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Three Essays on Trade and Local Labor Markets

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Abstract

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This dissertation studies the effect of trade on wage dispersion, crime rates and alcohol consumption at the local labor market level in the the U.S. The first chapter develops a new measure for skill to investigate the effects of offshoring on wages of three types of workers: high-skilled, medium-skilled, and low-skilled. I also look at the effect of offshoring on wages of offshorable occupations. Although the previous literature emphasizes the impact of offshoring on the skill premium, I find that job characteristics such as offshorability is critical in explaining the wage effect. Chapter 2 analyzes the effects of increasing import exposure from the top 6 trading partners of the US (China, Canada, Mexico, Germany, Japan and Korea) on property and violent crimes for the period 1992-2006 at the commuting zone level. My results indicate that a $1000 increase in Chinese exposure increases the property crimes by about 3 percent. On the other hand, the same amount of increase in import exposure from three other developed country trading partners, Germany, Japan and Korea, reduces property crimes between 2 to 4 percent. I find no evidence on the change of violent crimes from any of the countries. The last chapter examines the effects of increasing import competition from China on alcohol consumption at the county level for the years 2002-2006. Recent literature has shown that increasing import competition from China worsens the labor market outcomes. Lower cumulative earnings and the fear of job loss may increase financial stress for workers who may resort to alcohol as a coping mechanism. I find that increasing import exposure from China increases both the prevalence of drinking and binge drinking among workers. The effect is more pronounced for men than women. Further, for men, binge drinking has a larger effect than prevalence of drinking, whereas for women, prevalence of drinking has a larger effect than binge drinking.

Dedication

To my family for their love, unwavering support, encouragement and sacrifices.

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Table of Contents

List of Figures

List of Tables

Chapter 1

Offshoring and U.S. Wages: Evidence from Individual-Level Data

1.1 Introduction

In recent years, falling transportation costs and advancements in information technology have allowed firms to fragment their production process and to increase their offshoring activities. The inclusion of developing countries with low labor costs in the global market allows firms to shift their highly labor intensive production from the North to the South. This has led many market research companies to predict that offshoring would lead to a massive job loss in developed nations (McCarthy et al., 2002; Parker et al., 2004). As a result, offshoring has received a great deal of attention in policy discussions in the US.

A large number of studies have well-documented the change in wage structure and increase in skill-premium for the U.S.[1] The general consensus of the literature is that before the 1980's, the growth rates at different parts of the wage distribution were similar and the wage differences were relatively stable. However, since the late 80's, the wage gap between various groups has been widening. Goldin and Katz (2007) show that a large part of the increase in wage dispersion can be explained by the educational wage differential. Their study shows that the period before the 1980's saw an increase in both the demand for skilled labor and supply of skilled labor that allowed for a stable wage differential. Since the early

[1] See Burkhauser et al. (2011) Van Reenen (2011) Levy and Murnane (1992) Katz and Murphy (1992)

80's, using various data sources, Katz and Autor (1999) find an increase in skill premium for educated workers. The study estimates that real wages of those with less than 12 years of education fell by 13.4%, while real wages fell by 20.2% for workers with 12 years of education between 1979 and 1995. During the same period, wages of workers with a college degree or more rose by 3.4%.

There has been a considerable debate on whether the increase in skill premium is a result of technological change or growth in international trade and offshoring. Feenstra and Hanson (1996, 1999) argue that although technological change is an important factor in explaining the wage differential, focusing solely on technological change would obscure more fundamental questions regarding how firms respond to import competition and how these responses, in turn, affect the labor market.

Initial studies that looked at the effect of trade in final goods on skill-premium could not find empirical evidence to support the theory of factor abundance.[2] New theories were developed to understand the mechanism through which trade would affect wages, which increased theoretical literature on offshoring. Offshoring can lead to within-industry wage differential because when an industry relocates the unskill-intensive stages of its production process abroad, it expands the skill intensity of production at home. This increases the relative demand for skilled workers widening the wage differential between skilled and unskilled workers.

The data for direct measure of offshoring activities by firms, however, are only limited to a few subset of countries and are mostly confidential and not publicly available. Trade literature has used different measures to proxy offshoring, such as total employment of foreign affiliates among multinational U.S. firms, import penetration, and trade in intermediate inputs. One of the most widely used measure of offshoring was developed by Feenstra and Hanson (1996) that defines offshoring as the share of non-energy inputs that are imported. I will use this measure as a proxy for offshoring.

Initially, the above proxy was used to measure material offshoring for manufacturing

[2] Stolper and Samuelson (1941) predicted that high skilled workers wage would rise in the North but fall in the South. Many studies (Berman et al., 1994; Belkman et al., 1998) found empirical evidence contradicting the theory

industries, but was later modified to include service offshoring to reflect the fast growth of offshoring in services. Although early studies mainly focused on industry-level wage differential, a new wave of literature looks at the effect of offshoring activities of industries at individual-level wages. Individual level data allows us to control observable demographic characteristics that may affect wages.

In this paper, I investigate the effect of both material and service offshoring of manufacturing industries in the U.S. from 1999-2009 on individual wages obtained from the CPS March Supplement. Only a handful of studies so far have looked at the effect at an individual level. For instance, Egger et al. (2007), Ebenstein et al. (2014) look at individual data but only consider the effect of material offshoring. Liu and Trefler (2008) study service offshoring, but only those offshored to India and China. Geishecker and Görg (2013) look at the effect of both material and service offshoring on individual wages for the U.K. Tempesti (2015) looks at the effect on individual wages for the U.S; however, he only looks at material offshoring. Moreover, like Geishecker and Görg (2013), the study uses educational attainment as a proxy for skill.

I contribute to this growing literature by defining a novel measure for skill as a composite set of skill indicators using the O*NET database to look at the effects of material and service offshoring on skill premium. This measure captures the skill-set workers have acquired on the job without any formal education.[3] In addition, I also look at the effects of offshoring on wages for occupation that are offshorable.[4] My analysis finds that both material and service offshoring increases the skill premium for high-skill and medium-skill workers. I find that a 10 percentage point increase in material offshoring increases the skill premium by about 3 percent. I also find that material and service offshoring has a negative impact on wages of offshorable occupations. Offshorable occupations are primarily defined as those that require low face-to-face interaction, minimal decision-making, and are easily automated.

The remainder of the paper is structured as follows: Section 2 defines the measure for

[3]Most studies use level of education as a measure of skill. However, such a measure would not account for skills learned on the job. Thus, my measure of skill attempts to account for skills that are learned without formal education.

[4]I use Firpo et al. (2011) measure of classifying the occupation into offshorable jobs. Their study only looks at the return to occupational tasks, and do not specifically look at the direct effect of offshoring on the wages of these offshorable jobs.

offshoring and discusses the trend in service and material offshoring. Section 3 reviews the literature on the effect of offshoring on wages. Section 4 discusses the data and empirical methodology, and Section 5 presents the results. Section 6 includes robustness checks and Section 7 concludes.

1.2 Offshoring

When a firm relocates parts of its production process outside the firm, it is called outsourcing. The fragmentation may include both material and immaterial (service) stages of production. Further, outsourcing can be either domestic or foreign. When a firm in the U.S. contracts parts of its production process to a different firm within the U.S., it is called domestic outsourcing. If a firm in the U.S. contracts parts of its production process to a location outside the U.S., it is called foreign outsourcing. This paper will focus on foreign outsourcing, also called offshoring.

Offshoring includes both the procurement of inputs from foreign firms owned by the U.S. firm and the arm's length production by a foreign firm not affiliated with the U.S. firm. Material outsourcing takes the form of imported physical goods that are used as intermediate inputs in the production and assembly process. Likewise, service offshoring takes the form of customer call centers, business services, accountancy and tax services, and financial services.

1.2.1 Measuring Offshoring

It is difficult to get a direct measure of offshoring because consistent data on offshoring activities by U.S. firms are not easily available. As a result, the trade literature has used different measures for offshoring, such as total employment of foreign affiliates of multinational U.S. firms, import penetration and trade in intermediate inputs. One of the most widely used measure of offshoring was developed by Feenstra and Hanson (1996) (FH hereafter) that defines offshoring as the share of non-energy inputs that are imported.

I measure offshoring using the methodology introduced by FH for material offshoring and the method developed by Amiti and Wei (2009) to calculate service offshoring. The services included are 1) finance, 2) insurance, 3) telecommunication, computer and information services, and 4) business services.[5]

For a given industry i at time t, material offshoring OSM_{it} is defined as the share of the industry's total non-energy inputs that are imported. Mathematically, it is calculated as:

$$OSM_{it} = \sum_{j} \left[\frac{M_{jit}}{N_{it}}\right] \times \left[\frac{I_{jt}}{Y_{jt}}\right] \tag{1.1}$$

where, M_{jit} is the purchases of input j by industry i at time t, N_{it} is the total non-energy inputs used by industry i at time t, I_{jt} is the imports of inputs j at time t, and Y_{jt} is the total domestic supply of input j at time t.[6]

The first term represents the share of input j as a proportion of the total non-energy inputs. The second term represents the share of good or service j that was imported nationally.Similarly, I can calculate the measure for service offshoring, OSS_{it}, if goods j that represent service inputs. Further, as the data on trade of each input is not available at an industry level, I cannot tell the amount of those imports used by a certain industry. Therefore, as in the literature, I rely on the "proportionality assumption" such that every industry that uses input j, uses the input in the same proportion. Data on input purchases is calculated using the annual input-output table constructed by the Bureau of Labor Statistics (BLS) based on the 2002 benchmark table of Bureau of Economic Analysis (BEA). Data on trade of materials comes from Schott (2008), and data on trade of services are obtained from the BEA International Economic Accounts.

However, there are a few potential problems with the offshoring measure used in this paper(Amiti and Wei, 2005; Houseman et al., 2011; Feenstra and Jensen, 2012). First, the measure has the "proportionality assumption" due to the lack of data on imports by individual industry. Studies for Germany (Milberg and Winkler, 2010) and Asia (Puzzello, 2012) show that this assumption does not hold well. Second, I can not ascertain whether the imported goods are intermediate inputs or final use commodities. Third, imports from affiliated foreign firms are cheaper than importing from independent firms; but I cannot differentiate the two types of imports and will use the same producers value for both. Despite

[5] I exclude other service imports such as travel and education because of minimal trade in these sectors.
[6] Total domestic supply is calculated as the total production plus net imports.

its problems, the measure has been frequently used in the literature as a reasonable proxy of offshoring.

1.2.2 Trends in Offshoring

Recent economic literature has well-documented the tremendous rise in offshoring by U.S. firms starting from the 1970's. FH measure offshoring as defined in equation 1.1 and find that imported material inputs has risen from 6.5% in 1972 to 11.6% in 1990. Shocks in exogenous factors in the 90s has led to a faster pace of globalization which has facilitated offshoring activities by firms. Bottini et al. (2007) point out three such factors: 1) reduction in trade barriers, 2) reduction in transportation cost, and 3) technological change.

First, regional free-trade agreements such as NAFTA eliminated red tape allowing firms to relocate their production process. Yi (2003) shows the non-linear response of trade volumes to tariff reduction; thus, even a small decrease in tariff rates leads to a large increase in trade volume. Baier and Bergstrand (2001) studied the relationship between transportation costs and trade volume for industrialized nations. They estimate that the reduction in transportation costs explains about 8% increase in the trade volume post World War II until the late 80s. However, the impact of falling transportation cost, plays a minor role in facilitating trade relative to the reduction in trade barriers (Hummels, 1999). Lastly, in the past few decades, the advances in computer, network technology, and access to internet has expanded service offshoring in the form of call centers, tax and accountancy services, and financial services.

In addition, as economies have converged in economic size, multinational firms have become more vertically specialized, which has increased trade in intermediate goods (Feenstra et al., 1998). More importantly, rapid globalization has introduced large developing economies such as China and India with different factor endowments in the global market, thus providing further opportunities for offshoring.

Initially, most offshoring activities involved material offshoring. This phenomenon was mainly led by labor intensive industries that had an incentive to fragment their relatively unskilled-intensive production process internationally to exploit the lower wages of unskilled labor in developing economies. Recently, however, the advancements in technology has increased service offshoring. However, it comprises only a tiny fraction compared to material offshoring. Figure 1.1 shows the average trend in both material and service offshoring from 1999-2009. Material offshoring has risen from about 14.5% in 1999 to 19.07% in 2008. Likewise, although service offshoring is a small part of manufacturing industries, it has risen at an average annual rate of 6.8%.

Figure 1.2 presents a clearer picture of the trend at the 3-digit NAICS industry level.[7] The electronic manufacturing sector's material offshoring has risen by more than 44% during the sample period. Within the sector, the sharp rise can be attributed to audio and video equipment manufacturing. There offshoring has risen from 32.3% in 1999 to 39.7% in 2004 and to 48.4% in 2009. We see similar increases in the appliance manufacturing industry and primary metal manufacturing, where material offshoring has risen by more than 36% and 31% , respectively. An industry that hasn't been affected as much is the food manufacturing industry, where material offshoring still stands below 5%. However, within the food manufacturing industry, offshoring by the grain and oilseed industry has increased by about 3 percentage point from 4.5% in 1999 to 7.1% in 2009. Likewise, the figure also shows the increase in service offshoring. Although service offshoring remains below 1% of the total production process, there's been a sharp increase in service offshoring activities. For instance, in wood product manufacturing, service offshoring has risen by over 200% from 1999-2009. Similarly, such sharp increases can be seen in the non-metallic mineral industry, transportation industry and chemical industry. Within the chemical industry, one of the fastest growing service offshoring industries is pharmaceutical and medicine manufacturing, which has seen its offshoring increased from about 0.4% to 0.9% during the period.

[7] In my analysis, I use industry at the 4-digit NAICS level to merge with the CPS industry classification. The graph shows it at the 3-digit industry level to see a trend at an aggregated industry level.

1.3 Literature Review

1.3.1 Conceptual Framework

Traditionally, the effect of trade on wages has been empirically tested from the Stolper and Samuelson (1941) theory that predicts trade will lead in an increase in wages for factors used intensively in the production of that good. The North is relatively abundant in skilled labor, whereas the South is relatively abundant in unskilled labor. Thus, the theory implies that the skill-premium for North would increase while the skill-premium for the South would decrease. However, empirical studies found that skill premium in both the North and South was increasing (Belkman et al., 1998). Furthermore, studies also found that there was an increase in the skill-intensity within industry and not an expansion of skill-intensive industries. This led to finding new mechanisms through which trade affects the wage and skill premium. Therefore, rather than focusing on the trade in final goods, recent theories have looked at trade affecting wages through trade in intermediate good. Thus, there is an increasing focus on the effect of offshoring on skill premium.

In seminal papers, Feenstra and Hanson (1996, 1999) emphasized the role of trade in intermediate goods within an industry. Their model had a single final goods sector that used a continuum of tradable inputs to produce the good. The production of these inputs differed in their skill-intensity. In the model, when capital share in production cost is the same across inputs and the trade costs are zero, then in equilibrium, countries that are skill-abundant specialized in the production of skill-intensive inputs, whereas countries that are unskill-abundant specialized in unskilled-intensive inputs. Hence, as trade costs have fallen, the production of less-skill intensive inputs has shifted from the North to South. Further, the production processes shifted to the South are more skill-intensive than the previous productions in the South. As a result, the fragmentation of the production process increases the relative demand for skilled labor in both North and South and thus increases the skill premium of the workers.

However, more recently, Grossman and Rossi-Hansberg (2008) propose a production process that mainly focuses on tasks that are tradable rather than focusing on the goods. Therefore, as it becomes easier to move tasks offshore, it will have a productivity effect, such that all factors can share the gains from the trade in tasks.

1.3.2 Empirical Literature

The initial literature that looked at the effect of material offshoring on skill premium focused on industry-level aggregates, where the relative demand for skilled workers was measured by the skilled labor share of the wage bill. Feenstra and Hanson (1999) (FH hereafter) used the offshoring proxy as defined in equation 1.1 and found that for the period during 1979-1990, offshoring explained 15-40% of the increase in the skilled workers' share in wage bill for the U.S. Yan (2006) employed the same measures as FH and studied the case for Canada by analyzing 84 manufacturing industries from 1981-1996 and found that offshoring increased the non-production share of the wage bill by 0.12 percent annually. Likewise, Hsieh and Woo (2005) studied how offshoring to China affected the relative demand for skilled workers in Hong-Kong from 1971-1996. China opened up its market for foreign investors in 1980, which allowed Hong Kong to easily offshore its production process due to its close proximity. They concluded that offshoring to China accounted for about 40% - 50% increase in the relative demand for skilled labor in Hong Kong.

More recently, the offshoring literature has started to focus not just on material offshoring, but also on service offshoring. Although service offshoring accounts for a very small percentage of the total offshoring activities, it is increasing at a fast rate as shown in section 1.2.2. As with material offshoring, direct data on service offshoring is hard to find. Therefore, Amiti and Wei (2005) employ a similar method as FH to proxy for offshoring in service inputs. They study the effects of service offshoring on labor productivity in the U.S. manufacturing industry from 1992-2000 by looking at the value-added per worker. Due to data constraints, they limit their measure for service offshoring to telecommunication, information technology, financial and insurance services. Apart from using industry fixed effects in their analysis, they also use the lagged value of offshoring to address the problem of endogeneity of offshoring decisions. However, unlike the previous studies, they find that the effects of material offshoring are insignificant, but service offshoring increases labor productivity by about 10%.

There are a few drawbacks in using industry-level aggregates to measure the impact of offshoring. First, there may be compositional changes in the workforce of industries in response to offshoring shocks so that it will change the average wages. Second, it doesn't account for worker heterogeneity within each industry. Therefore, using individual level data can control for observable individual characteristics that affect wages. Lovely and Richardson (2000) study the effect on individual wages by looking at the data from the Panel Study of Income Dynamics (PSID) for the 1981-1992 period. They define skilled workers based on the years of education. Further, they focus only on the effects of imports and exports and not on the measure of offshoring discussed above. They find that trade with newly industrialized countries increases the premium for skilled workers. Kosteas (2008) uses the National Longitudinal Survey of Youth (NLSY) for the period of 1979-1996 to look at the impact of imports from low-wage countries. He separates the workers into white-collars and blue-collars arbitrarily based on their occupation, and finds that rising imports from low-wage countries drives down the wages for all workers, but the effects are stronger for blue-collar wages. The study finds that a one-percentage-point increase in the low-wage import share results in a 2.8% decline in blue-collar wages. However, he doesn't interact offshoring with the white-collar dummy to get a clear picture of the effect of offshoring on wages. Furthermore, a problem with using data from the PSID and NLSY is the limited sample size. For instance, Kosteas (2008) sample is limited to workers who were between ages of 14-21 in 1979, thus failing to account for the effect of workers who were older than that during the period.

As a result, the recent literature has focused on individual data from the Current Population Survey (CPS) because of the availability of a larger sample. Liu and Trefler (2008) use this data to look at the effect of service offshoring to China and India from 1995-2006 on industry and occupation switching. They only look at the transactions that take place between unaffiliated parties. To look at occupation switching, they match workers in consecutive years. They find that offshoring to China and India has small effects on occupation and industry switching. Other studies ask a more subtle question of whether offshoring affects wages through occupation switching or industry switching. Ebenstein et al. (2014) create a measure of occupation exposure and industry exposure to look at the effect of offshoring.Their analysis finds that occupational exposure to globalization has significant wage effects, whereas industry exposure has no significant impact.

A more closely related paper is Tempesti (2015) who uses CPS March supplement data to look at the effect of offshoring on the skill premium from 1979-1990. The study looks at industry at a more aggregated level (SIC 2 digits) and only looks at the effect of material offshoring and doesn't consider the effect of service offshoring. In my analysis, I study the effect of service offshoring and material offshoring. Further, in his paper, skill is based on the education level of workers, whereas I develop a new proxy to include the skills that may have been learned on the job and not necessarily acquired through education.

1.4 Empirical Methodology

1.4.1 Data

My sample links individual level workers' data with industrial measures of offshoring and occupational measure of offshorability. Individual level data is collected from the Current Population Survey (CPS) March Supplement for the years 1999-2009. CPS randomly samples addresses in the US, where residents in the address are surveyed for four consecutive months, dropped for the next eight months and then surveyed again for four more months. The March supplement has additional questions about labor market activities allowing classification of individuals by industry and occupation. I restrict the sample to the civilian population aged 16-65, who worked at least one week during the past year. Hourly wage is calculated from earnings using the weeks worked last year and the usual hours worked per week. The wages are then converted to 2009 real dollars. I further restrict my sample to workers who earned at least 10 cents an hour and dropped workers who earned more than 1000 dollars per hour. As I am only able to construct material and service offshoring for manufacturing industries, I only look at workers in manufacturing industries.

Data to calculate the measure for material offshoring comes from the annual input-output table constructed by the Bureau of Labor Statistics (BLS) based on the 2002 benchmark table of Bureau of Economic Analysis (BEA). Data for imports and exports of material goods are obtained from Schott (2008) and data for trade in services comes from BEA International Economic Accounts. The industry level data on total factor productivity comes from NBER's calculations provided by Wayne Gary.

The proxy for skills and occupation offshorability comes from the Occupation Information Network (O*NET), a successor to the Department of Occupation Titles (DOT). O*NET collects data on standardized occupation-specific descriptors by surveying a broad range of workers from each occupation. The O*NET content model identifies six major domains that specify key attributes and characteristics of workers and occupations. These are: worker characteristics, worker requirements, experience requirements, occupational requirements, workforce characteristics and occupation-specific information. The skill index uses information from worker requirements and the information for occupation offshorability comes from worker characteristics and occupational requirements.

My final sample consists of 81,107 cross-section samples of manufacturing workers from 1999-2009. Table 1.1 provides the descriptive statistics of the variables. The sample mainly consists of married, white, citizens and full-time workers. About 16% of the workers in the sample are high-skilled, 40% are medium skilled and the rest are low-skilled. The average of lag material offshoring is 17.5% and 0.28% for service offshoring.

1.4.2 Skill Index

In the literature, a worker is usually classified into different skill-level based on either education level (college graduates vs non-college graduates) or years of experience. However, classifying skills based on only a single criterion like education does not account for skill-sets that workers learn and master on the job without any formal education. Therefore, by defining skills as a composite set of skill indicators such as critical thinking and complex problem solving skills, we can better classify individuals into different skill-levels.

O*NET collects data on skill requirements, among others, for more than 800 occupations. These skills are further characterized as Basic Skills and Cross-Functional Skills. Basic skills are defined as "developed capacities that facilitates learning or the more rapid acquisition of knowledge" and cross-functional skills are defined as "developed capacities that facilitates performance of activities that occur across jobs." To define my skill index, I combine two aspects of basic skills: reading comprehension and critical thinking, and two aspects of cross-functional skills: complex problem solving and judgment and decision-making. For each of these skills, the dataset provides a measure of "importance" based on how important the skill is to the job responsibilities and a value of "level" that shows the proficiency in the skill. The importance measure ranges from 0 to 5 (0 being least important and 5 being very important) and the level value ranges from 0 to 7 (0 being less proficient and 7 being highly proficient). To calculate the skill index, I arbitrarily assign Cobb-Douglas weights of two thirds to "importance" and one third to "level"[8]

Mathematically, the skill index can be written as

$$SI_o = \sum_{k \in S_p} I_{ok}^{2/3} * L_{ok}^{1/3} \tag{1.2}$$

where S_p is the skills elements.

Table 1.2 shows the occupations that receive high and low scores in the normalized measure.[9] The results agree with the general consensus of high-skill and low-skill occupations as presented in other studies. For instance, lawyers and chief executives have the highest scores in the index, whereas graders and sorters of agricultural products and cleaner of vehicles and equipments score low on the index. I then use this index to classify individuals into three different categories of skill: high, medium and low. I classify individuals as high skill if their skill index is above the 75^{th} percentile, as medium skill if the index ranges from the 25^{th} percentile to the 75^{th} percentile, and as low skill if the index is below the 25^{th} percentile.

1.4.3 Occupation Offshorability

I follow Firpo et al. (2011) to look at the potential offshorability of occupation by constructing an index based on three categories: automation, face-to-face, and decision-making.

[8] Blinder et al. (2009) assigns a similar Cobb-Douglas measure to create offshorability index for occupation using O*NET database

[9] Since the absolute value of the index has no particular meaning, I normalize the index by dividing them by the maximum value of the skill observed over all occupation. The normalized measure is useful in ranking the skill-level, whereas the absolute value have no particular meaning

The data comes from the work activities and work context criteria of occupational requirements domain of the O*NET database.

The "automation" category is constructed to reflect the degree of potential automation of the job. It includes five elements from the work context criteria. They are: "degree of automation", "importance of repeating same tasks", "structures versus unstructured work", "pace determined by speed of equipment", and "spend time making repetitive motions". In contrast, the "face-to-face" category reflects the need for the workers to interact with other colleagues so that these occupations are not easily offshorable to a different location. The category includes four work-activity elements and one work-context element. The work-activity elements are: "coaching and developing others", "establishing and maintaining interpersonal relationships", "assisting and caring for others", and "performing for or working directly with the public". It also adds the "face-to-face discussion" element from work-context. Likewise, the "decision-making" category reflects the responsibilities and creativity of the occupation. It is constructed using "making decision and solving problems", "thinking creatively", and "developing objectives and strategies" elements from the work-activities and "responsibility for outcomes and results" and "frequency of decision making" elements from work-context.

All work-activity elements contain information on the "level" and "importance" of the element. The work-context elements contain information on level and the frequency of five categorical levels.[10] The work-activity elements are arbitrarily assigned a Cobb-Douglas weight of two-thirds to "importance" and one-third to "level" for a weighed sum, and multiply the frequency (F) with the value of the level (V) for the work-context elements.

Matematically, the total composite score, CS_m, for occupation j in category m is computed as

$$OFF_o = \sum_{m \in A_p} I_{ok}^{2/3} L_{ok}^{1/3} + \sum_{l \in C_p} F_{ol} * V_{ol} \tag{1.3}$$

where A_p is the work activity elements, and C_p is the work context elements in the category OFF_o. [11]

[10] For instance, for "face-to-face discussion", the frequency is classified into five categories: a) never, b)once a year or more but not every month, c)once a month or more but not every week, d)once a week or more but not every day, e) everyday.

[11] Since the absolute value of the index has no particular meaning, I normalize the index by dividing them by the maximum value of the skill observed over all occupation. The normalized measure is useful in ranking

Using the above measures, I define "not face-to-face" and "not decision-making" categories as the reverse of "face-to-face" and "decision-making". I then combine the three categories: automation, not face-to-face and not decision-making into a single measure to look at the likelihood of offshorability. I hypothesize that occupations that are more likely to be offshorable will suffer a higher wage loss compared to other occupations as a result of material and service offshoring.

Table 1.3 shows the different occupations that score high on the the different categories calculated above. I use the normalized score to rank each worker in one of the categories based on its index score. For instance, if the score is above the mean in not-face-to-face category, the worker will be classified as not requiring to have many face-to-face interactions. Likewise, after I combine the three categories into a single offshorability category, if a worker scores above the mean, he is placed under the likelihood of his job being offshored. If the score is below the mean, the chances of the job being offshored falls. Under automation, computer control programmers and operators rank high, whereas teachers and clergy rank low. Likewise, for not face-to-face, telephone operators and pressers in the textile and garment industry rank high, whereas managers rank low. A similar result is seen in the not-decision-making as graders and sorters rank high and production managers rank low. Combining all three into a single measure, it shows that textile knitting and weaving occupations have a higher chance of being offshored compared to medical technicians and dentists.

1.4.4 Econometric Specification

I use the Mincer human capital wage equation to measure the effect of offshoring on individual wages. I regress the log wages of workers i in industry j in period t on the lagged measure of service and material offshoring at the industry level and individual skill-level while controlling for individual observable characteristics such as age, sex, marital status and race. I use the lagged measure of offshoring for two reasons. First, simultaneous shocks may affect both wage and offshoring in a given year. Second, the effect of offshoring decision will not affect wages in the same year as it takes time for the firms to implement them.

the skill-level, whereas the absolute value have no particular meaning

In addition, as Ebenstein et al. (2014) point out, there are further challenges in estimating the casual effect of offshoring on wages. Industries that are more likely to be involved in offshoring activities are also more likely to pay lower wages. I, therefore, include industry fixed-effects I_j to control for these. Also, there may be common time-varying shocks such as business-cycles that may affect both offshoring and wages. To address this concern, I include the time fixed-effects δ_t. In addition, I control for the lagged of total factor productivity at the industry level, TFP_{jt-1}, to account for any changes in productivity that would affect the relative demand for labor.

The basic regression model takes the following form:

$$ln(w_{zt}^{oi}) = \alpha + \beta_1 OSM_{i,t-1} + \beta_2 OSS_{i,t-1} + \beta_3 SI_o + \gamma X_{zt} + \delta_t + I_i + \epsilon_{zt} \tag{1.4}$$

where $ln(w)_{zoit}$ is the log of hourly wage of worker z in industry i and occupation o at time t. OSM_{it-1} and OSS_{it-1} is the measure for material and serving offshoring in industry i and time t, respectively. SI_o denotes the skill of the workers, X_{ot} is a vector of standard demographic variables like age, sex, and dummies for marriage, race and full-time/part-time status.

In addition, I also examine the effect of offshoring on the wages of different occupation based on their offshorability. To look at the effect, my specification becomes,

$$ln(w_{zt}^{oi}) = \alpha + \beta_1 OSM_{i,t-1} + \beta_2 OSS_{i,t-1} + \beta_3 OFF_o + \gamma X_{zt} + \delta_t + I_i + \epsilon_{zt} \tag{1.5}$$

where OFF_o represents the occupational offshorability of worker z at time t. I will also interact the offshorability of occupation with offshoring measures to see the effect of offshoring on the wage of workers whose jobs are offshorable.

1.5 Results

I first look at the effect of material offshoring and service offshoring on individual wages. The result is reported in table 1.4.[12] In column 1, I regress wages on only the demographic

[12] I provide the complete table with all the demographic variables in the appendix.

control variables and find that all the controls have the expected correlation. In columns 2 and 3, I regress log of hourly wage on material offshoring, service offshoring, and both measures of offshoring, respectively, while controlling for individual demographic characteristics and industry-specific measures. Consistent with the labor literature, compared to low-skill workers, I find that high-skill workers earned 40 percent more and medium-skill workers earned 18 percent more. Likewise, workers with college degree and some college classes earn more than high-school graduates. In the first column, when I only include material offshoring, I find a negative insignificant effect. Service offshoring has a positive effect on wages as seen on column 2. However, when I include both the measures in column 3, they are qualitatively the same, but are statistically insignificant.

A more interesting question to explore would be the effect of service and material outsourcing on individuals with different skill-level. If an industry is more likely to offshore mainly activities performed by a certain skill group to a foreign firm, then we can expect it to have a negative effect on wages of that skill group. In table 1.5, I look at the effect of both material and service offshoring on workers of different skill levels. The first column shows that a 10 percentage-point increase in material offshoring will increase the high-skill wage by 2.2 percentage and the medium skill wages by 2.4 percentage. In the second column, including interaction terms with service offshoring, I find that both high-skill and medium skill workers earn statistically significantly higher wages than low-skilled workers. Further, when I include all the interaction terms together, I find that material offshoring negatively affects low-skilled workers, whereas a 10 percentage point increase in material offshoring increases the wages of high-skilled workers by 2.9 percent and medium skilled workers by 3 percent. This result is consistent with the idea that if the low-skilled intensive part of the production process is offshored, it will reduce the relative demand for unskilled workers, thus negatively impacting their wages.

In addition, apart from the skill-level of the workers, recent theories show that offshoring may have significant effects on workers who perform tasks that are easily offshorable. Therefore, first, I will look at the wages of workers on different task spectrum and then look at the effect of offshoring on wages of these workers. In table 1.6, I look at the wages for workers under automation, not decision-making, and not face-to-face. I anticipate that since the tasks performed by workers in these classifications are easily offshored, offshoring should have a negative effect on their wages. In the first three columns, when I control for these tasks separately, I find that workers in all three tasks earn less than their counterparts. Further, when I regress all three together, I find that all three occupational tasks have negative effect on wages, but occupations with low requirements for face-to-face interactions suffer the most. Workers in automation category earn 7.7 percent less than workers with low risk of automation. Similarly, workers who do not require much decision-making earn 6.7 percent less and workers with few face-to-face interaction tasks earn 11 percent less.

I then combine the three measures of occupational tasks into a single measure of offshorability to look at the effect of material and service offshoring on these occupations. In table 1.7, column 1 shows the results for offshorability and the subsequent column adds the interaction term with material offshoring, service offshoring, and both the offshoring together. I find that people whose occupation have a higher chance of being offshored earn 17 percent less. However, when I interact with material offshoring, I find a negative effect but it is insignificant. However, it does show a statistically significant negative effect as a result of service offshoring. In the last column, I find that a 10 percentage point increase in material offshoring will result in lowering the wages of offshorable occupations by 0.8 percent. Similarly, a 10 percentage point increase in service offshoring will decrease their wages by 1.5 percent. This result is consistent with the idea that if the occupation requires low face-to-face interactions, can easily be automated and does not involve significant decision making, then these tasks can be more easily monitored offshore than more complex tasks, thus negatively impacting the wages for these workers.

1.6 Robustness Checks

In this section, I'll look at a different classification of skill for workers. In my main analysis, I classified workers who were above the 75th percentile as high-skill, between 25 to 75 percentile as medium skill and workers below the 25th percentile as low-skill. For a robustness check, I assign workers above 66 percentile to high-skill, between 33 and 66 percentile to medium skill and below 33 percentile to low skill. I run a regression using the same specification as my main analysis and present the result in table 1.8. Although the results differ slightly in their quantitative magnitude, they're qualitatively the same and statistically significant. I find that high-skill workers and medium-skilled workers earn 27 to 28 percent more than low-skill workers as a result of material offshoring. Likewise, the result for service offshoring are also similar to my main analysis and statistically significant.

1.7 Conclusion

This paper looks at the effect of material and service offshoring on individual workers wages based on two criteria: workers skill-level and the offshorability of their occupation. I examine the effect by combining the individual level data from the March Supplement of the CPS and the industry-level measures of service and material outsourcing for the period 1999-2009. For my analysis, I developed a new measure for skill using the O*NET database. Previous literature has focused only on education as a measure for skill; however, by using a singular measure for skill may overlook the new skills that workers have learned on the job without any formal education. Therefore, I utilize the information on the important and level of skills they perform on the job to create a skill-index to classify workers into three types of skill-level. Further, in my analysis, I also used the Firpo et al. (2011) classification of occupation offshorability to study the effect of material and service offshoring on the wages of workers in occupations that had a higher chance of being offshored.

My results showed that workers with high and medium skill earn about 3 percent more than workers with low skill as a result of a 10 percentage point increase in material offshoring. A greater impact is found for service offshoring, where high skill workers earn 3.2 percent more and medium-skilled workers earn 2.2 percent more for each percentage point increase in service offshoring. However, it is important to note that the current level of service offshoring stands well below 1 percent of the total production process. This result is consistent with the previous literature and theory that shows that offshoring of the less skill-intensive part of the production process will negatively impact the wages of workers involved in low-skill intensive production process. This result was robust to a different classification of skill-level based on the skill index I created.

I also looked at the effect of on wages of occupations that have a higher probability of being offshored. I found that occupations that required less decision-making, low face-to-face interaction and a higher possibility of being automated earn less than their counterparts. Combining all these three measures into a single measure of offshoring, I found that workers in occupation with higher chances of being offshored earned 0.8 percent less with a 10 percentage point increase in material offshoring. The result represented that it would be easier for firms to monitor the performance of these occupations in an offshore location relatively easily compared to occupations with complex tasks thus having a downward pressure on their wages.

Figure 1.1: Trends in Overall Material and Service Offshoring

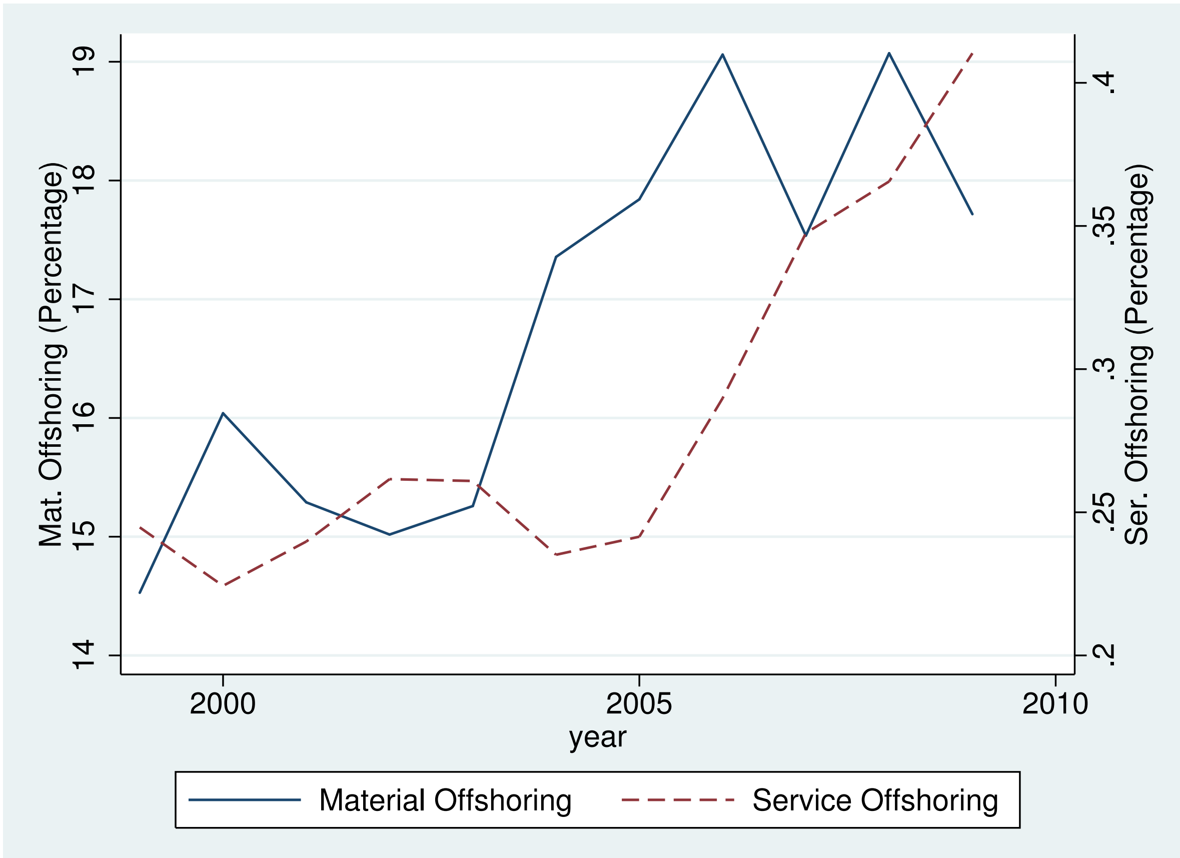

Figure 1.2: Trends in Sectoral Material and Service Offshoring

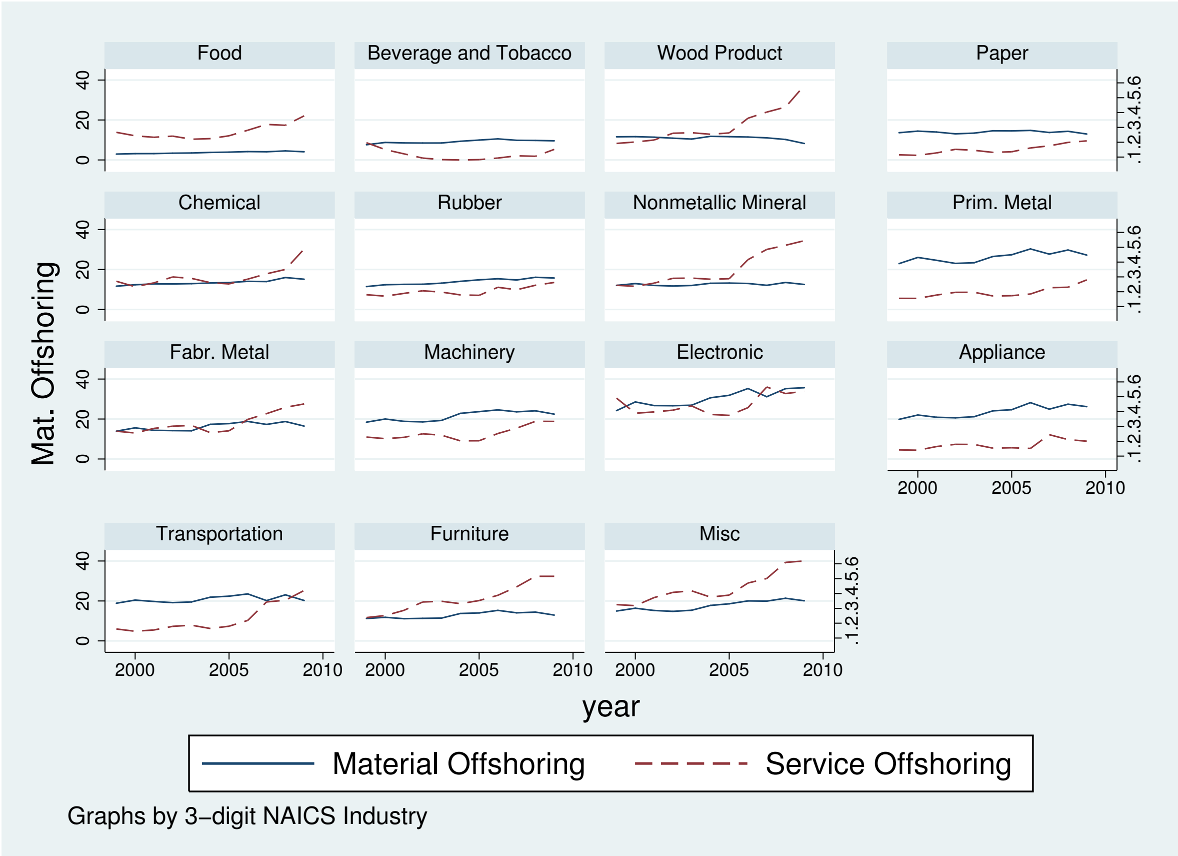

Table 1.1: Summary statistics

Variable	**Mean**	**Std. Dev.**
LnWage	2.896	0.666
Lag Mat. Offshoring	17.542	9.106
Lag Ser. Offshoring	0.285	0.16
Age1624	0.075	0.263
Age2539	0.356	0.479
High Skill	0.165	0.372
Med Skill	0.409	0.492
College	0.237	0.425
SomeCollege	0.262	0.439
lagTFP	1.014	0.254
Married	0.815	0.388
Male	0.699	0.459
Union	0.028	0.164
Full-Time	0.959	0.199
Citizen	0.827	0.378
White	0.838	0.369
N	81107	

Table 1.2: Occupation Skill Rank

Occupation Title	**Skill Index**
A: Occupation with High Skill Index	
Lawyers	1.000
Biomedical Engineers	0.995
Actuaries	0.994
Chief Executives	0.992
Physicans and Surgeons	0.976
Medical Scientist	0.963
Research Analyst	0.963
B: Occupation with Low Skill Index	
Janitors and Building Cleaners	0.524
Pressers, Textile, Garments and Related Materials	0.522
Food Preparation Workers	0.516
Dishwashers	0.512
Cafeteria Attendants	0.499
Cleaner of Vehicles and Equipments	0.418
Graders and Sorters, Agricultural Products	0.453

Table 1.3: Occupation Task Rank

Occupation Title	**Occupation with High Score**	**Occupation with Low Score**
Automation	Tire Builders, Hoist and Winch Operators, Etchers and Engravers, Computer Control Programmers and Operators	Models and Demonstrators, Teachers, Actors, Clergy
not Face To Face	Tire Builders, Pressers (Textile and Garments), Reinforcing Iron and Rebar Workers, Telephone Operators	Social and Community Service Managers, Public Relation Managers, Dentists, Physical Therapists
not Decision Making	Graders and Sorters (Agricultural Products), Lobby Attendants, Extraction Workers, Pressers(Textile and Garment)	Dentists, Pharmacists, Veterinarians, Production Managers
Offshorability	Tire Builders, Pressers (Textiles and Garments), Textile Knitting and Weaving, Paper Goods Machine Setters	Veterinarians, Clergy, Emergency Medican Technician, Dentists

Table 1.4: OLS Estimates of Offshoring on Skill-Premium

	(1)	(2)	(3)	(4)
VARIABLES	LnWage	LnWage	LnWage	LnWage
Lag Mat. Offshoring		-0.166		-0.0729
		(0.105)		(0.122)
Lag Ser. Offshoring			0.0938**	0.0800
			(0.0420)	(0.0487)
HighSkillOccOne		0.400***	0.400***	0.400***
		(0.00639)	(0.00639)	(0.00639)
Med Skill Occupation		0.183***	0.183***	0.183***
		(0.00408)	(0.00408)	(0.00408)
lagTFP	0.0345***	0.0235*	0.0215*	0.0232*
	(0.0126)	(0.0126)	(0.0123)	(0.0126)
Constant	1.957***	2.001***	1.993***	1.994***
	(0.0313)	(0.0306)	(0.0308)	(0.0309)
Observations	81,107	81,107	81,107	81,107
R-squared	0.368	0.403	0.403	0.403
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 1.5: OLS Estimates of Skill and Offshoring Interaction

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage
Lag Mat. Offshoring	-0.183	-0.0330	-0.224*
	(0.126)	(0.122)	(0.126)
Lag Ser. Offshoring	0.0810*	-0.0808	-0.0936*
	(0.0487)	(0.0516)	(0.0516)
High Skill Occupation	0.395***	0.347***	0.291***
	(0.0150)	(0.0122)	(0.0186)
Med Skill Occupation	0.180***	0.169***	0.112***
	(0.00925)	(0.00799)	(0.0120)
Lag Mat. Off * High Skill	0.221***		0.290***
	(0.0687)		(0.0686)
Lag Mat. Off * Med. Skill	0.248***		0.301***
	(0.0476)		(0.0477)
lagSerOut * High Skill		0.304***	0.324***
		(0.0354)	(0.0355)
lagSerOut * Med. Skill		0.200***	0.220***
		(0.0254)	(0.0255)
lagTFP	0.0307**	0.0309**	0.0272**
	(0.0127)	(0.0127)	(0.0127)
Constant	1.996***	2.011***	2.046***
	(0.0312)	(0.0312)	(0.0315)
Observations	81,107	81,107	81,107
R-squared	0.404	0.405	0.405
Demographic Controls	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 1.6: OLS Estimates on Occupational Measure of Offshorability

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage	(4) LnWage
Lag Mat. Offshoring	0.0556	-0.0406	0.00396	-0.00263
	(0.125)	(0.125)	(0.125)	(0.124)
Lag Ser. Offshoring	0.129***	0.104**	0.131***	0.123**
	(0.0500)	(0.0499)	(0.0498)	(0.0496)
AutomationOne	-0.0979***			-0.0778***
	(0.00444)			(0.00450)
notDecisionMakingOne		-0.106***		-0.0673***
		(0.00387)		(0.00405)
notFaceToFaceOne			-0.149***	-0.112***
			(0.00392)	(0.00419)
lagTFP	0.0338***	0.0392***	0.0341***	0.0334***
	(0.0128)	(0.0129)	(0.0130)	(0.0128)
Constant	2.027***	2.046***	2.095***	2.187***
	(0.0318)	(0.0318)	(0.0317)	(0.0320)
Observations	81,048	81,048	81,048	81,048
R-squared	0.372	0.374	0.379	0.383
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 1.7: OLS Estimates on Offshoring and Offshorability Interaction

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage	(4) LnWage
Lag Mat. Offshoring	0.0133	0.0481	-0.0197	0.0252
	(0.124)	(0.127)	(0.124)	(0.127)
Lag Ser. Offshoring	0.113**	0.112**	0.186***	0.187***
	(0.0496)	(0.0496)	(0.0511)	(0.0511)
Offshorability	-0.172***	-0.160***	-0.127***	-0.111***
	(0.00410)	(0.00912)	(0.00783)	(0.0116)
Lag Mat. Off. * Offshorability		-0.0658		-0.0863*
		(0.0448)		(0.0449)
Lag Ser. Off. * Offshorability			-0.153***	-0.157***
			(0.0242)	(0.0243)
lagTFP	0.0344***	0.0334***	0.0342***	0.0329**
	(0.0129)	(0.0129)	(0.0129)	(0.0129)
Constant	2.127***	2.121***	2.103***	2.095***
	(0.0318)	(0.0321)	(0.0320)	(0.0324)
Observations	81,048	81,048	81,048	81,048
R-squared	0.382	0.382	0.382	0.382
Demographic Controls	Yes	Yes	Yes	Yes

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Table 1.8: Robustness Check based on Skill Classification

	(1)	(2)	(3)
VARIABLES	LnWage	LnWage	LnWage
Lag Mat. Offshoring	-0.204	-0.0709	-0.249**
	(0.126)	(0.121)	(0.125)
Lag Ser. Offshoring	0.0785	-0.0859*	-0.0977*
	(0.0486)	(0.0514)	(0.0515)
HighSkillOccOne	0.418***	0.358***	0.305***
	(0.0140)	(0.0117)	(0.0176)
MedSkillOccOne	0.178***	0.169***	0.116***
	(0.00945)	(0.00811)	(0.0121)
lagMatOutHighSkillOne	0.201***		0.272***
	(0.0639)		(0.0640)
lagMatOutMedSkillOne	0.231***		0.283***
	(0.0486)		(0.0486)
lagSerOutHighSkillOne		0.325***	0.344***
		(0.0330)	(0.0332)
lagSerOutMedSkillOne		0.185***	0.203***
		(0.0260)	(0.0261)
lagTFP	0.0247*	0.0243*	0.0209*
	(0.0127)	(0.0126)	(0.0126)
Constant	2.011***	2.028***	2.060***
	(0.0312)	(0.0311)	(0.0315)
Observations	81,107	81,107	81,107
R-squared	0.407	0.408	0.408
Demographic Controls	Yes	Yes	Yes

All regression has demographic control and time and industry fixed effect

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Demographic controls include sex, age, race, education, whether in a union, whether a citizen, education, and industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

1.8 Appendix

Table 1.9: OLS Estimates of Offshoring on Skill-Premium

VARIABLES	(1) LnWage	(2) LnWage	(3) LnWage	(4) LnWage
Lag Mat. Offshoring		-0.166		-0.0729
		(0.105)		(0.122)
Lag Ser. Offshoring			0.0938**	0.0800
			(0.0420)	(0.0487)
HighSkillOccOne		0.400***	0.400***	0.400***
		(0.00639)	(0.00639)	(0.00639)
Med Skill Occupation		0.183***	0.183***	0.183***
		(0.00408)	(0.00408)	(0.00408)
College	0.614***	0.427***	0.427***	0.427***
	(0.00542)	(0.00611)	(0.00611)	(0.00611)
SomeCollege	0.194***	0.134***	0.135***	0.134***
	(0.00444)	(0.00441)	(0.00441)	(0.00441)
lagTFP	0.0345***	0.0235*	0.0215*	0.0232*
	(0.0126)	(0.0126)	(0.0123)	(0.0126)
Age1624	-0.363***	-0.341***	-0.341***	-0.341***
	(0.00895)	(0.00880)	(0.00880)	(0.00880)
Age2539	-0.109***	-0.101***	-0.101***	-0.101***
	(0.00405)	(0.00394)	(0.00394)	(0.00394)
Married	0.182***	0.158***	0.158***	0.158***
	(0.00564)	(0.00550)	(0.00550)	(0.00550)
Male	0.250***	0.247***	0.247***	0.247***
	(0.00425)	(0.00413)	(0.00413)	(0.00413)
Union	0.0658***	0.103***	0.102***	0.102***
	(0.0107)	(0.0105)	(0.0105)	(0.0105)
Full-Time	0.137***	0.124***	0.124***	0.124***
	(0.0159)	(0.0157)	(0.0157)	(0.0157)
Citizen	0.172***	0.138***	0.138***	0.138***
	(0.00569)	(0.00551)	(0.00551)	(0.00551)
White	0.0438***	0.0234***	0.0233***	0.0233***
	(0.00556)	(0.00542)	(0.00542)	(0.00542)
Constant	1.957***	2.001***	1.993***	1.994***
	(0.0313)	(0.0306)	(0.0308)	(0.0309)
Observations	81,107	81,107	81,107	81,107
R-squared	0.368	0.403	0.403	0.403

Notes: Robust standard errors are reported in parantheses below the coefficient estimates. Regressions include industry and time fixed effects. Significant at * 10%, ** 5%, ***1%

Chapter 2

Import Competition and Crime: A Study of US Top Trading Partners

2.1 Introduction

In the past few decades, there has been a phenomenal growth in world trade. Lowering of trade barriers, advancement in information technology and reduction in transportation costs have all contributed to the growth of trade among countries. As a result, the effect of trade on workers and local labor markets has been a fiercely debated topic. This has picked up further steam in the US especially because of the the North American Free Trade Agreement (NAFTA) and the tremendous rise of China in the global market. This has resulted in an increased import share of the US as a fraction of its GDP as shown in Figure 2.1. From 1991 to 2006, the import share of the US has increased from 10 percent to 18 percent. Most of this increase can be attributed to its top six trading partners: Canada, China, Mexico, Germany, Japan and South Korea.[1]

As a result of such an increase in US imports, a large number of growing literature has looked at the direct and indirect consequences of trade on labor markets. Recent empirical literature has shown that increase in import competition leads to reduction in wages and employment for workers that are more exposed to import competition.[2] In addition, the worsening labor market outcomes in terms of wages and employment for a large number of

[1]Figure 2.2 shows the trend of imports from these countries.

[2]See Borjas et al. (1992), Ebenstein et al. (2014), Pierce and Schott (2012)

workers may lead to other negative ancillary effects. This paper aims to study the effect of these increase in import competition on property and violent crimes at the local labor market level.[3]

The most recent wave of literature has mostly focused on the effects of Chinese import exposure. The economic reforms carried out in China after 1979 has significantly increased the exports industry in China. Chinese exports received a further bolstering after it joined the World Trade Organization (WTO) in 2001. This has resulted in a rapid growth of Chinese imports in the US. Furthermore, Chinese imports have been increasing at a faster pace compared to imports from other low-income countries. Autor et al. (2013) calls this the "China Syndrome" and their study shows that the import competition from China explains about one-quarter of the aggregate decline in U.S. manufacturing industry and also leads to an increase in government benefits payments in markets that have high exposure to Chinese imports. Likewise, Pierce and Schott (2012) exploit the accession of China to the WTO and show that the industries that had a higher exposure to Chinese imports experienced employment loss as plants shifted their labor intensive production process to China.

This has led to a spike in studies analyzing the ancillary consequences of increasing import competition from China. For instance, Feler and Senses (2015) show that Chinese import competition leads to a lower quality of public good provision, reduces business activities, decreases housing prices and increases property crimes. Likewise, Che and Xu (2015) find that the number of violent and property crimes at the county level increases as China's import exposure increases. This paper contributes to the growing literature on the ancillary effect of import competition by comparing the impact of the import exposure of China with the other top five import partners of the US on crime rates. To my knowledge, this is the first study that looks at the effect of import exposure on crime of these other countries at the local labor market level.

My study builds on the approach of Autor et al. (2013) by exploiting the variation in import exposure because of the differences in industry specialization across local labor markets. I examine three four year periods: 1992-1996, 1997-2001, 2002-2006, to study the effect of increasing import competition on property crimes (burglary, larceny, motor vehicle

[3] I define local labor markets in terms of commuting zones in this study.

theft, and arson) and violent crimes (murder, rape, assault and robberies) at the commuting zone level in the US. I find that a $1000 increase in Chinese import competition per worker increases the property crime rates by about 3 percent. In contrast, I find a negative relation for import exposure from Germany, Japan and Korea, but the evidence is not strong. In addition, I find no effect on violent crimes from increasing import exposure from any of the countries in the study.

The remainder of the paper is structured as follows: section 2 discusses the import competition from the six countries of interest, section 3 talks about the literature on import competition and crime, section 4 looks at the identification and empirical specification. Section 5 provides the results and section 6 looks at the possible channel of the effect. Robustness checks are provided in section 7 and section 8 concludes.

2.2 Import Competition

According to the World Development Indicators database, in the 1990s, exports grew nearly 140 percent faster than global GDP. The globalized nature of trade has also changed the trade patterns of the US. Its import share of GDP has increased over the past two decades. Among other aspects, this increase in import share can be attributed to several initiatives US has undertaken on trade negotiations such as the North American Free Trade Agreement (NAFTA) in the early 1990s, and inclusion of more countries in the World Trade Organization(WTO). The higher share of imports to GDP to the US is mainly attributable to its six largest trading partners: Canada, China, Mexico, Germany, Japan and South Korea. This section will look at the changes in the imports of the US from these six countries.

2.2.1 China

China instituted a series of economic reforms beginning in 1979.[4] It allowed for special economic zones (SEZ) along its coast that helped attract foreign investment and boosted its exports. The number of SEZs increased from 20 in 1991 to 150 by 2010 (Autor et al., 2016a).

[4]Some of these reforms were ownership incentives for farmers, and economic control of enterprises to provincial and local governments (Morrison, 2013)

As a result, according to World Bank, their share of inflows of foreign direct investment increased from an average of 0.7% of GDP in the 1980's to about 4.2% of its GDP in 2000's. Their share of world manufacturing exports has also risen from about 2.3% in 1991 to about 15% in 2007. Consequently, there has been a rapid increase in U.S. imports from China which stood at about $26 billion in 1992 to over $350 billion in 2008. The rate of imports from China has grown faster after it joined the WTO as shown in Figure 2.2. However, it is important to note that the increase in imports across industries is not uniform – some industries imports has increased substantially more compared to other industries. One of the highest imports in 1991 was in the Games, toys and dolls manufacturing industry. Its imports was $3.2 billion in 1991, which rose to $11.8 billion in 2000 and to $20.2 billion in 2007. Likewise, machinery and apparel industry has seen a massive growth in Chinese exports.

2.2.2 Canada

The US and Canada agreed on a free trade agreement in 1987 which was signed by the leaders of both the countries in early 1988. This agreement came to be known as the Canada-US Free Trade Agreement (CUSTA). The agreement planned to phase out various trade restrictions in different phases over a ten year period. In 1994, Mexico joined the agreement with the signing of NAFTA. Canadian imports increases from 91 billion in 1991 to about 310 billion in 2006. Panel C of Table 2.1 shows the highest and lowest import industries for the years 1992, 2001 and 2006. For all those years, crude petroleum and natural gas and motor vehicles and passenger car bodies were the top exporting industries for Canda to the US.[5] The lowest imports were mainly from the labaratory apparatus and lace and warp knit fabric mills. Furthermore, ice-cream and frozen desserts saw the highest growth in imports, whereas cellulosic manmade fibers saw a decline in imports.

[5]For these years, motor vehicle parts and accessories was the third highest import industry.

2.2.3 Mexico

The signing of NAFTA in 1992 eliminated many tariffs and non-tariff barriers to trade between Mexico and the US. The domestic reform in Mexico in the mid-1980s after the peso crisis saw an increase in Mexican export industries. The US has always been Mexico's biggest trading partner. For instance, in 1993, 83.3 percent of Mexico's exports and 71.2 percent of Mexico's imports were with the US.[6]. For the US, from 1991 to 2006, imports from Mexico rose by 393% from about 40 billion in 1993 to 201 billion in 2006. Crude petroleum and natural gas and motor vehicles and passenger car bodies has been the highest importing industries of the US in the past two decades as shown in panel B of Table 2.1.[7] During that period, one of its fastest growing industries was the gypsum products, whereas industries such as cottonseed oil mills and printing trades machinery and equipments saw a decline. However, it is important to note that the growth rate of imports from Mexico declined in the later years, accounting for only 46 percent growth from 2000 to 2006.

2.2.4 Germany

After the Berlin wall fell, the reunification of East and West Germany started a new era of partnership between the US and Germany. In 1992, BMW opened its first factory in the US. During the period of 1991-2006, imports from Germany increased from about 27 billion to 91 billion, a factor of more than 230%.[8] For my period of interest, the highest importing industries were motor vehicle and passenger car bodies followed by motor vehicles part and accessories as shown in panel D of table 2.1. In addition, truck and bus bodies industries saw the highest growth in imports, whereas knit outwear mills saw a decline in imports.

2.2.5 South Korea

Korea has seen a massive growth in its GDP in the past four decades. In the 1960s, its GDP per capita was comparable to other poor countries; however, by 2004, its nominal GDP was over a trillion dollars. The depreciation of the South Korean Won after the Asian

[6]This, however, accounted for less than 10 percent of U.S. imports and exports (Burfisher et al., 2001)
[7]In all these years, household audio and video equipment was the third highest importing industry.
[8]By 2015, US took over France as Germany's biggest trading partner.

financial crisis in 1997 increased the exports from South Korea. It is the sixth largest trading partner of the US, with the imports from the country increasing by more than 160% from about 18 billion in 1992 to 48 billion in 2006. The highest import industry of the US for South Korean good was the semiconductors and related devices in 1992, but was overtaken by motor vehicle and passenger car bodies by 2000.

2.2.6 Japan

Trade relations between Japan and US has not always been a smooth ride. The late 70s and early 80s saw a massive increase in imports of Japanese-made vehicles to the US. The competing pressure and falling sales of the US auto industry motivated the Reagan administration to persuade Japan to agree on voluntary export restraints in 1981. The Plaza Accord agreement in 1985 agreed on depreciating the US dollars to the Japanese Yen and other countries to ease import competition on US industries. Japan responded by establishing manufacturing plants in the US. These issue had been a major area of trade negotiations in the 1990s, with the Clinton administration negotiating the "United States-Japan Framework for a New Economic Partnership". Nonetheless, Japan remains one of the major trading partners of the US. Japanese exports to the US rose by 56% from 96 billion in 1991 to 150 billion in 2006. Compared to the other trading partners of the US, the growth of Japanese imports has been modest.[9] However, Cooper (2010) argues the relative importance of the US to Japan's trade because the Chinese exports to the US uses a significant portion of Japanese exports to China. As with most of the other developed countries, industries with the highest Japanese imports are motor vehicle and passenger car bodies and motor vehicle parts and accessories. It is also interesting to note that textile bags saw the highest growth in exports, whereas prefabricated metal buildings and components saw a decline in their imports.

[9] One of the major reasons for this is the sluggish growth of the Japanese economy for the past two decades

2.3 Import Competition and Crime

For the US, on average, the crime rates have been declining. Levitt (2004) pointed out four possible reasons for the decline in crime rates since the 1990s: 1) Increase in the number of police, 2) rising prison population, 3) receding crack epidemic, and 4) legalization of abortion. However, a lot of variation still exists at the local level.

Among other things, this variation in the local level can be attributed to unemployment rate. Most early studies that studied the relationship between unemployment and crime rates have found a small positive impact of unemployment on property crimes but not violent crimes (Freeman, 1999; Piehl, 1998). Raphael and Winter-Ebmer (2001) look at the variation in state level and find that a 1 percentage point increase in unemployment leads to an increase in property crime rates between 2.8 percent and 5 percent. Likewise, Gould et al. (2002) using a panel of US counties look at the "at risk" group of young, unskilled and low-educated males and find that one percentage point increase in unemployment would lead to a 1-2 percent increase in property crimes.

A number of recent literature focuses on the ancillary effect of trade liberalization and import competition. Carneiro et al. (2015) look at the effects of trade liberalization in Brazil and crime rates at the local labor market. They find that regions that experienced more import shocks also experienced large relative increase in crime rates in the medium term. However, they find that the effects disappeared in the long-term. Likewise, Iyer and Topalova (2014) study the case of trade shocks and crime in India. They find that trade shocks increased relative poverty, which also increased the incidence of violent crimes and property crimes. Furthermore, many studies have built on the study of Autor et al. (2013) by looking at the effect of Chinese import exposure. Feler and Senses (2015) find negative effect on public good provision and business activity and a positive effect on property crimes as a result of increasing Chinese import exposure. Specifically, they find that an increase of $1000 in Chinese import exposure increases property crimes by 3 percent. Similar to the study, Che and Xu (2015) also looks at the effect on property and violent crimes and find a positive impact on both violent and property crimes at the county level. This paper builds on these papers and looks at the effect of import exposure of other top trading partners of the US.

2.4 Identification and Empirical Specification

2.4.1 Commuting Zones

Commuting zone encompasses the idea of local labor markets. As Topel (1986) pointed out, local labor markets should be motivated by the idea that both the employers and workers interact within a space bounded by places of work and places of residence. Thus, the ideal geographical definition of a local labor market should be determined by the strong commuting ties within the local labor market, and weak commuting ties across the local labor market.

Empirical studies look at various geographical delineation to study the local labor markets. For instance, Raphael and Winter-Ebmer (2001) studies the effect of unemployment on crime at the state level. This geographic delineation provides various drawbacks because it is not evident why local labor market dynamics should be bounded by state lines.[10] Furthermore, many states are large enough to be characterized with within-state heterogeneity.

As a result, most studies also look at the Metropolitan Statistical Areas (MSAs) to study local labor markets because it may overlap state and county boundries as it covers a city and their suburbs. Although it has an economic appeal, it only covers major urban population centers and does not cover rural areas. Likewise, looking at counties may provide a greater geographic detail, but it limits the market to be within a single state and maybe too small to define one labor market as many different counties may cluster to form a single labor market.

Thus, for the purpose of my analysis, I use the concept of commuting zones(c-zone) to define local labor markets as they are not limited to any political boundaries and cover both rural and urban areas. They have been defined by Tolbert and Sizer (1996) as clusters of counties that are characterized by strong commuting ties within the c-zone. For the

[10] There are many urban areas overlapping with the state lines (e.g. New York City/Jersey City and Washington D.C/Arlington, Kansas City MO/Kansas city MS), notably because cities developed on both sides of rivers that serve as state boundaries(Dorn, 2009).

mainland US, the 1990 data provides 741 commuting zones, with the average commuting zone consisting of four counties (Dorn, 2009). Further, given that c-zones are based on commuting distance, it provides with the notion that employers and workers should be located within commuting distances to be affected by any changes in the labor market.

For my study, I get a variation in import exposure across c-zones based on the industry specialization and employment across the c-zones. As a result, I hypothesize that c-zones that are specialized in industries with high import competition should see an increasing rates of crime if import competition deteriorates labor market conditions. Likewise, if the import competition improves the labor market conditions, I expect to see declining crime rates.

2.4.2 Measuring Import Exposure

Data on imports to the US are collected at the industry level and are not available at the local labor market level. I employ the method used by Autor et al. (2013) to study exposure to import competition at the c-zone level. The exposure to import competition is defined as the change in import exposure per worker in a commuting zone, where imports are apportioned to a commuting zone based on its share of national industry employment. Mathematically, it can be written as:

$$\Delta Exposure_{ct} = \sum_j \frac{L_{jct}}{L_{ct}} * \frac{\Delta imports_{jt}}{L_{jt}} \tag{2.1}$$

where L_{jct} is the total employment of industry j in c-zone c in year t, L_{ct} is the total employment of the c-zone c at time t, L_{jt} is the national employment of industry j in time t, and $\Delta imports_{jt}$ is the change in national U.S. imports in industry j between time t and $t+5$. The measure weights national changes in national imports per worker between time t and $t+5$ in industry j by the share of a c-zone employment accounted for by industry j. This is then aggregated over all industries, which will yield a c-zone specific measure of change in import competition. The variation across c-zone results from the variation in imports across different industries, and the variation in industry specialization and industry employment structure of the c-zone. A higher value of $\Delta Exposure_{ct}$ indicates a greater exposure per worker to import competition.

2.4.3 Instrumental Variable

One of the concerns in estimating the effect of import exposure on local labor markets is that the rise in imports may be correlated with the industry import demand shocks. This may result in a biased OLS estimate. Therefore, to correctly identify the casual effect and to isolate the supply-side channel, I apply the instrumental variable approach. Here, I follow Autor et al. (2013) by instrumenting the import exposure by looking at the exports of the country of interest to other high income countries over the same time period and lagging employment by five years to mitigate the effect of any anticipated response to contemporaneous employment levels to future Chinese imports and thus reducing simultaneity bias. The instrument can be represented as

$$\Delta IV_{ct} = \sum_j \frac{L_{jct-5}}{L_{jt-5}} * \frac{\Delta imports_{jt}^{others}}{L_{ct-5}} \tag{2.2}$$

where the subscripts represent the same meanings as used to define the change in exposure in equation 3.1. The only two difference with equation 3.1 is that the change in exports now consists of imports of other high-income countries, and the start of period employment is now lagged by five years.

2.4.4 Data and Summary Statistics

For my analysis, I aggregate the county level data at the c-zone level to study the impact on local labor market level. I then link the import exposure measure with the county-level violent and property crimes aggregated at the c-zone level. I use the crosswalk developed by Autor et al. (2013) to match the county-level data with the commuting zones.

My crime data comes from the Uniform Crime Reports (UCR) database issued by the Federal Bureau of Investigation (FBI). These data are collected at the reporting agency level and then aggregated to the county level. The county level data includes crimes divided into various subcategories. I divide the crimes into two categories: i) violent and ii) property. Violent crimes include murder and non-negligent manslaughter, forcible rape, robberies and aggravated assaults. The property crimes include burglary, larceny, motor vehicle theft and arson. The crime data is computed at per 1000 population for standardization. I aggregate the county level data to commuting zone level. However, it is important to note the two major limitations of the data. First, the program administered by the FBI is voluntary, therefore some agencies may not report the crimes. This leads to many missing observations. Second, it only contains data that were either reported or discovered by the agency; hence, I cannot account for crimes that were not reported. Nonetheless, the crime literature uses the data source extensively. For my analysis, I only include the commuting zones that has complete crime data. Therefore, for the time periods in my analysis, 1992-1996, 1997-2001, and 2002-2006, I only include those c-zones if all the counties within that c-zone report crime data (both violent and property) at the start of the period and at the end of the period. My dependent variable is constructed by taking the difference of log of crime at the end of the period and the log of crime at the beginning of the period.

The trade data comes from the UN Comtrade database that provides information on the product at the six-digit Harmonized System (HS 1992). I match these data with the SIC87 industry code by using the crosswalk provided by Autor et al. (2013). To create the import exposure measure, I need data on total employment of industry j at the national level, total employment of the commuting zone, and the total employment for each industry j in a commuting zone. I get data for the above measures from the Census County of Business Pattern (CBP) at the county-level. I then aggregate this at the commuting-zone level.[11]

I also control for various county level demographic measures that may affect the crime rates. Following Levitt (1997), I control for the percentage of population that are college educated, the percentage of people that are below 25 years of age, and the percentage of people that are black. The data for all these variables comes from the census. For education, I only have data on decennial census; therefore, I interpolate to get the data for in-between

[11]CBP provides the information for each year starting from 1986. However, for the years in my sample, they define industries initially at the SIC87 level, and later at different NAICS level based on the year. Thus, following Autor et al. (2013), I convert all industry into SIC87 code. For instance, the CBP data from 1992-1997 uses SIC 87 industry classification, NAICS97 industry code is used for years 1998-2002, and NAICS02 code is used for data 2003-2007. Therefore, I initially convert all NAICS02 code to NAICS97 using concordance table provided by the Census Bureau. I then use the concordance file provided by Dorn that creates weight for NAICS97 codes to be split into two or more SIC87 groups and use the same weights to calculate the employment at the SIC87 industry level. Therefore, my data will have consistent SIC87 level for all industries in different years

years.

Table 2.2 provides the summary statistics which illustrates considerable variation in import exposure and percentage change in property and violent crimes across commuting zones. Both property and violent crime has been decreasing during my sample period. Property crime have fallen by about 8 percent whereas violent crime has decreased by 4.3 percent. The average c-zone experienced a $1047, $599 and $570 per worker import exposure from Canada, Mexico and China respectively. Likewise average c-zone exposure from both Germany and Japan were over $100 per worker, with the 75th percentile of c-zones exposure being over $200 per worker.

I also report my subsamples with top 20 percent and bottom 20 percent c-zone exposure with respect to Chinese and Canadian import exposure separately as seen in Table 2.3 and 2.4.[12] The top 20 percentile commuting zone exposures to Chinese imports had a mean exposure of $2834, whereas the the top 20 percentile c-zones for Canadian import exposure had an average exposure of $5786. However, it is interesting to note that both property crimes and violent crimes was increasing for the top 20 percentile c-zones with exposures to Chinese imports, but the crimes were decreasing for the top 20 percentile c-zones with exposure to Canadian imports. Likewise, the bottom 20 percentile c-zone of Chinese import exposure had a higher exposure to import competition than the bottom 20 percentile c-zones with exposure to Chinese import competition. Furthermore, property crimes have been decreasing for the c-zones, while there is a slight increase in violent crimes for both set of bottom 20 percentile c-zones. Also, comparing the bottom and top exposure c-zones for Chinese imports, we see that the property crimes has been increasing for c-zones with more exposure, whereas property crimes have been decreasing for c-zones with low exposure.

2.4.5 First-Difference specification

For my analysis I use the first-difference approach, which elinimates any unobserved time-invariant hetereogeneity among the c-zones. I then stack the first differences of the three time periods (1992-1996, 1997-2001, and 2002-2006), and include separate time dummies for

[12]The choice of these countries were based on the mean exposure of import competition.

each period. The stacked first difference model is similar to fixed-effect models with slightly less restrictive assumption made on the error term.[13] Furthermore, this method also removes any time invariant heterogeneity between import competition and crime; thus, ruling out any time-invariant factors that affect crime rates within a given c-zone. The inclusion of time dummy captures factors that have a time-varying effect on crime common to all c-zones.

My primary regression specification takes the following form:

$$\Delta crime_{ct} = \beta_0 + \beta_1 \Delta Exposure_{ct} + \beta_2 M_{ct} + \beta_3 X_{ct} + \delta_{reg} + \gamma_t + \epsilon_{ct} \tag{2.3}$$

where $\Delta crime_{ct}$ is the difference of crime rate for c-zone c between beginning of period and end of period. $\Delta Exposure_{ct}$ is the key explanatory variable of interest and represents the change in exposure per-worker of c-zone c to import competition, M_{ct} is the start of the period c-zone employment that was accounted for by manufacturing, γ_t indicates time-dummies for each period, and δ_{reg} controls for census region fixed effects. The vector X_{ct} controls for the c-zone's start of the period demographic variables. These include the percentage of population that is college educated, the share of population between 18-25 years, and the share of population that is black.

During my period of analysis, a host of studies has talked about the changes in the broader economy, specifically the declining manufacturing employment as a result of technological changes (Acemoglu and Autor, 2011; Dorn et al., 2015). Thus, all of these controls allow the changes in outcomes to be a function of initial conditions, time trends to vary by geographic regions, and the aggregate time period to vary by five years. I cluster my standard errors at the state level.

2.5 Result

In this section, I discuss my findings on the impact of import exposure from the top six trading partner for the US on crime at the c-zone level. In discussing the magnitude of the findings, I evaluate coefficient estimates for a $1000 increase in import exposure per worker

[13]Please see footnote 26 of Autor et al. (2013)

at the c-zone. I will first present the OLS results, then look at the IV results for the case of China. I will then highlight the potential mechanism through which import exposure affects crime.

2.5.1 OLS Result

I present my OLS findings in table 2.5 and 2.6. For both the tables, the dependent variables is the change in log of property crime rates in columns 1 and 2, and the change in the log violent crime rates in columns 2 and 3 between 1992-1996, 1997-2001, and 2002-2006. Columns 1 and 3 controls for share of manufacturing employment in the c-zone, time fixed effects and census region fixed effects. I introduce additional demographic controls in column 2 and 4 that may potentially impact crime such as the share of population under 25, share of population that is black and the share of population that has a college degree. All the standard errors are clustered at the state level.

Panel A of Table 2.5 shows the results for China. The first column, with baseline controls, show that a $1000 increase in import exposure per worker increased the c-zone property crime rate by about 2.06 percent. Introducing demographic controls in column 2, I find that it slightly decreases my point estimates, but the results are still significant at the 5 percent level. For Canada and Mexico the results are presented in Panel B and C in Table 2.5. For Mexico, the results show that an increase in Mexican import exposure increases the property crimes by 0.2 percent with the baseline controls. The estimate decreases to 0.08 percent for property crimes when I introduce additional demographic controls in the model. However, the estimates are not statistically significant. The effect for Canada for property crimes decreases by 0.3 percent, but I can not reject the null hypothesis of no effect.

The estimation for Germany, Japan and Korea show the opposite effect for property crimes compared to China. Panel A of Table 2.6 shows the results for Germany in Panel A. I find that a $1000 increase in exposure from Germany reduces the c-zone property crimes by 4.8 percent with my baseline controls. The inclusion of demographic controls reduces the point estimate to 4.5 percent, but the result is still significant at the 5 percent level. In addition, the results for Japan, as presented in Panel B, shows that a $1000 increase in

Japanese import exposure decreases property crimes by 2.8 percent with baseline controls, which decreases slightly to 2.7 percent with the inclusion of demographic controls. The estimation for Korea is reported in Panel C, and it is comparable to that of Germany. Increase in import exposure from Korea reduces the property crimes by 4.5 percent in column 1. In column 2, when I introduce additional demographic controls, the point estimate decreases slightly to 4.0 percent, but it is still statistically significant at the 5 percent level.

Columns 3 and 4 of Table 2.5 and 2.6 shows the point estimates for violent crimes. The magnitude of the effect are small for China, Canada and Mexico as compared to their effect on property crimes. Further, violent crimes are negatively correlated with the import exposure of China and Canada, and positively correlated with those of Mexico. However, none of the estimates are statistically significant. In comparision, the magnitude of the effect for Germany, Japan and Korea are considerably larger than those for Chiana, Canada and Mexico. The results are presented in Panel A, B and C of Table 2.6. Similar to the effect on property crimes, I find a negative effect on violent crimes as a result of exposure from the three countries. The magnitude is slightly higher for Germany and Korea compared to that for Japan. For instance, a $1000 increase in Germany import exposure, reduces violent crimes by 6 percent compared to 4.2 percent for Korea and 1.5 percent for Japan. However, none of the estimates are significant even at the 10 percent level.

The results are interesting as I only find effect on property crimes but not violent crimes. This give further plausibility to my hypothesis that people resort to criminal behavior as a result of financial pressures of lower cumulative earnings and job loss as the potential financial benefit of property crimes are higher than those for violent crimes.

2.5.2 Instrumental Variable and 2SLS Results

One of the concerns when working with the import exposure from China is that there maybe a reverse causality problem. For instance, c-zones with deteriorating economic potential and higher inclination for crime growth may be the ones that experience more exposure from Chinese import competition. Therefore, to mitigate the problem of demand shocks on Chinese imports, I need to emphasize the growth in imports from China to the US was supply-driven and not US demand-driven. To resolve this issue, I employ the plausible exogenous variation developed by Autor et al. (2013). I look at the change in other high income countries imports of Chinese goods as an instrument for US changes in imports per worker as shows in equation 3.2. It has also been lagged with five year employment levels to mitigate the possibility that employment would adjust to an anticipated increase in Chinese imports.

The findings are presented in the table 2.7. In column 1, I show the second stage estimated results, controlling for my baseline controls. I find a positive effect of a 3 percent increase in property crimes. I also present my first stage F-statistics and the partial R-square, which confirms the validity of the model. In column 2, I include additional demographic controls. My results are similar to column 1, with only a slight increase in point estimate. Likewise, the result from the first stage estimate of the F-stat and the partial R-square confirms the validity of the model. Hence, even when I employ an instrumental variable approach, I do find that property crimes increased by about 3 percent as a result of $1000 increase in exposure from Chinese imports.

2.6 Potential Channel

One of the potential channels through which the trade induced shocks can increase the property crime rates is through financial pressures on worker through lower cumulative earnings. Recently, a number of studies have pointed out the negative effects on employment and earnings of Chinese import competition.[14] Thus, it is a possibility that I find a positive effect on property crimes as a result of Chinese import exposure because of either i) the resulting loss of jobs , which results in higher unemployment or ii) a reduction in wages, which lowers the workers lifetime cumulative earnings. Both these possibilities would induce a person to commit property crimes as it then increases their relative benefit of it.

I test the first channel in this paper: the increase in crime is because the exposure of import competition increases unemployment at the c-zone level.[15] I provide the regression

[14] Please see Autor et al. (2013), Acemoglu and Autor (2011)

[15] The data available to look at the effect on wages at a commuting zone is not reliable (Autor et al., 2013), therefore it will be a subject of further study

results using the following estimation equation:

$$\Delta crime_{ct} = \beta_0 + \beta_1 \Delta URate_{ct} + \beta_2 X_{ct} + \delta_{reg} + \gamma_t + \epsilon_{ct} \tag{2.4}$$

where $\Delta crime_{ct}$ is the difference in the log of property crime rate for c-zone c between beginning of period and end of period. $\Delta URate_{ct}$ is the average change in unemployment rate in the c-zone γ_t indicates time-dummies for each period, and δ_{reg} controls for census region fixed effects. The vector X_{ct} controls for the c-zone's start of the period demographic variables. These include the percentage of population that is college educated, the share of population between 18-25 years, and the share of population that is black.

The findings are reported in table 2.8. In the first column, I do find a positive effect on property crimes as a result of increasing unemployment, however these are not statistically significant. In column 2, I include controls for various demographic variables and find that unemployment rate has a statistically significant positive effect on property crimes. This leads credibility to my mechanism.

Therefore, I need to look at the effect of import exposure from the country of interest on the unemployment rate. I do that by estimating the following equation:

$$\Delta URate_{ct} = \beta_0 + \beta_1 \Delta Exposure_{ct} + \beta_2 X_{ct} + \delta_{reg} + \gamma_t + \epsilon_{ct} \tag{2.5}$$

where $\Delta URate_{ct}$ is the change in unemployment rate in the commuting zone, $\Delta Exposure_{ct}$ is the commuting zone exposure to import competition as specified in equation 3.1, and all other controls are the same as specified in equation 2.4.

The estimation is provided in table 2.9 and table 2.10. Here I summarize the results in terms of Chinese exposure and 'other' countries exposure given that Chinese exposure had a positive impact on crime and 'other' countries had a negative impact on crime.[16].

China Panel A of table 2.9 shows the result for China. Including only the baseline controls in column 1, I find a positive effect on unemployment as a result of increasing Chinese exposure, but these are not statistically significant. In column 2, I include further demographic controls. This increases my point estimate and the results are statistically

[16]Ohter countries here include Canada, Mexico, Germany, Japan and Korea

significant. Hence, I can conclude that increasing Chinese exposure resulted in increasing property crimes through the unemployment channel.

Other Countries Panel B of table 2.5 shows my results for Canada. Including only the baseline controls in column 1, I find a statistically significant negative impact on employment as a result of Canadian import exposure; however the statistical significance no longer exists when I include demographic controls in column 2. For the case of Mexico, I do not find any significant impact on unemployment. Estimates for Germany, Japan and Korea is presented in panels A, B and C, respestively, in table 2.10. For all the three countries, I do not find any significant results for unemployment. Therefore, there is a possibility that the decrease in property crime rates as a result of increasing import exposure of these countries may work through the wage effect. That is, increasing import exposure of these countries may result in higher wages of workers, thus reducing their tendency to engage in criminal behavior.

2.7 Robustness Checks

I conduct two robustness checks. First, I cluster the standard errors at the c-zone level rather than the state level. Second, I introduce state level fixed effect with standard errors clustered at the c-zone level instead of a region fixed effect with standard errors clustered at the state level as in my initial estimation.

Table 2.11 provides the first robustness check results for the four countries for which I find statistical significant results in my analysis. The robustness check shows that the point estimates are similar to my initial analysis with all the variables still significant. The second robustness check are provided in table 2.12. The point estimates for China decreases by about 0.1 percent, but they are still significant at the 5 percent level. For Germany, the point estimates when I control for only the baseline specification increases by about 0.5 percent. Adding additional controls, the point estimates increases slightly and are now significant at the 10 percent level rather than at the 5 percent level as in my original estimation. For Japan, the point estimates increases by 0.5 percent compared to my orginal estimation and are still significant at the 1 percent level. The estimates decreases for Korea. Compared to my original estimation, my point estimates decreases from a negative impact of about 4 percent to a negative impact of about 3 percent. This is significant at the 10 percent level.

2.8 Conclusion

A wave of recent empirical studies have looked at the ancillary effects of import exposure from China, including crime. To the best of my knowledge this is the first empirical study that looks at effect of increasing import exposure on crime from the top trading partners of US and compares that with the effect from Chinese exposure. I provide evidence that, in contrast to Chinese import exposure that has a positive effect on property crimes, the increasing import exposure from Germany, Japan and Korea has a negative effect on the change in property crimes. Furthermore, there is no evidence linking the effect of import exposure to changes in violent crimes from any of the countries studied here. I find no significant effect from Canada and Mexico, albeit the mean exposure at the c-zone level is higher from Canadian imports than Chinese imports.

The study also presents a possible channel through which this effect works. I show that the increasing in Chinese exposure leads to increasing unemployment, thus raising the financial pressure on workers. This induces workers to engage in property crimes. In contrast, the negative impact on crime from Germany, Japan and Korea may be because of a potential impact on wages of workers, which needs to be studied further. This paper provides an interesting insight: increasing exposure from developing countries (such as China) has the opposite effect than increasing exposure from developed countries (Germany, Japan and Korea). A possible reason may be because of the types of imports that comes from these countries. Table 2.1 provides further information on the highest and lowest import industries from all the countries. As it can be noted, the imports of from China are mainly concentrated in labor-intensive production industries. As a result, firms may respond to this increasing import competition by offshoring these production to China, thus either putting a downward pressure on wages of low-skilled workers or by laying off workers. This would raise the financial pressures on workers, which induces people to engage in property crimes for financial gain. On the other hand, most of the imports from developed countries are concentrated in motor vehicle parts and accessories. Further analysis needs to be done in order to look at the potential effect of such imports.

Given these effects of a trade shock may work through the channels of financial pressures, there are various policy implications. Given that financial stress and pressure may be a potential channel, it would be interesting to look at the effect of unemployment insurance on trade-induced increase in crime rates. Likewise, policies to help increase the human capital accumulation for low-skill, low-wage workers may reduces these effects of import competition.

Figure 2.1: US Import Share of GDP

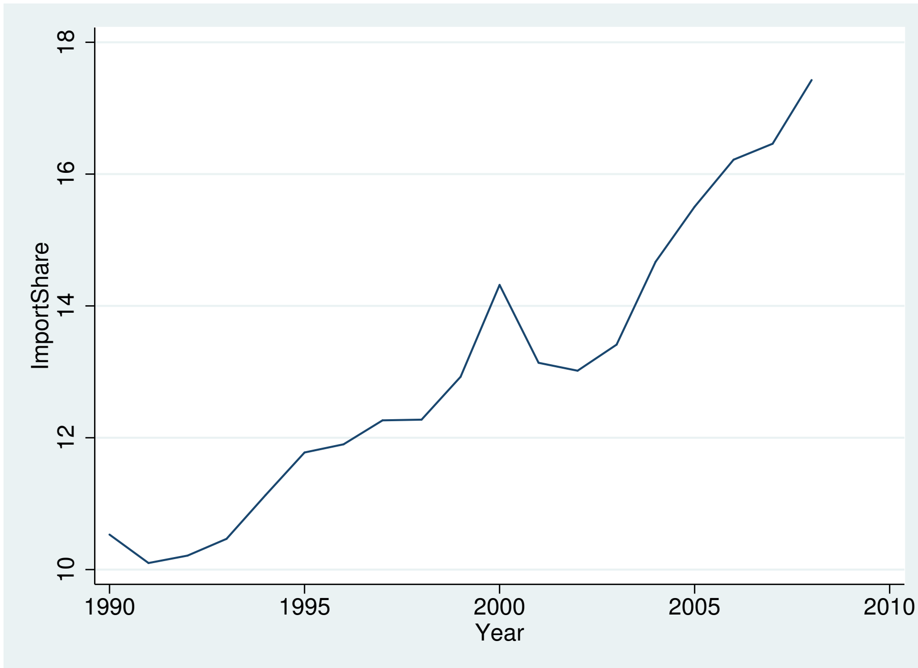

Figure 2.2: US Imports from its trading partners

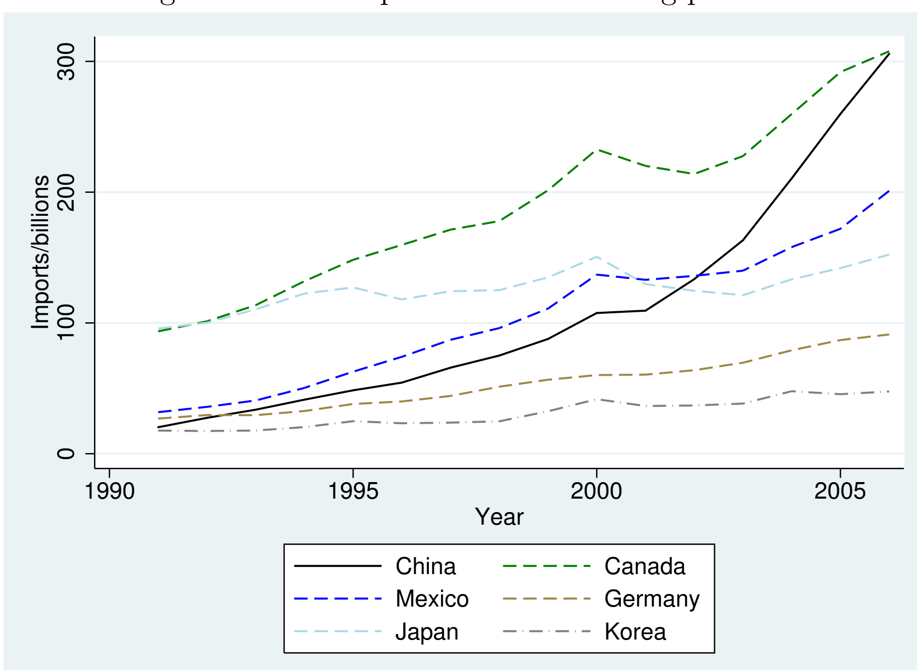

Table 2.1: Ranking imports by country

	High Import Industries	**Low Import Industries**
A:CHN		
1992:	Vitreous China Table,Leather and Sheep-Lined Clothing	Plumbing and Heating, Manifold Business Forms
2000:	Leather and Sheep-lined Clothing, Women's Footwear, Games and Toys	Industrial Gases, Asphalt Felts
2006:	Electronic Computers, Computer Storage Devices	Primary Smelting Copper, Metal Ores
B:MEX		
1992:	Crude Petroleum and Natural Gas, Motor Vehicle and Passenger Car Bodies	Natural Processsed, and Imitation Cheese, Kaolin and Ball Clay
2000:	Motor Vehicle and Passenger Car Bodies, Crude Petroleum and Natural Gas	Tanks and components, Mobile Homes
2006:	Crude Petroleum and Natural Gas, Motor Vehicle and Passenger Car Bodies	Newspaper Printing, Products of coal
C:CAN		
1992:	Crude Petroleum and Natural Gas, Motor Vehicle and Passenger Car Bodies	Lab. Apparatus, Kaolin and Ball Clay
2000:	Motor Vehicle and Passenger Car Bodies, Crude Petroleum and Natural Gas	Phosphate Rock, Lab. Apparatus
2006:	Crude Petroleum and Natural Gas, Motor Vehicle and Passenger Car Bodies	Ordance Accessories, Lace and Warp Knit Fabric Mills
D:GER		
1992:	Motor vehicle and passenger car bodies, motor vehicle parts and accessories	Wood Preserving, Electrical Work
2000:	Motor vehicle and passenger car bodies, motor vehicle parts and accessories	Logging, Drapery Hardware
2006:	Motor vehicle and passenger car bodies, motor vehicle parts and accessories	Uranium ores, Logging
E:JPN		
1992:	Motor vehicle and passenger car bodies, motor vehicle parts and accessories	Wood Preserving, Logging
2000:	Motor vehicle and passenger car bodies, motor vehicle parts and accessories	Mobile Homes, Logging
2006:	Motor vehicle and passenger car bodies, motor vehicle parts and accessories	Logging, Cigarettes
F:KOR		
1992:	Semiconductors and Related Devices, Household A&V Equipment	Lab. Apparatus, Imitation Cheese
2000:	Motor vehicle and passenger car bodies, Radio and TV Broadcasting equipment	Logging, Lab. Apparatus
2006:	Motor vehicle and passenger car bodies, Petroleum Refining	Logging, Cigarettes

Table 2.2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P75
LnChangeProperty	1319	-0.079	0.240	-1.795	1.654	-.189	.037
LnChangeViolent	1319	-0.043	0.404	-1.624	3.496	-.232	.123
CHN Imp Exp	1319	0.57	.857	-0.103	12.937	.104	.709
CAN Imp Exp	1319	1.047	2.074	-2.216	31.136	.263	1.029
GER Imp Exp	1319	0.162	.22	-0.374	3.767	.038	.201
JPN Imp Exp	1319	0.140	.421	-8.356	4.950	.008	.211
KOR Imp Exp	1319	0.083	.218	-1.199	3.008	.001	.106
MEX Imp Exp	1319	0.599	1.137	-1.529	17.112	.140	.638

Note: All import exposure are in $ 1000 per worker in the c-zone as defined in equation 3.1

Table 2.3: Top 20% of county exposure: China and Canada

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: China					
LnChangeViolent	94	.01	.315	-.97	1.01
LnChangeProperty	94	.026	.169	-.335	.576
CHN Imp Exp	94	2.834	1.541	1.79	12.937
Pct Black	94	10.729	14.177	.131	65.571
Pct College	94	14.506	4.541	9.1	29.5
Pct Below 25	94	33.78	2.859	25.659	45.976
Panel B: Canada					
LnChangeViolent	94	-.024	.354	-.82	1.344
LnChangeProperty	94	-.086	.223	-1.08	.683
CAN Imp Exp	94	5.786	5.16	1.799	31.136
Pct Black	94	7.368	11.517	.112	65.571
Pct College	94	14.954	4.145	7.4	36.367
Pct Below 25	94	34.384	3.584	27.712	45.179

Notes: The table shows the top 20 percent commuting zone with exposure to China and Canada (Panel A and Panel B respectively) for the period 2002-2006. The demographic characteristics are at the initial period level.

Table 2.4: Bottom 20% of county exposure: China and Canada

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: China					
LnChangeViolent	95	.064	.581	-1.624	3.496
LnChangeProperty	95	-.116	.253	-1.725	.519
CHN Imp Exp	95	.244	.121	.006	.432
Pct Black	95	3.93	6.553	0	31.12
Pct College	95	18.703	7.517	7.4	44.1
Pct Below 25	95	34.349	5.613	23.284	54.312
Panel B: Canada					
LnChangeViolent	94	.025	.493	-1.316	3.496
LnChangeProperty	94	-.093	.27	-1.725	.874
CAN Imp Exp	94	.151	.097	-.338	.28
Pct Black	94	7.795	10.753	0	60.746
Pct College	94	19.473	6.948	10.4	42.5
Pct Below 25	94	33.374	4.896	23.284	54.312

Notes: The table shows the bottom 20 percent commuting zone with exposure to China and Canada (Panel A and Panel B respectively) for the period 2002-2006. The demographic characteristics are at the initial period level.

Table 2.5: OLS Estimates of Import Exposure to Crime

	Δ ln(PropertyCrime)		Δ ln(ViolentCrime)	
	(1)	(2)	(3)	(4)
VARIABLES				
Panel A: China				
CHN Imp Exp	0.0206**	0.0203**	-0.00411	-0.00330
	(0.00780)	(0.00772)	(0.0203)	(0.0211)
Observations	1,319	1,319	1,319	1,319
R-squared	0.121	0.129	0.017	0.031
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Panel B: Canada				
CAN Imp Exp	-0.00189	-0.00342	-0.000352	-0.00338
	(0.00272)	(0.00262)	(0.00472)	(0.00494)
Observations	1,319	1,319	1,319	1,319
R-squared	0.118	0.127	0.017	0.032
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Panel C: Mexico				
MEX Imp Exp	0.00221	0.000888	0.00707	0.00487
	(0.00707)	(0.00692)	(0.0131)	(0.0140)
Observations	1,319	1,319	1,319	1,319
R-squared	0.118	0.126	0.017	0.032
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include year fixed effects, region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree. All standard errors are clustered at the state level.

Table 2.6: OLS Estimates of Import Exposure to Crime

	Δ ln(PropertyCrime)		Δ ln(ViolentCrime)	
	(1)	(2)	(3)	(4)
VARIABLES				
Panel A: Germany				
GER Imp Exp	-0.0484**	-0.0456**	-0.0634	-0.0608
	(0.0221)	(0.0224)	(0.0879)	(0.0903)
Observations	1,319	1,319	1,319	1,319
R-squared	0.119	0.128	0.018	0.032
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Panel B: Japan				
JPN Imp Exp	-0.0284***	-0.0276***	-0.0156	-0.0134
	(0.00875)	(0.00821)	(0.0303)	(0.0316)
Observations	1,319	1,319	1,319	1,319
R-squared	0.120	0.129	0.017	0.032
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Panel C: Korea				
KOR Imp Exp	-0.0458**	-0.0407**	-0.0505	-0.0426
	(0.0205)	(0.0195)	(0.0578)	(0.0591)
Observations	1,319	1,319	1,319	1,319
R-squared	0.119	0.128	0.018	0.032
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include year fixed effects, region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree. All standard errors are clustered at the state level.

Table 2.7: 2SLS Estimate of Chinese exposure on crime

	(1)	(2)
VARIABLES	LnChangeProperty	LnChangeProperty
CHN Imp Exp	0.0336**	0.0337**
	(0.0133)	(0.0132)
Observations	1,319	1,319
R-squared	0.119	0.128
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Partial R-square	0.563	0.561
F-stat	69.5	70.05

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include year fixed effects, region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree. All standard errors are clustered at the state level.

Table 2.8: OLS Estimates of Unemployment on Property Crime

	(1)	(2)
VARIABLES	LnChangeProperty	LnChangeProperty
URate Change	0.00650	0.00866*
	(0.00464)	(0.00445)
Population Below 25		0.000766
		(0.00231)
Percent College Edu		-0.00768***
		(0.00168)
Percent Black		0.000916
		(0.000752)
Observations	1,319	1,319
R-squared	0.091	0.115
Year FE	Yes	Yes
Region FE	Yes	Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. All standard errors are clustered at the state level.

Table 2.9: OLS Estimates of Exposure on Unemployment

	(1)	(2)
VARIABLES	URate Change	URate Change
Panel A: China		
CHN Imp Exp	0.0839	0.104*
	(0.0581)	(0.0592)
Observations	1,319	1,319
R-squared	0.107	0.121
Demographic Control		Yes
Panel B: Canada		
CAN Imp Exp	-0.0370*	-0.0215
	(0.0203)	(0.0211)
Observations	1,319	1,319
R-squared	0.108	0.120
Demographic Control		Yes
Panel C: Mexico		
MEX Imp Exp	-0.0240	-0.00253
	(0.0387)	(0.0374)
Observations	1,319	1,319
R-squared	0.106	0.119
Demographic Control		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. All models include year fixed effects, region fixed effects. All standard errors are clustered at the state level.

Table 2.10: OLS Estimates of Exposure on Unemployment

VARIABLES	(1) URate Change	(2) URate Change
Panel A: Germany		
GER Imp Exp	0.160	0.218
	(0.211)	(0.207)
Observations	1,319	1,319
R-squared	0.106	0.120
Demographic Control		Yes
Panel B: Japan		
JPN Imp Exp	0.0726	0.0828
	(0.0723)	(0.0724)
Observations	1,319	1,319
R-squared	0.106	0.120
Demographic Control		Yes
Panel C: Korea		
KOR Imp Exp	0.304	0.317
	(0.233)	(0.228)
Observations	1,319	1,319
R-squared	0.107	0.121
Demographic Control		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. All models include year fixed effects, region fixed effects. All standard errors are clustered at the state level.

Table 2.11: Robustness Checks for Import Exposure to Crime

	(1)	(2)
VARIABLES	LnChangeProperty	LnChangeProperty
Panel A: China		
CHN Imp Exp	0.0206***	0.0203**
	(0.00768)	(0.00772)
Observations	1,319	1,319
R-squared	0.121	0.129
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Panel B: Germany		
GER Imp Exp	-0.0484*	-0.0456**
	(0.0256)	(0.0224)
Observations	1,319	1,319
R-squared	0.119	0.128
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Panel C: Japan		
JPN Imp Exp	-0.0284***	-0.0276***
	(0.00802)	(0.00821)
Observations	1,319	1,319
R-squared	0.120	0.129
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Panel D: Korea		
KOR Imp Exp	-0.0458**	-0.0407**
	(0.0212)	(0.0195)
Observations	1,319	1,319
R-squared	0.119	0.128
Baseline Controls	Yes	Yes
Demographic Controls		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include year fixed effects, region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree. All standard errors are clustered at the cz level.

Table 2.12: Robustness Checks for Import Exposure to Crime

VARIABLES	(1) LnChangeProperty	(2) LnChangeProperty
Panel A: China		
CHN Imp Exp	0.0192***	0.0198***
	(0.00718)	(0.00733)
Observations	1,319	1,319
R-squared	0.164	0.168
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Panel B: Germany		
GER Imp Exp	-0.0513*	-0.0464*
	(0.0283)	(0.0256)
Observations	1,319	1,319
R-squared	0.163	0.166
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Panel C: Japan		
JPN Imp Exp	-0.0336***	-0.0326***
	(0.00809)	(0.00777)
Observations	1,319	1,319
R-squared	0.164	0.168
Baseline Controls	Yes	Yes
Demographic Controls		Yes
Panel D: Korea		
KOR Imp Exp	-0.0333	-0.0285*
	(0.0213)	(0.0161)
Observations	1,319	1,319
R-squared	0.162	0.165
Baseline Controls	Yes	Yes
Demographic Controls		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include year fixed effects, state fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree. All standard errors are clustered at the cz level.

Chapter 3

Import Competition and Alcohol Consumption at Local Labor Markets

3.1 Introduction

The increased nature of globalized trade has changed the the trade patterns of the US, with both exports and imports comprising a much larger share in the US GDP. The import share of US GDP has increased from 10 percent in 1992 to 18 percent in 2007. The rise of China as the global manufacturing factory has significantly increased the volume of global trade. The reforms carried out in China since the late 1970s has propelled China's economic growth, and by 2007 its manufacturing exports accounted for more than 10 percent of the world market share.[1] 89 percent of the growth of imports to the US from low-income countries can be accounted for by the growth of Chinese imports. Although trade is a positive sum game, the spectacular rise of China allows us the opportunity to analyze the distributional costs of trade to better understand the effects of a trade shock, and discuss the relevant policies to make the adjustments smooth.

Two waves of economic literature are relevant to my study. First, the labor market adjustment costs in terms of employment, wages and labor force participation from a trade shock; second, the effect on health because of worsening labor market conditions. Recent literature takes the exogenous growth of Chinese exports and find that it reduces wages and employment; thus, lowering the cumulative lifetime earnings and labor force participation

[1] In 1991, China's exports only accounted for about 2 percent of the world market share.

among affected workers.[2] These labor market outcomes of higher unemployment and lower cumulative earnings also affects, among other things, the mental and physical well being of workers. Studies have shown that worsening labor market outcomes and fear of job loss are linked with greater stress and anxiety, increasing heart diseases and stroke, and a higher mortality rate.[3]

The intersection of the two literature, shows many channels through which workers health are affected by trade shocks. Studies by McManus and Schaur (2016) show that the increasing import exposure from China in the US leads to an increase in workplace injuries and illness, as firms try to cut costs by reducing spending on worker safety and increase the workload of workers. Likewise, Hummels et al. (2015) also find that export shocks lead to higher workloads which increases workplace injuries and hospitalizations. My paper contributes to this literature by looking at additional health effects of trade shocks. More specifically, I hypothesize that the worsening labor market outcomes and fear of jobs losses will increase workers tendency to engage in stress coping mechanisms such as alcohol consumption.

My empirical results indicate that higher import exposure from China has a statistically significant positive correlation with both prevalence of drinking and binge drinking. The effect on men are more pronounced than that for women. In addition, binge drinking in men has a larger effect than the prevalence of drinking. However, for women, prevalence of drinking has a larger effect than binge drinking. This study complements the literature that have found increasing workplace injuries, illness and higher mortality rates because of increasing Chinese import exposure.

The paper is structured as follows. Section 2 presents the overview of the rise of China and the changes in imports for the US. Section 3 discusses the previous literature. Section 4 describes the identification strategy and Section 5 describes the data. Section 6 presents the empirical results and Section 7 offers my conclusion.

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[2]Please see Autor et al. (2013), Pierce and Schott (2016a) and Acemoglu et al. (2016) for the adjustment costs from increasing Chinese import competition.

[3]Please see Sullivan and Von Wachter (2009), Cheng and Chan (2008), McKee-Ryan et al. (2005) for the health effects of worsening labor market conditions.

3.2 The Rise of China

Post World War II, China followed a centrally-planned system until the death of its leader Mao Zedong in 1978. The next leader, Deng Xiaoping, initiated a series of reforms, moving China towards a more market-based system. Many of these reforms set China on the pace for faster growth. There are mainly two explanations for the economic growth of China after the reforms. The first emphasizes the role of foreign investments in the Special Economic Zones (SEZ) to spur growth. The other focuses on the internal reforms in rural and interior regions of agricultural pricing system, land contracting and the entry of rural businesses known an township and village enterprises. Huang (2012) argues that the internal reform played a much larger role than the foreign investments in manufacturing. He finds that even at its peak, foreign funded firms only employed 18 million people; in contrast, even in its trough, the employment in township and village enterprises employed 28 million people. The financial liberalization of these township and village enterprises brought more than 154 million people out of poverty.[4]

Nonethess, these reforms increased the enterprises that were foreign-funded and unleashed the productivity that was latent during the Mao era. According to World Bank, the share of inflows of foreign direct investment to China increased from an average of 0.7% of GDP in the 1980's to about 4.2% of its GDP in 2000's. The Penn World Table ranked China 126th out of 167 countries it monitors in terms of GDP per capita in 1991. By 2001 it had risen to 101st.[5] One key feature of China's economic turnaround is the growth in its exports - especially manufacturing exports. China's share of world manufacturing exports increased from about 2.3% in 1991 to about 15% in 2007. China turned into a global manufacturing factory as its revealed comparative advantage (RCA) turned from a disadvantage to advantage in 1992 (Autor et al., 2016b).[6] One of the major reasons for its strength in manufacturing is its abundant supply of labor relative to the rest of the world, which allows it specialize in more labor-intensive industries. Thus, China has a positive net exports

[4]Please see Huang (2012) for a more detailed discussion on the relative influence of foreign funded firms and township and village enterprises in the growth of Chinese economy.

[5]The data is based on constant 2005 dollars from Penn World Tables 8.0 database.

[6]Revealed comparative advantage is described as a country's share of global exports in an industry divided by its share of aggregate global exports.

in manufacturing, and the growth in Chinese exports have been pervasive in all countries. Husted and Nishioka (2013) use the Constant Market Share (CMS) analysis to show that the growth in Chinese exports have not decreased the export shares of developing countries, but have come at the expense of exporters based in developed countries such as Japan and the US.

Figure 3.1 shows the US imports from China for the period 1991-2008. Imports from China has increased from 26 billion in 1992 to over 350 billion in 2008, a growth of more than 1200%. Chinese exports received a boost after it joined the World Trade Organization (WTO) in 2001. As shown in the figure, the growth of import from China increases sharply after it joins the WTO. The road to WTO mattered for China because in moving towards compliance with WTO provisions, it idled many state-owned manufacturing enterprises, which allowed capital and labor to reallocate from less productive, small state-owned companies to privately owned manufacturing companies, raising productivity and output (Hsieh and Song, 2015). However, it is important to note that the increase in imports across industries is not uniform – some industries imports has increased substantially more compared to other industries. Looking at the changes in import penetration of industries, women footwear industries penetration has increased by almost a 100 percent from 1991 to 2007, while the import penetration of industries such as automotive and coated fabrics reveal almost a zero penetration.[7]. Likewise, imports in the games, toys and dolls manufacturing industry was \$3.2 billion in 1991, which rose to \$11.8 billion in 2000 and to \$20.2 billion in 2007. This variation in import penetration of Chinese goods coupled with the variation in industry specialization within different regions of the US gives us the opportunity to study the effects of these trade shocks at a more local, regional level.

3.3 Literature Review

Recent literature has shown that the increasing import competition from China worsens the labor market outcomes for a large number of workers. Pierce and Schott (2016a) look

[7]Import penetration at an industry level is defined as the change in imports of the industry from 1991 to 2007 divided by the 1991 total domestic supply. (Domestic supply equals total production plus imports minus exports)

at the elimination of potential tariff increases in 2000 after China joined the WTO at manufacturing employment in the US and find a sharp drop in employment. At the plant level, they respond to the import competition by switching to more less labor-intensive production process, which contributes to the decline in employment. Likewise, Autor et al. (2013) show that the increasing exposure from China also leads to fall in employment and reduction in wages. In addition, the labor force participation also decreases.

The response of firms have many health consequences for the workers. Firms respond to increasing import competition by cutting down their cost, including those related to worker safety. This may increase work-related injuries and sickness. McManus and Schaur (2016) show that worker injuries and illness increased in industries competing with Chinese imports over the short and medium run, especially in smaller establishments. Their calculation show that injury risk increases by 13%. Likewise, firms can also reduce costs by increasing the workload of the workers who do not lose their job. A higher workload also has many potential health effects on workers. Hummels et al. (2015) look at the effects of export shocks for Danish firms. They find that exogenous demand shocks increases worker injures and illness. Further, the increasing workload of workers lead them to take fewer sick-days, but it also increased hospitalizations of workers due to heart attacks and strokes by 15%.

The increasing threat of job insecurity, lower labor force participation can result in a higher mental and physical stress level due to additional financial pressures on workers. In the meta-analytic study by McKee-Ryan et al. (2005), they show that unemployed people had lower psychological and physical-well being than people who were employed. Likewise Paul and Moser (2009) find that, on average, 34% of unemployed exhibited psychological problems compared to only 16% of employed people. It is important to note that the health effects are not only limited to job loss, but also job insecurity. Cheng and Chan (2008) present findings that show employees with longer tenure had a negative effect on health outcomes compared to shorter tenure workers. This finding was consistent across gender. In addition, job insecurity of a worker may have spillover effects on their family members. Wilson et al. (1993) demonstrate that a workers fear of losing their job also has an adverse impact on the emotional and mental well-being of their spouses.

Sullivan and Von Wachter (2009) looked at the employment and earnings of Pennsylvanian workers in the 1970s and 1980s and found that mortality rates in the year after displacement are 50% - 100% higher for high-seniority male workers than would otherwise have been expected. Interestingly, they find that although the mortality hazards decreases over time, the annual death hazards is 10%-15% higher even after twenty years after displacement. Recently, Pierce and Schott (2016b) look at the effect of increasing Chinese exposure on mortality at the county level for the US. Using proprietary data that summarizes the death certificates, they find that counties that were more exposed to Chinese competition have higher rates of suicide, which are primarily concentrated among white males. However, they do find that more exposed counties had lower rates of fatal heart attacks.

Literature analyzing the effect of job loss or job insecurity on alcohol consumption find different results. For instance, Dee (2001) finds that overall drinking decreases during economic downturns, and Ruhm and Black (2002) find that when state unemployment rates increases, overall drinking decreases, largely among existing drinkers. On the other hand, French and Davalos (2011) find that binge drinking and drunk-driving increases as unemployment rate increases; Dooley and Prause (1998) find that job loss is positively related with alcohol misuse.

My study aims to capture both health effects in a region due to higher displacement of workers by import competition and the ancillary consequences of higher import exposure in the affected regions. I hypothesize that worker respond to the worsening labor market outcomes by resorting to consuming more alcohol to cope up with the higher stress.

3.4 Identification Strategy

3.4.1 Import Exposure Measure

I follow the measure developed by Autor et al. (2013) to look at import exposure from China. To construct this measure, I first map the US imports from China at the HS6 product level data with the SIC87 industries that manufactures each product.[8] I then apportion each of these industry's imports to counties based on their share of national industry employment. I weight this with the share of employment of the industry in a county with the total

[8] My crosswalk for the mapping comes from David Dorn's website.

employment of the county. This will measure the per-worker share of the change in import exposure from China for each individual county. Mathematically, it can be expressed as:

$$\Delta Exposure_{ct} = \sum_{j} \frac{L_{jct}}{L_{ct}} * \frac{\Delta imports_{jt}}{L_{jt}} \tag{3.1}$$

where $\frac{L_{jct}}{L_{ct}}$ is the share of county c workers employed in industry j in year t and $\frac{\Delta imports_{jt}}{L_{jt}}$ is the change in imports from China per-worker employed in industry j. The variation in the import exposure measure comes from the heteregenous specialization of industry in different counties, and the differences in import growth from China at the industry level.

3.4.2 Instrumental Variable

One of the concerns in estimating the effect of increasing import competition from China in the US local labor market is that there maybe a reverse causality problem. That is, import competition in a county may increase in those counties that have deterioated labor market conditions. Hence, it is important to establish that the increasing import competition from China is "supply-side" driven. Therefore, to isolate this effect, I look at Chinese imports in eight other high income countries. These are are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Chinese imports to these countries is uncorrelated with the demand shocks at the county level in the US. I then construct the instrumental variable as follows:

$$\Delta IV_{ct} = \sum_{j} \frac{L_{jct-5}}{L_{ct-5}} * \frac{\Delta imports_{jt}^{others}}{L_{jt-5}} \tag{3.2}$$

where $\frac{L_{jct-5}}{L_{ct-5}}$ is the share of county c workers employed in the industry j at time $t-5$, and $\frac{\Delta imports_{jt}^{others}}{L_{jt-5}}$ is the Chinese import change in the eight other high income countries as a share of total industry j employed at time $t-5$. The employment level is five-year lagged as this would mitigate the concern of employments changing in anticipation of future increase in imports from China. This reduces the simultaneity bias. However, one concern about the instrument is that the imports from China for these eight other high income countries are driven by the same demand shocks that increases the Chinese imports to the US. Nonetheless, the instrument is widely used in the literature that studies the effect of

Chinese import exposure to the US.

3.4.3 Empirical Specification

The estimation model for my analysis follows the first difference equation. The benefit of employing the first difference equation is that it will difference out any time invariant county-level characteristics related to the health outcomes. The reduced form model for the change in alcohol consumption is given by the following equation:

$$\Delta AC_{ct} = \beta_0 + \beta_1 \Delta Exposure_{ct} + \beta_2 M_{ct} + \beta_3 X_{ct} + \delta_{reg} + \epsilon_{ct} \tag{3.3}$$

where ΔAC_{ct} is the difference of alcohol consumption for county c between the beginning of period and the end of period. $\Delta Exposure_{ct}$ is the key explanatory variable of interest and represents the change in exposure per-worker of county c to import competition, M_{ct} is the start of the period county employment that was accounted for by manufacturing, and δ_{reg} controls for census region fixed effects. The vector X_{ct} controls for the c-zone's start of the period demographic variables. These include the percentage of population that is college educated, the share of population between 18-25 years, and the share of population that is black.

The health effect associated with the rise in Chinese import exposure may suffer from the reverse causality problem; if the growth in import exposure from China is correlated with the demand shocks, the OLS estimation from my specification will be biased. Therefore, I instrument the exposure from China with the instrumental variable as described in equation 3.2. I will estimate the effect using the two-stage least squares method, where the first stage will regress the endogenous chinese exposure to my instrument including my controls for the second stage regression. The additional assumption that the error term is not related with my instrument will result in a consistent estimation.[9]

[9] To further check the validity of the instrument, Autor et al. (2013) employ gravity identification strategy to exogenously capture the supply-side effect and find that the increase in Chinese import exposure is not driven by the same demand shocks in the US and the other eight high income countries.

3.5 Data

In order to create my variable of interest, $\Delta Exposure_{ct}$, I need data on the Chinese imports to the US at industry level and the specialization of industry at the county level. The data for Chinese imports comes from the United Nation's Commodity Trade Statistics Database (UN Comtrade). The data is provided at the six digit Harmonized System (HS) product level. I match the product level data with the industries that produce these products at the SIC87 classification using the crosswalk provided by Autor et al. (2013). The industry specialization at the county level is based on the employment of each industry in the county. If a county has a higher share of its employment in industry j, the county is more specialized in industry j. I get the data on the number of employees by industry-county from the Census County Business Pattern (CBP) database. Since the employment data is provided only in brackets, a fixed point algorithm is used to estimate the employment numbers within the bracket.[10]

CBP provides the information for each year starting from 1986. However, for the years in my sample, they define industries at the North American Industry Classification System(NAICS) of 1992 for the year 2002, and the NAICS2002 code for the year 2006. Therefore, I use the concordance table provided by the Census to convert these industries into the SIC87 classification to match with my trade data.[11]

The data for alcohol consumption comes from the Institute for Health Metrics and Evaluation (IHME) at the University of Washington which provides "rigorous and comparable measurement of the world's most important health problems". The data provides the age standardized prevalence of drinking at the county level. The county level data is estimated using the small area models to the Behavioral Risk Factor Surveillance System (BRFSS) data taking into account any of methodical changes to the BRFSS during the sample period. For my sample period, I can get the prevalence data for "any" and "binge" drinking. "Any"

[10]David Dorn provides the code to estimate the employment in his website. It is available at http://www.ddorn.net/data.htm.

[11]Many industries that were classified in the SIC87 classification were consolidated into a single industry in the NAICS02 and NAICS06 classification. Therefore, I use the crosswalk provided by David Dorn to split these industries into the two or more industries at the SIC87 groups. I use the weights provided for each split, to calculate the employment at the SIC87 industry level. This will ensure that all my data will be consistent at the SIC87 industry classification for the different years.

drinking is defined as having at least one drink of any alcoholic beverage in the past thirty days. "Binge" drinking is defined as the consumption of more than four drinks for women or five drinks for men on a single occasion at least once in the past thirty days.

Table 3.1 provides the summary statistics of my variables. The average increase in Chinese import exposure across counties was $1344 per worker, with the maximum exposure of $36, 358 per worker. Given the standard deviation of $2043 per worker, there is considerable variation in import exposure across counties because of the variation in imports from China and the variation in county industry specialization. Binge drinking has been declining by 0.5 percentage point, with the decline for men being five times more than that for women. However, the prevalence of drinking has been increasing by 0.7 percentage point, with the average increase in female drinking by 1.5 percentage points. The prevalence of drinking for men has been declining. There is also a large variation in the prevalence of drinking and binge drinking between counties. Figures 3.2 and 3.3 show the distribution of percentage point change in "any" drinking and binge drinking of counties.

3.6 Results

I first estimate equation 3.3 to study the effect of increasing import exposure on alcohol consumption. In discussing the magnitude of the findings, the estimates are in per $1000 change in import exposure at the county level. All changes in alcohol consumption are in percentage points. I first present the OLS results, and then look at the IV specification.

3.6.1 OLS Result

The OLS findings are reported in Table 3.2, 3.3 and 3.4. Columns 1 and 2 of Table 3.2 presents the results for "any" drinking, and columns 3 and 4 provides the results for binge drinking. The baseline controls are the share of manufacturing employment and region fixed effect. In columns 3 and 4, I add additional demographic controls. Column 1 shows that a $1000 increase in Chinese exposure increases the prevalence of any drinking by 0.03 percentage points. The magnitude increases slightly when I add demographic controls to the specification, but are significant at 5 percent. In terms of binge drinking, the import exposure seems to have a larger effect than "any" drinking. The estimates with baseline and demographic controls show that a thousand dollar increase in exposure, increases binge drinking by a little over 0.04 percentage point. This shows that financial stress and the fear of job loss because of increasing import competition increases the binge drinking tendency in workers.

However, it may be that males and females take to drinking differently to cope with the stress. Therefore in Table 3.3, I look at this effect on subsamples of male and female population. In terms of "any" drinking, the magnitude of my estimates are similar between males and females. The estimates show that increasing import competition increases the prevalence of drinking in both males and females by over 0.03 percentage point. The point estimates are statistically significant at 5 percent. Next, I estimate the effect on binge drinking. Based on my hypothesis, the fear of job loss and lower cumulative earnings must increase the binge drinking tendency of the workers under the assumption that alcohol serves as a coping mechanism. I present the result in Table 3.4. Unlike the prevalence of drinking, I find that binge drinking tendency is different for men and women. My estimates show that the binge drinking in men increases by 0.05 percentage point, whereas it only increases by 0.02 percentage in women. The higher effect in men are more in line with the results of Pierce and Schott (2016a) who show a higher mortality rates for men than women because of increasing import competition from China.

3.6.2 Instrumental Variable and 2SLS Results

If Chinese exposure are correlated with the demand shocks, my OLS estimates will have a downward bias. To mitigate this effect and to tease out the "supply-side" effect, I make use of the instrumental variable approach to look at the effect of an exogenous rise in Chinese exposure at the county level. I use the instrument measured as described in equation 3.2 to get a more consistent estimate on alcohol consumption. The results are presented in Tables 3.5, 3.6 and 3.7.

The first two columns of Table 3.5 presents the estimates for drinking prevalence and columns 3 and 4 shows the results for binge drinking. I also show the first stage F-stat and r-square for my first stage regression. Compared to the OLS regression, my point estimates are significantly larger for both drinking prevalence and binge drinking. I find that a $1000 increase in Chinese import exposure increases the prevalence of drinking by 0.16 percentage points, whereas binge drinking increases by 0.14 percentage points. These estimates are statistically significant at the 1 percent level.

Next, I look at the effect for the prevalence of drinking on my subsamples by sex. I find that the drinking prevalence for men are higher than that for women. For men, I find that Chinese exposure increases drinking by 0.18 percentage points, whereas for women it increases by 0.13 percentage points. Likewise, Table 3.7 shows the effect for binge drinking for men and women. The magnitude of my estimates are larger than my OLS estimates. However, just as in the OLS case, I do find that binge drinking increases in men compared to women. For men, when I include both baseline and demographic controls, I find that binge drinking increases by 0.17 percentage points. However, for women, it increases by 0.11 percentage points. It is also interesting to note that the binge drinking in men increases by more than prevalence of drinking for men. For women, increasing Chinese exposure has a larger effect on prevalence of drinking than binge drinking.

3.7 Conclusion

This paper studies the effect of increasing Chinese import exposure on alcohol consumption measured by prevalence of drinking and binge drinking. I find empirical evidence that Chinese import exposure increases both the prevalence of drinking and binge drinking. Furthermore, I find that these effects are different for men and women. Men have a higher percentage point change in drinking prevalence and binge drinking as compared to women. In addition, the effect on binge drinking is larger than the prevalence of drinking for men, whereas the prevalence of drinking is affected more for women than their binge drinking.

My results shed more light on the recent adjustment costs of trade shocks from China. Further, they do support a wave of recent literature that find that increasing Chinese exposure increases the illness, work place injury and mortality rates among workers. Thus, it is important to mitigate these problems with relevant policy measure. Further research on the other health effects of Chinese trade shock will give us a better insight into the health costs of the trade shock.

Table 3.1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
China Imp. Exp.	3052	1.344	2.043	-1.659	36.358
BingeDrinkingChangeBoth	3052	-.554	1.252	-8.9	9.5
BingeDrinkingChangeFemale	3052	-.024	1.122	-6.5	10.5
BingeDrinkingChangeMale	3052	-1.106	1.727	-12.4	8.6
AnyDrinkingChangeBoth	3052	.722	2.002	-10.8	9.8
AnyDrinkingChangeFemale	3052	1.526	2.18	-10.6	11.9
AnyDrinkingChangeMale	3052	-.111	2.173	-11.1	12.3

Note: All import exposure are in $ 1000 per worker in the county as defined in equation 3.1. All changes in alcohol consumption are in percentage terms.

Table 3.2: OLS Estimates of Import Exposure on Drinking

	(1)	(2)	(3)	(4)
VARIABLES	AnyDrink	AnyDrink	BingeDrink	BingeDrink
China Imp. Exp.	0.0373**	0.0387**	0.0437***	0.0403***
	(0.0159)	(0.0154)	(0.0109)	(0.0107)
Observations	3,052	3,052	3,052	3,052
R-squared	0.156	0.183	0.158	0.167
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree and unemployment rate, all at the beginning of period level. Robust standard errors.

Table 3.3: OLS Estimates of Import Exposure on "Any" Drinking by sex

	(1)	(2)	(3)	(4)
VARIABLES	AnyDrink_Male	AnyDrink_Male	AnyDrink_Fem	AnyDrink_Fem
China Imp. Exp.	0.0365**	0.0395**	0.0380**	0.0378**
	(0.0186)	(0.0175)	(0.0163)	(0.0163)
Observations	3,052	3,052	3,052	3,052
R-squared	0.145	0.179	0.122	0.153
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree and unemployment rate, all at the beginning of period level. Robust standard errors.

Table 3.4: OLS Estimates of Import Exposure on "Binge" Drinking by sex

	(1)	(2)	(3)	(4)
VARIABLES	BingeDrink_Male	BingeDrink_Male	BingeDrink_Fem	BingeDrink_Fem
China Imp. Exp.	0.0602***	0.0550***	0.0280***	0.0263***
	(0.0153)	(0.0149)	(0.00858)	(0.00857)
Observations	3,052	3,052	3,052	3,052
R-squared	0.134	0.147	0.190	0.196
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree and unemployment rate, all at the beginning of period level. Robust standard errors.

Table 3.5: 2SLS Estimates of Import Exposure on Drinking

VARIABLES	(1) AnyDrink	(2) AnyDrink	(3) BingeDrink	(4) BingeDrink
China Imp. Exp.	0.172***	0.163***	0.160***	0.147***
	(0.0525)	(0.0496)	(0.0357)	(0.0349)
Observations	3,052	3,052	3,052	3,052
R-squared	0.141	0.170	0.130	0.143
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Partial R-square	0.306	0.307	0.306	0.307
F-stat	135.4	95.94	135.4	95.94

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree and unemployment rate, all at the beginning of period level. Robust standard errors.

Table 3.6: 2SLS Estimates of Import Exposure on "Any" Drinking by Sex

VARIABLES	(1) AnyDrink_Male	(2) AnyDrink_Male	(3) AnyDrink_Fem	(4) AnyDrink_Fem
China Imp. Exp.	0.183***	0.195***	0.165***	0.136***
	(0.0564)	(0.0551)	(0.0571)	(0.0524)
Observations	3,052	3,052	3,052	3,052
R-squared	0.130	0.163	0.111	0.146
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Partial R-square	0.306	0.307	0.306	0.307
F-stat	135.4	95.94	135.4	95.94

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree and unemployment rate, all at the beginning of period level. Robust standard errors.

Table 3.7: 2SLS Estimates of Import Exposure on "Binge" Drinking by Sex

	(1)	(2)	(3)	(4)
VARIABLES	BingeDrink_Male	BingeDrink_Male	BingeDrink_Fem	BingeDrink_Fem
China Imp. Exp.	0.202***	0.176***	0.119***	0.119***
	(0.0526)	(0.0497)	(0.0321)	(0.0322)
Observations	3,052	3,052	3,052	3,052
R-squared	0.112	0.131	0.168	0.174
Baseline Controls	Yes	Yes	Yes	Yes
Demographic Controls		Yes		Yes
Partial R-square	0.306	0.307	0.306	0.307
F-stat	135.4	95.94	135.4	95.94

Notes: ***, **, * denotes statistical significance at 1, 5 and 10 percent respectively. Constants are included in the model but are not reported. Baseline controls include region fixed effects and start of period manufacturing share. Demographic controls include share of population under 25, share of population that is black, and share of population that has a college degree and unemployment rate, all at the beginning of period level. Robust standard errors.

Figure 3.1: US Import from China

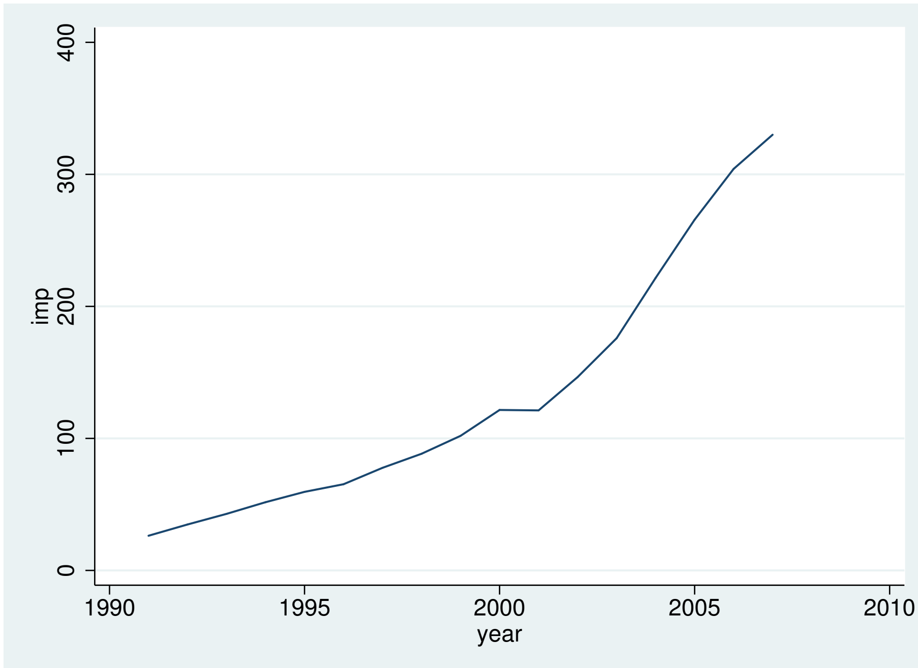


Figure 3.2: Percentage Point Change for "Any" Drinking

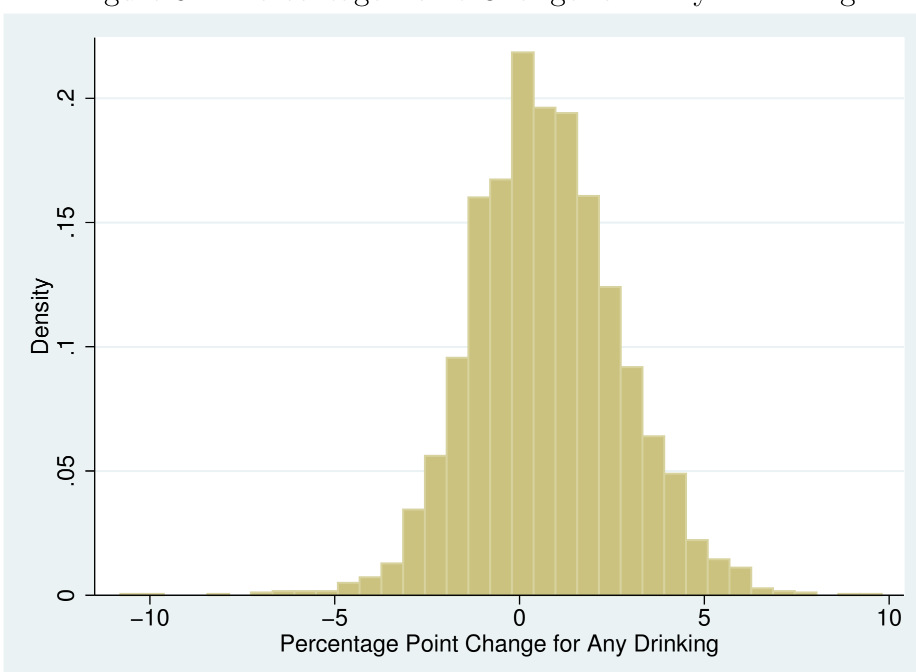
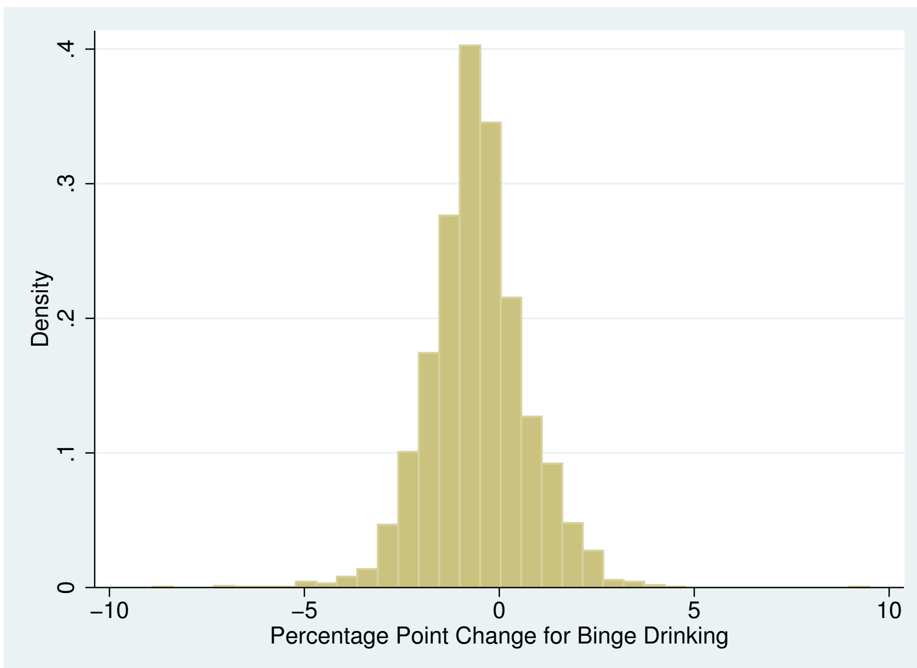


Figure 3.3: Percentage Point Change for Binge Drinking



References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of labor economics*, 4:1043–1171.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Amiti, M. and Wei, S.-J. (2005). Fear of service outsourcing: is it justified? *Economic policy*, 20(42):308–347.

Amiti, M. and Wei, S.-J. (2009). Service offshoring and productivity: Evidence from the us. *The World Economy*, 32(2):203–220.

Autor, D., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *The American Economic Review*, 103(6):2121–2168.

Autor, D., Dorn, D., and Hanson, G. H. (2016a). The china shock: Learning from labor market adjustment to large changes in trade. Technical report, National Bureau of Economic Research.

Autor, D. H., Dorn, D., and Hanson, G. H. (2016b). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8:205–240.

Baier, S. L. and Bergstrand, J. H. (2001). The growth of world trade: tariffs, transport costs, and income similarity. *Journal of international Economics*, 53(1):1–27.

Belkman, E., Bound, J., and Munchin, S. (1998). Implications of skill-biased technological change: International evidence. *The Quaterly Journal of Economics*, pages 1245–1279.

Berman, E., Bound, J., and Griliches, Z. (1994). Changes in the demand for skilled labor within us manufacturing: Evidence from the annual survey of manufacturers. *The Quarterly Journal of Economics*, pages 367–397.

Blinder, A. S. et al. (2009). How many us jobs might be offshorable? *World Economics*, 10(2):41.

Borjas, G. J., Freeman, R. B., and Katz, L. F. (1992). On the labor market effects of immigration and trade. In *Immigration and the workforce: economic consequences for the United States and source areas*, pages 213–244. University of Chicago Press.

Bottini, N., Ernst, C., and Luebker, M. (2007). *Offshoring and the labour market: What are the issues?* Internat. Labour Office.

Burfisher, M. E., Robinson, S., and Thierfelder, K. (2001). The impact of nafta on the united states. *The Journal of Economic Perspectives*, 15(1):125–144.

Burkhauser, R. V., Feng, S., Jenkins, S. P., and Larrimore, J. (2011). Estimating trends in us income inequality using the current population survey: the importance of controlling for censoring. *The Journal of Economic Inequality*, 9(3):393–415.

Carneiro, R. D., Soares, R. R., and Ulyssea, G. (2015). Local labor market conditions and crime: Evidence from the brazilian trade liberalization.

Che, Y. and Xu, X. (2015). The china syndrome in us: Import competition, crime, and government transfer.

Cheng, G. H.-L. and Chan, D. K.-S. (2008). Who suffers more from job insecurity? a meta-analytic review. *Applied Psychology*, 57(2):272–303.

Cooper, W. H. (2010). Us-japan economic relations: Significance, prospects, and policy options. DTIC Document.

Dee, T. S. (2001). Alcohol abuse and economic conditions: Evidence from repeated cross-sections of individual-level data. *Health economics*, 10(3):257–270.

Dooley, D. and Prause, J. (1998). Underemployment and alcohol misuse in the national longitudinal survey of youth. *Journal of Studies on Alcohol*, 59(6):669–680.

Dorn, D. (2009). *Essays on inequality, spatial interaction, and the demand for skills*. PhD thesis, University of St. Gallen.

Dorn, D., Hanson, G. H., et al. (2015). Untangling trade and technology: Evidence from local labour markets. *Economic Journal*, 125(584):621–46.

Ebenstein, A., Harrison, A., McMillan, M., and Phillips, S. (2014). Estimating the impact of trade and offshoring on american workers using the current population surveys. *Review of Economics and Statistics*, 96(4):581–595.

Egger, P., Pfaffermayr, M., and Weber, A. (2007). Sectoral adjustment of employment to shifts in outsourcing and trade: evidence from a dynamic fixed effects multinomial logit model. *Journal of applied Econometrics*, 22(3):559–580.

Feenstra, R. C. and Hanson, G. H. (1996). Globalization, outsourcing, and wage inequality. *American Economic Review*, 86(2):240–45.

Feenstra, R. C. and Hanson, G. H. (1999). The impact of outsourcing and high-technology capital on wages: estimates for the united states, 1979-1990. *Quarterly Journal of Economics*, pages 907–940.

Feenstra, R. C. and Jensen, J. B. (2012). Evaluating estimates of materials offshoring from us manufacturing. *Economics Letters*, 117(1):170–173.

Feenstra, R. C., Markusen, J. A., and Rose, A. K. (1998). Undertstanding the home market effect and the gravity equation: The role of differentiating goods. Technical report, National bureau of economic research.

Feler, L. and Senses, M. Z. (2015). Trade shocks and the provision of local public goods. *Revise and Resubmit, American Economic Journal: Economic Policy.*

Firpo, S., Fortin, N. M., and Lemieux, T. (2011). Occupational tasks and changes in the wage structure.

Freeman, R. B. (1999). The economics of crime. *Handbook of labor economics*, 3:3529–3571.

French, M. T. and Davalos, M. E. (2011). This recession is wearing me out! health-related quality of life and economic downturns. *Journal of Mental Health Policy and Economics*, 14.

Geishecker, I. and Görg, H. (2013). Services offshoring and wages: Evidence from micro data. *Oxford Economic Papers*, 65(1):124–146.

Goldin, C. and Katz, L. F. (2007). Long-run changes in the us wage structure: narrowing, widening, polarizing. Technical report, National Bureau of Economic Research.

Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime rates and local labor market opportunities in the united states: 1979–1997. *Review of Economics and statistics*, 84(1):45–61.

Grossman, G. M. and Rossi-Hansberg, E. (2008). Trading tasks: A simple theory of offshoring. *The American Economic Review*, 98(5):1978–1997.

Houseman, S., Kurz, C., Lengermann, P., and Mandel, B. (2011). Offshoring bias in us manufacturing. *The Journal of Economic Perspectives*, 25(2):111–132.

Hsieh, C.-T. and Song, Z. M. (2015). Grasp the large, let go of the small: the transformation of the state sector in china. Technical report, National Bureau of Economic Research.

Hsieh, C.-T. and Woo, K. T. (2005). The impact of outsourcing to china on hong kong's labor market. *American Economic Review*, pages 1673–1687.

Huang, Y. (2012). How did china take off? *The Journal of Economic Perspectives*, 26(4):147–170.

Hummels, D. (1999). Have international transportation costs declined? *University of Chicago*.

Hummels, D., Munch, N. J., Xiang, I. C., et al. (2015). No pain, no gain: The effects of exports on job injury and sickness. Technical report, International Agricultural Trade Research Consortium.

Husted, S. and Nishioka, S. (2013). Chinas fare share? the growth of chinese exports in world trade. *Review of World Economics*, 149(3):565–585.

Iyer, L. and Topalova, P. B. (2014). Poverty and crime: evidence from rainfall and trade shocks in india. *Harvard Business School BGIE Unit Working Paper*, (14-067).

Katz, L. F. and Autor, D. H. (1999). Changes in the wage structure and earnings inequality. *Handbook of labor economics*, 3:1463–1555.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963-1987: Supply and demand factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Kosteas, V. D. (2008). Manufacturing wages and imports: Evidence from the nlsy. *Economica*, 75(298):259–279.

Levitt, S. D. (1997). Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review*, 87(3):270–90.

Levitt, S. D. (2004). Understanding why crime fell in the 1990s: Four factors that explain the decline and six that do not. *The Journal of Economic Perspectives*, 18(1):163–190.

Levy, F. and Murnane, R. J. (1992). Us earnings levels and earnings inequality: A review of recent trends and proposed explanations. *Journal of Economic Literature*, pages 1333–1381.

Liu, R. and Trefler, D. (2008). Much ado about nothing: American jobs and the rise of service outsourcing to china and india. Technical report, National Bureau of Economic Research.

Lovely, M. E. and Richardson, J. D. (2000). Trade flows and wage premiums: does who or what matter? In *The impact of international trade on wages*, pages 309–348. University of Chicago Press.

McCarthy, J. C., Dash, A., and Liddell, H. (2002). 3.3 million us services jobs to go offshore. *TechStrategyTM Research, Forrester Research (November).*

McKee-Ryan, F., Song, Z., Wanberg, C. R., and Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: a meta-analytic study. *Journal of applied psychology*, 90(1):53.

McManus, T. C. and Schaur, G. (2016). The effects of import competition on worker health. *Journal of International Economics*, 102:160–172.

Milberg, W. and Winkler, D. E. (2010). Errors from the'proportionality assumption'in the measurement of offshoring: Application to german labor demand.

Morrison, W. M. (2013). China's economic rise: history, trends, challenges, and implications for the united states. *Current Politics and Economics of Northern and Western Asia*, 22(4):461.

Parker, A. et al. (2004). Two-speed europe: Why 1 million jobs will move offshore. *Forrester Research, August*, 18:2004.

Paul, K. I. and Moser, K. (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational behavior*, 74(3):264–282.

Piehl, A. M. (1998). Economic conditions, work, and crime. *Handbook of crime and punishment*, pages 302–19.

Pierce, J. R. and Schott, P. K. (2012). The surprisingly swift decline of us manufacturing employment. Technical report, National Bureau of Economic Research.

Pierce, J. R. and Schott, P. K. (2016a). The surprisingly swift decline of us manufacturing employment. *The American Economic Review*, 106(7):1632–1662.

Pierce, J. R. and Schott, P. K. (2016b). Trade liberalization and mortality: Evidence from us counties. Technical report, National Bureau of Economic Research.

Puzzello, L. (2012). A proportionality assumption and measurement biases in the factor content of trade. *Journal of International Economics*, 87(1):105–111.

Raphael, S. and Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. *The Journal of Law and Economics*, 44(1):259–283.

Ruhm, C. J. and Black, W. E. (2002). Does drinking really decrease in bad times? *Journal of health economics*, 21(4):659–678.

Schott, P. K. (2008). The relative sophistication of chinese exports. *Economic policy*, 23(53):5–49.

Stolper, W. F. and Samuelson, P. A. (1941). Protection and real wages. *The Review of Economic Studies*, 9(1):58–73.

Sullivan, D. and Von Wachter, T. (2009). Job displacement and mortality: An analysis using administrative data. *The Quarterly Journal of Economics*, 124(3):1265–1306.

Tempesti, T. (2015). Offshoring and the skill-premium: Evidence from individual workers data. *The World Economy*.

Tolbert, C. M. and Sizer, M. (1996). Us commuting zones and labor market areas: A 1990 update.

Topel, R. H. (1986). Local labor markets. *Journal of Political economy*, 94(3, Part 2):S111–S143.

Van Reenen, J. (2011). Wage inequality, technology and trade: 21st century evidence. *Labour economics*, 18(6):730–741.

Wilson, S. M., Larson, J. H., and Stone, K. L. (1993). Stress among job insecure workers and their spouses. *Family Relations*, pages 74–80.

Yan, B. (2006). Demand for skills in canada: the role of foreign outsourcing and information-communication technology. *Canadian Journal of Economics/Revue canadienne d'économique*, 39(1):53–67.

Yi, K.-M. (2003). Can vertical specialization explain the growth of world trade? *Journal of political Economy*, 111(1):52–102.