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No Pain, No Gain:

The Effects of Exports on Job Injury and Sickness

David Hummels, Purdue University and NBER

Jakob Munch, University of Copenhagen and IZA

Chong Xiang, Purdue University

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Abstract: We live in a century of globalization and rising expenditures on health, but little rigorous research has been done to understand the impacts of globalization on individuals' health. We combine Danish data on individuals' health with Danish matched worker-firm data to understand how increases in exports by firms affect their employees' job injuries and sickness during 1995-2006. We find that rising exports lead to higher rates of injury and sickness, mainly for women. A 10% exogenous increase in exports increases women's chance of severe job injury by 6.35%, severe depression, 2.51%, using antithrombotic drugs, 7.70%, and hospitalizations due to heart attacks or strokes, 17.44%. Rising exports also lead to higher work efforts by both men and women: less minor sick-leave days and more total hours (regular plus over-time). During the 2007-2009 recession, Danish exports and on-the-job injuries fell significantly. An out-of-sample prediction using our estimates accounts for 12%- 62% of the actual decrease in job injury counts in this period. Finally, we develop a framework to calculate the contemporaneous welfare losses due to higher rates of multiple types of injury and sickness, and show that for the average male and female worker, the welfare loss from the adverse health outcomes is substantial but small relative to the wage gains from rising exports (4.16% for men but 18.83% for women).

1. Introduction

A large literature examines how globalization affects wages and pecuniary welfare; e.g. Feenstra and Hanson (1999), Autor, Dorn and Hanson (2013), and Hummels, Jørgensen, Munch and Xiang (2014), or HJMX 2014. Another large literature examines how individuals' health is shaped by economic conditions; e.g. Marmot et al. (1991), Ruhm (2000), and Sullivan and von Wachter (2009). In this paper we take a small step to bridge the gap between the two literatures by examining how globalization, in particular exports, affects workers' health.

We do so by using Danish administrative data that match the population of Danish workers to the universe of private-sector Danish firms. For each individual we have rich information about work intensity (total hours worked, including over-time) and health outcomes, including on-the-job injuries, number and severity of worker absences due to illness, and utilization of the healthcare system, including prescription drug use, doctor visits and hospitalization. For each firm, we have detailed information on production characteristics and international trade (imports, exports) disaggregated by partner country and product. The comprehensive and panel structure of our Danish data allow us to study effects that occur within job spells, and to avoid the following issue that confounds identification with previous work on health and labor market using U.S. data (e.g. as surveyed in Currie and Madrian 1999). Since Danish health care is free and universal, changes in income or job status do not affect workers' access to health care. We can then attribute changes directly to the work environment itself.

Using these data we can match worker health outcomes to characteristics of the firms and industries in which they work, and to study how exogenous changes in those characteristics affect worker health outcomes. The richness of the data allows us to describe work intensity and access to health care in novel ways. For example, because we see both counts and dates, we can distinguish between workers' "major" and "minor" sick-leave days. Major-leave sick days correspond to time off of work in which workers also access the health care system (seeing a doctor or buying prescription drugs) within a week. Minor sick-leave days correspond to time off work in which workers do not access the health care system. This may represent actual sickness of sufficiently mild severity that health professionals are not required or shirking (e.g. claiming additional vacation time in the guise of a medical event).

Our hypothesis is as follows. Suppose a firm faces an upward sloping labor supply curve (due to, e.g. labor market frictions) and a rise in demand for its products. To respond to this demand shock the firm increases labor quantities, either by hiring more workers or increasing work intensity. Examples of the latter channel include working additional hours, choosing to work rather than to stay home in case of mild sickness, and working at a more rapid pace on the job. If an increase in work intensity leads to increased risk of adverse health outcomes, then we will see a positive relationship between three variables within the firm: rising exports, rising work intensity, and adverse measures of employee health. The reverse may occur during recessions: reductions in exports, work intensity, and adverse health outcomes.

We face a significant identification challenge in taking our hypothesis to the data. Firms may differ in task composition, technology employed, and the strength of work ethic in ways that are correlated with output and with health outcomes. For example, better technology may increase sales and reduce injury risk, but a hard-driving corporate culture may increase sales while increasing injury risk. Similarly, changes in worker health, especially for smaller firms, may significantly reduce worker and firm productivity and firm sales. To address this problem, we rely on shocks to demand arising from exogenous changes in export markets.

The work intensity and health outcome effects of changes in output could in principle be the same regardless of whether they arise from domestic or foreign shocks. However, the output of the firms in our data is highly oriented toward export markets and relying on exports to identify the effects yields several significant benefits. First, within the same industry, otherwise similar firms sell products to different markets. 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. Second, trade-related shocks may be more transient than domestic demand shocks (c.f. the literature on short export durations as in Besedeš and Prusa, 2006). This makes it more likely that firms will respond to a positive foreign demand shock by increasing work intensity rather than hiring additional workers.

In our base regressions, we condition on job-spell fixed effects so that the source of our variation is the change over time within a given worker-firm relationship. 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, 2.51%, using antithrombotic drugs, 7.70%, and hospitalizations due to heart attacks or strokes, 17.44%. These adverse effects on workers' health are likely due to increased efforts/work intensity. Following an export shock, both men and women reduce the numbers of minor sick-leave days but increase total hours (regular hours plus over-time hours), and the elasticity of hours is smaller than the elasticity of injury rates. These results are novel to the literature.

To provide some context for these estimates we perform two exercises. First, our estimates from micro data may provide a new channel through which the reduction in work intensity during economic recessions affects injury. Using our estimates and the actual decrease in exports for Denmark, we predict the fall in job-injury counts due to the fall in exports during the Great Trade Collapse for Denmark. We find that declining output due to exports accounts for 12% - 62% of the actual decrease in job-injury counts in this period. Second, while our injury result captures the "pain" from globalization, our earlier work, HJMX 2014, shows the "gain" from globalization: wage rises in response to exogenous increases in exports. Which is more substantial? The literature that estimates the economic values of better health focuses on reduced mortality and longer life span,[1] and so we develop a framework to calculate the contemporaneous welfare loss due to higher rates of multiple types of injury and sickness. Using this framework we show that the injury-and-sickness pain from rising exports is small but substantial, as compared with the wage gain.

Our work mainly speaks to the following strands of literature. In the trade literature, one line of work examines the effects on wages and/or employment of offshoring (e.g. Feenstra and Hanson 1999), exports (e.g. Verhoogen 2008), import competition (e.g. Autor, Dorn and Hanson 2013), offshoring and exports (e.g. HJMX 2014), and the threat of import competition (e.g. Pierce and Schott 2014).[2] Autor, Dorn, Hanson and Song (2013) and McManus and Schaur (2014) examine, respectively, how U.S. imports from China affect the social-security-disability-insurance (SSDI) take-up rates and injury rates. Another line of work estimates pecuniary welfare gains from trade (e.g. Broda and Weinstein 2006, Arkolakis, Costinot and Rodriguez-Clare 2012). In the health literature,[3] one line of work studies how economic recessions affect mortality rates (e.g. Ruhm 2000, Coile, Levine and McKnight 2014),[4] a second line of work studies the effects of displacement and plant closures on mortality and hospitalization (e.g. Sullivan and von Wachter 2009, Browning and Heinesen 2012),[5] and a third line of work estimates the economic values of better health (see note 1). Relative to the trade literature we explore the non-pecuniary effects of globalization on individual workers' health. Relative to the health literature, we explore a unique set of exogenous trade shocks that change the competitive environment of firms and study the micro channels through which these shocks affect workers' injury and sickness.

In addition, our work is also related to other studies, such as those using similar dependent

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[1] E.g. Murphy and Topel (2003), Becker, Philipson and Soares (2005), and Egan, Mulligan and Philipson (2013). An exception is Finkelstein, Luttmer and Notowidigdo (2013), who estimate the effects of chronic diseases on marginal utility using data on subjective happiness.

[2] For recent surveys see Goldberg and Pavcnik (2007), Harrison, McLaren and McMillan (2011), and Hummels, Munch and Xiang (2014).

[3] For surveys of older work see Currie and Madrian (1999) and Smith (1999).

[4] See also Stevens, Miller, Page and Filipski (2011), Lindo (2013), Tekin, McClellan and Minyard (2013), and Ruhm (2013).

[5] See also Black, Devereaux and Salvanes (2012), Browning, Dano and Heinesen (2006), Eliason and Storie (2007, 2009).

variables. We will bring them up later in the paper (e.g. we discuss the literature that uses sick-leave days in sub-section 2.5). 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 severe depression, heart attacks, strokes, and other stress-related illness. Section 5 shows our results for injury, and section 6 for work efforts. Section 7 calculates the non-pecuniary welfare effects of exports, and Section 8 concludes.

2. Data, Danish Labor Market, and Danish Healthcare System

2.1 Data on Workers, Firms, and Trade, and Danish Labor Market

In previous work (HJMX 2014) we have used Danish[6] administrative data that matches workers to firms and the import and export transactions of those firms. The data 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. This link enables us to study exogenous shocks to each firm's trading environment and how those shocks are translated into changes in firm outcomes (output, employment) as well as labor market outcomes for each worker. We again use this strategy, but augmented to include measures of health outcomes and work intensity for workers. Table 1 shows that Danish firms are very export oriented, which is useful for our identification strategy. Exports as a share of firm sales is 0.66 on averagein our sample.

We have three ways to measure worker health outcomes. One, individual-transactions data on doctor visits, prescriptions and hospitalizations. Two, data on individual's work-related injuries. Three,

[6] 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 (e.g. Botero et al. 2004).

episodes in which individuals miss work due to illness. Each has its advantages and disadvantages. Individual transactions data provide the most comprehensive look at health care utilization. However, utilization may not indicate an adverse health outcome (as in well-patient visits) or it may indicate an adverse health outcome that is unrelated to employment. Work-related injuries are clearly adverse health outcomes related to employment, but are relatively rare. The use of sick leave is much more common, and in many cases represents an adverse health outcome but may or may not be related to employment, and it is possible that workers may "shirk" by falsely claiming illness. We will use each of these in different ways to try and understand the effects of export shocks on worker's health.

2.2 Data on Individual Transactions within the Danish Healthcare System

For this paper 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.[7] These datasets are organized by the same worker identifiers as the data in sub-section 2.1, allowing us to merge them.

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 Anatomical Therapeutic Chemical classification system (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

[7] 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.

(ICD10).

In the literature, a common concern for data on the utilization of medical 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 would be especially serious for care-utilization data for the U.S., since the majority of healthcare in the U.S. is employer-based. For example, an unemployed worker in the U.S. might visit doctors less, not because he/she is healthier, but because he/she has lost access to healthcare. However, 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.[8]

There are two main exceptions to free healthcare in Denmark. Dental care is not covered and a small portion of prescription-drug expenses are borne by the patients. We do not consider dental visits in our data, 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.[9] Given the free and universal nature of the Danish healthcare system, access to healthcare in Denmark is independent of economic shocks to individual workers.[10] Therefore, our data provides us a unique opportunity to study the effects of economic shocks on individual workers' health, because any time a Danish individual interacts with the Danish healthcare system, we observe this interaction and its detailed information in our data.

2.3 Severe Depression and Related Illness

We first consider the following dummies that indicate severe depression: whether an individual has positive expenses on any anti-depressant prescription drug, and whether an individual purchases

[8] There are private hospitals in Denmark which suggests queuing might be an issue for hospitalization. We do not address quality of care issues in this paper.

[9] For all Danish full time workers aged 20-60 during 1995-2009, the median out-of-pocket expense is 404 DKK while the median labor income is 296,379 DKK (1 DKK is about 0.18 USD in this time period).

[10] Even if a worker is unemployed, the unemployment benefits are generous, as discussed in sub-section 2.1.

anti-depressants or visits a psychiatrist.[11] 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. In our main sample, the workers with large manufacturing firms that import and export at some point during 1995-2006,[12] 2.93% of worker-years have positive expenses on anti-depressant drugs, and 3.24% either purchase anti-depressants or visit psychiatrists.[13] Table 1 also shows that women are more likely to have severe depression than men (e.g. 3.95% of women use anti-depressants, vs. 2.43 of men), consistent with medical research.[14]

Medical research also suggests that depression is highly correlated with insomnia, and also correlated with substance abuse and self injury. It is also a risk factor for heart diseases and strokes (e.g. DiMatteo, Lepper and Croghan, 2000). In addition, men and women experience depression differently: women tend to feel sad and guilty while men feel restless and angry.[15] Anger could lead to the "dark side", such as assault (e.g. fighting in the bar). Therefore, we also consider the following dummy variables for prescription drugs and hospitalization, and report their summary statistics in Table 1. Our prescription-drug dummies are: i) hypnotics and sedatives, for sleep disorder (sample mean = 2.32%), ii) cardiac glycosides and other drugs for heart disease (0.6%), and iii) antithrombotic agents,

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[11] 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.

[12] We focus on these workers and firms in order to construct instruments, which we will explain in sub-section 3.4. In Table A1 we show the summary statistics for several variables for the "Full" sample, which consists of all Danish workers aged 20-60 during 1995-2009, and the "Mfg." sample, those with the manufacturing sector. These summary statistics are similar to our main sample.

[13] 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.

[14] e..g. http://www.cdc.gov/mentalhealth/data_stats/depression.htm.

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

which reduce the likelihood of heart attacks and strokes (1.7%).[16] Our hospitalization dummies are: i) sleep disorder (0.06%), ii) poisoning, self-harm or assault (0.15%), and iii) heart attack or strokes (0.06%).[17] Table 1 also shows that women have lower probability to be on drugs for heart attacks, strokes, and other heart diseases, consistent with the medical literature (e.g. Roger et al., 2012).

2.4 Job-Related Injury

When a worker is injured on the job, 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 Danish government.

We observe all the petitions filed during 1995-2009, and the final decision by NBII for each petition. 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. The main injury variable we use is a dummy that equals 1 if worker *i* is injured in year *t*, and the injury is severe enough to warrant positive monetary compensation.[18]

One potential concern with our main 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

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[16] The ATC codes are i) N05C for sleep disorder, ii) C01 for heart disease, and iii) B01 for heart attack and strokes.

[17] The ICD10 codes are i) G47 for sleep disorder, ii) T36-T39, T4, T5, X7, X8, X9 and Y0 for poisoning, self-harm and assault, and iii) I21, I61 and I63 for heart attack or stroke.

[18] 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).

accepted around 51% of all petitions, while during the pre-recession years of 2004-2006, NBII accepted about 48% of all petitions.

Table 1 shows that the mean injury rate is about 4 per thousand in our sample. This injury rate is lower than in the U.S. data, probably because we only include severe injuries while the U.S. data includes all injuries. 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 in our main sample.[19] Men's injury rate is higher than women's (4.3 per thousand vs. 3.2).

Note that in Denmark, workers typically do not exit the labor force after receiving monetary compensation. In our data, most workers stay employed with the same firm after injury. This is different from the U.S., where workers typically exit the labor force upon receiving Social Security Disability Insurance (SSDI).

2.5 Minor and Major Sick-leave Days

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. The reasons for absences are self-reported, which suggests the possibility of shirking, or workers calling in sick when they are not. This kind of variables has been used in the literature before as a measure for shirking/efforts (e.g. Ichino and Maggi 2000, Hesselius et al., 2009). The interpretation is that more sick-leave days are more days of absence from work, and so more shirking, less efforts.[20] Taking full

[19] The mean injury rate and injury compensation in our main sample are very similar to the sample of all manufacturing worker-years, the "Mfg" sample in Table A1.

[20] 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.

advantage of our data we are able to go one step further than the literature, to show exactly what the workers do during their sick-leave spells.

We split the sick-leave variable into two components by cross-checking the exact dates of every sick-leave spell in the sick-leave Register data against the precise dates of every individual's prescription drug purchases and doctor visits. Since our prescription-drug Register and doctor-visit Register data cover the *universe* of these transactions in Denmark, 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. 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.[21]

Table 1 shows that for our main sample, the average is 6.11 per worker per year for major sick-leave days, and 0.21 per worker per year for minor sick-leave days.[22] 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).

2.6 Work Hours

We observe over time hours and total hours (over time plus regular hours) for a sub-sample of our workers from the "Wage Statistics Register". 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 A2 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.

[21] 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.

[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.

Table 1 shows that the mean number of total hours is 1532.6 per year in our main sample. Of these, 50.6 hours are over time. 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.

To summarize, our dataset provides several advantages. First, the data cover the population of Danish workers and firms. Second, we consistently track the actual health utilization of individual workers over time so we control for unobserved worker heterogeneity. Finally, the large number of variables in the data provides rich information, and this helps us to pinpoint the specific channels through which exports affect health, as we explain below.[23]

3. Framework and Specification

3.1 Conceptual Framework

Figure 1 shows our conceptual framework. Firm j faces an upward sloping labor supply curve (e.g. Manning 2011). Its demand for labor is derived from the firm's production function and (domestic plus foreign) demand for firm j's output. The intersection of firm j's labor demand and supply curves determine wage and the quantity of labor supplied to firm j. Suppose an exogenous shock increases firm j's exports so that j's demand for labor increases. It follows that wages rise for firm j (which HJMX 2014 has shown), and that the quantity of labor supplied to the firm also rises (which we will show below). Labor supplied to the firm can increase either through an increase in the number of workers, or an increase in work intensity holding the number of workers constant. Examples of the latter channel include working additional hours, taking fewer minor sick-leave days off, and working at a more rapid pace on the job.

[23] Two very well-known panel datasets with individuals' health information are the Framingham heart sample (e.g. Hubert et al. 1983), and the Whitehall sample (e.g. Bosma et al. 1997, Marmot et al. 1997). These samples are not fully representative of the population: those in the Framingham heart sample are relatively obese, and those in the Whitehall sample British civil servants located in London.

Medical research has shown that working long and extended hours is associated with a wide range of negative health outcomes, including higher blood pressure, higher cortisol level (an indicator for stress), more depression, higher probability of coronary heart disease, strokes, and even death (e.g. Virtanen et al. 2012, O'Reilly and Rosato 2013, Kivimaki and Kawachi 2015).[24] In addition, prolonged squatting and working with hands are associated with widespread body pain (e.g. Harkness et al., 2004).[25] Following this line of work we hypothesize that an increase in work intensity increases the likelihood of injury and sickness. It then follows that a rise in exports should be associated with higher injury and sickness rates. These are our main hypotheses.

On the other hand, offshoring[26] is likely to have ambiguous effects on injury. An exogenous increase in offshoring may either increase or decrease firm j's labor demand, depending on the complementarity between labor and imported inputs, and could also change the task composition within firm j (e.g. firm j could have offshored more hazardous tasks).[27] Therefore, our main focus in this paper is exports, but we also control for offshoring in our estimation.

We face two challenges in taking our hypotheses to the data. First, exports are endogenous. Productive firms may export more and use better technology, which could reduce injury rates. Second, individual workers' work intensity is typically unobservable to researchers. We will follow the instrument-variable strategy of HJMX 2014 to address the endogeneity of exports, and our data allows us to observe over-time hours and numbers of sick-leave days. We spell out the details below.

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[24] 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), and "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).

[25] These studies in the medical literature focus on identifying risk factors and correlation patterns, and do not separate exogenous changes in work intensity from the tendency of certain individuals to work hard and suffer adverse health consequences.

[26] Given previous work (e.g. Autor, Dorn, Hanson and Song 2013) we do not focus on the effects of import competition.

[27] 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.

3.2 Theory

We first formalize the conceptual framework laid out in sub-section 3.1 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.[28] The firm produces output Q using capital, K, materials, M, and labor, the quantity of which depends on employment, L, and effort of individual workers, e. Assume that the firm's production function is continuously differentiable and concave (e.g. Cobb-Douglas, CES), and that individual workers' 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 (Stole and Zwiebel 1996, and Helpman, Itskhoki and Redding 2010, or HIR 2010). The solution of this bargaining process has the firm collecting the fraction $1 - \beta$ of the total surplus, while each individual worker collects the fraction β of total surplus per worker. The parameter β is a constant.[29] We assume that the workers' outside options are 0. The firm's outside option equals the fraction $1 - \theta_f$ of total revenue, ψY.

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[28] E.g. consider the following monopolistic-competition framework. Preferences are CES with substitution elasticity $\sigma > 1$. There is a single foreign market, and the ice-berg trade cost between Denmark and the foreign market is $\tau > 1$. 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 $Y = Q^{\frac{\sigma-1}{\sigma}}$.

[29] 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.

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 $(1 - \beta)[\psi Y - p_M M - rK - (1 - \theta_f)\psi Y] + (1 - \theta_f)\psi Y - b(L)$, where b(L) is search/hiring cost. The optimally chosen employment, L, is the extensive margin for labor quantity. For the rest of the paper we push the firm's problem into the background and focus on the workers' problem.[30]

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

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

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*, which is the intensive margin for labor quantity.

Equation (2) 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 total 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 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.

[30] The firm takes as given individual workers' optimal choices of effort level, which we derive below.

To make the transition from (2) to an estimation equation we add the following specifications for effort cost and revenue per worker:

$$ac(e) = ae^{\eta}, 1 < \eta . \quad (4)$$

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

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.[31]

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

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

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). 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

[31] A special case of (5) is for the production function to be Cobb-Douglas (i.e. $Q = BK^{\delta_K} M^{\delta_M} (eL)^{\delta_L}, \delta_K + \delta_M + \delta_L = 1$), and for preferences to be CES so that revenue is a power function of output (see note 10, where we show that Y = $Q^{\frac{\sigma-1}{\sigma}}$, where σ > 1 is the substitution elasticity).

worker characteristics (e.g. union status).[32] Adding worker, firm and year subscripts to equation (6) we get

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

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

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

In equation (8), $\beta_1 \ln X_{jt} + \beta_2 C_i \ln X_{jt}$ 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 overtime hours, 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-

[32] 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.

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 $\frac{1}{\eta_i - \gamma} \ln F(K_{jt}, M_{jt}, L_{jt})$.

3.3 Empirical Specifications

Motivated by (8), we first estimate the effects of exports on IOS_{ijt}, the injury or sickness status 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

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

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. α_{ij}, α_R, and $\alpha_{IND,j}$ represent job-spell, region and industry-by-time fixed effects. Relative to (8), we have only 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 $\beta_1 + \beta_2$.

Of the variables we have discussed in section 2, we use the following dummy variables for IOS_{ijt}: (1) severe job injuries; (2) severe depression; (3) prescription drugs for, and hospitalizations due to, sleep disorders; (4) prescription drugs for, and hospitalizations due to, heart attacks and strokes; and (5) hospitalizations due to poisoning, self harm or assault. If higher efforts by individual workers 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

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

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). Of the variables we have discussed in section 2, we use the following for WK_{ijt}: (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. However, the export coefficients for minor sick-leave days should 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.

We also use the number of major sick-leave days as our dependent variable. For this variable the interpretation of the estimation results is more subtle, because it could measure both sickness and efforts. Suppose our results suggest that worker i has more major sick-leave days in year t. This clearly 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.[33] On the other hand, suppose worker i reduces his/her major sick-leave days. This likely implies more time at work and so more efforts on the part of worker i. 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.[34] 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

[33] 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.

[34] 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).

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).[35] 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 exporting (see HJMX 2014 for evidence on this point within our sample). Productivity may also co-vary with worker health outcomes for two reasons. Firms may be more productive because they use more modern, and safer, technology that reduces injury rates. This implies a negative correlation between X_{jt} and ε_{ijt}. Alternatively, firms may be more productive in an output-per-worker sense precisely because they have a corporate culture of high work intensity. This implies a positive correlation between X_{jt} and ε_{ijt}. Therefore, ex ante, it is unclear how X_{jt} is correlated with ε_{ijt}. Below we explain how we deal with the endogeneity of export.

3.4 Instrumental Variables

We follow HJMX 2014 and use external shocks to Denmark's trading environment to construct instruments for X_{jt}. First, world import demand WID_{ckt} 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*.

In addition, changes in transport costs capture shocks to the delivered price of particular inputs purchased by Denmark. To get transportation costs we first estimate cost functions using US imports data following Hummels (2007). We 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,

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

tc_{ckt}. The key source of variation is an interaction between distance, modal use, and oil prices. In our sample period real oil prices fell from \$20 to \$11 per barrel between 1995 and 1998, and then rose sharply to \$45 per barrel in 2005. These fuel prices have an especially strong effect on goods air shipped long distances and a very weak effect on goods moved short distances via train. This implies that changes over time in fuel prices affect the level of costs, the relative cost of employing air v. ocean v. land transport and the relative cost of distant versus proximate partners.

The 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).[36] Then to construct a time varying instrument for firm *j* we have $I_{jt} = \sum_{c,k} s_{jck} I_{ckt}$.

The idea behind this strategy 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*, 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*.

Our strategy for instrumenting offshoring is similar. 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

[36] 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.

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*.

To summarize, 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. The use of these instruments implies that we focus on large manufacturing firms that both import and export, as in HJMX 2014. Table 1 shows the summary statistics of the following worker characteristics: 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 A1).

4. Severe Depression and Related Illness

In this section we present the results for severe depression and related illness. Our estimation sample spans 1995-2006 and includes nearly 2 million observations, each being worker-i by firm-j by year-t. We include job-spell fixed effects in the estimation; i.e. we ask, during worker i is employed by firm j, if j changes how much it exports for exogenous reasons, does worker i become more likely to have severe depression? Since our main explanatory variable, export, varies by firm-year, we cluster standard errors by firm-year.

4.1 Severe Depression

Table 2 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,[37] and job pressure is the No. 2 cause of such stress after financial worries, according to a recent Wall-Street-Journal report.[38] This fits well with regression (9), which investigates the contemporaneous effects (i.e. within the same year) of exports. In addition, depression is a mental issue and so closely related to subjective feelings. Exogenous rises in exports raise wages (HJMX 2014) and higher income leads to higher self-rated subjective happiness (e.g. Finkelstein et al, 2013). This additional channel works against our hypothesis that exports tend to increase incidence of severe depression because of increased efforts/work intensity.

In Column 1 of Table 2, 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 coefficient estimate of 0.6 per thousand (precisely estimated, 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 A2 in the Appendix reports the first stage results. They are similar to HJMX 2014.

We report the IV estimates in column 2 of Table 2, 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

[37] 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).

[38] "To Cut Office Stress, Try Butterflies and Medication?", by Sue Shellenbarger, The Wall Street Journal, October 9, 2012.

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. This is consistent with increased subjective feelings of happiness due to higher wages, as we discussed earlier. 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 2 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.[39]

4.2 Depression Related Illness

Table 3 reports our results for stress-related diseases. 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

[39] 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.

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.[40] For each dependent variable we 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 3 that there is no statistically significant result for men. For women, Table 3 shows the following results. First, there is no effect for heart-disease drugs, hospitalizations due to sleep disorder, or those due to poisoning, self-harm or assault. Second, 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. Finally, rising exports lead to higher incidences of antithrombotic agents (significant), as well as hospitalizations due to heart attacks or strokes (marginally significant). These results suggest that rising exports increases the incidences of heart attacks and strokes for women, but not for men. This pattern is consistent with our findings in Table 2.

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).

5. Job Injury

5.1 The Effects of Exports on Injury

We report our results in Table 4. The dependent variable equals 1 if worker i, employed by firm j, gets injured in year t, and 0 otherwise. Column 1 reports the OLS estimate. The coefficient for log

[40] The other coefficient estimates are available upon request.

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, 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 estimate is four times as large as the OLS estimate, consistent with our earlier discussions (sub-section 3.2) 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 4.1 per thousand in our estimation sample, and the elasticity of injury rate is 2.0/4.1 = 0.488 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.[41] Interacting the export quartile dummies with the two gender dummies, we get 8 dummies with 6 degrees of freedom.[42] 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 4 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 disrete-export-shock variables, 5 are statistically significant under IV. The effects of exports on injury rate are similar for 2nd-quartile

[41] 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.
[42] The four export quartile dummies sum up to the constant and so do the two gender dummies.

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. Finally, Table 4 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, 3rd quartile shocks increase men's injury rate by 0.5 per thousand and women's by 0.6 per thousand, and 4th 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 the total value of Danish export fell by 17%. 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 2 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 0.4-2.0 per thousand when export is a continuous variable.[43] Using this, and the 17% drop in Danish export, we get a predicted reduction in injury rate of 0.068 - 0.34 per thousand, which is 15.1% - 75.6% of the actual reduction in injury rate.

Turning to total injury count, we can predict its levels in 2008 and 2009 in the following way. We hold Danish employment at its 2007 level, and multiply it by our predicted injury rates, which we obtain using our estimated elasticity of 0.4-2.0 per thousand and the actual decline in Danish export in 2008 and 2009 (relative to 2007). Figure 3 plots the actual injury count and the series of predicted injury count. The predicted series tracks the actual data well. The predicted drop in total injury count between 2007 and 2009 is 200-1025 cases, and it accounts for 12%-62.44% of the actual decline of 1641 cases.

In summary, 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. These findings 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. Work Efforts

In sections 4 and 5 we show that exports increase workers' incidence of injury, severe depression, and related illness. 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, even though we do not directly observe the intensive margin in our data.

[43] Our other estimate is 0.36 per thousand when export is a discrete shock exceeding 10% (column 3 of Table 2). It is less clear how this can be used to make predictions.

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 5 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.[44] The coefficient estimates in column 2 suggest that the elasticity of hours is 0.109 (0.1159 – 0.0071), which is substantially lower than the elasticity of employee-based injury rate, 0.488 (see sub-section 5.1). This shows that hours-based injury rate also increases, consistent with increases in work intensity holding hours constant.

Since the coefficient estimate in Column 2 is only marginally significant, 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. At first glance this seems a strike against our hypothesis. We revisit this result at the end of the next sub-section, where we show that this is, in fact, consistent with our hypothesis.

6.2. Minor and Major Sick-Leave Days

Another way to observe changes in workers' efforts in our data 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

[44] We use the total-hours sub-sample for the first-stage IV estimation, and report the results in Table A3. They are similar to our first-stage results for the full sample.

visit doctors nor make new purchases of prescription drugs, a reduction in their number likely reflects 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 6 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 2^{nd}-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 3^{rd}-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 3^{rd}-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 4^{th}-quartile export shocks have insignificant coefficient estimates. This is reminiscent of our findings in Table 5, and seems puzzling for our hypothesis. We come back to this point below.

We now turn to the number of major sick-leave days. As we discussed earlier (e.g. sub-section 3.3), this variable reflects both sickness and efforts. A reduction in the number of major sick-leave days clearly indicates more efforts, but has ambiguous implications for sickness, as workers may work while sick. Similarly, more major sick-leave days clearly indicate worse health, but have ambiguous implications for efforts, as workers may be too sick to work. Therefore, under our hypothesis, the number of major sick-leave days may either increase or decrease when exports increase.

Table 7 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 5 and 6, 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 5 and 6: as exports increase, workers neither decrease total hours nor increase minor sick-leave days, *despite* having more major sick-leave days. We believe this is evidence that workers have increased efforts.

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 welfare gain that the literature has reported, how large is the pain? In this section we calculate the net effect of exports on individual workers' welfare.

While the framework to calculate the welfare effects of injury and mortality is well-established in the literature (e.g. Viscusi and Aldy 2003), there has been no comparable framework for the welfare effects of non-fatal diseases, such as depression. One approach in the economics literature (the only one we are aware of) requires survey data on subjective happiness (Finkelstein, Luttmer and Notowidigdo 2013). Outside of economics, the DALY (Disability-Adjusted Life Years) approach is used (e.g. Murray and Acharya 1997), where a life year with diseases is converted into disease-free life years using disease-specific discount factors. These discount factors, in turn, 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. Given this status of the literature, we first develop our own computation framework for non-fatal diseases. This framework allows us to aggregate across disease types and injury to calculate the total welfare effect.

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

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

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' 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 welfare gain in response to rising exports due to higher income, and the second term shows the welfare loss due to higher injury and sickness rates.

We observe all the variables in equation (13) that determine the welfare 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, welfare gain amounts to 1465 DKK for men and 1158 DKK for women. Women have lower welfare gains than men because they have lower average wages in our sample.

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

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

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

Equation (14) implies that

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

Equation (15) says that welfare loss is the product of two terms: H, the total welfare 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 $\beta_0 \dots \beta_n$.

We now calculate the welfare 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.[45] 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 8. 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 174.38%, for women's odds to be hospitalized due to heart attacks or strokes. They are largebecause 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 A4 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 8, 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* welfare loss of 1.16% for men and 5.41% 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* welfare 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),

[45] We do not include sleep-disorder drugs because the coefficient estimates are not significant under IV.

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

We observe all the variables on the left hand side of equation (16). $\frac{\partial H}{\partial d_0}$ is the welfare loss the workers suffer in response to an increase in injury rate. Assuming that the injury compensation scheme in Denmark fully compensates the workers for their sufferings after injury, we can measure it using the average injury compensation in our data, 381,660 DKK for men and 397,103 DKK for women.[46] d_0 is the mean injury rate and β_0 the share weight of injury, both of which we have listed in Table 8. Plugging these values into (16), we obtain the total health cost of 52,597.5 DKK for men and 40,296.2 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.

We can now calculate how workers' welfare changes in response to a 10% exogenous increase in exports. For men this is 61.0 DKK (10% x 52597.5 x 1.16%) and for women, 218.0 DKK. 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 4.16% of welfare gain, and for women, 18.83%. In other words, the pain from rising exports, due to more injury and sickness rates, are small, but substantial, relative to the gain due to higher wages. For net welfare change we obtain an estimate of 1404 DKK for men and 940 DKK for women.

There are several caveats for our estimates. First, we may underestimate the total health cost if the Danish government does not fully compensate injured workers, or if total spending on prescription drugs and hospitalization is lower than consumer surplus. In addition, we do not observe leisure in our

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[46] These are roughly \$68699 and \$71479, respectively, and comparable to the estimates of the value of a statistical injury (e.g. Viscusi and Aldy 2003).

data and so have left it out, and our results are for contemporaneous changes in welfare. We leave these questions for future research.

8. Conclusion

In this paper we use matched worker-firm data from Denmark to study how exports affect individual workers' work efforts and health. For each individual in our data we observe his/her every transaction with the Danish healthcare system, and we are able to match his/her health information with detailed data on his/her employers' exposure to global trade. This allows us to base our identification on changes within worker-firm specific matches (i.e. within job spells), and on the 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 by reducing the number of minor sick-leave days and increase total work hours (regular plus over time). They also suffer several adverse health outcomes: 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. Despite the negative health outcomes, rising exports do not necessarily decrease the welfare of the *average* worker if the rates of injury and sickness are low. We develop a framework to calculate the contemporaneous welfare loss due to higher rates of multiple types of injury and sickness. Our calculations show that the welfare losses are small, but substantial, relative to the wage gains from rising exports (4.16% for men but 18.83% for women).

Our results for injury rates, obtained using micro data, could account for a substantial fraction 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. 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.[47] 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."

However, 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.[48] 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, recent years have seen several government policy changes to address this issue. In 2014, the U.S. required its health insurers to cover mental-health care, and Australia launched a week-long TV campaign to encourage open discussions of mental illness. Many employers are also 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. [49] Our results suggest that such endeavor may be especially useful for the female workers whose employers are rapidly expanding in the global market.

[47] See a discussion in, e.g. https://en.wikipedia.org/wiki/Civilization_and_Its_Discontents.

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

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

Appendix

Table A1 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
Injury Payment (DKK)	106698	430571	845591	23238	450467	863345
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 A2 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

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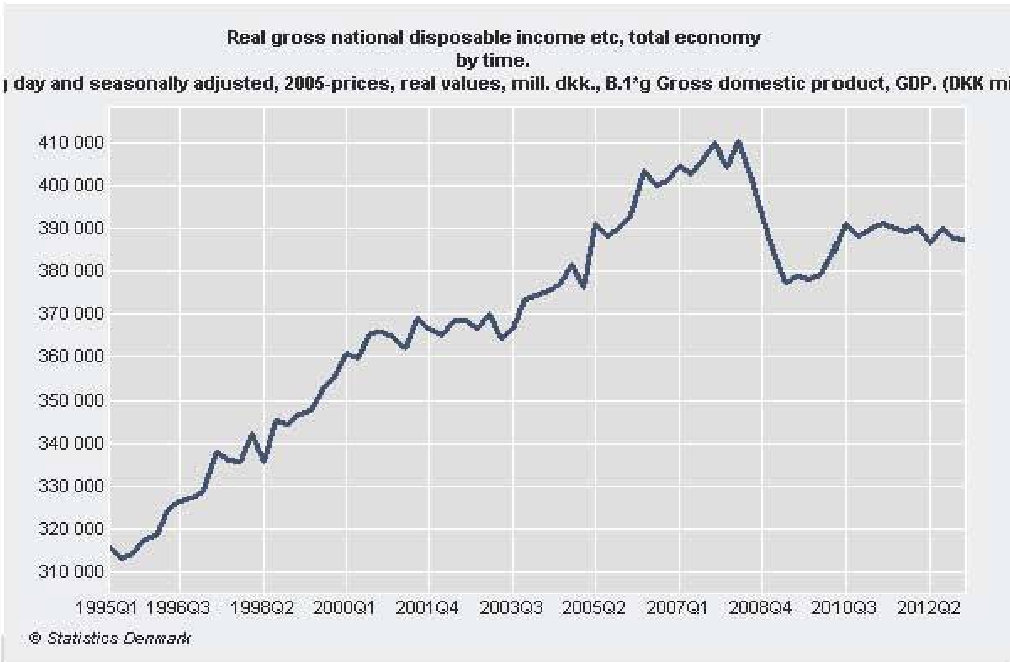

Figure A1 Quarterly GNP (Seasonally Adjusted) of Denmark

Table A3. 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

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

Table A4 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%).

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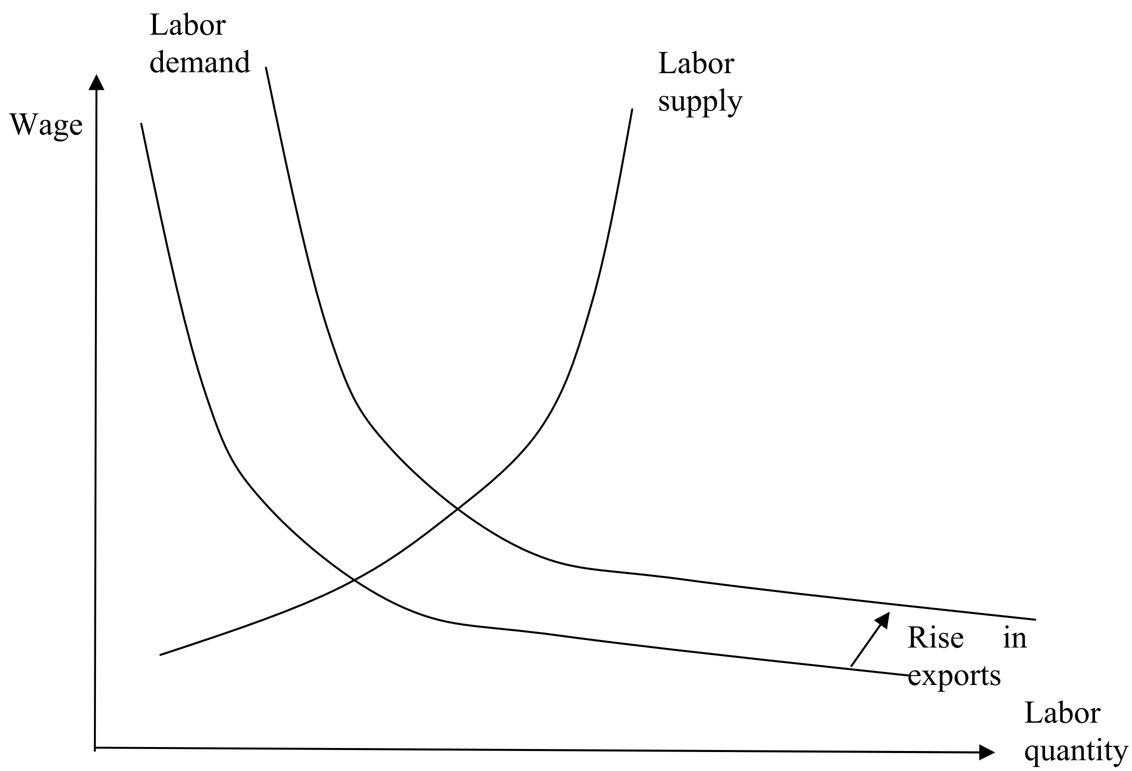

Figure 1 Conceptual Framework

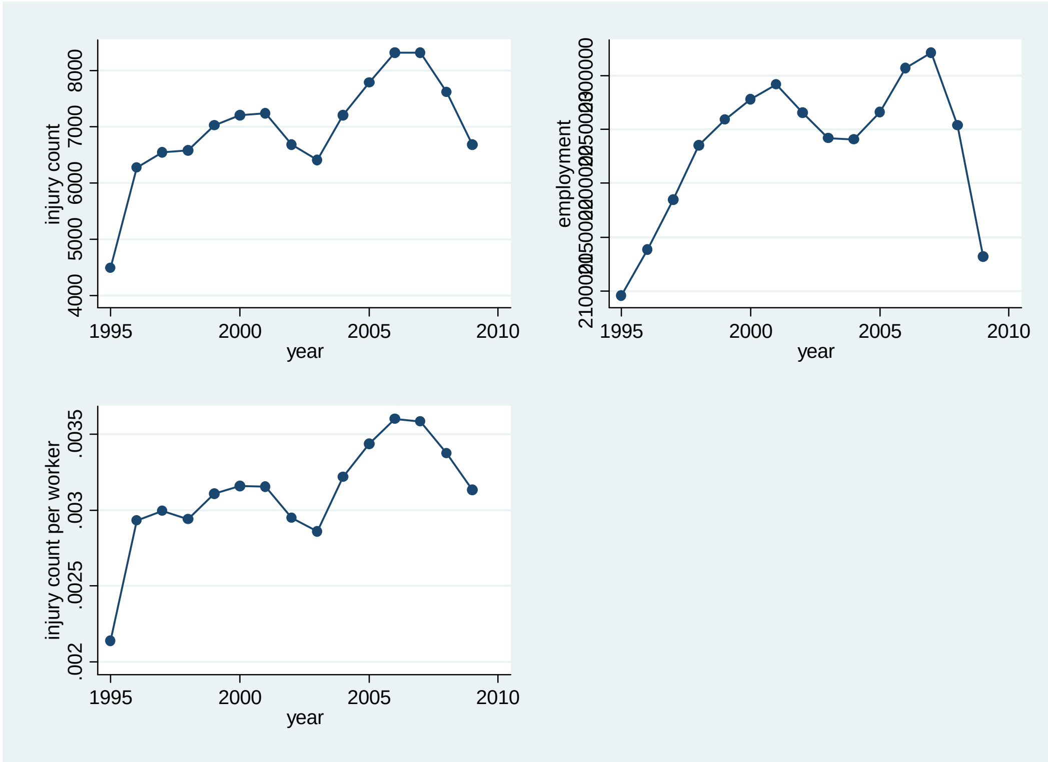

Figure 2 Total Injury Count, Employment, and Injury Rate for Denmark

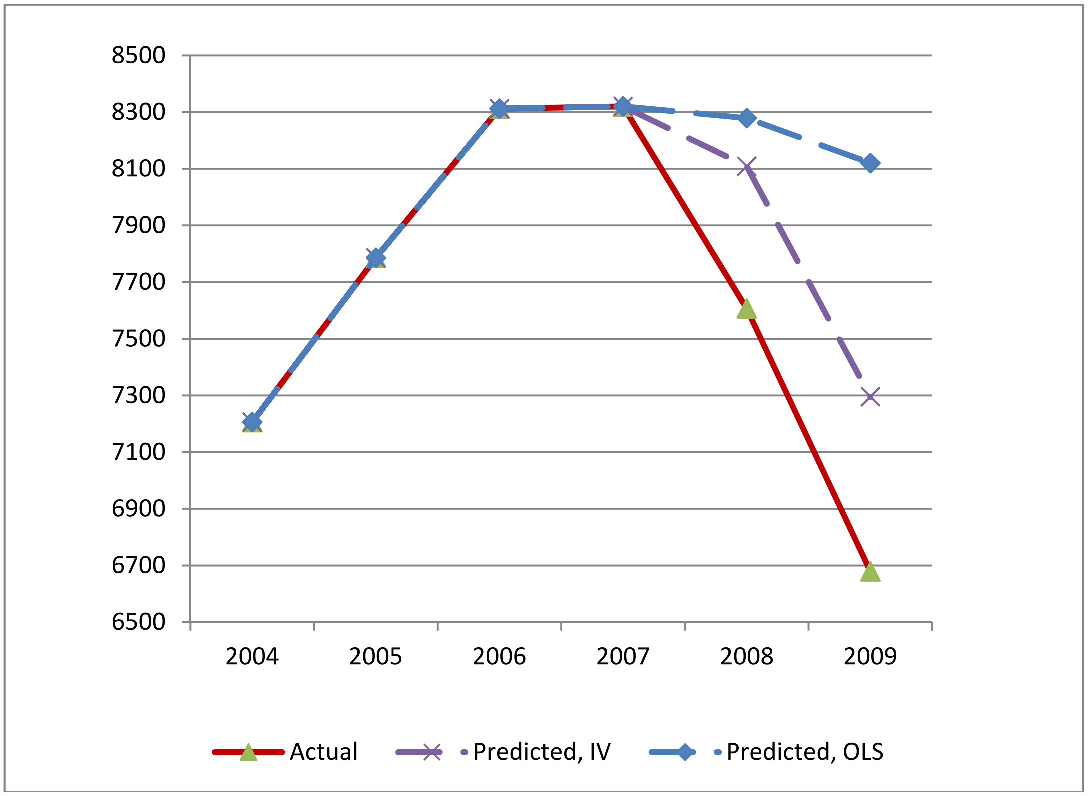

Figure 3 Actual and Predicted Total Injury Counts for Denmar

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

Notes: The summary statistics is for our main sample, which covers the workers with large manufacturing firms in years during 1995-2006 where they both export and import.

Table 2 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 3 Stress-Related Diseases

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 are in footnote 16, and the ICD-10 codes for the hospitalization diagnoses in footnote 17.

Table 4 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 = 2^{nd} quartile, etc.

Table 5 Total Work Hours

	Dep. Var. = log (Tot. Hours)			
	FE	FE-IV	FE	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***
			[3.24]	[3.02]
Exp. 2q x female			0.0386***	0.0388***
			[5.30]	[5.57]
Exp. 3q x male			0.0327***	0.0311***
			[3.95]	[3.57]
Exp. 3q x female			0.0508***	0.0389***
			[6.49]	[4.61]
Exp. 4q x male			0.0009	-0.0042
			[0.08]	[-0.32]
Exp. 4q x female			0.0091	0.0142
			[1.03]	[1.39]
Log offshoring	0.0081***	0.0270	0.0069**	0.0263
	[2.67]	[0.74]	[2.29]	[0.72]
Log offshoring x female	-0.0031	-0.0757***	-0.0023	-0.0367**
	[-0.77]	[-2.71]	[-0.58]	[-2.32]
Log employment	0.1015***	0.0799	0.0963***	0.0869**
	[4.97]	[1.32]	[4.46]	[1.97]
Log capital-labor ratio	0.0013	0.0019	0.0004	0.0020
	[0.23]	[0.32]	[0.07]	[0.35]
Share, high-skilled workers	0.1533	0.1899	0.1367	0.1729
	[1.35]	[1.09]	[1.21]	[1.31]
Exp. 5-20 years	0.0986***	0.0997***	0.0968***	0.0981***
	[24.95]	[25.43]	[24.89]	[24.78]
Exp. 20+ years	0.0906***	0.0920***	0.0890***	0.0905***
	[23.17]	[23.89]	[22.99]	[23.08]
Union	0.0020	0.0026	0.0020	0.0017
	[0.56]	[0.72]	[0.58]	[0.49]
Married	0.0070***	0.0067***	0.0065***	0.0067***
	[3.14]	[3.04]	[2.94]	[2.97]
Observations	1,161,807	1,161,807	1,161,807	1,161,807
R2	0.0267	0.0265	0.0284	0.0279
Number of job spell fixed effects	321,863	321,863	321,863	321,863

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

Table 6 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 7 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 8 Data Used for Welfare Calculation

	Change w.r.t. Exports	Mean Rate	% Change w.r.t. Exports	Share Weight, %
	(1)	(2)	(3) = (1)/(2)	(4)
Men's Incidences of				
Anti-Depressants	-0.0049	0.0242	-20.21%	0.41%
Heart Attacks or Stroke (drugs)	-0.0012	0.0204	-5.87%	0.05%
Heart Attacks or Stroke (hospitalization)	-0.0002	0.0019	-10.70%	1.89%
Injury	0.002	0.0043	46.76%	3.10%
Women's Incidences of				
Anti-Depressants	0.0099	0.0395	25.09%	0.41%
Heart Attacks or Stroke (drugs)	0.0077	0.0100	77.01%	0.05%
Heart Attacks or Stroke (hospitalization)	0.0011	0.0006	174.38%	1.89%
Injury	0.002	0.0031	63.50%	3.10%

Notes: The numbers in column (1) are our estimates in Tables 2-4. 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 A4 and they are the values for β_g in (15), g = 0, 1, …n.