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
JEL No. F1,F6,I1,J2,J3

ABSTRACT

Increased job effort can raise productivity and income but put workers at increased risk of illness and injury. We combine Danish data on individuals' health with Danish matched worker-firm data to understand how rising exports affect individual workers' effort, injury, and illness. We find that when firm exports rise for exogenous reasons: 1. Workers work longer hours and take fewer sick-leave days; 2. Workers have higher rates of injury, both overall and correcting for hours worked; and 3. Women have higher sickness rates. For example, a 10% exogenous increase in exports increases women's rates of injury by 6.4%, and hospitalizations due to heart attacks or strokes by 15%. Finally, we develop a novel framework to calculate the marginal dis-utility of any non-fatal disease, such as heart attacks, and to aggregate across multiple types of sickness conditions and injury to compute the total utility loss. While the ex-ante utility loss for the average worker is small relative to the wage gain from rising exports, the ex-post utility loss is much larger for those who actually get injured or sick.

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

A online appendix is available at http://www.nber.org/data-appendix/w22365

1. Introduction

Increased job effort by workers may raise productivity and income both for those workers and the firms who employ them. But increased effort may come with a potential downside: putting in longer hours or working more intensively may endanger health.[1]

Sorting out the linkages between effort, productivity and health can be difficult. Healthier workers may be capable of working harder or longer hours, or conversely, "type A" individuals may desire to work harder and suffer health consequences, not as a result of work, but as a result of a comprehensively intensive approach to life. Working more intensively may also raise income and many studies show that higher income or wealth leads to better health (e.g. Marmot et al. 1991, Smith 1999, and Sullivan and von Wachter 2009). In contrast, Ruhm(2000)'s finding that the U.S. mortality rate is pro-cyclical suggests a competing channel: rising labor demand may lead to increased effort and so higher health risks. While the intellectual heritage of this effort channel can be traced back to Rosen (1986), its identification has remained elusive. Stevens, Miller, Page and Filipski (2015), for example, argue that Ruhm (2000)'s result for mortality is driven by staffing changes at nursing homes.[2]

In this paper we provide tight identification for the effort channel. Our matched worker-firm data allows us to look at changes in *worker-level* effort, injury and illness within job-spells, and changes in exporting activity provides a source of *exogenous* shocks to labor demand within the firm. We find that this increase in labor demand can be met by inducing workers to expand hours and increase work intensity, a potentially important adjustment mechanism that has been largely overlooked in the literature on globalization and labor markets (e.g. Verhoogen 2008, Autor, Dorn and Hanson 2013, and Hummels, Jørgensen, Munch and Xiang 2014, or HJMX 2014)[3]. Taking this a step

---

[1] In the extreme, people *might* literally work themselves to death; e.g. "Hard Work Really Can Kill, as Longer Hours Increase Risk of Stroke", the Telegraph (http://www.telegraph.co.uk/news/health/news/11811993/Hard-work-really-can-kill-as-longer-hours-increase-risk-of-stroke.html)

[2] See also Lindo (2013), Tekin, McClellan and Minyard (2013), Ruhm (2013) and Coile, Levine and McKnight (2014).

[3] For recent surveys see Goldberg and Pavcnik (2007), Harrison, McLaren and McMillan (2011), and Hummels, Munch and Xiang (2016).

further, and in the spirit of Rosen (1986), we develop a novel framework to compare workers' pain versus gain. We calculate both the ex-ante utility losses, from higher rates of multiple types of non-fatal illness, and the ex-post utility losses, for those who actually get sick, and then compare these losses with the wage gains due to rising exports. Recent studies have examined the implications of health status 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) by focusing on mortality. Our framework may help broaden the scope of the inquiry to also examine non-fatal injuries and diseases.

We draw on Danish administrative data that match the population of Danish workers to the universe of private-sector Danish firms. For each firm, we have detailed information on its characteristics, including trade activity. For each individual we observe socio-economic characteristics and rich details about *every* interaction between *every* individual and the Danish healthcare system. For example, we observe the universe of prescription drug purchases made by every individual in Denmark, plus the date (by week), total cost and the type of drug (by 4-digit classification) of every purchase. We have similar information for doctor visits and hospitalization. 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.[4]

How does exporting affect individual workers' health? We consider a framework where workers bargain with their employer. Each worker chooses the optimal effort level by equalizing the marginal benefit of effort, determined through bargaining, with the marginal cost of effort. When exports rise exogenously, demand for the firm's output rises, and so the marginal benefit of efforts

[4] See, e.g., Currie and Madrian (1999) for a survey.

increases. As a result, workers choose to increase efforts in response. The medical literature provides cross-sectional correlations linking work effort (e.g. self-reported long hours and job strain) to higher rates of body pain and injury; blood pressure; cortisol levels (an indicator for stress); depression; coronary heart disease, strokes, and even death (e.g. Harkness et al., 2004, Virtanen et al. 2012, O'Reilly and Rosato 2013, Kivimaki and Kawachi 2015).[5] If these correlations suggest a causal linkage, then rising exports should also result in higher injury and sickness rates. In particular, we focus on stress and depression, heart attacks and strokes, and injury, following the aforementioned medical research.

We face several significant challenges in taking our hypotheses to the data. One, individuals' health is affected by many idiosyncratic and time-invariant factors, such as early-childhood and pre-natal development.[6] Two, individual workers' effort levels are very hard to observe in the data. Finally, exports are endogenous. A firm may export a lot because it uses superior technology and good management practices, which, in turn, may reduce its employees' injury and sickness rates.

The comprehensive and panel structure of our Danish data allow us to deal with the first two issues. First, we consistently track each worker and each firm over time and so we are able to 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, a salient feature of our sample is that exports and output per worker have strong positive correlation at the firm level, and the richness of our data allows us to describe both the extensive and intensive margins of efforts at the worker level. We observe total hours worked, including over-time, by individual workers, which is an indicator for the extensive margin of efforts. This then allows us to construct hours-based injury rate for individual workers, an indicator for the intensive margin of efforts. Following the literature (e.g. Ichino and Maggi 2000, Hesselius et al., 2009,

[5] These have recently received media coverage, e.g. "Get a life – or face the consequences", January 30, 2014, the Economist (http://www.economist.com/blogs/freeexchange/2014/01/working-hours?fsrc=rss),. The medical literature focuses on risk factors and correlation patterns, and does not separate exogenous changes in work intensity from the tendency of certain individuals to work hard and suffer adverse health consequences.

[6] See, e.g. Case and Paxson 2008. Almond and Currie (2011) provide a recent survey.

Ichino and Moretti 2009) we also use workers' sick-leave days as an indicator for efforts.[7] However, we can go one step further to distinguish between their "major" and "minor" sick-leave days because we observe the universe of healthcare transactions. Major-leave sick days correspond to time off work in which workers also access healthcare, see a doctor or buy prescription drugs, within a week. Minor sick-leave days correspond to time off work in which workers do not access healthcare. We show that major and minor sick days have different responses to exports.

To address the endogeneity of exports, we follow our previous work, HJMX 2014, and construct instruments for exports. A key feature of firms' exporting behavior in our data is that within the same industry, otherwise similar firms sell different 6-digit products to different destination countries.[8] This allows us to construct instruments, transportation costs and importer demand shocks, that are specific to a particular partner country x product x year, but whose impact varies across firms. These instruments generate large exogenous firm-year variation in the exports, providing an excellent source of identification for changing work intensity and health outcomes.

We find that rising exports lead to higher rates of injury, for both men and women, and sickness, mainly for women. A 10% exogenous increase in exports increases women's chance of severe job injury by 6.35%, severe depression by 2.51%, the use of antithrombotic drugs by 7.70%, and hospitalizations due to heart attacks or strokes by 15.01%. These adverse effects on workers' health are likely due to increased efforts. For the extensive margin of efforts, both men and women increase total hours (regular hours plus over-time hours) as exports rise exogenously. For the intensive margin, the elasticity of hours with respect to exports is smaller than the elasticity of injury rates, and workers have higher hours-based injury rate. In addition, exports have non-linear effects on sick-leave days.

[7] Other measures for shirking/efforts include survey questions (e.g. Freeman, Kruse and Blasi, 2008) and outputs of individual workers at individual firms (e.g. Lazear 2000, Mas and Moretti 2009). The medical literature also uses the number of sick-leave days (e.g. Kivimaki et al, 2005), but, again, does not have information about what the workers do during sick-leave spells.

[8] As we show in our previous work, HJMX 2014, of the distribution of the number of firms exporting the same product to the same destination country, the median is 1 and the 90th percentile is 3.

Following modest export shocks both men and women reduce major and minor sick-leave days, consistent with adjustment along the extensive margin of efforts. Following large export shocks, workers experience more major sick-leave days but no change in minor sick-leave days, consistent with the intensive margin. These results are novel to the literature.

Our findings capture the pain from globalization, and we quantify its magnitude relative to the gains from globalization documented by previous research. We take advantage of the unique injury compensation scheme in Denmark, in which workers receive a one-time lump-sum payment for their injury. Assuming that this compensates the workers for their ex-post utility losses due to injury, we are able to pin down the values of the key parameters of our model. Our model then allows us to calculate the ex-ante utility loss of the average worker, due to higher rates of injury and multiple types of non-fatal illness. Relative to the wage gains from rising exports, the ex-ante utility loss amounts to 4.91% for the average man and 17.26% for the average woman. We are also able to calculate the marginal dis-utility of any non-fatal disease, such as heart attacks, and this represents the ex-post utility loss of those workers who actually get sick. The ex-post losses are much larger than the ex-ante losses, e.g. exceeding 1 million Danish Kroner for a woman who gets hospitalized due to a heart attack or stroke (1 DKK is about 0.18 USD in our sample period). The comparison between ex-ante and ex-post losses suggests that the pain from rising exports, or rising labor demand in general, is not evenly distributed across individuals.

In the literature, the utility losses of injury and mortality are well-established (e.g. Viscusi and Aldy 2002), but there is no comparable framework for non-fatal diseases. Finkelstein, Luttmer and Notowidigdo (2013) calculate utility losses for seven non-fatal diseases using a sample of older people and survey data on subjective happiness. Outside of economics, the DALY (Disability-Adjusted Life Years) approach (e.g. Murray and Acharya 1997) converts a life year with diseases into disease-free life years using disease-specific discount factors. These discount factors, however, are constructed from survey data (e.g. collected at World Health Organization meetings) that reflect the "social preferences" of public-health and other government officials. Relative to these studies, we can calculate both ex-ante and ex-post utility losses of any non-fatal disease, and our sample is more representative of the population. Our calculations are based on injury compensation and healthcare expenditures observed in our data, and so better reflect people's actual choices.

Our work also speaks to the studies that examine the effects of mass layoffs and plant closures on mortality and hospitalization using panel data (e.g. Sullivan and von Wachter 2009, Browning and Heinesen 2012),[9] and those that examine the non-pecuniary effects of import competition (e.g. Autor, Dorn, Hanson and Song 2014, McManus and Schaur 2015, Pierce and Schott 2016).[10] Relative to these studies we examine the effects of exports, explore a unique set of exogenous shocks that change the competitive environment of firms, and study the micro channels through which these shocks affect workers' injury and sickness.

In what follows, section 2 describes our data. Section 3 provides a theoretical framework to motivate our empirical specifications, and describes how we construct our instrument variables. Section 4 presents our results for stress and depression, heart attacks and strokes, and related illness. Section 5 shows our results for injury. Section 6 shows our results for efforts. Section 7 develops our framework to calculate utility losses, and Section 8 presents the robustness exercises. Section 9 concludes.

2. Data

In this section we discuss the main features of our data and our variables for efforts, injury and

[9] See also Browning, Danø and Heinesen (2006), Eliason and Storie (2007, 2009), and Black, Devereaux and Salvanes (2012). Outside of economics the Framingham heart sample (e.g. Hubert et al. 1983) and the Whitehall sample (e.g. Bosma et al. 1997, Marmot et al. 1997) are two widely-used panel data sets. The former is slightly obese relative to the population, and the latter, civil servants in London.

[10] See also Dix-Carneiro, Soares and Ulyssea (2015), Colantone, Crinò and Ogliari (2015) and Autor, Dorn and Hanson (2015).

illness. We report more details of data construction in the Appendix.

We start with Danish administrative data that matches workers to firms and the import and export transactions of these firms. The data are annual, cover the period 1995-2006, and match the population of Danish workers to the universe of private-sector Danish firms. Each firm's trade transactions are broken down by product, and origin and destination countries. The primary data sources are the Firm Statistics Register, the Integrated Database for Labor Market Research ("IDA"), the link between firms and workers ("FIDA"), and the Danish Foreign Trade Statistics Register. [11] Our identification strategy, which we discuss in detail in sub-section 3.3, requires that we look at exporting firms. We also focus on the sectors where firms export a large share of their output, and job-related injury is not uncommon, in order to give our hypotheses a decent chance with data. These considerations take us to our main sample of large manufacturing firms spanning 1995-2006 with nearly 2 million worker-firm-year observations.[12] Table 1 shows the summary statistics of log hourly wage, experience, marital status and union status. These values are similar for our main sample as compared with the samples of the Danish labor force, or the Danish labor force in manufacturing (see Table A2).

Table 1 also shows that the firms in our sample are highly export oriented, with an average export-to-sales ratio of 0.66. This implies that exports and output are likely to move together for a given firm. Further, exports and output move more than employment. We calculate the absolute values of the deviations from within-job-spell means for log export, log output, and log employment. On average, export deviates from its job-spell mean by 0.275 log points, output by 0.143 log points, and employment by 0.106 log points. As a result, changes in output per worker, a firm-level proxy for

[11] As we describe in HJMX 2014, Denmark is a good candidate for studying the effect of labor demand shocks on wages because it has one of the most flexible labor markets in the world. HJMX 2014 also has more detailed discussions of the worker-firm-trade data.

[12] In Table A1 we list the export-to-sales ratio, injury rate and number of observations (by worker-firm) by sector for the exporting firms in the full sample for 2005. Agriculture-and-Fishing also has a high export-to-sales ratio and a high injury rate, but it has few worker-year observations relative to Manufacturing.

efforts, are positively correlated with changes in exports. In Table 2 we show this correlation by regressing log output per worker on exports, conditional on firm fixed effects and weighted by firm size.[13] In columns 1 and 2 we use log export, and in columns 3 and 4 we use the quartile dummies of log exports. The coefficients of exports are always positive and highly significant, suggesting that the co-movement of output per worker and exports is a main feature of our data. This also means that our data is fertile ground for examining our hypothesis, namely, how *worker-level* effort, injury and illness respond to *exogenous* changes in exports.

To study individual workers' sickness and injury rates, we bring in additional administrative datasets that contain comprehensive information about individuals' health care utilization during 1995-2009. We observe the *universe* of *transactions* for every person within the Danish healthcare system, including doctors visits, prescription drug purchases, and hospitalization. Most of these data are collected at weekly frequencies, and we aggregate them to annual frequencies to match our worker-firm-trade data. In addition, 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.[14] Table 1 shows the summary statistics of our variables for worker-level sickness, injury and efforts.

For stress and depression we consider whether an individual has positive expenses on any anti-depressant prescription drug, and whether an individual purchases anti-depressants or visits a

[13] We use job-spell means because we rely on changes within job spells for identification. Firm size is employment in the first year the firm is observed in our data.

[14] 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.

psychiatrist. Table 1 shows that women have a higher depression rate, 3.95%, than men, 2.43%, consistent with medical research.[15] Part of the reason could be that men and women have different responses to stressful events: women tend to feel sad and guilty while men feel restless and angry.[16] This difference between men and women motivates our empirical specification, where we estimate the differential impacts of exports on men vs. women.

Medical research suggests that depression is highly correlated with insomnia, and also correlated with substance abuse and self injury. Therefore, we also consider these sickness conditions in our analyses. Table 1 also shows that women have lower probability to be on drugs for heart attacks, strokes, and other heart diseases, again consistent with medical research (e.g. Roger et al., 2012).

When a worker is injured on the job in Denmark, they 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 from the employers' mandatory insurance. 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 amount of injury compensation, on the other hand, will play a crucial role later in section 7, when we calculate utility losses from injury and illness. Table 1 shows that the mean injury rate is about 4 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.[17] After receiving injury compensation, most workers stay employed with the same firm in our data. This is different from the U.S., where workers typically exit

[15] e.g. http://www.cdc.gov/mentalhealth/data_stats/depression.htm. The U.S. National Institute of Mental Health (NIMH) estimates that 17% of U.S. adults experience depression sometime in their lives. This incidence is higher than ours because: 1. our sample spans 12 years, not the entire adult life; and 2. the NIMH data cover all forms of depression, including those that do not require anti-depressants or psychiatric visits.

[16] e.g. http://www.takingcharge.csh.umn.edu/conditions/anxiety-depression.

[17] A medical literature studies the risk factors of job injury using data for individual firms or industries (e.g. Bigos et al. 1991), and a small economic literature studies the "Monday effect", that the number of injury claims jumps on Mondays in U.S. data (e.g. Campolieti and Hyatt 2006). Finally, the U.S. data on injury rates by industry and occupation are widely used to estimate the value of a statistical injury (e.g. Viscusi and Aldy 2003).

the labor force upon receiving Social Security Disability Insurance (SSDI).

In our data, worker sick leaves are self-reported, which suggests the possibility of shirking, or workers calling in sick when they are not. We split the sick-leave variable into two components by cross-checking the exact dates of every sick-leave spell against the precise dates of every individual's prescription drug purchases and doctor visits. When we do not observe any drug purchase or doctor visit one week before, during, or one week after a sick-leave spell, we are confident that this particular worker never visited a doctor or purchased any prescription drug during his sick leave. (Recall that our prescription-drug and doctor-visit data cover the *universe* of these transactions in Denmark.) We count the number of such days as *minor* sick-leave days. We count all the other sick-leave spells as *major* sick-leave days.[18] Table 1 shows that on average, a worker has 6.11 major sick-leave days per year and 0.21 minor sick-leave days per year.

Finally, we observe over time hours and total hours (over time plus regular hours) for a sub-sample of our workers. Table 1 shows that the mean number of total hours is 1532.6 per year, and that of over-time hours is 50.6 per year. [19]

To summarize, our dataset covers the population of Danish workers and firms, and the universe of healthcare transactions. It allows us to measure worker-level injury, sickness and efforts, and to consistently track their changes over time. It also contains a large number of variables with rich information. These features help us identify the causal effects of exports on health and pinpoint the specific channels, as we explain below.

[18] Henrekson and Persson (2004) show that the number of sick-leave days responds to changes in sick-leave benefits in Sweden. There has been no major policy change regarding sick-leave benefits in Denmark in our sample period.

[19] The norm in Denmark is 37 hours per week. An average Danish worker is likely to care a lot about how his/her hours differ from his/her peer's, and to care much less how these hours differ from the norms in other countries, such as the U.S. In the 2015 Danish election the recently formed "The Alternative party" won 5% of the votes with a central proposal being the introduction of a 30 hours work week.

3. Theoretical Framework, Specification, and Identification

3.1 Theory

We first formalize the conceptual framework laid out in our Introduction and derive our estimation equations. To ease exposition we will drop subscripts during the initial derivation, but add them back when we transit to the empirical specifications.

Consider a single Danish firm selling in both domestic and foreign markets, and its total revenue is ψY. The parameter ψ is a demand shifter, and could potentially capture aggregate expenditure, elasticity of demand, trade cost to the destination markets, and so on. Y depends on the quantity of the firm's output, Q, and the elasticity of demand.[20] The firm produces output Q using capital, K, materials, M, and labor, L. Q also depends on workers' efforts, e. Assume that the firm's production function is continuously differentiable and concave (e.g. Cobb-Douglas, CES), and that an individual worker' effort cost is *ac(e)*, where *a* is a parameter, and the function *c*(.) is continuously differentiable and convex.

The firm 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, and Helpman, Itskhoki and Redding 2010, or HIR 2010).[21] The solution of this bargaining problem has the firm collecting the fraction 1 – β of the total surplus, while each individual worker collects the fraction β of total surplus

---

[20] E.g. consider the following monopolistic-competition framework. Preferences are CES with substitution elasticity σ > 1. There is a single foreign market, and the ice-berg trade cost between Denmark and the foreign market is τ > 1. Let "*" denote the variables for the foreign market. Then it is easy to show that the firm's total revenue, from both the domestic and foreign markets, equals $(\frac{E}{P^{1-\sigma}}+\frac{E^{*}\tau^{1-\sigma}}{P^{*1-\sigma}})^{\frac{1}{\sigma}}Q^{\frac{\sigma-1}{\sigma}}$, where E is consumer expenditure and P the CES price index (e.g. Helpman, Itskhoki and Redding 2010). In this example, $\psi = (\frac{E}{P^{1-\sigma}}+\frac{E^{*}\tau^{1-\sigma}}{P^{*1-\sigma}})^{\frac{1}{\sigma}}$ and Y = $Q^{\frac{\sigma-1}{\sigma}}$.

[21] The gist of our results also holds if the firm faces an upward sloping labor supply curve (e.g. Manning 2011), and so our intuition is more general than our bargaining framework. To see this, the intersection of the firm's labor demand and supply curves determine wage and quantity of labor. An exogenous increase in the firm's exports increases its demand for labor. It follows that the quantity of labor supplied to the firm also rises. Labor supplied to the firm can increase through an increase in work intensity, holding the number of workers constant; i.e. increases in efforts.

per worker. The parameter β is a constant.[22] We assume that the workers' outside options are 0. The firm's outside option equals the fraction $1 - \theta_f$ of total revenue, ψY.

The total surplus of the bargaining game is then $\psi Y - p_M M - rK - (1 - \theta_f)\psi Y = \theta_f \psi Y - p_M M - rK$, where p_M is the price of materials, including domestic materials and imported/offshored inputs, and r is the price of capital. We assume that the firm takes p_M and r as given. The firm's problem is to choose L, M and K to maximize its take $(1 - \beta)[\theta_f \psi Y - p_M M - rK] + (1 - \theta_f)\psi Y - b(L)$, where b(L) is search/hiring cost. From this problem the firm optimally chooses the quantities of inputs, including employment, L. For the rest of the paper we push the firm's problem into the background and focus on the workers' problem.[23]

The workers take the firm's optimal choices of L, M and K as given and[24]

$$\max_e \{\beta \frac{\theta_f \psi Y - rK - p_M M}{L} - ac(e)\}. \tag{1}$$

Let y = Y/L be revenue per worker. Then the first-order condition for (1) is

$$\beta\theta_f \psi \frac{\partial y}{\partial e} = ac'(e). \tag{2}$$

Equation (2) determines the optimal effort level, e, and implies that

$$\frac{\partial e}{\partial \psi} = \frac{\beta\theta_f (\partial y / \partial e)}{ac''(e) - \beta\theta_f \psi \frac{\partial^2 y}{\partial e^2}}. \tag{3}$$

Because $\partial y / \partial e > 0$ (effort makes a positive contribution to output), $c''(e) > 0$ (effort cost is convex), and $\frac{\partial^2 y}{\partial e^2} < 0$ (diminishing returns with respect to effort level), equation (3) says that $\frac{\partial e}{\partial \psi} > 0$; i.e. as

[22] β, in turn, depends on such parameters as the elasticity of demand (e.g. HIR 2010). For our purpose, how β depends on these other parameters does not matter, as long as β is a constant.
[23] The firm takes as given individual workers' optimal choices of effort level, which we derive below.
[24] We have dropped the worker subscript, and assume that each worker takes all the other workers' optimally chosen efforts as given in his/her decision making.

export increases for exogenous reasons, effort level rises. The intuition is simply that the increase in export raises returns to effort. Therefore,

Proposition 1. Effort level rises as export rises for exogenous reasons.

Proposition 1 says that rising exports unambiguously increases efforts. In comparison, an increase in offshoring is likely to have ambiguous effects on efforts, because it may either increase or decrease the firm's labor demand, depending on the substitutability between labor and imported inputs. In addition, an increase in offshoring may directly affect individual workers' injury and sickness rates by changing the task composition within the firm.[25] Therefore, our focus in this paper is exports, and we control for offshoring in our estimation.

We now make the transition from (2) to an estimation equation. We first make the following specifications for effort cost and revenue per worker:

$$ac(e) = ae^{\eta}, \;\; \eta > 1 . \tag{4}$$

$$y = e^{\gamma} F(K, M, L), \;\; 0 < \gamma < 1 . \tag{5}$$

Equation (4) specifies a power function for effort cost. The power, η, exceeds 1 to ensure that effort cost is a convex function. One special case of specification (4) is the quadratic functional form $c(e) = \frac{1}{2}e^2$. On the other hand, equation (5) says that effort level enters revenue per worker in a multiplicative way and as a power function. The parameter value for the power γ is to ensure that revenue per worker is increasing and concave in effort level.[26]

---

[25] HJMX 2014 show that exogenous increases in offshoring lead to higher (lower) wages for skilled (unskilled) workers, and lower wages for the workers of more hazardous occupations conditional on skill. These results are consistent with firms offshoring hazardous tasks.

[26] A special case of (5) is for the production function to be Cobb-Douglas: $Q = BK^{\delta_K} M^{\delta_M} (EL)^{\delta_L}$, $\delta_K + \delta_M + \delta_L = 1$, where B is a constant. In this expression $E = \prod_i e_i$, where *i* indexes individual workers. Preferences are CES so that revenue is a power function of output (see note 10, where we show that Y = $Q^{\frac{\sigma-1}{\sigma}}$, where $\sigma > 1$ is the substitution elasticity).

Plugging (4) and (5) into equation (2) yields $e^{\eta-\gamma} = \frac{\beta\gamma\theta_f\psi}{a\eta} F(K,M,L)$, or

$$\ln e = \frac{1}{\eta-\gamma}(\ln\beta + \ln\theta_f + \ln\psi + \ln\frac{\gamma}{\eta} - \ln a) + \frac{1}{\eta-\gamma}\ln F(K,M,L)\,. \tag{6}$$

We now specify how the variables in (6) change across workers, i, firms, j, and years, t. We assume that β and γ are constant, since they reflect inherent input-output relationship in firm-level production and elasticity of demand. The firm's demand shifter, ψ, and input uses, K, L, and M, all vary by firm by year, while the firm's outside option, θ_f, varies across firms but not over time (since we do not have good measures for θ_f in the data). Intuitively, the input uses, K, L, and M, show up on the right-hand side of (6) because they affect the marginal benefit of efforts. For the workers' variables, effort level, e, varies by worker by year. We assume that the shape of the effort cost function, η, captures time-invariant worker characteristics (e.g. gender), while the shifter of the effort cost function, *a*, captures time-varying worker characteristics (e.g. union status).[27] Adding worker, firm and year subscripts to equation (6) we get

$$\ln e_{it} = \frac{1}{\eta_i-\gamma}(\ln\beta + \ln\theta_{f,j} + \ln\psi_{jt} - \ln a_{it} + \ln\frac{\gamma}{\eta_i}) + \frac{1}{\eta_i-\gamma}\ln F(K_{jt},M_{jt},L_{jt})\,. \tag{7}$$

Equation (7) implies that $\frac{\partial \ln e_{it}}{\partial \ln\psi_{jt}} = \frac{1}{\eta_i-\gamma} > 0$. This simply echoes Proposition 1. In addition, it suggests the following interaction effect. A given exogenous change in export has larger effects on the effort levels of the workers whose effort costs, η_i, are smaller. We will estimate both the direct effect of exports and how it interacts with time-invariant worker characteristics.

In our data, we use exogenous changes in export, X_{jt}, to measure changes in the demand shifter, ψ_{jt}. Let C_i be time-invariant worker characteristics that may affect the shape of the cost function, η_i. Equation (7) then implies the following regression

[27] Implicitly we have also assumed that the relationship between η_i and a_{it} and individual effort costs cannot be verified with third parties, so that they do not affect the bargaining game between workers and the firm.

$$\ln e_{it} = \alpha_{ij} + \beta_1 \ln \mathrm{X}_{jt} + \beta_2 C_i \ln \mathrm{X}_{jt} + \mathbf{x}_{it} b_1 + \mathbf{z}_{jt} b_2 + \mathbf{x}_{it} \mathbf{z}_{jt} b_3 + \alpha_R + \alpha_{IND,t} + \varepsilon_{ijt} \,. \tag{8}$$

In equation (8), $\beta_1 \ln \mathrm{X}_{jt} + \beta_2 C_i \ln \mathrm{X}_{jt}$ represent the way we estimate the term $\frac{1}{\eta_i - \gamma} \ln \psi_{jt}$ in equation (7). β_1 captures the direct effect of exogenous changes in export on effort, and by Proposition 1, $\beta_1 > 0$. β_2 captures how the effects of exports interact with time-invariant worker characteristics, and $\beta_2 > 0$ if an increase in C_i means a decrease in effort cost by equation (7).

The motivation for the other variables in equation (8) is as follows. α_{ij} is job-spell fixed effects and it controls for the terms $\frac{1}{\eta_i - \gamma} \ln \beta$ and $\frac{1}{\eta_i - \gamma} \ln \theta_{f,j}$ in (7), and also absorbs the portion of $\frac{1}{\eta_i - \gamma} \ln F(K_{jt}, M_{jt}, L_{jt})$ that is worker-firm specific. α_R and $\alpha_{IND,t}$ represent region and industry-by-year fixed effects. The vector of firm characteristics, $\mathbf{z}_{jt}$, and worker characteristics, $\mathbf{x}_{it}$, control for the terms $\frac{1}{\eta_i - \gamma} \ln a_{it}$ and $\frac{1}{\eta_i - \gamma} \ln F(K_{jt}, M_{jt}, L_{jt})$.

3.2 Empirical Specifications

Motivated by (8), we first estimate the effects of exports on IOS_{ijt}, the injury or sickness rate of worker *i* employed by firm *j* in year *t*. We then estimate how export affects WK_{ijt}, measures for how much or how hard worker *i* works for firm *j* in year t. The estimation for IOS_{ijt} shows how export affects individual workers' health, while that for WK_{ijt} helps identify the micro channels of these effects.

To be specific, for IOS_{ijt} we estimate

$$IOS_{ijt} = \beta_1 \ln \mathrm{X}_{jt} + \beta_2 F_i \ln \mathrm{X}_{jt} + \mathbf{x}_{it} b_1 + \mathbf{z}_{jt} b_2 + b_3 F_j \ln M_{jt} + \alpha_{ij} + \alpha_R + \alpha_{IND,t} + \varepsilon_{ijt} \,. \tag{9}$$

Equation (9) comes from (8). F_j is the dummy for female. The vector of time-varying worker characteristics, $\mathbf{x}_{it}$, includes union status, marital status and experience. The vector of time-varying firm controls, $\mathbf{z}_{jt}$, includes value of offshoring, M_{jt}, employment, capital/labor ratio, and the share of skilled workers in employment. Relative to (8), we have included the interaction between the female dummy and offshoring in (9), and not the other interaction terms between the vectors $\mathbf{x}_{it}$ and $\mathbf{z}_{jt}$. The effects of exports on men's health are β_1, and those for women $\beta_1 + \beta_2$. If higher exports by firms lead to more injury and sickness, by (8) we have $\beta_1 > 0$, $\beta_1 + \beta_2 > 0$, or both.

To identify the micro channels through which exports affect injury and sickness, we estimate

$$WK_{ijt} = \beta_1 \ln \mathrm{X}_{jt} + \beta_2 F_i \ln \mathrm{X}_{jt} + \mathbf{x}_{it} b_1 + \mathbf{z}_{jt} b_2 + b_3 F_j \ln M_{jt} + \alpha_{ij} + \alpha_R + \alpha_{IND,t} + \varepsilon_{ijt} \,. \tag{10}$$

The right-hand side variables of equation (10) are the same as in (9), and we think about the dependent variable of (10), WK_{ijt}, as a proxy for the unobservable effort level, e_{it}, of (8). For the extensive margin of efforts we use: (1) the number of *minor* sick-leave days; and (2) the number of total work hours. We expect the coefficients of exports for total hours to be positive, and those for minor sick-leave days to be negative, for the following reason. When a worker claims sick leave but never visits a doctor or purchases any prescription drug one week before and one week after his spell of absence, there are two possibilities. One, the worker could be shirking. Or, his sickness could be so mild that he could have chosen to work. In either case, we interpret a reduction in the number of *minor* sick-leave days as evidence for increased effort level. The intensive margin of efforts, on the other hand, is harder to measure, and we use injury rate adjusted by total hours. The idea is that, while we do not observe changes in work intensity within a given number of hours, we do observe one of their likely consequences: changes in hours-based injury rate. According to our hypothesis, then, the coefficient of exports should be positive for hours-based injury rate.

We also consider the number of major sick-leave days in (10). For this variable the interpretation of the estimation results is more subtle, because it could measure both sickness and efforts. Suppose worker i has more major sick-leave days in year t. This likely shows that worker i has more sickness in t, because we know that he/she either visited doctors or made new purchases of prescription drugs during the sick-leave spells. Whether worker i has decreased efforts, however, is unclear.[28] On the other hand, suppose worker i reduces his/her major sick-leave days. This clearly implies more time at work and so more efforts on the extensive margin. But whether worker i has less sickness is unclear, since he/she may choose to work while sick, which is not uncommon. A recent survey by the National Foundation for Infectious Diseases shows that in the U.S., 66% of workers still go to the office while showing flu symptoms.[29] We will re-visit these points when we present our results in section 6. We will also use our results for the other dependent variables to help interpret the results for major sick-leave days.

In both equations (9) and (10) we control for job-spell fixed effects α_{ij}. This allows us to sweep out individual-level time-invariant factors that could affect health (e.g. Case and Paxson 2008).[30] Job-spell fixed effects pose a computational challenge for non-linear specifications of (9), 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 nearly 400,000 of them in our sample. As a result, we use the linear specification for (9), and think about our results as a linear approximation around the sample means of the injury-or-sickness variables. When we discuss our results or draw out inferences we always stick to small changes, such as a 10% increase in exports.

A central concern for our estimating strategy is that exports, X_{jt}, could be correlated with the error term, ε_{ijt}. For example, variation in firm-year productivity is correlated with X_{jt} (e.g. Melitz 2003). Productivity may also co-vary with workers' health outcomes because productive firms use more modern, and safer, technology and/or good management practices that reduce their employees' injury and sickness rates. This implies a negative correlation between X_{jt} and ε_{ijt}. Below we explain

---

[28] More major sick-leave days likely imply more absence from work, and absenteeism has been used in the literature as a measure for shirking/efforts (see sub-section 2.5). However, worker i may be too sick to show up to work, and the sickness could be a consequence of more efforts on the intensive margin.

[29] This survey result was recently mentioned in the media (e.g. http://www.newrepublic.com/article/119969/new-york-city-ebola-case-why-did-dr-craig-spencer-go-bowling).

[30] We also control for industry x year fixed effects, which sweep out the effects of import competition at the industry level.

how we deal with the endogeneity of export.

3.3 Instrumental Variables

We follow HJMX 2014 and use external shocks to Denmark's trading environment to construct instruments for X_{jt}. Our first instrument is world import demand, WID_{ckt} . It is country *c*'s total purchases of product *k* from the world market, less purchases from Denmark, at time *t*. A rise in *WID* could result from shocks to demand (either consumer tastes or industrial uses of particular products) or reflect a loss of comparative advantage by *c* in product *k*. Our second instrument is transport costs. Here we first estimate cost functions using US imports data following Hummels (2007) and then use the estimated coefficients plus pre-sample information on the destination, bulk, and modal use for Danish imports to construct *c*-*k*-*t* varying cost measures, tc_{ckt}. The key source of variation is an interaction between distance, modal use, and oil prices. Both instruments have country-product-time variation. To get a single value for each firm-year we aggregate as follows. Let I_{ckt} represent instrument $I \in (tc, WID)$ for importing country *c*, selling HS 6 product *k*, at time *t*, and let s_{jck} represent the share of *c*-*k* in total exports for firm *j* in the pre-sample year (1994).[31] Then to construct a time varying instrument for firm *j* we have $I_{jt} = \sum_{c,k} s_{jck} I_{ckt}$.

The idea behind our instruments is the following. For some reason firm *j* exports a particular product *k* to country *c*. Firm *j* may have a long standing business relationship with a firm in *c*, or the products that *c* makes might be a particularly good fit for the firms in *j*. This relationship is set in the pre-sample and is fairly consistent over time (see HJMX 2014). Over time there are shocks to the desirability of exporting product *k* to country *c*. Transportation costs become more favourable or country *c* experiences changes in its production costs or consumer demand that are exogenous to firm *j*,

[31] Some firms enter or begin exporting within sample. For these firms we use export patterns in their first years of exports to construct pre-sample weights and employ data from year 2 and onwards for the regression analyses.

and these are reflected in changing imports from the world as a whole by country *c*. Because firm *j* exports product *k* to country *c* more than other firms it disproportionately benefits from these changes. HJMX 2014 show that firms have very few export-product-by-destination-country in common and that in most cases, firm *j* is the *only* firm that exports product *k* to country *c*.

We now discuss threats to identification. We examine changes within job spells, and leave out the effects of exports on health when workers separate from their employers. To see how separation affects our estimates, suppose exports rise exogenously for firm j. This is a positive economic shock, and so workers likely receive higher wages and firm j is unlikely to lay them off. Workers may quit randomly, and this clearly has no effect on our estimates. Workers may also quit because of higher injury and sickness rates, due to rising exports. This, however, is unlikely, because we show, in section 7, that the ex-ante utility losses from higher injury and sickness rates are less than one quarter of the wage gains.

Another issue is, our WID and transport-cost instruments may be correlated with imports. Imports by manufacturing firms are offshoring, and it may have different effects on injury and sickness rates than exports.[32] We explicitly control and instrument for offshoring, as well as its interaction with the female dummy, in our estimation. Our instruments for offshoring are similar to those for exports. Rather than *WID*, we use World export supply, or WES_{ckt}, country *c*'s total supply of product *k* to the world market, minus its supply to Denmark, in period *t*. *WES* captures changes in comparative advantage for the exporting country, arising from changes in production price, product quality, or variety. For transport costs we focus on those for Danish imports, and we use the firm's pre-sample shares of imports from *c*-*k*.

[32] We focus on exports in this paper because offshoring likely has multiple effects on injury and sickness rates, which are difficult to tease out. These effects could work through (see, e.g., Hummels, Munch and Xiang 2016): 1. changes in labor demand, which depend on workers' education; 2. changes in the task composition within firms (e.g. firms may offshore hazardous tasks); and 3. the possibility of layoffs and displacement.

Finally, equations (9) and (10) estimate the contemporaneous effects of exports, within the same calendar year. Could the effects of exports on injury and sickness be persistent over time? And do our coefficient estimates, β_1 and β_2, capture the effects of year-to-year fluctuations in exports, or longer-term effects? We address these questions, plus other potential issues and concerns, in section 8.

To re-cap, we instrument for exporting (offshoring) using the weighted averages of world import demand (world export supply), and transport costs. The weights are pre-sample export (import) shares, and these differ significantly across firms.

4. Results for Sickness Rates

We present our main results in sections 4-6, and relegate all robustness exercises to section 8. We include job-spell fixed effects in the estimation. That is, suppose worker i is employed by firm j. We ask: if j changes how much it exports for exogenous reasons, does worker i become more likely to to get sick or injured? Since our main explanatory variable, export, varies by firm-year, we cluster standard errors by firm-year.

4.1 Severe Depression

Table 3 reports how export affects individual workers' likelihood of severe depression. Our dependent variable is a dummy that equals 1 if worker i, employed by firm j, has positive expenses for prescription anti-depressant drugs in year t. We report these results first for two reasons. First, depression can develop quickly once triggered by stressful life events,[33] and job pressure is the No. 2 cause of such stress after financial worries, according to a recent Wall-Street-Journal report.[34] This fits well with regression (9), which investigates the contemporaneous effects (i.e. within the same year) of

[33] According to the National Institute of Mental Health in the U.S., "any stressful situation may trigger a depression episode" (http://www.nimh.nih.gov/health/publications/depression/index.shtml#pub5).
[34] "To Cut Office Stress, Try Butterflies and Medication?", by Sue Shellenbarger, The Wall Street Journal, October 9, 2012.

exports.

In Column 1 of Table 3, labeled “FE” (for job-spell fixed effects), we report the OLS estimate for regression (9). The results show that for women, the incidence of severe depression rises as export increases, with a precisely estimated coefficient of 0.6 per thousand (0.0012 – 0.0006). However, as we discussed in sub-section 3.2, this estimate may be biased downward due to the endogeneity of exports. We then construct instruments for export (and offshoring) as described in sub-section 3.3. Following Wooldridge (2002), we instrument the interactions of export and offshoring with the female dummy using the interactions of the export-instruments and offshoring-instruments with the female dummy, and include the full set of instruments in the first stage of each of the four endogenous variables (exports, offshoring, and their interactions). Table A4 in the Appendix reports the first stage results. They are similar to HJMX 2014.

We report the IV estimates in column 2 of Table 3, labeled “FE-IV”. The coefficient estimate for women is now about 1 per *hundred* (0.0148 – 0.0049), precisely estimated, and much larger than the OLS estimate. The difference between IV and OLS estimates is intuitive, because productive firms likely export a lot and use good technology or management practices that make the workplace less stressful. To see the economic significance of our IV estimate, suppose a firm’s exports rise exogenously by 10%. Then the likelihood that the female employees of this firm take prescription anti-depressants rises by (0.0148 – 0.0049) x 10% = 0.0010, or 1 per thousand. This represents a large effect since in our sample, 3.95% of women use anti-depressants. Column 2 also shows that getting married reduces the likelihood of using anti-depressants by 0.0049 (highly significant). Comparing the effects of exports with the sample mean and the effects of marriage, we see that a 10% exogenous rise in exports, not uncommon in our sample, increases the fraction of severely depressed women by about 2.5% (0.0010/3.95%), and its effect on severe depression is roughly one fifth the size of getting married (0.0010/0.0049).

We now turn to the results for men. Exports reduce men's incidence of severe depression, under both OLS and IV. However, these results are not robust under alternative specifications, as we show in section 8 and Table 11. Still, the coefficients for men are negative, and the reason could be that depression is a mental issue and so closely related to subjective feelings. Exogenous rises in exports raise wages (HJMX 2014), and higher income likely leads to higher subjective happiness. This additional channel works against our hypothesis that exports tend to increase severe depression rates because of increased efforts. The contrasting results for men and women also point to the underlying mechanism of our results. As exports rise exogenously, both men and women get higher wages. However, despite higher wages, women develop higher rates of severe depression. This strongly suggests increased job pressure and efforts, which is the mechanism we hypothesize. We show the results for work efforts in section 6.

In columns 3 and 4 of Table 3 we broaden our analyses to include less severe stress and depression: our dependent variable equals 1 if in year t, worker i ever uses prescription anti-depressants or visits a psychiatrist. The results are very similar to columns 1 and 2.[35]

4.2 Other Sickness

Table 4 reports our results for other sickness. In the top panel, our dependent variables are dummies for worker i using the following prescription drugs in year t: (a) hypnotics and sedatives, for sleep disorder; (b) cardiac glycosides and other drugs for heart diseases; and (c) antithrombotic agents, which reduce the likelihood of heart attacks and strokes. The bottom panel reports the results for the dummy variables for the following causes of hospitalization: (i) sleep disorder; (ii) poisoning, self-harm or assaults; and (iii) heart attacks or strokes. We report only the coefficient estimates for log exports and its interaction with the female dummy, to save space. For each dependent variable we

[35] In recent work Dahl (2011) shows that changes in organizational structures of the firm increase the likelihood that their employees take anti-depressants using Danish data.

report the results both with and without IV, and we highlight the significant and marginally significant coefficient estimates in bold-face.

It is clear from Table 4 that there is no statistically significant result for sleep disorder or hospitalization due to poisoning, self-harm or assault.[36] There is no significant result for men, either. For women, however, rising exports lead to higher incidences of antithrombotic agents (significant), as well as hospitalizations due to heart attacks or strokes (marginally significant).[37] In both cases, the IV estimates are substantially larger than the OLS estimates. To show the economic significance of these results we compare our coefficient estimates with the sample means. A 10% exogenous rise in exports increases the fraction of women on antithrombotic agents by 7.7% ((0.0089-0.0012) x 10%/0.01), and raises women's odds to be hospitalized by heart attacks or strokes by 17.4% ((0.0013-0.0002) x 10%/0.0006). These results suggest that rising exports increases the incidences of heart attacks and strokes for women, consistent with our findings in Table 3.

5. Results for Injury Rate

5.1 The Effects of Exports on Injury

We report our results in Table 5. The dependent variable equals 1 if worker i, employed by firm j, gets injured in year t. Column 1 reports the OLS estimate. The coefficient for log export is 0.4 per thousand (precisely estimated). Column 2 reports the IV estimate. The coefficient for log export is marginally significant at the 10% level,[38] and suggests that if export rises by 100 log point for exogenous reasons, the workers' likelihood of injury rises by 2.0 per thousand within job spells. The IV

[36] Rising exports is positively correlated (marginally significant) with higher incidences of sleep-disorder drugs; however, when we use IV, we fail to find significant results.

[37] We have used three dependent variables to measure heart diseases in Table 4 and so one may be concerned about multiple testing. Our results are robust to this issue, because the p-value for women's anti-thrombotic agents is 0.00045, well below even the most conservative Bonferroni threshold of 0.05/3=0.0167. In addition, we show in section 8 and Table 11 that the coefficient estimate for stroke hospitalization becomes significant when we look at the sub-sample with long job spells, use 3-year moving averages of our WID instruments, or include interactions with old age.

[38] It is significant when we look at the sub-sample with long job spells (7+ years), or use 3-year moving averages of our WID instrument. See Table 11 and section 8.

estimate is four times as large as the OLS estimate, consistent with our discussions in sections 3 and 4 that productive firms may export more and use good technology that reduces injury rate. The IV estimate is also economically significant, since the mean injury rate is 3.9 per thousand in our estimation sample, and the elasticity of injury rate is 2.0/3.9 = 0.513 for the average worker in our sample.

One reason for the marginal significance of the export coefficient can be non-linearity: large export shocks could have different effects than small ones. To investigate this we calculate, within each job spell, the deviation of log exports (by firm by year) from the mean within the job spell. We then use the quartiles of the distribution of the mean-deviations in our sample to construct four export quartile dummies: the 1st quartile dummy is for all the observations where the mean-deviations of log exports fall into the first quartile, and so on.[39] Interacting the export quartile dummies with the two gender dummies, we get 8 dummies with 6 degrees of freedom.[40] We leave out the first quartile dummies and estimate the effects of 2nd – 4th quartile export shocks on injury rate, and how these effects vary across gender.

Column 3 of Table 5 reports the OLS estimates for the discrete export shocks. The effects of exports are the most pronounced when export shocks are large, in the 4th quartile. In response to these export shocks, injury rate rises by 0.4 per thousand for women and 0.6 per thousand for men. Column 4 reports the IV estimates, and they are again larger than OLS. For our 6 discrete-export-shock variables, 5 are statistically significant under IV. The effects of exports on injury rate are similar for 2nd-quartile and 3rd-quartile export shocks, but they are much larger for 4th quartile export shocks. This non-linearity may explain why our estimate is marginally significant when the export variable is continuous.

[39] The cut-off points for the quartiles for observed exporting are -0.117, 0.005 and 0.134, and for predicted exporting they are -0.088, 0.004 and 0.101. For predicted exporting in the total hours sub-sample they are -0.071, 0.000 and 0.065.
[40] The four export quartile dummies sum up to the constant and so do the two gender dummies.

Finally, Table 5 shows that the effects are similar for men and women. When export is a continuous variable, the interaction of the female dummy and log export has insignificant coefficient estimates. When export is discrete, for example, 3^{rd} quartile shocks increase men's injury rate by 0.5 per thousand and women's by 0.6 per thousand, and 4^{th} quartile shocks raise both men and women's injury rate by 1.1 per thousand.

5.2 The Economic Significance of the Results for Injury

One might be concerned that our estimation results are narrow, and not readily applicable outside our estimation sample (large manufacturing firms) and our estimation framework (within job-spell changes). To address this concern, and to highlight the economic significance of our results, we investigate whether, and how much, our estimates from *micro* data help us understand the changes in the injury rate and total injury count for the entire Danish economy during the Great Recession, both *macro* variables.

Like the U.S. (and many other countries), Denmark suffered a large drop in both aggregate output and trade during 2007-2009 (Figure A1 in the Appendix). During the Great Trade Collapse Danish export fell by 9.5%, measured in constant prices. If our hypothesized micro channel is generally applicable, we should expect to see declines in the injury rate and total injury count for Denmark, a (small) silver lining for the Great Recession.

This is what we see in the data. Figure 1 plots the total injury count, employment, and injury rate for Denmark over time, and all three macro variables fall during 2007-2009. In particular, injury rate falls from 3.58 per thousand in 2007 to 3.13 per thousand in 2009, a decline of 0.45 per thousand. Now our micro-data produce an elasticity of 2.0 per thousand when export is a continuous variable. Using this, and the 9.5% drop in Danish export, we get a predicted reduction in injury rate of 0.19 per thousand, which is 42.2% of the actual reduction in injury rate. To predict the total injury count in

Denmark in 2009, we hold Danish employment at its 2007 level, and multiply it by our predicted injury rate, The predicted drop in total injury count between 2007 and 2009 is 452 cases, and it accounts for 27.6% of the actual decline of 1641 cases.

These results show that the empirical relationship between export and injury rate that we have obtained using micro data, for 1995-2006, and conditional on within-job-spell changes, helps account for substantial fractions of the actual changes in injury rate and total injury count during 2007-2009, both macro variables for the entire Danish economy. They highlight the economic significance of our micro-data estimates, and suggest that they have broader implications beyond our estimation sample of large manufacturing firms and estimation framework of within-job-spell changes.

6. Results for Efforts

In sections 4 and 5 we show that exports increase workers' incidences of injury, depression, and heart attacks and strokes. We now investigate the mechanism of these results by examining whether workers increase efforts in response to rising exports. Efforts may respond through both the extensive margin (e.g. number of hours) and intensive margin (e.g. higher intensity per hour). Below we provide evidence for both margins.

6.1. Total Work Hours

Our first measure of work efforts is the total number of work hours per worker per year, which is the sum of regular and overtime hours. This variable is available for a subset of our sample, about 1.2 million observations. Table 6 shows our results. In columns 1 and 2 we have continuous export variables. The coefficient of log exports is not significant, but its interaction with the female dummy is marginally significant at the 10% level, suggesting that women increase total hours as exports rise exogenously.[41] In columns 3 and 4 we use discrete export variables. All the 2nd and 3rd quartile export variables are statistically significant. They show that men increase total hours by 0.022 to 0.033 log points, while women increase them by 0.039 and 0.051 log points. The magnitudes of women's responses tend to be larger than men's. Columns 3 and 4 also show that the coefficient estimates for the 4th-quartile export shocks are statistically insignificant.

These results for total hours provide evidence for the extensive margin of efforts. For the evidence for the intensive margin, we note that the coefficient estimates in column 2 suggest an elasticity of total hours of 0.109 (0.1159 – 0.0071), substantially lower than the elasticity of employee-based injury rate, 0.513 (see sub-section 5.1). This suggests that hours-based injury rate also increases, consistent with increases in work intensity holding hours constant. To show this more rigorously, we construct hours-based injury rate by normalizing our injury dummy by the number of thousands of total hours, and report how this variable responds to rising exports in column 5. We use discrete export variables since exports have non-linear effects on total hours. All the coefficient estimates are positive, and we have statistical significance for men for the 4th-quartile export dummy.[42] This suggests that for the 4th-quartile export shocks, efforts still increase, but along the intensive margin, rather than the extensive margin. We re-visit this point below.

6.2. Minor and Major Sick-Leave Days

Another way to find evidence for the extensive margin of efforts is to look at the changes in the number of minor sick-leave days. Since these are sick-leave spells during which the workers neither visit doctors nor make new purchases of prescription drugs, a reduction in their number likely reflects

[41] We use the total-hours sub-sample for the first-stage IV estimation, and report the results in Table A4. They are similar to our first-stage results for the full sample.

[42] As compared with Table 5 and columns 3 and 4 of Table 6, in column 5 of Table 6 we do not have as many statistically significant coefficient estimates. This could be because relative to those exercises, in column 5 we compress the variation of the dependent variable by using the *level* of total hours in its denominator. We cannot normalize injury rate by log(total hours) given that our worker-level injury variable is a dummy.

increased efforts (e.g. reducing shirking, or choosing to work rather than staying home in case of mild sickness/discomfort). As a result, according to our hypothesis, the number of minor sick-leave days should decrease in response to exports.

Table 7 reports our results. In columns 1 and 2 our export variable is continuous and we do not find significant results. In columns 3 and 4 our export variables are discrete, and we obtain precisely estimated coefficients. Under both OLS (column 3) and IV (column 4), men reduce their minor sick-leave days in the presence of 2nd-quartile export shocks. The magnitude of this reduction, 0.016 – 0.018 days per worker per year, is sizable given the sample mean of 0.21 days. In the presence of 3rd-quartile export shocks, men reduce their minor sick-leave days even more, by 0.031 – 0.048 days, or 14.6% - 22.9% of the sample mean. On the other hand, women also reduce minor sick-leave days (e.g. the coefficient estimate for the 3rd-quartile export shock is significant under IV). The magnitudes of women's responses tend to be smaller than men's. This could be because in our sample, the mean number of minor sick-leave days is lower for women (0.175 days/year) than for men (0.225 days/year). Finally, the 4th-quartile export shocks have insignificant coefficient estimates. These results match Table 6 and provide more evidence for the extensive margin of efforts.

We now turn to the number of major sick-leave days. As we discussed in section 3, this variable reflects both sickness and efforts. A reduction in the number of major sick-leave days clearly indicates more efforts on the extensive margin, but has ambiguous implications for sickness, as workers may work while sick. On the other hand, more major sick-leave days clearly indicate worse health, which could be the consequence of more efforts on the intensive margin. Therefore, under our hypothesis, the number of major sick-leave days may either increase or decrease when exports increase.

Table 8 reports our estimation results. When our export variables are continuous (columns 1 and 2), the IV and OLS estimates have opposite signs, making them hard to interpret. When our export variables are discrete (columns 3 and 4), however, the OLS and IV estimates are similar. In the presence of 2nd and 3rd quartile export shocks, men cut back on their number of major sick-leave days by 0.43 – 1.05 days per person per year (all the coefficient estimates for men are statistically significant). These are sizable effects, given that the number of major sick-leave days has the sample mean of 6.11. The evidence for women is also strong, showing that they reduce their major sick-leave days by 1.24 – 2.42 per person per year (3 out of 4 coefficient estimates for women are statistically significant). The magnitudes of women's responses tend to be similar to men's. These results corroborate our findings in Tables 6 and 7, and provide further evidence that workers increase efforts when exports rise exogenously (e.g. more working-while-sick).

On the other hand, when export shocks fall in the 4th quartile, our estimates show that men have *more* major sick-leave days (under IV), and women have even more than men (both OLS and IV). These results show that workers suffer more sickness as exports increase, and they corroborate our findings in sections 4 and 5. They also shed light on our earlier results for 4th-quartile export shocks in Tables 6 and 7: as exports increase, workers neither decrease total hours nor increase minor sick-leave days, *despite* having more major sick-leave days and higher hours-based injury rate. We believe this is evidence that workers have increased efforts along the intensive margin.

7. Pain vs. Gain from Rising Exports

In sections 4-6 we report a rich set of results showing that rising exports makes individual workers less healthy by increasing their injury and sickness rates. These results are novel to the literature, and they are a source of non-pecuniary welfare pain from globalization. Relative to the pecuniary wage gain that the literature has reported, how large is the pain? In this section we develop a novel framework to calculate the total utility losses due to higher rates of injury and multiple types of non-fatal diseases. We distinguish ex-ante losses, due to higher (expected) injury-and-sickness rates, vs. ex-post losses, for those who actually get injured or sick.

We use the workers' objective function in equation (1) as the measure for their well-being, W:

$$W = \max_e \{\beta \frac{\theta_f \psi Y - rK - p_M M}{L} - ac(e)) \, . \tag{11}$$

In order to relate equation (11) to the observables in our data, we assume that

$$\beta \frac{\theta_f \psi Y - rK - p_M M}{L} = C, \tag{12}$$

where C denotes the workers' monetary income. Plugging (12) into (11) and differentiating with respect to the export shock, we have

$$\frac{\partial W}{\partial \psi} = \frac{\partial C}{\partial \psi} - \frac{\partial [ac(e)]}{\partial \psi} = C \frac{\partial \ln C}{\partial \psi} - \frac{\partial [ac(e)]}{\partial \psi} \, . \tag{13}$$

The first term on the right-hand side of equation (13) shows the utility gain in response to rising exports due to higher income, and the second term shows the ex-ante utility loss due to higher injury and sickness rates.

We observe all the variables in equation (13) that determine the utility gain. For income, C, we use the average wage in our sample, 297,164 DKK for men and 234,995 DKK for women. $\frac{\partial \ln C}{\partial \psi}$, the percentage change in income in response to export, is the estimate for the wage elasticity of export in HJMX (2014), 0.0493. We thus obtain that, following a 10% exogenous increase in export, the utility gain amounts to 1465 DKK for men and 1158 DKK for women. Women have lower utility gains than men because they have lower average wages in our sample.

For the ex-ante utility loss, we assume that the cost function, *ac(e)*, relates to injury and sickness rates in the following way

$$ac(e) = H(d_0, d_1, ..., d_n) = Ad_0{}^{\beta_0} d_1{}^{\beta_1} ... d_n{}^{\beta_n}, \beta_0 + \beta_1 ... + \beta_n = 1, \tag{14}$$

where A is a constant. In equation (14), d_0 is the injury rate and $d_1 \ldots d_n$ the incidences of sickness 1 ~ n. The Cobb-Douglas functional form allows us to aggregate the utility losses due to multiple injury and sickness conditions, whose weights are the parameters $\beta_0 \ldots \beta_n$.

Equation (14) implies that

$$\frac{\partial[ac(e)]}{\partial\psi} = \frac{\partial H}{\partial\psi} = H\frac{\partial \ln H}{\partial\psi} = H(\beta_0\frac{\partial \ln d_0}{\partial\psi} + \beta_1\frac{\partial \ln d_1}{\partial\psi} + \ldots\beta_n\frac{\partial \ln d_n}{\partial\psi}). \qquad (15)$$

Equation (15) says that the ex-ante utility loss is the product of two terms: H, the total health cost itself, and its percentage change following the export shock, the terms in the brackets. This percentage change is, in turn, the weighted sum of the percentage changes of the incidences of individual injury and sickness conditions, the weights being $\beta_0 \ldots \beta_n$.

We now calculate the ex-ante utility loss using (15) in three steps. In step 1, we use our results from sections 4 and 5 to calculate the percentage changes of injury and sickness rates, $\frac{\partial \ln d_g}{\partial\psi}$, g = 0, 1, … n. We restrict our calculations to job injury, severe depression, and heart attacks or strokes, for which we have unequivocal results using continuous export variables, and we use our IV estimates, where we have addressed the endogeneity of exports.[43] Since our dependent variables in sections 4 and 5 are dummies, we divide our coefficient estimates by the mean rates of injury and sickness. We report these calculations in Table 9. For example, for women's injury rate, our coefficient estimate is 0.0020 (this is $\frac{\partial d_0}{\partial\psi}$, column 1). Given that 0.31% of women suffer from injury in our sample (this is d_0, column 2), the percentage change in injury rate for women is 0.002/0.0031 = 63.50% (this is $\frac{\partial \ln d_0}{\partial\psi} = \frac{\partial d_0}{\partial\psi} / d_0$, column 3); i.e. the elasticity of injury rate with respect to exports is 0.635. These percentage changes, or elasticities, range from -20.2%, for men's severe-depression rate, to 150.1%, for

[43] We do not include sleep-disorder drugs because the coefficient estimates are not significant under IV. For the same reason we set to 0 the effects of exports on men's rates of heart attacks and strokes.

women's odds to be hospitalized due to heart attacks or strokes. They are large because our coefficient estimates (column 1) are large relative to the sample means (column 2).

In step 2, we measure the share weight of each injury and sickness variable using its share in the total health-care spending in Denmark. In Appendix Table A5 we report Denmark's healthcare spending by category in 2010. For example, out of 132.1 billion DKK of healthcare spending, 2.5 billion goes to hospitalizations due to heart attacks or strokes, implying a share of 1.89%. We list these share weights in column 4 of Table 9, and they range from 0.05%, for antithrombotic agents, to 3.1%, for injury.

We now plug the percentage changes of injury and sickness rates and their share weights into equation (15), and obtain a *percentage* ex-ante utility loss of 1.37% for men and 4.95% for women. Our estimate for men is lower than for women because men's incidences of severe depression, heart attacks or strokes decrease with respect to exports, and their mean injury rate is higher.

In step 3, the last step, we calculate the total health cost, H, in order to turn these *percentage* utility losses into losses in *levels*. While H is not directly observable in our data, we can back it out using the following first-order condition. By (14),

$$\frac{\partial H}{\partial d_0}\frac{d_0}{\beta_0} = \frac{d_0}{\beta_0}(A\beta_0 d_0^{\beta_0 - 1} d_1^{\beta_1} ... d_n^{\beta_n}) = H \ . \tag{16}$$

We observe all the variables on the left hand side of equation (16). d_0 is the mean injury rate and β_0 the share weight of injury, both of which we have listed in Table 9. $\frac{\partial H}{\partial d_0}$ is the utility loss, ex post, that injured workers actually suffer. Assuming that the injury compensation scheme in Denmark fully compensates the injured for their sufferings, we can measure it using the average injury compensation for the injured workers in our data, 381,660 DKK for men and 397,103 DKK for women.[44]

[44] These are roughly $68,699 and $71,479, respectively, and comparable to the estimates of the value of a statistical injury (e.g. Viscusi and Aldy 2003).

We now calculate the value of H using (16): 52,660.5 DKK for men and 40,344.4 DKK for women. These estimates are small relative to average wages because the average worker has low injury and sickness rates in our sample. The estimate for men is higher because they have higher mean injury rate. Plugging these values back into (15), the ex-ante utility loss in response to a 10% exogenous increase in exports is 72.0 DKK for men (10% x 52,660.5 x 1.37%) and 200.0 DKK for women. These estimates are small because injury compensation and spending on anti-depressants, heart attacks or strokes together have a low share weight of 5.46% in Danish healthcare spending. For men, this loss amounts to 4.91% of wage gain, and for women, 17.26%. Using (13) we obtain a net utility gain of 1,393 DKK for men and 958 DKK for women.

Our calculations so far show the ex-ante utility losses for the average man and woman. Ex post, however, the utility losses are not evenly distributed, that is, they are much higher for those who actually get injured or sick. In our framework, these ex post utility losses correspond to the marginal dis-utilities. We have already shown the marginal dis-utility of injury, and we now calculate the marginal dis-utility of any non-fatal disease type g, $\frac{\partial H}{\partial d_g}$.

$$\frac{\partial H}{\partial d_g}\frac{d_g}{\beta_g} = \frac{\partial H}{\partial d_0}\frac{d_0}{\beta_0} = H \;\; \forall g = 1,2...n.. \tag{17}$$

Equation (17) says that the marginal dis-utility is high if sickness rate, d_g, is low relative to the share in healthcare spending, β_g. An example is hospitalization due to heart attacks or strokes for women. It happens with the frequency of 0.7 per thousand but accounts for 1.89% of healthcare spending, implying a marginal dis-utility of 1,041,921 DKK. We report these values in the last column of Table 9. They range from 1,365 DKK, for men's anti-thrombotic agents, to over 1.9 million DKK, for men's hospitalization due to heart attacks or strokes. With the exception of men's anti-thrombotic agents, the marginal dis-utilities exceed the wage gains from a 10% rise in exports, suggesting that rising exports could potentially lead to very large utility losses for the workers who actually get sick.

To summarize our results, the ex-ante utility loss from rising exports, due to higher injury and sickness rates, is small but substantial relative to the gain from higher wages. Ex post, however, those who actually suffer the injury or sickness sustain much larger utility losses. Several caveats apply to our estimates. First, we may underestimate the total health cost if the assessments of the National Board of Industrial Injuries do not fully compensate injured workers, or if total spending on prescription drugs and hospitalization is lower than consumer surplus. Second, we may not have captured all possible health consequences of increased effort with our set of injury and sickness variables. In addition, our framework does not take into account the utility loss due to longer hours, and our results are for contemporaneous changes in utility. We leave these caveats for future research.

8. Robustness

We have done a number of robustness exercises and obtained similar results. We report them in Tables 10 and 11 and discuss them in this section. To save space we only report and discuss the results with IV.

The first issue we address is, do exports affect individual workers' future injury and sickness rates because these conditions may persist over time? We first examine whether log exports and our injury and sickness variables have serial correlation. In column (2) of Table 10 we show the correlation coefficients between these variables and their 1-year lagged values. Some correlation coefficients are high, such as those for log exports and anti-thrombotic drugs. These correlation coefficients, however, do not reflect the variations we use for identification, where we control for job-spell fixed effects. Thus in column (3) of Table 10 we show the correlation coefficients for the deviations of these variables from their within-job-spell means. They are all small in magnitude, and have decreased substantially relative to column (2); e.g. for log exports it goes down from 0.97 to 0.37. These results suggest that persistence is unlikely a main feature of the within-job-spell variations that we use for identification.

The second set of issues concerns our control variables. In Tables 3-8 we have discrete variables for worker experience, and in the 1st panel of Table 11 we show the results of using continuous worker experience and its square instead.[45] In Tables 3-8 we do not control for domestic output, and the concern is that rising exports may simply divert products from the domestic market to international markets, leaving total output unchanged. In the 2nd panel of Table 11 we have the log of domestic output as an additional control, calculated as gross output minus the value of exports. The results in the 1st and 2nd panels of Table 11 are similar to our main results, except that the effects of exports on men's depression rates are not statistically significant.

The third set of questions is about the nature of our identification. Given that we use job-spell fixed effects our approach should work better where job spells are longer. We construct the sub-sample where all job spells last at least 7 years and report the results in the 3rd panel of Table 11. Relative to our main results we have far fewer observations here but get stronger results. A related question is whether our results reflect short-term, year-to-year fluctuations in exports, or longer-term effects. We replace the contemporaneous values of our WID (world import demand) instrument with their 3-year moving averages,[46] and show the results in the 4th panel of Table 11. Again we get stronger results, except for total hours. In both the 3rd and 4th panels of Table 11, exports have statistically significant effects on the rate of hospitalization due to heart attacks or strokes, and on the injury rate. On the other hand, the effects of exports on men's depression rates are insignificant.

We next investigate whether the effects of exports vary with the tightness of the local labor market. Suppose the unemployment rate in the local labor market is high. Then the firm has a large pool of workers it could potentially employ to replace its workforce should bargaining fail; i.e. the firm has a strong outside option in the bargaining game. In this case the workers extract a small share of the

---

[45] To save space we only report the coefficient estimates of log exports and its interaction with the female dummy, and for the dependent variables measuring severe depression, heart attacks and strokes, injury and total hours. The rest of the results are available upon request.

[46] Following Bertrand (2004) we use contemporaneous values for the 1st years of data and 2-year-average values for the 2nd.

surplus and so have weak incentives to increase efforts as exports increase exogenously. As a result, the effects of exports are small in magnitude.[47] We calculate unemployment rate by commuting zone by year,[48] augment our regressions with the interaction between unemployment rate and log exports, and instrument for this interaction term in the first stage. The results are in the 5th panel of Table 11 and they are mixed. The coefficient estimate of the unemployment-rate interaction is negative for the rates of depression and anti-thrombotic drugs, and negative and significant for injury rate, consistent with the hypothesis. However, this estimate is positive for total hours (marginally significant) and for the rate of hospitalization due to heart attacks or strokes (insignificant).

We now study how the effects of exports vary across occupations. Our results for injury motivate us to examine the role of physical strength. Our idea is that the effects of exports on job injury may be more pronounced for the occupations where workers use body muscles a lot. Our results for depression, on the other hand, lead us to examine whether rising exports have weaker impacts on mental health for the occupations that require self control and stress tolerance. We obtain occupation-characteristics data from the U.S. O*NET. Physical strength is the principal component of static strength, explosive strength, dynamic strength, trunk strength and stamina. Mental strength is the principal component of self control and stress tolerance. We normalize both variables to mean 0 and standard deviation 1 and interact them with log exports.[49] We then augment our regressions with the interaction terms and instrument for them in the first stage.

The results for physical strength are in the 6th panel of Table 11. The coefficient estimate of

---

[47] In the Appendix we use our bargaining framework in sub-section 3.1 to show that $\frac{\partial^2 e}{\partial \psi \partial \theta_f} > 0$ under certain parameter values. Here a low θ_f means strong outside options for the firm.

[48] 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%.

[49] More details are in the Appendix. Mental strength has negative correlation with physical strength (-0.28) and positive correlation with the dummy for management occupations (0.25). Physical strength has negative correlation with the management-occupation dummy (-0.24).

physical strength x log exports is positive in all 6 cases and significant in 4 out of 6. To see the economic significance of these estimates compare two workers of the same gender whose occupational requirements for physical strength are 1 standard deviation apart; e.g. pelt dressers, tanners and fellmongers, 7441, where physical strength = 0 (sample mean), vs. ore and metal furnace operators, 8121, where physical strength = 1 (1 standard deviation above the mean). The effects of a 10% exogenous increase in exports on depression rates are larger by about 1 per thousand for the latter, those on rates of anti-thrombotic drugs larger by 0.7 per thousand, and those on injury rate by 0.2 per thousand. The results for mental strength are in the 7th panel of Table 11. The coefficient estimates of mental strength x log exports are negative in all 6 cases and significant in 4 out of 6. They tend to be smaller in magnitudes than the coefficient estimates of physical strength x log exports in the 6th panel.

Finally, we have also examined how the effects of exports vary across age groups, and report the results in the last panel of Table 11. The interaction between log exports and the older-worker dummy (age 40 and above in 1995) is statistically significant for the rates of stroke hospitalization and stroke drugs, but not for the rates of depression or injury. Recently there have been discussions about raising the retirement age for social-security and pension benefits in the U.S. and Europe.[50] Our results suggest that the potential effects of this policy on the elderly's health should be taken into consideration.

9. Conclusion

In this paper we use matched worker-firm data from Denmark to study how exogenous shocks to labor demand affect workers' effort, injury and illness. For each individual in our data we observe her every transaction with the Danish healthcare system, and we are able to match her health information with detailed data on her employers' exposure to global trade. This allows us to base our

[50] E.g. for the U.S., http://www.fool.com/retirement/general/2016/03/18/will-social-security-raise-my-retirement-age.aspx. For Europe, http://www.thisismoney.co.uk/money/pensions/article-1696682/Rising-retirement-ages-in-Europe-compared.html.

identification on changes within worker-firm specific matches (i.e. within job spells), and on exogenous export shocks that originate outside of Denmark but whose impacts vary across Danish firms.

We obtain the following results that are novel to the literature. In response to an exogenous increase in exports, workers increase efforts along both the intensive and extensive margins. Evidence for the former includes higher hours-based injury rate, and evidence for the latter includes fewer sick-leave days and more total work hours (regular plus over time). As efforts rise, so do rates of injury and sickness: higher rates of job injury and more genuine sick days for both men and women, and higher rates of severe depression, heart attacks and strokes for women.

In the spirit of Rosen (1986), we develop a novel framework to quantify the ex-ante and ex-post utility losses due to higher rates of injury and multiple types of non-fatal diseases. For the average worker, the ex-ante utility losses are small, but substantial, relative to the wage gains from rising exports (4.91% for men but 17.26% for women), since the mean rates of injury and sickness are low. For the workers who actually get injured or sick, however, the ex-post utility loss is much higher, e.g. exceeding 1 million Danish Kroner for a woman who gets hospitalized due to a heart attack or stroke.

Our results for injury rates, obtained using micro data, could account for over one quarter of the reduction in total injury counts in the Danish macro economy during the 2007-2009 recession. Our results for stress and depression highlight the importance of mental health in today's global economy, as exports continue to grow in both developed and developing countries.[51] This implication is 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.[52]

[51] The work intensity and health outcome effects of changes in output could in principle be similar, whether they arise from domestic or foreign shocks. We examine only exports in this paper because they provide exogenous variations for our identification. Such variations for domestic shocks are not straightforward to identify. For example, while the change in GDP during the 2007-09 recession is clearly exogenous, the changes in individual firms' outputs may or may not be.
[52] The recent hit song, Stressed Out, by the group Twenty One Pilots, echoes this theme (https://www.youtube.com/watch?v=pXRviuL6vMY).

This point also complements Case and Deaton (2015), who show that the mortality of middle-aged white Americans has increased substantially during 1999-2013, driven by rises in drug and alcohol poisoning, suicides, and chronic liver diseases. They also report that, “Concurrent declines in self-reported health, mental health, and ability to work, increased reports of pain, and deteriorating measures of liver function all point to increasing midlife distress.”

Unfortunately, in many countries the provision of mental-health care lags far behind demand; e.g. in 44 U.S. states the biggest mental-health institution is a prison.[53] Part of the reason could be that mental illness carries significant stigma. Bharadwaj, Pai and Suziedelyte (2015) use Australian data to show that, in surveys, seniors under-report stress and depression relative to other diseases. Fortunately, many employers are taking action. Large U.S. companies are offering trainings in cognitive behavioral skills, scented relaxation rooms, “living walls” decorated with plants, and outdoor cafes with wildflowers, in order to help their employees combat stress at work. [54] Our results suggest that such endeavor may be especially useful for the female workers whose employers are rapidly expanding in the global market.

[53] ‘Mental Health: Out of the Shadows”, Economist, April 25, 2015, 56-57.

[54] See “To Cut Office Stress, Try Butterflies and Medication?”, by Sue Shellenbarger, The Wall Street Journal, October 9, 2012.

Appendix

1. More on Data Construction

To construct our main sample, we start from the manufacturing firms that both import and export. We select 20-60 year old full-time workers, and we drop all observations where the employment relationship lasts a single year. We select larger firms to get high quality data on capital (those with at least 50 employees and 0.6 million DKK in imports), and drop the observations with missing information about key firm variables (output, capital-labor ratio and the share of high-skilled workers). We also drop the observations with missing education and wage information, since the other worker characteristics of these observations might be prone to measurement errors as well.

Prescription drugs data are drawn from the "Register of Medicinal Product Statistics" maintained by Statens Serum Institut (SSI). These data hold all individual transactions at pharmacies. There is information about the transaction price, the price paid by the consumer, a detailed ATC drug code and the date of the transaction. 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 by a visit date and a doctor type (e.g. general practitioner, specialized doctor, dentist, psychologists etc.). We disregard all dental visits in the data, because dental care is not free.

The data on doctors visits includes each individual's visit dates (by week), type of doctors visited (e.g. general practitioner, psychiatrist), and total cost of the visit. The data on prescriptions include each individual's prescription date, detailed drug classification following the 4-digit Anatomical Therapeutic Chemical classification (ATC), copay (out-of-pocket expenses by patients) and total prescription drug cost. The data on hospitalization includes dates for first and last day of the hospitalization period and the diagnosis which follows the International Classification of diseases (ICD10). 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).

2. ATC Codes and ICD 10 Codes

Anti-depressants are defined as ATC code N06A, which includes the subgroups N06AA (Non selective monoamine reuptake inhibitors), N06AB (Selective serotonin reuptake inhibitors), N06AF (Monoamine oxidase inhibitors, non-selective), N06AG (Monoamine oxidase type a inhibitors) and N06AX (Other antidepressants). Of these Selective serotonin reuptake inhibitors account for the bulk of anti-depressant purchases. For example Prozac belongs to this group of anti-depressants. As in many developed countries, the number of antidepressants prescribed in Denmark has increased markedly over the past decades. Danish sales of anti-depressants have increased from less than 10 per 1000 inhabitants in 1990 to 84 per 1000 inhabitants in 2010. Anti-depressants are often used as first-line treatment of severe depression and for treatment of mild to moderate depression that persist after alternative treatments such as cognitive therapy. Table 1 shows the summary statistics of these variables. 2.93% of worker-years have positive expenses on anti-depressant drugs, and 3.24% either purchase anti-depressants or visit psychiatrists.

Here are the ATC codes for the other prescription drugs we have examined. i) For sleep disorder (sample mean = 2.32%), we look at hypnotics-and-sedatives, N05C; ii) For the drugs that contain antithrombotic agents, which reduce the likelihood of heart attacks and strokes (sample mean = 1.7%), B01; iii) For other heart diseases, we look at cardiac glycosides and other prescription drugs (sample mean = 0.6%), C01.

Here are the ICD 10 codes for the hospitalization variables we have examined. i) For sleep disorder (sample mean = 0.06%), G47; ii) For poisoning, self-harm or assault (sample mean = 0.15%), T36-T39, T4, T5, X7, X8, X9 and Y0; iii) For heart attacks or strokes (sample mean = 0.06%), I21, I61 and I63.

3. More on Injury Data

Among those filed by Danish workers aged 20-60, NBII rejected 44% of petitions, accepted 28% but paid no compensation, and accepted 22% with compensation. For each petition with positive compensation, we observe: (1) the percentage damage to the workers' working and earning abilities (e.g. 15%), as determined by NBII; (2) the monetary compensation awarded; (3) detailed types of injury (e.g. "sprain, strain, etc.", and "toxic eczema"); and (4) the year of the injury and other information.

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.

The mean injury compensation across all workers, including those who do not receive positive compensation, is 1542.5 DKK; the mean conditional on receiving positive compensation, however, is 401,987 DKK. These averages are very similar to those of the sample of all manufacturing worker-years, the "Mfg" sample, in Table A2. Men's injury rate is higher than women's (4.3 per thousand vs. 3.2).

4. More on Sick-Leave Data

Worker sick leaves are recorded in the "Sickness benefit register", along with the reason for absence from work (sickness, birth of child, child care leave, child sick etc). We use this register to count the number of days absent from work due to sickness for each worker-year. Women have more major sick-leave days (8.24 vs. 5.06) but fewer minor sick-leave days than men (0.18 vs. 0.22). Most observations have 0 values for major (over 90%) and minor sick-leave days (over 95%). Among those with positive values, the mean is 38.9 per worker per year for major sick-leave days and 2.5 per worker per year for minor sick days.

5. More on Hours Data

Our work-hours data comes from the "Wage Statistics Register", which is available from 1997 and onwards. This register is based on reporting from the firms and covers in principle workers in all private sector firms with at least 10 employees. One potential concern is that our work-hour sub-sample may be subject to selection: some occupations (e.g. managers) may be more subject to the reporting rules than others (e.g. assembly line workers). Table A3 in the Appendix tabulates the fractions of 1-digit occupations in employment for our main sample and for the work-hour subsample. The employment shares are similar. Women have fewer hours than men (1461.7 vs 1568.5). In our analysis we focus on the number of total hours, because over-time hours take the value of 0 for a large fraction of our work-hour sub-sample.

6. O*NET Characteristics ID's

Static strength is 1.A.3.a.1, explosive strength = 1.A.3.a.2, dynamic strength = 1.A.3.a.3, trunk strength = 1.A.3.a.4, stamina = 1.A.3.b.1, self control = 1.C.4.a, and stress tolerance = 1.C.4.b.

7. The Effects of Exports on Efforts and Local Labor Market Tightness

We now prove that

Proposition A1 Under equations (4) and (5), the effect of exports on effort level is large if the firm's outside option is limited, i.e. $\frac{\partial^2 e}{\partial \psi \partial \theta_f} > 0$, if $\eta + \gamma \geq 2$.

Proof: First, it is easy to show the following results using equation (2):

$$\frac{\partial e}{\partial \theta_f} = \frac{\beta\psi(\partial y / \partial e)}{D} > 0, \frac{\partial e}{\partial a} = -\frac{c'(e)}{D} > 0, D = ac''(e) - \beta\theta_f\psi\frac{\partial^2 y}{\partial e^2} > 0\,. \tag{A1}$$

Using equation (3), we can show that

$$\begin{aligned}\frac{\partial^2 e}{\partial \psi \partial \theta_f} &= \frac{1}{D^2}[D(\beta\frac{\partial y}{\partial e} + \beta\theta_f\frac{\partial^2 y}{\partial e^2}\frac{\partial e}{\partial \theta_f}) - \beta\theta_f\frac{\partial y}{\partial e}(ac'''(e)\frac{\partial e}{\partial \theta_f} - \beta\psi\frac{\partial^2 y}{\partial e^2} - \beta\theta_f\psi\frac{\partial^3 y}{\partial e^3}\frac{\partial e}{\partial \theta_f})] \\ &= \frac{\beta}{D^2}\frac{\partial y}{\partial e}[D + 2\beta\theta_f\psi\frac{\partial^2 y}{\partial e^2} - \theta_f ac'''(e)\frac{\partial e}{\partial \theta_f} + \beta\theta_f^2\psi\frac{\partial^3 y}{\partial e^3}\frac{\partial e}{\partial \theta_f}] \\ &= \frac{\beta}{D^2}\frac{\partial y}{\partial e}[ac''(e) + \beta\theta_f\psi\frac{\partial^2 y}{\partial e^2} - \theta_f ac'''(e)\frac{\partial e}{\partial \theta_f} + \beta\theta_f^2\psi\frac{\partial^3 y}{\partial e^3}\frac{\partial e}{\partial \theta_f}]\,,\end{aligned} \tag{A2}$$

where the second and third equalities use equation (A1). Equations (3)-(5) and (A1)-(A2) then imply that

$$\begin{aligned}\frac{\partial^2 e}{\partial \psi \partial \theta_f} &= \frac{\beta}{D^2}\frac{\partial y}{\partial e}[\frac{\beta\theta_f\psi\frac{\partial y}{\partial e}}{ac'(e)}ac''(e) + \beta\theta_f\psi\frac{\partial^2 y}{\partial e^2} - \theta_f ac'''(e)\frac{\partial e}{\partial \theta_f} + \beta\theta_f^2\psi\frac{\partial^3 y}{\partial e^3}\frac{\partial e}{\partial \theta_f}] \\ &= \frac{\beta^2\theta_f\psi}{D^2}(\frac{\partial y}{\partial e})^2[\frac{c''(e)}{c'(e)} + \frac{\partial^2 y / \partial e^2}{\partial y / \partial e} - \frac{ac'''(e)}{D} + \frac{\beta\theta_f^2\psi}{D}\frac{\partial^3 y}{\partial e^3}] \\ &= \frac{\beta^2\theta_f\psi}{D^2}(\frac{\partial y}{\partial e})^2[(\eta + \gamma - 2)e^{-1} - \frac{ac'''(e)}{D} + \frac{\beta\theta_f^2\psi}{D}\frac{\partial^3 y}{\partial e^3}]\,.\end{aligned} \tag{A3}$$

Now $c'''(e) \leq 0$ by (4), $\frac{\partial^3 y}{\partial e^3} > 0$ by (5), and $\eta + \gamma - 2 \geq 0$, and so $\frac{\partial^2 e}{\partial \psi \partial \theta_f} > 0$ by (A3). Q.E.D.

8. Appendix figures and tables.

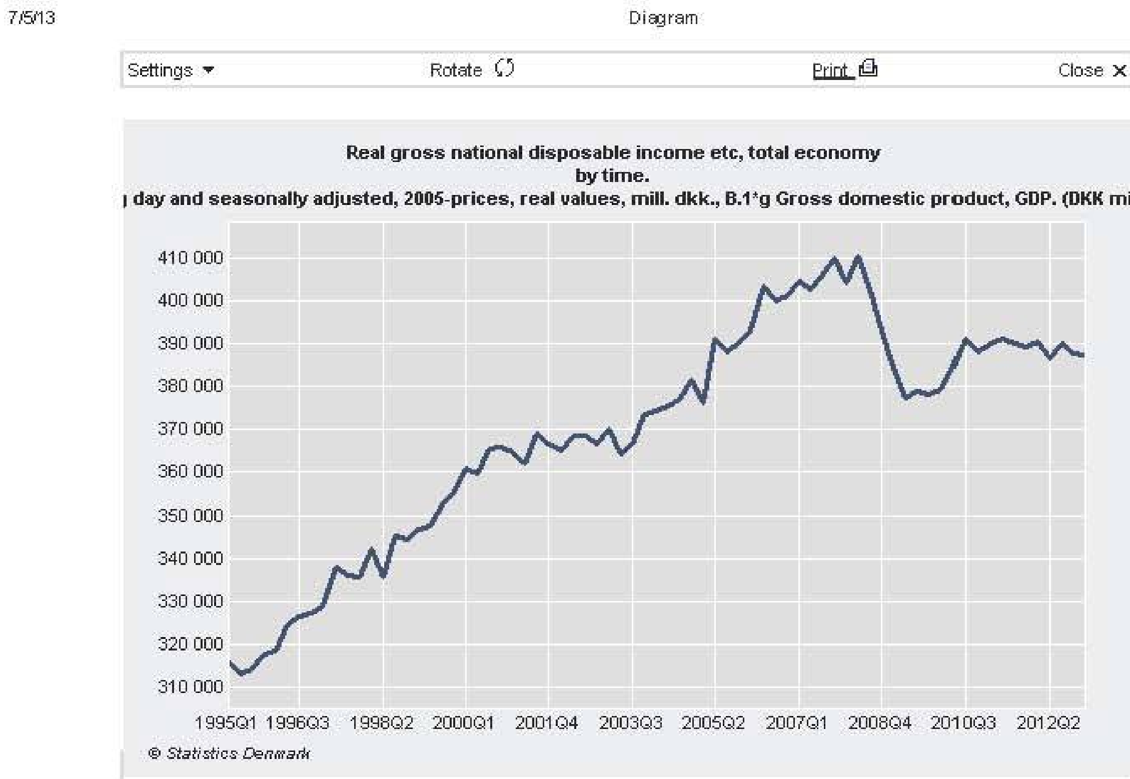

Figure A1 Quarterly GNP (Seasonally Adjusted) of Denmark

Table A1 Select Summary Statistics by Sector, Full Sample, Exporting Firms, 2005

Sector	Exp./Sales	Inj. Rate	Obs. No.
Ag. & Fishing	0.3162	0.0045	3308
Computer	0.0533	0.0006	13689
Construction	0.0193	0.006	22320
Education	0.0087	0.0017	33220
Finance	0.0259	0.0015	17636
Health	0.6304	0.0038	124736
Manufacturing	0.4609	0.0049	280713
Mining	0.0937	0.0034	2980
Other	0.264	0.0025	79419
Public & Defense	0.0461	0.0041	53417
Retail & Wholesale	0.1799	0.0021	167921
Transportation	0.0583	0.0037	31063
Utility	0.0878	0.0042	6954

Table A2 Additional Summary Statistics

	Full, 95-09			Mfg, 95-09		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Injury Dummy	33510639	0.0031	0.056	5503922	0.0041	0.064
log (Hourly wage)	31299066	5.280	0.469	5234344	5.356	0.382
Married (Dummy)	33510639	0.525	0.499	5503922	0.541	0.498
Experience	33510591	15.524	10.203	5503919	16.906	9.813
Union (Dummy)	33510564	0.713	0.452	5503912	0.779	0.415

Table A3 Employment Shares by 1-digit Occupation for the Estimation Sample and the Work-hours Subsample

Occupation (1 digit)	Main Sample Occp. Share	Hours Subsample Occp. Share
1	.032245	.0370792
2	.0715409	.0779478
3	.1439805	.1619491
4	.0627748	.0556741
5	.0115262	.0052905
6	.0042052	.0028871
7	.1983044	.1716986
8	.3877012	.3975089
9	.082292	.0891845
Missing	.0054299	.0007804

Table A4. First Stage Results

	Main Sample				Total-Hours Subsample			
	log(exp)	log(exp) x female	log(off)	log(off) x female	log(exp)	log(exp) x female	log(off)	log(off) x female
Log WID, exports	0.2600***	-0.0695***	-0.0751	-0.0980***	0.1655***	-0.0516***	-0.0135	-0.0731***
	[3.56]	[-4.37]	[-0.61]	[-5.37]	[2.76]	[-3.16]	[-0.20]	[-4.00]
Log transport costs, exports	-8.5867	-2.0056*	21.4485***	-4.3490***	-7.7960**	-1.7536	4.5822	-6.3907***
	[-1.48]	[-1.74]	[3.03]	[-2.72]	[-2.02]	[-1.26]	[0.70]	[-4.00]
Log WES, offshoring	0.0286	-0.0528***	0.2461***	-0.0728***	0.1596***	-0.0506**	0.3613***	-0.0720***
	[0.34]	[-3.54]	[3.34]	[-5.46]	[2.80]	[-2.41]	[5.38]	[-5.30]
Log transport costs offshoring	5.0655*	1.2004*	-15.3680***	0.5208	3.9780	0.4462	-13.1457**	-0.0294
	[1.84]	[1.86]	[-2.65]	[0.66]	[1.45]	[0.77]	[-2.48]	[-0.03]
Interactions with female dummy								
Log WID, exports	-0.1439***	0.3751***	0.0762	0.3114***	-0.0762**	0.2852***	0.1007*	0.3693***
	[-4.02]	[6.02]	[1.55]	[3.38]	[-2.37]	[5.43]	[1.90]	[4.79]
Log transport costs, exports	1.9843	0.7138	2.5683	30.7920***	1.1308	-1.7203	0.2134	19.9214***
	[1.10]	[0.19]	[0.90]	[5.92]	[0.65]	[-0.72]	[0.07]	[4.21]
Log WES, offshoring	0.0634	0.2489***	-0.0715	0.3779***	0.0288	0.2818***	-0.1477***	0.3800***
	[1.41]	[3.62]	[-1.53]	[5.70]	[0.67]	[5.45]	[-2.96]	[5.63]
Log transport costs offshoring	-2.2796	-2.5798	-3.1542	-19.7793***	-1.5877	-0.5908	0.1308	-12.3353**
	[-1.26]	[-0.81]	[-1.07]	[-3.64]	[-0.83]	[-0.20]	[0.04]	[-2.54]
Firm and worker controls								
log employment	0.7675***	0.2325***	0.9231***	0.2860***	0.7425***	0.2328***	0.9622***	0.3087***
	[14.12]	[13.72]	[12.61]	[11.91]	[11.64]	[9.38]	[11.58]	[9.72]
log capital-labor ratio	-0.0159	0.0038	0.0391	0.0177*	-0.0250	0.0005	-0.0024	0.0094
	[-0.77]	[0.51]	[1.27]	[1.74]	[-1.31]	[0.07]	[-0.08]	[0.88]
share, high-skilled workers	-0.9227*	-0.3596	-0.2364	-0.1575	-1.5839**	-0.5812	-1.5628*	-0.7224**
	[-1.72]	[-1.51]	[-0.33]	[-0.61]	[-1.99]	[-1.60]	[-1.74]	[-2.15]
experience	0.0100	-0.0042	0.0238**	-0.0049	0.0024	-0.0032	0.0068	-0.0204***
	[1.40]	[-1.05]	[2.50]	[-0.90]	[0.33]	[-0.81]	[0.56]	[-3.02]
experience squared	0.0000	-0.0001**	-0.0001**	-0.0001***	0.0001*	0.0000	0.0001	-0.0000
	[0.07]	[-2.08]	[-2.40]	[-2.72]	[1.66]	[0.05]	[1.02]	[-1.04]
union	-0.0195***	-0.0109***	0.0132*	0.0001	-0.0086*	-0.0067**	0.0035	0.0013
	[-3.25]	[-3.38]	[1.85]	[0.03]	[-1.65]	[-2.50]	[0.47]	[0.36]
married	0.0036	-0.0042***	0.0023	-0.0069***	0.0022	-0.0029*	0.0028	-0.0068***
	[1.40]	[-2.79]	[0.70]	[-3.42]	[0.79]	[-1.69]	[0.73]	[-2.91]
Observations	1,978,209	1,978,209	1,955,728	1,955,728	1,173,820	1,173,820	1,162,510	1,162,510
R-squared	0.1977	0.0911	0.1346	0.0809	0.1816	0.0833	0.1589	0.0894
Number of job spell FE	389,015	389,015	387,788	387,788	323,554	323,554	322,033	322,033
F-statistics for instruments	5.759	21.47	5.292	42.26	3.839	13.72	6.098	30.03

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: Clustered (firm-by-year) t-statistics in square brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A5 Danish Healthcare Spending by Category, 2010

Sickness Benefits	**19.8**
Sickness benefits paid out to employees	15.4
Sickness benefits paid out to employers (reimbursement)	3.7
Hospitals	**78.7**
Heart attacks and strokes	2.5
Prescription drugs	**7.4**
Anti-Depressant	0.54
Sleep disorder	0.37
Heart disease	0.09
Heart attack and stroke	0.07
Injury Compensation	**4.1**
Health insurance	**19.8**
Regular doctor visits	8.1
Specialized doctor visits	3.2
Subsidy to private dentists	1.4
Public dentists	2.1
Home care	3.8
Total health care expenses	**132.1**

Notes: Units = Billion DKK, 2010. The bold-faced are major categories and the others are sub-categories. The expense for prescription drugs is net of patients' own payments. The numbers for anti-depressants, sleep disorder, heart disease, heart attacks and strokes are found at medstat.dk/en. Hospital expenses for heart attack and strokes are based on DRG expenses. Using hospital data for 2010, the DRG expenses for records with the stroke diagnosis are 925M DKK while the total DRG expenses 28.598 billion DKK. Thus heart attacks and strokes have a share of 3.23%. Then heart attacks and strokes are imputed to have a total expense of 2.5 billion DKK (78.7 x 3.23%).

References

Almond, Douglas, and Janet Currie, 2011. Human Capital Development Before Age Five, Chapter 15, 1315-1486, in Handbook of Labor Economics, vol. 4B, edt. by David Card and Orley Ashenfelter, Elsevier.

Autor, David, David Dorn, and Gordon Hanson. 2013. “The China Syndrome: Local Labor Market Effects of Import Competition in the United States”. American Economic Review 103, pp. 2121-2168.

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.

Autor, David, David Dorn, Gordon Hanson, and Jae Song. 2014. “Trade Adjustment: Worker Level Evidence”, Quarterly Journal of Economics 129, pp. 1799-1860.

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.

Bharadwaj, Prashant, Mallesh M. Pai, Agne Suziedelyte, 2015, “Mental Health Stigma”, NBER wp 21240.

Bigos, Stanley J.; Battié, Michele C.; Spengler, Dan M.; Fisher, Lloyd D.; Fordyce, Wilbert E.; Hansson, Tommy H.; Nachemson, Alf L.; Wortley, Mark D. 1991, “A Prospective Study of Work Perceptions and Psychosocial Factors Affecting the Report of Back Injury”, Spine, January 1991.

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

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.

Case, Anne, and Angus Deaton. 2015. "Rising Morbidity and Mortality in Midlife Among White Non-Hispanic Americans in the 21St Century." *Proceedings of the National Academy of Sciences*, 1-6.

Case, Anne, and Christina Paxson. 2008. "Stature and Status: Height, Ability, and Labor Market Outcomes". Journal of Political Economy 116 (3), 499-532.

Campolieti, Michele, and Douglas E. Hyatt, 2006, "Further Evidence on the 'Monday Effect' in Workers' Compensation", Industrial and Labor Relations Review 59 (3), 438-450.

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, 2015. "Import competition and mental distress: The hidden cost of globalization", mimeo.

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.

Dahl, Michael S. 2011, "Organizational Change and Employee Stress", Management Science 57 (2), pp. 240-256.

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.

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.

Freeman, Richard, Douglas Kruse, and Joseph Blasi 2008. "Worker Responses To Shirking Under Shared Capitalism"   NBER Working Paper No. 14227.

Goldberg, Pinelopi K., and Nina Pavcnik. 2007. "Distributional Effects of Globalization in Developing Countries." *Journal of Economic Literature* 45(1), 39-82.

Harkness, Elaine F., Gary J. Macfarlane, Elizabeth Nahit, Alan J. Silman, and John McBeth, 2004, "Mechanical injury and psychosocial factors in the work place predict the onset of widespread body pain: a two-year prospective study among cohorts of newly employed workers", Arthritis & Rheumatism 50(5), 1655-1664.

Harrison, Ann, John McLaren and Margaret S. McMillan. 2011. "Recent Findings on Trade and Inequality". Annual Review of Economics 3, pp. 261-289.

Henrekson, Magnus, and Mats Persson, 2004, "The Effects on Sick Leave of Changes in the Sickness Insurance System", Journal of Labor Economics 22(1), 87-113.

Hesselius, P., J. P. Nilsson and P. Johansson 2009. "Sick Of Your Colleagues' Absence?" Journal of the European Economic Association 7(2-3): 583-594.

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, D., J. Munch, and C. Xiang. 2016. "Offshoring and Labor Markets", NBER working paper 22041.

Ichino, A. and G. Maggi 2000. "Work environment and individual background: Explaining regional shirking differentials in a large Italian firm." Quarterly Journal of Economics 115(3): 1057-1090.

Ichino, A. and E. Moretti (2009), "Biological Gender Differences, Absenteeism, and the Earnings Gap", American Economic Journal: Applied Economics 1:1, 183-218.

Jones, Charles, 2016, "Life and Growth", Journal of Political Economy 124(2), pp. 539-578.

Kivimäki, M., J. Head, J. E. Ferrie, H. Hemingway, M. J. Shipley, J. Vahtera, M. G. Marmot, 2005, "Working while ill as a risk factor for serious coronary events: the Whitehall II study", American Journal of Public Health, 95(1), 98-102.

Kivimäki, M., & Kawachi, I. 2015. Work Stress as a Risk Factor for Cardiovascular Disease. *Current cardiology reports*, *17*(9), 1-9.

Lazear, E. P. 2000. "Performance pay and productivity." American Economic Review 90(5): 1346-1361.

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

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, 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

Marmot, M. G., H. Bosma, H. Hemingway, E. Brunner and S. Stansfeld, 1997, "Contribution of Job Control and Other Risk Factors to Social Variations in Coronary Heart Disease Incidence", Lancet 350 (235-239).

Mas, A. and E. Moretti 2009. "Peers at Work." American Economic Review 99(1): 112-145.

McManus, T. C. and G. Schaur, 2015, "The Effects of Import Competition on Worker Health", mimeo, University of Tennessee.

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.

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.

Roger VL, Go AS, Lloyd-Jones DM, Benjamin EJ, Berry JD, Borden WB, et al. 2012, Heart disease and stroke statistics—2012 update: a report from the American Heart Association. *Circulation*. 125(1): e2–220.

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. 2013, "Recessions, Healthy No More?" NBER working paper 19287.

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

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.

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.

Verhoogen, Eric. 2008. "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector." *Quarterly Journal of Economics*, 123(2), 489-530.

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.

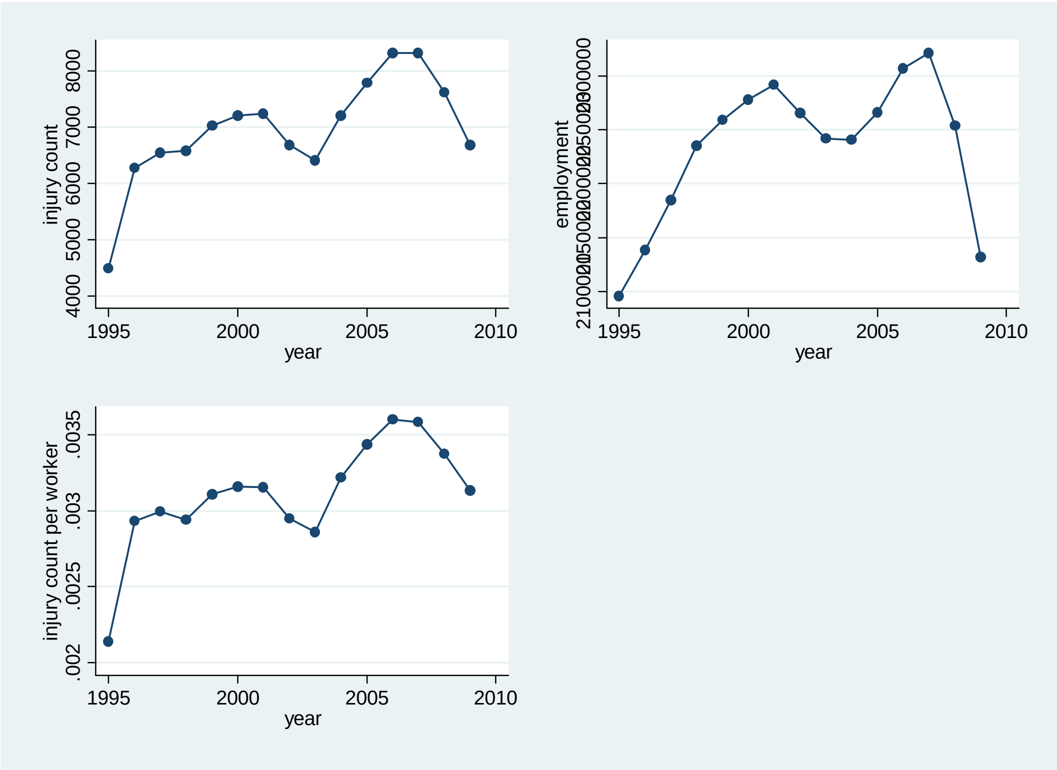

Figure 1 Total Injury Count, Employment, and Injury Rate for Denmark

Table 1 Summary Statistics

	All			Men			Women		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Injury Dummy	1955728	0.0039	0.0623	1306140	0.0043	0.0652	649588	0.0032	0.0561
Injury Payment (DKK)	1955728	1503.38	50173.68	1306140	1628.99	53628.04	649588	1250.81	42383.08
log (Hourly wage)	1955728	5.1925	0.3078	1306140	5.2517	0.3072	649588	5.0736	0.2728
Married (Dummy)	1955728	0.5862	0.4925	1306140	0.5763	0.4941	649588	0.6060	0.4886
Experience	1955728	17.8630	9.3083	1306140	18.9650	9.5341	649588	15.6473	8.4106
Union (Dummy)	1955728	0.8751	0.3307	1306140	0.8796	0.3255	649588	0.8660	0.3406
Overtime Hours (count)	1161807	50.6229	116.5142	771167	62.7186	130.3582	390640	26.7447	77.2639
Total Hours (count)	1163794	1532.60	365.04	772731	1568.46	364.86	391063	1461.73	354.90
Major Sick Days (count)	1955728	6.1147	30.6058	1306140	5.0586	27.1323	649588	8.2383	36.5134
Minor Sick Days (count)	1955728	0.2081	2.6386	1306140	0.2244	2.8058	649588	0.1754	2.2650
Anti. Dep. (Dummy)	1955728	0.0294	0.1688	1306140	0.0243	0.1539	649588	0.0395	0.1949
Anti. Dep. Or Psych. (Dummy)	1955728	0.0324	0.1771	1306140	0.0261	0.1594	649588	0.0452	0.2077
Drugs: sleep disorder (Dummy)	1955728	0.0232	0.1504	1306140	0.0202	0.1407	649588	0.0291	0.1680
Drugs: heart disease (Dummy)	1955728	0.0057	0.0752	1306140	0.0069	0.0826	649588	0.0033	0.0576
Drugs: heart attack or stroke (Dummy)	1955728	0.0170	0.1292	1306140	0.0205	0.1416	649588	0.0100	0.0995
Hospitalization: sleep disorder (Dummy)	1955728	0.0006	0.0239	1306140	0.0008	0.0279	649588	0.0002	0.0127
Hospitalization: poisoning, self-harm or assault (Dummy)	1955728	0.0015	0.0382	1306140	0.0019	0.0433	649588	0.0006	0.0252
Hospitalization: heart attack or stroke (Dummy)	1955728	0.0006	0.0243	1306140	0.0005	0.0229	649588	0.0007	0.0271
Export/Sales	1955728	0.6592	4.2406	1306140	0.6499	4.4249	649588	0.6779	3.8432

Table 2 Correlation between log(Output/Worker) and log(Export)

VARIABLES	(1)	(2)	(3)	(4)
log export	0.033***	0.018***		
	[130.86]	[76.10]		
Exp. 2q			0.033***	0.019***
			[56.52]	[35.63]
Exp. 3q			0.052***	0.022***
			[91.37]	[40.47]
Exp. 4q			0.099***	0.058***
			[184.12]	[115.53]
Year Fixed Effects	No	Yes	No	Yes
Observations	2,244,373	2,244,373	2,244,373	2,244,373
R-squared	0.0076	0.1550	0.0158	0.1579

Notes: t-statistics are in square brackets. 2q = 2^{nd} quartile, etc. The dependent variable is log(output per worker). All specifications are frequency-weighted by firm size, or employment in the first year when the firm is observed, and include firm fixed effects.

Table 3 Severe Depression

	Anti Depressant (Dummy)		Anti. Dep. Or Psych. Visit (Dummy)	
	(1)	(2)	(3)	(4)
	FE	FE-IV	FE	FE-IV
Log exports	-0.0006***	-0.0049**	-0.0007***	-0.0055**
	[-3.40]	[-2.08]	[-3.49]	[-2.19]
Log exports x female	0.0012***	0.0148***	0.0014***	0.0157***
	[2.77]	[3.87]	[2.94]	[3.90]
Log offshoring	-0.0001	-0.0032*	-0.0001	-0.0040**
	[-0.95]	[-1.91]	[-0.86]	[-2.25]
Log offshoring x female	0.0009***	0.0116***	0.0009***	0.0145***
	[3.57]	[5.10]	[3.17]	[6.09]
Log employment	0.0031***	0.0029	0.0031***	0.0030
	[4.82]	[0.94]	[4.49]	[0.91]
Log capital-labor ratio	-0.0001	-0.0003	-0.0003	-0.0006*
	[-0.24]	[-1.17]	[-0.85]	[-1.89]
Share, high-skilled workers	0.0069	0.0054	0.0074	0.0054
	[1.41]	[1.01]	[1.44]	[0.96]
Exp. 5-20 years	0.0017***	0.0014**	0.0032***	0.0028***
	[3.16]	[2.56]	[5.27]	[4.62]
Exp. 20+ years	0.0015**	0.0012	0.0030***	0.0025***
	[2.07]	[1.55]	[3.74]	[3.15]
Union	0.0006	0.0010**	0.0002	0.0007
	[1.17]	[1.97]	[0.40]	[1.26]
Married	-0.0051***	-0.0049***	-0.0064***	-0.0062***
	[-10.07]	[-9.74]	[-11.25]	[-10.91]
Observations	1,955,728	1,955,728	1,955,728	1,955,728
R2	0.0073	0.0075	0.0073	0.0075
Number of job spell fixed effects	387,788	387,788	387,788	387,788

Notes: Clustered (firm-by-year) t-statistics in square brackets.

Table 4 Other Sickness Conditions

Prescription Drugs for	(1)	(2)	(3)	(4)	(5)	(6)
	Sleep Disorder FE	Sleep Disorder FE-IV	Heart Disease FE	Heart Disease FE-IV	Heart Attack or Stroke FE	Heart Attack or Stroke FE-IV
Log exports	-0.0001	-0.0014	0.0002	0.0003	-0.0000	-0.0012
	[-0.52]	[-0.68]	[1.57]	[0.26]	[-0.00]	[-0.68]
Log exports x female	**0.0005***	0.0005	-0.0000	0.0009	-0.0002	**0.0089*****
	[1.85]	[0.16]	[-0.30]	[0.75]	[-0.84]	**[3.51]**
Observations	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728
R2	0.0017	0.0018	0.0011	0.0012	0.0138	0.0142
Number of job spell fixed effects	387,788	387,788	387,788	387,788	387,788	387,788

Hospitalization Due to						
	Sleep Disorder FE	Sleep Disorder FE-IV	Poisoning, Self-Harm or Assault FE	Poisoning, Self-Harm or Assault FE-IV	Heart Attack or Stroke FE	Heart Attack or Stroke FE-IV
Log exports	0.0000	0.0003	0.0000	-0.0003	0.0000	-0.0002
	[0.30]	[0.59]	[0.83]	[-0.81]	[0.15]	[-0.34]
Log exports x female	-0.0000	0.0003	-0.0001	-0.0006	-0.0000	**0.0013***
	[-0.11]	[0.81]	[-1.25]	[-1.10]	[-0.48]	**[1.90]**
Observations	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728
R2	0.0002	0.0002	0.0001	0.0001	0.0004	0.0004
Number of job spell fixed effects	387,788	387,788	387,788	387,788	387,788	387,788

Notes: Clustered (firm-by-year) t-statistics in square brackets. The ATC codes for the prescription drugs and the ICD-10 codes for the hospitalization diagnoses are in the Appendix.

Table 5 Job Injury

	Dep. Var = Injury Dummy			
	FE	FE-IV	FE	FE-IV
Log exports	0.0004***	0.0020*		
	[4.09]	[1.71]		
Log exports x female	-0.0001	-0.0017		
	[-0.71]	[-1.42]		
Exp.2q x male			-0.0004*	0.0003
			[-1.77]	[1.55]
Exp. 2q x female			-0.0002	0.0005**
			[-0.85]	[2.05]
Exp. 3q x male			0.0002	0.0005**
			[1.27]	[2.52]
Exp. 3q x female			0.0003	0.0006***
			[1.28]	[2.61]
Exp. 4q x male			0.0006***	0.0011***
			[3.41]	[4.34]
Exp. 4q x female			0.0004**	0.0011***
			[2.21]	[4.06]
Log offshoring	-0.0001	0.0022**	-0.0001	0.0023***
	[-0.94]	[2.56]	[-0.72]	[2.94]
Log offshoring x female	-0.0001	0.0008	-0.0001	-0.0001
	[-0.75]	[0.84]	[-0.89]	[-0.20]
Log employment	-0.0004	-0.0036**	-0.0006**	-0.0036***
	[-1.61]	[-2.44]	[-2.17]	[-4.20]
Log capital-labor ratio	0.0004**	0.0003*	0.0003**	0.0003*
	[2.45]	[1.88]	[2.33]	[1.92]
Share, high-skilled workers	-0.0060***	-0.0044*	-0.0060***	-0.0045**
	[-3.20]	[-1.94]	[-3.25]	[-2.35]
Exp. 5-20 years	0.0010***	0.0010***	0.0010***	0.0010***
	[4.35]	[4.30]	[4.33]	[4.26]
Exp. 20+ years	0.0008**	0.0008**	0.0008**	0.0008**
	[2.50]	[2.41]	[2.49]	[2.41]
Union	0.0001	0.0001	0.0001	0.0001
	[0.53]	[0.43]	[0.50]	[0.52]
Married	-0.0002	-0.0002	-0.0002	-0.0002
	[-0.94]	[-1.02]	[-0.93]	[-1.01]
Observations	1,955,728	1,955,728	1,955,728	1,955,728
R2	0.0006	0.0006	387,788	0.0006
Number of job spell fixed effects	387,788	387,788	0.0006	387,788

Notes: Clustered (firm-by-year) t-statistics in square brackets. 2q = 2nd quartile, etc.

Table 6 Extensive and Intensive Margins of Efforts

	Dep. Var. = log (Tot. Hours)				Dep. Var. = Injury/Tot. Hours
	FE	FE-IV	FE	FE-IV	FE-IV
Log exports	-0.0072	-0.0071			
	[-1.14]	[-0.08]			
Log exports x female	0.0112*	0.1159*			
	[1.73]	[1.95]			
Exp.2q x male			0.0266***	0.0220***	0.000328
			[3.24]	[3.02]	[0.68]
Exp. 2q x female			0.0386***	0.0388***	0.000170
			[5.30]	[5.57]	[0.46]
Exp. 3q x male			0.0327***	0.0311***	0.000441
			[3.95]	[3.57]	[0.86]
Exp. 3q x female			0.0508***	0.0389***	0.000010
			[6.49]	[4.61]	[0.02]
Exp. 4q x male			0.0009	-0.0042	0.001622**
			[0.08]	[-0.32]	[2.04]
Exp. 4q x female			0.0091	0.0142	0.000788
			[1.03]	[1.39]	[1.43]
Log offshoring	0.0081***	0.0270	0.0069**	0.0263	0.000870
	[2.67]	[0.74]	[2.29]	[0.72]	[0.47]
Log offshoring x female	-0.0031	-0.0757***	-0.0023	-0.0367**	0.002720**
	[-0.77]	[-2.71]	[-0.58]	[-2.32]	[2.08]
Log employment	0.1015***	0.0799	0.0963***	0.0869**	0.001343***
	[4.97]	[1.32]	[4.46]	[1.97]	[2.62]
Log capital-labor ratio	0.0013	0.0019	0.0004	0.0020	0.001420**
	[0.23]	[0.32]	[0.07]	[0.35]	[1.99]
Share, high-skilled workers	0.1533	0.1899	0.1367	0.1729	0.002045
	[1.35]	[1.09]	[1.21]	[1.31]	[1.41]
Exp. 5-20 years	0.0986***	0.0997***	0.0968***	0.0981***	-0.000330
	[24.95]	[25.43]	[24.89]	[24.78]	[-0.50]
Exp. 20+ years	0.0906***	0.0920***	0.0890***	0.0905***	-0.005133**
	[23.17]	[23.89]	[22.99]	[23.08]	[-2.32]
Union	0.0020	0.0026	0.0020	0.0017	0.000331
	[0.56]	[0.72]	[0.58]	[0.49]	[1.15]
Married	0.0070***	0.0067***	0.0065***	0.0067***	0.003271
	[3.14]	[3.04]	[2.94]	[2.97]	[0.56]
Observations	1,161,807	1,161,807	1,161,807	1,161,807	1,161,807
R2	0.0267	0.0265	0.0284	0.0279	0.0006
Number of job spell fixed effects	321,863	321,863	321,863	321,863	321,863

Notes: Clustered (firm-by-year) t-statistics in square brackets. 2q = 2nd quartile, etc.

Table 7 Minor Sick-Leave Days

	Dep. Var. = #. Minor Sick-Leave Days			
	FE	FE-IV	FE	FE-IV
Log exports	0.0021	0.0316		
	[0.63]	[0.68]		
Log exports x female	-0.0054	-0.0282		
	[-1.03]	[-0.59]		
Exp.2q x male			-0.0159**	-0.0179**
			[-2.18]	[-2.11]
Exp. 2q x female			-0.0136	-0.0189*
			[-1.51]	[-1.93]
Exp. 3q x male			-0.0306***	-0.0482***
			[-4.08]	[-5.47]
Exp. 3q x female			-0.0140	-0.0229**
			[-1.59]	[-2.18]
Exp. 4q x male			-0.0012	-0.0128
			[-0.18]	[-1.25]
Exp. 4q x female			-0.0063	-0.0180
			[-0.81]	[-1.57]
Log offshoring	-0.0027	0.0087	-0.0022	-0.0012
	[-0.94]	[0.27]	[-0.76]	[-0.04]
Log offshoring x female	0.0105**	0.0725**	0.0099**	0.0578***
	[2.46]	[2.24]	[2.31]	[2.67]
Log employment	-0.0260**	-0.0735	-0.0223*	-0.0192
	[-2.26]	[-1.40]	[-1.88]	[-0.58]
Log capital-labor ratio	-0.0031	-0.0044	-0.0026	-0.0046
	[-0.61]	[-0.85]	[-0.51]	[-0.89]
Share, high-skilled workers	-0.0505	-0.0271	-0.0385	-0.0697
	[-0.64]	[-0.31]	[-0.49]	[-0.89]
Exp. 5-20 years	-0.0706***	-0.0717***	-0.0699***	-0.0705***
	[-5.88]	[-5.96]	[-5.83]	[-5.87]
Exp. 20+ years	-0.0478***	-0.0493***	-0.0470***	-0.0482***
	[-3.03]	[-3.12]	[-2.98]	[-3.05]
Union	0.0018	0.0027	0.0017	0.0017
	[0.19]	[0.30]	[0.18]	[0.19]
Married	-0.0266***	-0.0264***	-0.0265***	-0.0259***
	[-2.79]	[-2.76]	[-2.78]	[-2.71]
Observations	1,955,728	1,955,728	1,955,728	1,955,728
R2	0.0002	0.0002	0.0002	0.0002
Number of job spell fixed effects	387,788	387,788	387,788	387,788

Notes: Clustered (firm-by-year) t-statistics in square brackets. 2q = 2nd quartile, etc.

Table 8 Major Sick-Leave Days

	Dep. Var. = #. Major Sick-Leave Days			
	FE	FE-IV	FE	FE-IV
Log exports	-0.0175	-2.2137***		
	[-0.31]	[-3.18]		
Log exports x female	0.5403***	0.0910		
	[4.59]	[0.10]		
Exp.2q x male			-1.0472***	-0.7396***
			[-6.79]	[-6.23]
Exp. 2q x female			-1.3747***	-0.5185***
			[-7.08]	[-2.75]
Exp. 3q x male			-0.6644***	-0.4284***
			[-5.85]	[-3.24]
Exp. 3q x female			-0.6795***	-0.1020
			[-3.71]	[-0.51]
Exp. 4q x male			-0.1329	0.7188***
			[-1.27]	[4.15]
Exp. 4q x female			1.0709***	1.9384***
			[6.61]	[8.93]
Log offshoring	-0.1632***	-1.4407***	-0.1508***	-0.4205
	[-4.76]	[-2.86]	[-4.54]	[-0.90]
Log offshoring x female	0.4570***	6.6662***	0.4057***	5.9006***
	[6.90]	[12.07]	[6.27]	[15.52]
Log employment	-0.4021**	0.8322	-0.5905***	-3.1137***
	[-2.16]	[0.90]	[-2.85]	[-5.54]
Log capital-labor ratio	-0.0995	-0.1993**	-0.0980	-0.1601*
	[-1.17]	[-2.22]	[-1.17]	[-1.75]
Share, high-skilled workers	-2.2972*	-4.5427***	-1.7705	-1.3008
	[-1.79]	[-3.03]	[-1.40]	[-0.99]
Exp. 5-20 years	0.2779**	0.1470	0.2988**	0.1942
	[2.34]	[1.24]	[2.52]	[1.64]
Exp. 20+ years	-0.7941***	-0.9620***	-0.7684***	-0.9032***
	[-5.16]	[-6.26]	[-4.99]	[-5.88]
Union	0.5574***	0.6214***	0.5543***	0.6940***
	[5.38]	[5.91]	[5.34]	[6.63]
Married	-0.9941***	-0.9321***	-0.9801***	-0.9423***
	[-9.98]	[-9.38]	[-9.85]	[-9.48]
Observations	1,955,728	1,955,728	1,955,728	1,955,728
R2	0.0088	0.0092	0.0091	0.0095
Number of job spell fixed effects	387,788	387,788	387,788	387,788

Notes: Clustered (firm-by-year) t-statistics in square brackets. 2q = 2nd quartile, etc.

Table 9 Welfare Calculation

	Change w.r.t. Exports	Mean Rate	% Change w.r.t. Exports	Share Weight, %	Marginal Dis-utility (DKK)
	(1)	(2)	(3) = (1)/(2)	(4)	(5)
Men's Incidences of					
Anti-Depressants	-0.0049	0.0242	-20.21%	0.41%	8906.76
Heart Attacks or Stroke (drugs)	0	0.0204	0.00%	0.05%	1365.08
Heart Attacks or Stroke (hospitalization)	0	0.0005	0.00%	1.89%	1903002.16
Injury	0.002	0.0043	46.76%	3.10%	381660.00
Women's Incidences of					
Anti-Depressants	0.0099	0.0395	25.09%	0.41%	4191.33
Heart Attacks or Stroke (drugs)	0.0077	0.0100	77.01%	0.05%	2138.20
Heart Attacks or Stroke (hospitalization)	0.0011	0.0007	150.11%	1.89%	1041921.06
Injury	0.002	0.0031	63.50%	3.10%	397103.00

Notes: The numbers in column (1) are our estimates in Tables 3-5. They are 0 for men's rates of heart attacks or strokes because the coefficient estimates are not statistically significant. The numbers in column (3) are the values for $\frac{\partial \ln d_g}{\partial \psi}$ in equation (15), g = 0, 1, …n. The numbers in column (4) are calculated using Table A5 and they are the values for β_g in (15), g = 0, 1, …n. The values in column (5) are calculated using columns (2), (4) and equation (17).

Table 10 Correlation Coefficients between Main Variables and Their 1-Year Lags

	(2) raw correlation	(3) Job spell demeaned
Log exports	0.9722	0.3737
Anti-depressant	0.5906	0.0851
Anti. Dep. Or Psych. Visits	0.5644	0.068
Drugs: Sleep Disorder	0.4853	-0.0748
Drugs: heart diseases	0.4554	-0.0323
Drugs: Anti-thrombotic	0.7524	0.3245
Hosp.: Sleep disorder	0.1368	-0.1476
Hosp.: poisoning, self-harm or assault	0.0436	-0.2818
Hosp.: heart attacks or strokes	0.1099	-0.1389
Injury	0.0075	-0.251
Minor Sick Days	0.1061	-0.1711
Major Sick Days	0.3044	-0.0577
Total hours	0.3258	-0.2234

Table 11 Results for Robustness Exercises

	Anti. Dep.	Anti. Dep. Or Psych.	Stroke Drug	Stroke Hosp.	Injury	Log. Tot. Hours
1. Continuous Exp.						
Log exports	-0.0039*	-0.0048*	-0.0016	-0.0002	0.0020*	-0.0120
	[-1.70]	[-1.81]	[-0.98]	[-0.33]	[1.80]	[-0.14]
Log exports x female	0.0157***	0.0167***	0.0072***	0.0013*	-0.0017	0.1116*
	[4.25]	[4.29]	[3.14]	[1.85]	[-1.35]	[1.90]
Observations	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728	1,161,807
R-squared	0.0082	0.0081	0.0201	0.0005	0.0006	0.0405
Number of fixed effects	387,788	387,788	387,788	387,788	387,788	321,863
2. Log Dom. Output						
Log exports	-0.0038	-0.0046*	-0.0010	0.0000	0.0021*	-0.0529
	[-1.58]	[-1.74]	[-0.55]	[0.07]	[1.87]	[-0.60]
Log exports x female	0.0115***	0.0123***	0.0074***	0.0012*	-0.0016	0.0845
	[3.06]	[3.13]	[2.89]	[1.65]	[-1.27]	[1.33]
Observations	1,861,512	1,861,512	1,861,512	1,861,512	1,861,512	1,113,834
R-squared	0.0074	0.0073	0.0143	0.0004	0.0006	0.0288
Number of fixed effects	384,154	384,154	384,154	384,154	384,154	317,922
3. 7+ years job spells						
Log exports	-0.0030	-0.0027	-0.0022	-0.0021***	0.0022**	-0.0667
	[-1.11]	[-0.94]	[-0.96]	[-2.75]	[1.98]	[-0.73]
Log exports x female	0.0171***	0.0200***	0.0136***	0.0034***	-0.0020	0.1052*
	[3.36]	[3.72]	[3.76]	[3.23]	[-1.21]	[1.74]
Observations	981,941	981,941	981,941	981,941	981,941	604,158
R-squared	0.0097	0.0098	0.0183	0.0006	0.0006	0.0306
Number of fixed effects	105,603	105,603	105,603	105,603	105,603	101,099
4. 3-year M.A. of WID						
Log exports	-0.0034	-0.0027	-0.0033**	-0.0006	0.0029***	0.0078
	[-1.56]	[-1.16]	[-1.99]	[-0.97]	[3.27]	[0.09]
Log exports x female	0.0090**	0.0096**	0.0142***	0.0015**	-0.0015	0.0993
	[2.34]	[2.37]	[5.67]	[2.16]	[-1.29]	[1.57]
Observations	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728	1,161,807
R-squared	0.0075	0.0074	0.0142	0.0004	0.0006	0.0265
Number of fixed effects	387,788	387,788	387,788	387,788	387,788	321,863

Notes: “Stroke Drug” refers to anti-thrombotic agents. All the results are with IV. Clustered (firm-by-year) t-statistics in square brackets.

Table 11 Results for Robustness Exercises, Continued

	Anti. Dep.	Anti. Dep. Or Psych.	Stroke Drug	Stroke Hosp.	Injury	Log. Tot. Hours
5. Local Labor Market Tightness						
Log exports	-0.0050**	-0.0055**	-0.0009	-0.0006	0.0015	0.0302
	[-2.21]	[-2.26]	[-0.50]	[-0.93]	[1.36]	[0.36]
Log exports x female	0.0147***	0.0156***	0.0088***	0.0015**	-0.0017	0.1429**
	[3.87]	[3.89]	[3.47]	[2.09]	[-1.37]	[2.27]
Log exports x UI Rate	-0.0000	-0.0000	-0.0000	0.0000	-0.000031***	0.0010*
	[-0.16]	[-0.40]	[-0.67]	[0.37]	[-3.25]	[1.93]
Observations	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728	1,161,807
R-squared	0.0075	0.0075	0.0142	0.0004	0.0006	0.0269
Number of fixed effects	387,788	387,788	387,788	387,788	387,788	321,863
6. Physical Strength at Occupation						
Log exports	-0.0099***	-0.0112***	-0.0014	-0.0006	0.0008	-0.0306
	[-3.91]	[-4.08]	[-0.69]	[-0.76]	[0.65]	[-0.35]
Log exports x female	0.0239***	0.0240***	0.0126***	0.0014*	-0.0013	0.1333**
	[5.64]	[5.34]	[4.52]	[1.81]	[-0.92]	[2.24]
Log exports x Physical	0.0107***	0.0105***	0.0066***	0.0005*	0.0019***	0.0231
	[8.01]	[7.29]	[7.19]	[1.70]	[4.95]	[1.20]
Observations	1,590,874	1,590,874	1,590,874	1,590,874	1,590,874	1,036,536
R-squared	0.0072	0.0071	0.0131	0.0004	0.0008	0.0248
Number of fixed effects	381,260	381,260	381,260	381,260	381,260	294,704
7. Mental Strength at Occupation						
Log exports	-0.0073***	-0.0090***	-0.0001	-0.0004	0.0019	-0.0261
	[-3.04]	[-3.44]	[-0.07]	[-0.58]	[1.54]	[-0.32]
Log exports x female	0.0197***	0.0201***	0.0097***	0.0013*	-0.0021	0.1173**
	[4.76]	[4.61]	[3.45]	[1.71]	[-1.53]	[2.17]
Log exports x mental	-0.0065***	-0.0071***	-0.0030***	-0.0004	-0.0023***	-0.0115
	[-5.32]	[-5.50]	[-3.43]	[-1.40]	[-4.88]	[-0.84]
Observations	1,590,874	1,590,874	1,590,874	1,590,874	1,590,874	1,036,536
R-squared	0.0072	0.0071	0.0131	0.0004	0.0008	0.0248
Number of fixed effects	381,260	381,260	381,260	381,260	381,260	294,704
8. Age						
Log exports	-0.0057**	-0.0058**	-0.0223***	-0.0016***	0.0016	0.0168
	[-2.30]	[-2.18]	[-9.16]	[-2.63]	[1.41]	[0.20]
Log exports x female	0.0150***	0.0157***	0.0164***	0.0018**	-0.0016	0.1093*
	[3.92]	[3.90]	[6.54]	[2.49]	[-1.26]	[1.85]
Log exports x Over-40	0.0024	0.0008	0.0624***	0.0040***	0.0011	-0.0539***
	[1.35]	[0.44]	[16.17]	[7.52]	[1.52]	[-2.78]
Observations	1,955,728	1,955,728	1,955,728	1,955,728	1,955,728	1,161,807
R-squared	0.0075	0.0075	0.0158	0.0004	0.0006	0.0265
Number of fixed effects	387,788	387,788	387,788	387,788	387,788	321,863

Notes: “Stroke Drug” refers to anti-thrombotic agents. All the results are with IV. Clustered (firm-by-year) t-statistics in square brackets.