The Health Toll of Import Competition*

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Abstract

This paper assesses the effect of import competition on the health of US workers by exploiting over 52 million individual observations on health and mortality. We first show that import shocks affect employment and income, but only in areas with a high proportion of routine tasks. In those areas, we find that import had a detrimental effect on physical and mental health, worsened health behavior, decreased health care utilisation and increased hospitalisation for a range of conditions. The mortality hazard of workers in manufacturing increased by 3 percent per billion dollar import increase.

Keywords: Import competition; routine tasks; health; health behavior; hospitalisation; mortality.

1 Introduction

Globalisation and in particular increased international trade have profoundly shaped the economies of both the developing and developed world over the last decades. While this process has enabled both the growth of poorer countries and access to cheaper consumer goods in richer ones, many worry that the effects of trade and particularly import competition have been poorly distributed across individuals in developed countries. The economic literature has focused on many aspects of the impact of trade, first on the manufacturing sector, but

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also its wider consequences on wages and employment in all sectors. This line of research has shown that imports in developed countries have led locally to higher unemployment, lower labor force participation and reduced wages. Autor et al. (2013), Autor et al. (2014), Ebenstein et al. (2014) or Autor et al. (2016) exploit the timing of imports from China on US local labor markets affected differently by those imports. The results show that the effect is concentrated on workers in the manufacturing sector, and especially those with low wages and low labor force attachment.

Building on this literature, the goal of our analysis is to provide a detailed picture of the effect of import shocks on health, including mental and physical health, health behavior, access to health care and ultimately mortality. Our empirical analysis draws on multiple and large datasets that record individual health in the United States over the last decades. We exploit data from the Behavioral Risk Factor Surveillance System (BRFSS) to get information on morbidity, interactions (or the lack of) with the health care system and health behavior. We complement this data with hospital records with detailed medical diagnosis to shed further light on the effect of import competition on morbidity, poor health behavior and health care access. Finally, we use longitudinal data following manufacturing workers to investigate the effect on mortality. Our empirical strategy differs with the type of data we analyze. When uncovering the effect of import competition on health, health behavior or hospitalisation, our research design is close to Autor et al. (2013), as we use the industry composition of local labor markets to compute an Import Per Worker measure at the commuting zone level. However, when analyzing the effect of import competition on mortality, we have information on the precise industry in which the respondents are working, which allows us to relate their hazard of death directly to the imports they face as well as detailed individual characteristics including their health when they are first observed.

One important feature of our analysis is the uncovering of heterogeneous effects of import competition. We show that significant declines in employment and income are confined to areas both hit by import competition *and* that had a higher share of industries with routine tasks, a distinction not made in the literature so far. The possibility of replacing humans by machines or robots in a well-defined set of tasks that require no human intelligence seem to have contributed to worsen or accelerate the decline in manufacture jobs due to increasing import competition from China. In areas within the bottom tercile in the distribution of routine tasks, we fail to find a significant effect of import competition on many labor market outcomes, while the effect in the upper third of the distribution is significant and larger by a factor 3 to 5. We also explore the time lag and show that import competition shocks lead to significant labor market effects four to eight years later. Our results therefore complement and extend those of Autor et al. (2013) or Autor et al. (2014). The literature has related routine tasks to offshoring, but has paid less attention to this measure as a mediator in the context of import competition.

We show that the effects of import competition on health are precisely restricted to those areas with industries with a high share of routine tasks. This heterogeneous effect of import competition allows us in effect to rely on a triple difference-in-difference design, using not only time and differential exposure to cheaper imports as in Autor et al. (2013), but also the task content of jobs in the area. The effect of import competition is increasing in the timing of the import shock, and affects both physical and mental health. Moreover, those shocks lead to poorer health behavior as well as less interaction with health care. Interestingly, we find that the magnitude of the effects on health are larger than what the loss of income alone would suggest. A potential consequence of an import shock is the loss of the employer-provided health insurance, which -in the case of the US- is not replaced by public coverage in most cases. This may lead to some health conditions, even those unrelated in the first place to import competition, to go untreated or diagnosed too late. Those results are confirmed when we analyze hospitalisation data. We find that an increase in import competition affects a range of conditions, including physical health (such as heart problems or infectious diseases), health behavior (endocrine diseases and alcohol abuse) or suicides. These effects of import competition are also restricted to areas with high routine tasks.

Finally, we show that increases in import competition have a subsequent effect on mortality. We follow workers in the manufacturing industry, controlling for industry and time specific effects as well as individual characteristics. The results show that a billion dollar increase in imports raise the hazard of dying by about 3 percent after 4 years.

Our results complement a new strand of the literature that has been looking directly at the impact of import competition on workers' health. Hummels et al. (2016) has exploited

Danish employer-employee data combined with individual health data to show how rising exports may lead to increased job effort, and increased productivity and income, but also put workers at increased risk of illness and injury. Closer to our research, a small number of studies have looked at the impact of import competition on workers' health. Colantone et al. (2015) and McManus and Schaur (2016) study the effect of import competition on workers' mental distress in the United Kingdom and on their self-reported mental and physical health in the US and find that an increase in import competition has a detrimental impact on mental distress. This effect goes through job displacement but also through worsening expectations or increased pressure for those whose labor market situation has not been impacted. A contemporaneous work by Pierce and Schott (2016) examines the potential link between trade liberalization and mortality, exploiting a change in U.S. trade policy that increased U.S. counties' exposure to foreign competition differentially via their industry structure. We add to this paper in several ways. We provide a more complete picture of the health mechanisms taking place by looking at a wider range of health outcomes, i.e health measures, health behavior, health care utilization and hospitalization. When looking at mortality, we use a unique dataset consisting in NHIS data linked with individual death certificates. This way, we are able to follow manufacture workers from their entry into the data up to their potential death. Instead of matching them with an import competition shock at the county level, we are able to assign to them the imports from their own specific industry, and see how their variation over time impacts their hazard rate of dying. Another major contribution of our work is to identify a source of heterogeneity in the effect of import competition on health and mortality, as we show that the adverse effects of import competition are consistently concentrated in areas where jobs are more intense in routine tasks.

The rest of the paper is organized as follows. Section 2 reviews the pathways from import competition to health. Section 3 presents the data and shows the effect of import competition on employment and income. Section 4 exploits data on self-assessed health, health behavior and health care utilization. In Section 5, we use data on hospitalization, while in Section 6 we estimate the effect of import competition on mortality. Finally Section 7 concludes.

2 Pathways from Import Competition to Health

As discussed above, the existing literature has shown that increased import competition has potentially contrasted effects. Access to cheaper goods increases purchasing power and acts as an increase in income for those consuming those goods. This effect is presumably diffuse and difficult to measure directly.[1] On the negative side, individuals working in industries that face increased competition from foreign firms have seen a decrease in employment and a loss of income. Both could potentially have an effect on health. The extant literature has analyzed the effect of both job loss or variations in income to identify the effect of economic shocks on health.

A large literature in social medicine has documented the relationship between income and health, emphasizing the role of material deprivation (see for instance Marmot et al. (1991)). In the field of economics, Smith (1999) provides an overview of the many aspects and channels through which income and health could be linked. Lindahl (2005) or Snyder and Evans (2006) use quasi-experimental settings to evaluate the causal pathway between income and health at the individual level and find that higher income leads to better health. Similarly, Lleras-Muney (2005) shows that higher education, possibly as a proxy for permanent income, causes better health. Exploiting firm closures, Martikainen et al. (2007) , Rege et al. (2009) and Sullivan and von Wachter (2009) investigate the mortality pattern of workers who have been laid-off in Finland, Norway and the US. They find a marked increase in mortality, which is consistent with the decrease in income for the individuals who lose their job (Huttunen et al. (2011)). Eliason and Storrie (2009) and Browning and Heinesen (2012) find similar effects using administrative data in Sweden and Denmark. Their data allow them to look at the cause of mortality to infer the mechanism. They find an increased mortality due to suicides, alcohol abuse and circulatory diseases. Schaller and Stevens (2015) investigates the short-run effects of job loss and shows evidence of reduced health care utilization, poor self-assessed health and poor mental health. In contrast, Kuhn et al. (2009) or Black et al. (2015) find little effects of job displacement.

[1] di Giovanni et al. (2014) calculate that mean welfare gain from adding China to world trade is 0.13 percent and about the same for the US. Caliendo et al. (2015) also find an overall positive effect, which is higher in the long-run.

The evidence using aggregate income shocks is more mixed. Ruhm (2000) finds that mortality declines during economic recessions. Similar evidence is found by Adda et al. (2009) using permanent shocks to household income for different birth cohorts. In subsequent work, Ruhm and Black (2002) and Ruhm (2005) show that part of the business cycle effect operates through changes in health behavior, as lower income leads to less alcohol or tobacco consumption, a better diet and more physical exercise (also due to an increase in leisure time). [2] However, more recent evidence points at recessions not being healthy anymore: Ruhm (2015) finds that over the 1976-2010 period, total mortality shifted from strongly procyclical to being weakly or unrelated to macroeconomic conditions, depending on which cause of death is looked at. While cardiovascular diseases and motor accidents are still procyclical, countercyclical patterns have emerged for mortality due to cancer and external causes. Stevens et al. (2015) show that the cyclicality in mortality is mainly due to the cyclicality of health care in nursing homes affecting the death of elderly individuals.

The literature on health behavior has found mixed evidence on the effect of income. While smokers are found to be price sensitive (see the review by Chaloupka and Warner (2000) or DeCicca et al. (2002)), Adda and Cornaglia (2006) find that compensation through a change in smoking intensity off-sets the decrease in the number of cigarettes smoked. That change in behavior can have detrimental effects and lead to more severe lung cancers. Alcohol consumption is generally income sensitive, leading to less drinking when income decreases (Chaloupka et al. (2002), Nelson (2013)). Hence, better health behavior during recessions can partly offset detrimental health effects.

An import shock is akin to an economic recession, but has important differences too, which means that drawing conclusions from that literature may not be warranted. While economic recessions last on average about two years, imports have been steadily rising for decades so this economic shock is far more persistent. This shock is also very specific to an industry, as the amount of imports varies widely even within a 2 or 3 digit industry category. The shock is also more persistent if industry specific human capital plays an important role.[3] In this case, even geographical mobility will not help to evade the shock, as the shock is an

[2] Adda (2016) find evidence of an alternative mechanism in which viral infections are more prevalent during economic expansions.

[3] Artuc et al. (2010) and Dix-Carneiro (2014) estimate important mobility costs between sectors.

aggregate one, albeit industry specific.[4] Finally, economic recessions may hurt a different population than those affected by import shocks. Hoynes et al. (2012) document that the last recession was more hurtful for men, black and Hispanic workers, youth, and low-education workers. The demography of workers in industries competing with imports from low-income countries may be dissimilar, with different health behavior or different health status. Hence, it is unclear how the effect of import competition on health compares to the effect of a recession, or at a more micro-economic level, to the closure of a firm.

Another potential consequence of an import shock -through job loss- is the loss of the employer-provided health insurance, which -in the case of the US- is not replaced by public coverage in most cases (i.e. before the recent implementation of the Affordable Care Act, when workers are not old enough to be covered by Medicare or do not fulfil the Medicaid requirements). Going through an unemployment spell could therefore impact a worker's health not directly through an income loss and the resulting change of behavior, but more subtly through a change in health care utilization. In contrast with his central results on procyclical mortality, Ruhm (2000) finds that preventive care, consisting in routine checkups, pap smears, mammograms, or digital rectal exams, decreases (although often insignificantly) as a result of economic downturns. A hindered access to health care could mean higher odds of dying from a life-threatening disease as a result of two different mechanisms: less screening could lead to some diseases being detected too late -if ever detected; on the other hand, even if an individual is aware of his/her condition, most treatments are not affordable to those non-insured.

Besides physical health, experiencing job-related distress, whether due to high levels of pressure at work, to actual or potential future job loss, or to being unable to find a new job, is likely to trigger or worsen mental health issues. The epidemiology literature has long recognised the role of psychosocial factors on health (Bartley (1994), Brunner (1997)). In the most extreme cases, this can translate into increased mortality due to suicide (in line with Ruhm (2000), Eliason and Storrie (2009) and Browning and Heinesen (2012)). More commonly, job loss has also been found to increase mental disorders (Ruhm (2003)) and the

[4] Autor et al. (2013) and Notowidigdo (2013) show that that low-skilled individuals who would be hit by such economic shocks are rather immobile.

consumption of antidepressants and related drugs, as well as hospitalizations due to mental health problems for men (but not for women) (Kuhn et al. (2009)). The consequences of mental stress go beyond mental health conditions. Deaton et al. (2006) review a number of experiments and analyses concluding that psychological stress is responsible for higher odds of developing a disease, particularly a cardiovascular one[5]. A recent study (see Tawakol et al. (2017) confirmed a causal link between brain stress and heart stress, offering novel insights into the mechanism through which brain stress converts into subsequent cardiovascular disease events, such as heart diseases and strokes. To sum up, this particular literature emphasises the effect of income loss on a varied set of health outcomes, both physical and mental.

3 Data on Trade

3.1 The Import Competition Schock

In the two following analyses, the import shock is defined at the commuting zone level (CZ), i.e. an individual living in CZ c is exposed to a composite shock affecting all industries of the CZ. Following Autor et al. (2013), the Import per Worker (IPW) shock in CZ c at time t is constructed as:

$$IPW_{c,t} = \sum_{j \in Manuf} \frac{L_{c,j,t-10}}{L_{US,j,t-10}} \frac{Import_{j,t}}{L_{c,All,t-10}}, \tag{1}$$

where j is an industry belonging to the set of manufacturing industries $Manuf$. $L_{c,j,t-10}$ is the employment in industry j and commuting zone c, in year $t-10$, while $L_{US,j,t-10}$ is the employment in the same industry j over the whole country in year $t-10$. The greater the share of the CZ in the US employment in industry j (given by the ratio between these two terms in the equation), the greater the shock. The import shock measuring the imports from China in industry j in billion 2009 US$, denoted $Import_{j,t}$, is rescaled by total non-agriculture employment in the commuting zone, hence expressed "per worker".

[5]This argument is sometimes used to explain part of the life expectancy gradient between low-income and high-income individuals: the "low-status" group is more likely to suffer from "psychosocial stress", which leads to a higher probability of death.

Trade data: US imports from China US imports from China are extracted from COMTRADE for the 1991-2011 period, and from Schott's International Economics Resource Page (`http://faculty.som.yale.edu/peterschott/sub_international.htm`) for the 1979-1990 period. Our trade data cover years from 1988 to 2011.[6] We follow the methodology described in Autor et al. (2013) and modify the original crosswalk -from 10-digit HS products to 4-digit SIC industries- so that each of the 4-digit manufacturing industries matches to at least one 6-digit HS code. When the data are already at the 4-digit SIC level, we apply the same changes to the SIC codes. This way, all manufacturing industries will be exposed to competition with Chinese imports, even if sometimes at a very low level. When series are incomplete, which is the case for 53 out of 397 4-digit SIC87 industries, we fill missing values by interpolation, and then proceed to checking the consistency of the interpolation case by case. Most series only miss 1 to 3 years, and missing values seem to be zero - or extremely close to 0- values. All trade values are deflated or inflated to 2009 US$ and expressed in billion US$.

Trade data: Other countries' imports from China In order to tackle potential endogeneity in the impact of imports from China on manufacturing employment and subsequently workers' health, we adopt the same instrumentation strategy as Autor et al. (2013): because the US rising imports from China could be the result of a domestic demand shock in the US rather than an exogenous supply shock in China, we use Chinese imports in 4 other countries[7] to instrument for Chinese imports in the US. This way, we identify the causal

[6]Without the instrumentation strategy described in next paragraph, we could use trade series back to 1979, but data limitations in the trade series of the other countries we use lead to restricting the time period to 1988-2011. Starting in 1995, we will therefore be able to look at the impact of imports form China on several outcomes allowing for up to 7 lags. From 1989 on, imports are measured at the commodity level (6-digit HS). We therefore apply a crosswalk to convert them into 4-digit SIC codes (corresponding to the SIC87 classification of industries). For year 1988, the data are already made available in the SIC87 classification (they were initially in TSUSA, then converted to 4-digit SIC72, and finally 4-digit SIC87).

[7]We chose those countries to be Australia, Finland, Japan, and Switzerland, for two reasons: first, all of those countries are high-income countries that have comparable trade data over the period 1988-2014. Second, we had to exclude Germany (the trade series start in 1991), and Denmark, New Zealand and Spain, whose series start in 1989. Had we included those last 3, our results would be qualitatively unchanged, and

effect of Chinese imports in the US on local labor market outcomes.

The instrumented key variable in most of our regressions can therefore be defined as the same as before, where $Import_{j,t}$ has been regressed on the sum of Chinese imports to the other countries previously mentioned, at the year-industry (4-digit SIC) level, and year and industry fixed effects, yielding the supply-driven component of US imports from China: $\widehat{Import}_{j,t}$ (See results of the first stage regression in Table 4). The resulting instrumented Import per Worker (IPW) shock in CZ c at time t is:

$$IPW\_IV_{c,t} = \sum_{j \in Manuf} \frac{L_{c,j,t-10}}{L_{US,j,t-10}} \frac{\widehat{Import}_{j,t}}{L_{c,All,t-10}}, \tag{2}$$

where j is an industry belonging to the set of manufacturing industries $Manuf$. $L_{c,j,t-10}$ is the employment in industry j and commuting zone c, in year $t-10$, while $L_{US,j,t-10}$ is the employment in the same industry j over the whole country in year $t-10$.

Other commuting-zone level characteristics In order to construct an import shock at the commuting zone level, we need data on the industry composition of each commuting zone, i.e. the number of workers working in each 4-digit SIC industry over the 1985-2011 period (since employment appears with a 10-year lag in the definition of the Import Per Worker shock). We extract this information from the County of Business Patterns (CBP), which is an annual series that provides subnational economic data by industry. It includes the number of employees at the county level during the week of March 12th. Since it has been produced as a consistent, annual series since 1964, we have the information at the industry∗county level for all years between 1979 and 2011.[8] We then aggregate these numbers to the commuting

we would be able to study the lagged effect of Chinese imports up to 6 years instead of 7. Had we included Germany, we would only be able to study 4 lags, we therefore chose to discard it.

[8]The data is available at `http://www.census.gov/econ/cbp/download/` from 1986 onward, and via ICPSR (upon request by a member of ICPSR) before 1986. Industries are coded in 1972 SIC up to 1987, then in 1987 SIC for 1988 to 1997, in NAICS 1997 for 1998-2002, in NAICS 2002 for 2003-2007, in NAICS 2007 for 2008-2011. We construct weighted crosswalks from these classification into 1987 SIC, using the bridges made available by the Census Bureau from NAICS 2007 to NAICS 2002, and from NAICS 2002 to NAICS 1997. For each year with a change of classification, we find the redistribution of employment from the new classification into the old one.) The crosswalk from NAICS 1997 to SIC 1987 was kindly made available by David Dorn. The CBP sometimes reports brackets instead of exact values for employment or number

zone level.

Finally, we compute commuting zone characteristics using the IPUMS Census data for years 1980, 1990, 2000 and the American Community Survey (ACS) for years 2005 and 2010. Years in between (and year 2011) are obtained by interpolating (or extrapolating) the information for those years. The variables computed at the commuting-zone∗year level are the proportions of individuals in the commuting zone who are: male, white, black, belonging to a certain age group, employed, unemployed, not in the labor force, working in manufacture (all CZ-level characteristics are detailed in Table 1). We compute the average equivalized household income (including losses), reported as the total pre-tax money income earned by one's family from all sources for the previous year, divided by the square root of the family size; and the average personal income, reported as each respondent's total pre-tax personal income (including losses) from all sources for the previous year. We also use detailed occupations at the individual level from the census: following Autor and Dorn (2013) we assign to each occupation a routine, manual, and abstract index depending on the content of the tasks defining each occupation (each occupation is assigned a value between 0 and 10 for these three dimensions of task content). We compute the Routine Task Intensity measure for occupation k , defined as $RTI_k = ln(Routine_k) - ln(Manual_k) - ln(Abstract_k)$. The RTI index sums up the likelihood for a job of going through automation, which consists in reducing or eliminating the human labour needed to perform a task, by replacing it by machines. When computing this RTI measure at the commuting-zone level, we consider jobs in the manufacture sector in 1990, so that the average of the RTI measure in a commuting zone reflects the intensity of routine occupations only in the manufacture sector and for year 1990, i.e. when exposure to import competition was still very low over all the US territory.

We divide the US territory into three Routine Task Intensity (RTI) terciles, so that each tercile is made of around 240 commuting zones, as displayed in Figure 3: low, medium, and high RTI (based on the average RTI in manufacture jobs in the commuting zone). Darker shades, mostly present in the Mid-West and more locally in South-East and North-East

of establishments in one of the 9 categories of firm size. We impute employment at the 4-digit SIC∗county level by using the method proposed in Autor et al. (2013) for years 1980, 1990, and 2000, and generalize it to the entire period.

regions of the US, mean that jobs within the manufacture sector are more prone to be subject to automation in those commuting zones, due to their high content in routine tasks and/or their low content in abstract and manual tasks.

Table 2 displays commuting zone characteristics across RTI tercile groups. While the amount of imports per workers increase with the RTI index, demographic and labor-related characteristics are very similar across terciles. Table 3 lists the most important occupations and industries in each tercile of RTI (within manufacture). Although industries and occupations look very similar across the RTI terciles, a higher RTI is associated with higher shares of assemblers of electrical equipment, machine operators, and textile machine operators, and lower shares of managers and administrators. Regarding the industries, textile (apparel and yarn) seems to be more pervasive in the highest tercile of RTI; meat processing and motor vehicles do not appear in the lowest tercile of RTI while printing has a lower prevalence in higher RTI commuting zones.

3.2 Evidence on Employment from the CBP

We first investigate the effect of import competition from China on employment and firms. This analysis helps to understand and interpret the effects of import competition on health and health behavior we present below. In the left panel of Table 5, we look at the impact of the import shock at the industry level (imports from China in 2009 billion US$) on the number of individuals employed, the number of firms, and the number of workers per firm. These data come from the CBP for the period 1995 to 2010 (using 5-year intervals), and are disaggregated at the 4-digit industry level. The number of observations is therefore 1,143,648 (722 commuting zones, 396 SIC4 and 4 years). In the right panel of Table 5, we replicate the work of Autor et al. (2013), for the period that we use in our subsequent analysis. The outcomes (share of working-age population employed, unemployed, not in labor force, in manufacture) are extracted from the IPUMS Census data for years 1995, 2000, 2005 and 2010. The key explanatory variable- i.e. the IPW shock- is computed as explained in Section 3.1 using both CBP and trade data. This analysis is therefore at the commuting-zone*year level (N=2,888, i.e. 722 commuting zones over 4 years.).[9]

Denote Y_{jct} the outcome of interest in an industry j, in commuting zone c and in year t (ignoring the j subscript for columns (4)-(7)). We relate it to a measure of trade- imports from China for the first 3 columns and the IPW measure in the last 4- and we control for time-varying commuting zone characteristics (share of working-age population in the commuting zone who is male, black, white, low educated, and belonging to each age group).

$$Y_{j,c,t} = \alpha_0 + \alpha_1 IPW_{c,t-k} + \alpha_X X_{c,t} + \delta_j + \delta_c + \delta_t + \epsilon_{j,c,t}. \tag{3}$$

All regressions include commuting zones, industry (for the first three columns of Table 5), and year fixed effects. We cluster the standard errors at commuting zone level, to allow for serial correlation and spatial correlation within commuting zones. Both the non-instrumented and the instrumented import competition measures will be used in these regressions.

We first look at the effect of import shocks on the employment of the exposed industry (in the manufacturing sector), at a 4-digit level of aggregation and by commuting zone. Table 5 presents the results, with OLS results in the first panel and IV results in the second one. A 1-billion dollar increase in imports from China in that industry leads to a drop in employment within the industry, with a decline between 4 to about 10 jobs depending on the time lag. Note that the mean of imports from China over the period 1995-2010 equals 0.51 billion, its standard deviation is 1.90 and that the mean number of employed workers in a SIC4-commuting-zone cluster is equal to 55.5. The effect of import competition is increasing with the time lag between the import shock and the outcome. We also find evidence that the number of firms in a given 4-digit industry slightly decreases as a result of import competition. The effect is negative and statistically different from zero, although economically very small. After 6 years, we see a decrease of 0.016 firms (out of a mean of 1.27) in a SIC4-commuting zone cluster. Column (3) presents the number of workers per firm, which is also negatively affected by imports from China. In other words, when exposed to import competition, firms tend to downsize, rather than to close. Our results on the impact of import competition from China on the number of establishments echo the negative association uncovered by Bernard et al. (2006) between plant survival and exposure

[9] We consider the entire US but Hawaii and Alaska in all our analysis because of the many changes of counties over time in those two states.

to trade from low-income countries. The fact that the number of workers by establishment is more impacted than the total number of establishments is in line with Bloom et al. (2015), which found that Chinese import competition had increased TFP and innovation within surviving firms in Europe. In other words, the firms that do not close but are still facing rising imports from China may adjust by increasing their productivity and reducing their workforce.

It is noteworthy that the instrumented and non instrumented regressions yield qualitatively similar results. If anything, the instrumented imports from China seem to have a greater impact on employment and firms than the non-instrumented imports.

The last four columns of Table 5 display the effect of import competition from China at the commuting zone level, looking at the share of people who are employed, unemployed, out of the labor force or in the manufacturing sector. The trade variable is standardised to show the effect of a one standard deviation shock (i.e. of a $2,000 increase in imports per worker[10]). The results show that imports from China decrease the proportion of people working (including non-manufacture employment) but have a negligible (positive) effect on the unemployment rate. Instead, they increase the likelihood of being out of the labor force and decrease that of working in the manufacturing sector. These results are in line with those presented in Autor et al. (2013) but extends them as we allow the import shock to impact local labor markets with several lags, and also look at the impact of imports at the industry level.

There is no reason why the import shock should affect homogeneously the whole territory. If the firms that are hit by Chinese imports react by upgrading their product mix, as shown in Bernard et al. (2006), and by accelerating the automation process within the surviving plants, then production workers are likely to be more affected than non-production workers. This trade-induced skill-biased technological change is at the core of the work by Bloom et al. (2015). Going further, Jaimovich and Siu (2012) show that jobs focusing on routine tasks are more likely to disappear during an economic downturn, and less likely to rebound when the recovery shows up. We therefore expect the impact of the import shock to be more acute

[10] This is for years 1995-2000-2005-2010, where all 722 commuting zones are weighted by their population in 1980 as in the regressions. The two IPW measures have very comparable means and standard deviations.

where jobs are more intense in routine tasks. We estimate the previous equation allowing for heterogeneous effects of the import shock across the US territory, i.e. across high, medium, and low-RTI commuting zones:

$$Y_{j,c,t} = \alpha_0 + \sum_{r \in \{L,M,H\}} \alpha^r_{Import} IPW\_IV_{c,t-k} I_{RTI_c = r} + \alpha_X X_{c,t} + \delta_j + \delta_c + \delta_t + \epsilon_{j,c,t}. \quad (4)$$

All the regressions that follow will use the instrumented trade measure as key explanatory variable. The coefficients of interest are α^r_{Import}, where r indexes the tercile of the routine task index of the area. Table 6 shows that the negative impact of the import shock on local labor markets outcomes is mostly concentrated in the top-RTI-tercile commuting zones, and to a lesser extent in the medium tercile group. A 1 standard deviation increase in the import shock (i.e. a \$2,000 increase in imports per worker) leads to a 1.1 percentage-point drop in the share of individuals employed in high-RTI commuting zones, 2 years after the shock. The magnitude of this effect is similar when allowing for a 6-year lag (a 1.2 percentage-point drop). Medium-RTI commuting zones are also affected, but the point estimates of the effects are lower. The shock has no significant effect in low-RTI commuting zones. Again, import competition does not significantly increase the share of individuals who are unemployed, even though the coefficient is positive and of greater magnitude after 6 years. The (positive) impact of the import shock on the share of individuals out of the labor force is also concentrated on the high-RTI commuting zones, and in the medium tercile commuting zones to a lesser extent. Only the share in manufacturing is negatively affected across all commuting zones as a result of rising imports from China, but again, the impact is of a greater magnitude (more than twice as large) as the average routine content of jobs in manufacturing increases.

Finally, we investigate the effect of import competition on household equivalized income. We focus on the average household income as well as the share of individuals with a family equivalized income less than \$ 15,000 per year, about half the median income. This measure, coming from IPUMS Census, refers to total pre-tax money income earned by one's family, from all sources for the previous year, which we divide by the square root of family size. Our results point at individuals becoming poorer as a result of the import shock, more particularly in areas where RTI is medium or high. In high or medium RTI areas, where the

the drop in income is about 700 dollar on average, it corresponds to a 1.7 percent loss on average. In low RTI areas, import competition has an insignificant effect on income.

The results so far point to a detrimental effect of trade, but with considerable heterogeneity across US commuting zones. If the effect of trade on health operates through a loss of income or through a loss of employer-sponsored health care plan, we expect to see a stark difference in terms of health outcomes across different industries and low and high RTI areas.

4 Impact of Trade on Health and Health Behavior

In this section we investigate the impact of an import shock at the commuting-zone level on many dimensions of individuals' health, health-related behavior, and health care utilization.

4.1 Data

We use data from the BRFSS to characterise the effect of import competition from China on morbidity and health behavior. We use annual cross-sections from 1995 to 2011. After 2011, the data does not record the county of residence. Before 1995, we would not be able to use as many lags as in the previous analysis. Besides, before 1990 the BRFSS contains fewer health variables and survey a small number of individuals. Our sample is made of individuals aged between 18 and 65, who were interviewed at some point between 1995 and 2011. The BRFSS size has increased over time, so that more than 85% of our sample belong to the 2000s. The data on county of residence is used to assign individuals to commuting zones.[11] Using information at commuting zone-year level, we add information on imports per workers.

4.2 Evidence from the BRFSS

Let $Y_{i,c,t}$ be the outcome of interest for individual i in commuting zone c and year t. We denote by $IPW\_IV_{c,t-k}$ the instrumented import per worker quantity at the commuting zone

[11] 649 commuting zones (out of 722) are present in the BRFSS data. Alaska and Hawaii are excluded from all analyses, due to many changes of counties over time in these two states.

level k years prior and by RTI_c the routine task index of the commuting zone, categorized as above into low, medium or high ($\{L, M, H\}$). The model we estimate is written as:

$$Y_{i,c,t} = \alpha_0 + \sum_{r \in \{L,M,H\}} \alpha^r_{Import} IPW\_IV_{c,t-k} I_{RTI_c=r} + \alpha_X X_i + \delta_c + \delta_t + \delta_{s,t} + \epsilon_{i,c,t}. \quad (5)$$

The coefficients of interest are α^r_{Import}, where r indexes the tercile of the routine task index of the area. Comparing the coefficients α^r_{Import} across areas with different task contents is akin to a triple diff-in-diff design, given that we have shown in the previous section that areas with a low share of routine tasks appear to be unaffected by import shocks. Such a research design allows to weaken the traditional diff-in-diff identifying assumption of parallel trends. All the regressions include a commuting zone fixed effect, year dummies, state specific trends and individual characteristics (gender, age, race and education, to be consistent with the aggregate characteristics of the commuting zone used in the previous analysis on employment). We cluster the standard errors at commuting zone level, to allow for serial correlation and spatial correlation within commuting zones.

Given the number of variables in the BRFSS, we start by grouping them in three main categories, a measure of (good) health, of health care utilisation and (good) health behavior. For each of these groups, we extract the main factor using a principal-component factor analysis to construct composite measures. We detail the effect of import competition on any of the original variables we use from the BRFSS below. The composite measure of health is constructed by including self-assessed health, indicators for strokes, diabetes, asthma, a body mass index and an indicator of poor mental health. The measure of health care utilisation is using an indicator for having a health plan, for having had a flushot, the time since last medical checkup and whether a doctor visit was forgone due to its cost. The composite index of health behavior includes smoking, alcohol consumption and exercise.[12] By construction, the composite indices have mean zero and a standard deviation of one.

A first issue is to determine the relevant lag (k) to use. To shed some light, we provide estimates for the coefficients of equation (5), using our three composite indices for lags ranging from 0 to 7 years. The results are displayed in Table 8. From the first years, import

[12]We restricted the number of variables in the principal-component factor analysis due to missing variables, as some variables are not collected each year so that a factor based on all existing variables would have close to no observations.

competition from China appears to have a negative and statistically significant effect on the good health factor. A one standard deviation increase in import per worker leads to changes in the measure of good health by 0.01 of a standard deviation. However, as we increase the lag, this effect increases in magnitude, more particularly for those living in areas with a medium or high share of routine jobs in the manufacturing sector. The effect appears to culminate at lag 6, with a magnitude of about 0.016 standard deviations. We find a similar pattern for health care utilisation, with less access to health care for those in high routine areas. The magnitude of the effect keeps increasing with lags, with a drop of a 0.023 standard deviation in health care utilisation at lag 7. Finally, the last columns of Table 8 show the effect of import competition on health behavior. Although health behavior seem to deteriorate over time in areas with a high share of routine jobs, the coefficient never appears statistically different from zero. We also find a beneficial (but not significant) effect of import competition in terms of health behavior in areas with a low share of routine jobs.

The results for health seem to align rather well with the patterns we uncovered in Section 3.2 in terms of loss of income and jobs as a function of time lag and across areas with different shares of routine jobs. An important question is whether the health effects we find are small or large. To put these results into perspective, we assess whether the health deterioration is comparable to the effect of an income loss of the size shown in Table 6. From our results in Table 6, a one standard deviation in the import shock leads to a reduction of about \$700 in household income in high routine areas, or a decrease of 1.7 percent. We then regress our measures of health on log income and a set of covariates (age, sex, race, education, year and commuting zone effects). We show in the bottom panel of Table 8 that the effect of a unit increase in log income is associated with an improvement of 0.27 of a standard deviation in health. Hence, a 1.7 percent loss in income is associated with a deterioration of about 0.0046 standard deviations. In other terms, we observe a deterioration in health that is larger than what the loss of income would imply, by a factor 3 to 4. Hence, the effect of import competition on health is rather large. There is an abundant literature that shows that there is more to health than income, with a role for status (reviewed in Deaton et al. (2006)) and social isolation for instance (Valtorta et al. (2016)). Another point to stress is that the loss of income we found is very persistent over time. This effect may be anticipated by the individuals affected by the shock and lead to detrimental health effects over and above the pure income effect.

We find that health care utilisation and (good) health behavior are also linked to income. A one percent increase in income improves utilisation and behavior by 0.4 and 0.2 of a standard deviation. Hence the loss of income we see would decrease health care utilisation by up to 0.007 of a standard deviation and health behavior by up to 0.004 standard deviation. Again, we find that the effect of import competition is larger than what the income loss alone would suggest.

A look at Table 9 provides insight into the mechanisms driving the latter results. In that table we display the effect of import per worker (at a four year lag) on each of the individual outcomes we used to calculate the health indices. In terms of the "good health" measure, an increase in IPW leads - in the high RTI areas- to the worsening of self-assessed health, increased blood pressure, more diabetes as well as more days with mental health problems.

Table 9 is also helpful in explaining how health-care utilization is affected by import competition: most likely due to the loss of the employer-provided health insurance following one's layoff, individuals seem to forgo more doctor visits, be less covered by a health plan, receive less flushots, undergo fewer bloodstool test (used as a screening method for colon cancer) in higher routine areas compared with the lower ones. It is noteworthy that even when these effects are not significantly different from zero in the highest tercile of RTI, the difference between the impact of IPW in low and high RTI areas indicate worsening health-care utilization indicators in the latter with respect to the former.

Health behavior, which didn't show up as significant when using the factored indicator, is barely affected when looking separately at its components. Individuals do not change their smoking, eating or exercising habits. If anything, exposure to import competition seems to decrease drinking, both in low and high routine intensity areas. This could be the result of tightening budget constraint as well as of less social drinking. The finding that alcohol consumption is pro-cyclical is in line with the income effect and evidence found in earlier work such as Ruhm (1995), confirmed in Freeman (1999), and again in Ruhm and Black (2002). Given that the main part of our data covers the 2000s, our results are also consistent with Ruhm (2015) that have shown the absence of overall health behavior effects in more recent periods.

Uncovering the health effects of import competition is not straightforward at the commuting zone level, as the data does not allow us to zoom in and observe manufacturing workers. We therefore compute an employment score- more exactly the probability of being working- $EmplScore_i$ and interact it with the Import per Worker shock, focusing on the high-RTI commuting zones. The latter score comes from a regression of an employment dummy variable on gender, race, education and age group dummies in the National Health Interview Survey. We use the coefficients of that regression to compute it at the individual level in our BRFSS sample.[13] The resulting variable is modified so that it lies between 0 and 1, with an average of 0.57 as showed in Table 7, and is closer to 1 for individuals who are more likely to be employed, such as males, whites, the highly educated and middle aged (between 26 and 50). The equation we estimate is

$$Y_{i,c,t} = \alpha_0 + \alpha_1 IPW\_IV_{c,t-k} + \alpha_2 IPW\_IV_{c,t-k} * EmplScore_i + \alpha_X X_i + \alpha_C C_{ct} + \delta_c + \delta_t + \epsilon_{i,c,t} \quad (6)$$

where α_1 is the effect of Import Per Worker for those who have a probability of employment of zero, while α_2 is the additional effect for those with a probability of 1. Table 10 displays the results of this specification in high-RTI commuting zones, where the previous analysis has shown most of the adverse effects of import competition were concentrated.

We expect those who have a high probability of employment/re-employment to be less affected by import competition. We find that those with low employment probability have worse health outcomes when exposed to more IPW. This includes good self-assessed health as seen above, but also high blood pressure, strokes, high cholesterol levels and diabetes. We also find a significant effect on mental health. A one standard deviation change in IPW leads to 0.2 more days with mental health problems in the last month for those with low employment probability. Regarding health behavior outcomes, as before, import competition does not change much individuals' behavior. It is still associated with less drinking but

[13] In other words, $EmplScore = 0.1467 * male - 0.0580 * black - 0.0566 * other + 0.1228 * educ2 + 0.1750 * educ3 + 0.1946 * age2650 + 0.0241 * age5165$, where the reference categories are : $white$ for race, $educ1$, i.e. high school or less, for education, and $age1825$ for age. The same regression could have been estimated using the BRFSS data, but we chose to use the NHIS in order to be consistent with Section 6, where our preferred specification interacts the import shock with the employment score.

this result is reversed for the most employable individuals, which is consistent with the previously mentioned income effect and social drinking hypotheses. Health-care utilization on the contrary is greatly impacted by exposure to trade: the lower the probability of re-employment, the higher the probability of not seeing a doctor due to cost, to space out more dentist visits, and -probably linked with these latter outcomes- to be covered by a health plan. Individuals may lose their health insurance at the same time as they lose their job, which translates into more durable loss of health coverage for those whose "employability" is lower.

5 Evidence from Hospital Discharges

In this section we look at the impact of trade on hospital discharges, which provides further insight on the role of import competition in shaping health, health behavior and health care utilisation.

5.1 Data

We use data from the Healthcare Cost and Utilization Project (HCUP) and more specifically from the National Inpatient Sample (NIS). The NIS is the largest publicly available all-payer inpatient health care database in the United States, covering the years 1993 to 2011. It consists of a 20-percent stratified sample of all discharges from U.S. community hospitals. In each of those years, 20 percent of the hospitals were sampled and all discharges within those hospitals were recorded. After 2011, the design of the survey changed and hospital identifiers are no longer available.

The data we analyse record the identity of the hospital and its zipcode, which allows us to match it to a commuting zone. For each patient, the data contain basic demographics (sex, age, race, the quartile of income within the zipcode of living), but does not record the sector of occupation of the patient nor education. Hence, these data do not allow direct evaluation of the effect of import shocks on individuals employed in the manufacturing sector (nor did the BRFSS analysis, but the mortality analysis in Section 6 will). To overcome this issue, we proceed in a similar way as we did in Section 4. We use information on the composition in terms of industry for each of the commuting zones and we look at areas where routine tasks are more or less abundant.

The data contain information on up to 15 diagnostic codes (coded using the ICD 9 classification) as well as information on the length of stay, total charges incurred and how charges were covered. We restrict the sample to look at individuals who are between the age of 18 to 65, and excluded all discharges related to births. The resulting sample contains close to 50 million observations. We grouped the diagnostic codes into 15 categories, not mutually exclusive. We consider discharges where at least one of the diagnostic codes mention heart problems, infectious, respiratory or endocrine diseases, cancers (we also distinguish tobacco and non tobacco related cancers), mental disorders, suicide attempts, injuries, homicides, alcohol abuse and substance abuse. We also define two categories which may be relevant for the shock we consider. The first is related to stress and groups various conditions like mental disorders but also skin problems, ulcers or backache. The second is related to diet.[14]

The information on diagnoses and types of hospital stays is aggregated at hospital level for each year. We follow 2,981 hospitals over time, totalling 12,264 hospital-year observations. Table 11 provides descriptive statistics on the number of diagnosis and proportion of patients by age, sex and race. In the following, we provide evidence at hospital level with import shocks matched at commuting zone levels.

5.2 Empirical Strategy

The design of the data is different from the one in the BRFSS. As we do not observe the universe of hospitals in a commuting zone, we estimate the effect of trade within a commuting zone at hospital level instead. Let $Y_{h,c,t}$ be an outcome observed in hospital h belonging to commuting zone c in year t. We relate this outcome to the import per worker in the commuting zone c, k years prior, to hospital or commuting zone time-varying characteristics (including state specific linear trends), as well as time and hospital fixed effects:

$$Y_{h,c,t} = \alpha_0 + \sum_{r \in \{L,M,H\}} \alpha^r_{Import} IPW_{c,t-k} I_{RTI_c = r} + \alpha_X X_{h,c,t} + \delta_h + \delta_t + \varepsilon_{h,c,t}. \qquad (7)$$

[14]Table A2 in the appendix provides a classification of the categories with the ICD 9 codes we use. The two latter groupings were defined based on discussions with medical doctors.

We instrument the import competition measure as explained in Section 3. To probe the role of import shocks further, we interact it with a measure of the share of routine jobs within the commuting zone in 1990 as we have done when studying the effect of import shocks on employment, income or health presented above.

5.3 Results using Hospitalisation Data

The outcome variable is the number of admissions for a particular cause, scaled by population at commuting zone level and multiplied by 1,000. For ease of interpretation we report effects in terms of standard deviation changes both in the import competition measure and in the outcome. Table 12 presents the results. We first look at the global effect of the import shock, without introducing any heterogeneity linked to routine task intensity. The results displayed in column 1 show that an increase in import competition tends to increase admissions for all causes, although few of the effects are significant. We find evidence of significant effects at the 5 percent level for admissions related to suicides, alcohol abuse, injuries and homicides. For instance, a one standard deviation increase in import competition raises the number admissions related to suicides by 0.17 of a standard deviation and alcohol abuse by 0.1 of a standard deviation. The next 3 columns display the effects of import competition across areas with low, medium or high routine task intensity shares. As in previous sections, the detrimental effects of import competition are concentrated in areas with a high RTI share. In those regions, a one standard deviation increase in import competition leads to an increase of between 0.1 and 0.18 standard deviations in admissions for heart problems, infectious, respiratory or endocrine diseases. The most common endocrine diseases in our data are diabetes and hypercholesterolemia, two conditions related to poorer health behavior. The most common respiratory diseases include asthma and pneumonia. These conditions are linked to stress and lack of preventive care, among others factors. We do not find significant effects of import competition on the share of patients admitted with cancers in general, nor when we break them down into tobacco and non tobacco related cancers. One reason could be that cancers induced by a change in behavior take considerable more time to develop than the time span we are considering.

Those results are consistent with the findings using the BRFSS in Section 4, as we already showed the effect of import competition on general health, endocrine diseases such as diabetes, or elevated blood pressure. In addition, we did not find evidence of a change in smoking behavior when using the BRFSS.

Table 12 next displays admissions related to mental issues, suicides and homicides. We find large and significant effects in areas with a high RTI share. The largest effects can be found for hospital admissions linked to suicide attempts and alcohol abuse, with an effect of around 0.22 to 0.25 standard deviations. Other effects of import competition include increased admissions due to mental health, stress, homicides and to some extent injuries. The hospitalisation results differ from the results using the BRFSS for alcohol consumption. The BRFSS captures day to day consumption, but the hospitalisation records relates rather to alcohol abuse. The results suggest that areas hit by an import shock see a decrease in overall alcohol consumption, but also a sharp increase in the upper tail of the distribution of alcohol consumption that health surveys such as the BRFSS miss.

We present in Table 13 the effect of import competition on the types of admissions and the composition of patients. We do not find evidence of an overall increase in the number of admissions. However, we find strong evidence that in high RTI areas, admissions are more likely to be emergency ones. This could be due to the nature of some of the causes of hospitalisation, such as suicides. To investigate this further we also compute the number of emergency admissions, excluding admissions due to suicides, homicides and injuries. We still find a significant and large effect of import shocks on emergency admissions for all other causes. This could be due to an increase in life-threatening conditions such as acute cardiovascular diseases, and generally to the fact that some pathologies may have gone untreated. By the time these patients show up in hospital, they could be more likely to have acute conditions. There is also some evidence that in those areas, hospital charges and the length of admissions are higher, which would support the hypothesis of the occurrence of more serious diseases. Table 13 next shows the effect of import competition on number of patients covered by Medicaid, with a significant increase of 0.17 standard deviations in high RTI areas.

We also find that admitted individuals are more likely to be white, and to some extent males in their late 40s to mid 50s. These results align well with those of Case and Deaton

(2015), who found rising mortality amongst non-hispanic middle-aged whites, due to suicides, drug and alcohol abuse, along with self-reported declines in health and mental health, with most of the toll borne by the low educated. Our results point to import shocks as a possible factor explaining those results.

6 Impact of Trade on Mortality

In this section we look at the impact of exposure to import competition from China in the worker's industry (rather than in his commuting zone) on his hazard rate of dying. Looking into cause-specific mortality allows us to relate the new results to those of the previous sections about the impact of import competition on health.

6.1 Data

We use data from the National Health Interview Survey (NHIS), over the period from 1986 to 2009. The NHIS is the principal source of information on the health of the civilian noninstitutionalized population of the United States. The NHIS offers a rich set of individuals characteristics, including gender, race, education, self-assessed health, occupation and most importantly, industry, at a very disaggregated level (3-digit Census 1990 based on 3-digit SIC, 4-digit Census 2002 based on 4-digit NAICS); and county of residence.[15] All our estimations will include these socio-demographic variables as baseline controls. Our sample is made of 126,625 workers in the manufacturing industry, aged 18-65 at baseline, i.e. when they are surveyed. As displayed in Table 14, most individuals are male (66%), white (81%), low-educated (62%), and their average age at baseline is 39.

The NHIS provides a linkage to death certificate records from the National Death Index. Individuals who are surveyed at any point between 1986 and 2009 are observed again when they die, if they do before December 31st, 2011.[16] We can therefore construct a panel, in

[15]Detailed industry and occupation codes, as well as the county of residence are available only through an application for restricted data.

[16]The NHIS-NDI is available through an application to the NHIS restricted data. The NHIS-NDI matching is made through a probabilistic algorithm using combinations of several variables, including Social Security number, date of birth, first and last name.

which each respondent is observed from the year they are surveyed until the year they die, or up to 2011 if they survive until then. For instance, a person entering the survey in 1990 and dying in 2002 is observed for 13 years. In principle, we can observe individuals until they die if they do before December 2011, but because the focus of our study is on how exposure to import competition in one's own industry affects one's chances of dying, we restrict the sample in the following way: first, a worker remains at most 15 years in the sample, so that the assumption that he will still be affected by a shock in his industry is more reasonable; second, since most workers retire at about 65, individuals exit the sample once they are 70, allowing for lags in the effect of trade. This way, we focus on the impact of import competition at the industry level on premature deaths, of individuals who are more likely to be still working. Of the 126,625 manufacture workers we observe at baseline, 12,302 die before December 2011, but only 5,569 of those deaths will be considered in our analysis, for the restrictions above-mentioned. We use the NHIS mortality follow-up classification of causes of death, based on ICD-9 or ICD-10 codes extracted from the death certificates, and create broader categories, as displayed in Table A1. For instance, the list of cancers whose risks increase due to tobacco use goes well beyond lung cancer, and includes cancers of the mouth, lips, nose and sinuses, larynx, pharynx, oesophagus, stomach, pancreas, kidney, bladder, uterus, cervix, colon−rectum, ovary, and acute myeloid leukemia. (Source: Cancer Facts & Figures 2014). Table 14 lists the causes of death observed in our data.

Trade data In this section, data on imports are aggregated from 4 to 3 digits, so that it can match worker's industry from the NHIS. The import shock is now defined as $Import_{j,t-k}$, the imports from China in industry j and year $t-k$, where k is a lag varying between 0 and 6 years, in order to leave time for the import shock to potentially impact the worker's mortality.[17] It is now assigned to worker i working in industry j at year t, rather than to a commuting zone. We use trade series from 1980 to 2011, to match the NHIS data from 1986 (allowing for a maximum of 6 lags) to 2011 (date of end of observation of NHIS individuals).

[17]Although we have NHIS data back to 1986, we can still go back as far as 6 lags as we have US trade data from 1980.

6.2 Empirical Strategy

We start by estimating the impact of import competition on all-cause mortality using a Cox survival model, as described in the following equation:

$$h(age_{it}|Import_{j,t-k}, X_{i,j,c,t}) = h_0(age_{it}|X_{i,j,c}) \qquad (8)$$
$$exp(\alpha Import_{j,t-k} + \beta Import_{j,t-k} * EmplScore_{i,t} + \delta_t),$$

where the baseline hazard h_0 is stratified by industry j, commuting zone c and individual characteristics such as education, race, gender and health when interviewed. A Cox model allows us to specify only a functional form for the influence of import competition while leaving the shape of the hazard rates as unspecified as possible. In this case, each group of individuals defined by a combination of education, race, gender, industry, and commuting zone, has a specific shape for the baseline hazard function. The model also includes a yearly trend δ_t, which- like our key explanatory variables- shifts the baseline hazard upward or downward.

As mentioned before, the NHIS sample has the great advantage that it allows us to focus on individuals working in manufacture at baseline and look at how they were affected by the shock in their own specific industry. In that sense, the research design is more precise than the ones we have relied on in the previous sections. Nevertheless, not all manufacture workers are exposed in the same way to import competition even within a given industry. We therefore construct an employment score, as explained in Section 4, and interact this employment score (see descriptive statistics in Table 14) with the import shock[18]. This score is then modified so that it lies between 0 and 1; the closer it is to 1, the more likely it is for the individual to be employed (or to find a job if out of work). Next, we exploit the information on causes of death to estimate cause-specific hazard mortality rates:

$$h_{cause}(age_{it}|Import_{j,t-k}, X_{i,s,a,t}) = h_{0,cause}(age_{it}|X_{i,j,c}) \qquad (9)$$
$$exp(\alpha_{cause} Import_{j,t-k} + \beta_{cause} Import_{j,t-k} * EmplScore_{i,t} + \delta_t),$$

where *cause* is a specific cause of death such as suicide or cancer.

[18] Here, $EmplScore = 0.1478 * male - 0.0599 * black - 0.0468 * other + 0.06 * educ1 + 0.2213 * educ2 + 0.2721 * educ3 + 0.2002 * age2650 + 0.0338 * age5165$, where the reference categories are : $white$ for race, $educ0$, i.e. less than high school for education, and $age1825$ for age.

Both equations will also be estimated in a specification allowing no differential impact depending on the employability score, i.e. assuming that β or β_{cause} is null. Although we still share the same concern as Autor et al. (2013), i.e. we are interested in the impact of the supply-driven component of the Chinese import competition, we choose here not to instrument our measure of imports by the imports of other countries from China. In our Cox setting, one way of identifying the right component is to follow a control-function approach, i.e. regressing the US imports from China on the contemporaneous non-US imports from China with industry and year fixed effects, obtain the residuals at the industry-year level, and plug them into the above equations as controls. Nevertheless, as explained before, non-US imports series start in year 1988 at best (adding Germany for instance would lead to series starting in 1991), and we consider the possibility of imports affecting workers' health and even more mortality with several years of lags as paramount. Therefore, due to death events being too scarce in our NHIS data, we prefer using more years of data and exploiting more deaths rather than instrumenting our key variables.

6.3 Results

As the first column of Table 15 shows, the import shock moves the mortality hazard upwards by around 2% at first, with an increasing impact as we allow more time for the shock to impact mortality. The effect goes as high as 4% with a 6-year lag. These results suggest that import competition affects mortality contemporaneously but also increasingly with time,which echoes the results presented before since we had found that the import per worker shock had adverse effects on health from lag 0. We then look at how import competition affects cause-specific mortality[19]. Only suicides are affected by contemporaneous imports. The suicide hazard increases by 7.5%, and goes up to 15 and 21 percent in lags 4 and 6, which looks like a large effect, but has to be compared to a much lower baseline hazard compared to other causes of death. Amongst the categories we chose to focus on, no other cause comes up as significantly affected by import competition when no heterogeneity is introduced in

[19]in all of these regressions, we include a yearly trend. As robustness checks, we also estimated the same equation with year fixed effects instead. The results were very similar. For computational reasons we therefore estimate the remaining regressions using the yearly trend.

the model.

When interacting the import shock with the employment score, we uncover heterogeneous effects on some causes of death that did not appear to be significant before (see Table 16). While deaths due to suicides are not differentially impacted by the import shock depending on one's likelihood of being employed, the increase in the hazard of cardio-related deaths at lag 0 and 2 is concentrated on the least employable. Likewise, mortality due to alcohol and diet-related factors increases for this same group at lag 0. Conversely, it decreases for the most employable workers. Again, the magnitude of these effects look high but in the case of alcohol/diet-related deaths as in the case of suicides, the baseline hazard is very low (see the descriptive statistics of our sample in Table 14.). We find no significant effect on tobacco-related cancer, which is consistent with the results found before, and find important effects on mortality due to cancers that are not tobacco-induced. This finding is to be put in perspective with our previous results on health care utilization: as more individuals lose their health insurance, some diseases that could have been prevented or treated end up killing those affected. This effect only becomes significant from lag 4, as those deaths would occur after a larger period than for suicides or cardio-related deaths. It is also noteworthy that cancers that are not due to smoking only increase as a consequence of import competition for those more likely to have lost their job (with a lower employability score). These individuals are also more likely to have lost their health insurance, which could lead to a higher mortality rate from cancer.

7 Conclusion

Our results complement and extend the work by Autor et al. (2013), Autor et al. (2014) or Autor et al. (2016) by emphasising the role of technology and tasks in understanding the effect of trade on the economy, and in particular employment, income and health. Exploiting multiple and large data sets covering about two decades, we confirm that import competition has an effect on employment and in particular non-employment more than unemployment. However, this effect is essentially confined to areas both hit by an import shock and that have a large share of jobs with a routine content. This heterogenous effect is a new finding.

The task content of occupations has been mainly studied in the context of the effect of technological progress on labor markets pioneered by Autor et al. (2003). In those areas, import competition has led to a significant decrease in labor market participation, as well as household income. We show that many aspects of health deteriorated in areas with a high share of routine jobs but not in areas with a low share. This allows us to rely as well on a triple diff-in-diff strategy to identify the effect of import competition on health. We show that health behavior deteriorated as a result of an import shock and that health care utilisation declined. As a result, individuals rated their health lower, with several health conditions such as diabetes having worsened. We confirm and extend these results using hospitalisation data. In areas with a high share of routine tasks, we see an increase in admissions for heart problems, infectious diseases, suicides, mental health issues, stress and alcohol abuse. These results align well with those of Case and Deaton (2015) and uncovers one of the determinants of this unprecedented decline in health.

Following workers in the manufacturing industry over time, we find that import shocks significantly raise their hazard of dying. This effect is obtained controlling for time, commuting zone and industry fixed effects, as well as the individual's health at baseline. A one billion increase in import competition raises the hazard of death by about 3 percent after 4 years. Exploiting information on causes of death, we find evidence of an increase in suicide rates.

We show that the effect of import competition on health is larger than what the loss of income would imply. This suggests that the effect of import competition is more pronounced than other shocks that have been studied in the literature so far. There could be several reasons to that. First, an import shock could lead to lower income as well as a lack of insurance which could compound the effect. Second, an import shock is a more persistent shock than a recession or a recession induced firm closure. The literature has pointed to the large cost of moving from one sector to the other, and an import shock could be a large and permanent shock for a subset of older workers with lower human capital. Further research should take into account the effect of import competition on health and mortality when assessing the welfare effects of trade.

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Figure 1: Import per Worker: Heterogeneity across US territory in 1980

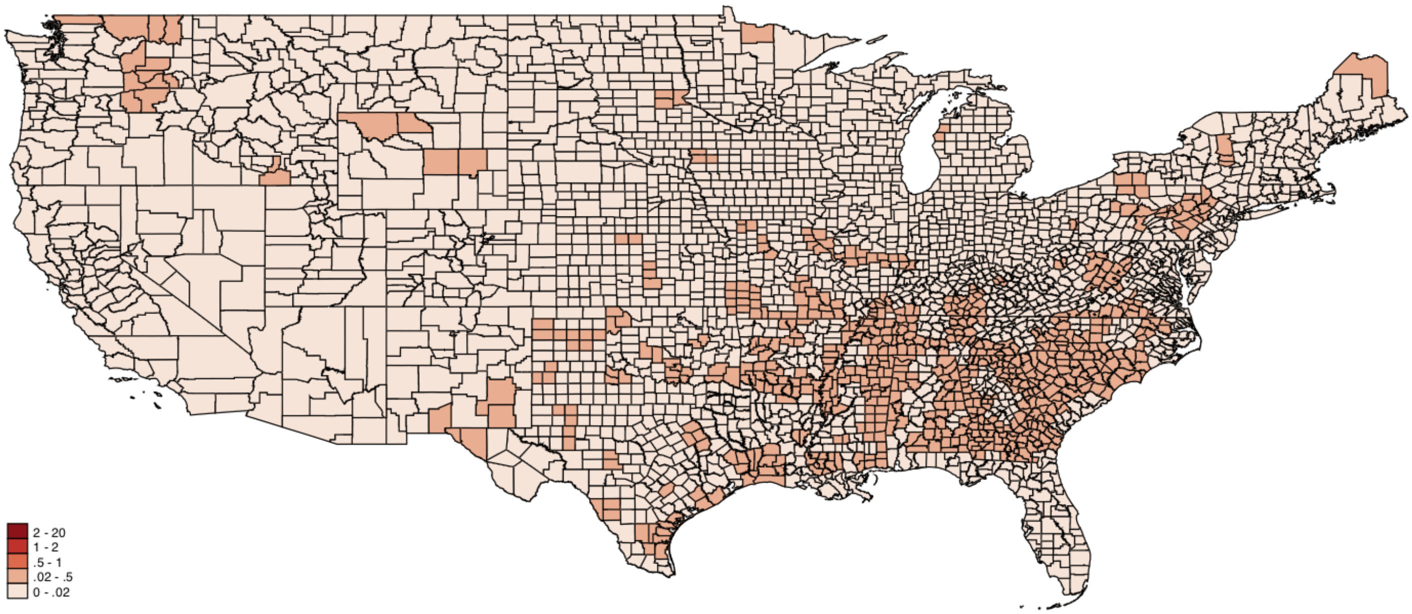
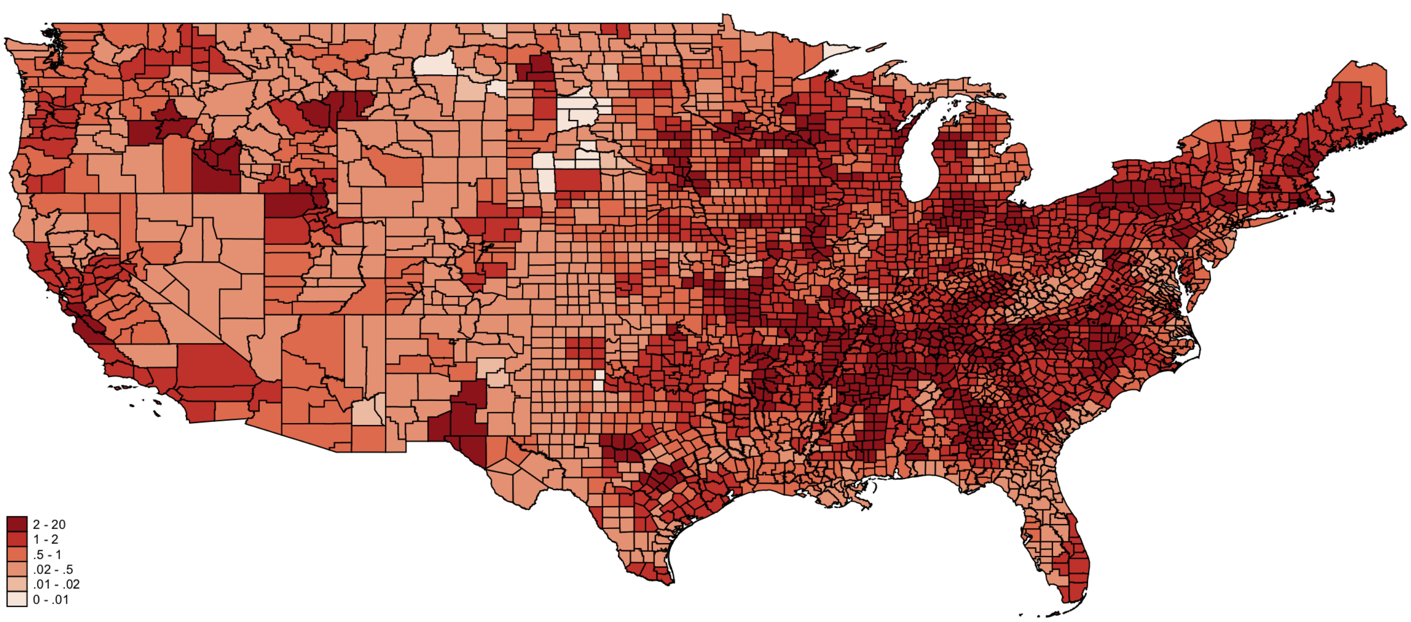
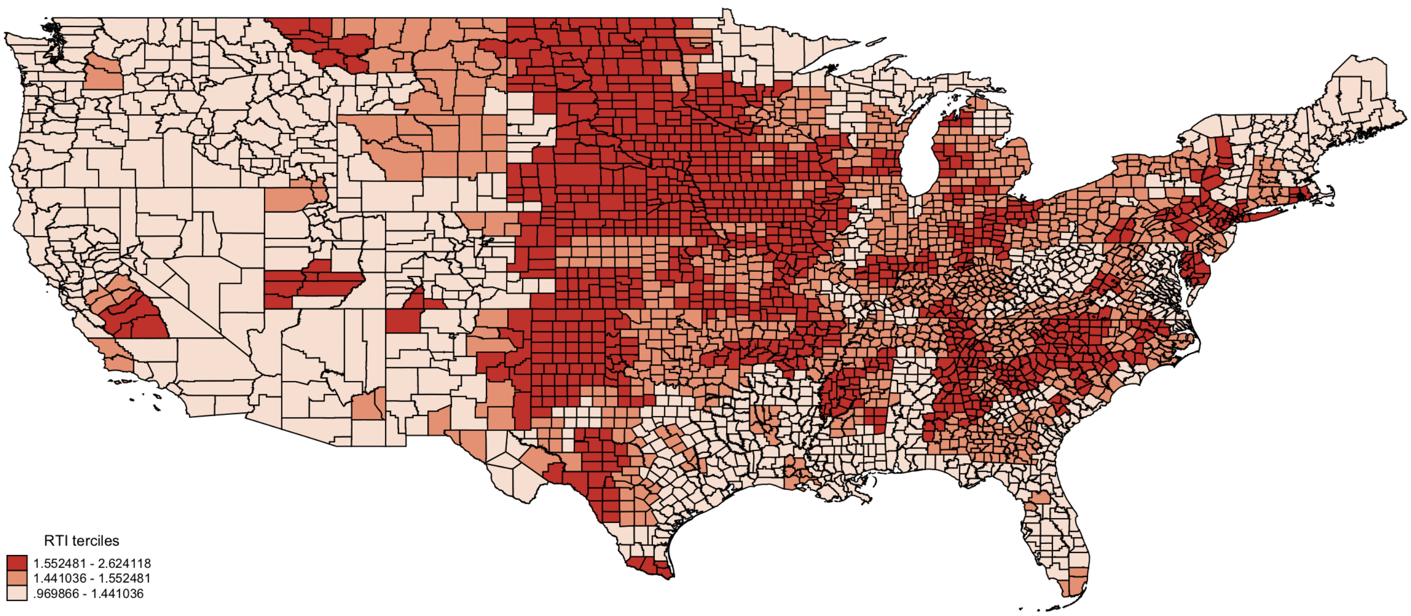


Figure 2: Import per Worker: Heterogeneity across US territory in 2011



Note: The Import per Worker (IPW) shock in commuting zone c at time t is constructed as: $IPW_{c,t} = \sum_{j \in Manuf} \frac{L_{c,j,t-10}}{L_{US,j,t-10}} \frac{Import_{j,t}}{L_{c,All,t-10}}$, where j is an industry belonging to the set of manufacturing industries $Manuf$. The first ratio corresponds to the share of the commuting zone in the US employment in industry j. The import shock (imports from China in industry j in billion 2009 US\$) $Import_{j,t}$ is rescaled by total non-agriculture employment in the commuting zone, hence expressed "per worker". Scale is expressed in standard deviations of IPW.

Figure 3: Routine Task Index across US territory in 1990



Note:We match detailed occupation codes from IPUMS Census 1990 with the routine, abstract, and manual task contents based on the job task requirements of each occupation as described in the Dictionary of Occupational Titles. We compute the Routine Task Intensity measure for occupation k, defined as $RTI_k = ln(Routine_k) - ln(Manual_k) - ln(Abstract_k)$, for the manufacturing sector. We then average the RTI index (for manufacture only) at the commuting zone level, and divide the US territory into three terciles of RTI.

Table 1: Descriptive Statistics: Commuting Zone Characteristics, in 1990 and 2011

	year 1995		year 2011	
	mean	sd	mean	sd
Import				
IPW (in $ 1,000)	0.781	0.885	3.319	2.511
IPW_IV (in $ 1,000)	0.784	1.087	3.324	2.382
Demographics				
Percent. of male	0.495	0.010	0.496	0.011
Percent. of white individuals	0.786	0.120	0.745	0.127
Percent. of black individuals	0.117	0.094	0.128	0.100
Percent. of low educated individuals	0.153	0.050	0.115	0.041
Percent. of individuals aged less than 25	0.184	0.025	0.180	0.026
Percent. of individuals aged 25-34	0.254	0.019	0.204	0.022
Percent. of individuals aged 35-44	0.246	0.010	0.207	0.015
Percent. of individuals aged 45-54	0.181	0.011	0.226	0.016
Percent. of individuals aged 55 and over	0.135	0.020	0.183	0.024
Labor				
Percent. of employed individuals	0.712	0.045	0.669	0.049
Percent. of unemployed individuals	0.043	0.009	0.086	0.019
Percent. of not in labor force	0.245	0.039	0.245	0.044
Percent. of individuals in manufacture	0.144	0.054	0.090	0.037
Routine Task Intensity (mean)	1.220	0.087	1.088	0.076
Routine Task Intensity (mean) in Manufacture	1.434	0.132	1.310	0.181
Income				
Income (mean, household equivalized)	42547	7691	44518	8208
Percent. individuals w. eq. fam income$<15k$	0.179	0.058	0.203	0.048
Percent. individuals w. eq. fam income$<20k$	0.259	0.076	0.282	0.063
Percent. individuals w. income$<15k$	0.392	0.057	0.397	0.050
Percent. individuals w. income$<20k$	0.474	0.065	0.478	0.056

Note: N=722 commuting zones. Commuting zones are weighted by their population the corresponding year. All dollar amounts are expressed in 2007$.

Table 2: Descriptive Statistics: Commuting Zone Characteristics by RTI group, in 1990

	RTI Low		**RTI Medium**		**RTI High**		**All**	
	mean	sd	mean	sd	mean	sd	mean	sd
Import								
IPW (in $1,000)	0.582	(0.60)	0.833	(0.83)	1.135	(1.32)	0.781	(0.88)
IPW_IV (in $1,000)	0.568	(0.74)	0.806	(0.99)	1.243	(1.67)	0.784	(1.09)
Demographics								
Percent. of male	0.499	(0.01)	0.492	(0.01)	0.491	(0.01)	0.495	(0.01)
Percent. of white individuals	0.760	(0.12)	0.809	(0.10)	0.797	(0.15)	0.786	(0.12)
Percent. of black individuals	0.105	(0.09)	0.127	(0.09)	0.123	(0.11)	0.117	(0.09)
Percent. of low educated individuals	0.153	(0.05)	0.145	(0.04)	0.169	(0.06)	0.153	(0.05)
Percent. of individuals aged less than 25	0.184	(0.02)	0.184	(0.03)	0.186	(0.02)	0.184	(0.02)
Percent. of individuals aged 25-34	0.260	(0.02)	0.251	(0.02)	0.246	(0.02)	0.254	(0.02)
Percent. of individuals aged 35-44	0.248	(0.01)	0.246	(0.01)	0.241	(0.01)	0.246	(0.01)
Percent. of individuals aged 45-54	0.179	(0.01)	0.183	(0.01)	0.184	(0.01)	0.181	(0.01)
Percent. of individuals aged 55 and over	0.129	(0.02)	0.137	(0.02)	0.142	(0.01)	0.135	(0.02)
Labor								
Percent. of employed individuals	0.709	(0.05)	0.717	(0.04)	0.710	(0.05)	0.712	(0.05)
Percent. of unemployed individuals	0.043	(0.01)	0.043	(0.01)	0.043	(0.01)	0.043	(0.01)
Percent. of not in labor force	0.248	(0.04)	0.239	(0.03)	0.247	(0.04)	0.245	(0.04)
Percent. of individuals in manufacture	0.121	(0.04)	0.158	(0.05)	0.170	(0.08)	0.144	(0.05)
Routine Task Intensity (mean)	1.190	(0.07)	1.243	(0.08)	1.237	(0.11)	1.220	(0.09)
Routine Task Intensity (mean) in Manufacture	1.321	(0.09)	1.476	(0.04)	1.606	(0.10)	1.434	(0.13)
Income								
Income (mean, household equivalized)	43124	(7567)	42969	(7728)	40251	(7539)	42547	(7691)
Percent. individuals w. eq. fam income$< 15k$	0.183	(0.06)	0.170	(0.06)	0.191	(0.06)	0.179	(0.06)
Percent. individuals w. eq. fam income$< 20k$	0.264	(0.07)	0.247	(0.08)	0.277	(0.08)	0.259	(0.08)
Percent. individuals w. income$< 15k$	0.388	(0.06)	0.388	(0.05)	0.409	(0.05)	0.392	(0.06)
Percent. individuals w. income$< 20k$	0.470	(0.07)	0.470	(0.06)	0.496	(0.06)	0.474	(0.06)
Observations	240		241		241		722	

Note: RTI is the routine task index defined in Section 3.1. Commuting zones are weighted by their population the corresponding year.

Table 3: Descriptive Statistics: Occupation and Industry Composition of Commuting Zones by RTI Group

5 most important occupations		5 most important industries	
Occupation	Share	Industry	Share
RTI: Low			
assemblers of electrical equipment	6.7%	printing, publishing, and allied industries, except newspapers	5.8%
managers and administrators, n.e.c	6.5%	electrical machinery, equipment, and supplies, n.e.c	5.1%
machine operators, n.e.c	5.8%	apparel and accessories, except knit	4.9%
production supervisors or foremen	4.8%	sawmills, planing mills, and millwork	4.4%
textile sewing machine operators	3.5%	machinery, except electrical, n.e.c	4%
RTI: Medium			
assemblers of electrical equipment	8.7%	motor vehicles and motor vehicle equipment	7.6%
machine operators, n.e.c	6.7%	printing, publishing, and allied industries, except newspapers	6.1%
managers and administrators, n.e.c	5.2%	apparel and accessories, except knit	5.9%
production supervisors or foremen	4.8%	machinery, except electrical, n.e.c	5.5%
textile sewing machine operators	4.6%	electrical machinery, equipment, and supplies, n.e.c	4.4%
RTI: High			
assemblers of electrical equipment	8.8%	apparel and accessories, except knit	7.5%
textile sewing machine operators	6.6%	yarn, thread, and fabric mills	6.2%
machine operators, n.e.c	6.6%	printing, publishing, and allied industries, except newspapers	5.5%
managers and administrators, n.e.c	4.4%	meat products	5.1%
production supervisors or foremen	4.9%	motor vehicles and motor vehicle equipment	5.1%

Note: Sample: manufacture workers in 1990 IPUMS census. N=589,720 individuals in low RTI commuting zones; 814,761 individuals in Medium RTI commuting zones; 486,382 individuals in High RTI commuting zones. "Share" refers to the share of manufacture employment represented by those occupations and industries in each RTI group of commuting zones.

Table 4: First Stage Regression of Imports of US from China on Imports of other countries from China

	Imports US
Imports other countries	2.234***
	(0.010)
Observations	10,322
R^2	0.921

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This regression includes industry (SIC4) and year fixed effects. "Other countries" refer to Australia, Finland, Japan, and Switzerland, for the period 1988-2013. Imports are here expressed in 2009 USD.

Table 5: Effect of Import Shocks on Employment and Number of Firms

	Employment	Number establishments	Employment per establishment	Share employed	Share unemployed	Share not in labor force	Share manufacture
	At 4 digit industry level * commuting zone			In commuting zone			
OLS estimates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Import Lag 0	-4.432***	-.008**	-.559***	-.003*	0.0009	0.003**	-.005***
	(0.754)	(0.003)	(0.116)	(0.002)	(0.0008)	(0.001)	(0.002)
Import Lag 2	-6.414***	-.014**	-.703***	-.005**	0.0008	0.004***	-.008***
	(0.916)	(0.006)	(0.112)	(0.002)	(0.001)	(0.002)	(0.002)
Import Lag 4	-6.892***	-.017***	-.734***	-.006***	0.0009	0.005***	-.009***
	(0.938)	(0.006)	(0.101)	(0.002)	(0.001)	(0.002)	(0.002)
Import Lag 6	-9.577***	-.016**	-.974***	-.007***	0.001	0.006***	-.011***
	(1.301)	(0.008)	(0.132)	(0.003)	(0.001)	(0.002)	(0.002)
IV estimates							
Import Lag 0 IV	-5.463***	-.020***	-.727***	-.004**	0.001	0.003**	-.006***
	(0.884)	(0.005)	(0.121)	(0.002)	(0.0009)	(0.001)	(0.001)
Import Lag 2 IV	-7.695***	-.030***	-1.038***	-.006***	0.0007	0.005***	-.009***
	(1.110)	(0.008)	(0.14)	(0.002)	(0.001)	(0.002)	(0.002)
Import Lag 4 IV	-8.036***	-.035***	-1.074***	-.008***	0.0007	0.007***	-.011***
	(1.144)	(0.009)	(0.138)	(0.002)	(0.001)	(0.002)	(0.002)
Import Lag 6 IV	-8.681***	-.039***	-1.236***	-.007***	0.0005	0.007***	-.010***
	(1.232)	(0.01)	(0.149)	(0.003)	(0.001)	(0.002)	(0.002)
Mean	55.53	1.27	14.67	0.69	0.05	0.26	0.13
Observations		1,143,648			2,888		

Note: Each cell corresponds to one regression. Instruments used in to produce the estimates in the bottom part of the table are the sum of Chinese imports to the other countries. The first stage is displayed in Table 4. All regressions include year, industry-SIC4 and commuting zone fixed effects. The regressions also control for commuting zone characteristics (proportion of males, whites, African-Americans, low educated, and five age groups between 18 and 65). Regressions in columns (4)-(7) are weighted by commuting zone population in 1980. Standard errors clustered at commuting zone level. Data from the CBP and IPUMS Census, years 1995-2000-2005-2010. Columns (1)-(3) use data at SIC4 and commuting zone level (CBP), columns (4)-(7) use only CZ level (the dependent variables are shares within commuting zones, from IPUMS Census). Imports are measured as SIC4-year-level imports in columns (1)-(3) and import per worker at commuting zone-year-level in columns (4)-(7).

Table 6: Effect of Import Shocks on Local Labor Markets, by Routine Task Intensity

	Areas with		
	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)
Share employed, after 2 years	-.002	-.007**	-.011**
	(0.003)	(0.003)	(0.004)
Share employed, after 6 years	-.003	-.007**	-.012**
	(0.004)	(0.003)	(0.005)
Share unemployed, after 2 years	-.0001	0.001	0.001
	(0.002)	(0.001)	(0.002)
Share unemployed, after 6 years	0.0001	0.0004	0.0009
	(0.003)	(0.001)	(0.002)
Share not in labor force, after 2 years	0.002	0.006***	0.009***
	(0.003)	(0.002)	(0.003)
Share not in labor force, after 6 years	0.002	0.007***	0.011***
	(0.004)	(0.003)	(0.004)
Share in manufacturing, after 2 years	-.006**	-.008***	-.014***
	(0.002)	(0.002)	(0.004)
Share in manufacturing, after 6 years	-.007**	-.009***	-.016***
	(0.003)	(0.002)	(0.005)
Income (hh equivalized, mean), after 2 years	194.798	-763.186***	-654.842*
	(392.635)	(289.836)	(355.540)
Income (hh equivalized, mean), after 6 years	78.877	-757.658**	-588.740
	(516.884)	(318.120)	(391.060)
Share family income (eq.)$< 15,000$, after 2 years	-.004	0.008***	0.01**
	(0.003)	(0.002)	(0.005)
Share family income (eq.)$< 15,000$, after 6 years	-.006	0.008***	0.009*
	(0.004)	(0.003)	(0.005)

Note: Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Data from the CBP and IPUMS Census, years 1995-2000-2005-2010. Imports are measured as import per worker (the instrumented version) at commuting zone-year level with a lag of 2 or 6 years. RTI is calculated for the occupations in the manufacturing sector. All regressions include year, and commuting-zone fixed effects. The regressions also control for commuting zone characteristics (proportion of males, whites, African-Americans, low educated, and five age groups between 18 and 65). Regressions are weighted by commuting zone population in 1980. Standard errors clustered at commuting zone level. Each line corresponds to one regression, where the outcome is for instance the share of unemployed individuals in the commuting zone, and the key explanatory variable IPW is interacted with the 3 RTI terciles.

Table 7: Descriptive Statistics, BRFSS

	mean	sd	min	max	count
Demographics					
age	40.155	12.993	18	65	2,946,137
male	0.498	0.500	0	1	2,946,137
race: white	0.770	0.421	0	1	2,941,089
race: black	0.119	0.324	0	1	2,941,089
race: other	0.110	0.313	0	1	2,946,137
educ: high school or less	0.385	0.487	0	1	2,942,323
educ: some college	0.280	0.449	0	1	2,942,323
educ: college graduate	0.335	0.472	0	1	2,942,323
Health					
(very) good health	0.869	0.337	0	1	2,946,137
ever told blood pressure high	0.209	0.406	0	1	1,686,343
ever diagnosed with a stroke	0.016	0.124	0	1	2,026,454
ever told blood cholesterol high	0.280	0.449	0	1	631,721
ever told diabetes	0.071	0.257	0	1	2,942,408
still has asthma	0.082	0.275	0	1	2,572,454
overweight	0.351	0.477	0	1	2,836,070
obese	0.239	0.427	0	1	2,836,070
nb of days mental health not good	3.586	7.585	0	30	2,817,562
satisfaction with life	0.942	0.234	0	1	1,444,530
Health behavior					
how many days with alcohol in past 30	4.292	7.208	0	31	2,537,090
currently smoking	0.230	0.421	0	1	2903406
how many times eat vegetables per day	1.170	0.951	0	30	1,168,719
exercise in past 30 days	0.768	0.422	0	1	2,738,913
Health care utilization					
could not see dr. because of cost	0.146	0.353	0	1	2,664,825
has any health care coverage	0.827	0.378	0	1	2,939,105
seasonal flu shot past 12 months	0.266	0.442	0	1	2,718,891
ever had blood cholesterol checked	0.733	0.442	0	1	820,150
ever had blood stool test	0.344	0.475	0	1	628,077
time since last routine checkup	1.376	1.910	1	10	2,323,477
time since last visited dentist	1.423	1.844	1	10	1,377,929
Labor and Income					
currently working	0.707	0.455	0	1	2,938,326
income level	68,180	41,304	5,382	158,211	2,638,911
annual household income less than 20000	0.106	0.307	0	1	2,946,137
annual household income less than 30000	0.191	0.393	0	1	2,946,137
annual household income less than 50000	0.379	0.485	0	1	2,946,137
employability score	0.567	0.255	0	1	2,937,292

Note: Weighted by BRFSS weights.

Table 8: Effects of imports on health, health care utilisation and health behavior, by routine task intensity

	Good health			Health care utilisation			Health behavior		
	Low RTI	Medium RTI	High RTI	Low RTI	Medium RTI	High RTI	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trade, Lag 0	-.001	-.0009	-.010*	0.009	-.008	-.008	-.0006	0.008	0.002
	(0.006)	(0.005)	(0.006)	(0.012)	(0.008)	(0.008)	(0.006)	(0.005)	(0.005)
Trade, Lag 1	-.0004	-.007	-.011*	0.006	-.011*	-.010	-.003	0.004	0.0005
	(0.005)	(0.005)	(0.007)	(0.011)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)
Trade, Lag 2	0.002	-.012**	-.011	0.008	-.014**	-.014*	-.002	-.0003	0.002
	(0.005)	(0.005)	(0.007)	(0.012)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)
Trade, Lag 3	0.007	-.011**	-.012*	0.007	-.009	-.017**	-.001	-.001	-.003
	(0.005)	(0.005)	(0.007)	(0.013)	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)
Trade, Lag 4	0.001	-.009*	-.012*	0.006	-.006	-.018**	0.0009	-.002	-.005
	(0.006)	(0.005)	(0.007)	(0.014)	(0.006)	(0.009)	(0.007)	(0.006)	(0.007)
Trade, Lag 5	-.001	-.008*	-.015*	0.007	-.006	-.021**	0.004	-.002	-.006
	(0.006)	(0.005)	(0.008)	(0.016)	(0.007)	(0.01)	(0.008)	(0.007)	(0.008)
Trade, Lag 6	-.002	-.006	-.016*	0.008	-.005	-.022*	0.006	-.002	-.006
	(0.008)	(0.005)	(0.009)	(0.018)	(0.009)	(0.011)	(0.009)	(0.007)	(0.009)
Trade, Lag 7	0.0004	-.005	-.016	0.008	-.007	-.023**	0.006	-.001	-.003
	(0.01)	(0.007)	(0.01)	(0.02)	(0.01)	(0.011)	(0.011)	(0.008)	(0.01)
Obs		1,848,212			2,047,682			2,338,381	
Log income		0.273***			0.412***			0.248***	
		(0.009)			(0.009)			(0.009)	
Obs		1,678,897			1,845,771			2,105,187	

Note: Data from BRFSS, years 1995-2011. Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. The Import Per Worker measure is instrumented, using imports of other countries from China as the instrument for imports of the US from China. Good health is the first factor from a principal-component factor analysis including self-assessed health, indicators for strokes, diabetes, asthma, a body mass index and an indicator of poor mental health. Health care utilisation is the first factor from a principal-component factor analysis including an indicator for having a health plan, for having had a flushot, a medical checkup and whether a doctor visit is too expensive. Health behavior is the first factor from a principal-component factor analysis including smoking, alcohol consumption and exercise. All regressions include age dummies, sex, race, education and year and commuting zone fixed effects as well as state linear trends. Weighted by BRFSS weights. The second panel displays the regression of the different health measures on individual log income and controls. Standard errors clustered at commuting zone level.

Table 9: Health Effects of Imports, by Routine Task Intensity

	Imports$_{t-4}$ Low RTI (1)	Medium RTI (2)	High RTI (3)	Difference (1)-(3)	Obs
Panel A: Health measures					
Health good	-.0003	-.0009	-.005***	0.005*	2,937,292
	(0.002)	(0.001)	(0.002)	(0.003)	
Ever told bp high	-.0002	0.002	0.005*	-.005	1,681,250
	(0.003)	(0.002)	(0.003)	(0.003)	
Ever diagnosed stroke	0.0002	-.0001	0.0009	-.0007	2,020,073
	(0.0007)	(0.0005)	(0.001)	(0.001)	
Ever told cholesterol high	0.004	-.006	0.01	-.006	630,142
	(0.012)	(0.008)	(0.011)	(0.015)	
Ever told diabetes	0.002	0.0003	0.006***	-.004**	2,933,620
	(0.001)	(0.001)	(0.001)	(0.002)	
Has asthma now	-.003**	-.0003	0.001	-.005**	2,564,461
	(0.002)	(0.001)	(0.002)	(0.002)	
Overweight	0.001	0.001	0.001	0.0002	2,828,613
	(0.003)	(0.002)	(0.003)	(0.003)	
Obese	0.002	0.003*	0.001	0.001	2,828,613
	(0.002)	(0.002)	(0.003)	(0.003)	
Underweight	0.0003	0.001	-.003**	0.003	2,828,613
	(0.002)	(0.001)	(0.001)	(0.002)	
Days mental health pb	-.048	0.003	0.111**	-.159**	2,809,292
	(0.043)	(0.037)	(0.056)	(0.065)	
Panel B: Health behavior					
Drink any alcohol	-.0007	-.002	-.007*	0.006	2,705,816
	(0.003)	(0.003)	(0.004)	(0.005)	
Days had alcohol past 30 days	-.112***	0.028	-.105*	-.006	2,529,794
	(0.04)	(0.037)	(0.058)	(0.065)	
Smokes now	-.0006	0.002	0.002	-.002	2,894,770
	(0.003)	(0.002)	(0.002)	(0.004)	
Vegetables per day	0.011	0.0008	0.006	0.005	1,165,488
	(0.01)	(0.008)	(0.01)	(0.013)	
Exercise past 30 day	0.004	-.002	-.004	0.008	2,730,580
	(0.005)	(0.003)	(0.003)	(0.005)	
Panel C: Health care utilisation					
No doctor cause cost	-.004	0.001	0.002	-.006*	2,656,790
	(0.003)	(0.002)	(0.003)	(0.003)	
Has any hlth plan	0.002	-.004	-.006**	0.007	2,930,389
	(0.004)	(0.003)	(0.002)	(0.005)	
Flushot	0.001	0.003	-.008*	0.01*	2,711,006
	(0.004)	(0.004)	(0.004)	(0.006)	
Ever check cholesterol high	-.007	-.007	0.003	-.009	817,947
	(0.014)	(0.007)	(0.013)	(0.018)	
Bloodstool test	0.011	-.007	-.008	0.019	626,572
	(0.012)	(0.01)	(0.006)	(0.012)	
Time since checkup	-.001	0.0007	-.005	0.004	2,316,501
	(0.017)	(0.012)	(0.017)	(0.022)	
Time since last seen dentist	0.024	-.004	-.003	0.026	1,374,113
	(0.03)	(0.015)	(0.02)	(0.032)	

Note: Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Imports measure lagged 4 years. Weighted by BRFSS weights. Standard errors clustered at commuting zone level. All regressions include age, gender, education, race, year, commuting zone fixed effects and state specific trends.

Table 10: Health Effects of Imports in High RTI Areas Interacted with Employability Score

	Imports	Imports*Employability Score	Obs
	(1)	(2)	(3)
	Panel A: Health measures		
Health good	-.011***	0.018***	554,504
	(0.003)	(0.005)	
Ever told bp high	0.008**	-.019***	317,621
	(0.004)	(0.005)	
Ever diagnosed stroke	0.004**	-.009***	392,404
	(0.002)	(0.003)	
Ever told cholesterol high	0.013	-.038**	115,882
	(0.017)	(0.019)	
Ever told diabetes	0.012***	-.016***	554,073
	(0.002)	(0.004)	
Has asthma now	0.005*	-.009***	488,935
	(0.003)	(0.004)	
Overweight	-.001	0.0005	533,216
	(0.004)	(0.005)	
Obese	-.004	0.014**	533,216
	(0.004)	(0.006)	
Underweight	0.003	-.006***	533,216
	(0.002)	(0.002)	
Days mental health pb	0.204**	-.418***	530,270
	(0.086)	(0.152)	
	Panel B: Health behavior		
Drink any alcohol	-.009*	0.016***	510,936
	(0.005)	(0.006)	
Days had alcohol past 30 days	-.076	-.009	478,632
	(0.052)	(0.096)	
Smokes now	0.005	-.011	547,459
	(0.005)	(0.011)	
Vegetables per day	-.012	0.023	216,889
	(0.014)	(0.017)	
Exercise past 30 day	0.00003	0.006	517,698
	(0.004)	(0.004)	
	Panel C: Health care utilisation		
No doctor cause cost	0.009**	-.015**	501,609
	(0.004)	(0.006)	
Has any hlth plan	-.010***	0.012**	553,172
	(0.004)	(0.005)	
Flushot	0.0004	-.003	512,959
	(0.005)	(0.007)	
Ever check cholesterol high	-.017	0.002	151,561
	(0.016)	(0.017)	
Bloodstool test	-.0008	-.019	118,218
	(0.008)	(0.018)	
Time since checkup	0.011	-.003	438,813
	(0.017)	(0.032)	
Time since last seen dentist	0.085**	-.174***	268,312
	(0.036)	(0.061)	

Note: Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Imports measure (the instrumented version) lagged 4 years. Weighted by BRFSS weights. Standard errors clustered at commuting zone level. All regressions include age, education, race, year and commuting zone fixed effects, as well as state specific linear trends.

Table 11: Descriptive Statistics, Hospital Discharges (NIS)

	Number or Mean	Sd. dev
Total discharges	47,451,298	
Suicides related discharges	660,445	
Homicides related discharges	256,180	
Heart related diagnostics	9,869,924	
Infectious diseases related diagnostics	5,119,026	
Respiratory diseases related diagnostics	9,365,226	
Mental disorders related diagnostics	14,027,780	
Injuries related diagnostics	1,829,616	
Alcohol abuse related discharges	3,865,456	
Endocrine diseases related discharges	16,962,558	
Tobacco related cancers related discharges	1,208,453	
Cancer related discharges	4,716,411	
Non tobacco related discharges	4,119,485	
Stress related discharges	15,473,809	
Diet related discharges	12,448,799	
Substance abuse related discharges	2,893,461	
Total deaths in hospital	544,243	
Average age	42.19	(13.84)
Proportion male	.37	(.48)
Proportion white	.5	(.50)
Proportion African-American	.13	(.34)
Proportion urgent	.22	(.41)
Proportion emergency	.38	(.48)
Length of stay (days)	4.36	(7.19)
Proportion stay > 7 days	.12	(.33)
Proportion stay > 14 days	.04	(.20)
Average charges (2016 dollars)	24,617	(43,000)
Proportion self-pay	.08	(.27)
Proportion medicaid	.22	(.41)
Proportion medicare	.13	(.34)
Number of hospitals in sample	2,981	
Average number of observations per hospital	4.40	(2.88)
Hospital - year observations	13,127	
Average annual number of discharges per hospital	4,056	(5,087)
Number of commuting zones	386	

Note: For definitions of the morbidity categories, see Table A2 in the appendix.

Table 12: Effect of import shocks on hospitalization by cause

	All areas	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)
Admissions heart problems	0.034	0.011	-.005	0.106**
	(0.026)	(0.028)	(0.044)	(0.051)
Admissions infectious diseases	0.077	0.037	0.032	0.177**
	(0.056)	(0.068)	(0.076)	(0.076)
Admissions respiratory diseases	0.047	0.027	0.013	0.113*
	(0.035)	(0.047)	(0.055)	(0.058)
Admissions endocrine diseases	0.049	0.033	-.006	0.135**
	(0.044)	(0.06)	(0.072)	(0.061)
Admissions diet related	0.042	0.029	-.020	0.135*
	(0.056)	(0.075)	(0.093)	(0.072)
Admissions cancers	0.002	-.042	0.014	0.033
	(0.033)	(0.034)	(0.051)	(0.056)
Admissions tobacco rel cancers	0.028	-.040	0.018	0.11
	(0.044)	(0.042)	(0.059)	(0.068)
Admissions non tob rel cancer	-.0008	-.042	0.018	0.019
	(0.032)	(0.034)	(0.049)	(0.052)
Admissions stress related	0.071	0.041	0.03	0.155*
	(0.052)	(0.062)	(0.09)	(0.081)
Admissions mental problems	0.075	0.039	0.033	0.165*
	(0.053)	(0.061)	(0.089)	(0.085)
Admissions suicides	0.17***	0.178	0.1	0.251***
	(0.063)	(0.118)	(0.074)	(0.059)
Admissions alcohol abuse	0.1**	-.001	0.087	0.223**
	(0.052)	(0.045)	(0.07)	(0.088)
Admissions substance abuse	0.061	0.03	0.02	0.147
	(0.068)	(0.074)	(0.108)	(0.124)
Admissions homicides	0.058**	0.06	0.037	0.083***
	(0.024)	(0.039)	(0.027)	(0.024)
Admissions injuries	0.069**	0.058	0.072	0.078*
	(0.027)	(0.039)	(0.045)	(0.043)

Note: Data from NIS for the years 1993-2011. Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Imports measure (the instrumented version) lagged 4 years. Effect of a one standard deviation import shocks on a one standard deviation of admissions of patients with a certain condition. All regressions include year fixed effects, state trends, hospital fixed effects, hospital size dummies and commuting zone time-varying characteristics (sex, marital status, race, education, age composition and number of hospitals by year). Weighted by hospital weights. Standard errors clustered at commuting zone level.

Table 13: Effect of import shocks on hospitalization

	All areas	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)
Total admissions	0.02	-.003	-.002	0.072
	(0.019)	(0.022)	(0.033)	(0.046)
Admissions emergency	0.041	0.047	-.100	0.213***
	(0.064)	(0.06)	(0.073)	(0.068)
Admissions emergency, excluding	0.036	0.04	-.107	0.212***
suicides, homicides and injuries	(0.064)	(0.062)	(0.075)	(0.066)
Average charge	0.011	0.005	-.005	0.037*
	(0.014)	(0.021)	(0.019)	(0.022)
Admissions length>7 days	0.063	-.002	0.042	0.158*
	(0.04)	(0.036)	(0.041)	(0.092)
Admissions Medicaid	0.066**	0.015	0.024	0.172**
	(0.033)	(0.049)	(0.044)	(0.08)
Admissions white	0.065	0.069	0.017	0.12**
	(0.051)	(0.072)	(0.084)	(0.058)
Admissions males	0.035	0.004	0.012	0.095*
	(0.023)	(0.027)	(0.036)	(0.055)
Admissions age 45-55	0.02	-.033	-.002	0.103*
	(0.032)	(0.034)	(0.056)	(0.062)

Note: Data from NIS for the years 1993-2011. Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Imports measure (the instrumented version) lagged 4 years. Effect of a one standard deviation import shocks on a one standard deviation of admissions of patients with a certain condition. All regressions include year fixed effects, state trends, hospital fixed effects, hospital size dummies and commuting zone time-varying characteristics (sex, marital status, race, education, age composition and number of hospitals by year). Weighted by hospital weights. Standard errors clustered at commuting zone level.

Table 14: Descriptive Statistics, NHIS

Sample characteristics	NHIS 1986-2009. Manufacture workers, aged 18-65 at baseline.
Observations	2,161,941
Subjects	126,625
Average age at baseline	39
Average health at baseline (1-5)	2.04 (sd=0.96)
Birth cohorts	1921-1991
Male	66%
White	81%
Low education	62%
Employability score	0.65 (sd=0.21)
Number of deaths	5,569
Causes of death	Freq.
Cardio-related	1,671
Diet/alcohol-induced	312
Neoplasm not tobacco-induced	736
Neoplasm tobacco-induced	1,208
Suicide	276
Other	1,366

Table 15: Impact of Chinese imports on cause-specific mortality

Cause of death	All	Suicide	Neoplasm tobacco	Neoplasm non-tobacco	Cardio-related	Alcohol-diet
Trade, Lag 0	0.018***	0.075*	0.013	-0.016	0.018	-0.075
	(0.006)	(0.044)	(0.017)	(0.021)	(0.014)	(0.054)
Trade, Lag 2	0.022***	0.105	0.012	0.003	0.002	-0.085
	(0.007)	(0.090)	(0.023)	(0.026)	(0.010)	(0.068)
Trade, Lag 4	0.025***	0.153*	0.006	-0.002	-0.000	-0.160
	(0.007)	(0.091)	(0.047)	(0.015)	(0.020)	(0.110)
Trade, Lag 6	0.039**	0.212**	0.002	-0.011	0.029	-0.215*
	(0.016)	(0.105)	(0.066)	(0.025)	(0.039)	(0.115)
N	1,584,167					

Note: Baseline hazard stratified by 3-digit industry codes, commuting zones, gender, race, education and self-assessed health. Regressions control for a yearly trend. Each entry corresponds to a separate regression. Standard errors clustered at industry 3-digit sector.
$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Impact of Chinese imports (interacted with employability score) on cause-specific mortality

Cause of death	All	Suicide	Neoplasm tobacco	Neoplasm non-tobacco	Cardio-related	Alcohol-diet
Trade Lag 0	0.053	0.074	0.056	0.025	0.131**	1.412**
	(0.048)	(0.332)	(0.063)	(0.096)	(0.055)	(0.633)
Trade Lag 0∗Employability Score	-0.046	0.001	-0.063	-0.053	-0.165**	-2.474**
	(0.059)	(0.364)	(0.067)	(0.099)	(0.077)	(1.025)
Trade Lag 2	0.064	-0.537	0.063	0.174	0.098**	0.778
	(0.055)	(0.546)	(0.066)	(0.117)	(0.050)	(0.565)
Trade Lag 2∗Employability Score	-0.056	0.875	-0.096	-0.214*	-0.137**	-1.428
	(0.066)	(0.682)	(0.081)	(0.129)	(0.066)	(0.977)
Trade Lag 4	0.072	-0.403	0.054	0.203**	0.067	1.103
	(0.061)	(1.212)	(0.128)	(0.088)	(0.066)	(0.783)
Trade Lag 4∗Employability Score	-0.060	0.752	-0.090	-0.246**	-0.104	-2.127
	(0.073)	(1.615)	(0.185)	(0.101)	(0.099)	(1.299)
Trade Lag 6	0.188**	-0.717	0.075	0.340**	0.064	1.960
	(0.085)	(1.735)	(0.295)	(0.136)	(0.133)	(1.389)
Trade Lag 6∗Employability Score	-0.190*	1.207	-0.120	-0.414***	-0.055	-3.599
	(0.102)	(2.188)	(0.423)	(0.157)	(0.216)	(2.260)
N	1,584,167					

Note: Baseline hazard stratified by 3-digit industry codes, commuting zones, gender, race, education and self-assessed health. Regressions control for a yearly trend. Each entry corresponds to a separate regression. Standard errors clustered at industry 3-digit sector.
$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table A1: Regrouping of Causes of Death, NHIS

Condition	**NHIS Mortality file**	**ICD-10**
Cardio-related	53-74	I00-I78
Homicides and crime	128, 129, 130, 132	*U01.4, X93-X95, *U01.0-*U01.3, *U01.5-*U01.9, *U02, X85-X92, X96-Y09, Y87.1, Y35,Y89.0, Y22-Y24
Diet/alcohol-induced	45-49, 90, 94, 95, 96	D50-D64, E10-E14, E40-E64, E40-E46, E50-E64, K25-K28, K70, K73-K74, K80-K82
Neoplasm not tobacco-induced	19, 24, 28, 29, 33, 36-44	C00-C97, C22, C43, C50, C61, C70-C72, C81-C96, C81, C82-C85, C91-C95, C88, C90, C96, C17, C23-C24, C26-C31, C37-C41, C44-C49, C51-C52, C57-C60, C62-C63, C66, C68-C69, C73-C80, C97, D00-D48
Neoplasm tobacco-induced	20-23, 25-27, 30-32, 34, 35	C00-C14, C15, C16, C18-C21, C25, C32, C33-C34, C53, C54-C55, C56, C64-C65, C67
Suicide	122, 125, 126	X40-X49, *U03,X60-X84,Y87.0
Other	other codes	other codes

Table A2: Category definition, NIS

Condition	**ICD-9 codes**
Suicide	E850-E859 E868.2 E950-E960
Homicides and crime	E960-E979
Heart problems	410-438
Infectious diseases	001-139
Respiratory diseases	460-519
Mental disorders	290-311
Injury	800-869
Alcohol abuse	305, 291-292, 303, 571.0-571.4, E860.0
Endocrine, nutritional and metabolic diseases	240-280
Neoplasm (all)	140-239
Neoplasm (tobacco related)	162, 140-151, 153-154, 157, 160-161 179-180, 183, 188-189, 205
Stress:	
Mental disorder	300-311, 316
Tachycardia	427.2
Asthma	493.00
Ulcers	531-533
Colitis	556
Functional disorders of intestine	564
Dermatitis , eczema, urticaria	691- 692, 708
Backache	724.0/724.99
Diet related:	
Diabetes	250
Nutritional deficiencies	260-269, 280.1
Anemia	285.9
Eating disorder	307.1,307.5
Calculus of kidney	592
Chronic kidney disease	585.3-583.5
Hyper cholesterolemia, glyceridemia, lipidemia	272
Abnormal weight change	783
Obesity	V85.3-V85.45, 278
Inappropriate diet	V69.1