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working paper 2012

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June 2020

CENTRO DE ESTUDIOS
MONETARIOS Y FINANCIEROS
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CEMFI Working Paper No. 2012
June 2020

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Abstract

This paper assesses the effect of import competition on the labor market and health outcomes of US workers. We first show that import shocks affect employment and income, but only in areas where jobs are more intense in routine tasks. Exploiting over 40 million individual observations on health and mortality, we find that import had a detrimental effect on physical and mental health that is concentrated in those areas and exhibits strong persistence. It decreased health care utilisation and increased hospitalisation for a large set of conditions, more difficult to treat. The mortality hazard of workers in manufacturing increased by up to 6 percent per billion dollar import increase.

JEL Codes: F16, I12, I18.

Keywords: Import competition, routine tasks, health, health behaviour, hospitalisation, mortality.

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Acknowledgement

We are grateful to David Dorn and Gordon Hanson for sharing data with us, to Tito Boeri, Italo Colantone, Rosario Crino, Jonathan Dingel, Simone Ferro, Teresa Fort and participants in seminars at many universities and conferences for helpful comments and discussion as well as constructive comments of the referees and the editor. Forthcoming in The Economic Journal.

1 Introduction

Globalisation and in particular increased international trade has 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 also on 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 labour force participation and reduced wages. Autor et al. (2013a), Autor et al. (2014), Ebenstein et al. (2014), Pierce and Schott (2016) or Autor et al. (2016) exploit the timing of imports from China on US local labour 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 labour force attachment.

We build and extend this body of work, contributing to the literature on trade and health is three different ways. First, we show that the labour market effects of import competition are mediated by the average routine task intensity in the manufacturing sector in the area. In areas where this intensity is low, import competition has no discernible effects on employment, unemployment or family income. In contrast, most of the economic effects are concentrated in areas where jobs are more characterised by routine tasks. Bernard et al. (2006) shows that firms react to trade from low-wage countries by moving to industries that are more intense in high-skilled labour and capital, when they survive. In that process, production workers are likely to be more affected than non-production workers. This trade-induced skill-biased technological change is also at the core of the work by Bloom et al. (2015). Our results align well with this body of research and characterize the geographical concentration of import competition, a distinction not made in the literature so far.

Second, we characterise the dynamic effects of import competition. The extant literature has linked labour market outcomes to contemporaneous measures of imports. We show that not only do import shocks have a lasting effect of many years, but their effect on employment and income is also increasing with time. In some cases the effect doubles within a span of six years. This feature shows that import competition is of a different nature than other aggregate shocks. For instance, economic recessions last only for one or two years. A large number of studies look at the effect of recessions on labour market or health outcomes, but it is likely that import competition leads to different long-term effects, worth exploring on their own.

Third, we provide a detailed picture of the effect of import shocks on health, including mental and physical health, health behaviour, 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 behaviour. 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 behaviour and health care access. Finally, we use longitudinal data following manufacturing workers to investigate the effect of import competition on mortality. We investigate how the geographical concentration of economic effects and their dynamics affect the disparity and timing of a large set of health outcomes.

Our empirical strategy differs with the type of data we analyze. When uncovering the effect of import competition on health, health behaviour or hospitalisation, our research design is close to Autor et al. (2013a), as we use the industry composition of local labour 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.

We show that the effects of import competition on health are precisely restricted to those areas where manufacturing jobs are more routine-oriented. The effect of import competition on health is also increasing in the timing of the import shock, and affects both physical and mental health. The results are remarkably similar across the different data we use, coming either from survey data or from larger hospital records. We then investigate the possible pathways leading from poorer labour market outcomes to poorer mental and physical health.

We find mixed effects of import competition on health behaviour: on average, they improve following an import shock, but at the same time, there is a worsening in the upper tail. To uncover this complex pattern requires the very large sample size of hospitalisation data as health surveys such as the BRFSS miss it. Importantly, we show that the decline in health is too large to be explained by the observed decrease in family income. Another channel can be the reduced interaction with the health care system that we document. Two factors could be at play: the decrease in family income and the loss of the employer-provided health insurance, which -in the case of the US- is not replaced by public coverage in most cases. We show that the decrease in income is not enough to explain such a reduction in care. The consequence of this lack of access is that it may lead to some health conditions to go untreated or diagnosed too late, leading to more serious conditions later on. Our analysis of the hospitalisation data reveals that import shocks lead patients to be admitted with more serious conditions that require longer treatments. Finally, we show that increases in import competition have a subsequent effect on mortality that is growing over time. By analysing individual and longitudinal data, we can rule out prior sorting into industries based on health. The results show that a billion dollar increase in imports raises the hazard of dying by about six percent after seven 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) exploits 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. McManus and Schaur (2016) combines plant-level injury outcomes at US manufacturers with measures of import competition, and shows that greater increases in imports are associated with greater increases in injury rates. Closer to our research, a small number of studies have looked at the impact of import competition on workers' health. Colantone et al. (2015) finds a large negative impact of import competition at the industry level on workers' mental health in Great Britain, with spillover effects on their children, whose self-esteem and well-being are undermined. This effect goes through job displacement as well as gloomier expectations and increased likelihood of job displacement for those still in their job. Lang et al. (2019) uses the BRFSS data to estimate the impact of import competition on several dimensions of health, and finds a detrimental effect on mental and general self-assessed health in the US. As a mechanism, they find less health care utilization (individuals more exposed to import competition are more likely to forgo a doctor visit due to its cost) but no effect on health care access (no effect on the share of individuals having a health insurance plan in the commuting zone). A contemporaneous work by Pierce and Schott (forthcoming) examines the causal link between trade liberalization and mortality, exploiting a change in U.S. trade policy that increased U.S. counties' exposure to foreign competition from China differentially via their industry structure. They find that counties more exposed to the change in US trade policy exhibit relative increases in the so-called deaths of despair (at the core of Case and Deaton (2015)), especially among working-age whites, and that the impact of the policy change on mortality coincides with a deterioration in labour market conditions and uptake of disability insurance.

We add to this literature in several ways by showing the geographic concentration and the timing of detrimental effects of import shocks on health. As the effects are clustered precisely where we uncover poorer labour market outcomes and follow a similar dynamic, our analysis provide a more stringent test of the role of import competition on health. We show that prior sorting cannot explain the effect of import competition on health. The data on hospitalisation we exploit allow us to uncover the unexpectedly large set of health outcomes that are affected by import shocks. While we find detrimental effects on mental health and its manifestation through suicides, substance abuse (and in particular opioid abuse), import shocks affect also many aspects of physical health that have not been documented before. Those include heart, endocrine, respiratory, skin or infectious diseases as well as cancers, revealing that import competition has a much heavier toll than previously found.

The rest of the paper is organized as follows. Section 2 describes how we measure import competition and routine tasks and how they relate to each other. Section 3 shows the dynamic impact of import competition and its geographical concentration in areas that are characterized by a high routine task intensity. Section 4 presents the effect of import competition on health, health behaviour and health care utilization. Finally Section 5 concludes.

2 Import Competition and Routine Tasks

2.1 Exposure to Import Competition From China

Commuting Zones. In the following analyses, we first provide new evidence about the impact of exposure to US imports from China on labour market outcomes, then investigate how exposure to import competition from China affects individual health outcomes. Whether outcomes are local labour markets or individual health (with the exception of the last section where the outcome is mortality), we follow seminal work by in Autor et al. (2013a), Autor et al. (2013b), and Autor et al. (2015) (hereafter Autor-Dorn-Hanson) and define the commuting zone as our unit of analysis. Commuting zones are the most logical geographical unit of analysis when looking at the impact of Chinese imports on local labour markets as well as health as we expect labour market outcomes to drive the health effects. We consider the entire US territory with the exception of Hawaii and Alaska in all our analysis because of the many changes of counties over time in those two states, which leaves us with 722 commuting zones.

The Import Per Worker Shock: Definition. We construct the Import Per Worker (IPW) measure defined in Autor-Dorn-Hanson for every year from 1990 to 2011, using the following definition:

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

where $L_{c,j,t}$ is the employment in industry j - which belongs to the set of manufacturing industries $Manuf$- and commuting zone c, in year t, while $L_{US,j,t}$ is the employment in the same industry j across the whole country in year t. The greater the share of the commuting zone (CZ) in the US employment in industry j (given by the ratio between these two terms in the equation), the greater the shock. Imports from China in industry j are expressed in billion 2009 US\$, and denoted $Import_{j,t}$. They are rescaled by total non-agriculture employment in the commuting zone, hence expressed "per worker". We construct this measure for every year of data (from 1991 to 2011) and as a level variable, instead of a difference with respect to the previous period. This will allow us to use all available years of data when exploiting unbalanced health panel data. To put things in perspective we also rebuild the exact Δ IPW measure defined in the Autor-Dorn-Hanson literature, and replicate their findings using 20 one-year periods rather than two decennial changes.

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-Dorn-Hanson: 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 eight other high-income countries to instrument for Chinese imports in the US.[1]

The non-US exposure-to-Chinese-export variable is defined similarly, but differs in two respects from the IPW variable: $Import_{j,t}$ is replaced by $Import_{j,t}^{OTH}$, i.e. the imports from China to the 8 countries mentioned above, in industry j in year t; second, it uses employment levels from the prior decade, precisely from 10 years before, alleviating the risk of a simultaneity bias.

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

The Import Per Worker Shock: Data Sources. Imports from China are extracted from COMTRADE. Although US imports are available from other sources for prior decades as well, the instrumentation strategy we use leads to restricting the time period to 1991-2011. Starting in 1997, we will therefore be able to look at the impact of imports from China on several outcomes allowing for up to 6 lags. 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). All import values are deflated or inflated to 2009 US$. 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 1981-2011 period (since employment appears with a 10-year lag in the definition of the instrument version of the Import Per Worker

[1] These eight countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland, all high-income countries that have comparable trade data over the period 1991-2011. Costa et al. (2016) improve on this procedure to deal with the possibility of correlated world-level shocks by using auxiliary regressions.

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.[2] We then aggregate these numbers to the commuting zone level.

2.2 Automatability as a Source of Heterogeneity

The Routine Task Intensity measure. In order to assign a value of Routine Task Intensity (RTI) to each commuting zone, we 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 $RTI_k = ln(Routine_k) - ln(Manual_k) - ln(Abstract_k)$.[3]

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. Because this approach is based on the task content of each occupation rather than on the use of machines or computers by industry for instance, it reflects more the concept of *automatability*, i.e. the propensity for workers to be displaced as a result of the computerization or robotization of the tasks they used to perform. It has been widely used as an indicator of computerization or of technological change in the Autor-Dorn-Hanson

[2] The data is available at `http://www.census.gov/econ/cbp/download/` from 1986 onward, and via 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 found on David Dorn's webpage. The CBP sometimes reports brackets instead of exact values for employment or number 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. (2013a) for years 1980, 1990, and 2000, and generalize it to the entire period.

[3] Following Autor-Dorn-Hanson, when an occupation has a zero value for one of those task contents, we replace zero by the minimum non-zero value of the variable for the other occupations.

literature. When computing this RTI measure at the commuting-zone level, we consider jobs in the manufacturing sector in 1990, so that the average of the RTI measure in a commuting zone reflects the routine task intensity of occupations only in the manufacturing sector and for year 1990, i.e. when exposure to import competition was still very low over all the US territory.

We then sort the 722 commuting zones into 3 terciles of RTI based on the average RTI amongst manufacturing workers in each CZ. 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 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 1 displays commuting zone characteristics across RTI tercile groups. While the highest RTI tercile accounts for less population that the first two, all demographic and labour-related characteristics are very similar across the three RTI terciles.[4] The only CZ-level characteristic that differs substantially across RTI terciles is the amount of imports per worker, which increases with the RTI index. We next address the question of how import competition and automatability correlate across the US.[5]

The Interplay between Import Competition and Automatability. One important question is whether treating the IPW shock at the CZ level as exogenous to exposure to automation in the manufacturing sector at the CZ is reasonable. The concern would be that the industry composition that makes a commuting zone more exposed to import competition from China also contains more routine jobs that are prone to go through automation. If this

[4] IPW data correspond to years 1991, the remaining CZ characteristics correspond to years 1990. Commuting zone characteristics are derived from IPUMS Census data. We compute the average equivalized family 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

[5] Table A1 in the appendix lists the most important occupations and industries in each tercile of RTI, for the manufacturing sector. Although the shares of each industry and occupation vary across terciles, the most important industries and occupations are very similar.

was the case, and, provided that the two processes occur over the same period with the same adverse consequences in terms of employment, it would be hard to disentangle the impact of the import shock on local labour markets from that of automatability. Below we verify the extent of the overlap between the two phenomenons. Autor et al. (2015) is centered on this very issue, i.e. juxtaposing and untangling import competition and technology effects on employment in US local labour markets, from 1980 to 2007. Their findings are threefold: first, technology (defined as the RTI measure) and import competition (defined as the IPW measure) have distinct effects on employment: while import competition leads to worse outcomes in terms of employment, unemployment and non-employment, technological change has only minor adverse effects on employment; second, technological change gives rise to occupational polarization, as losses in routine intensive jobs are largely compensated by gains in jobs that are intensive in abstract or manual tasks. This compensation does not occur in the case of the import shock, which affects the whole manufacturing sector across all occupation groups, i.e. jobs intensive in manual and abstract tasks as well. Third, the timing of the two processes differ, as technological change has its greatest impact on employment in manufacturing (which is the technological change measure we focus on) in the 1980s, its smallest impact in the 2000s, when imports from China were skyrocketting. Those findings show that import competition and technology are separate phenomenons in terms of the magnitude and timing of their effects. Since we use technology at one moment in time (in 1990) as a source of heterogeneity across the territory, the two phenomenons should also be explored together at the geographical level. As described in Table 1, the IPW measure in 1990 increases across the RTI terciles, but the correlation between the two measures is quite low, i.e. less than 0.06 over the period. This is in line with Autor et al. (2013b), which explores the geographic overlap of trade and technology shocks in US local labour markets, and finds them to be largely uncorrelated across the territory.

In the following analyses we will therefore interact the IPW measure with the three terciles of RTI as defined in 1990, i.e. after most of the technological change has occurred in the manufacturing sector but before the so-called China shock has hit the US.

3 The Dynamic Impact of Import Competition on Local labour Markets

We first investigate the effect of import competition from China on the share of manufacturing employment amongst the working age population (18-65 years old), replicating the work of Autor et al. (2013a) for the 1991-2011 period, i.e. adding the 2007-2011 period to their two periods (1990-2000 and 2000-2007). Both the dependent variable and the import per worker shock are defined in differences with respect to the beginning of the period, all regressions include year and region fixed effects, and a set of CZ characteristics, such as the share of individuals in routine occupations at the start of the period (see Table 2 for all the controls). We define an occupation as a routine intensive occupation if it belongs to the highest tercile of the RTI measure in 1980, so that 33% of employment in 1980 corresponds to those routine occupations. We aggregate this measure to the commuting zone level for every year, to obtain the share of routine-intensive occupations for every CZ and year. Both the outcome and the controls (except for the share of manufacturing workers amongst all workers at the start of the period, which comes from the CBP) are extracted from the IPUMS Census data for years 1990, 2000, 2007 and 2010. The key explanatory variable- i.e. the IPW shock- is computed as explained above using both CBP and trade data. This analysis is therefore at the commuting-zone*year level (N=2,166, i.e. 722 commuting zones over 3 periods.).

Denote Y_{jct} the outcome of interest in commuting zone c and in year t. We relate it to the IPW shock in the following way:

$$\Delta Y_{c,t} = \alpha_0 + \alpha_1 \Delta IPW_{c,t} + \alpha_X X_{c,t} + \delta_r + \delta_t + \epsilon_{c,t}. \qquad (1)$$

where δ_r are region fixed effects, δ_t year fixed effects, $X_{c,t}$ are CZ characteristics. We cluster the standard errors at state level, to account for spatial correlation across commuting zones within states. The change in import exposure $IPW_{c,t}$ is instrumented by the change in exposure to Chinese imports in other countries $IPW_{c,t}^{OTH}$. Autor et al. (2013a) enumerates three threats to identification: first, product-demand shocks may be correlated amongst high-income countries; second, US -rather than Chinese- productivity shocks may be driving the growth in imports from China; third, technology shocks common to high-income countries may affect negatively their labour-intensive industries. Autor et al. (2013a) addresses the first concern by estimating a gravity model and showing that the IV and gravity model lead to similar conclusions. They also construct the IPW shock without considering the computer industry, in which demand does increase at the same time in all high-income countries. The robustness of the results allow us to be confident that the labor market and the resulting health effects of the IPW shock are not driven by positive demand shocks that would occur in all high-income countries at the same time. It is also worth mentioning that had it been the case, we would be estimating a lower bound of the effect of import competition on local labour markets and health outcomes. The second concern is very unlikely: that a surge in US productivity would drive the growth of US imports from China does not seem to reflect the reality. This is also supported by Brandt et al. (2012), which estimates that productivity in China increased by 8% over 1998-2007, i.e. more that twice that of the US. The third concern is that automation could be the hidden force behind the growth in US imports from China, and that this process would be undermining employment in industries that are labour-intensive. We believe -as in Autor et al. (2013a)- that this story is unlikely, as the growth in Chinese exports seems to be mainly due to factors that are specific to China such as policy reforms and rapid productivity growth. Nevertheless we add a control for the share of routine occupations at the CZ level in all our specifications. We use the same definition of a routine occupation as Autor et al. (2013a), incorporating both white-collar jobs that are at risk of being computerized, suck as clerks and administrative support, and blue-collar production occupations, which involve repetitive tasks at risk of being replaced by machines. By including this control, we make sure that the adverse effects of a higher share of routine-intensive occupations in a CZ on labour and health outcomes -which are significant and negative, and similar whether we introduce RTI-heterogeneity or not- are not captured by the IPW coefficient.[6]

Table 2 presents the estimation of equation (1) with the share of working-age individuals working in manufacturing as the outcome. In other words, it replicates and extends the

[6] Autor (2017) addresses a more recent discussion about the growth in housing prices potentially driving the effects of the IPW shock: controlling for housing prices does not affect the initial findings about the impact of import competition from China on local labour markets).

well-established results of Autor et al. (2013a) on the effect of the IPW shock on the share of individuals working in manufacturing, adding a third period (2007-2011) to it. Columns (1) to (5) show a significant and negative coefficient for the IPW measure across all specifications, but of lesser magnitude than in the two-period model (i.e. until 2007), as the start-of-period percentage of employment in manufacturing correlates more with the outcome than in the initial results.

We then add to these established results by introducing the Routine Task Intensity as a spatial source of heterogeneity in the impact of exposure to import competition on local labour markets. Bernard et al. (2006) shows that import competition from low wage countries leads US manufacturing to reallocate over time towards industries that are more capital and skill intensive. Firms that are hit the hardest - i.e. firms intense in low skilled labour- by import competition either close down or react by upgrading their product mix. Low-skilled production workers are therefore likely to be more affected than high-skilled non-production workers. When hit by import competition, they may lose their jobs due to plant closure, or see their job automated away, precisely because low-skilled jobs in manufacturing are intense in tasks that require less human intelligence and are more prone to being robotized. Chinese import competition has also been showed to induce more technological change (R&D, patenting, IT and productivity) in the firms that were not driven out (Bloom et al. (2015)). Going further, Jaimovich and Siu (2012) show that once routine jobs are destroyed during an economic downturn, they are less likely to rebound when the recovery shows up than jobs in non-routine occupations. Manufacturing workers in areas where jobs are more routine intensive are then under the double pressure of plants closing down due to a shrinking domestic market, and an automation process threatening the existence of their jobs. We should therefore observe more dramatic consequences of the import competition shock in those areas. Areas where jobs are the least intense in routine tasks are still exposed to import competition from China, but these effects are not amplified by import-induced technological change.

To investigate this issue, we introduce interactions between the IPW shock and the three RTI terciles in equation (1), which are now instrumented by the interactions of $IPW_{c,t}^{OTH}$ and the three terciles of RTI. As shown in column (6), the IPW effect increases with the intensity of automatability across the territory: the higher the average RTI, the higher the impact of the import shock on manufacturing decline. All three coefficients are statistically different, with the estimate of the IPW coefficient in the highest RTI tercile being more than twice that in the lowest RTI tercile.[7]

We then investigate the effect of import competition from China on other labour market outcomes such as the share of individuals who are employed, unemployed, or out of the labour force, and the average equivalized family income. In the left panel of Table 3, we estimate again equation (1) for the 1991-2011 period, but with annual differences, i.e. considering 20 one-year periods. All regressions control for the share of individuals in routine occupations at the start of the period. A comparison with Table 2 which used exactly the same set of controls as in Autor et al. (2013a) shows that results are unchanged. In Table 3 and for the remainder of the analyses we control for the share of routine occupations at the CZ level and in the health analysis section we add individual controls for the other characteristics such as race, education and gender. All the outcomes, and the share of routine occupations, are extracted from the IPUMS Census data for years 1990, 2000, 2007 and 2010. Years in-between (and 2011) are interpolated (or extrapolated). The IPW shock is defined from 1991 to 2011 using the CBP and trade data for every year. This analysis is therefore at the commuting-zone*year level (N=14,440, i.e. 722 commuting zones over 20 years.). We check that the previous results are not driven by one atypical year amongst the very few that were exploited in the literature before. By using 21 years of data instead of 4, our estimates of the local labour market effects of the import shock will be more robust. This will be even more important for the health section of the paper as we will exploit annual data for the outcomes as well.

In the right panel of Table 3, we move to a fixed effects model, which we adopt in the remainder of the text either because we estimate the model from repeated cross-sections at

[7] The increasing effect of the IPW shock across RTI terciles is robust to restricting the model to the first two periods, and to other definitions of the RTI terciles such as one using the RTI of all jobs within a CZ in 1980 instead of 1990 to divide the territory into three terciles, one based on the share of routine occupations instead of the average RTI of a CZ, or to a definition of RTI that incorporates all sectors instead of only manufacturing. In the latter case, there is no statistical difference between the coefficients of IPW in the medium and high RTI areas, but their effect is still much larger than in the lowest RTI area.

the individual level, or because of the unbalanced nature of our panel data.

We estimate regressions of the corresponding outcome at the CZ-year level on the level of the IPW (instrumented by the level of $IPW_{c,t}^{OTH}$), year and CZ fixed effects, region-specific trends and CZ characteristics. This model is therefore equivalent to the first differenced model: CZ and year fixed effects ensure we estimate within-CZ effects, and the region-specific trends allow us to control for any trend that would affect differentially local labour markets across regions.

Results in the left panel (the first differenced model) column (4) suggest that a commuting zone going through a 1,000$ IPW increase from one year to another will suffer a decline in the share of the working age population employed across all sectors (0.22 percentage point), employed in manufacture (0.34 percentage points), and an increase of the share of the working age population who are unemployed (very small: 0.06 percentage points), out of the labour force (0.16 percentage points), or whose average family income is below 15,000$ (0.2 percentage point). Columns (1) to (3) show that the negative impact of the import shock on local labour markets is mostly concentrated in the top-RTI-tercile commuting zones, and to a lesser extent in the medium tercile group. The shares of individuals who are employed or out of the labour force are impacted by exposure to import competition only in the medium and highest RTI terciles. It therefore seems that those who exit the manufacturing sector in the low-RTI commuting zones do not exit employment or the labour force as a result of the import shock, but reallocate out of the manufacturing sector, and consequently do not suffer a drop in income, unlike those in the medium and highest RTI terciles. The corresponding estimates in the right panel are very similar.

Last, we introduce lags in the IPW shock, so that we can look at how local labour markets are affected immediately and a few years after imports per worker have increased in a CZ. The fixed-effects model we estimate now allows for lags and RTI heterogeneity. Table 4 displays the results for years 1997 to 2011 - so that the sample is the same across all lags - for areas with a high RTI. All regressions point at an increasing effect of the IPW shock across lags, more so after 4 years. 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 4 years. Column (1) also shows that the point estimates are higher when years 1991-1996 are omitted (compared with column (8) of Table 3.), which suggests the import competition effects on local labour markets were lesser in the early 90s than afterwards.

The results so far point to a detrimental effect of import competition, with considerable heterogeneity across US commuting zones. If the effect of imports 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 commuting zones depending on their degree of exposure to import competition from China, differentially for low and high RTI areas.

4 Impact of Import Competition on Health and Mortality

In this section we investigate the effects of import competition on health using three different datasets which bring new light on the many aspects of the relationship between import competition and health. We first exploit large survey data with information on self-assessed health, health behaviour and health care utilisation. We next draw on extensive data on hospitalisations to refine the analysis. Finally, we exploit longitudinal individual data where we can directly assign workers to a particular industry and where we can control for prior sorting based on health. We first review the different potential pathways that the literature has uncovered and we discuss whether import competition shocks may generate different effects.

4.1 Potential Pathways

We have shown that import competition, in affected areas, leads to a loss of employment and a loss of income over many years. How changes in income and labour market status is related to health has been a topic of interest across disciplines.

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. 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. 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.

The results in Section 3 show that the import shock is much more sustained than recessions. While a recession lasts on average for about 1 to 2 years, we find effects lasting for many years. This is a reason why it is difficult to extrapolate the health effects from results based on aggregate shocks such as business cycle variations.

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 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.

The health effects of the import shock could be amplified by the interplay between mental and physical health. Experiencing job-related distress, whether due 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 consumption of antidepressants and related drugs, as well as hospitalizations due to mental health problems (Kuhn et al. (2009)). The consequences of mental stress go beyond mental health conditions. Deaton et al. (2006) reviews a number of experiments and analyses concluding that psychological stress is responsible for higher odds of developing a disease, particularly a cardiovascular one.[8] 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. Last, losing one's job also leads to greater risk of social isolation, which is associated with higher mortality risk (see Steptoe et al. (2013)).

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). Kuka (forthcoming) shows that variations in unemployment insurance affect health care coverage and health. Untreated or delayed treatment could lead to more serious conditions and more fatal ones.

4.2 Impact of Imports on Health, Health Behaviour, and Health Care Utilization

4.2.1 Data and Empirical Strategy

We pool annual cross-sections of the BRFSS from 1997 to 2011. After 2011, the data does not record the county of residence. As in the case of the CBP, we focus on the post-1997 period in order to be able to look at the impact of exposure to import competition on health

[8]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.

with an up-to-6-years lag. Our sample is made of individuals aged between 18 and 65, who were interviewed at some point between 1997 and 2011. The data on county of residence is used to assign individuals to commuting zones.[9] We rely on a similar specification as in Section 3, equation (1), but we define the outcome as $Y_{i,c,t}$ for individual i in commuting zone c and year t. Our variable of interest is the instrumented import per worker measured in commuting zone c and in year $t-k$. We also interact this measure with the routine task index of the commuting zone c, categorized as above into low, medium or high (L, M, H). Contrasting the effect of import competition across those three areas is akin to a triple diff-in-diff design, given that we have shown in the previous section that areas with lower routine task intensity appear to be much less affected by import shocks.

The model includes year and commuting zone fixed effects, and state-specific trends instead of region-specific trends, in order to control for potential state health care policy changes across years. We also include controls at the commuting zone level, i.e. the share of routine occupations in manufacturing employment in a commuting zone and individual controls such as gender, age, race and education. We estimate the model by fixed effects rather than with a first difference method because the dataset is cross-sectional with regards to the individual and because not all health variables are collected every year. Following Abadie et al. (2017), we cluster standard errors at the level of variation of the shock, i.e. the commuting zone level.[10] We weight each observation by its weight in the CZ, based on observable characteristics.[11]

The BRFSS offers a wide variety of outcomes of interest regarding the individuals' health. We focus on a subset of outcomes that is common to most years of observation. As the survey contains many measures of health and we want to explore the dynamic effects of

[9] 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.

[10] Section 3 used state level clustering to follow closely the ADH approach. In practice, the two clusterings deliver very similar results.

[11] We construct the weighting in the following way: for each individual we compute the share of his/her group in the corresponding CZ in terms of gender, race, and age group, in the BRFSS for all years, and in the Census for 2000, then the Census share is divided by the corresponding share in the BRFSS, and this ratio is multiplied by the share of the CZ in the population for each year. Our BRFSS estimates therefore reflect the proportions of individuals from a certain age group-race-sex cell in the IPUMS Census 2000 data.

import competition by exploring its effect over many years, we first reduce the dimensionality of the data. We construct three indexes relating to health, health behaviour and health care utilisation, using principal component analysis. The composite measure of health is constructed by including self-assessed health, indicators for diabetes, being obese (with a BMI that is superior to 30), and poor mental health (number of days with mental health problems in the past 30 days). We also build a composite measure of health behaviour, summarizing drinking, smoking and exercise habits. The index of health care utilization is composed of an indicator for having a health plan, for having had a flushot, whether a doctor visit was forgone due to its cost, and the time since last medical checkup. By construction, the composite indices have mean zero and a standard deviation of one hundred (see Table A2 in the appendix for descriptive statistics). All indexes are such that higher values mean better health outcomes.

4.2.2 Evidence on Health and its Dynamics

We provide estimates of the effect of import competition in Table 5, columns (1) to (4) using our general health composite index for lags ranging from 0 to 6 years. At the aggregate level (column (1)), the impact of the import shock on individuals' health peaks at lag 0 (driven largely by mental and self-assessed health), then decreases until it loses significance after two years. A $ 1,000 increase in the import competition measure reduces the health index by about 1.5 units at lag zero. This translates into a one per cent reduction of a standard deviation of health for a one standard deviation change in imports.

When looking at the differential effect of import competition across areas with different propensity to automate (columns (2) to (4)), most of the negative effect of exposure to imports is concentrated in the high-RTI area, where it shows a U-shaped pattern with the time lag. The areas in the low or middle-RTI terciles show insignificant and much smaller effects on this general health measure. These health results align well with the patterns we uncovered in Section 3 both in terms of geography and in terms of the dynamic effects of import shocks on the labour market.

Table 6, Panel A disaggregates the health index into its different components allowing for a lag of four years for the import shock to have an effect. We find that import competition affects negatively a range of health measures and almost only in areas with high RTI. Those health measures include worse cardio-vascular diseases (strokes), endocrine diseases (diabetes), respiratory diseases (asthma) and diet (obesity). We also find a worsening of mental health in high RTI areas, although this effect is not statistically significant at a four year lag, but results show that mental health problems peak at earlier lags. We now explore possible mechanisms to this general deterioration in health. We focus first on proximal causes such as changes in health behaviour or health care utilisation. We then look at more distal causes such as income effects and job loss.

4.2.3 Health Behaviour and Health Care Utilisation

Some of the health deterioration described above may originate in changes in health behaviour. For instance, smoking has strong links with cardio-vascular health and exercise affects obesity. Table 5, columns (5) to (8) show the effect of import competition on the health behaviour score. We find that import competition induces people to adopt a healthier lifestyle, but this is the case only in areas that are less prone to automation in the manufacturing sector, where the China import shock consequences exist but are less acute. It therefore seems that changes in health behaviour resulting from increased exposure to import competition cannot explain the adverse health effects of the import shock, as those changes are small in the highest-RTI area, and beneficial in the low and medium-RTI areas.

We find that the effect of import competition on health behaviour is rather similar to the effect of recessions. Ruhm and Black (2002) and Ruhm (2005) show that part of the business cycle effect operates through changes in health behaviour, 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).[12] The literature on health behaviour 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

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

number of cigarettes smoked. That change in behaviour 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)).

Another possibility to the lack of an effect on health behaviour is that the BRFSS is not large enough as a survey to pick up changes in health behaviour of a smaller population affected by the import shock. To identify effects on subgroups or on rarer conditions, we rely on the very large samples available from the hospitalisation discharge data presented in Section 4.3 below.

Another channel through which health could deteriorate is the lack of access to treatment. We explore the consequences of the import shock on a composite measure that summarizes both health care access (whether the individual has "any kind of health care") and health care utilization (whether the individual has received a flus hot in the past 12 months, whether he/she had to forgo a doctor visit due to its cost).[13] Results displayed in columns (9) to (12) of Table 5 show that health care access/utilization has been significantly undermined by the import shock in those areas where jobs were more likely to be automated away in manufacturing. The coefficients appear both significant and big (compared with the estimated effects of the IPW measure on the "good health" and "good health behaviour" factors). Those effects are again concentrated in the highest-RTI tercile. Looking at individual measures in Table 6, the effects are driven by those who could not see a doctor because of the cost, and fewer individuals taking preventive measures such as flushots or not having any health plan. Delayed treatment, discontinuing the treatment of pre-existing conditions or delaying the diagnosis and treatment of new conditions is likely to lead to more severe health issues later on. The information in the BRFSS does not allow to check this mechanism directly, and we use the information in hospitalisation discharges in Section 4.3 to explore the issue further.

In the US, health insurance is often employer-provided and the increased proportion of individuals without a health plan is therefore a consequence of the rise in individuals out of the labour market documented in Section 3.

[13]Although the BRFSS includes many other items that are related to health care utilization such as bloodstool test, mammograms and dentist visits, those are not asked every year, so that incorporating them would lead to a much smaller sample for the main factor of health care utilization.

4.2.4 Is Income Loss Enough to Explain the Decline in Health?

In addition to loss of health care, income variation is also a likely mechanism behind the health effects of the China shock. The extant literature has pointed at contrasted effects of the import shock itself: 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.[14] On the negative side, individuals working in industries that were the most exposed to increased competition with China have been faced with higher unemployment and income loss (due to job loss and lower wages), which could both affect their health.

As pointed out in Table 3, increasing exposure to import competition leads to lower income, except for the low-RTI area, in line with the absence of effect on the share of individuals being employed or out of the labour force. Evidence from the BRFSS confirms these findings, with less people working, and more people with low income, as a consequence of the import shock in high-RTI commuting zones (a 1,000 dollar increase in IPW leads to a 0.9 percentage point decrease in the probability of working, and a 0.54 percentage point increase in the probability of earning less than 20 thousand dollars a year. See Table 6, Panel D).

As the import shock leads to potentially a loss of income, a higher likelihood of not working and a loss of health insurance, it is difficult to separate each effect in a precise and causal way. Estimating the causal effect of income on health in general is beyond the scope of this paper. We approach the issue of the effect of income loss through a bounding method. We compare the causal effect of increased exposure to import competition from China with the non-causal association between income and health. The estimate of the effect of income on health we get can be considered as an upper bound, due to reverse causality and omitted variables.[15] We regress our health composite measure on ajusted income (reported in the BRFSS and then adjusted for inflation by the CPI) and the same set of controls as in the

[14] di Giovanni et al. (2014) calculates 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 finds an overall positive effect, which is higher in the long-run.

[15] Causal estimates of the effect of income on health can be found in Lindahl (2005), Snyder and Evans (2006) or Adda et al. (2009) for instance, using different identification schemes.

IPW regressions (age, sex, race, education, year and commuting zone effects, state-specific time trends, and share of routine occupations), and display the results in the bottom panel of Table 5. We find that for this population, a 1,000$ decrease in income is associated with a decrease of at most 0.5 units of the health factor. The effect of a 1,000$ increase in IPW is therefore equivalent to (at least) 3 to 5 times a $1,000 loss of income in terms of the associated health deterioration. Taking the highest estimate of the income loss triggered by import competition in Table 3, i.e. a $570 loss, a $1,000 increase in IPW would lead to at most a 0.29 decrease in the "good health" factor, which is much less than the estimates displayed in Table 5. In other terms, we observe a deterioration in health that is much larger than what the loss of income alone would imply.[16]

In a similar way, Table 5 reports the association between income and health care utilisation. We find that a $1,000 decrease in income associated with a decrease of -0.8 units of the health care utilisation index. This effect is much smaller than the (causal) effect of import competition on utilisation. This confirms that part of the lack of interaction with the health care system operates through a loss of access rather than a lack of resources alone. We explore further this issue in the next section.

4.3 Evidence from Hospital Discharges

In this section we look at the impact of import competition on hospital discharges, which provides further insight on the role of import competition in shaping health, health behaviour and health care utilisation. The advantage of hospital data compared to health surveys such as the BRFSS is two-fold. First, it consists of "hard" outcomes, established by doctors, whereas health surveys rely mostly on self-declaration. Second, sample sizes are of a larger order of magnitude and allow to detect rarer outcomes as well as changes in health behaviour, not just on average but at the right tail of the distribution.

[16] In addition, results in Table 5 are robust to the inclusion of income as a control in the regressions of the composite health measure on the IPW shock (at all lags). This suggests that income is not the only pathways to poor health.

4.3.1 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 4.4 will). To overcome this issue, we proceed in a similar way as we did in Sections 3 and 4.2. 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 40 million observations. We grouped the diagnostic codes into 18 categories, not mutually exclusive. We consider discharges where at least one of the diagnostic codes mention heart problems, infectious, respiratory, skin, digestive or endocrine diseases, cancers (we also distinguish tobacco and non tobacco related cancers), the occurrence of pain, mental disorders, suicide attempts, injuries, homicides, alcohol abuse, substance abuse and opioid 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.[17]

[17]Table A3 in the appendix provides a classification of the categories with the ICD 9 codes we use. The

We partition the discharges into ten groups defined by birth year and gender. We define five birth-year groups for years before 1940 to after 1970. For each hospital, we then compute the number of diagnoses of a given type within those birth year-gender groups and by year. We restrict the sample to the years 1997 to 2011 to be consistent with the analysis in the previous sections. We follow 1,990 hospitals over time, totalling 91,229 hospital-year-group observations. Table A4 in the appendix 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.

4.3.2 Empirical Strategy

The design of the data is different from the one in the BRFSS and the CBP. As we do not observe the universe of hospitals in a commuting zone, we estimate the effect of imports within a commuting zone at hospital level instead. Our specification is similar to the one we used before (see equation (1)), but we now define the outcome as $Y_{h,g,c,t}$, observed in hospital h, for group g, 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. We control for time and hospital fixed effects as well as birth-year-gender fixed effects. In addition, the regressions include county and commuting zone time-varying characteristics (e.g. the share of routine occupations in manufacturing employment, the racial and gender composition of the commuting zone or the number of hospital beds in the county) and state specific trends.[18] The variable measuring the import per worker is instrumented as explained in Section 2. We cluster the error term at commuting zone level. To probe the role of import shocks further, we interact it with terciles of average routine task intensity, computed for manufacturing jobs in each commuting zone in 1990 as we have done above.

two latter groupings were defined based on discussions with medical doctors.

[18]Given that our panel is unbalanced - not all hospitals are observed in each year - we estimate the model using a fixed effect estimator.

4.3.3 Results using hospitalisation data

The outcome variable is the log number of one plus admissions for a particular cause.[19] We measure import competition in $ 1,000 per worker. On average during the period we consider, its mean is 1.3 with a standard deviation of 1.6 (see also Table 1). Table 7 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 the first column show the effect of import competition across all commuting zones on the health measures we consider. In general, the effects are positive but not always significant at the 5 percent level. For instance, a one thousand dollar increase in import competition raises the number of admissions for stress related symptoms by about 0.01 log points and for mental health problems by about 0.02 log points, the latter translating into a 1.2 percent increase for a one standard deviation shock in imports. We find significant import competition effects for admissions for injuries and homicide injuries, although most effects are modest in size. The results using hospital discharge are thus in line with those found using the BRFSS in the previous section. At an aggregate level, import competition has a small impact on most health measures.

The next three columns display the effects of import competition across areas with low, medium or high routine task intensity. As in previous sections, the detrimental effects of import competition are concentrated in areas with high RTI. In those regions, a one thousand dollar increase in imports per worker leads to an increase of about 0.1 to 0.2 log points for most outcomes we consider. The effect of import competition is particular strong for mental health problems, substance abuse and especially substance abuse linked to opioid abuse. Case and Deaton (2015) have documented the recent rise of "deaths of despair" in the US. A recent literature has linked opioid abuse to local levels of unemployment (Hollingsworth et al. (2017)) or to import competition (Pierce and Schott (forthcoming), using data on mortality by cause). We also document a rise in injuries. While it is possible that import competition may lead to more work accidents through increased stress at work or pressure to increase work productivity, it is well known that a number of injuries reported in hospitals are in

[19] In smaller hospitals there are years where we do not observe any discharge for a particular cause and a particular age-gender group. The results are robust to excluding those observations.

fact mislabeled suicide attempts (Phillips and Ruth (1993)). We find a significant increase in suicide attempts as well in high RTI areas, following an increase in import competition. We also find a substantial increase in homicide injuries. This finding corroborates those of Deiana (2018) that documents an increase in crime in areas with higher import competition.

In Section 4.2, we did not find a significant increase in alcohol consumption. 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 to alcohol abuse. The results suggest that areas hit by an import shock see a decrease in overall alcohol consumption, perhaps through an income effect, but also an increase in the upper tail of the distribution of alcohol consumption that health surveys such as the BRFSS miss.

Table 7 next displays results on physical health, as opposed to the first set of results that relate to mental health and its consequences. We first document a rise in the occurrence of pain in high RTI areas. The most frequent issues related to pain are chronic pain, backaches and chest pain. These are often manifestations of other medical problems, but constitute also a pathway to substance abuse, distinct from a deterioration in mental health. Consumption of painkillers can lead to addictive behaviour which are picked up in our analysis as opioid abuse.

The results in Section 4.2 showed an effect of import competition on general health, cardiovascular diseases, endocrine diseases such as diabetes, or respiratory diseases. The results using hospitalisation data confirm those results and shows increased rates of hospitalisations due to heart problems, infectious diseases or respiratory diseases. The most common respiratory diseases include asthma and pneumonia. These conditions are linked to stress and lack of preventive care, among others factors. We find a large effect on skin diseases, where a leading cause are skin infections, often linked to diabetes or obesity. The effect is lower but still significant for endocrine diseases. The most common endocrine diseases in our data are diabetes and hypercholesterolemia, two conditions related to poorer health behaviour. In addition, we find an increased rate of admissions related to cancers driven both by tobacco related causes as well as non tobacco related ones. The effect of import competition is considerably lower in areas with low or medium RTI and often not significant.

We present in Table 8 the effect of import competition on the types of admissions and the composition of patients. We find evidence of a small increase in the number of admissions overall, mainly driven by high RTI areas. We find evidence that in those areas, admissions are more likely to be categorised as 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 cardio-vascular diseases, and generally to the fact that some pathologies may have gone untreated for too long. By the time these patients show up in hospital, they could be more likely to have acute conditions. This is also in line with the increased mortality within hospitals as shown in the table. Looking at diagnostics for each individual, the occurrence of hospital deaths are far more prevalent for cardio-vascular, endocrine and respiratory diseases than for causes linked to mental health issues such as suicides or drug abuse.

Another sign of the increased complexity of cases is shown in the rise in the length of admissions, which is significantly higher in areas with a high RTI. The distribution for the length of admission is skewed and we also find an increase for admissions lasting for more than a week. In those areas, hospital charges tend to be higher, although we do not find a significant effect. Table 8 next shows the effect of import competition on number of patients covered by Medicaid, with a significant increase of 0.10 log points as well as those covered by Medicare in high RTI areas. The latter ones are individuals below 65 that are recipients of Social Security Disability benefits or have end stage renal disease.

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. However, ascribing all of those results to mental health is not warranted, as we show that import competition also leads to the deterioration of a range of health conditions.

4.3.4 Dynamic Effects of Import Competition

Figure 4 displays the effect of import competition at various leads and lags for a subset of the outcomes. Given that we find strong and significant effects of import competition in high RTI areas, we limit the analysis to those areas. The figure displays the coefficients on import competition obtained from regressions similar to those in Table 7, that control for hospital, time, socio-demographic fixed effects, as well as state trends, and time varying characteristics at commuting zone or county level. We find that the effect of import competition gets stronger over time and become significant at the 5 percent level after one or two years. Remarkably, the effect of future import shocks is much smaller and statistically insignificant. This shows that pre-trends or prior sorting into industries that will be hit by import competition are not causing a spurious effect.

4.4 Impact of Import Competition on Mortality

In this section we look at the impact of exposure to import competition from China. While some studies have analysed mortality in relation to import competition (Pierce and Schott (forthcoming)), they rely on aggregate mortality patterns at commuting zone level matched to imports in that area. In contrast, we rely on restricted use individual data following individuals over time. This design has two advantages. First, as the data record 3-digit occupations, we can match the individual to a precise measure of imports of that industry as opposed to an import mix at commuting zone level. Second, as the data comes from a health survey, we are able to control for health when we first observe the individual, which allows us to control for potential sorting into particular industries based on health.

4.4.1 Data

We use data from the National Health Interview Survey (NHIS), over the period from 1988 to 2009. The NHIS is the principal source of information on the health of the civilian non-institutionalized 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.[20] All our estimations 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.[21]

The NHIS provides a linkage to death certificate records from the National Death Index. Individuals who are surveyed at any point between 1988 and 2009 are observed again when they die, if they do before December 31st, 2011.[22] We can therefore construct a panel, in 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, an individual remains at most 15 years in the sample, so that the assumption that the worker will still be affected by a shock in the industry at baseline 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 imports. 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 are considered in our analysis, for the restrictions mentioned above.

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. It is now assigned to worker i working in industry j at year t, rather than to a

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

[21]Table A5 in the appendix provides descriptive statistics.

[22]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.

commuting zone. We use imports series from 1988 to 2011 for both the US and the four high-income countries that are used to construct the instrument.[23]

4.4.2 Empirical Strategy

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

$$h(age_{it}|Import_{j,t-k}, X_{i,j,c,t}) = h_0(age_{it}|X_{i,j,c})\ exp(\alpha Import_{j,t-k} + \delta_t), \tag{2}$$

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. Note that the stratification by 3-digit industry and commuting zone is equivalent to consider (interacted) industry and area fixed effects. The identification of import shocks comes from the differential mortality over time, areas and industries. We instrument the imports from China using the instrument presented in Section 2.1. Given that our Cox model is non-linear, we implement the instrumentation through a control-function approach, i.e. by including the first-stage residuals in the estimating equation.

4.4.3 Results

As the first column of Table 9 shows, the import shock moves the mortality hazard upwards by around 1% at first, with an increasing impact as we allow more time for the shock to impact mortality. The effect increases to 6% with a 7-year lag. These results brings additional weight to the one we have using health surveys and administrative data from hospitals. The contemporaneous effect is in line with an immediate worsening in mental health found in

[23] Only 4 countries (Australia, Finland, Japan and Switzerland) of the eight used before have imports data over this period

Section 4.2, potentially leading to suicides. As the time lag increases, the rise in mortality comes increasingly from other causes, as we found effects of import competition on cardio-vascular, endocrine or respiratory diseases at longer lags in Section 4.3.

5 Conclusion

In this paper we make three main contributions to the literature on trade and health. We first show how import competition effects on the labour market are mediated by the composition of tasks in the industry. We show that import competition effects are concentrated in areas in the US where routine tasks are the most prevalent, and largely absent elsewhere. Our results therefore complement and extend the work by Autor et al. (2013a), Autor et al. (2014) or Autor et al. (2016) by emphasising the role of technology and tasks in understanding the effect of import competition on the economy. 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 labour markets pioneered by Autor et al. (2003).

Second, we investigate the dynamic effects of import shocks and show that they display considerable inertia. Their effects are growing with time, at least over a span of six years.

Third, exploiting multiple and large datasets covering about two decades, we show that the geographical and temporal patterns of labour market effects are also found for a very large array of health measures. Import competition has led to a significant deterioration of health in areas where jobs are the most intense in routine tasks but it has not in areas with the lowest routine task intensity. We find a worsening in mental health and associated outcomes such as suicides or substance abuse. Those results align well with those of Case and Deaton (2015) and show that import competition is one of the determinants of this unprecedented decline in health. However, import competition is also related to many aspects of physical health. Those include cardio-vascular problems and endocrine diseases which can be linked to stress and poorer health habits, but also other problems such as infectious diseases or skin problems, which are often the consequences of distinct diseases such as diabetes.

We investigate the pathways to this deterioration in health and find mixed evidence on health behaviour as an explanation. We also show that income loss alone cannot explain this worsening in health, so that part of the effects goes through a lack of access to health care. This in turn can lead to worse health outcomes later on. Indeed we also find that hospitalisations are more likely to be classified as emergencies and that patients stay longer in hospital following an import shock. We show that the effects we find are not due to sorting of individuals into areas or industries prone to face import competition.

Our results suggest that the effect of import competition is more pronounced than other studies investigating this same shock but also other aggregate shocks. One reason that economic recessions seem to be less harmful than import shocks is due to the persistence of those shocks. The literature has also 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 1990

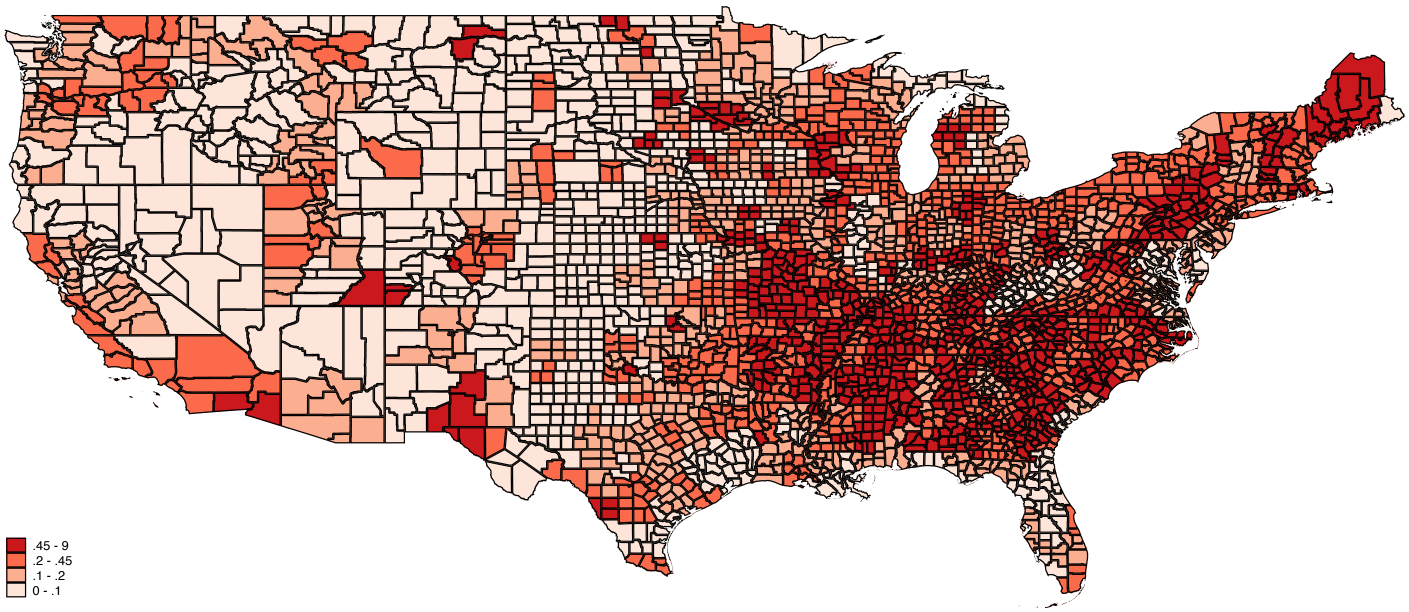
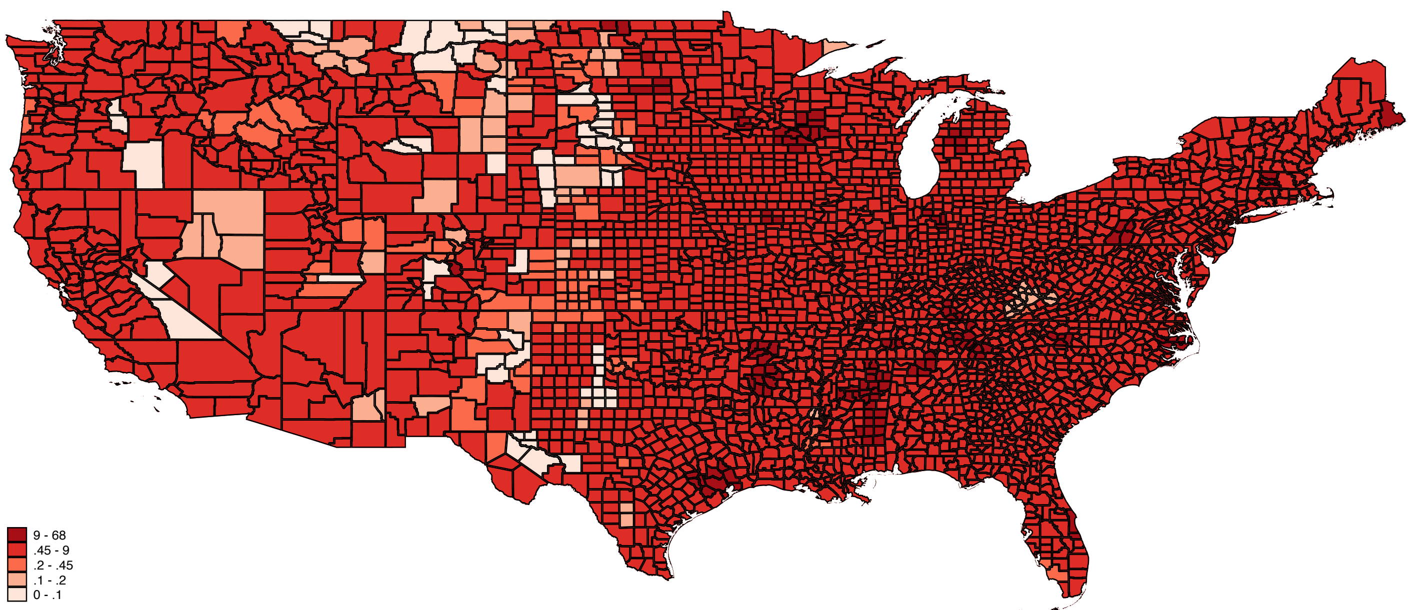
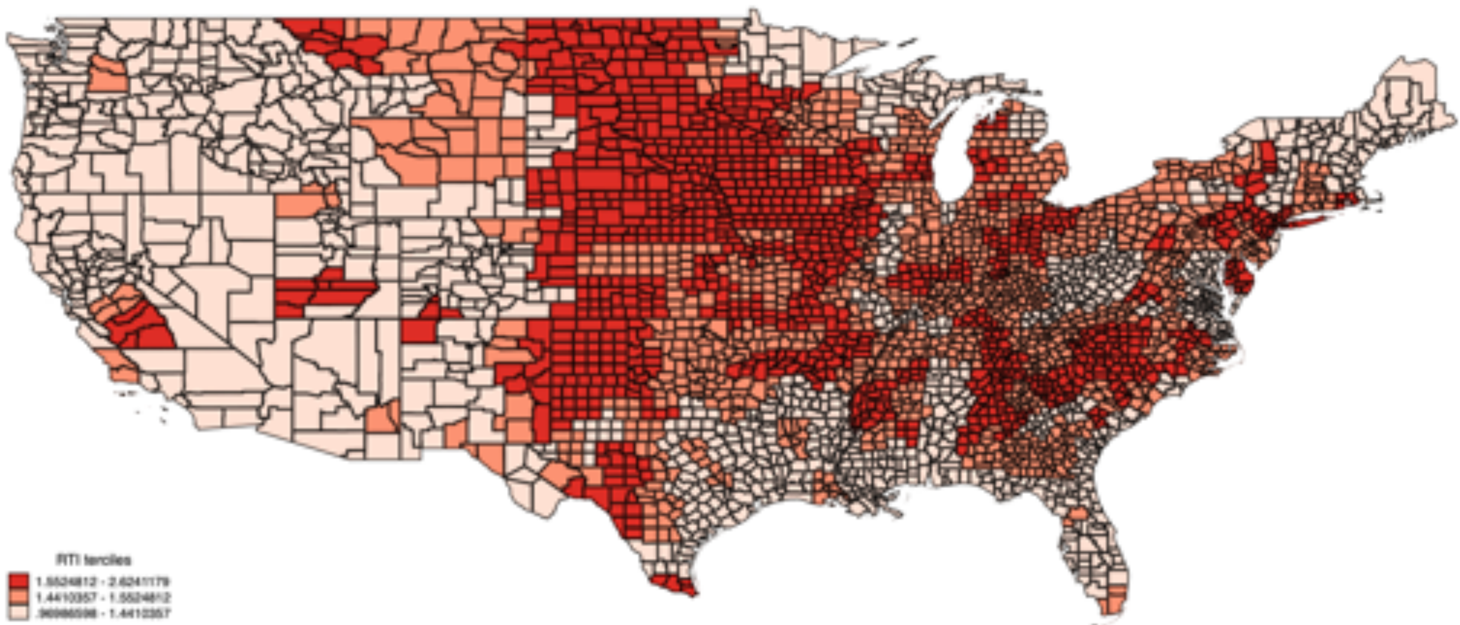


Figure 2: Import per Worker: Heterogeneity across US territory in 2011



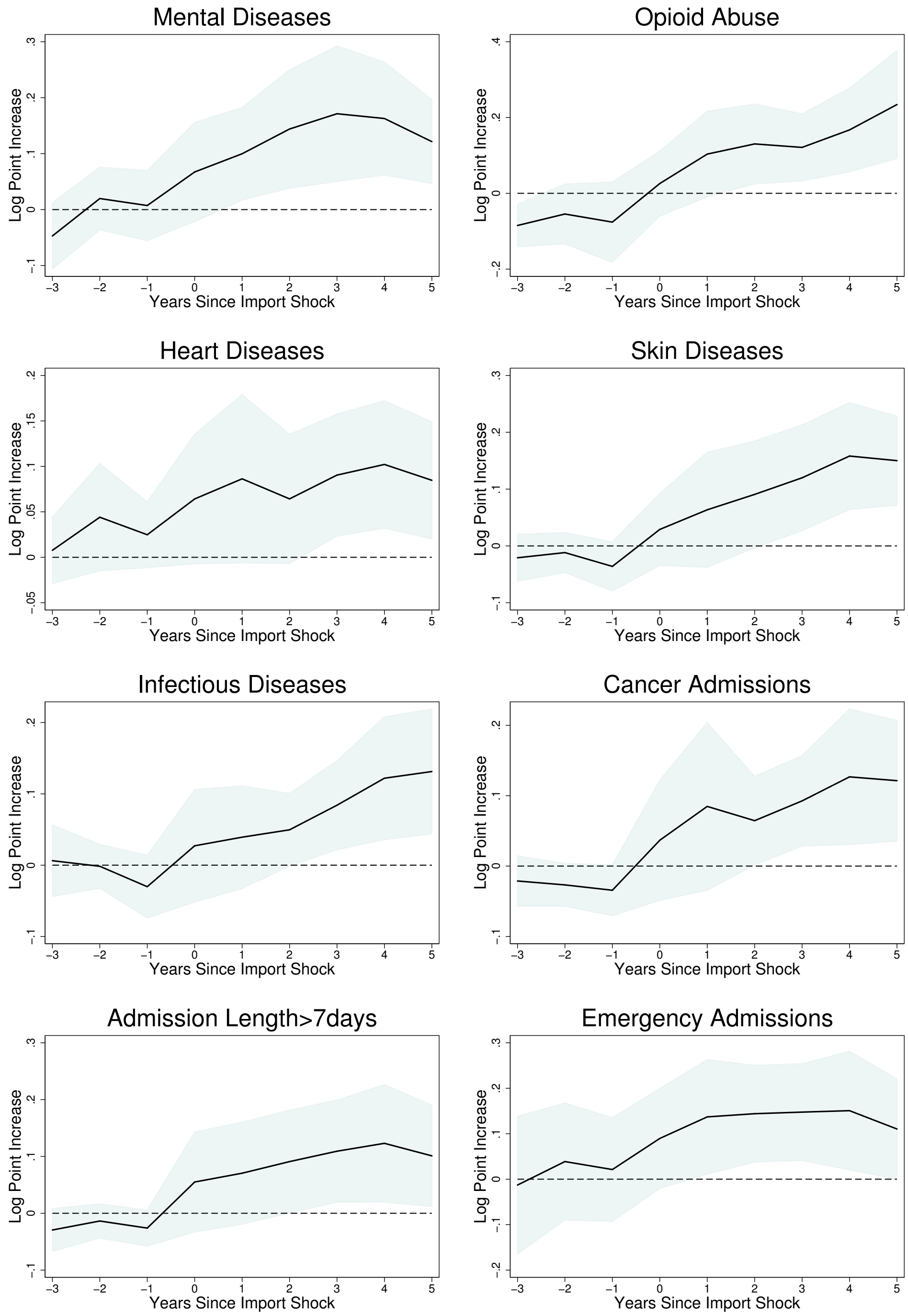
Note: The Import per Worker (IPW) shock in commuting zone c at time t is constructed as: $IPW_{c,t} = \sum_{j \in Manuf} \frac{L_{c,j,t}}{L_{US,j,t}} \frac{Import_{j,t}}{L_{c,All,t}}$, where j is an industry belonging to the set of manufacturing industries $Manuf$. The first ratio corresponds to the 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".

Figure 3: Routine Task Intensity 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.

Figure 4: Import Shocks and Hospital Admissions in High RTI Areas



Note: The figures displays the coefficients and 95 percent confidence intervals for the effect of import competition on different hospitalisation outcomes. The data is drawn from NIS. All regressions are done separately for outcomes and for lags or leads of the import shock. All regressions include hospital, year, socio-demographic fixed effects, and control for state trends, time varying commuting zone and county characteristics.

Table 1: Commuting Zone Characteristics by Routine Task Intensity tercile, in 1990

	All		**RTI Low**		**RTI Medium**		**RTI High**	
	mean	sd	mean	sd	mean	sd	mean	sd
Imports and RTI								
IPW (in \$1,000)	0.30	(0.33)	0.21	(0.24)	0.32	(0.34)	0.45	(0.42)
IPW^{OTH} (in \$1,000)	0.40	(0.34)	0.29	(0.21)	0.41	(0.32)	0.62	(0.47)
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)
Demographics								
Percent. of male	49.33	(1.11)	49.88	(1.11)	48.99	(0.86)	48.84	(1.08)
Percent. of white individuals	81.23	(11.21)	79.02	(11.20)	83.22	(9.29)	81.90	(13.95)
Percent. of black individuals	11.51	(9.16)	10.49	(8.94)	12.28	(8.56)	12.14	(10.65)
Percent. of low educated individuals	16.71	(5.40)	16.27	(5.17)	16.27	(4.95)	18.70	(6.36)
Percent. of individuals aged less than 25	19.42	(2.43)	19.39	(2.45)	19.43	(2.40)	19.47	(2.48)
Percent. of individuals aged 25-34	27.91	(1.94)	28.71	(2.06)	27.57	(1.63)	26.81	(1.46)
Percent. of individuals aged 35-44	23.26	(1.22)	23.56	(1.49)	23.12	(0.94)	22.88	(0.85)
Percent. of individuals aged 45-54	15.79	(1.10)	15.43	(1.12)	15.95	(0.96)	16.27	(1.08)
Percent. of individuals aged 55 and over	13.62	(2.14)	12.90	(2.48)	13.93	(1.73)	14.56	(1.54)
Labour								
Percent. of employed individuals	71.82	(4.58)	71.78	(5.11)	71.97	(4.12)	71.59	(4.26)
Percent. of unemployed individuals	4.57	(0.98)	4.56	(0.94)	4.60	(0.96)	4.51	(1.12)
Percent. of not in labor force	23.61	(3.91)	23.65	(4.45)	23.43	(3.52)	23.90	(3.35)
Percent. of individuals in manufacture	12.92	(4.91)	10.95	(3.76)	14.00	(4.04)	15.02	(6.98)
Income								
Income (mean, household equivalized)	38,738	(7,221)	39,251	(6,990)	39,075	(7,211)	36,814	(7,497)
Percent. individuals w. eq. fam income$<15k$	18.82	(6.52)	19.12	(6.45)	17.96	(6.38)	20.03	(6.77)
Percent. individuals w. eq. fam income$<20k$	27.57	(8.49)	27.87	(8.24)	26.39	(8.53)	29.48	(8.60)
Percent. individuals w. income$<15k$	39.01	(6.25)	38.55	(6.66)	38.87	(5.94)	40.37	(5.79)
Percent. individuals w. income$<20k$	47.26	(7.06)	46.78	(7.27)	46.95	(6.90)	49.07	(6.66)
Observations	240		241		241		722	
Average size of each CZ	429,880		413,836		186,930		343,429	

Note: RTI is the routine task index defined in Section 2.2. Commuting zones are weighted by their population in 1990.

Table 2: Imports from China and Change of Manufacturing Employment in Commuting Zones. 2SLS Estimates - Stacked differences, 1990-2011 (3 periods).
Dependent Variable: 10 x Annual Change in Manufacturing Emp/Working Age Pop (in %pts)

	(1)	(2)	(3)	(4)	(5)	(6)
Δ IPW^{CHN}	-0.732***	-0.345***	-0.282***	-0.278***	-0.347***	
	(0.086)	(0.096)	(0.103)	(0.102)	(0.106)	
Δ IPW^{CHN} X (Low RTI=1)						-0.255**
						(0.129)
Δ IPW^{CHN} X (Medium RTI=1)						-0.445***
						(0.163)
Δ IPW^{CHN} X (High RTI=1)						-0.577***
						(0.130)
Percent of manufacturing workers		-0.101***	-0.110***	-0.111***	-0.095***	-0.083***
		(0.018)	(0.019)	(0.019)	(0.016)	(0.017)
Percent. of college-educated individuals				-0.000	0.018	0.011
				(0.013)	(0.013)	(0.013)
Percent. of foreign born individuals				0.002	0.034***	0.035***
				(0.008)	(0.011)	(0.012)
Percent. of employed individuals among women				-0.046**	-0.016	-0.008
				(0.022)	(0.020)	(0.022)
Percent. of individuals in routine occupations					-0.273***	-0.254***
					(0.046)	(0.047)
Task offshorability (mean)					-0.000	-0.004
					(0.011)	(0.011)
Constant	-2.263***	-1.233***	-1.733***	1.507	5.850***	4.882**
	(0.272)	(0.303)	(0.320)	(1.353)	(1.927)	(2.073)
Census division dummies	No	No	Yes	Yes	Yes	Yes
R^2	.	0.151	0.210	0.220	0.235	0.193

Note: N=2,166=722 commuting zones x 3 time periods (1990-2000, 2000-2007, 2007-2011).
All regression include a constant and a dummy for each time period. First stage estimates also include the control variables that are indicated in the corresponding columns (taken at the start of the period). Routine occupations are defined such that they account for 1/3 of U.S. employment in 1980. The offshorability index variable is standardized to mean of 0 and standard deviation of 10 in 1980. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. *p <0.10, **p <0.05, ***p <0.01.

Table 3: Imports from China and Change of Labour Market Outcomes in Commuting Zones, by Routine Task Intensity Tercile.
2SLS Estimates - Stacked **1-year** differences, 1990-2011.

Dependent Variables: Annual Change in Labour Market Outcome/Working Age Pop (in %pts) for the left panel. Level of Labour Force Outcome/Working Age Pop (in %pts) for the right panel.

	Δ IPW interacted with					IPW (in levels) interacted with		
	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share employed	-0.22***	-0.08	-0.33***	-0.40***	-0.31*	-0.11	-0.44***	-0.50***
	(0.05)	(0.06)	(0.09)	(0.07)	(0.16)	(0.14)	(0.16)	(0.18)
Share unemployed	0.06***	0.05*	0.08**	0.07**	0.06	0.05	0.09	0.07
	(0.02)	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.06)
Share not in labor force	0.16***	0.03	0.25***	0.32***	0.25*	0.07	0.35***	0.43***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.14)	(0.12)	(0.12)	(0.14)
Share manufacturing	-0.34***	-0.23***	-0.36***	-0.55***	-0.92***	-0.70***	-0.97***	-1.20***
	(0.05)	(0.05)	(0.05)	(0.07)	(0.17)	(0.14)	(0.2)	(0.22)
Mean family income (eq.)	-164.34**	-71.66	-252.00**	-252.97**	-323.72	-57.67	-492.66*	-569.98**
	(78.02)	(70.67)	(110.86)	(105.54)	(235.96)	(201.69)	(271.47)	(230.44)
Family income (eq.)<15k	0.2***	0.11	0.27***	0.3***	0.25*	0.13	0.37***	0.31**
	(0.05)	(0.07)	(0.09)	(0.07)	(0.14)	(0.17)	(0.14)	(0.15)

Note: N=722 commuting zones x 20 years for the left panel, N=722 x 21 years for the right panel.
Dependent variables are listed in each row. The left panel displays the results of 2 regressions: in columns (1) to (3) the IPW measure is interacted with 3 RTI terciles, in column (4) it is not. The right panel is similar to the left panel, with the dependent variable and IPW variable being defined in levels instead of as differences. All regressions include a constant and a dummy for each time period, percent of individuals in routine occupations, region fixed effects. The right panel also includes region-specific trends and commuting zone fixed effects. Routine occupations are defined such that they account for 1/3 of U.S. employment in 1980. RTI terciles are defined using the RTI measure for the manufacturing sector in 1990. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population. *p <0.10, **p <0.05, ***p <0.01.

Table 4: Imports from China and Labour Market Outcomes in Commuting Zones, in High-Routine-Task-Intensity Tercile, with lags.
2SLS Estimates - Fixed-effects model, 1997-2011.
Dependent Variable: Level of Labour Force Outcomes/Working Age Pop (in %pts).

	IPW interacted with High RTI						
	Lag0	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share employed	-0.41*	-0.42**	-0.44**	-0.43**	-0.50**	-0.63***	-0.81***
	(0.21)	(0.21)	(0.21)	(0.21)	(0.2)	(0.22)	(0.28)
Share unemployed	0.03	0.04	0.04	0.01	0.03	0.04	0.07
	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.1)	(0.13)
Share not in labor force	0.38**	0.39**	0.4**	0.41***	0.47***	0.59***	0.74***
	(0.17)	(0.16)	(0.16)	(0.15)	(0.15)	(0.17)	(0.21)
Share manufacturing	-1.22***	-1.20***	-1.16***	-1.16***	-1.19***	-1.31***	-1.60***
	(0.21)	(0.18)	(0.17)	(0.17)	(0.18)	(0.19)	(0.23)
Mean family income (eq.)	-447.69*	-430.04*	-375.86	-279.13	-300.58	-385.56	-532.06
	(258.18)	(252.94)	(246.20)	(249.05)	(256.40)	(281.99)	(340.93)
Family income (eq.)<15k	0.45***	0.48***	0.46***	0.43**	0.47**	0.56***	0.68***
	(0.17)	(0.17)	(0.18)	(0.18)	(0.18)	(0.2)	(0.25)

Note: For all regressions, N=10,830=722 commuting zones x 15 years. Years 1991 to 1996 are omitted in order to have the same set of observations for all lags.
Dependent variables are listed in each row. Each column corresponds to a different lag of the IPW variable. Each cell displays the coefficient of the IPW variable interacted with the highest RTI tercile in the corresponding regression. All regressions include a constant and a dummy for each time period, percent of individuals in routine occupations, region-specific trends, and commuting zone fixed effects. Routine occupations are defined such that they account for 1/3 of U.S. employment in 1980. RTI terciles are defined using the RTI measure for the manufacturing sector in 1990. Robust standard errors in parentheses are clustered on state. Models are weighted by annual commuting zone share of national population. *p <0.10, **p <0.05, ***p <0.01

Table 5: Imports from China and Composite Measures of Health, Health Behaviour and Health Care Utilisation, by Routine Task Intensity Tercile.
Dependent variables: Composite Measures of Health, Health behaviour and Health Care Utilisation.

	Good health				Good Health Behaviour				Health care utilisation			
	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag 0	-1.551**	-1.289*	-1.890	-2.468***	0.944	0.904	1.621	0.8	-1.358	-1.188	-1.353	-2.158
	(0.729)	(0.693)	(1.297)	(0.744)	(1.086)	(0.981)	(2.537)	(1.167)	(1.500)	(1.389)	(2.846)	(1.461)
Lag 1	-1.219	-1.207	-0.999	-1.715***	0.77	0.711	0.996	0.721	-1.161	-0.947	-2.594	-2.148
	(0.749)	(0.865)	(0.855)	(0.557)	(0.809)	(0.69)	(1.513)	(0.731)	(1.314)	(1.210)	(2.920)	(1.423)
Lag 2	-0.977*	-0.874	-0.975	-1.704***	0.181	0.121	0.257	0.3	-1.657*	-1.175	-2.967*	-2.625***
	(0.572)	(0.611)	(0.735)	(0.553)	(0.513)	(0.512)	(0.878)	(0.514)	(0.962)	(0.96)	(1.549)	(0.882)
Lag 3	-0.418	-0.433	-0.143	-1.473**	0.49	0.453	0.608	0.238	-0.758	-0.413	-1.086	-2.615***
	(0.598)	(0.588)	(0.704)	(0.575)	(0.524)	(0.551)	(0.647)	(0.504)	(0.811)	(0.895)	(1.059)	(0.927)
Lag 4	-0.669	-0.773	-0.324	-1.614***	0.75*	0.897*	0.65	0.391	-0.354	-0.200	-0.234	-2.109***
	(0.699)	(0.65)	(0.8)	(0.575)	(0.451)	(0.534)	(0.509)	(0.455)	(0.739)	(0.902)	(0.838)	(0.657)
Lag 5	-0.714	-0.948	-0.266	-1.808***	0.831**	0.943*	0.813*	0.123	-0.540	-0.444	-0.333	-2.370***
	(0.749)	(0.709)	(0.761)	(0.549)	(0.415)	(0.524)	(0.453)	(0.427)	(1.089)	(1.167)	(1.183)	(0.774)
Lag 6	-0.664	-0.839	-0.252	-2.236***	0.901**	1.249*	0.722*	0.232	-0.063	0.124	0.122	-1.920**
	(0.695)	(0.724)	(0.637)	(0.521)	(0.452)	(0.669)	(0.408)	(0.495)	(1.122)	(1.650)	(0.971)	(0.844)
Obs	2,558,350				2,310,087				1,960,926			
Upper bound of $ 1,000 loss	-0.515***				-0.446***				-0.762***			
	(0.011)				(0.023)				(0.034)			
Obs	2,317,766				2,080,098				1,768,292			

Note: Data from BRFSS, years 1997-2011. Good health is the first factor from a principal-component factor analysis including self-assessed health, indicators for diabetes, obesity and 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 behaviour 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. We also include the percent of individuals in routine occupations. The bottom panel displays the regression of the different health measures on individual log income and controls. RTI terciles are defined using the RTI measure for the manufacturing sector in 1990. Robust standard errors in parentheses are clustered at commuting zone level. Models are weighted in a way that the BRFSS population at the commuting zone level reflects the proportions of individuals from a certain age group-race-sex cell in the IPUMS Census 2000 data.

Table 6: Health Effects of Imports from China - with a four-year lag, by Routine Task Intensity Tercile
Dependent variables: Health and Labour Outcomes (no composite measures)

	All Areas	Low RTI	Medium RTI	High RTI	Obs
	(1)	(2)	(3)	(4)	
Panel A: Health measures					
Health good	-0.141	-0.188	-0.042	-0.271	2802175
	(0.21)	(0.221)	(0.246)	(0.224)	
Ever diagnosed stroke	0.091	0.121**	0.057	0.135**	2013389
	(0.059)	(0.059)	(0.058)	(0.056)	
Ever told diabetes	0.292**	0.316**	0.244*	0.352***	2798653
	(0.137)	(0.148)	(0.146)	(0.109)	
Has asthma now	0.125	0.104	0.116	0.289***	2561978
	(0.103)	(0.117)	(0.127)	(0.103)	
Overweight	-0.092	-0.100	-0.104	0.016	2680234
	(0.187)	(0.257)	(0.172)	(0.165)	
Obese	0.242	0.193	0.264	0.484**	2680234
	(0.212)	(0.231)	(0.239)	(0.207)	
Underweight	-0.044	-0.070	-0.015	0.003	2680234
	(0.056)	(0.066)	(0.055)	(0.054)	
Mental health pb	-0.151	-0.165	-0.192	0.147	2675623
	(0.14)	(0.167)	(0.14)	(0.107)	
Panel B: Health behaviour					
Days had alcohol past 30 days	0.073*	0.081**	0.083*	-0.022	2449825
	(0.039)	(0.037)	(0.047)	(0.036)	
Smokes now	0.064	0.15	-0.064	0.068	2792750
	(0.155)	(0.177)	(0.205)	(0.148)	
Exercise past 30 day	0.181	0.284	0.093	-0.055	2645923
	(0.228)	(0.307)	(0.28)	(0.18)	
Panel C: Health care utilisation					
No doctor cause cost	0.085	0.057	0.036	0.544***	2521971
	(0.23)	(0.243)	(0.244)	(0.164)	
Has any hlth plan	-0.183	-0.099	-0.244	-0.473**	2795626
	(0.248)	(0.38)	(0.288)	(0.197)	
Flushot	0.269	0.536	0.105	-0.676**	2623346
	(0.312)	(0.345)	(0.392)	(0.267)	
Time since checkup	0.011	0.019	-0.0007	0.002	2182957
	(0.011)	(0.014)	(0.013)	(0.013)	
Panel D: Labor and Income					
Currently working	-0.409	-0.583	-0.045	-0.883***	2796782
	(0.333)	(0.495)	(0.293)	(0.245)	
Income less than 20k	0.399	0.592	0.078	0.555**	2802175
	(0.379)	(0.504)	(0.346)	(0.268)	

Note: Data from BRFSS, years 1997-2011. Dependent variables are listed in each row. All regressions include age dummies, sex, race, education and year and commuting zone fixed effects as well as state linear trends. We also include the percent of individuals in routine occupations. Standard errors clustered at commuting zone level. RTI terciles are defined using the RTI measure for the manufacturing sector in 1990. Robust standard errors in parentheses are clustered at commuting zone level. Models are weighted in a way that the BRFSS population at the commuting zone level reflects the proportions of individuals from a certain age group-race-sex cell in the IPUMS Census 2000 data.

Table 7: Imports from China and Hospitalization: Discharges by Cause

	All areas	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)
Stress related symptoms	0.01	0.002	0.028	0.138***
	(0.025)	(0.023)	(0.022)	(0.047)
Mental health problems	0.018	0.002	0.057**	0.163***
	(0.029)	(0.024)	(0.027)	(0.052)
Suicides attempts	0.018	0.02	0.029	0.12***
	(0.022)	(0.018)	(0.035)	(0.042)
Alcohol abuse	-0.004	-0.009	0.018	0.092*
	(0.028)	(0.026)	(0.024)	(0.05)
Substance abuse	-0.025	-0.012	-0.018	0.164**
	(0.029)	(0.026)	(0.034)	(0.066)
Opioid abuse	-0.023	0.019	-0.042	0.17***
	(0.033)	(0.028)	(0.039)	(0.057)
Injuries	0.059**	0.058***	0.015	0.157**
	(0.025)	(0.019)	(0.029)	(0.069)
Homicide injuries	0.046**	0.042***	0.012	0.207**
	(0.018)	(0.015)	(0.035)	(0.087)
Driving accidents	0.057	0.054*	-0.033	0.089
	(0.043)	(0.028)	(0.049)	(0.067)
Pain	0.051*	0.051**	0.021	0.12**
	(0.028)	(0.023)	(0.035)	(0.06)
Diseases of skin	0.004	0.002	0.032	0.155***
	(0.023)	(0.02)	(0.026)	(0.044)
Heart problems	0.024	0.028	0.016	0.101***
	(0.019)	(0.018)	(0.018)	(0.034)
Infectious diseases	-0.0006	-0.005	0.028	0.119***
	(0.023)	(0.019)	(0.024)	(0.043)
Respiratory diseases	0.03*	0.033**	0.018	0.089**
	(0.017)	(0.017)	(0.019)	(0.036)
Endocrine diseases	0.035*	0.046**	0.007	0.068**
	(0.02)	(0.02)	(0.02)	(0.031)
Diseases of digestive system	0.003	0.003	0.014	0.074
	(0.02)	(0.018)	(0.025)	(0.045)
Diet related diseases	0.034	0.044**	0.013	0.111***
	(0.022)	(0.022)	(0.023)	(0.038)
Cancers	0.003	0.008	0.011	0.125***
	(0.019)	(0.013)	(0.021)	(0.048)
Tobacco related cancers	0.005	0.015	0.019	0.138***
	(0.021)	(0.015)	(0.018)	(0.048)
Non tobacco rel cancers	0.002	0.006	0.01	0.115**
	(0.019)	(0.014)	(0.021)	(0.047)

Note: Data from NIS for the years 1997-2011. Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Instrumented imports are lagged 4 years. The table reports the effect of a $ 1000 import shocks on the log of 1 + the number of admissions of patients with a certain condition. All regressions include year fixed effects, state trends, hospital fixed effects, birth year-gender fixed effects of patients, commuting zone time-varying characteristics (demographic composition of the commuting zone in terms of gender, race, education, age composition and share of routine occupations). Weighted by hospital weights and population weights. Standard errors clustered at commuting zone level.

Table 8: Imports from China and Hospitalization: Composition of Discharges

	All areas	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)
Total admissions	0.019	0.017	0.01	0.095***
	(0.014)	(0.013)	(0.017)	(0.03)
Admissions emergency	0.004	-0.012	0.007	0.138**
	(0.04)	(0.057)	(0.034)	(0.061)
Admissions emergency excluding suicides, injuries and homicides	0.024	0.036	0.029	0.114**
	(0.04)	(0.059)	(0.034)	(0.054)
Died in hospital	0.039**	0.03**	0.051***	0.09***
	(0.016)	(0.013)	(0.016)	(0.034)
Admissions length	0.011	-0.002	0.016	0.088***
	(0.015)	(0.015)	(0.018)	(0.034)
Admissions length>7	0.015	-0.009	0.04*	0.135***
	(0.022)	(0.021)	(0.022)	(0.05)
Average charge	0.037*	0.036**	-0.012	0.072
	(0.02)	(0.014)	(0.025)	(0.049)
Admissions Medicaid	-0.010	-0.015	0.038	0.101**
	(0.027)	(0.027)	(0.031)	(0.042)
Admissions Medicare	0.031	0.026*	0.027	0.133***
	(0.02)	(0.016)	(0.022)	(0.042)
Admissions white	0.036	0.028	0.049	0.079
	(0.036)	(0.018)	(0.046)	(0.052)
Admissions males	0.024	0.025	0.009	0.107***
	(0.017)	(0.016)	(0.022)	(0.037)
Admissions age 51-65	0.019	0.009	0.017	0.086***
	(0.013)	(0.015)	(0.021)	(0.031)

Note: Data from NIS for the years 1997-2011. 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 $ 1000 import shocks. The outcome variable is the log of 1 + the number of admissions of patients with a certain condition. All regressions include year fixed effects, state trends, hospital fixed effects, birth year-gender fixed effects of patients, commuting zone time-varying characteristics (demographic composition of the commuting zone in terms of gender, race, education, age composition and share of routine occupations). Weighted by hospital weights and population weights. Standard errors clustered at commuting zone level.

Table 9: Imports from China and All-Cause Mortality

	coeff.	s.e.	obs.
Imports, Lag 0	0.015**	(0.007)	1,561,678
Imports, Lag 1	0.021***	(0.006)	1,534,308
Imports, Lag 2	0.022***	(0.006)	1,496,911
Imports, Lag 3	0.018***	(0.005)	1,449,259
Imports, Lag 4	0.021***	(0.006)	1,392,098
Imports, Lag 5	0.024***	(0.009)	1,325,529
Imports, Lag 6	0.036**	(0.012)	1,250,632
Imports, Lag 7	0.059***	(0.015)	1,167,249

Note: NHIS data 1988-2009 (mortality up to 2011) for lag 0, 1989-2009 for lag 1, ..., 1995-2009 for lag 7. Imports are instrumented using a control function approach, where the instrument is the imports from from China of four other high-income countries (Australia, Finland, Japan, Switzerland) for which we have comparable imports data over all the period. 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

A Robustness of Results

In this section we further probe the robustness of our results. We first present falsification tests, looking at the effect of future import shocks on health and hospitalisation. Table A6 presents the results for the health scores defined in Section 4.2 with data from the BRFSS, for leads of import varying from 1 to 4. We find few effects that are significant, apart for health care utilisation at lead 1 and 2. Table A7 displays the results for a shock 4 years ahead. For effects at different leads, we refer the reader to Figure 4 in the main text. The table shows that contrary to Table 7 - where the effects for the high RTI areas were mainly positive and significant - the effects at lead 4 are mostly insignificant, or significant and negative. Those results suggest either no sorting of workers across commuting zone or a negative selection that would imply that our results in the text are even stronger.

As our sample contains the financial crisis of 2007-2008, some of the effects we find may be due to the recession rather than import competition. Our regressions control for time fixed effects which would control for that event, but it is still possible that commuting zones with a mix of industries in competition with foreign imports were more susceptible to the recession. We therefore display in Table A8 and Table A9 results similar to those presented in Tables 5 and 7, but where we discarded two years of data, 2009 and 2010, leaving one year for the 2008-2009 recession to have an effect on health outcomes. The exclusion of that time period does not change the results. This could be due to the fact that either the recession had a general negative effect across the whole of the US, or that recessions do not affect the health of working age adults substantially, a phenomenon described in Ruhm (2000).

Table A1: Occupation and Industry Composition of Commuting Zones by RTI Terciles

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. Weighted by person weights. 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 A2: Descriptive Statistics, BRFSS 1997-2011

	mean	sd	min	max	count
Demographics	ref.				
age	40.08	12.54	18	65	2810752
male	0.49	0.50	0	1	2810752
race: white	0.73	0.45	0	1	2805798
race: black	0.13	0.33	0	1	2805798
educ: high school or less	0.32	0.47	0	1	2807113
educ: some college	0.26	0.44	0	1	2807113
educ: college graduate	0.41	0.49	0	1	2807113
Health	ref.				
Index of good health	0.00	100.00	-465	61	2564920
(very) good health	87.97	32.53	0	100	2810752
ever told blood pressure high	21.16	40.85	0	100	1592224
ever diagnosed with a stroke	1.34	11.49	0	100	2019757
ever told diabetes	6.95	25.42	0	100	2807176
still has asthma	8.65	28.11	0	100	2569959
overweight	34.83	47.64	0	100	2687250
obese	22.06	41.47	0	100	2687250
mental health pb	10.11	30.14	0	100	2683631
satisfaction with life	93.77	24.17	0	100	1442919
Health behaviour	ref.				
Index of good health behaviour	0.00	100.00	-271	70	2316894
drink any alcoholic beverages in past 30	61.47	48.67	0	100	2622339
more than 14 days with alcohol in past 30	11.93	32.41	0	100	2456971
currently smoking	20.56	40.41	0	100	2801199
exercise in past 30 days	78.85	40.84	0	100	2654080
Health care utilization	ref.				
Index of health care utilization	0.00	100.00	-361	92	1966660
could not see dr. because of cost	13.58	34.26	0	100	2529740
has any health care coverage	85.28	35.43	0	100	2804080
seasonal flu shot past 12 months	27.76	44.78	0	100	2631076
ever had blood stool test	36.69	48.20	0	100	624499
last checkup more than 5 years ago	8.92	28.50	0	100	2189677
last dentist visit more than 5 years ago	7.64	26.56	0	100	1323363
Labour and Income	ref.				
currently working	72.04	44.88	0	100	2804625
annual household income less than 20000	10.28	30.36	0	100	2810752

Note: Weights are computed in a way that the BRFSS population at the commuting zone level reflects the proportions of individuals from a certain age-race-sex cell in the IPUMS Census 2000 data.

Table A3: 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
Substance abuse	304 292.0 305.2/305.95 E850.0 E850.1 970.8
Opioid abuse	304.00 304.01 304.02 304.03 304.70 304.71 304.72 304.73 305.50 305.51 305.52 305.53 965.00 965.09 E850.2 E935.2
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

Table A4: Descriptive Statistics, Hospital Discharges (NIS)

	Number or Mean	Sd. dev
Total discharges	38,993,549	
Stress related discharges	13,511,276	
Mental disorders related diagnostics	12,233,836	
Suicides related discharges	544,608	
Alcohol abuse related discharges	3,231,085	
Substance abuse related discharges	2,452,091	
Opioid abuse	909,042	
Injuries related diagnostics	1,459,136	
Homicides related discharges	200,209	
Driving accidents	419,259	
Pain	3,394,255	
Skin diseases	2,171,924	
Heart related diagnostics	8,241,802	
Infectious diseases related diagnostics	4,310,245	
Respiratory diseases related diagnostics	7,975,590	
Endocrine diseases related discharges	14,762,212	
Diseases of digestive system	8,899,713	
Diet related discharges	11,118,927	
Tobacco related cancers related discharges	984,200	
Cancer related discharges	3,856,961	
Non tobacco related discharges	3,368,833	
Total deaths in hospital	435,605	
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	1,990	
Average number of years per hospital	2.9	(1.7)
Hospital - year - group observations	91,229	
Average annual number of discharges per hospital	4,228	(5,304)
Number of commuting zones	386	

Note: For definitions of the morbidity categories, see Table A3 in the appendix.

Table A5: Descriptive Statistics, NHIS

Sample characteristics	NHIS 1988-2009. Manufacture workers, aged 18-65 at baseline.
Observations	1,591,587
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%
Number of deaths	5,569

Table A6: Future Imports from China and Health, Health Behaviour and Health Care Utilisation, by Routine Task Intensity Terciles

	Good health				Good Health behaviour				Health care utilisation			
	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lead 1	-0.725	-0.488	-0.984	-1.159*	-1.395	-1.202	-2.463	-1.097	-2.127***	-1.750**	-3.005**	-2.155**
	(0.686)	(0.708)	(1.069)	(0.605)	(1.160)	(0.955)	(2.373)	(1.212)	(0.806)	(0.774)	(1.340)	(0.993)
Lead 2	-0.470	-0.361	-0.422	-0.859	-2.025	-2.137	-5.773	-2.127	-2.385**	-2.307**	-2.964*	-1.936*
	(0.955)	(1.046)	(1.404)	(0.751)	(1.574)	(2.371)	(7.425)	(3.097)	(1.022)	(1.044)	(1.640)	(1.023)
Lead 3	0.993	1.450	0.415	-0.151	-1.321	-8.530	-29.735	-15.143	0.343	0.726	-0.852	-0.168
	(1.292)	(1.360)	(2.165)	(1.198)	(3.253)	(112.104)	(375.046)	(204.729)	(1.020)	(1.031)	(1.554)	(1.040)
Lead 4	0.027	0.253	0.213	-0.643	-1.211	-1.756	-4.361	-1.219	-0.526	-0.347	-1.161	-0.922
	(1.225)	(1.176)	(2.235)	(1.202)	(2.901)	(3.852)	(10.629)	(7.362)	(1.929)	(1.707)	(3.742)	(2.225)
Obs	1,531,603				1,318,554				914,648			

Note: Data from BRFSS, years 1997-2007. Good health is the first factor from a principal-component factor analysis including self-assessed health, and indicators for diabetes, obesity and 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 behaviour 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. We also include the percent of individuals in routine occupations. The second panel displays the regression of the different health measures on individual log income and controls. RTI terciles are defined using the RTI measure for the manufacturing sector in 1990. Robust standard errors in parentheses are clustered at commuting zone level. Models are weighted in a way that the BRFSS population at the commuting zone level reflects the proportions of individuals from a certain age group-race-sex cell in the IPUMS Census 2000 data.

Table A7: Future Imports from China (Four Years Ahead) and Hospitalization: Discharges by Cause

	All	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)
Stress related symptoms	-0.030	-0.036	-0.014	0.012
	(0.024)	(0.026)	(0.025)	(0.026)
Mental health problems	-0.007	-0.022	0.003	0.011
	(0.036)	(0.03)	(0.034)	(0.033)
Suicides attempts	-0.009	-0.010	-0.007	-0.007
	(0.03)	(0.035)	(0.022)	(0.037)
Alcohol abuse	-0.050**	-0.046*	-0.039*	0.021
	(0.024)	(0.028)	(0.021)	(0.023)
Substance abuse	-0.067	-0.031	-0.060**	-0.071*
	(0.043)	(0.044)	(0.029)	(0.036)
Opioid abuse	-0.063	-0.029	-0.056	-0.086**
	(0.041)	(0.037)	(0.041)	(0.04)
Injuries	0.017	0.023	-0.003	-0.004
	(0.023)	(0.022)	(0.024)	(0.017)
Homicide injuries	0.007	-0.006	0.024	-0.037
	(0.032)	(0.029)	(0.032)	(0.028)
Pain	0.017	0.002	0.018	0.024
	(0.029)	(0.028)	(0.027)	(0.024)
Skin disease	-0.039	-0.019	-0.038*	-0.036***
	(0.025)	(0.027)	(0.022)	(0.013)
Heart problems	-0.017	-0.023	-0.018	0.045
	(0.021)	(0.021)	(0.018)	(0.034)
Infectious diseases	-0.039*	-0.018	-0.046**	-0.015
	(0.022)	(0.022)	(0.02)	(0.017)
Respiratory diseases	-0.016	-0.018	-0.015	0.022
	(0.022)	(0.02)	(0.023)	(0.024)
Disease of digestive system	-0.033	-0.033	-0.025	0.008
	(0.026)	(0.022)	(0.024)	(0.018)
Endocrine diseases	-0.009	-0.024	0.002	0.038
	(0.025)	(0.022)	(0.023)	(0.027)
Diet related diseases	-0.004	-0.011	-0.006	0.028
	(0.028)	(0.028)	(0.023)	(0.024)
Cancers	-0.030*	-0.018	-0.020	-0.040***
	(0.016)	(0.018)	(0.018)	(0.015)
Tobacco related cancers	0.006	0.012	0.016	-0.067**
	(0.019)	(0.017)	(0.024)	(0.032)
Non tobacco rel cancers	-0.038**	-0.030	-0.023	-0.036**
	(0.016)	(0.019)	(0.017)	(0.014)
Died in hospital	-0.003	-0.0002	0.006	-0.030
	(0.028)	(0.025)	(0.026)	(0.036)

Note: Data from NIS for the years 1997-2011. Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Instrumented imports are leaded 4 years. The table reports the effect of a $ 1000 import shocks on the log of 1 + the number of admissions of patients with a certain condition. All regressions include year fixed effects, state trends, hospital fixed effects, birth year-gender fixed effects of patients, commuting zone time-varying characteristics (demographic composition of the commuting zone in terms of gender, race, education, age composition and share of routine occupations). Weighted by hospital weights and population weights. Standard errors clustered at commuting zone level.

Table A8: Imports from China and Health, Health Care Utilisation and Health Behaviour, by Routine Task Intensity- Excluding the Great Recession

	Good health				Good Health behaviour				Health care utilisation			
	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI	All	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lag 0	-1.627**	-1.466*	-1.716	-2.133***	1.252	0.97	2.398	1.107	-1.555	-1.400	-1.388	-2.276*
	(0.769)	(0.781)	(1.113)	(0.685)	(1.137)	(0.879)	(2.412)	(1.077)	(1.375)	(1.232)	(2.750)	(1.304)
Lag 1	-0.973	-0.831	-1.114	-1.469**	0.991	0.631	1.657	1.203	-0.658	-0.550	-0.255	-1.339
	(0.715)	(0.779)	(0.846)	(0.585)	(0.838)	(0.715)	(1.307)	(0.735)	(1.447)	(1.365)	(3.486)	(1.519)
Lag 2	-0.791	-0.627	-0.981	-1.287**	0.492	0.069	1.020	0.888	-0.442	-0.196	-0.681	-1.787**
	(0.663)	(0.766)	(0.667)	(0.603)	(0.586)	(0.685)	(0.778)	(0.556)	(0.872)	(0.854)	(1.285)	(0.761)
Lag 3	-0.520	-0.582	-0.300	-1.225**	0.842*	0.475	1.306**	0.807	0.407	0.442	0.641	-2.016**
	(0.58)	(0.695)	(0.54)	(0.598)	(0.494)	(0.569)	(0.508)	(0.574)	(0.897)	(1.024)	(0.908)	(0.894)
Lag 4	-0.652	-0.689	-0.269	-1.291**	1.272*	1.064	1.771*	0.985	0.667	0.76	1.527	-1.685*
	(0.655)	(0.686)	(0.808)	(0.599)	(0.752)	(0.724)	(0.945)	(0.655)	(1.246)	(1.228)	(1.524)	(0.971)
Lag 5	-0.419	-0.559	0.185	-1.219*	1.532	1.281	2.320*	0.742	0.486	0.579	1.165	-2.171*
	(0.846)	(0.832)	(1.028)	(0.69)	(1.001)	(0.823)	(1.337)	(0.752)	(1.743)	(1.464)	(2.442)	(1.258)
Lag 6	-0.236	-0.632	0.194	-1.630***	1.193**	1.266*	1.164**	0.519	0.571	0.799	0.638	-2.143**
	(0.663)	(0.93)	(0.477)	(0.611)	(0.489)	(0.737)	(0.457)	(0.675)	(1.079)	(1.505)	(0.933)	(0.998)
Obs	2,058,380				1,822,949				1,449,127			

Note: Data from BRFSS, years 1997-2011, excluding 2009-2010. Good health is the first factor from a principal-component factor analysis including self-assessed health, and indicators for diabetes, obesity and 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 behaviour 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. We also include the percent of individuals in routine occupations. The second panel displays the regression of the different health measures on individual log income and controls. Standard errors clustered at commuting zone level. RTI terciles are defined using the RTI measure for the manufacturing sector in 1990. Robust standard errors in parentheses are clustered at commuting zone level. Models are weighted in a way that the BRFSS population at the commuting zone level reflects the proportions of individuals from a certain age group-race-sex cell in the IPUMS Census 2000 data.

Table A9: Effect of Import Shocks on Hospitalization by Cause, excluding the Great Recession

	All	Low RTI	Medium RTI	High RTI
	(1)	(2)	(3)	(4)
Stress related symptoms	0.009	-0.003	0.043	0.219***
	(0.032)	(0.027)	(0.029)	(0.067)
Mental health problems	0.005	-0.007	0.041	0.255***
	(0.036)	(0.029)	(0.033)	(0.073)
Suicides attempts	0.031	0.02	0.068	0.178***
	(0.03)	(0.024)	(0.059)	(0.061)
Alcohol abuse	-0.003	-0.016	0.046	0.102
	(0.026)	(0.024)	(0.033)	(0.064)
Substance abuse	-0.028	-0.007	-0.049	0.194**
	(0.039)	(0.033)	(0.047)	(0.084)
Opioid abuse	-0.0007	0.044	-0.061	0.183***
	(0.038)	(0.033)	(0.048)	(0.071)
Injuries	0.035	0.039	0.008	0.203**
	(0.032)	(0.025)	(0.034)	(0.092)
Homicide injuries	0.062	0.051	0.031	0.19*
	(0.041)	(0.034)	(0.053)	(0.102)
Heart problems	0.013	0.015	0.009	0.128***
	(0.022)	(0.019)	(0.021)	(0.042)
Infectious diseases	-0.015	-0.017	0.024	0.19***
	(0.029)	(0.022)	(0.027)	(0.058)
Respiratory diseases	0.032	0.033*	0.016	0.137***
	(0.021)	(0.018)	(0.023)	(0.048)
Endocrine diseases	0.043**	0.048**	0.004	0.09**
	(0.021)	(0.021)	(0.026)	(0.041)
Diet related diseases	0.051*	0.056**	0.014	0.162***
	(0.027)	(0.025)	(0.028)	(0.053)
Cancers	0.017	0.021	0.005	0.127**
	(0.017)	(0.014)	(0.026)	(0.052)
Tobacco related cancers	0.047***	0.052***	0.04	0.117*
	(0.017)	(0.014)	(0.029)	(0.062)
Non tobacco rel cancers	0.021	0.023	0.005	0.113**
	(0.018)	(0.015)	(0.027)	(0.05)
Died in hospital	0.00003	-0.002	0.037	0.129**
	(0.024)	(0.019)	(0.023)	(0.052)

Note: Data from NIS for the years 1997-2011, excluding 2009 and 2010. Instrumental variable estimates using the sum of Chinese imports to the other countries as instruments for US imports. Instrumented imports are leaded 4 years. The table reports the effect of a $ 1000 import shocks on the log of 1 + the number of admissions of patients with a certain condition. All regressions include year fixed effects, state trends, hospital fixed effects, birth year-gender fixed effects of patients, commuting zone time-varying characteristics (demographic composition of the commuting zone in terms of gender, race, education, age composition and share of routine occupations). Weighted by hospital weights and population weights. Standard errors clustered at commuting zone level.