutaneous tissue			0.0838 (0.05711)	0.0836 (0.05716)

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
Wholesale/retail/restaurants x External causes			0.0284	0.0276
			(0.03205)	(0.03196)
Wholesale/retail/restaurants x Digestive system			0.0666**	0.0665**
			(0.03238)	(0.03239)
Wholesale/retail/restaurants x Circulatory system			0.116**	0.116**
			(0.05377)	(0.05375)
Wholesale/retail/restaurants x Genitourinary system			0.0519	0.0489
			(0.05087)	(0.05097)
Wholesale/retail/restaurants x Neoplasms			0.127	0.116
			(0.08877)	(0.08821)
Wholesale/retail/restaurants x Musculoskeletal system			0.0351	0.0332
			(0.07979)	(0.07969)
Wholesale/retail/restaurants x Respiratory system			0.0328	0.0291
			(0.07602)	(0.07621)
Wholesale/retail/restaurants x Mental disorders			0.322***	0.321***
			(0.10836)	(0.10809)
Wholesale/retail/restaurants x Endocrine/nutritional/metabolic			0.0495	0.0474
			(0.13817)	(0.13662)
Wholesale/retail/restaurants x Skin and subcutaneous tissue			-0.0158	-0.0163
			(0.08109)	(0.08076)
Finance/real estate x External causes			0.130***	0.128***
			(0.02845)	(0.02834)
Finance/real estate x Digestive system			0.195***	0.194***
			(0.02890)	(0.02888)
Finance/real estate x Circulatory system			0.139***	0.138***
			(0.05231)	(0.05232)
Finance/real estate x Genitourinary system			0.147***	0.144***
			(0.04970)	(0.04981)
Finance/real estate x Neoplasms			0.295***	0.280***
			(0.08748)	(0.08643)
Finance/real estate x Musculoskeletal system			0.182**	0.181**
			(0.07286)	(0.07284)
Finance/real estate x Respiratory system			0.124*	0.120*
			(0.07147)	(0.07159)
Finance/real estate x Mental disorders			0.268**	0.266**
			(0.10553)	(0.10534)

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
Finance/real estate x Endocrine/nutritional/metabolic			0.247**	0.252**
			(0.12612)	(0.12576)
Finance/real estate x Skin and subcutaneous tissue			0.0517	0.0507
			(0.07250)	(0.07251)
Education/health x External causes			0.108***	0.101***
			(0.03087)	(0.03079)
Education/health x Digestive system			0.145***	0.144***
			(0.03130)	(0.03132)
Education/health x Circulatory system			0.195***	0.192***
			(0.05201)	(0.05202)
Education/health x Genitourinary system			0.156***	0.151***
			(0.05421)	(0.05427)
Education/health x Neoplasms			0.189**	0.144
			(0.09251)	(0.09118)
Education/health x Musculoskeletal system			0.183**	0.183**
			(0.07328)	(0.07324)
Education/health x Respiratory system			0.0670	0.0633
			(0.07951)	(0.07966)
Education/health x Mental disorders			0.375***	0.373***
			(0.10564)	(0.10556)
Education/health x Endocrine/nutritional/metabolic			0.158	0.150
			(0.14729)	(0.14610)
Education/health x Skin and subcutaneous tissue			0.139*	0.137*
			(0.07347)	(0.07369)
Any past shock=1 x External causes				0.121***
				(0.02583)
Any past shock=1 x Digestive system				0.0320
				(0.02531)
Any past shock=1 x Circulatory system				0.0358
				(0.04822)
Any past shock=1 x Genitourinary system				0.0498
				(0.03677)

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Table 6 – continued from previous page

	(1)	(2)	(3)	(4)
Any past shock=1				0.237***
x Neoplasms				(0.04484)
Any past shock=1				0.0533
x Musculoskeletal system				(0.03706)
Any past shock=1				0.0524
x Respiratory system				(0.04909)
Any past shock=1				0.0413
x Mental disorders				(0.06438)
Any past shock=1				0.136*
x Endocrine/nutritional/metabolic				(0.07944)
Any past shock=1				0.0157
x Skin and subcutaneous tissue				(0.06516)
Worker fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Within R^2	0.0827	0.0858	0.0859	0.0860
Number of individuals	101,574	101,574	101,574	101,574
Observations	7,829,210	7,829,210	7,829,210	7,829,210

Note: Standard errors clustered on individual workers in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Models of Health: Using the specific diagnoses as proxies for θ, dependent variable: employment

	(1)	(2)	(3)	(4)
Age	0.0297***	0.0303***	0.0303***	0.0303***
	(0.00143)	(0.00139)	(0.00139)	(0.00139)
Age-sq	-0.000384***	-0.000392***	-0.000392***	-0.000392***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
External causes	-0.0293***	-0.0339***	-0.0535***	-0.0666***
	(0.00468)	(0.00466)	(0.00941)	(0.00948)
Digestive system	-0.0246***	-0.0247***	-0.0441***	-0.0537***
	(0.00476)	(0.00473)	(0.01082)	(0.01088)
Circulatory	0.0175**	0.0101	-0.0238	-0.0273
system	(0.00877)	(0.00866)	(0.02106)	(0.02109)
Genitourinary	0.0113	0.00893	-0.0259	-0.0331
system	(0.00936)	(0.00929)	(0.02085)	(0.02091)
Neoplasms	0.0156	-0.000309	-0.0743**	-0.0831**
	(0.01568)	(0.01535)	(0.03463)	(0.03453)
Musculoskeletal	-0.0130	-0.0149	-0.0339	-0.0438**
system	(0.00944)	(0.00933)	(0.02199)	(0.02214)
Respiratory	0.0138	0.00889	-0.0298	-0.0396*
system	(0.00973)	(0.00966)	(0.02080)	(0.02089)
Mental disorders	-0.112***	-0.124***	-0.147***	-0.170***
	(0.01280)	(0.01271)	(0.02722)	(0.02758)
Endocrine/nutritional/metabolic	-0.00341	-0.0151	0.0379	0.0128
	(0.02151)	(0.02110)	(0.05491)	(0.05592)
Skin and	-0.00823	-0.00853	-0.0462*	-0.0548**
subcutaneous tissue	(0.01297)	(0.01288)	(0.02732)	(0.02740)
High school	-0.000197	0.00424	-0.000772	-0.000964
degree x External causes	(0.00812)	(0.00810)	(0.00818)	(0.00817)
High school	0.0138*	0.0171**	0.0129*	0.0125
degree x Digestive system	(0.00762)	(0.00758)	(0.00764)	(0.00764)
High school	-0.00987	-0.00382	-0.00842	-0.0101
degree x Circulatory system	(0.01378)	(0.01363)	(0.01381)	(0.01382)
High school	0.0111	0.0140	0.00977	0.00886
degree x Genitourinary system	(0.01458)	(0.01445)	(0.01456)	(0.01457)

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Table 7 – continued from previous page

	(1)	(2)	(3)	(4)
High school degree x Neoplasms	-0.00659	0.00590	-0.00994	-0.00969
	(0.02371)	(0.02336)	(0.02364)	(0.02366)
High school degree x Musculoskeletal system	0.0174	0.0201	0.0150	0.0150
	(0.01424)	(0.01414)	(0.01409)	(0.01409)
High school degree x Respiratory system	-0.00614	0.00000401	-0.00370	-0.00395
	(0.01680)	(0.01664)	(0.01695)	(0.01695)
High school degree x Mental disorders	-0.0201	-0.0181	-0.0234	-0.0238
	(0.02267)	(0.02249)	(0.02256)	(0.02253)
High school degree x Endocrine/nutritional/metabolic	-0.000608	0.00890	0.0127	0.0125
	(0.03920)	(0.03872)	(0.03866)	(0.03864)
High school degree x Skin and subcutaneous tissue	0.0218	0.0268	0.0247	0.0244
	(0.02146)	(0.02130)	(0.02141)	(0.02140)
Post-secondary educ. x External causes	0.0197	0.0242*	0.00809	0.00862
	(0.01324)	(0.01323)	(0.01348)	(0.01348)
Post-secondary educ. x Digestive system	0.0395***	0.0428***	0.0305***	0.0310***
	(0.01096)	(0.01085)	(0.01107)	(0.01108)
Post-secondary educ. x Circulatory system	-0.00260	0.00563	-0.00447	-0.00609
	(0.01982)	(0.01960)	(0.02000)	(0.02002)
Post-secondary educ. x Genitourinary system	-0.00370	0.0000232	-0.00988	-0.0104
	(0.01913)	(0.01893)	(0.01946)	(0.01945)
Post-secondary educ. x Neoplasms	0.0302	0.0434	0.0249	0.0254
	(0.02790)	(0.02739)	(0.02760)	(0.02764)
Post-secondary educ. x Musculoskeletal system	0.0479***	0.0522***	0.0362**	0.0379**
	(0.01751)	(0.01738)	(0.01752)	(0.01746)
Post-secondary educ. x Respiratory system	-0.00255	0.00425	-0.00435	-0.00378
	(0.02094)	(0.02069)	(0.02122)	(0.02117)
Post-secondary educ. x Mental disorders	0.0277	0.0326	0.0152	0.0136
	(0.03740)	(0.03689)	(0.03735)	(0.03739)
Post-secondary educ. x Endocrine/nutritional/metabolic	-0.0314	-0.0172	-0.0136	-0.0102
	(0.05242)	(0.05109)	(0.05162)	(0.05137)
Post-secondary educ. x Skin and subcutaneous tissue	0.0113	0.0102	0.00275	0.00287
	(0.03393)	(0.03370)	(0.03400)	(0.03407)
Labor experience		0.00588***	0.00587***	0.00586***
		(0.00009)	(0.00009)	(0.00009)
Mining x Labor experience		-0.00170***	-0.00170***	-0.00170***
		(0.00014)	(0.00014)	(0.00014)

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Table 7 – continued from previous page

	(1)	(2)	(3)	(4)
Manufacturing x Labor experience		-0.000944***	-0.000942***	-0.000941***
		(0.00009)	(0.00009)	(0.00009)
Construction/transportation x Labor experience		-0.000232***	-0.000233***	-0.000232***
		(0.00007)	(0.00007)	(0.00007)
Wholesale/retail/restaurants x Labor experience		-0.000895***	-0.000892***	-0.000894***
		(0.00009)	(0.00009)	(0.00009)
Finance/real estate x Labor experience		-0.00110***	-0.00109***	-0.00110***
		(0.00008)	(0.00008)	(0.00008)
Education/health x Labor experience		-0.00166***	-0.00165***	-0.00165***
		(0.00010)	(0.00010)	(0.00010)
Mining x External causes			0.0441	0.0434
			(0.02788)	(0.02784)
Mining x Digestive system			0.0109	0.0111
			(0.02564)	(0.02569)
Mining x Circulatory system			0.00698	0.00605
			(0.05138)	(0.05180)
Mining x Genitourinary system			0.0325	0.0326
			(0.03244)	(0.03239)
Mining x Neoplasms			0.0244	0.0238
			(0.05745)	(0.05737)
Mining x Musculoskeletal system			-0.0270	-0.0248
			(0.04466)	(0.04482)
Mining x Respiratory system			0.0833*	0.0834*
			(0.04509)	(0.04526)
Mining x Mental disorders			0.0250	0.0229
			(0.08578)	(0.08451)
Mining x Endocrine/nutritional/metabolic			-0.0239	-0.0222
			(0.09012)	(0.08990)
Mining x Skin and subcutaneous tissue			0.0560	0.0581
			(0.07218)	(0.07255)
Manufacturing x External causes			0.0265*	0.0261*
			(0.01491)	(0.01490)
Manufacturing x Digestive system			0.0195	0.0193
			(0.01500)	(0.01500)

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Table 7 – continued from previous page

	(1)	(2)	(3)	(4)
Manufacturing x			0.0331	0.0327
Circulatory system			(0.02788)	(0.02785)
Manufacturing x			0.0266	0.0281
Genitourinary system			(0.02982)	(0.02978)
Manufacturing x			0.122***	0.121***
Neoplasms			(0.04532)	(0.04526)
Manufacturing x			0.0131	0.0129
Musculoskeletal system			(0.02898)	(0.02895)
Manufacturing x			0.0408	0.0408
Respiratory system			(0.03019)	(0.03016)
Manufacturing x			0.0132	0.0120
Mental disorders			(0.04592)	(0.04603)
Manufacturing x			-0.115	-0.112
Endocrine/nutritional/metabolic			(0.07559)	(0.07576)
Manufacturing x			-0.0380	-0.0361
Skin and subcutaneous tissue			(0.04509)	(0.04516)
Construction/transportation			-0.00652	-0.00680
x External causes			(0.01131)	(0.01130)
Construction/transportation			-0.00250	-0.00289
x Digestive system			(0.01236)	(0.01236)
Construction/transportation			0.0142	0.0132
x Circulatory system			(0.02348)	(0.02338)
Construction/transportation			0.0248	0.0252
x Genitourinary system			(0.02388)	(0.02388)
Construction/transportation			0.0327	0.0330
x Neoplasms			(0.03984)	(0.03975)
Construction/transportation			-0.0389	-0.0389
x Musculoskeletal system			(0.02491)	(0.02492)
Construction/transportation			0.0410*	0.0407*
x Respiratory system			(0.02436)	(0.02433)
Construction/transportation			-0.00175	-0.000542
x Mental disorders			(0.03286)	(0.03294)
Construction/transportation			-0.0639	-0.0615
x Endocrine/nutritional/metabolic			(0.06130)	(0.06158)
Construction/transportation			0.0395	0.0391
x Skin and subcutaneous tissue			(0.03145)	(0.03138)

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Table 7 – continued from previous page

	(1)	(2)	(3)	(4)
Wholesale/retail/restaurants x External causes			0.0354**	0.0352**
			(0.01445)	(0.01444)
Wholesale/retail/restaurants x Digestive system			0.0347**	0.0345**
			(0.01432)	(0.01433)
Wholesale/retail/restaurants x Circulatory system			0.0476*	0.0467*
			(0.02830)	(0.02825)
Wholesale/retail/restaurants x Genitourinary system			0.0511*	0.0535*
			(0.02802)	(0.02806)
Wholesale/retail/restaurants x Neoplasms			0.0771*	0.0768*
			(0.04394)	(0.04389)
Wholesale/retail/restaurants x Musculoskeletal system			0.0216	0.0227
			(0.02857)	(0.02860)
Wholesale/retail/restaurants x Respiratory system			0.0185	0.0193
			(0.02991)	(0.02995)
Wholesale/retail/restaurants x Mental disorders			-0.00711	-0.00834
			(0.03777)	(0.03763)
Wholesale/retail/restaurants x Endocrine/nutritional/metabolic			-0.0561	-0.0549
			(0.07740)	(0.07697)
Wholesale/retail/restaurants x Skin and subcutaneous tissue			0.0148	0.0152
			(0.04105)	(0.04099)
Finance/real estate x External causes			0.0461***	0.0455***
			(0.01315)	(0.01314)
Finance/real estate x Digestive system			0.0508***	0.0505***
			(0.01357)	(0.01357)
Finance/real estate x Circulatory system			0.0534**	0.0538**
			(0.02556)	(0.02541)
Finance/real estate x Genitourinary system			0.0677***	0.0691***
			(0.02560)	(0.02563)
Finance/real estate x Neoplasms			0.102**	0.102**
			(0.04290)	(0.04282)
Finance/real estate x Musculoskeletal system			0.0688***	0.0697***
			(0.02560)	(0.02557)
Finance/real estate x Respiratory system			0.0645**	0.0652**
			(0.02798)	(0.02796)

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	(1)	(2)	(3)	(4)
Finance/real estate x Mental disorders			0.0686*	0.0650*
			(0.03742)	(0.03742)
Finance/real estate x Endocrine/nutritional/metabolic			-0.0727	-0.0685
			(0.06811)	(0.06821)
Finance/real estate x Skin and subcutaneous tissue			0.0798**	0.0802**
			(0.03661)	(0.03662)
Education/health x External causes			0.0960***	0.0950***
			(0.01438)	(0.01438)
Education/health x Digestive system			0.0794***	0.0794***
			(0.01475)	(0.01476)
Education/health x Circulatory system			0.0956***	0.0989***
			(0.02604)	(0.02601)
Education/health x Genitourinary system			0.0501*	0.0537*
			(0.02845)	(0.02849)
Education/health x Neoplasms			0.202***	0.204***
			(0.04135)	(0.04152)
Education/health x Musculoskeletal system			0.103***	0.103***
			(0.02590)	(0.02587)
Education/health x Respiratory system			0.0863***	0.0870***
			(0.03137)	(0.03134)
Education/health x Mental disorders			0.110***	0.108***
			(0.03846)	(0.03845)
Education/health x Endocrine/nutritional/metabolic			-0.0282	-0.0306
			(0.06874)	(0.06885)
Education/health x Skin and subcutaneous tissue			0.105***	0.107***
			(0.03937)	(0.03948)
Any past shock=1 x External causes				0.00698
				(0.01200)
Any past shock=1 x Digestive system				-0.0300**
				(0.01245)
Any past shock=1 x Circulatory system				-0.0593***
				(0.01790)
Any past shock=1 x Genitourinary system				-0.0457**
				(0.02026)
Any past shock=1 x Neoplasms				-0.0179
				(0.02087)

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Table 7 – continued from previous page

	(1)	(2)	(3)	(4)
Any past shock=1				-0.0249
x Musculoskeletal system				(0.01703)
Any past shock=1				-0.0253
x Respiratory system				(0.02275)
Any past shock=1				0.0623**
x Mental disorders				(0.02441)
Any past shock=1				0.0571
x Endocrine/nutritional/metabolic				(0.04666)
Any past shock=1				-0.0367
x Skin and subcutaneous tissue				(0.02995)
Worker fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Within R^2	0.0104	0.0227	0.0228	0.0230
Number of individuals	101,574	101,574	101,574	101,574
Observations	10,757,300	10,757,300	10,757,300	10,757,300

Note: Standard errors clustered on individual workers in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.