NBER WORKING PAPER SERIES

NO PAIN, NO GAIN: THE EFFECTS OF EXPORTS ON EFFORT, INJURY, AND ILLNESS

David Hummels
Jakob Munch
Chong Xiang

Working Paper 22365
http://www.nber.org/papers/w22365

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2016

We thank the Danish Council for Independent Research/Social Sciences for funding. For helpful comments we thank Osea Giuntella, Nils Gottfries and seminar participants at NHH Bergen, University of Oslo, University of Oxford, ESWC Montreal, University of Lund, Singapore Management University, University College Dublin, Copenhagen Business School, Aarhus University, IFN Stockholm, University of Chicago, Uppsala University and University of Oxford Trade and Health Workshop. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

No Pain, No Gain: The Effects of Exports on Effort, Injury, and Illness
David Hummels, Jakob Munch, and Chong Xiang
NBER Working Paper No. 22365
July 2016, Revised August 2019
JEL No. F1,F6,I1,J2,J3

ABSTRACT

In this paper we address two questions. First, how do changes in demand for work affect workers' health? Second, how do we translate these health effects into meaningful economic terms so that we can compare the income gains associated with increased demand for work with the pain of adverse health? We combine Danish data on individuals' health with Danish matched worker-firm data. Within job-spells, we find that as firm sales increases, workers work longer hours and suffer higher incidences of adverse health events, including work-related hospitalizations and increased use of prescription drugs for depression and heart diseases. Tracking worker cohorts over time, we show that the effects of prescription drug uses persist beyond shocks to work demand. We then develop a novel framework to compute the marginal disutility of diseases, and to quantify the average worker's ex-ante utility loss due to higher rates of sickness. Our approach accommodates moral hazard and does not require the values of structural parameters as inputs. It also provides a straightforward and intuitive extension of VSLI, from mortality and work injury to morbidity. Our marginal-disutility values have sensible and intuitive variation across diseases, and we find that the average worker's utility loss accounts for almost one fifth of her wage gains from rising firm sales.

David Hummels
Krannert School of Management
403 West State Street
Purdue University
West Lafayette, IN 47907-1310
and NBER
hummelsd@purdue.edu

Jakob Munch
Department of Economics
University of Copenhagen
Øster Farimagsgade 5
Building 26
DK-1353 Copenhagen K
Jakob.Roland.Munch@econ.ku.dk

Chong Xiang
Department of Economics
Purdue University
403 West State Street
West Lafayette, IN 47907-2506
cxiang@purdue.edu

1. Introduction

In this paper we address two questions. First, how do changes in demand for work affect workers' health? Higher demand likely raises income, and many studies show that higher income or wealth leads to better health. Reinforcing this view, the recent literature on "deaths of despair" suggest a connection between declining economic opportunities and worsening health, as do papers that implicate mass layoffs, plant closures and import competition.[1] Yet, the evidence is mixed. Increasing demand for labor that requires greater effort and longer hours may increase work stress, and a medical literature has shown that self-reported work hours and stress are correlated with coronary heart diseases, strokes, and even mortality.[2] In addition, at the population health level, mortality and correlates of bad health (e.g. smoking, excess weight, physical inactivity) have been shown to be pro-cylical, even though the exact channels remain an open question.[3]

Second, how do we translate these health effects into meaningful economic terms so that we can compare the income gains associated with increased demand for work with the pain of adverse health? While estimates for the marginal disutility of mortality and injury, or VSLI (value of a statistical life/injury), have been well-established and widely used by U.S. regulatory agencies[4], similar estimates for diseases remain elusive.[5]

To answer the first question – how do changes in demand for work affect worker health – we draw on Danish administrative data that match the universe of private-sector Danish firms to the

---

1 See Case and Deaton (2015) on "deaths of despair", Sullivan and von Wachter (2009) for mass layoffs, Browning and Heinesen (2012) for plant closure and McManus and Schaur (2015) for import competition.

2 E.g. Kivimaki et al. (2012), Fransson et al. (2016), Virtanen et al. (2012), and O'Reilly and Rosato (2013).

3 See Ruhm (2000, 2003, 2005) for pro-cylicality of US mortality and specific channels, Stevens, Miller, Page and Filipski (2015), argue that Ruhm (2000)'s result for mortality is driven by staffing changes at nursing homes. See also Lindo (2013), Tekin, McClellan and Minyard (2013), and Coile, Levine and McKnight (2014).

4 See Viscusi (1993) and Viscusi and Aldy (2003).

5 For example, Jones and Klenow (2016)'s well-being index incorporates mortality but leaves out morbidity Recent studies have also examined the implications of mortality, but not morbidity, for GDP (e.g. Murphy and Topel 2003, Becker, Philipson and Soares 2005), macro-economic fluctuations (e.g. Egan, Mulligan and Philipson 2013) and economic growth (e.g. Jones 2016).

population of Danish workers. We examine how changes in firm sales translate to changes in hours worked for each individual and to changes in worker health. The latter is possible because for each individual, we observe her socio-economic characteristics and rich details about *every* interaction with the Danish healthcare system. For example, we observe all prescription drug purchases (including cost and drug type) made by each individual, along with doctor visits and hospitalization (with corresponding diagnostic codes). This rich data on individuals' health is available to us because Danish health care is free and universal, and every individual has access to health care, regardless of income and employment status. This distinguishes our work from previous research on health and labor market using U.S. data, where workers' access to health care is correlated with income and employment status.[6]

We face several challenges in taking our first question to the data. One, individuals' health may be affected by many idiosyncratic and time-invariant factors, such as pre-natal and early-life environment, birth weight, and genetic differences.[7] Two, it can be difficult to observe effort levels exerted by individual workers and to determine whether individual health outcomes are related to effort levels at work, or other external factors. Three, short-term changes in work demand may have longer-term effects on workers' health that persist even after workers move between jobs or employers.

The comprehensive and panel structure of our Danish data allow us to deal with these challenges. First, we consistently track each worker and each firm over time, and so in our main specification we condition on job-spell fixed effects; i.e. the source of our variation is the change over time within a given worker-firm relationship. Second, the richness of our data allows us to directly measure both effort levels and work-related health outcomes for each worker. For effort we observe each worker's total hours worked, including over-time hours. For health outcomes we are particularly interested in those connected to workplace stress. Here we observe the universe of anti-depressant purchases, visits to psychiatrists,

[6] See, e.g., Currie and Madrian (1999) for a survey.
[7] See Maccini and Yang (2000) and Black, Devereux and Salvanes (2007).

and hospitalization records of every worker. The diagnostic codes of our hospitalizations data are particularly helpful as they specifically identify the hospitalizations that are caused by work effort. We can then estimate how work-effort related hospitalizations respond to changes in firm sales. Third, we are able to estimate the longer-term effects of changes in work demand even as workers transition between jobs, between locations, or to unemployment, because our data allow us to track workers over extended periods of time.

Our main findings, based on within-job-spell variation, are as follows. First, workers log longer hours and obtain higher earnings as their employers experience sales increases. Second, increases in firm sales also lead to higher probabilities that workers purchase anti-depressants or visit psychiatrists (elasticity 0.024-0.025). Third, workers suffer higher incidences of work-effort related hospitalizations as firm sales increases (elasticity 0.43-0.45), and they also experience higher rates of hospitalizations due to stress and depression, heart attacks and strokes, and severe liver diseases, an indicator of alcoholism (elasticity 0.054-0.29).

Finally, these within job-spell findings are corroborated by our multi-period difference-in-difference estimates (e.g. Jacobson, LaLonde and Sullivan 1993, or JLS) that follow workers across job-spells. To be specific, large sales increases have significant contemporaneous effects for the hospitalization variables we study, and significant longer-tem effects for our prescription-drug variables (2-5 years post-shock). Our within-job-spell and JLS results are novel to the literature, and strongly suggest that economic shocks affect individuals' health through the effort-and-stress channel.

To quantify the economic consequences of disease, we develop a novel theoretical approach. The average worker derives expected utility from one healthy state and multiple sick states. The welfare loss due to positive sickness rates is the compensating variation that equates this expected utility to the utility level in the completely healthy state. The marginal disutility of disease g, then, is the partial derivative of this compensating variation with respect to g's frequency, and the average worker's expected utility loss due to higher rates of multiple diseases is the total derivative of compensating variation.

One approach for computation is to identify the full set of structural parameters, such as the utility functions in the healthy and sick states, which may differ due to state dependence. The literature has not reached a consensus about how to identify these parameters.[8] We take a more reduced-form approach, and relate the change in compensating variation to several reduced-form parameters that can be estimated or observed in the data. The comparison between our approach and the full structural approach has the flavor of Chetty (2008). On the one hand, we are unable to calculate the ex-post utility losses, or quality of life, for those who actually get sick. On the other hand, we can be agnostic about state dependence and the values of the other structural parameters, because different combinations of these parameters may correspond to the same values of the reduced-form parameters that we need for computation.

Our first set of reduced-form parameters is utility share weights, or the weights that the average worker attaches to diseases in the change of expected utility. We show that the utility share weight of disease g is high if g happens with a high frequency or if it is severe. We show, next, that relative to disease l, the marginal disutility of disease g is high if g happens with a low frequency but has a high utility share weight. This result is intuitive, because a low frequency tends to reduce utility share weight, other things equal. The fact that utility share weight is high despite low frequency indicates high severity, or high marginal disutility.[9]

Because the severity of diseases is hard to quantify,[10] we take a revealed-preference approach, and show that if individuals optimally choose treatment, then the expenditure shares of diseases are

[8] For example, Viscusi and Evans (1990) and Finkelstein, Luttmer and Notowidigdo (2013) report negative state dependence, Lillard and Weiss (1998), Edwards (2008) and Ameriks, Briggs, Caplin, Shapiro and Tonetti (2016) report positive state dependence, while Evans and Viscusi (1991) report no state dependence.

[9] In our framework, severity is post-treatment, and so our marginal disutility takes medical technology for treatment into account.

[10] A literature measures quality of life, or ex-post utility loss in sickness, using survey data. Examples include QALY, or Quality-Adjusted Life Years, (e.g. Torrance 1986, Cutler, Richardson, Keeler and Staiger 1997), and DALY, or Disability-Adjusted Life Years (e.g. Murray and Acharya 1997). Quality of life is related to, but distinct from, severity and marginal disutility of diseases in our framework (see subsection 6.4).

informative about their utility share weights. This result is intuitive, because expenditure shares reflect disease frequency and severity, which also affect utility share weights.[11] In deriving this result, we allow the private- and social-cost functions to differ, and so we accommodate moral hazard, a very important feature of the healthcare system.[12] This result then allows us to compute the marginal disutility of diseases by using their frequencies and expenditure shares.

We find that marginal disutility has intuitive variation across diseases. For example, the marginal disutility of stress that can be treated with anti-depressants is DKK 31,370, but the marginal disutility of stress that requires hospitalization is sharply higher, DKK 403,530, and reaches DKK 3.47 million for hospitalization due to heart attacks and strokes (1 DKK = 0.18 USD in our sample). Using these values of marginal disutility, we find that as firm sales increases, the average worker's ex-ante expected utility loss from adverse health effects is equal to 16.9% of her wage gains.

We now discuss how our work complements previous research. A line of work uses cross-sectional variation to estimate how economic shocks affect health (e.g. Marmot, Rose, Shipley and Hamilton 1978, Marmot et al. 1991, Case and Deaton 2009, Black, Devereux and Salvanes 2012) by drawing on health-diagnostics data (e.g. blood pressure). We use panel data that allow us to both control for unobserved worker characteristics that affect health, and to assess a wide range of health outcomes and track them over time.

We also contribute to a literature that assesses the pro-cyclicality of health and mortality, including Ruhm (2000, 2003, 2005), Lindo (2013), Tekin, McClellan and Minyard (2013), and Coile, Levine and McKnight (2014). As this literature uses population health data, an important question is whether the economic shocks affect individuals' health directly, or through other external economic

[11] A literature examines aggregate healthcare spending, focusing on the U.S. (e.g. Newhouse 1992, Hall and Jones 2007, Chandra and Skinner 2012). We focus on the expenditure shares of individual diseases within aggregate health spending, and propose the conditions under which expenditure shares relative to frequency provide useful approximations for marginal disutility.

[12] See Cutler and Zeckhauser 2000

activities (e.g. Miller, Page, Stevens and Filipski 2009, Stevens et al. 2015).[13] Our use of matched worker-firm data and identification of shocks within job spells enables us to specifically isolate the mechanism linking increased firm sales to longer hours and adverse health outcomes specifically related to work stress.

For the income channel of economic shocks, a literature shows that negative shocks, including mass layoff (e.g. Sullivan and von Wachter 2009), plant closure (e.g. Browning and Heinesen 2012), and import competition (e.g. McManus and Schaur 2015), tend to have adverse effects on health.[14] Our highlighted finding shows a seemingly opposite effect -- increases in firm sales lead to increases in earnings and adverse health outcomes for individual workers. However, we reconcile our results with this literature in specifications that examine asymmetric effects. We show that sharp decreases in sales decrease hours worked but lead to some adverse health outcomes. Because of universal medical coverage in Denmark, this is not caused by lack of access to the healthcare system. Rather, it appears that both sharp increases and sharp decreases in firm sales stress workers out!

Bauer, Lakdawalla and Reif (2018) use the values of state dependence and quality of life as inputs in a structural model, and extend VSL to multiple diseases by examining the effects of these diseases on mortality risk. This framework provides exact values of marginal disutility. Our approach remains agnostic about the values of structural parameters, accommodates moral hazard, and delivers approximate values of marginal disutility. Our approach also applies to non-fatal diseases. On the other hand, Viscusi (1993) extends VSLI to specific types of diseases by surveying individuals for the compensation they would like for hypothetical sickness. Our approach covers multiple diseases,

[13] For example, changes in nursing home staffing can lead to decreased quality of care and increased mortality. There can be more traffic-accident deaths during economic expansion because (1) time-pressed and stressed drivers pay less attention to safety; or (2) there are more vehicles on the road.

[14] See also Browning, Danø and Heinesen (2006), Eliason and Storie (2007, 2009), Colantone, Crinò and Ogliari (2015), Schaller and Stevens (2015), Pierce and Schott (2016), and Adda and Fawaz (2017). Some studies of import competition examine health-related outcome, such as marriage (e.g. Autor, Dorn and Hanson 2015) and crime (e.g. Dix-Carneiro, Soares and Ulyssea 2015). Goldman-Mellor, Saxton and Catalano (2010) survey the studies at the intersection of economics and epidemiology that focus on mental health.

incorporates the representative consumer's optimization, and utilizes expenditure data that reflect individuals' actual choices.

More broadly, the VSLI estimates have been widely used to quantify the gains or losses in the changes of mortality and injury rates, to conduct cost-benefit analyses of government regulations and policies, and to provide a target for the calibration of structural parameters (e.g. Murphy and Topel 2003, Hall and Jones 2007). We hope that our marginal-disutility estimates may also be of use in these areas, since they extend VSLI to diseases.[15]

The paper is organized as follows. Section 2 describes our data. Section 3 presents our main hypothesis and identification strategy. Section 4 shows our main results, identified from within-job-spell variation. Section 5 presents our results for asymmetric effects and those based on propensity-score matching. Section 6 develops our theoretical framework for marginal disutility, and section 7 implements the computation using our data and estimation results. Section 8 collects our robustness exercises, and section 9 concludes.

2. Data

In this section we discuss the main features of our data and our variables for stress, efforts and illness. We report more details of data construction in Data Appendix 1.

We start with Danish administrative data that matches workers to firms and the domestic production of these firms. The data are annual, cover the period 1995-2012, and match the population of Danish workers to the universe of private-sector Danish firms. The primary data sources are the Firm Statistics Register, the Integrated Database for Labor Market Research ("IDA"), the link between firms

[15] For example, studies have shown that the housing vouchers program by the U.S. HUD and the expansion of Medicaid in Oregon both improve program participants' mental health (e.g. Ludwig et al. 2012, Baicker et al. 2013). How do the health benefits compare with the program costs?

and workers ("FIDA"), Account Statistics and the Prodcom database[16], which breaks down each firm's production by product.

To construct our main sample, we start from all the private-sector firms and workers in the Prodcom sales data/registry. We keep the firms with positive imports and exports, since we use offshoring and the numbers of export products and export destination countries as controls. We select larger firms (those with at least 50 employees) to get high quality data on capital, and to limit the impacts of individual workers' health on firm sales. We also drop the observations with missing information about key firm variables (sales, capital-labor ratio and the share of high-skilled workers). We select 20-60 year old full-time workers, and we drop all observations where the employment relationship lasts a single year.[17] Table 1 reports the summary statistics of the firm- and worker-characteristics variables that we use in our analyses.

We then bring in additional administrative datasets that contain comprehensive information about individuals' health care utilization during 1996-2012. We observe the *universe* of *transactions* for every person within the Danish healthcare system, including prescription drug purchases, doctor visits, and hospitalization. These datasets are organized by the same worker identifiers as our worker-firm data, allowing us to merge them. In the literature, a common concern for data on the utilization of health care is that access to care could be correlated with individuals' socio-economic conditions (e.g. income and employment status), and that this correlation could contaminate the care-utilization data (e.g. Currie and Madrian 1999). This concern is unlikely to be a main issue for us, because the Danish healthcare system is almost entirely funded by the government, available to all Danish residents regardless of employment status, and virtually free to all.[18]

[16] The Prodcom database is a survey used by Eurostat to provide comparable production statistics for EU countries. Bernard et al. (2019) is a recent example using the Belgian version of the database.
[17] We have experimented with different sample cuts, and obtained similar results (see section 8).
[18] There are two main exceptions. 1. Dental care is not covered. 2. Patients bear some co-payments for prescription-drug expenses. We do not consider dental visits in our study, and the prescription co-pays are small enough (roughly 0.13 percent of median income) that income constraints on access are unlikely to be binding.

Many studies of mental health use self-reported survey data and measure stress by the Center for Epidemiological Studies Depression Scale (CESD). Our administrative data allows us to construct indicator variables for stress- and efforts-related diseases, which are higher thresholds than CESD.[19] Table 1 shows the summary statistics of our sickness variables. The first set includes prescription drugs, doctor visits and hospitalizations due to stress/depression.[20] The second set includes hospitalizations that are diagnosed as efforts- and work-related, and we will discuss them in detail in sub-section 4.2 below. The last set includes prescription drugs and hospitalizations due to heart diseases and strokes, as well as hospitalizations due to liver diseases, a commonly used measure for alcoholism. We include these variables because studies in epidemiology and cardiology have shown that work stress and job strain are risk factors for coronary heart diseases (e.g. Kivimaki and Kawachi 2015), and it is common for studies of mental health to examine alcoholism (e.g. Goldman-Mellor et al. 2010).[21]

Finally, we complement these annual data with monthly payroll records with information about worker-level earnings and hours worked as well as monthly firm-level sales for the years 2008-2012. The worker-level data is based on the "eIncome" register, which holds third-party reported information about monthly earnings and hours worked for all employees in Danish firms. The firm-level data comes from "FIKS", which has information total sales and total purchase of materials for all firms liable for value added taxation on a monthly basis. To be consistent with the sample restrictions above, we select in this dataset all 20-60 year old fulltime workers employed by firms with non-missing Prodcom sales and at least 50 employees. Table 1 shows the summary statistics of our monthly variables.

To summarize, our dataset covers the population of Danish workers and firms, and the universe

[19] This implies that our results likely provide conservative estimates of the effects of work demand on general mental health (e.g. an individual with no stress-related disease may still feel unhappy and lonely), and that the effects of work demand we identify are economically significant (see sections 6 and 7).

[20] In medical research, Olsen et al. (2007) show that the prevalence of depression is 3-4% in the Danish population, which is comparable to the mean rate of anti-depressant uses in our sample.

[21] We do not look at sleep disorder for two reasons. One, there is a U-shaped relationship between self-reported stress and hours of sleep in some survey data (e.g. De Quidt and Haushofer 2016). Two, Goldman-Mellor et al. (2010) survey a large number of studies on mental health, and none of them examines sleep disorder.

of healthcare transactions. It allows us to measure worker-level stress, sickness, and efforts, and to consistently track their changes over time. These features help us identify the causal effects of sales on health and efforts, as we explain below.

3. Main Hypothesis, Specification, and Identification

In this section, we clarify our main hypothesis, derive our main specifications, present our main identification assumption, and discuss threats to identification.

3.1 Main Hypothesis and Specification

Assume that firm *j* has a continuously differentiable and concave production function (e.g. Cobb-Douglas, CES), and uses labor, capital and materials as inputs. The quantity of the labor input depends on the number of workers, and individual workers' effort. Assume that the effort-cost function is continuously differentiable and convex. Worker *i* optimizes by equalizing the marginal cost of effort to the marginal benefit.

We assume that the marginal cost of effort captures the marginal disutility from the adverse health effects induced by that effort. (Below, for brevity, we term the adverse health effects "stress", in the broad sense of increased pressure on the mental and physical health of the worker.)[22] The marginal benefit of effort, on the other hand, derives from firm *j*'s demand for labor. Suppose that *j* experiences a positive demand shock for its output, or a positive shock to its TFP. Then *j*'s demand for labor increases, and the marginal benefit for effort also increases if *j* faces an upward sloping labor supply curve (e.g. Manning 2011, Hummels, Jørgensen, Munch and Xiang 2014). As a result, worker *i* chooses to increase effort in response. This rise in effort level also raises *i*'s total effort cost, since the effort-cost function is

[22] Our assumption is motivated by the strong correlation between work hours and stress documented in medical research (e.g. Virtanen et al. 2011).

increasing, and so worker i's stress increases as well.

To formalize this intuition, let e_{ijt} denote worker i's effort in year t for her employer j, E_{ijt} denote i's total effort cost, and W_{ijt} denote her earnings. ψ_{jt} is a composite term that includes j's output demand and TFP in year t. In Theory Appendix 1, we use a multi-lateral bargaining model (e.g. Stole and Zwiebel 1996, Helpman, Itskhoki and Redding 2010) to show that shocks to output demand or TFP result in $\partial e_{ijt} / \partial \psi_{jt} > 0$, $\partial E_{ijt} / \partial \psi_{jt} > 0$ and $\partial W_{ijt} / \partial \psi_{jt} > 0$. These results imply that workers' stress (i.e. adverse health events) increases with ψ_{jt} as well, given our assumption that effort cost represents disutility from stress. Summarizing, we have

Proposition 1 Following an increase in output demand or TFP for firm j, j's employees increase their effort and experience higher effort cost, higher stress and higher earnings.

In Theory Appendix 2, we derive the following expressions for e_{ijt}, E_{ijt}, and W_{ijt}, under additional assumptions about the functional forms of the production function and effort-cost function

$$\ln X_{ijt} = \mathbf{constant} + \phi_1 \ln \psi_{jt} + \mathbf{z}_{jt} b, \; X_{ijt} = e_{ijt}, E_{ijt}, \text{ or } W_{ijt}. \tag{1}$$

In equation (1), $\phi_1 > 0$ by Proposition 1. The vector $\mathbf{z}_{jt}$ includes the variables for firm j's inputs in year t, and it enters (1) because j's input uses may affect the marginal benefit of effort.

Motivated by equation (1), we first use our monthly data from 2008-2012 to estimate the dependence of hours (effort) and earning on firms sales

$$\ln(Z_{ijm}) = \phi \ln Y_{jm} + \mathbf{x}_{it} b_1 + \mathbf{z}_{jt} b_2 + \alpha_{ij} + \alpha_R + \alpha_D + \alpha_m + \alpha_t + \varepsilon_{ijt}, \; Z_{ijm} = H_{ijm} \text{ or } W_{ijm} \tag{2}$$

In equation (2), m indexes calendar month, and t continues to index year. H_{ijm} is the total number of hours, including over-time hours, of worker i for firm j in month m, W_{ijm} is i's total earnings with j in m, and Y_{jm} is firm j's total sales in m. Relative to equation (1), we have added the vector $\mathbf{x}_{it}$ of time-varying worker characteristics as controls in (2). We have also added α_{ij}, α_R, α_D, α_m, and α_t, which represent, respectively, job-spell, region, industry, month and year fixed effects.

The monthly data on hours and sales are available for only 5 of the 17 years of our sample but we can use the full 17 years of annual data to relate changes in workers' health outcomes to changes in firm sales. The longer time series is important for identifying within job-spell changes in health because reported adverse events occur infrequently. We estimate

$$S_{ijt} = \phi \ln Y_{jt} + \mathbf{x}_{it} b_1 + \mathbf{z}_{jt} b_2 + \alpha_{ij} + \alpha_R + \alpha_D + \alpha_t + \varepsilon_{ijt} . \tag{3}$$

In equation (3), we measure effort cost and stress level, E_{ijt}, using S_{ijt}, an indicator variable for whether worker i suffers adverse health events in year t while working for firm j. Y_{jt} is j's total sales in year t. In equations (2)-(3), Proposition 1 implies that $\phi > 0$.

Note that our job-spell fixed effects pose a computational challenge for non-linear specifications of (3), such as Probit or Logit, because the marginal effects there depend on the values of all the fixed-effects parameters (e.g. Wooldridge 2002), and we have over 700,000 of them in our estimation. As a result, we use the linear specification for (3), and think about our results as a linear approximation around the sample means of the indicator variables for stress-related diseases.

3.2 Main Identification Assumption and Comparison with Literature

We now present our main identification assumption and compare it with the literature. There are two main elements in the comparative static exercises in Proposition 1, and equation (1). One, a shock to output demand or firm TFP, ψ_{jt}, affects demand for work effort. Two, the workers take the change in ψ_{jt} as exogenous. The estimation equations (2) and (3) employs firm sales rather than ψ_{jt} since ψ_{jt} is difficult to measure. However, they closely match Proposition 1 and equation (1), because sales changes net of changes in input uses are likely due to changes in output demand or TFP. Therefore, our main identification assumption is that firm sales affect demand for work effort and they are exogenous to individual workers, conditional on the control variables in our estimation.

We now compare our identification assumption with the literature. In the studies on the pro-cyclicality of health (e.g. Ruhm 2000, Coile et al. 2014, Stevens et al. 2015), the main explanatory variable is unemployment by U.S. state by year, which is clearly exogenous to individual workers. This literature does not distinguish whether state unemployment is caused by state productivity or aggregate demand, because they have similar effects on demand for work effort. The literature on the health effects of mass layoffs and plant closures (e.g. Eliason and Storie 2007, Sullivan and von Wachter 2009, Browning and Heinesen 2012) takes these variables as exogenous to workers.[23] This literature does not distinguish whether mass layoffs and plant closures are caused by firm productivity or output demand, because they have similar effects on workers' income and employment status. The studies in both literatures typically do not control for worker fixed effects.[24,25]

In summary, our main identification assumption is similar to the literature. Our rich data allow us to include a rich set of control variables in our estimation.[26]

3.3 Threats to Identification

We next describe six threats to identification and our strategy to address each in turn. The primary threat to our identification is that workers' adverse health events may be triggered by many hard-to-measure individual characteristics and worker-firm characteristics. Examples of individual characteristics include pre-natal factors (e.g. Maccini and Yang 2009), birth weight (e.g. Black et al. 2007), and genetic differences. In addition, unobserved individual characteristics may interact with unobserved firm characteristics, if workers selectively sort into the firms that lead to high matched

---

[23] E.g. Quoting Sullivan and von Wachter (2009), "Firm-level employment declines should be exogenous to individual workers' health developments."

[24] They are also unable to do so if the dependent variable is mortality.

[25] The Framingham heart sample has panel data, and is used in cardiology to study the physiological and behavioral risk factors of heart diseases, such as obesity (e.g. Hubert et al. 1983). These studies do not focus on economic shocks. The Whitehall sample is also panel data, and is used in epidemiology to study the psychosocial and behavioral risk factors of health, such as job control (e.g. Bosma et al. 1997). The main explanatory variables in these studies are typically self-reported.

[26] Our identification comes from the rich variations of firm sales over time relative to the job-spell mean (e.g. note 27). This distinguishes our approach from the difference-in-difference estimation strategy, where there is little meaningful variation in the periods before and after the policy changes (Bertrand, Duflo and Mullainathan 2004).

worker-firm productivity (e.g. Helpman et al. 2010). This match specific productivity, in turn, may correlate with both firm sales and worker stress; e.g. type-A-personality individuals may be more likely to work with firms with good growth potential. We control for both individual characteristics and worker-firm characteristics using the job-spell fixed effects, α_{ij}, in equations (2)-(3). With α_{ij}, our identification comes from variation within job spells, over time. Conditioning on the match, we ask whether individual workers suffer an increased risk of adverse health outcomes when their firms experience increased sales.

Second, firm *j* may face a perfectly elastic supply curve for employment, in which case the marginal benefit of effort would not rise in response to an increase in work demand, and Proposition 1 would not hold. This conjecture is inconsistent with our data, for two reasons. One, sales have more variation over time, within job spells, than employment.[27] Two, we will show, in section 4 below, that hours and earnings tend to increase with firm sales within job spells.

Third, firm sales may not be exogenous to worker health. Suppose that a worker gets sick for reasons unrelated to work. They become less productive, which might lower firm sales, and so reverse causality biases the estimation against our main hypothesis. This channel will be strongest when an individual worker represents a larger share of employment, or if the worker is in a key position to influence the effectiveness of the firm as a whole. We explore robustness to including/excluding small firms and including/excluding managers in Section 8.

Fourth, other changes in firm structure can alter sales or worker stress but not act through the effort-stress channel. Two examples include organizational changes (e.g. Dahl 2011) that can lead to worker stress, and the adoption of new technology in the firm. It is unclear how these would operate, as organizational change may be either positively or negatively correlated with firm performance, and new technology might increase or decrease worker stress depending on its nature and implementation.

[27] We calculate the absolute values of the deviations from within-job-spell means for log sales and log employment. On average, log sales deviates from its job-spell mean by 0.24 log points, while log employment deviates by 0.12 log points.

Nonetheless, we address these by including organizational change variables in our regression, and by using an instrumental variables strategy to predict exogenous changes in sales, in Section 8.

Fifth, our identification examines changes within job spells, and leaves out the effects of sales changes on stress for the workers who separate. An increase in firm sales is a positive shock, and so unlikely to lead to layoffs. Workers may quit in response to adverse health outcomes, but this biases against our main hypothesis. On the other hand, a decrease in sales could lead to layoffs. Our main hypothesis implies that sales decreases lead to less worker stress, and this prediction might be threatened by firms selectively laying off unhealthy workers in response to sales drops. We address these issues in Section 5 in two ways. We explore whether sales decreases and sales increases have asymmetric effects on worker stress and we address the problem of selection out of the firm using cohort analysis and propensity-score matching.

Finally, some previous work (e.g. Moran and Simon 2006) shows that demand for prescription drugs varies with income using data from the U.S., where income is correlated with access to healthcare.[28] We have shown, in section 2, that prescription-drug copays in Denmark are very low relative to annual earnings. Still, high-income patients may choose branded drugs while low-income ones stay with generic drugs. As a result, we use indicator variables of prescription-drug purchases in our estimation, even though we observe individuals' prescription-drug expenses in our data.

4 Results with Log-Linear Specifications

4.1 Hours and Earnings

Table 2 reports the results of estimating equation (2) using our monthly data. The dependent variable is the log of total hours, or earnings, by worker i for firm j in month m, and the main explanatory

---

[28] This correlation is important for many studies using U.S. data. Sometimes it is a key mechanism (e.g. Sullivan and von-Wachter 2009, Coile et al. 2014), and other times it is an important threat to identification (e.g. Ruhm 2003).

variable is the log of j's sales in month m. We cluster our standard errors by firm by calendar month by year, since sales has no variation across workers within a firm-month-year group. From columns (1) through (4), we sequentially expand the set of control variables in the estimation. In column (1), we start with job-spell fixed effects. In column (2), we add calendar month fixed effects and control for the time-varying worker characteristics of union status, marital status and experience, and the time-varying firm characteristics of log offshoring, log employment, log capital/labor ratio, and the share of college-educated workers in employment. In column (3), we add the log of firm j's total material purchases in month m. In column (4), we replace the worker and firm characteristics with worker-by-year fixed effects and firm-by-year fixed effects. The elasticity of hours with respect to sales is significant in all specifications, and ranges from 0.013 to 0.041. In the second panel of Table 2, we drop the observations where the workers' monthly hours are imputed. This reduces the number of observations from about 8.8 million to 8.5 million, but we obtain similar results. These results are likely conservative estimates of the response of worker effort, since work intensity (i.e. how much a worker produces during a given hour on the job) may also increase with firm sales.

In the third panel of Table 2, we examine log monthly earnings, dropping the observations with imputed hours. The elasticity estimates of earnings with respect to sales are significant in all specifications, and they are similar in magnitude to the elasticity of hours.

Overall, Table 2 shows that, within job-spells, workers increase effort and obtain higher earnings when their employers experience positive economic shocks. These results provide evidence for the underlying mechanism of our main hypothesis.

4.2 Stress, and Hospitalization related to Effort and Work

We now examine how changes in firm sales affect individual workers' adverse health events, by using our annual data. As compared with our monthly data, our annual data span a longer horizon, which is important for isolating relatively infrequent adverse health events within the job-spell. Our main explanatory variable is the log of *j*'s sales in *t*. We control for job-spell fixed effects, as well as industry, year and region fixed effects, and we cluster our standard errors by firm by year. We also control for the same set of worker and firm characteristics as in column (2) of Table 2.

We first measure stress by the use of anti-depressant drugs, with the dependent variable taking the value of 1 if a worker purchases anti-depressants in year *t*, and 0 otherwise. We report the coefficient estimates normalized by the mean rate of anti-depressant use to express the effect as the elasticity of stress with respect to sales, in column (1) of Table 3. We obtain an elasticity estimate of 0.024, which is statistically significant. In column (2) of Table 3, we broaden our measure for stress to take a value of 1 if workers purchase anti-depressants or visit a psychiatrist in year *t*. We abbreviate this variable as ADPV (Anti-Depressant or Psychiatrist Visit). Our elasticity estimate is positive and significant and similar in magnitude to column (1).

Taking stock of our results so far, we see that increases in firm sales lead to longer hours and more stress. Is the increase in stress work related? Survey data consistently show that the leading cause of self-reported stress is financial problems, followed closely by work.[29] External factors, such as death or sickness of family members, and trauma from violent crime, are also common causes of stress. We can exclude financial problems because earnings increase (Table 2), and the other external factors are unlikely to correlate with sales increases in the worker's firm. This leaves us with work.

Still, we can take another step in pinning the increase in stress on work effort by drawing on diagnostic information in our hospitalization data. Specifically, the Danish health system provides diagnostic codes for hospitalization associated with "burn-out", "lack of relaxation and leisure" and "stressful work schedule". We call this group narrow burnout. We then broaden our inquiry to include

[29] A recent example is https://www.cbsnews.com/news/the-biggest-cause-of-stress-in-america-today/. Some survey data put work ahead of financial problems; e.g. https://www.webmd.com/balance/guide/causes-of-stress#1.

other work-related hospitalizations, such as "discord with boss and workmates" and "uncongenial work environment", while excluding those that are clearly related to job insecurity, such as "threat of job loss" and "change of job". We refer to this second group as broad burnout.

We report the results for narrow and broad burnout in columns (1)-(2) of Table 4. The R^2 is low because hospitalization due to burnout is rare, with mean rates of 0.05 per thousand for narrow burnout and 0.06 per thousand for broad burnout.[30] Despite this, we obtain large elasticity estimates ranging from 0.43 to 0.45, and they are all statistically significant. These results establish a tight connection between effort and stress, because narrow burnout is related to effort by construction, and broad burnout is both related to work by construction and is likely related to effort as well.

In column (3) of Table 4, we broaden our dependent variable and assign a value of 1 if workers experience hospitalizations due to either broad burnout or stress. This more than triples our sample mean, to 0.20 per thousand. In column (4) we broaden our scope further to burnout, stress, or depression, and obtain an even higher sample mean of 0.26 per thousand. The elasticity estimates are all statistically significant, and range from 0.21 to 0.30, and they provide additional evidence that workers suffer higher incidences of stress as their employers experience positive economic shocks.

4.3 Other Stress Related Outcomes: Heart Diseases and Alcoholism

We now further expand the scope of our inquiry, to examine whether changes in firm sales affect workers' rates of heart diseases, and hospitalization due to heart attacks, strokes, or alcoholism.

Our first dependent variable is whether workers purchase prescription drugs for heart diseases and strokes in year *t*. We obtain a significant elasticity estimate, 0.036 in column (3) of Table 3. In column (5) of Table 4, our dependent variable is whether workers are hospitalized because of heart attacks or strokes in year *t*. Our elasticity estimate is again significant, 0.054. In column (6) of Table 4,

[30] Many individuals are never hospitalized, for any reason, during our sample period, and we include them in our analyses.

our dependent variable is hospitalizations due to liver diseases, a commonly used measure for alcoholism. We obtain a significant elasticity estimate of 0.12.

Summarizing, our results in Tables 2-4 focus on within job-spell changes that condition on worker and worker-firm characteristics. They show that when a firm experiences a positive economic shock, the workers work longer hours and obtain higher earnings while experiencing higher usage of anti-depressants and visits to see psychiatrists. They also suffer an elevated chance of hospitalization due to effort-related burnout, stress and depression, heart attacks and strokes, and alcoholism. These results provide evidence that increases in work demand affect individuals' health through the effort-and-stress channel.

5 Results with Non-Linear Specifications

In this section, we explore whether changes in firm sales have non-linear effects on stress-related diseases. We start with the contemporaneous effects of sales changes, and then explore the effects of large sales increases over time.

5.1 Effects of Increases vs. Decreases in Sales

As we discussed in Introduction, a literature links increased worker stress and adverse health outcomes to worsening economic conditions at the state or firm-level. Yet we have shown, in section 4, that improvements in economic conditions, within job spells, also lead to adverse health outcomes. To reconcile our results with this literature, we consider the following non-linear specifications of equations (2) and (3). We calculate the deviations of log firm sales relative to their job-spell means, then obtain the deciles of this distribution. We then construct 10 decile dummies, D_1 though D_{10}. D_1 indicates large decreases in sales, while D_{10} indicates large sales increases (see Data Appendix 2 for the cut-off points).

We then replace log firm sales in (2) and (3) with the decile dummies, leaving out the median dummy, D_5.

These non-linear specifications are more flexible than (2) and (3), and allow us to examine whether increases and decreases in firm sales have asymmetric effects on hours and stress. However, they also involve more parameters, and we may not have enough variation in the data to precisely estimate all the additional parameters when our dependent variable occurs with low frequency. (see Table 1). Finally, since our main explanatory variables are now dummies, we follow Bertrand et al. (2004) and cluster our standard errors one-level up (see also note 26).

We first estimate the decile-dummy regression for hours using our monthly data, and plot the coefficient estimates and their 95% confidence intervals in Figure 1. Decile 5 is the omitted category, and so its coefficient is 0 by construction. Figure 1 shows a pattern familiar from the linear regressions in Table 2: the coefficient estimates are negative when sales decreases (deciles 1-4), and they are positive when sales increases (deciles 6-10) and are significant for most deciles. These results suggest that changes in firm sales have nearly monotonic effects on work hours.

We next estimate the decile-dummy regression for health outcomes using our annual data, plotting coefficients and 95% confidence intervals. Our first dependent variable is workers' ADPV (corresponding to column (4) of Table 3), shown in Figure 2.[31] Here we see a very different pattern. The use of anti-depressants and visits to psychiatrists is U-shaped, increasing for both large sales decreases and sales increases. A similar pattern is found in Figure 3 using alcohol-related hospitalizations.

Figures 2-3 suggest that the health benefits of reduced hours are offset, and dominated, by the direct effect of decreases in firm sales.[32] This direct effect can arise because sales decreases lead to lower

[31] Note that the magnitudes of these estimates are not comparable to the elasticity estimates in Tables 3-5.
[32] It is beyond the scope of our paper to quantify the exact magnitudes of these two channels.

earnings (see Table 2 and Figure 1), or because they are correlated with the potential for the more severe and stressful shock of job losses. That is to say, while these results are estimated within job-spell, a sharp decline in firm sales may sharply increase worker stress because they indicate job losses to come. We show (Data Appendix 2) that decreases in firm sales are significantly correlated with mass layoff, a commonly-used and well-studied adverse economic shock in the literature. In short, our results from Tables 3-4 do not contradict findings in the literature showing adverse health outcomes from worsening economic conditions. Rather, they show that workers' health suffers from both sharp increases and sharp decreases in sales.

Finally, we examine effects across deciles for prescription drugs for heart diseases in Figure 4, and broad burnout in Figure 5. In these cases we do not see the pronounced U-shaped patterns but we do see nonlinearities such that the effects are strongest in the upper deciles. These results suggest that large increases in sales have especially large effects on stress, since a large increase in workload may be especially hard to cope with. The insignificant results for sales decreases are consistent with the direct effect of sales drops offsetting the effect through reduced hours. We offer this interpretation cautiously since we may not have enough variation in the data to obtain precise estimates of all the decile dummies when our dependent variables are rare events (e.g. broad burnout).[33]

5.2 Effects of Large Sales Increases Over Time

So far we have focused on the contemporaneous effects of firm sales on worker stress, and used changes within job spells for identification. An important question is whether the contemporaneous effect of these shocks persist, both over time and across job-spells, i.e. even in the event of a job separation. Job separations might be problematic for job-spell regressions if they occur because of the adverse health effects we seek to identify. Getting at these persistent effects requires us to employ a

[33] Our results for the other hospitalization variables are similar to Figure 5.

different methodology.

In this sub-section, we examine the longer-term effects of sales changes by using the multi-period difference-in-difference estimation of Jacobson et al. (1993), or JLS, where we construct the control group using propensity score matching.[34] We begin by defining the treatment and control groups, and then describe the matching procedure.

We focus on the health variables for the workers whose employers experienced the largest sales increases, defined as the top decile of the distribution of year-to-year changes.[35] We compare them to the workers whose employers had sales changes falling in deciles 2 through 9 of the distribution.[36] Following the job-displacement literature (e.g. Couch and Placzek 2010, Davis and von Wachter 2011), we focus on medium-tenure workers (3+ years) with relatively large firms (50+ employees) that are 25-54 years old (in the middle of the sample period, so that we can track them five years before and after a demand shock).

We control for the following pre-shock worker characteristics, to ensure that our control-group and treatment-group workers are similar: age, gender, marriage, children, education and union membership status. We also control for pre-shock firm sales, industry affiliation, and year. In addition, for each sickness variable we study, we require that both treatment-group and control-group workers are free of this condition for 5 consecutive years before the shock, thereby setting the pre-trend to 0.[37]

We estimate the effects of large sales increases up to 5 years after the shock. Because we fix the

[34] As compared with recent studies that use the JLS-type identification strategy (e.g. Lachowska, Mas and Woodbury 2018, Powell and Seabury 2018), we are unable to use workers within the same firm to construct the control group, because sales increases affect all workers at a given firm. However, we are able to set the pre-trend to 0, by construction, because our dependent variables are indicator variables for sickness.

[35] Note that the decile cutoff here is different from the previous sub-section, where the distribution is sales changes relative to job-spell means. See Data Appendix 2 for the details.

[36] We leave out decile 1 because our results in the previous sub-section suggest that large decreases in firm sales may also increase worker stress. We have experimented with including decile 1 in the control group, and obtained similar results.

[37] Because the mean sickness rates are low for our sample of working-age adults, this restriction does not cost us many observations. Our matching procedure delivers similar means of the control variables for our treatment and control groups (see Data Appendix 2).

compositions of both treatment and control groups, by construction, and our data allow us to track every worker over time, our analyses in this sub-section include the workers who separate from their employers after large sales increases. This enables us to examine longer run health effects free of selection.

Figure 6a shows the results for narrow burnout over an 11 year window, where 0 is the year of the large sales increases. By construction, there is no hospitalization related to work effort for five years before the large sales increases. When the shock arrives, however, the mean rate of work-effort related hospitalizations is significantly higher for the treatment group than for the control group. The magnitude of this effect is comparable to the mean value of narrow burnout in Table 1. The point estimate remains above zero for two years, but is not statistically significant in the five years after the shock.

Figure 6b shows the results for hospitalizations due to liver diseases, an indicator for alcoholism, and its pattern is similar to Figure 6a. We have examined the effects for the other hospitalization variables as well, and found that they are similar to Figures 6a and 6b.

Figures 7a and 7b show, respectively, the results for anti-depressants and heart-disease drugs, and their patterns are different from Figures 6a and 6b. In Figure 7a, we see that the effects of large sales increases on anti-depressants are somewhat persistent, being marginally significant 1 year post-shock and significant 2 years post-shock. Figure 7b shows that the effects on heart-disease drugs are persistent, and in fact continue growing in magnitude, being statistically significant for all the 5 post-shock years. This persistence is plausible, because depression and heart diseases are chronic conditions from which full recovery may be difficult.

To summarize, we have used a different sample, a different specification, and a different identification strategy, to study the effects of firm sales on worker stress. Despite these differences, our results in this sub-section corroborate our previous results in section 4 and sub-section 5.1. We have also enriched our previous results, by showing that large sales increases have significant effects on anti-depressants and heart-disease drugs up to 2-5 years post-shock. These findings suggest that firm-level economic shocks may have long-term effects on individual workers' health, and effects outside of job spells as well.

6. Marginal Disutility and Utility Loss from Diseases: Theory

In sections 4-5 we report a rich set of results showing that increases in firm sales make individual workers less healthy. We now draw out the economic significance of these results, by quantifying the average worker's expected utility loss from increased stress, and then comparing this loss with the average worker's wage gains. An important step in our quantification is to calculate the marginal disutility of diseases using readily available data. This is accomplished by deriving a formula for the ratios of marginal disutility of pairs of diseases. Using an estimate of the marginal disutility of work injury we can then find the level of marginal disutility of each disease. This reduced-form approach allows us to remain agnostic about hard-to-measure structural parameters, such as the state dependence of utility, and severity of diseases.

We lay down the theoretical foundation for our approach in this section, and perform quantification in the next section.

6.1 Framework: Expected Utility

Consider an average worker employed in firm j. She may live in the healthy state, with income I and utility $u(.)$, or sick state $g = 1 \ldots S$, with utility $v_g(.)$ and income I_g, where I_g includes both monetary income and disutility from sickness (we will spell out the expression for I_g in sub-section 6.3 below). We note that $I_g < I$ for all g and $v_g(x) \leq u(x)$ for all income level x, given that utility is lower when sick. We assume that both $u(.)$ and $v_g(.)$ are continuous, increasing, twice differentiable, and weakly concave. We make no assumptions about how the first-order derivatives, $u'(.)$ and $v_g'(.)$, compare with each other, so that our analyses do not depend on the nature of state dependence.

Let the probability of sick state g be $p_g > 0$, and that of the healthy state $1 - \Sigma_g p_g > 0$. The average worker's expected utility is

$$(1-\sum_g p_g)u(I)+\sum_g p_g v_g(I_g)=u(I)+\sum_g p_g[v_g(I_g)-u(I)]\,. \qquad (4)$$

On the right-hand side of (4), the first term represents utility in a hypothetical disease-free world, and the second-term represents utility loss of the real world relative to this benchmark.[38] To express this utility loss in monetary value, consider compensation M, invariant across state, that equates the expected utility of (4) with the disease-free benchmark of $u(I)$:

$$u(I)=u(I+M)+\sum_g p_g[v_g(I_g+M)-u(I+M)]\,. \qquad (5)$$

In equation (5), M is the compensating variation relative to the disease-free benchmark, and provides the monetary value of the average worker's disutility from the presence of the sick states. Although an explicit, analytical expression for M is generally unavailable,[39] equation (5) specifies M as an implicit function of the other variables, including the sickness rates, p_g. It follows, then, that the average worker's expected utility loss from higher sickness rates equals

$$\frac{\partial M}{\partial \psi}=\sum_g \frac{\partial M}{\partial p_g}\frac{\partial p_g}{\partial \psi}\,, \qquad (6)$$

where ψ represents shocks to TFP or demand facing the firm (proxied in our empirics using firm j's sales). Since we have estimated how sickness rates respond to sales, $\partial p_g / \partial \psi$, in section 4, equation (6) says that we can calculate the average worker's expected utility loss, $\partial M / \partial \psi$, if we know the values of the marginal disutility, $\partial M / \partial p_g$.

Equation (5) also implies that (Theory Appendix 3)

[38] The second-term is negative because $v_g(I_g) \leq u(I_g) < u(I)$, and so $v_g(I_g) - u(I) < 0$ for all g.
[39] When $u(.)$ and $v_g(.)$ are all linear functions and $u(.) = v_g(.)$ for all g, (5) implies that $M = \Sigma_g p_g(I - I_g)$; i.e. disutility from the sick states equals the expected value of income losses in these states.

$$\frac{\partial M}{\partial p_g} = \frac{u(I+M) - v_g(I_g+M)}{(1-\sum_l p_l)u'(I+M) + \sum_l p_l v_l'(I_l+M)} > 0\,. \tag{7}$$

Equation (7) says that the marginal disutility, $\partial M / \partial p_g$, is positive,[40] and that its intuition is similar to the value of a statistical life or injury, or VSLI; i.e. it shows the monetary compensation that the average worker demands in exchange for heightened risk of disease g.

One approach to calculate the marginal disutility is to identify the full set of structural parameters and then plug them into equations (5) and (7). As we discussed in Introduction, the literature has not reached a consensus about how to identify these parameters. To be agnostic about state dependence and the values of the other structural parameters, we take a more reduced-form approach, which we outline below.

6.2 Reduced-Form Approach: Utility Share Weights

Our reduced-form approach starts with the utility share weight,

$$\beta_g \equiv \frac{\partial \ln M / \partial \ln p_g}{\sum_g \partial \ln M / \partial \ln p_g}\,. \tag{8}$$

To see the intuition of the utility share weight, suppose β_g is high. This means that the elasticity of disutility with respect to disease g is high, relative to the other diseases; i.e. an increase in the sick rate of g, p_g, has a large effect on the average worker's expected utility loss. In addition, we have $\beta_g > 0$ (by equation (7)) and $\Sigma_g \beta_g = 1$ (by definition (8)).

[40] We also show that under some technical assumptions, $\frac{\partial^2 M}{\partial p_g \partial p_l} \geq 0$ and $\frac{\partial^2 M}{\partial (p_g)^2} \geq 0$ (Theory Appendix 3). These results, together with equation (7), suggest that the relationship between M and p_g is reminiscent of a cost function.

To think about how β_g varies across disease types, we assume $v_g(.) = v_l(.)$, a common assumption in the state-dependence literature.[41] Equations (7) and (8) imply that

$$\frac{\beta_g}{\beta_l} = \frac{p_g[u(I+M) - v_g(I_g + M)]}{p_l[u(I+M) - v_l(I_l + M)]}. \tag{9}$$

To see the intuition of equation (9), consider diseases g and l. Suppose, first, that g happens with a higher frequency ($p_g > p_l$). Equation (9) says that other things equal (i.e. $I_g = I_l$), the average worker attaches a larger utility share weight to g; i.e. $\beta_g > \beta_l$. Now suppose, instead, that g is more damaging to health; i.e. $I_g < I_l$. Equation (9) says that other things equal ($p_g = p_l$), the average worker again attaches a larger utility share weight to g. In summary, equation (9) says that β_g is high if disease g happens with a high frequency, or if it is severe (i.e. low I_g).

Suppose that we know the values of β_g (we will explain how we do so in the next sub-section). Then equations (9) and (7) imply that we can compute the marginal disutility using β_g and the sickness rates, p_g:

$$\frac{\partial M / \partial p_g}{\partial M / \partial p_l} = \frac{\beta_g / p_g}{\beta_l / p_l} \text{ for all } g \neq l \tag{10}$$

The intuition of equation (10) is as follows. From equation (9), we know that β_g reflects both the frequency and severity of g. From equation (7), we know that the marginal disutility, $\partial M / \partial p_g$, captures the severity of g, but not its frequency. This is why we normalize β_g by p_g on the right-hand side of (10). Put another way, equation (10) says that relative to disease l, the marginal disutility of disease g is high if g has a low frequency, p_g, but a high utility share weight, β_g. This is intuitive, because a low frequency

[41] One exception is Evans and Viscusi (1990), who allow $v(.)$ to differ across two injury types but find results consistent with $u(.) = v_1(.) = v_2(.)$. Note that this assumption does not imply the same utility level for diseases g and l, since I_g and I_l can be different. In addition, it does not specify how $v_g(.)$ and $v_l(.)$ compare with $u(.)$; i.e. we still accommodate positive, negative or zero state dependence.

tends to reduce utility share weight, by (9). The fact that utility share weight is high despite low frequency indicates high severity, or high marginal disutility.

Equation (10) delivers the ratios of marginal disutility, but not the levels. We can follow the literature to estimate the marginal disutility of work injury, which is VSI, for our sample. We then combine VSI with the *ratios* of marginal disutility, delivered by (10), to obtain the *levels* of marginal disutility. Intuitively, our approach extends VSI to any disease, and so the marginal-disutility values we obtain may help measure the economic benefits of government policies and regulations that reduce the risks of diseases, just like VSI.

We can now calculate the average worker's expected utility loss using (6), because we have obtained the values of all the variables on the right-hand side of this equation.

6.3 Utility Share Weights: Expenditure Shares

In the previous sub-section, we have outlined our reduced-form approach, and shown that a critical component there is to obtain the values of the utility share weights, β_g. We show, in this sub-section, that expenditure shares provide a useful measure for β_g.

We start from equation (9), which says that β_g depends on both the frequency and severity of g. While frequency, p_g, is readily observable, severity is hard to quantify. We therefore take a revealed-preference approach; i.e. if individuals optimally choose treatment, then their choices reveal information about severity. To be specific, we lay out a simple framework of optimal treatment choice, and derive the relationship between treatment and severity. We then use this relationship to relate expenditure shares to β_g.

Let s_g denote the pain of disease g in monetary equivalent terms. If sick, the average worker optimally chooses treatment, t_g, which ranges in effectiveness from 0 to 100%. The private cost of treatment is $c(t_g)$.[42] Assume that $c(0) = 0$, $c'(.) > 0$ and $c''(.) > 0$. The average worker's problem, conditional on being sick, is

$$\max_{t_g} \{I_g = I - s_g\left(1 - t_g\right) - c\left(t_g\right)\} \tag{11}$$

In equation (11), $I - s_g\left(1 - t_g\right)$ is the average worker's demand for treatment, and $c(t_g)$ is the supply of treatment, as perceived by the worker.[43] $c(t_g)$ captures both monetary costs (e.g. co-pay) and non-monetary costs (e.g. disutility from treatment), and is affected by the state of medical technology and institutional features of the healthcare system.[44] The literature has considered two types of solutions for (11): an interior solution, or partial recovery, with $t_g < 1$, and a corner solution, or full recovery, with $t_g = 1$. We examine partial recovery first, and then full recovery.

Under partial recovery, the optimization of (11) implies that $v_g'(.)[s_g - c'(t_g)] = 0$, or that $s_g = c'(t_g)$. We differentiate $s_g = c'(t_g)$ with respect to s_g, and then apply the Envelope Theorem, to get

$$\frac{\partial t_g}{\partial s_g} = \frac{1}{c''(t_g)} > 0, \; \frac{\partial I_g}{\partial s_g} = -(1 - t_g) < 0 \; . \tag{12}$$

To see the intuition of equation (12), suppose disease g is painful; i.e. s_g is high. Then equation (12) says that because g leads to a large utility loss if untreated, the marginal benefit of treatment is high, and so treatment, t_g, is also high. In addition, after treatment, severity remains high, because treatment is less than 100% effective and also costly.[45]

Equation (12) says that treatment depends on pain, s_g, but not on frequency, p_g. This is intuitive, because people seek treatment after they get sick, not before (i.e. (11) and (12) are ex-post to, and

---

[42] We show, in Proposition 4 below, that our results hold for the more general specification of $c(t_g, s_g)$.

[43] Equation (11) shows how the average worker allocates her resources for treatment, and we have implicitly assumed that the amount of resources, I, is not affected by sickness. This is a common assumption in the literature (e.g. Hall and Jones 2007, Finkelstein et al. 2013).

[44] A literature studies whether physicians' financial incentives may lead them to prescribe suboptimal treatments (e.g. McGuire 2000), and most studies focus on the U.S. We assume, following this literature, that physicians have patients' best interests in mind, and abstract away from physicians' financial incentives, given the differences in the healthcare system between Denmark (and many other high-income countries) and the U.S. We discuss capacity constraints in note 48 below.

[45] Note that severity, I_g, is post treatment, but pain, s_g, is pre-treatment.

conditional on, sickness). Equation (12) also shows that we can make inferences about severity, I_g, using treatment, t_g. Although t_g itself is also hard to quantify, its total expenditure is not. Let $C(t_g)$ denote the social monetary cost of treatment, with $C(0) = 0$ and $C'(.) > 0$. Then the total expenditure for t_g (normalized by population) is $E_g = p_g C(t_g)$. $C(.)$ differs from the private cost, $c(.)$, because healthcare expenses are typically paid for using public resources or through health insurance. Assume that

$$C(t_g) < C(t_l) \text{ if and only if } c(t_g) < c(t_l). \tag{13}$$

Assumption (13) says that we need private and social costs to have the same rank order, but do not need them to be identical; i.e. the average worker's choice of treatment in equation (11) may not be socially optimal. This means that our results accommodate moral hazard, a very important feature of the healthcare system (e.g. Cutler and Zeckhauser 2000).[46]

We can now relate the utility share weight, β_g, to expenditure, E_g. Compare two diseases, g and l, with the same frequency, $p_g = p_l$. Suppose g is more painful ($s_g > s_l$). Then by equation (12), treatment for g is higher ($t_g > t_l$), and expenditure for g is also higher ($E_g > E_l$), by (13). In addition, by (12), post-treatment net income is lower under g ($I_g < I_l$), and so by (9), the utility share weight of g is higher ($\beta_g > \beta_l$). Let $\mu_g = E_g/(\sum_g E_g)$ denote the expenditure share of g. Clearly, $\mu_g > \mu_l$ if and only if $E_g > E_l$. We then have

Proposition 2 Under partial recovery and assumption (13), $\mu_g > \mu_l$ if and only if $\beta_g > \beta_l$, for all diseases $l \neq g$ with $p_g = p_l$.

Proposition 2 says that expenditure shares, which are readily observable, vary across diseases in the same direction as utility share weights, β_g, and so they provide a useful measure for β_g. One concern is that Proposition 2 does not guarantee $\mu_g = \beta_g$. We are unable to derive stronger results under partial recovery, because severity, I_g, varies across diseases. In this case, state dependence (i.e. how $u(.)$

[46] In the U.S., low-health-risk individuals may choose not to buy health insurance. Adverse selection is likely to be far less important for Denmark, and many other high-income countries, where healthcare is universal.

compares with $v_g(.)$ and $v_l(.)$) matters for the exact value of β_g, by equation (9). In addition, social and private costs also differ due to moral hazard.

Although it is beyond the scope of our paper to provide solutions to these difficult problems, we are able to show that (Theory Appendix 4)

Proposition 3 Under assumption (13), $\mu_g/\mu_l = \beta_g/\beta_l$ for all diseases $l \neq g$ that feature either $s_g = s_l$ or full recovery.

Proposition 3 says that expenditure shares are the exact measure for utility share weights, up to a scalar, for the diseases with similar pain or with full recovery. Intuitively, these conditions give us stronger results than Proposition 2, because they imply that (post-treatment) severity, I_g, is the same across diseases, so that β_g is linear in frequency, by (9). In addition, frequency does not affect treatment, by (12), and so expenditure, $E_g = p_g C(t_g)$, is also linear in frequency.

We now outline three extensions of Propositions 2-3. First, we relax the assumption that both private- and social-cost functions depend only on treatment, and show that (Theory Appendix 5)

Proposition 4 Propositions 2 and 3 hold if $c(t_g, s_g)$ and $C(t_g, s_g)$ are increasing, convex, and have the same rank order; i.e.

$$C(t_g, s) < C(t_l, s) \Leftrightarrow c(t_g, s) < c(t_l, s), \text{ and } C(t, s_g) < C(t, s_l) \Leftrightarrow c(t, s_g) < c(t, s_l). \qquad (14)$$

Next, the logic of Propositions 2-4 is that patients with large pain, s_g, demand high treatment, t_g, which is associated with high expenditure per patient, $C(.)$. Whether the pain is caused by disease symptoms, heightened mortality risk, or both, is not important. Formalizing this intuition, we show that (Theory Appendix 6)

Proposition 5 Suppose s_g captures the total effect of disease symptoms and mortality risk, and treatment technology is more general than (11). Then Propositions 2-4 hold if the treatment technology has similar properties to (11).

Finally, the state of medical technology may vary across diseases, so that the cost functions, $c(t_g, s_g)$ and $C(t_g, s_g)$, may be decreasing with respect to pain, s_g, and Propositions 2-5 do not apply. We show that (Theory Appendix 7)

Proposition 6 $\mu_g > \mu_l$ if and only if $\beta_g > \beta_l$, for all diseases $l \neq g$ with $p_g = p_l$, if $c(t_g, s_g)$ and $C(t_g, s_g)$ are increasing and convex with respect to t_g, and

$$\partial c(.)/\partial s_g < 0,\ \partial C(.)/\partial s_g < 0, \text{ and both are large in magnitude} \qquad (15)$$

To see the intuition of Proposition 6, consider bacterial infection. It's painful if untreated (i.e. s_g is high), but antibiotics offers very effective treatment at low cost (i.e. Assumption (15) holds). As a result, severity, which is after treatment, is low, and so is expenditure, implying that both the true and measured marginal disutility are low.

Following Propositions 2-6, we use expenditure shares to measure the utility share weights, β_g. This is intuitive, because expenditures reflect disease frequency and severity, two important factors that also affect β_g.

6.4 Discussion and Comparison with Literature

In this sub-section, we discuss the qualifications and caveats of our approach in the context of the literature. Cutler et al. (1997) and Murray and Acharya (1997) use survey data to measure quality of life, or $v_g(I_g)/u(I)$. These surveys do not necessarily reflect individuals' actual choices. It is also necessary to take a stand on state dependence, in order to translate $v_g(I_g)/u(I)$ to our variables of interest, such as utility share weights and marginal disutility (see equations (9) and (10)).

In the framework of Hall and Jones (2007), there is no uncertainty about sickness, and healthcare spending reduces mortality risk. As a result, the marginal utility of consumption matters for the optimal healthcare spending.[47] In our framework, however, this variable does not affect treatment and expenditure, because we assume, as in Ma and McGuire (1997), that the average worker takes the sickness rates as given, and seeks treatment after sickness, not before. We make these assumptions because our focus is the distinction among healthy and sick states.

Medical technology also matters for healthcare spending (e.g. Newhouse 1992, Cutler 2005). Proposition 6 shows that medical technology fits within our framework unless it has very different effects on $c(.)$ and $C(.)$. Howard, Bach, Berndt, and Conti (2015) argue that anticancer drugs are expensive partly because of their producers' market power. To see how this affects our approach, suppose that the treatment providers of disease g charge a higher price than those of disease l, and this leads to higher expenditures on g than l. Our approach works in this case if g is more severe than l. [48]

In summary, many factors affect healthcare spending, and high expenditure may not always imply large health benefits (e.g. Chandra and Skinner 2012).[49] In general, it is challenging to quantify, for a large number of diseases, the exact health benefits, including quality-of-life benefits. Propositions 2-6 clarify the conditions under which expenditure shares relative to frequency provide a useful approximation for marginal disutility. On the plus side, our framework accommodates moral hazard, and does not require the values of structural parameters (e.g. state dependence) as inputs. In addition, data on disease frequencies and expenditures are easy to obtain. Finally, if we know, ex ante, that assumptions (13)-(15) do not hold for certain diseases, we can drop them. Their exclusion does not affect the marginal-disutility values of the remaining diseases, because these values are based on *ratios* of expenditure shares.

---

[47] The marginal utility of consumption may also matter for the design of optimal health insurance (e.g. Cutler and Zeckhauser 2000). In our framework, we abstract away from the differences in health insurance across consumers, because Denmark, like many other high-income countries, has universal health care. We allow the private cost of treatment to differ from the social cost, and do not take a stand on the efficiency of the Danish healthcare system.

[48] As another example, suppose that the provision of treatment is capacity constrained in Denmark. Intuitively, what matters for our framework is how this constraint varies across diseases; i.e. whether assumptions (13) - (15) hold for the treatment, t_g, that the average worker chooses under capacity constraints.

[49] E.g. Cutler (2005) argues that "where we have spent a lot, we have received a lot in return". Chandra and Skinner (2012) note that the literature has reported both positive and negative correlations between healthcare spending and outcome for the U.S., and provide evidence that expensive treatments with limited benefits are more widely used in the U.S. than in Europe.

In the next section, we show that we obtain intuitive values of marginal disutility using our framework.

7. Marginal Disutility and Utility Loss from Diseases: Quantification

We now apply the framework developed in the previous section to calculate the marginal disutility from diseases. We then use the marginal disutility to quantify the average worker's utility loss from the adverse health outcomes that are caused by rising firm sales.

7.1 Marginal Disutility

We start with equation (10), where the disease frequency, p_g, comes from the mean values that we report in Table 1, and the utility share weight, β_g, comes from the expenditure shares in Table 1. For ease of reference, we gather these data in columns 1 and 2 of Table 5. We focus on the following sickness: anti-depressants or psychiatrist visits (ADPV); hospitalization due to burnout, stress, or depression (BSD); use of heart-disease drugs; hospitalization due to heart attacks or strokes; and alcoholism-related hospitalizations. We also include work injury in the last row of Table 5, because we need its marginal disutility, VSI, to compute the marginal disutility of the other diseases.

Table 5 shows that the variation of sickness rates and expenditure shares across diseases is both intuitive and consistent with our theory. For example, the stress and heart diseases that can be treated with prescription drugs happen with high frequencies but have low expenditure shares, suggesting that these conditions are not very severe. In comparison, the hospitalizations due to heart attacks and alcoholism are severe. Consistent with this, they have high expenditure shares despite low frequencies.

We now estimate the marginal disutility of work injury by following the VSLI literature. Compatible with our framework, the VSLI approach is also agnostic about the state dependence of utility.[50] This approach also produces standard errors of the VSI estimate, and we use them to construct the 95% confidence interval of VSI. We report our VSI estimate, 1.56 million DKK, in column 3 of Table 5. Our VSI estimate is larger than those obtained using U.S. data, because our data includes severe injuries only (see Data Appendix 3 for the details).

We then calculate the marginal disutility using equation (10), by combining our VSI estimate with the data for sickness rates and expenditure shares. We report our results in column 3 of Table 5. To see the intuition of our computation, consider the example of stroke hospitalization. As compared with injury, its expenditure share is slightly lower (2.02% vs. 2.26%), but its frequency is much lower (1.6 per thousand vs. 3.9 per thousand). As a result, equation (10) says that its marginal disutility is 2.23 times that of injury, or DKK 3.47 million (= 1.56 x 2.23). Since our VSI estimate has its 95% confidence interval, our marginal-disutility values have theirs, too, and we report them in Column 4 of Table 5.

Table 5 shows that the values of marginal disutility and their rankings across diseases are both intuitive. The two sickness conditions that can be treated by prescription drugs have low marginal disutility, 31,370 DKK and 35,450 DKK. Stress that can be treated with prescription drugs has a much lower marginal disutility (31,370 DKK) than stress that requires hospitalization (403,530 DKK). Both BSD and strokes require hospitalization, but strokes are more severe than BSD, and so have a higher marginal disutility (3.47 million DKK) than BSD (0.40 million DKK). The marginal disutility of strokes hospitalization, in turn, is lower than that of mortality, which is $5-6.2 million (Viscusi and Aldy 2003), or DKK 27.78-34.44 million.

7.2 Expected Utility Loss, and Compensating Differential

[50] The main idea of the VSI approach is that workers take injury risks into account when making occupational choices, demanding high wages as compensation where occupational injury rates are high. This is premised on: (1) injury data is readily available and widely publicized; and (2) injury risks are closely related to work hazards. These two conditions are unlikely to hold, in general, for diseases, implying that the VSI approach may not be readily applicable to them.

We now calculate the average worker's expected utility loss using equation (6). We first translate our elasticity estimates in Tables 3-4, $\partial \ln p_g / \partial \psi$, into estimates for level changes, $\partial p_g / \partial \psi$, by multiplying the elasticity estimates by the sickness rates, p_g. We report 100 times these estimates in column 5 of Table 5. Plugging these estimates and the values of marginal disutility into (6), we obtain that, in response to a 10% increase in firm sales, the average worker suffers an expected utility loss of 52.9 DKK.

In order to clarify the economic significance of this utility loss, we compare it with the increases in earnings from rising sales. In Data Appendix 3, we use our annual data to obtain an elasticity estimate of 0.0085 for annual earnings.[51] We thus obtain that, following a 10% increase in firm sales, earnings increase by 313.1 DKK. As a result, the average worker's expected utility loss amounts to 16.9% of her earnings gain. This result suggests that a substantial fraction of the monetary gains from rising sales can be attributed to compensating differential, for higher risks of sickness, in the spirit of Rosen (1986).

Finally, we note that the expected utility losses are small relative to the values of marginal disutility (columns 3 and 4 of Table 5), suggesting that the individuals who actually get sick suffer much larger ex-post utility losses.[52]

8. Robustness Exercises and Heterogeneous Effects

In this section, we first show that our main results, in Tables 3-4, hold for a number of robustness exercises. We present these exercises in the same order in which we presented identification threats in sub-section 3.3 above. We then explore how the effects of firm sales on worker stress and sickness vary with gender and local-labor-market tightness. Table 6 reports the results for log hours, anti-depressants,

[51] Note that our elasticity estimates in Table 2 are based on monthly data. We also experimented with annual earnings (wage income plus labor-market pension), and obtained similar results.

[52] We are unable to calculate the exact ex-post utility loss, because we have chosen not to take a stand on the values of the structural parameters.

ADPV, and heart-disease drugs. Table 7 reports the results for our hospitalization variables. The results for log hours are based on monthly data, where we control for firm-year and worker-year fixed effects.[53] The other results are based on annual data.[54]

First, we tackle reverse causality between worker health and sales by adding small firms and dropping managers. In Panel 1 of Tables 6-7, we add the firms with employment between 10 and 50 into our sample, which increases our sample size to roughly 3.8 million observations.[55] The elasticity estimate for hours are similar to Table 2, while the elasticity estimates for the stress-and-sickness variables are slightly smaller than our main results, in Tables 3-4. These results suggest that, while reverse causality might play some role for the smaller firms, their effects are likely to be limited. In Panel 2 of Tables 6-7, we drop all the managers from our sample. We obtain very similar elasticity estimates for the stress variables, as compared with Tables 3-4, and very similar elasticity estimates for hours as well, as compared with Table 2. These findings suggest that our main results are not driven by managers.

In Panel 3 of Tables 6-7, we include additional controls for organizational change occurring within the firm. We include the number of management layers by firm by year, constructed as in Caliendo, Monte and Rossi-Hansberg (2015). We also include the numbers of imported and exported products, and the numbers of import source countries and export destination countries. These five variables proxy for the complexity of the firm as an organization, and we normalize them by firm sales, and then include the logs of these ratios in our estimation. Columns (1) and (2) of Table 7 show that, as the number of management layers increases relative to firm sales, workers have higher rates of effort-related and work-related hospitalizations. This finding suggests that changes in organizational

[53] i.e. we use the same specification as column (4), panel 2, Table 2. The fixed effects here preclude us from performing some of the robustness exercises below, where we bring in additional control variables that vary by firm by year.

[54] To save space, we only report sample size, and the coefficient estimates of firm sales and other explanatory variables of interest. The results for the other control variables are available upon request.

[55] To get these smaller firms we also add the firms that are not engaged in international trade, and drop the log of offshoring from the set of controls.

complexity tend to increase worker stress,[56] consistent with Dahl (2011). We also see, from Panel 3 of Tables 6-7, that the coefficient estimate of log firm sales remains positive and significant for most measures of sickness and stress;[57] i.e. changes in firm sales still have significant impacts on worker stress, conditional on organizational changes.

In Panel 4 of Tables 6-7, we address the potential endogeneity of firm sales to improvements in technology that may also affect worker stress and health. We do this by constructing the following Bartik-style/shift-share instrument for firm sales.[58] Let Q_{kt} denote the aggregate output of product k in year t in Denmark, and s_{jk} denote product k's share in firm j's output in the pre-sample year of 1994. Then our instrument for j's sales, Y_{jt}, is $I_{jt} = \sum_k s_{jk} Q_{kt}$. The intuition of our instrument is as follows. To the extent that output demand, Q_{kt}, fluctuates over time for exogenous reasons, firm j's exposure to these fluctuations depends on the pre-sample output shares, s_{jk}. While some Danish firms may produce large shares of the aggregate national output, Q_{kt}, for some products, our identification requires that the shocks are exogenous to individual workers, and predicted firm sales are likely to be less correlated with omitted variables and more exogenous to individual workers than actual sales.

Our shift-share variable is positive and significant in the first stage estimation, and its F-statistics is 117.3 (see Data Appendix 4 for more details). We see, from Panel 4 of Tables 6-7, that we obtain similar elasticity estimates here, using predicted sales, as compared with Tables 3-4, where we use actual sales. These estimates are statistically significant in most cases, although they are less precise for some of our hospitalization variables, which have low frequencies. The similarity between our estimates for

[56] The coefficient estimate of the number of layers relative to firm sales is insignificant for the other measures of worker stress. The coefficient estimates of the other complexity variables are mostly insignificant, too.

[57] Note that the elasticity of stress with respect to firm sales depends on the coefficient estimates of log sales and the complexity variables. We therefore choose not to normalize these estimates by the mean values of the dependent variables.

[58] This type of instrument is widely used in the literature (e.g. Blanchard and Katz 1992, Card 2009, Luttmer 2006, Hummels et al. 2014, and Nakamura and Steinsson 2014).

actual and predicted sales[59] is consistent with our discussions in sub-section 3.3 that omitted variables likely have ambiguous effects on our results. It is also consistent with the common practice in the literature to treat firm-level changes, such as employment, as exogenous to individual workers (e.g. Sullivan and von-Wachter 2009).

We now explore whether firm sales have different effects for men vs. women. We do so for two reasons. One, men and women have different responses to stressful events (e.g. Altemus, Sarvaiya, and Epperson 2014). Two, they also have different rates of stress; e.g. in our data, while 3.04% of men use anti-depressants, 4.71% of women do (Data Appendix 4).

In Panels 5 and 6 of Tables 6-7, we do our estimation separately for the sub-samples of men and women. Our results show that the elasticity estimates for firm sales are significant for most stress-and-sickness measures for both genders; i.e. increases in firm sales lead to adverse health outcomes for both men and women. Firm sales are also significant for hours for both men and women. We also see that men and women have different elasticity estimates, and this difference varies across measures of stress and sickness. Men have stronger responses for effort- and work-related hospitalizations, while women show stronger responses for anti-depressants, psychiatrist visits, heart-disease drugs, and hospitalizations due to strokes and alcoholism. Men and women have similar responses for hospitalizations due to burnout, stress or depression.

Finally, we investigate whether the effects of firm sales vary with the tightness of the local labor market. A high unemployment (UI) rate in the local labor market may weaken the workers' bargaining power and reduce their incentives for effort. It may also provide a large pool of potential workers, so that the firms find it easy to increase employment when sales increases. Alternatively, the high UI rate may decrease the workers' outside option and induce them to provide more effort (e.g. Lazear, Shaw and

[59] Note that the high correlation between our instrument and firm sales does not mechanically imply similar results for OLS and IV. E.g. Boustan, Fereira, Winkler and Zolt (2013)'s instrument has a first-stage F-stat of over 900, and their IV estimates are substantially different from OLS.

Stanton 2016). As a result, how the effects of firm sales vary with labor-market tightness is ambiguous. We calculate UI rate by commuting zone by year (see Data Appendix 4 for the details), augment our regressions with the interaction between UI rate and log firm sales, and report our results in Panel 7 of Tables 6-7. [60] The coefficient estimate of the UI rate interaction is sometimes negative and sometimes positive, and it is positive and significant for anti-depressant or psychiatrist visits, and hospitalizations due to burnout, stress, or depression. Meanwhile, the coefficient estimate for log sales remains positive and significant.

9. Conclusion

In this paper we use matched worker-firm data from Denmark to study how changes in firm sales, which are exogenous to individual workers, affect workers' stress and effort. Our rich data allow us to directly measure individual workers' effort and stress. When we base our identification on changes within worker-firm matches, we find that as firm sales increases, workers work longer hours and suffer higher risks of stress, such as anti-depressant uses, psychiatrist visits, hospitalization, and in particular, hospitalizations that are specifically diagnosed as effort- and work-related. The effects of sales increases on worker stress are robust to the use of multi-period difference-in-difference (e.g. Jacobson et al. 1993, or JLS), and our JLS estimates also show that large sales increases have longer-term effects on anti-depressants and heart-disease drugs. These results are novel to the literature, and provide tight identification that work demand affects health through the effort-and-stress channel.

We then develop a novel framework to compute the marginal disutility of diseases, and to quantify the average worker's ex-ante utility loss due to higher rates of stress. Although our approach delivers approximate values of marginal disutility, it accommodates moral hazard, uses readily-available

[60] Note that the elasticity of stress with respect to firm sales depends on the UI rate, and so we have not normalized the coefficient estimates by the mean values of the dependent variables.

data that reflects individuals' actual choices, and does not require the values of structural parameters (e.g. state dependence) as inputs. Our marginal-disutility values have sensible and intuitive variation across diseases, and we find that the average worker's utility loss accounts for a sizeable fraction of her earnings gains from rising firm sales. Our framework provides a straightforward and intuitive extension of VSLI, from mortality and work injury to morbidity.

Finally, our results highlight the importance of workplace stress, which is emerging as an important public-health concern in the U.S.[61] For example, the U.S. CDC (Centers for Disease Control and Prevention) lists work-related stress as the leading workplace health problem, ahead of physical inactivity and obesity,[62] and Goh, Pfeffer and Zenios (2015) argue that workplace stress contributes $190 billion, annually, to U.S. healthcare costs. Unfortunately, the public provision of mental-health care lags far behind demand; e.g. in 44 U.S. states the biggest mental-health institution is a prison.[63] Fortunately, many employers are taking action. Large U.S. companies are offering training in cognitive behavioral skills, scented relaxation rooms, smart phone apps for mental-health issues, "living walls" decorated with plants, and outdoor cafes with wildflowers.[64] Perhaps these endeavors reflect a growing private sector recognition of the connection between work demand, work effort and employee stress identified in our study.

References

Adda, Jérôme, and Yarine Fawaz. The health toll of import competition. mimeo, Bocconi University, 2017.

Altemus, M., Sarvaiya, N., & Epperson, C. N. (2014). Sex differences in anxiety and depression clinical perspectives. Frontiers in neuroendocrinology, 35(3), 320-330.

[61] Our results are also reminiscent of Sigmund Freud. In his classic, "Civilization and Its Discontents", he postulates that, as the civil society grows in terms of technology and profits, its citizens become neurotic and discontent. The recent hit song, Stressed Out, by the group Twenty One Pilots, echoes this theme.

[62] E.g. https://www.cdc.gov/chronicdisease/resources/publications/aag/pdf/2016/aag-workplace-health.pdf

[63] 'Mental Health: Out of the Shadows", Economist, April 25, 2015, 56-57.

[64] E.g. "To Cut Office Stress, Try Butterflies and Medication?", by Sue Shellenbarger, The Wall Street Journal, October 9, 2012, and "Management: Tackling Mental Health, One Text at a Time …", by Rachel Emma Silverman, the Wall Street Journal, July 20, 2016.

Ameriks, John, Joseph Briggs, Andrew Caplin, Matthew Shapiro and Christopher Tonetti, 2016. "Late-in-Life Risks and the Under-Insurance Puzzle", NBER working paper 22726.

Autor, David, David Dorn, and Gordon Hanson. 2015. "The Labor Market and the Marriage Market: How Adverse Employment Shocks Affect Marriage, Fertility, and Children's Living Circumstances". Working paper, MIT.

Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., ... & Finkelstein, A. N. (2013). The Oregon experiment—effects of Medicaid on clinical outcomes. New England Journal of Medicine, 368(18), 1713-1722.

Bauer, Daniel, Darius Lakdawalla, and Julian Reif. Mortality Risk, Insurance, and the Value of Life. No. w25055. National Bureau of Economic Research, 2018.

Becker, Gary S., Tomas J. Philipson, and Rodrigo R. Soares, 2005. "The Quantity and Quality of Life and the Evolution of World Inequality", American Economic Review March 2005, 95(1), pp. 277-291.

Bernard, Andrew B., Emily J. Blanchard, Ilke Van Beveren and Hylke Vandenbussche "Carry-along trade." The Review of Economic Studies 86.2 (2019): 526-563.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. How much should we trust differences-in-differences estimates?. No. w8841. National Bureau of Economic Research, 2002.

Black, Sandra E., Paul J. Devereux and Kjell G. Salvanes. 2012. "Losing Heart? The Effect of Job Displacement on Health". NBER working paper 18660.

Bosma, H., M. G. Marmot, H. Hemingway, A. C. Nicholson, E. Brunner, and S. A. Stansfeld, 1997, "Low Job Control and Risk of Coronary Heart Disease in Whitehall II (prospective cohort) Study", British Medical Journal 314:558-565.

Browning, Martin and Eskil Heinesen, 2012, "Effect of job loss due to plant closure on mortality and hospitalization", Journal of Health Economics 31: 599-616.

Browning, Martin, Anne Møller Danø, and Eskil Heinesen, "Job Displacement and Stress-Related Health Outcomes", Health Economics 15 (2006), 1061-1075.

Caliendo, Lorenzo, Ferdinando Monte, and Esteban Rossi-Hansberg. "The anatomy of French production hierarchies." Journal of Political Economy 123.4 (2015): 809-852.

Case, A and Deaton, A (2009): "Health and Wellbeing in Udaipur and South Africa", Chapter 10 in *Developments in the Economics of Aging*. D. Wise (ed.) University of Chicago Press.

Chandra, A., & Skinner, J. (2012). Technology growth and expenditure growth in health care. Journal of Economic Literature, 50(3), 645-80.

Coile, Courtney C., Phillip B. Levine, and Robin McKnight, 2014, "Recessions, Older Workers, and Longevity: How Long Are Recessions Good for Your Health", American Economic Journal: Economic Policy, 6(3), 92-119.

Colantone, Italo, Rosario Crinò, and Laura Ogliari. "The hidden cost of globalization: Import competition and mental distress." (2015).

Couch, Kenneth A., and Dana W. Placzek. "Earnings losses of displaced workers revisited." American Economic Review 100.1 (2010): 572-89.

Currie, Janet, and Brigitte Madrian. 1999. *Health, Health Insurance and the Labor Market.* In Orley Ashenfelter and David Card edts., Handbook of Labor Economics, North-Holland.

Cutler, David M. Your money or your life: Strong medicine for America's health care system. Oxford University Press, 2005.

Cutler, D. M., Richardson, E., Keeler, T. E., & Staiger, D. (1997). Measuring the health of the US population. Brookings papers on economic activity. Microeconomics, 1997, 217-282.

Cutler, David M., and Richard J. Zeckhauser. "The anatomy of health insurance." Handbook of health economics 1 (2000): 563-643.

Davis, Steven J., and Till M. Von Wachter. Recessions and the cost of job loss. No. w17638. National

Bureau of Economic Research, 2011.
Dahl, Michael S. 2011, “Organizational Change and Employee Stress”, Management Science 57 (2), pp. 240-256.
De Quidt, J., & Haushofer, J. (2016). Depression for economists (No. w22973). National Bureau of Economic Research.
Dix-Carneiro, Rafael, Rodrigo R. Soares, and Gabriel Ulyssea. "Economic shocks and crime: Evidence from the brazilian trade liberalization." American Economic Journal: Applied Economics 10.4 (2018): 158-95.
Edwards, Ryan D., 2008. “Health Risk and Portfolio Choice”, Journal of Business and Economic Statistics, 26(4), pp 472-485.
Egan, Mark L., Casey B. Mulligan, and Tomas J. Philipson. 2013 “Adjusting Measures of Economic Output For Health: Is the Business Cycle Countercyclical?”, NBER working paper 19058.
Eliason, Marcus, and Donald Storrie, 2007, “Does Job Loss Shorten Life?”, Journal of Human Resources 44(2), 277-302.
Eliason, Marcus, and Donald Storrie, 2009, “Job Loss is Bad for Your Health – Swedish Evidence on Cause-Specific Hospitalization Following involuntary Job Loss”, Social Science and Medicine 68, 1396-1406.
Evans, William N. and W. Kip Viscusi, “Estimation of State-Dependent Utility Functions Using Survey Data”, the Review of Economics and Statistics, 73(1), Feb. 1991, pp. 94-104.
Finkelstein, Amy, Erzo P. Luttmer and Matthew J. Notowidigdo, 2013, “What Good is Wealth Without Health? The Effect of Health on the Marginal Utility of Consumption”, Journal of European Economic Association 11(S1): 221-258.
Fransson, Eleonor I., et al. "Job strain and the risk of stroke: an individual-participant data meta-analysis." Stroke 46.2 (2015): 557-559.
Goh, Joel, Jeffrey Pfeffer, and Stefanos A. Zenios. "The relationship between workplace stressors and mortality and health costs in the United States." Management Science 62.2 (2015): 608-628.
Goldman-Mellor, S. J., Saxton, K. B., & Catalano, R. C. (2010). Economic contraction and mental health: a review of the evidence, 1990-2009. International Journal of Mental Health, 39(2), 6-31.
Hall, R. E., & Jones, C. I. (2007). The value of life and the rise in health spending. The Quarterly Journal of Economics, 122(1), 39-72.
Helpman, Elhanan, Oleg Itskhoki and Stephen Redding. 2010. “Inequality and Unemployment in a Global Economy”. *Econometrica* 78(4), 1239-1283.
Howard, D. H., Bach, P. B., Berndt, E. R., & Conti, R. M. (2015). Pricing in the market for anticancer drugs. Journal of Economic Perspectives, 29(1), 139-62.
Hubert, H. B., M. Feinleib, P. M. McNamara, and W. P. Castelli, 1983, “Obesity as an Independent Risk Factor for Cardiovascular Disease: A 26-year Follow-up of Participants in the Framingham Heart Study”, Circulation 67: 968-977.
Hummels, D., R. Jørgensen, J. Munch, and C. Xiang, 2014. “The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data”, American Economic Review, 104 (6), 1597-1629.
Hummels, David, Jakob R. Munch, and Chong Xiang. "Offshoring and labor markets." Journal of Economic Literature 56.3 (2018): 981-1028.
Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. "Earnings losses of displaced workers." The American economic review (1993): 685-709.
Jones, Charles, 2016, “Life and Growth”, Journal of Political Economy 124(2), pp. 539-578.
Jones, Charles I. and Peter J. Klenow, “Beyond GDP? Welfare across Countries and Time”, American Economic Review 2016, 106(9), pp 2426-2457.
Kivimäki, M., & Kawachi, I. 2015. Work Stress as a Risk Factor for Cardiovascular Disease. *Current cardiology reports*, *17*(9), 1-9.

Kivimäki, Mika, et al. "Job strain as a risk factor for coronary heart disease: a collaborative meta-analysis of individual participant data." The Lancet 380.9852 (2012): 1491-1497.

Lachowska, Marta, Alexandre Mas, and Stephen A. Woodbury. Sources of displaced workers' long-term earnings losses. No. w24217. National Bureau of Economic Research, 2018.

Lazear, Edward P., Kathryn L. Shaw, and Christopher Stanton. "Making do with less: working harder during recessions." Journal of Labor Economics 34.S1 (2016): S333-S360.

Lillard, Lee A. and Yoram Weiss, 1997, "Uncertain Health and Survival: Effects on End-of-Life Consumption", Journal of Business and Economic Statistics, 15(2), pp. 254-268.

Lindo, Jason M. 2013, "Aggregation and the Estimated Effects of Local Economic Conditions on Health", NBER working paper 19042.

Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., & Sanbonmatsu, L. (2012). Neighborhood effects on the long-term well-being of low-income adults. Science, 337(6101), 1505-1510.

Ma, Ching-To Albert and Thomas G. McGuire, "Optimal Health Insurance and Provider Payment", the American Economic Review, 87(4), Sep. 1997, pp. 685-704.

Maccini, Sharon, and Dean Yang. "Under the weather: Health, schooling, and economic consequences of early-life rainfall." American Economic Review 99.3 (2009): 1006-26.

Manning, A., 2011, Imperfect Competition in the Labor Market, in O. Ashenfelter and D. Card, eds., Handbook of Labor Economics Vol. 4B, Amsterdam: North Holland.

Marmot, M. G., Rose, G., Shipley, M., & Hamilton, P. J. (1978). Employment grade and coronary heart disease in British civil servants. Journal of Epidemiology & Community Health, 32(4), 244-249.

Marmot, M. G, G. D. Smith, S. Stansfeld, C. Patel, F. North, J. Head, I. White, E. Brunner and A. Feeney, 1991, "Health Inequalities Among British Civil Servants: the Whitehall II Study", Lancet 337: 1387-1393

McGuire, T. G. (2000). Physician agency. In Handbook of health economics (Vol. 1, pp. 461-536). Elsevier.

McManus, T. C. and G. Schaur, 2015, "The Effects of Import Competition on Worker Health", Journal of International Economics, forthcoming.

Miller, D. L., Page, M. E., Stevens, A. H., & Filipski, M. (2009). Why are recessions good for your health?. American Economic Review, 99(2), 122-27.

Moran, J. R., & Simon, K. I. (2006). Income and the use of prescription drugs by the elderly: evidence from the Notch cohorts. Journal of Human Resources, 41(2), 411-432.

Murphy, K. M. and R. H. Topel. 2003, "The Economic Value of Medical Research," in Kevin M. Murphy and Robert H. Topel, eds., Measuring the Gains from Medical Research: An Economic Approach. Chicago: University of Chicago Press.

Murray, Christopher J.L, and Arnab K. Acharya, 1997. "Understanding DALYs", Journal of Health Economics 16, 703-730.

Newhouse, Joseph P. "Medical care costs: how much welfare loss?." Journal of Economic perspectives 6.3 (1992): 3-21.

Olsen, LR, Munk-Jorgensen P, and Bech P, 2007. "The Prevalence of Depression in Denmark", Ugeskr Laeger, April 2007, 169(16), 1425-1426.

O'Reilly, Dermot and Michael Rosato. 2013. "Worked to death? A census-based longitudinal study of the relationship between the number of hours spent working and mortality risk", International Journal of Epidemiology 42(6), 1820-1830.

Pierce, Justin R. and Peter K. Schott. 2016. "Trade Liberalization and Mortality: Evidence from U.S. Counties", Working paper, Yale University.

Powell, David, and Seth Seabury. "Medical Care Spending and Labor Market Outcomes: Evidence from Workers' Compensation Reforms." American Economic Review 108.10 (2018): 2995-3027.

Rosen, Sherwin. 1986. “The Theory of Equalizing Differences”, Chapter 12 in Handbook of Labor Economics, volumn 1, eds. by Orley Ashenfelter and Richard Layard, 641-692. Amsterdam: North-Holland.

Ruhm, Christopher, 2000. “Are Recessions Good for Your Health?”. Quarterly Journal of Economics May 2000, 617-650.

Ruhm, Christopher J. "Good times make you sick." Journal of health economics 22.4 (2003): 637-658.

Ruhm, Christopher J. "Healthy living in hard times." Journal of health economics 24.2 (2005).

Smith, James, 1999. “Healthy Bodies and Thick Wallets: the Dual Relations between Health and Economic Status”, Journal of Economic Perspectives 13(2), 145-166.

Schaller, Jessamyn, and Ann Huff Stevens. "Short-run effects of job loss on health conditions, health insurance, and health care utilization." Journal of health economics 43 (2015): 190-203.

Stevens, Ann Huff, Douglas L. Miller, Marianne E. Page, and Mateusz Filipski. 2015 “The Best of Times, the Worst of Times: Understanding Pro-Cyclical Mortality”, American Economic Journal: Economic Policy 7, pp. 279-311.

Sullivan, Daniel and Till von Wachter. 2009. “Job Displacement and Mortality: An Analysis Using Administrative Data”. Quarterly Journal of Economics, , 1265-1306.

Torrance, George W. "Measurement of health state utilities for economic appraisal: a review." Journal of health economics 5.1 (1986): 1-30.

Tekin, Erdal, Chandler McClellan, and Karen J. Minyard. “Health and Health Behaviors During the Worst of Times: Evidence from the Great Recession”, NBER working paper 19234 July 2013.

Virtanen, Marianna, Katriina Heikkila, Markus Jokela, Jane E. Ferrie, G. David Batty, Jussi Vehtera, Mika Kivimaki, 2012 “Long working hours and coronary heart disease: a systematic review and meta-analysis”, American Journal of Epidemiology, 176 (7), 586-596.

Viscusi, W. Kip and Aldy, Joseph E., 2003, “The Value of A Statistical Life: A Critical Review of Market Estimates Throughout the World”, Journal of Risk and Uncertainty 27, 5–76.

Viscusi, W. Kip and William N. Evans, “Utility Functions that Depend on Health Status: Estimates and Economic Implications”, the American Economic Review, 80(3), June 1990, pp 353-374.

Wooldridge, Jeffrey M. 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge and London.

Table 1 Summary Statistics

	Obs. #	Mean	Std. Dev.	Expenditure Share
Monthly Data				
log Hours (workers)	8834846	5.0352	0.3660	N.A.
log Earnings (workers)	8834846	10.3295	0.4244	N.A.
log Material Use (firms)	8829857	11.1757	1.8019	N.A.
Annual Data				
Firm Characteristics				
Log employment	3336244	6.4324	1.6615	N.A.
Log capital labor ratio	3336244	19.7345	0.9550	N.A.
Share of high-skilled workers	3336244	0.2111	0.1552	N.A.
Log offshoring	3336244	17.3404	4.0138	N.A.
Worker Characteristics				
Experience (years)	3336244	18.8202	9.8158	N.A.
Union membership (dummy)	3336244	0.8591	0.3479	N.A.
Married (dummy)	3336244	0.5774	0.4940	N.A.
Stress (Dummies)				
Anti-Depressant (Drug)	3336244	0.0358	0.1857	0.3012%
Anti-Dep./Psychiatrist Visit	3336244	0.0399	0.1958	0.4668%
Narrow Burnout (Hosp.)	3336244	0.00005	0.00718	0.0005%
Broad Burnout (Hosp.)	3336244	0.00006	0.00778	0.0006%
Broad Burnout/Stress (Hosp.)	3336244	0.00020	0.01397	0.0111%
Broad Burnout/Stress/Depression (Hosp.)	3336244	0.00026	0.01623	0.0396%
Heart Disease (Drug)	3336244	0.0245	0.1546	0.3237%
Heart Attack or Stroke (Hosp.)	3336244	0.0016	0.0395	2.0200%
Alcoholism (Hosp.)	3336244	0.0009	0.0301	0.4653%

Table 2 Hours and Wages

	(1)	(2)	(3)	(4)
Hours: Full Sample				
log(sales)	0.0408***	0.0243***	0.0132***	0.0226***
	[16.42]	[8.36]	[4.95]	[8.35]
log(materials)			0.0335***	0.0474***
			[6.51]	[7.67]
Obs. No.	8,834,846	8,640,464	8,635,513	8,828,145
R^2	0.0033	0.0207	0.0217	0.5468
Hours: Dropping Imputed Hours				
log(sales)	0.0260***	0.0156***	0.0089***	0.0139***
	[17.75]	[9.37]	[5.14]	[7.68]
log(materials)			0.0202***	0.0302***
			[7.92]	[9.43]
Obs. No.	8,503,975	8,321,194	8,316,412	8,497,033
R^2	0.0052	0.0295	0.0310	0.4144
Earnings: Dropping Imputed Hours				
log(sales)	0.0367***	0.0140***	0.0079**	0.0124***
	[11.23]	[4.52]	[2.28]	[3.52]
log(materials)			0.0186***	0.0165***
			[4.15]	[3.04]
Obs. No.	8,503,975	8,321,194	8,316,412	8,497,033
R^2	0.0055	0.0819	0.0826	0.7818
worker-firm FE	Yes	Yes	Yes	Yes
month FE	No	Yes	Yes	Yes
worker & firm char.	No	Yes	Yes	N.A.
worker-year FE	No	No	No	Yes
firm-year FE	No	No	No	Yes

Notes: t-statistics in brackets, with clustering at firm-year-month level in all columns. *** p<0.01, ** p<0.05, * p<0.1. All specifications include year, industry and region fixed effects. The set of worker characteristics includes union status, marital status and experience, and the set of firm characteristics includes log offshoring, log employment, log capital/labor ratio, and the share of college-educated workers in employment.

Table 3 Stress: Prescription Drugs and Doctoral Visits

VARIABLES	Anti-Depressants (1)	(1) + Psychiatrist Visits (2)	Stroke Drugs (3)
log(sales)	0.0237***	0.0247***	0.0360***
	[4.11]	[4.46]	[4.25]
Exp. 5-20 years	0.0029***	0.0050***	-0.0126***
	[6.12]	[9.50]	[-44.04]
Exp. 20+ years	0.0030***	0.0048***	-0.0208***
	[4.80]	[6.98]	[-43.55]
Union	0.0008*	0.0003	0.0031***
	[1.79]	[0.65]	[9.21]
Married	0.0003	0.0022***	-0.0055***
	[0.72]	[4.89]	[-21.39]
log(employment)	0.0007	0.0006	-0.0016***
	[1.46]	[1.32]	[-4.10]
log(K/L)	-0.0000	-0.0001	-0.0005***
	[-0.21]	[-0.57]	[-2.72]
Skilled-labor share	0.0064**	0.0059**	-0.0122***
	[2.27]	[1.96]	[-4.59]
log(offshoring)	0.0000	0.0000	-0.0001
	[0.28]	[0.26]	[-1.09]
Obs. No.	3,432,554	3,432,554	3,432,554
R^2	0.0062	0.0061	0.0139
Job-Spell No.	723,664	723,664	723,664

Notes: t-statistics in brackets, with clustering at firm-year level in all columns. *** p<0.01, ** p<0.05, * p<0.1. All specifications include job-spell fixed effects, plus industry, year and region fixed effects.

Table 4 Effort-, Work- and Stress-Related Hospitalizations

VARIABLES	Narrow Burnout (1)	Broad Burnout (2)	(2) + Stress (3)	(3) + Depression (4)	Strokes (5)	Alcoholism (6)
log(sales)	0.446**	0.430**	0.292***	0.213**	0.0537**	0.122**
	[2.29]	[2.41]	[2.73]	[2.35]	[2.07]	[2.60]
Exp. 5-20 years	-0.000045**	-0.00004*	-0.000020	0.000019	-0.000651***	-0.000728***
	[-1.98]	[-1.67]	[-0.43]	[0.35]	[-9.27]	[-6.70]
Exp. 20+ years	-0.000035	-0.000030	0.000040	0.000103	-0.000767***	-0.000678***
	[-1.08]	[-0.88]	[0.64]	[1.41]	[-5.97]	[-5.19]
Union	-0.000003	0.000009	0.000072	0.000050	0.000189*	-0.000101
	[-0.13]	[0.31]	[1.58]	[1.00]	[1.76]	[-1.18]
Married	0.000066***	0.000079***	0.000224***	0.000268***	-0.000247***	-0.000148**
	[3.79]	[4.25]	[5.60]	[5.74]	[-2.91]	[-2.09]
log(employment)	-0.000020	-0.000028	-0.000054	-0.000028	-0.000037	0.000095
	[-0.96]	[-1.26]	[-1.41]	[-0.63]	[-0.35]	[1.27]
log(K/L)	-0.000018	-0.000020*	-0.000031*	-0.000009	-0.000005	-0.000059
	[-1.64]	[-1.84]	[-1.79]	[-0.43]	[-0.09]	[-1.51]
Skilled-labor share	0.000057	-0.000017	0.000164	0.000463	-0.000791	0.000362
	[0.46]	[-0.14]	[0.64]	[1.43]	[-1.16]	[0.79]
log(offshoring)	0.000008*	0.000008*	0.000003	0.000009	0.000000	-0.000015
	[1.68]	[1.69]	[0.49]	[1.02]	[0.02]	[-0.88]
Obs. No.	3,432,554	3,432,554	3,432,554	3,432,554	3,432,554	3,432,554
R^2	0.0000	0.0000	0.0001	0.0001	0.0003	0.0000
Job-Spell No.	723,664	723,664	723,664	723,664	723,664	723,664

Notes: t-statistics in brackets, with clustering at firm-year level in all columns. *** p<0.01, ** p<0.05, * p<0.1. All specifications include job-spell fixed effects, plus industry, year and region fixed effects.

Table 5 Marginal Disutility of Diseases

	Frequency	Utility Share Weight	Marginal Dis-utility (DKK 000)	95% Confidence Interval for 3 (DKK 000)	Change of Sick Rate w.r.t. Sales x 100
Sickness	1	2	3	4	5
ADPV	0.0399	0.47%	31.37	[2.70, 60.05]	0.0984
BSD (Hospitalization)	0.00026	0.040%	403.53	[34.72, 772.35]	0.0056
Stroke (hospitalization)	0.0016	2.02%	3466.65	[298.24, 6635.06]	0.0084
Heart diseases (drugs)	0.0245	0.32%	35.45	[3.05, 67.84]	0.0883
Alcoholism (Hosp.)	0.0009	0.47%	1374.75	[118.27, 2631.23]	0.0111
Injury	0.0039	2.26%	1556.84	[133.94, 2979.75]	N.A.

Notes: ADPV = anti-depressant or psychiatrist visits (column (2) of Table 3), BSD = burnout, stress, or depression (column (4) of Table 4). The numbers in column 5 are our elasticity estimates in Tables 3-4 multiplied by sample means multiplied by 100.

Table 6 Additional Results: Hours, Prescription Drugs and Doctoral Visits

	log(Hours)	Anti-Depressants	(2) + Psychiatrist Visits	Stroke Drug
	(1)	(2)	(3)	(4)
1. Add Small Firms (elasticity)				
log(sales)	0.0145***	0.0222***	0.0231***	0.0308***
	[9.10]	[3.91]	[4.24]	[3.90]
Obs. No.	9,316,944	3,820,473	3,820,474	3,820,475
2. Drop Managers (elasticity)				
log(sales)	0.0148***	0.0256***	0.0270***	0.0379***
	[7.54]	[4.09]	[4.46]	[4.43]
Obs. No.	8,773,869	3,199,217	3,199,217	3,199,217
3. Organizational Controls				
log(sales) x 100	N.A.	0.294***	0.335***	0.117
		[3.11]	[3.32]	[1.50]
log(# layers/sales) x 100		-0.0161	0.0004	0.107
		[-0.20]	[0.00]	[1.61]
Obs. No.		3,316,650	3,316,650	3,316,650
4. Predicted Firm Sales (elasticity)				
log(predicted sales)	N.A.	0.0290**	0.0317***	0.0360***
		[2.44]	[2.82]	[2.60]
Obs. No.		3,336,244	3,336,244	3,336,244
5. Men Only (elasticity)				
log(sales)	0.0158***	0.0151**	0.0191***	0.0322***
	[8.41]	[2.21]	[2.96]	[3.92]
Obs. No.	6,372,945	2,259,936	2,259,936	2,259,936
6. Women Only (elasticity)				
log(sales)	0.0085***	0.0344***	0.0293***	0.0755***
	[4.13]	[3.84]	[3.49]	[5.13]
Obs. No.	2,943,999	1,076,119	1,076,119	1,076,119
7. Local Labor Market Tightness				
log(sales) x 100	N.A.	0.0073***	0.0084***	0.0098***
		[3.25]	[3.46]	[4.66]
log(sales) x UI_rate x 100		0.240	0.313**	-0.214
		[1.61]	[1.97]	[-1.55]
Obs. No.		3,336,244	3,336,244	3,336,244

Notes: t-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1. Column (1) uses monthly data, includes job-spell, region, month, worker-year and firm-year fixed effects, and clusters by firm-year-month. The other columns use annual data, include job-spell, region, industry and year fixed effects, and cluster by firm-year. Panel 3 includes the logs of the numbers of imported and exported products, and the numbers of import source countries and export destination countries.

Table 7 Additional Results: Hospitalizations

	Narrow Burnout (1)	Broad Burnout (2)	(2) + Stress (3)	(3) + Depression (4)	Strokes (5)	Alcoholism (6)
1. Add Small Firms (elasticity)						
log(sales)	0.407**	0.397**	0.236**	0.171**	0.0461*	0.110**
	[2.41]	[2.50]	[2.40]	[2.04]	[1.76]	[2.56]
Obs. No.	3,820,473	3,820,473	3,820,473	3,820,473	3,820,473	3,820,473
2. Drop Managers (elasticity)						
log(sales)	0.485***	0.479***	0.308***	0.220**	0.0601**	0.124***
	[2.59]	[2.68]	[3.02]	[2.47]	[2.30]	[2.69]
Obs. No.	3,199,217	3,199,217	3,199,217	3,199,217	3,199,217	3,199,217
3. Organizational Controls						
log(sales) x 100	0.0146***	0.0148***	0.0181**	0.0173*	0.0513**	-0.013
	[3.08]	[2.89]	[2.03]	[1.66]	[1.98]	[-0.66]
log(# layers/sales) x 100	0.0095**	0.0090**	0.0098	0.0063	0.0191	-0.0193
	[2.46]	[2.11]	[1.28]	[0.69]	[0.85]	[-1.16]
Obs. No.	3,316,650	3,316,650	3,316,650	3,316,650	3,316,650	3,316,650
4. Predicted Firm Sales (elasticity)						
log(predicted sales)	0.504*	0.512*	0.400**	0.334**	0.0505	0.167**
	[1.65]	[1.76]	[2.27]	[2.25]	[1.23]	[2.23]
Obs. No.	3,336,244	3,336,244	3,336,244	3,336,244	3,336,244	3,336,244
5. Men Only (elasticity)						
log(sales)	0.704***	0.698***	0.308***	0.209**	0.036	0.0772*
	[3.24]	[3.27]	[2.59]	[2.23]	[1.42]	[1.75]
Obs. No.	2,259,936	2,259,936	2,259,936	2,259,936	2,259,936	2,259,936
6. Women Only (elasticity)						
log(sales)	0.136	0.105	0.281**	0.224*	0.201**	0.357***
	[0.51]	[0.45]	[2.14]	[1.77]	[2.54]	[3.95]
Obs. No.	1,076,119	1,076,119	1,076,119	1,076,119	1,076,119	1,076,119
7. Local Labor Market Tightness						
log(sales) x 100	0.0024**	0.0028***	0.0047**	0.0040*	0.0088*	0.0107**
	[2.52]	[2.62]	[2.35]	[1.66]	[1.94]	[2.52]
log(sales) x UI_rate x 100	-0.0030	-0.0034	0.0206*	0.0337**	-0.0088	0.0089
	[-0.54]	[-0.58]	[1.83]	[2.34]	[-0.20]	[0.31]
Obs. No.	3,336,244	3,336,244	3,336,244	3,336,244	3,336,244	3,336,244

Notes: t-statistics in brackets, with clustering at firm-year level in all columns. *** p<0.01, ** p<0.05, * p<0.1. All specifications include job-spell fixed effects, plus industry, year and region fixed effects. Panel 3 includes the logs of the numbers of imported and exported products, and the numbers of import source countries and export destination countries.

Figure 1 Log Hours, by Decile of Sales Changes

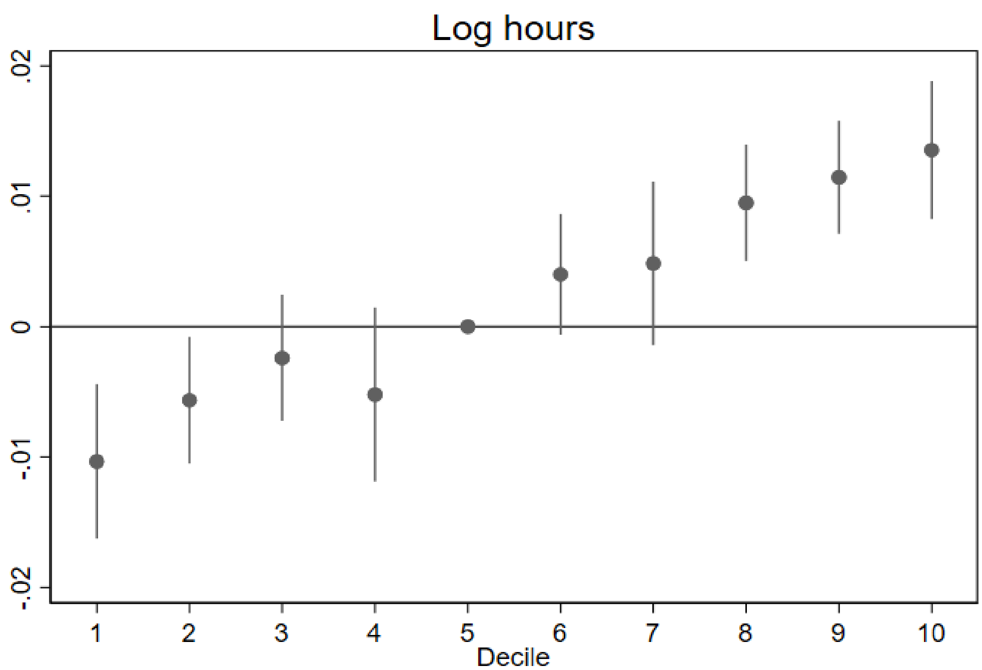


Figure 2 ADPV: by Deciles of Sales Changes

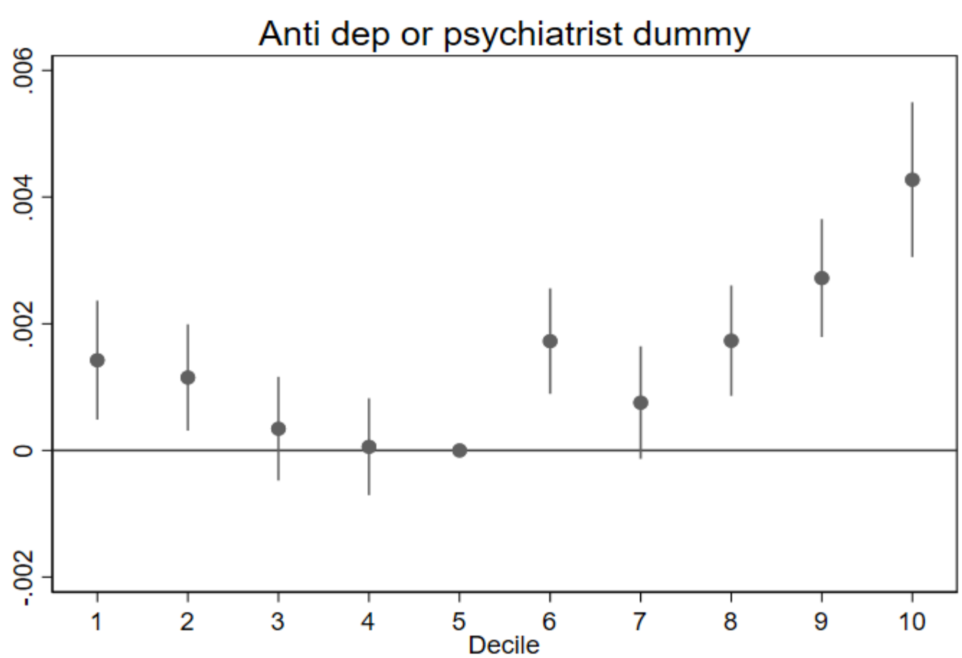


Figure 3 Alcoholism: by Deciles of Sales Changes

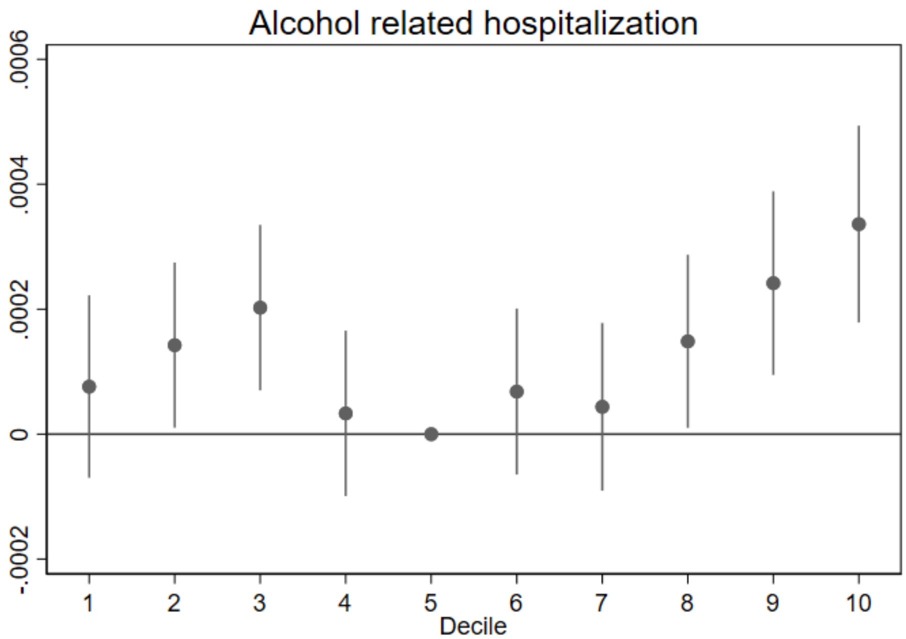


Figure 4 Heart or Stroke Drugs: by Deciles of Sales Changes

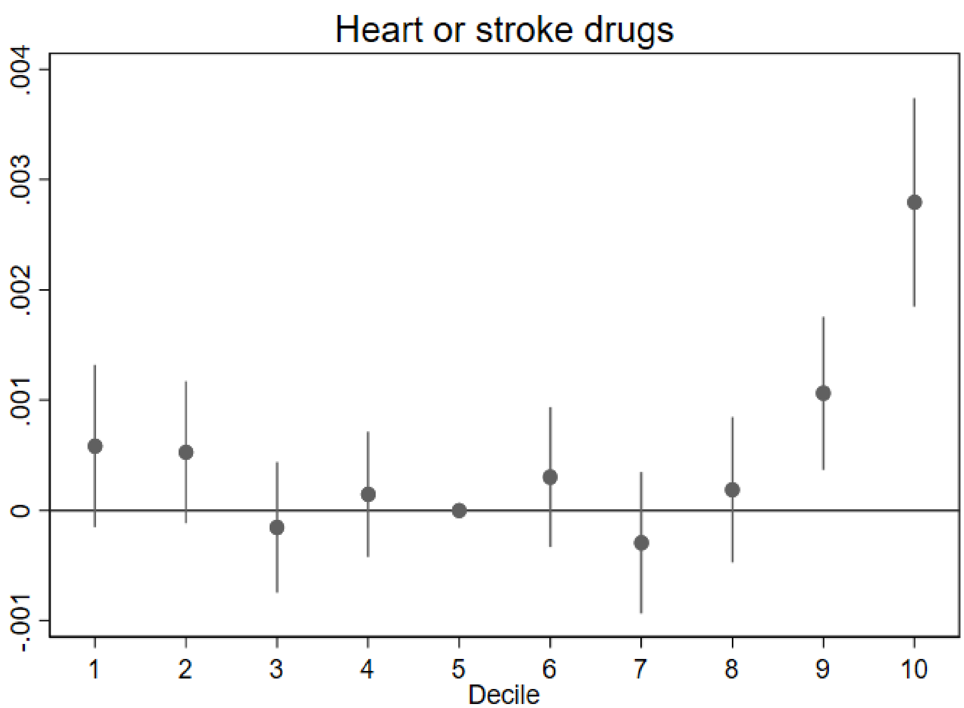


Figure 5 Broad Burnout: by Deciles of Sales Changes

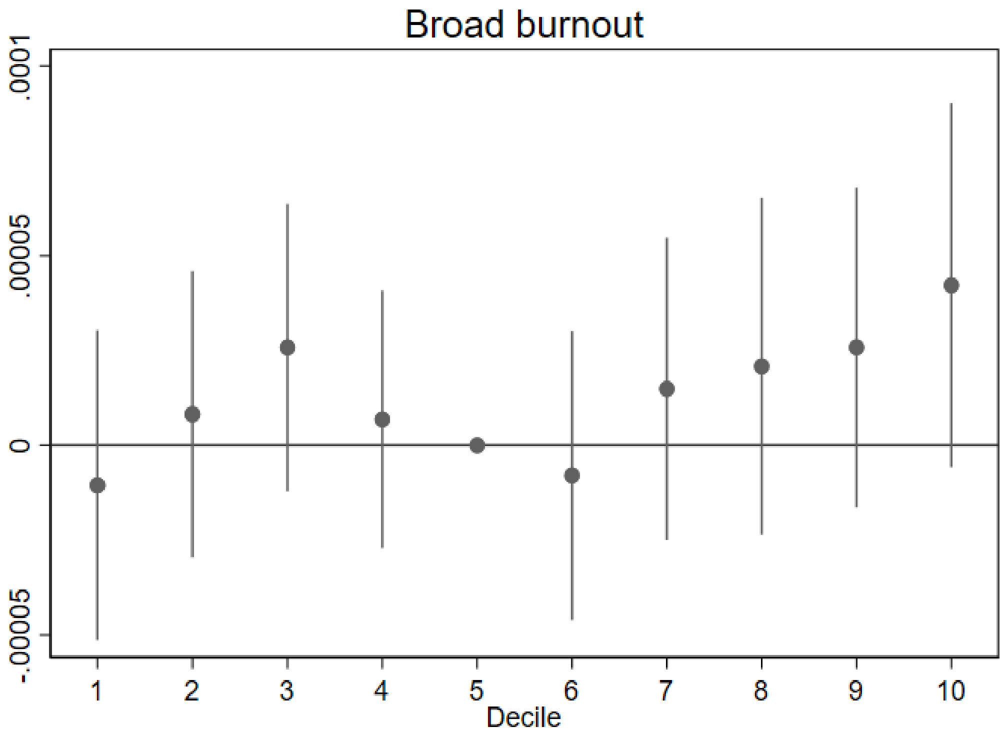


Figure 6a Effects of Large Sales Increases on Narrow Burnout

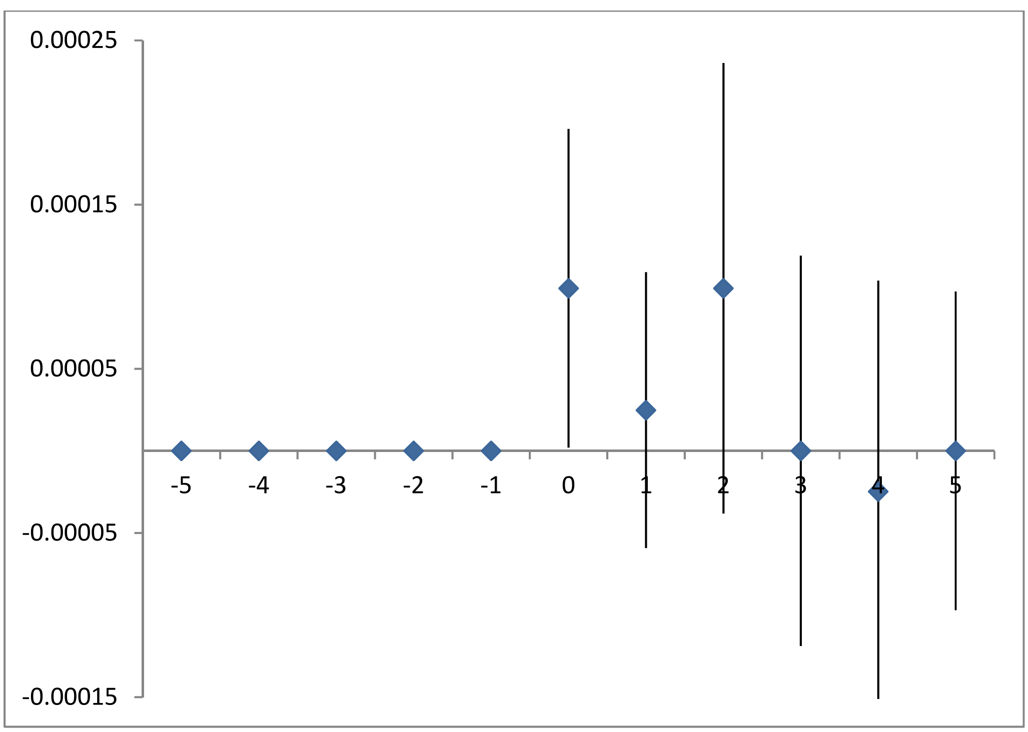


Figure 6b Effects of Large Sales Increases on Alcoholism

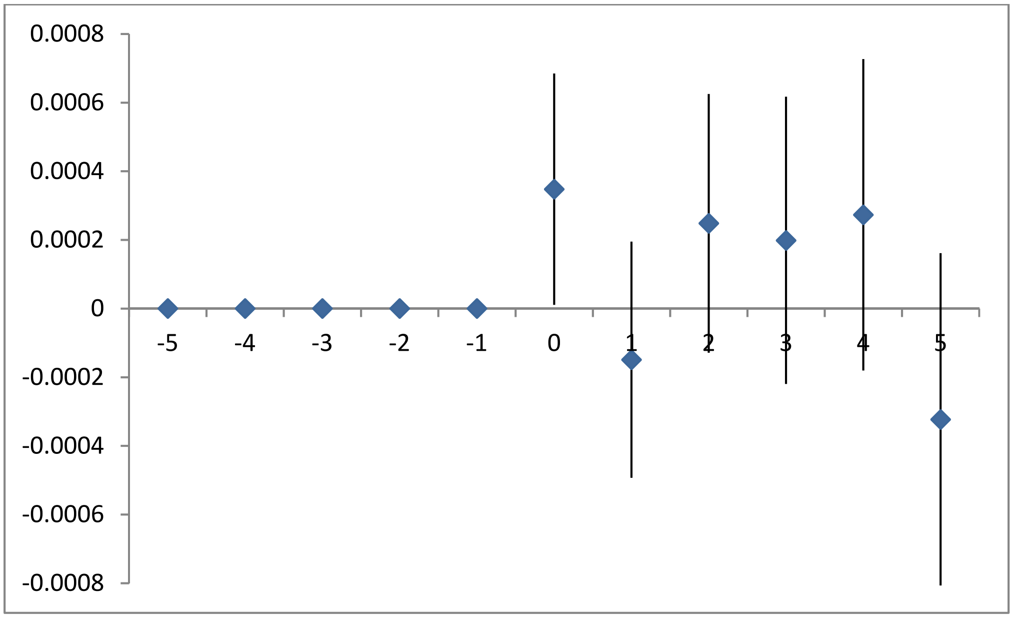


Figure 7a Effects of Large Sales Increases on Anti-Depressants

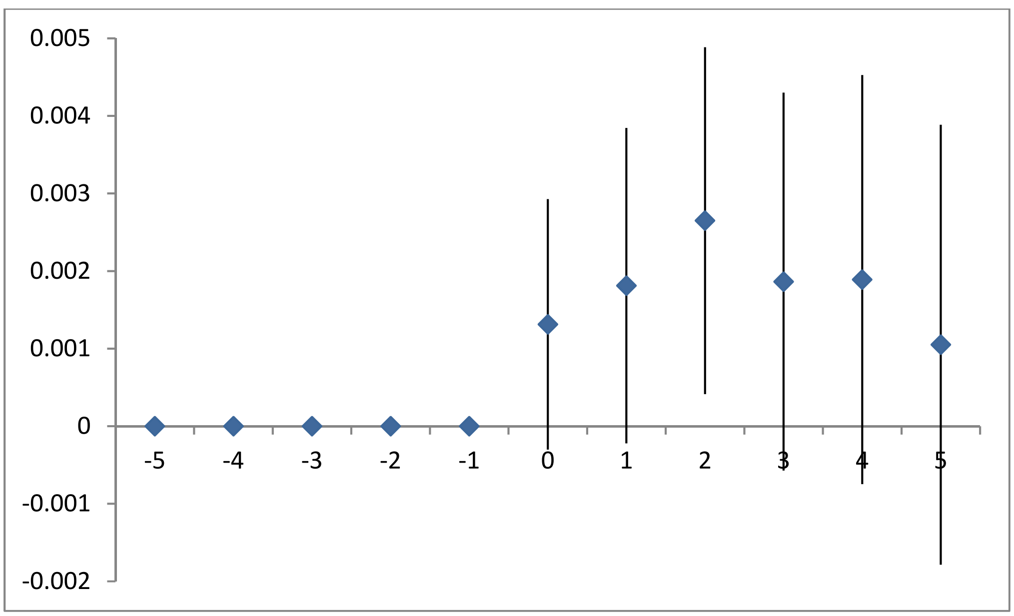
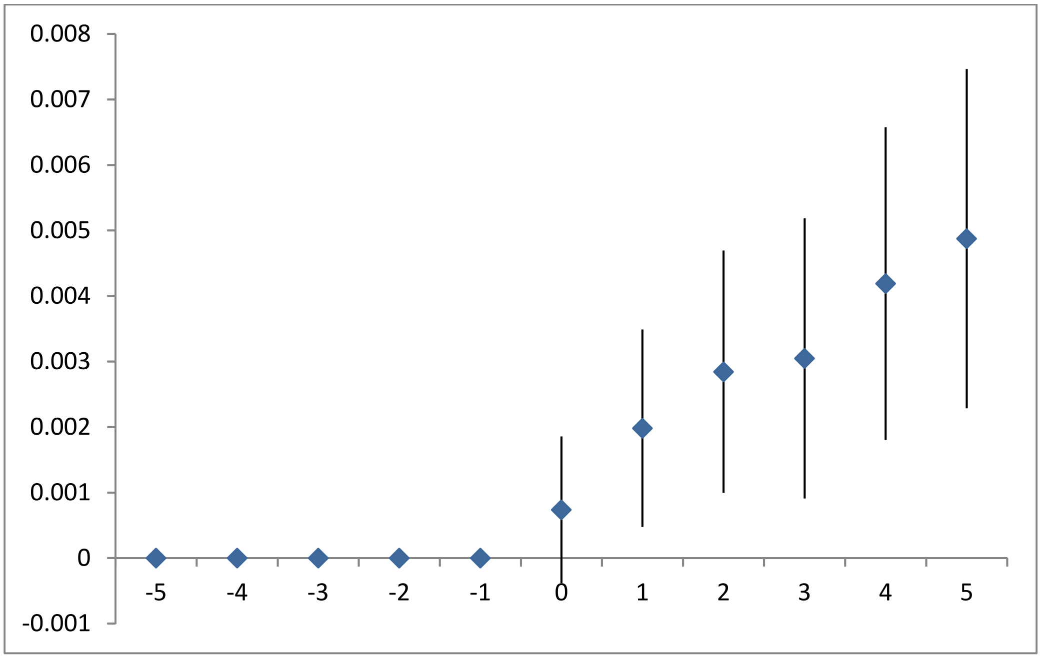


Figure 7b Effects of Large Sales Increases on Heart & Stroke Drugs



Data Appendix

1. More Details for Data Construction (Section 2)

1.1 Administrative Data on Health

Prescription drugs data are drawn from the "Register of Medicinal Product Statistics" maintained by Statens Serum Institut (SSI). These data include each individual's drug classification following the 4-digit Anatomical Therapeutic Chemical (ATC) codes, copay (out-of-pocket expenses by patients) and total prescription drug cost for the Danish government. For all Danish full time workers aged 20-60 during 1995-2009, the median out-of-pocket expense for prescription-drug copay is 404 DKK while the median labor income is 296,379 DKK (1 DKK is about 0.18 USD in this time period).

Data for contacts with the doctor are drawn from the "Doctoral Visits Register". In this register every visit to the doctor (including phone calls) is identified, and we observe each individual's visit dates (by week), type of doctors visited (e.g. general practitioner, psychiatrist), and total cost of the visit for the Danish government. We disregard all dental visits in the data, because dental care is not free.

Finally, the data on hospitalization includes the diagnosis, by the International Classification of diseases (ICD10), and the total cost of in-patient care for the Danish government.

The ATC codes of our prescription-drug variables are as follows. Anti-depressants = N06AA, AF, AG and AX. Drugs for heart diseases = B01 and C01. The ICD 10 codes for our hospitalization variables are as follows. Narrow burnout = Z730, 731, 732, 733, Z563 and Z566. Broad burnout = narrow burnout plus Z564, 565, 568 and 569. Heart attacks or strokes = I21, 61 and 63. Alcoholism = F100, 102, 104, 105, I85, K70, 860, T500 and 510.

1.2 Healthcare Expenses

Table A1 reports the share of healthcare expenses in GDP for Denmark by year, for the period 2010-2015. This share is stable over time. Total health care expenditure includes all private expenditure related to doctors and medicinal products (drugs plus medical equipment, such as hearing aid). It also includes all public expenditure, the category health in COFOG (Classification of the Functions of Government) by Statistics Denmark, which includes doctors, medicinal products, hospital service and R&D. Total health care expenditure excludes elderly care and income transfers, such as cash benefits for sick leave.

Table A2 breaks the healthcare expenses into the following categories for 2010. Hospital services include regular hospitals, plus costs to birthing clinics and rehabilitation centers. Within non-hospital services, medical products and equipment include all products used in the interest of health not related to hospitals; e.g. prescription drugs, experimental medicine, prosthesis equipment and glasses. Paramedic care includes all non-doctoral care that is not related to hospitals. Other public health care is mainly administrative costs, R&D and preventive services (such as vaccine).

We obtain the Diagnosis-Related Group (DRG) expenses for our hospitalization variables from the hospitalization registry. The DRG expenses have narrower coverage than the category of hospital services in Table A2. As a result, we compute the shares of our hospitalization variables within the total DRG expense, and assume that they are equal to the shares within the category of hospital services. For example, since heart attacks and strokes have a share of 3.23% within the total DRG expense, their total expense is 113.15 x 3.23% = 3.65 billion DKK.

2. Notes for Non-Linear Specifications (Section 5)

Cut-off Points of the Decile Dummies: In section 5.1, we construct the decile dummies for the distribution of the deviations of log firm sales relative to their job-spell means. For our monthly data, the cut-off points are, respectively, -0.758, -0.285, -0.161, -0.080, -0.021, 0.035, 0.096, 0.175, 0.301 and 0.697. For our annual data, they are -0.788, -0.189, -0.083, -0.021, 0.028, 0.080, 0.148, 0.233, 0.363 and 0.784.

Mass Layoff and Decreases in Firm Sales We denote the indicator variable for mass layoffs by F_{jt}; i.e. $F_{jt} = 1$ if employment of firm j in year t is 30% or more lower than in year $t - 1$ (here we use the 30% cutoff following Sullivan and von-Wachter 2009). We then regress F_{jt} on decreases in firm sales, controlling for firm fixed effects and year fixed effects. We report the results in Table A3. In column (1), we use change in firm j's log sales from year $t - 2$ to $t - 1$, and obtain a negative and significant coefficient estimate. In column (2), we use the dummy variable indicating whether year $t - 1$ is in the first decile of deviations from firm-level average sales, and obtain a positive and significant coefficient estimate.

Additional Details of PSM We now present additional details of the propensity-score matching (PSM) procedure, using the antidepressant sample (the results for the other sickness variables are similar). In section 5.2, we make use of the top and bottom deciles of the distribution of year-to-year changes in log firm sales. The cutoff point is 0.47 for the top decile, and -0.23 for the bottom decile.

Table A4 shows the Probit model used to predict the propensity score values for each individual. The model changes slightly across sickness outcomes analyzed because we require that both treatment-group and control-group workers are free of this condition for five consecutive years before the shock. After imposing the sample selection criteria explained in the text, we end up with more than 38,000 workers in the treatment group (i.e. their firms have experienced an increase in sales between year t-1 and t that belongs to the top decile in the distribution of sales changes, and we can track them five years before and five years before the shock within the sample window). The control group has more than 136,000 observations and consists of workers that did not experience large sales decreases, i.e., decile 2 through 9 of the distribution.

After having obtained the propensity score for each individual, we use simple nearest neighbor matching without replacement to match one control observation to each treatment observation. This reduces the differences in observed characteristics across the two groups substantially, and we end up with mean differences between the two groups that are fairly small, as shown in Table A5 (a mean difference of less than 10% is typically considered sufficient in the PSM literature).

3. Data for Marginal Disutility and Ex-Ante Utility Loss (Section 7)

Injury Data: In order to estimate VSI, we draw on the following data for severe work injury in Denmark. When a worker is injured on the job, he/she may file a petition for compensation with the National Board of Industrial Injuries (NBII). If the job injuries are severe enough to cause permanent damages to the workers' earning and working abilities, then the workers are also eligible for a one-time, lump-sum monetary compensation. We observe all the petitions filed during 1995-2009, and the final decision by NBII for each petition. To measure injury we consider whether an individual receives positive monetary compensation from NBII. The mean injury rate is 3.9 per thousand in our sample, lower than in the U.S. data, probably because we only include severe injuries while the U.S. data includes all injuries. In addition, most workers stay employed with the same firm after injury in our data.

One potential concern with our injury dummy is that the standard used by NBII to award compensation may endogenously respond to economic fluctuations (e.g. tougher standards during recessions). This is not the case in our data. During 2007-2009, Denmark's Great Depression, NBII accepted around 51% of all petitions, while during the pre-recession years of 2004-2006, NBII accepted about 48% of all petitions.

Estimation of VSI: To carry out the estimation, we examine all full-time Danish workers in the private sector aged 18-65 in 2006. We follow the literature (e.g. Viscusi and Aldy 2003) and run a Mincer regression, augmented by the occupational injury rate. Our dependent variable is the log of annual wage. Our controls include age, experience, experience square, tenure, dummies for marriage, kids, white-collar occupations, vocational education, college education, and native-born Danish. We cluster our standard errors by occupation.

We report the results in Table A6. Our estimate for the log-wage-injury gradient is 5.24, with the 95% confidence interval [0.45, 10.03]. This is consistent with the literature, given that our sample mean is 0.0039 (e.g. Hersch 1998 obtains an estimate of 1.2~1.6 using U.S. data of all injuries, where the sample mean is 0.03, and Martinello and Meng 1992 obtain 3.2~4.1 using Canadian data of severe injuries, where the sample mean is 0.023). Because the average wage in this sample is 297,164 DKK, our estimate for the marginal disutility of injury is DKK 1.56 million (= 297,164 x 5.24), with the 95% confidence intervals of [0.134, 2.978] million DKK.

Expenditure Share for Injury: In Denmark, injury-related expenses consist of medical expenses, for treatment, and cash benefits, such as the monetary compensation we discussed earlier in this section. For our quantification in section 7, we need medical expenses, not cash benefits. However, we observe cash benefits through our NBII injury data, but do not observe medical expenses. On the other hand, in the U.S., the medical expenses for work injury are typically fully covered through insurance (e.g. Powell and Seabury 2018), like in Denmark. The categories of injury-related expenses in the U.S. are also well studied, with medical expenses accounting for roughly 50% of all expenses (medical expenses plus cash benefits) (e.g. Baldwin and McLaren 2016). Assuming that the Danish share of medical expenses is the same as in the U.S. data, we obtain that, for 2010, total medical expenses for injury are equal to the total cash benefits of $4.1 billion DKK. The expenditure share for injury, therefore, is 2.26% (= 4.1/181.2).

Elasticity of Earnings with respect to Sales: In order to provide a benchmark for workers' ex-ante utility losses, we regress the log of workers' annual earnings on the log of firm sales in Table A7. We use the same sample and the same set of controls as in Tables 3-4, and obtain an elasticity estimate of 0.0085.

4. Notes for Robustness Exercises and Heterogeneous Effects (Section 8)

First Stage Results We present our first-stage results in Table A8. Our instrument is $\log(I_{jt}) = \log(\sum_k s_{jk} Q_{kt})$, where Q_{kt} is the aggregate output of product k in year t in Denmark, and s_{jk} is product k's share in firm j's output in the pre-sample year of 1994. We include the same set of fixed effects and the same set of worker- and firm-characteristics as controls as in Tables 3-4, and cluster our standard errors by firm by year. The coefficient estimate of our instrument is 0.726, and the F-statistic for our instrument is 117.3.

Additional Summary Statistics: Table A9 shows the mean values of our sickness variables by gender. We use these mean values to calculate the elasticities in panels 5 and 6 of Tables 6-7.

Commuting Zones: Commuting zones are based on geographically connected municipalities. 275 municipalities in Denmark are merged into 51 commuting zones such that the internal migration rate is 50% higher than the external migration rate. The commuting zone unemployment rate has substantial variation across workers and over time ranging from 1.4% to 16.8% with a mean of 5.3%.

Theory Appendix

1. Proposition 1

To ease exposition, we suppress the subscripts *i*, *j*, and *t* in this section. Firm *j*'s output is *AV*, where *A* denotes j's TFP, and *V* denotes *j*'s output net of TFP. Let *K* note *j*'s capital, *M* its materials, and *L* labor employment. One individual worker's effort is, again, *e*. The production function relates *Q* to *K*, *M*, *L*, and *e*, and we assume that it is continuously differentiable and concave (e.g. Cobb-Douglas, CES). We assume that an individual worker' effort cost is $E = ah(e)$, where $a > 0$ is a parameter, and the function $h(.)$ is continuously differentiable and convex. The effort cost, *E*, represents the worker's stress, or the adverse health effects induced by effort.

Let ψY denote firm *j*'s revenue, where ψ represents both *j*'s output demand and TFP, and *Y* is a monotonic function of *V*. The functional forms of ψ and *Y* depend on market structure. For example, suppose that consumer preferences are CES with substitution elasticity $\sigma > 1$, and that the market for *j*'s output is monopolistic competition. Then it is easy to show that firm *j*'s total revenue equals $(\frac{BA^{\sigma-1}}{P^{1-\sigma}})^{\frac{1}{\sigma}} V^{\frac{\sigma-1}{\sigma}}$, where *B* is consumer expenditure and *P* the CES price index. In this example, $\psi = (\frac{BA^{\sigma-1}}{P^{1-\sigma}})^{\frac{1}{\sigma}}$ and $Y = V^{\frac{\sigma-1}{\sigma}}$.

We assume that firm *j* takes the price of materials, p_M, and rental rate of capital, *r*, as given. Firm *j* and its employees engage in multi-lateral bargaining, where each worker receives the same weight in the bargaining process (e.g. Stole and Zwiebel 1996, Helpman et al. 2010). At the equilibrium of the bargaining game, firm *j* takes workers' optimal effort choices as given, and choose *K*, *M* and *L* to maximize its surplus. An individual worker, on the other hand, takes *j*'s optimal choices of *K*, *M* and *L* and other workers' optimal effort choices as given, and chooses *e* to maximize her surplus.

We now spell out the firm's and workers' objective functions. At the Nash equilibrium of the bargaining game, firm *j* collects the fraction $1 - \beta$ of the total surplus, while each worker collects the fraction β of total surplus per worker, where β is a constant. We assume that the workers' outside options are 0, and firm *j*'s outside option is the fraction $1 - \theta_f$ of its total revenue, ψY. The parameter θ_f is a constant, too. The total surplus of the bargaining game is then $\psi Y - p_M M - rK - (1 - \theta_f)\psi Y = \theta_f \psi Y - p_M M - rK$.

Firm *j*'s objective, then, is to choose *L*, *M* and *K* to maximize its surplus of $(1 - \beta)[\theta_f \psi Y - p_M M - rK] + (1 - \theta_f)\psi Y - b(L)$, where $b(L)$ is search/hiring cost. For our derivations in this section, we do not need to explicitly solve for the firms' optimal choices, and so we postpone this task to the next section.

Meanwhile, an individual worker's objective is to

$$\max_e \{W - ah(e)\}, W = \beta \frac{\theta_f \psi Y - rK - p_M M}{L}. \quad \text{(A1)}$$

In this expression, *W* is the individual workers' surplus. Let $y = Y/L$. Then the first-order condition for (A1) is

$$\beta \theta_f \psi \frac{\partial y}{\partial e} = ah'(e). \quad \text{(A2)}$$

Note that in our derivation, effort, *e*, does not affect the economic shock, ψ; i.e. individual workers take ψ as given. Equation (A2) determines the optimal effort level, *e*, and implies that

$$\frac{\partial e}{\partial \psi} = \frac{\beta\theta_f (\partial y / \partial e)}{ah''(e) - \beta\theta_f \psi \dfrac{\partial^2 y}{\partial e^2}}. \tag{A3}$$

Because $\partial y / \partial e > 0$ (effort makes a positive contribution to output), $h''(e) > 0$ (effort cost is convex), and $\frac{\partial^2 y}{\partial e^2} < 0$ (diminishing returns with respect to effort level), equation (A3) says that $\frac{\partial e}{\partial \psi} > 0$; i.e. as demand for firm *j*'s output increases for exogenous reasons, effort level increases.

Because the effort cost function is increasing, we have, immediately, that $\frac{\partial E}{\partial \psi} > 0$; i.e. effort cost, which represents stress, also increases with output demand. We now apply the Envelope Theorem to equation (A1), and obtain $\frac{\partial W}{\partial \psi} = \beta\theta_f y > 0$; i.e. workers' income increases with output demand.

2. Derivation of Equation (1)

We now make the transition from (A2) to estimation equations. We first make the following specifications for *E* and *y*

$$E = ah(e) = ae^{\eta}, \eta > 1. \tag{A4}$$

$$y = e^{\gamma} F(K, M, L), \ 0 < \gamma < 1. \tag{A5}$$

Equation (A4) specifies a power function for effort cost, and $\eta > 1$ ensures that effort cost is convex. Equation (A5) says that effort enters output in a multiplicative way, and $0 < \gamma < 1$ ensures that output is increasing and concave in effort.

To illustrate equation (A5), suppose the production function is Cobb-Douglas, with $V = K^{\delta_K} M^{\delta_M} (DL)^{\delta_L}, \delta_K + \delta_M + \delta_L = 1$, where $D = \prod_i e_i$ is the aggregate of all the workers' efforts. In addition, suppose preferences are CES and the output market has monopolistic competition, so that Y = $V^{\frac{\sigma-1}{\sigma}}$, where $\sigma > 1$ is the substitution elasticity (see the previous section). In this example, $\gamma = \delta_L \frac{\sigma - 1}{\sigma}$.

Plugging (A4) and (A5) into equation (A2), we have the following expressions for effort and effort cost

$$e^{\eta-\gamma} = \frac{\beta\gamma\theta_f\psi}{a\eta} F(K, M, L), \ E = a[\frac{\beta\gamma\theta_f\psi}{a\eta} F(K, M, L)]^{\frac{\eta}{\eta-\gamma}}. \tag{A6}$$

We now derive the expression for workers' income, *W*. We start by solving for firm *j*'s optimal choices

$$\max_{K,M,L} \{(1-\beta)\left[\theta_f \psi Y - p_M M - rK\right] + (1-\theta_f)\psi Y - b(L)\}.$$

The first order conditions for *K* and *M* are, respectively

$$[(1-\beta)\theta_f\psi + (1-\theta_f)\psi]\frac{\partial Y}{\partial V}\frac{\partial V}{\partial K} = r, \ [(1-\beta)\theta_f\psi + (1-\theta_f)\psi]\frac{\partial Y}{\partial V}\frac{\partial V}{\partial M} = p_M.$$

Let $c_0 = (1 - \beta)\,\theta_f + (1 - \theta_f)$, we can re-write these expressions as

$$c_0\psi\frac{\partial Y}{\partial V}\frac{\partial V}{\partial K}K = rK\,, c_0\psi\frac{\partial Y}{\partial V}\frac{\partial V}{\partial M}M = p_M M\ .$$

They imply that

$$c_0\psi\frac{\partial Y}{\partial V}(\frac{\partial V}{\partial K}K + \frac{\partial V}{\partial M}M) = rK + p_M M\ .$$

Plugging this expression into the expression $W = \beta\frac{\theta_f \psi Y - rK - p_M M}{L}$, we obtain

$$W = \frac{\beta}{L}\psi[\theta_f Y - c_0\frac{\partial Y}{\partial V}(\frac{\partial V}{\partial K}K + \frac{\partial V}{\partial M}M)] = \beta y\psi[\theta_f - c_0\frac{\partial Y}{\partial V}\frac{1}{Y}(\frac{\partial V}{\partial K}K + \frac{\partial V}{\partial M}M)]$$

$$= \beta y\psi H(\psi,K,M,L), H(\psi,K,M,L) = [\theta_f - c_0\frac{\partial \ln Y}{\partial \ln V}(\frac{\partial \ln V}{\partial \ln K} + \frac{\partial \ln V}{\partial \ln M})] \qquad \text{(A7)}$$

In equation (A7), the elasticities in the term *H(.)* depend on the parameters of firm *j*'s production function and output demand. To illustrate these elasticities, consider, again, the following special case. The production function is $AV = AK^{\delta_K}M^{\delta_M}(DL)^{\delta_L}, \delta_K + \delta_M + \delta_L = 1$, where $D = \prod_i e_i$ is the aggregate of all the workers' efforts. Preferences are CES and the output market has monopolistic competition, so that Y = $V^{\frac{\sigma-1}{\sigma}}$. It is easy to see that in this special case, *H(.)* = $\theta_f - c\frac{\sigma-1}{\sigma}(\delta_K + \delta_M)$. In general, however, *H(.)* may depend on *V*, which, in turn, depends on ψ, *K*, *L* and *M*. Plugging equations (A5) and (A6) into (A7), we obtain

$$W = [\frac{\gamma\theta_f}{a\eta}]^{\frac{\gamma}{\eta-\gamma}}[\beta\psi F(K,M,L)]^{1+\frac{\gamma}{\eta-\gamma}}H(\psi,K,M,L)\,. \qquad \text{(A8)}$$

It is easy to see that we obtain equation (1) for *e* and *E* by taking the logs of both sides of equation (A6), where the vector $\mathbf{z}_{jt}$ represents $\ln F(K_{jt}, M_{jt}, L_{jt})$. On the other hand, although equation (A8) may not be log linear in output demand, ψ, it shows that income, *W*, depends on ψ and the input uses, *K*, *M*, and *L*. This means that we can take a first-order Taylor approximation with respect to the logs of ψ, *K*, *M*, and *L*. This gives us equation (1) for *W*.

3. Derivation of Equation (7), and the Second Order Derivatives of *M*

Let $p_H = 1 - \Sigma_g p_g > 0$ denote the probability of the healthy state. Differentiate both sides of equation (5)

$$\frac{\partial M}{\partial p_g}\sum_g p_g[u'(I+M) - v_g'(I_g+M)] + u(I+M) - v_g(I_g+M) = \frac{\partial M}{\partial p_g}u'(I+M)\,. \qquad \text{(A9)}$$

This implies

$$\frac{\partial M}{\partial p_g} = \frac{u(I+M) - v_g(I_g+M)}{u'(I+M) + \sum_l p_l[v_l'(I_l+M) - u'(I+M)]} = \frac{u(I+M) - v_g(I_g+M)}{p_H u'(I+M) + \sum_l p_l v_l'(I_l+M)}\,,$$

which is equation (7). $\partial M/\partial p_g > 0$ because $v_g(I_g+M) \le u(I_g+M) < u(I+M)$, and $u'(.) > 0$ and $v_g'(.) > 0$ for all g.

We now show that if $\partial M/\partial p_g$ is large, $\frac{\partial^2 M}{\partial (p_g)^2} > 0$ and $\frac{\partial^2 M}{\partial p_g \partial p_l} > 0$. To economize on notation, let $u'(.)$ denote $u'(I+M)$, and $v_g'(.)$ denote $v_g'(I_g+M)$, etc. We differentiate both sides of equation (A9) with respect to p_g, to obtain

$$\frac{\partial^2 M}{\partial (p_g)^2}\sum_g p_g[u'(.)-v_g'(.)]+(\frac{\partial M}{\partial p_g})^2\sum_g p_g[u''(.)-v_g''(.)]+2\frac{\partial M}{\partial p_g}[u'(.)-v_g'(.)]$$
$$=\frac{\partial^2 M}{\partial (p_g)^2}u'(.)+u''(.)(\frac{\partial M}{\partial p_g})^2$$

Re-arranging, we get

$$-\frac{\partial^2 M}{\partial (p_g)^2}\underbrace{[p_H u'(.)+\sum_g p_g v_g'(.)]}_{>0}=(\frac{\partial M}{\partial p_g})^2\underbrace{[p_H u''(.)+\sum_g p_g v_g''(.)]}_{<0}-2\frac{\partial M}{\partial p_g}\underbrace{[u'(.)-v_g'(.)]}_{??}.$$

In this expression, the sign of $u'(.) - v_g'(.)$ depends on the nature of state dependency and so is hard to determine. However, since $\partial M/\partial p_g$ is large, the first term on the right-hand side dominates, meaning that the right-hand side is negative. As a result, $\frac{\partial^2 M}{\partial (p_g)^2} > 0$.

We then differentiate both sides of equation (A9) with respect to p_l, to obtain

$$\frac{\partial^2 M}{\partial p_g \partial p_l}\sum_g p_g[u'(.)-v_g'(.)]+\frac{\partial M}{\partial p_g}\frac{\partial M}{\partial p_l}\sum_g p_g[u''(.)-v_g''(.)]+\frac{\partial M}{\partial p_g}[u'(.)-v_l'(.)]+\frac{\partial M}{\partial p_l}[u'(.)-v_g'(.)]$$
$$=\frac{\partial^2 M}{\partial p_g \partial p_l}u'(.)+u''(.)\frac{\partial M}{\partial p_g}\frac{\partial M}{\partial p_l}$$

Re-arranging, we get

$$-\frac{\partial^2 M}{\partial p_g \partial p_l}\underbrace{[p_H u'(.)+\sum_g p_g v_g'(.)]}_{>0}=$$
$$\frac{\partial M}{\partial p_g}\frac{\partial M}{\partial p_l}\underbrace{[p_H u''(.)+\sum_g p_g v_g''(.)]}_{<0}-\frac{\partial M}{\partial p_g}\underbrace{[u'(.)-v_l'(.)]}_{??}-\frac{\partial M}{\partial p_l}\underbrace{[u'(.)-v_g'(.)]}_{??}.$$

Again, the signs of $u'(.) - v_g'(.)$ and $u'(.) - v_l'(.)$ depend on the nature of state dependency, but the first term on the right-hand side dominates since $\partial M/\partial p_g$ is large. Thus the right-hand side is negative, and so $\frac{\partial^2 M}{\partial p_g \partial p_l} > 0$.

4. Proposition 3

Suppose, first, that $s_g = s_l$ but $p_g > p_l$ for diseases g and l. Then equation (12) says that $t_g = t_l$, and assumption (13) says that $C(t_g) = C(t_l)$. Therefore, expenditures are proportional to frequency ($E_g/E_l = p_g/p_l$). Equation (12) also says that net income, post treatment, is the same under g and l ($I_g = I_l$), and so by (9), utility share weights are also proportional to frequency ($\beta_g/\beta_l = p_g/p_l$ since $v_g(.) = v_l(.)$). As a result, $E_g/E_l = \beta_g/\beta_l = \mu_g/\mu_l$.

Next, suppose we have full recovery instead of partial recovery. This means that treatment is 100% effective; i.e. $t_g = t_l = 1$ for all diseases g and l. Clearly, $E_g/E_l = \beta_g/\beta_l = \mu_g/\mu_l$, as in the previous case.

5. Proposition 4

We start by noting that $I_g = I - s_g(1 - t_g) - c(s_g,t_g)$, and $E_g = p_gC(s_g,t_g)$.

First, suppose $p_g = p_l$ but $s_g > s_l$. We show below that $E_g > E_l$ and $\beta_g > \beta_l$ if the cross-partial of the private-cost function is lower than the 1, which equals the cross-partial of the benefit to utility of treatment, s_gt_g; i.e. $\frac{\partial^2 c(.)}{\partial t_g \partial s_g} < 1$.

Consider partial recovery first. Utility maximization implies that $\partial I_g/\partial t_g = 0$, or that $s_g = \partial c(.)/\partial t_g$. This implies that

$$\frac{\partial t_g}{\partial s_g} = \frac{1 - \frac{\partial^2 c(.)}{\partial t_g \partial s_g}}{\frac{\partial^2 c(.)}{\partial (t_g)^2}} > 0 . \tag{A10}$$

The numerator is positive by the assumption that $\frac{\partial^2 c(.)}{\partial t_g \partial s_g} < 1$, and the denominator is positive by convexity of the function $c(.)$. Meanwhile, using the envelope theorem on the expression $I_g = I - s_g(1 - t_g) - c(s_g,t_g)$, we get

$$\frac{\partial I_g}{\partial s_g} = -(1 - t_g) - \frac{\partial c(.)}{\partial s_g} < 0 . \tag{A11}$$

Equations (A10) and (A11) show that equation (12) still holds. We can then follow similar steps as in the text, to show Proposition 2.

Now consider full recovery. We immediately have $t_g = t_l = 1$, and so $I_g = I - c(s_g,1) < I_l = I - c(s_l, 1)$. This means $\beta_g > \beta_l$. On the other hand, $E_g = p_gC(s_g,1) > E_l = p_lC(s_l,1)$ since $s_g > s_l$. Note that we get weaker results than in Proposition 3, because now pain itself affects expenditure directly.

Finally, suppose $p_g > p_l$ but $s_g = s_l$. Under partial recovery, $t_g = t_l$ and $I_g = I_l$ by equations (A10) and (A11). As a result, $E_g/E_l = \mu_g/\mu_l = p_g/p_l = \beta_g/\beta_l$. Under full recovery, again $t_g = t_l = 1$, and $I_g = I_l$ since $s_g = s_l$. As a result, $E_g/E_l = \mu_g/\mu_l = p_g/p_l = \beta_g/\beta_l$. This completes the proof.

6. Proposition 5

Suppose that sickness g is associated with the mortality risk of p_{gD}, and p_{gD} is monotonically related to s_g with $\partial p_{gD} / \partial s_g > 0$. We also assume that treatment may reduce mortality risk; i.e. $\partial p_{gD} / \partial t_g \leq 0$.

Let v_D denote the utility level under mortality, and $v_{g1}(.)$ denote the utility function in sick state g, conditional on being alive. We normalize $v_D = 0$, as in Murphy and Topel (2003) and Hall and Jones (2007), and assume that the utility function $v_{g1}(.)$ has the same properties as the utility function we use in the text, $v_g(.)$.

Let I_{g1} denote the severity of g caused by the symptoms of g. We assume, as in the text, that I_{g1} depends on the pain, s_g, and treatment, t_g, with $\partial I_{g1} / \partial s_g < 0$. Then the expected utility in sick state g is equal to $(1 - p_{gD})v_{g1}(I_{g1}) + p_{gD}v_D = (1 - p_{gD})v_{g1}(I_{g1})$.

Given treatment, t_g, this expected utility is a monotonic function of s_g. To see this, suppose s_g increases. On the one hand, mortality risk, p_{gD}, increases, and this tends to decrease expected utility. On the other hand, severity also increases (i.e. I_{g1} decreases), and this also tends to decrease expected utility. In other words, this setting formalizes the intuition that s_g captures the total effect of disease symptoms and mortality risk.

We now relate the expected utility to our framework in section 6, by noting that there exists I_g such that

$$v_g(I_g) = (1 - p_{gD})v_{g1}(I_{g1}). \tag{A12}$$

Equation (A12) defines I_g as an implicit function of t_g and s_g. This implicit function is the counterpart of equation (11), and gives us a chance to work with a more general functional form than (11). Below, we list the properties of this function that are important for our results (these properties all hold for equation (11), with cost $c(s_g,t_g)$). 1. I_g is continuous and differentiable with respect to t_g and s_g. 2. If $t_g = t_l = 1$ and $s_g > s_l$, then $I_g < I_l$. 3. The choice of t_g to maximize I_g is a well-defined problem. 4. For the optimal treatment t_g, $\partial t_g / \partial s_g > 0$.

First, suppose $p_g = p_l$ but $s_g > s_l$. Under partial recovery, optimization sets $\partial I_g / \partial t_g = 0$. Apply the Envelop Theorem to equation (A12), and we have

$$\frac{\partial I_g}{\partial s_g} v_g^{'}(.) = -v_{g1}(.)\frac{\partial p_{gD}}{\partial s_g} + (1 - p_{gD})v_{g1}^{'}(.)\frac{\partial I_{g1}}{\partial s_g}. \tag{A13}$$

Equation (A13) says that $\partial I_g / \partial s_g < 0$, because $\partial p_{gD} / \partial s_g > 0$ and $\partial I_{g1} / \partial s_g < 0$. This result, together with the property that $\partial t_g / \partial s_g > 0$, implies that equation (12) holds in this case. We can follow the same steps as in the previous sub-section, to show that $\mu_g > \mu_l$.

Under full recovery, we have $t_g = t_l = 1$, and so $I_g < I_l$, because $s_g > s_l$. We can follow the same steps as in the previous sub-section, to show that $\mu_g > \mu_l$.

Finally, suppose $p_g > p_l$ but $s_g = s_l$. We can follow the same steps as in the previous sub-section, to show that $E_g/E_l = \mu_g/\mu_l = p_g/p_l = \beta_g/\beta_l$.

7. Proposition 6

We assume that the treatment technology is (11) with private cost $c(t_g, s_g)$. Because $c(t_g, s_g)$ and $C(t_g, s_g)$ are increasing and convex with respect to t_g, the average worker's optimal choice of treatment is a well-defined problem.

Under partial recovery, the Envelope Theorem implies that

$$\frac{\partial I_g}{\partial s_g} = -(1 - t_g) - \frac{\partial c(.)}{\partial s_g}$$

Under full recovery, we have

$$\frac{\partial I_g}{\partial s_g} = -\frac{\partial c(.)}{\partial s_g}$$

In both cases, $\partial I_g/\partial s_g > 0$ under Assumption (15) (i.e. $\partial c(.)/\partial s_g < 0$ and is large in magnitude).

On the other hand, the expenditure on g is $E_g = p_gC(.)$, and so

$$\frac{\partial E_g}{\partial s_g} = p_g\left(\frac{\partial C(.)}{\partial s_g} + \frac{\partial C(.)}{\partial t_g}\frac{\partial t_g}{\partial s_g}\right)$$

We have $\partial E_g/\partial s_g < 0$ under Assumption (15) (i.e. $\partial C(.)/\partial s_g < 0$ and is large in magnitude).

Now consider the diseases $l \neq g$ with $p_g = p_l$ and $\beta_g > \beta_l$. Equation (9) implies that $I_g < I_l$. We then have $s_g < s_l$, because $\partial I_g/\partial s_g > 0$. Thus $E_g > E_l$ and $\mu_g > \mu_l$, because $\partial E_g/\partial s_g < 0$. This completes the proof.

References:

Hersch, Joni, 1998. “Compensating Differentials for Gender-Specific Job Injury Risks”, American Economic Review June 1998, 88(3), pp. 598-607.

Martinello, F. and R. Meng, 1992. “Workplace Risks and the Value of Hazard Avoidance”, Canadian Journal of Economics, 25(2), 333-345.

McLaren, Christopher F., and Marjorie L. Baldwin. "Workers’ Compensation: Benefits, Coverage, and Costs,(2015 data)." National Academy of Social Insurance: Washington, DC (2016).

Table A1 Total Danish health care expenditure as percentage of GDP

2010	2011	2012	2013	2014	2015
10.00%	9.91%	10.11%	9.94%	10.00%	9.97%

Notes: Our sources are Statistics Denmark, http://medstat.dk/, Forsikring & Pension, and Arbejdsmarkedets erhvervssikring.

Table A2 Danish Healthcare spending by category 2010 (billion DKK)

Hospital Expenses		**113.15**
Non-Hospital Expenses		**56.37**
	Medical products and equipment	24.81
	Doctor Visits	23.48
	Paramedic Care	8.10
Other Expenses		**11.60**
	Other Public Health Care Expenses	9.98
	Expenses by None-Profit Institutions	1.62
Grand Total		**181.15**

Notes: Our sources are Statistics Denmark, http://medstat.dk/, Forsikring & Pension, and Arbejdsmarkedets erhvervssikring.

Table A3 Correlation between Mass Layoff and Decreases in Firm Sales

VARIABLES	(1)	(2)
Large-Sales-Drop		0.163***
		[18.89]
Δlog(sales)	-0.0971***	
	[-12.37]	
Obs. No	19,364	24,028
R2	0.1023	0.0946

Notes: t-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the indicator variable for mass layoff. All specifications include firm fixed effects and year fixed effects.

Table A4 Probit Model of Propensity Scores

	Coeff.	Std. Err.	z-value
Age	0.0148	0.0005	27.51
Female	-0.0636	0.0083	-7.63
Children	0.0245	0.0061	4.03
Married	0.0084	0.0086	0.98
Union status	0.0572	0.0129	4.44
High skilled	-0.0382	0.0107	-3.57
Log(Prodcom sales)	-0.1235	0.0026	-46.64
Industry dummies	Yes		
Year dummies	Yes		
Pseudo R squared	0.22		
Observations	174,850		
Treated	38,123		
Control	136,727		

Notes: The data used are for the anti-depressant sample. The explanatory variables are (unless otherwise indicated) from t-1, the year before the large increases in firm sales.

Table A5 Mean Differences between Treatment & Control Groups in PSM

Variables:	Mean Treated	Mean Controls	% Bias
Age	40.4590	39.6260	10.5
Female	0.2969	0.3120	-3.2
Children	0.3620	0.3969	-5.2
Married	0.5928	0.5839	1.8
Union status	0.9074	0.8843	7.6
High skilled	0.1463	0.1746	-7.5
Log(Prodcom sales) in year t-1	12.3950	12.4320	-2.0

Notes: The standardized bias for a given variable is defined as the difference in means between the treated group and the matched comparison group, scaled by the average variances. The explanatory variables are (unless otherwise indicated) from t-2, two years before the sales shock hits.

Table A6 Estimation of VSI

Dep. Var. = log(annual wage)	
Occp. Injury Rate	5.239**
	(2.443)
female	-0.209***
	(0.0090)
kids	-0.0341***
	(0.0076)
married	0.0383***
	(0.0031)
native	-0.0907***
	(0.0098)
vocational school	0.0923***
	(0.011)
college	0.233***
	(0.013)
age	-0.0056***
	(0.0007)
experience	0.0569***
	(0.0019)
experience2	-0.0011***
	(3.98e-05)
tenure	0.0047***
	(0.0004)
Obs. No.	890,650
R^2	0.429

Notes: standard errors (clustered by occupation) in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A7 Elasticity of Annual Wages w.r.t. Sales

VARIABLES	(1) log(annual wage)
log(sales)	0.0085***
	[6.36]
Exp. 5-20 years	0.174***
	[81.27]
Exp. 20+ years	0.171***
	[84.76]
Union	0.0404***
	[20.41]
Married	0.0114***
	[16.31]
log(employment)	0.0637***
	[17.55]
log(K/L)	-0.0011
	[-1.19]
Skilled-labor share	0.139***
	[9.99]
log(offshoring)	0.0005
	[1.52]
Obs. No.	3,467,642
R2	0.0577
Job-Spell No.	727,879

Notes: t-statistics in brackets, with clustering at firm-year level in all columns. *** p<0.01, ** p<0.05, * p<0.1. All specifications include job-spell fixed effects, plus industry, year and region fixed effects.

Table A8 First Stage Estimation for Predicted Sales

VARIABLES	log(sales)
log(instrument)	0.7261***
	[10.83]
log(employment)	0.4340***
	[12.25]
log(K/L)	0.0267**
	[2.37]
Skilled-labor share	-0.7684***
	[-4.83]
log(offshoring)	0.0287***
	[4.23]
Exp. 5-20 years	-0.0065
	[-1.61]
Exp. 20+ years	-0.0088**
	[-2.05]
Union	0.0022
	[0.58]
Married	-0.0056***
	[-4.27]
Obs. No.	3,468,419
R2	0.4533
Job-Spell No.	727,945
F-stat	117.3

Notes: t-statistics in brackets, with clustering at firm-year level in all columns. *** p<0.01, ** p<0.05, * p<0.1. All specifications include job-spell fixed effects, plus industry, year and region fixed effects.

Table A9 Mean Sickness Rates by Gender

	Men		Women	
	Obs. #	Mean	Obs. #	Mean
Anti-Depressant (Drug)	2259936	0.0304	1076119	0.0471
Anti-Dep./Psychiatrist Visit	2259936	0.0329	1076119	0.0546
Narrow Burnout (Hosp.)	2259936	0.00004	1076119	0.00007
Broad Burnout (Hosp.)	2259936	0.00005	1076119	0.00009
Broad Burnout/Stress (Hosp.)	2259936	0.00015	1076119	0.00030
Broad Burnout/Stress/Depression (Hosp.)	2259936	0.00021	1076119	0.00038
Heart Disease (Drug)	2259936	0.0289	1076119	0.0152
Heart Attack or Stroke (Hosp.)	2259936	0.0020	1076119	0.0007
Liver Disease (Hosp.)	2259936	0.0011	1076119	0.0005