Local Labour Market Effects of Unemployment on Crime Induced by Trade Shocks*

Claudio Deiana[†] [‡]

[†]Department of Economics, University of Essex, UK
[‡]CRENoS, University of Cagliari, Italy

Abstract

This paper analyses the effect of a long-term change in unemployment on crime in the US local labour markets (1990-2007). During these last two decades, the US economy has experienced severe structural changes caused by international trade shocks, and China has played a crucial role as a major global exporter. The rapid growth of US exposure to China products triggers the increase in US local unemployment rates. This study documents whether this increasing exposure to Chinese competitiveness has indirectly contributed to the change in the propensity to commit crime through the displacement of workers. I exploit the cross-market variation in import exposure stemming from initial differences in industry specialisation to instrument the unemployment rate. The empirical evidence suggests that a one per cent increase in unemployment rate, induced by a change in Chinese import products, leads to almost a one per cent rise in the total crime rate.

Keywords: Crime; Unemployment; Trade; Import Competition, Local Labour Markets
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1 Introduction

Economists and policy-makers have long been interested in the relationship between labour market conditions and crime. Since the seminal contributions both by Becker (1968) and Ehrlich (1973), joblessness has been identified as one of the most significant risk factors for criminal activity. Nevertheless, the existing literature on the link between crime and unemployment still faces considerable challenges to causal inference due to omitted variable bias and reverse causality (see Mustard, 2010, and references therein).

This paper contributes to this literature by taking advantage of a trade shock episode induced by China's growth in exports. I analyse whether the US exposure to Chinese imports - in a context in which China has unexpectedly emerged as a major global economic power - have indirectly contributed to the rise the US crime rate through displacement of workers. The connection between trade-induced labor market shocks and crime has never been explored before in such context.[1] Thus, I consider the link between trade shock and crime in the US local labour markets (LLM hereafter), investigating how unemployment reacts to both international trade and crime. In order to do so, I exploit the cross-market variation in import exposure stemming from initial differences in US industry specialisation to instrument the unemployment rate. Think of two almost identical US LLM economies, for instance with similar GDP per capita, population and density, e.g. Buffalo, NY and Orlando, FL, which hypothetically only differ from each other in their initial industry specialisation. These two counties belong to the highest and the lowest 10th percentile of the exposure to Chinese imports distribution, respectively. Thus, Buffalo, NY faces, *ceteris paribus*, a major increase in crime rates caused by a (greater) worsening of LLM opportunities, deteriorated by an increase in Chinese import competition.[2]

The effect of trade on crime is interesting in itself, since it highlights a dimension of adjustment costs, beyond those directly associated with labor market reallocation, that has been overlooked in the past. Illegal activities may be considered as an additional *collateral* adjustment cost of trade through an increase in the unemployment rate at the local level. Illegality and unemployment impose tremendous economic and social costs for the society with unemployment itself playing an important role in the supply function of crime (Becker, 1968). In particular, US public expenditure on criminal justice amounts to approximately \$630 per capita which is about 2.5% of GDP and private expenditure on crime prevention is at least as large (US Census 2007). The aggregate cost of crime to society exceeds \$1 trillion, which is approximately the size of the US healthcare sector (Anderson, 1999).[3] Moreover, the US economy has been dramatically shaped by international trade shocks, which brought about important structural changes in US LLMs over the last two decades.

[1] The only other papers considering a somewhat similar aspects are Iyer and Topalova (2014) and Dix Carneiro et al. (2016).

[2] I compute the ten-year equivalent values of (Δ imports from China to US)/worker in kUS\$ for the cities with the largest population in 1990 (Autor et al., 2013a). Buffalo, NY and Orlando, FL register an average Chinese import exposure per worker of around 2 and 0.4, respectively.

[3] For example, Cohen et al. (1996) estimate the annual cost of crime in the United States which was about \$450 billions. This is equivalent to \$1,800 per capita per year. On top of this, the prison population has doubled since the early 1990s and currently stands at over 2.2 million inmates, putting further pressure on the US welfare State.

During the same period, China's transition from a central planning to a market-oriented economy and the reduction of its trade costs through World Trade Organization (WTO) accession played a crucial role in the success of Chinese exports.[4] US spending on Chinese goods quickly increased from 0.6% in the early 1990s to 4.6% in 2007, with an even faster tendency after 2000, when China joined the WTO. The greater US exposure to China products triggers the increase in US local unemployment rates between 1990 to 2007.[5] Therefore, estimating the trade-induced variations in labour market conditions on crime is stil a relevant issue for economists and policy makers.

On the one hand, the early empirical literature on crime-unemployment generally finds an inconsistent weak positive relationship between slowdowns and illegality (Cullen and Levitt, 1999; Chiricos, 1987). As discussed by Freeman (1983), the effect tends to be modest and typically it neglects to take into account the endogeneity issue behind this relationship. As a general result, the estimates are downward biased. On the other hand, the most recent contributions explicitly tackle the potential endogeneity in the relationship and Raphael and Winter-Ember (2001) represents one of the few exceptions.[6] This new evidence, mostly based on national surveys, suggests a (larger) positive significant effect on property crimes (Lin, 2008) and on the subgroups more at risk of committing crime, e.g. low-skilled, young men (Gould et al., 2002). Differently from the previous literature, I analyse the effect of a long-term change in unemployment on crime rate bearing in mind that individuals may take some time to switch from legal to illegal sectors.

First, to mitigate the omitted variables bias, I extensively control for observable demographic and economic variables at the local level. Additionally, I estimate a first-difference specification in order to wipe out time-invariant heterogeneity. Finally, I exploit the cross-market variation in import exposure due to initial differences in industry specialisation to instrument the unemployment rate. To the best of my knowledge, this study provides the first powerful causal test of the long-term change of unemployment on crime rates following a trade shock. To do so, I identify the trade shocks to local unemployment considering cross-industry and cross-LLM variations in import competition favoured by China's spectacular rising productivity and falling barriers to trade after its admission in the WTO. This represents a unique attempt to explain how crime rates react to a large trade shock, i.e. whether the exogenous rise in competition from Chinese products explains the change in arrest and offense rates though a displacement effect of workers over the period 1990-2007.[7]

In order to carry out my analysis, I empirically map the industry-specific trade shocks into a number of aggregate outcomes. I then define US LLMs as sub-economies subject to heterogeneous

[4] Wood (1995) argues that the main cause of the deteriorating economic position of unskilled workers in developed countries has been the expansion of trade with developing countries.

[5] Figure A.1 in Appendix shows this extraordinary growth.

[6] Mustard (2010) provides a detailed discussion about how recent research, primarily since the late 1990s, makes substantial progress in resolving the endogeneity between crime and labour market conditions.

[7] A comprehensive literature review can be found in the Handbook on the Economics of Crime (Benson and Zimmerman, 2010). Mustard (2010) offers a detailed discussion of the most recent papers that explicitly tackle the endogeneity issues between crime and socio-economic conditions. The only other studies which reckon a possible link between trade, labour conditions and crime are Iyer and Topalova (2014) and Dix Carneiro et al. (2016) but with completely different settings with respect to this one.

trade shocks according to their initial industry specialisation. The Commuting Zone (hereafter CZ), which includes all metropolitan and non-metropolitan areas in the United States, is the logical geographic units for defining LLMs (Tolbert and Sizer, 1996; Autor et al., 2013a, 2015, for instance). The analysis of the CZs is motivated by the notion that employers and workers interact within a space bounded by places of work and places of residence. Generally, the empirical studies on crime, due to the lack of precise geographical information, often consider the 50 States in the US (Raphael and Winter-Ember, 2001) and/or the counties as LLM (Gould et al., 2002). The latter provides a substantially more detailed geographic structure than States but raises similar methodological issues: there is no economic motivation why the boundaries of LLM should coincide with State/counties ones, which are administrative definitions. Moreover, States are too large for being considered a single LLM which may be characterised by huge heterogeneity. On the contrary, the counties may often be too small and information is usually not available in publicly accessible micro data. The possibility to map the crime phenomenon across US CZs represents a further contribution to the current crime literature.[8]

The main findings suggest that the downturn, stemming from an increase in imports from China, has a significant effect on those criminal activities to which individuals can easily turn when their economic conditions worsen. Specifically, a $1,000 exogenous decadal rise in a CZ's import exposure per worker is predicted to reduce its unemployment rate by 0.13 percentage points. In contrast to previous research, I generally find significant and sizable positive effects: a percentage point increase in unemployment rate leads to a rise (i) in total crimes by 120, (ii) in violent crimes by 21 and (iii) in property crimes by almost 98 per 100,000 residents. Differently from the (few) previous studies, I estimate a greater elasticity leading to almost a one-to-one relationship.

There are several reasons that can explain these results. Firstly, it is worth noting, before anything else, that State level aggregation yields downward biased results when estimating the relationship between unemployment and crime due to the large heterogeneity effects within States. Cornwell and Trumbull (1994) claim that national level data overstate the role of many explanatory variables and, more recently, Levitt (2001) argues that "[...] national level data are only crude tool in untangling the link between unemployment and crime because it wastes local variation and it does not allow for a wide range of covariates". Secondly, these results reflect the local average treatment effect for those whose unemployment status is affected by the change in exposure to China imports. The compliers, suffering more from these Chinese trade shocks, undergo longer unemployment spells, which possibly explain the larger effect on crime. Finally, the analysis does not show any particularly strong evidence of population adjustments at the CZ level with such substantial exposure to Chinese imports. In fact, local effects of import shocks may partly diffuse

[8] CZs are clusters of counties that are characterised by strong commuting ties within each CZ, and weak ones across CZs. The CZ's boundaries are appropriate in analysing the relationship between local economic conditions and the change in crime since CZs have been created exactly to capture, more than any other administrative definition, the economic notion of local labour markets in the US (Tolbert and Sizer, 1996). The most popular concept for LLM in recent research are Metropolitan Statistical Areas which are used, e.g. , by Card (2001), but they only cover areas of the US with major urban population and the geographic definition of MSAs changes over time (Autor et al., 2013a, 2014).

through migration between CZs. If labour is highly mobile across regions, trade may influence workers (and potentially criminals) with its results not being identifiable at the regional level. Nevertheless, it seems not to be the case, and also the recent literature on regional adjustment to labour market shocks suggests that mobility responses to labour demand shocks across US cities and States are slow and incomplete.[9]

It is therefore somewhat surprising that so little is known by economists and policy-makers about how crimes react to trade shocks as a result of their disruptive effects on LLM structure and job opportunities. Interestingly, despite the increasing role of China as a predominant worldwide exporter, no one before attempted to understand whether trade-induced variations in economic labour conditions may cause crime. In this regard, an increase in crime rate can be considered as a further additional cost for the society. Therefore, if policy-makers were able to figure out and forecast this potential link between trade and crime, they could dramatically limit the costs of LLM displacement and finally reduce the probability of committing a crime. Developing effective tools to regulate and alleviate the costs of trade adjustments, should be a high priority on the agenda for policy-makers and applied economists. This is especially true when these costs translate into criminal activities.

The remainder of the paper is organized as follows: Section 2 discusses the background in crime, unemployment and trade shock. Section 3 illustrates the identification, the empirical specification, the data sources and the descriptive statistics. The results, the main mechanism and different robustness checks are presented in Section 4. In the conclusions, I summarize the empirical findings and I briefly discuss some policy implications.

[9] Topel (1986); Glaeser et al. (2006); Notowidigdo (2010); Autor et al. (2013a) reach similar conclusions.

2 Background: Crime, Unemployment and Import from China

The past two decades have seen an abundant debate on the impact of international trade shocks on US LLM opportunities and how these external forces have reshaped the developed economy. Over the same period, China has played a role of guidance as emerging leader in the export sector (Rodrik, 2006; Amiti and Freund, 2010). In particular, the general interest of trade scholars in China relies on both its enormous influence as main exporter of (manufactured) goods all over the world and by the scarse possibility to have "exogenous variation" in international trade. According to Rodrik (2006), again the great success of China as the most relevant exporter around the world was determined by a combination of its comparative advantage in producing tradable goods, the opening to free markets and above all Chinese government itself which has played a crucial guide for this prodigious growth. As a result, China has ended up with an export basket that is significantly more sophisticated than what would normally be expected for a country at its income level. Recently, Amiti and Freund (2010) find that China's export is dramatically changed with increasing export shares in electronics and machinery and a decline in agriculture and apparel.

All these factors - including opening to market economy which has involved rural-to-urban migration of over 150 million workers and reducing the trade barriers with the WTO accession - determine the remarkable China's export growth. These elements create an "artificial" setting to test different implications. Depending on the differences in the initial industry specialisation, the impact of Chinese penetration asymmetrically affects the US LLM economy causing higher unemployment.[10] Bernard et al. (2006) find that US industries facing greater increases in exposure to trade from low-wage countries, attributable in large account to China, are subject to higher rates of plant exits. Similar effects are observed for other countries: growing Chinese import competition increases plant closures and reduces firm growth in Mexico according to Iacovone et al. (2013) and Utar and Ruiz (2013). Greater exposure to Chinese competition reduces employment growth in Belgian firms (Mion and Zhu, 2013), Danish firms (Utar, 2014), and in a panel of firms from twelve European countries (Draca et al., 2015). A novel study examines the impact of trade on the structure of marriage and child-rearing in US households (Autor et al., 2014). The authors conclude that import shocks concentrate on male employment, reduce marriage rates and fertility, raise the fraction of births due to teen mothers, and, most significantly, increase the proportion of children living either in poverty or in single-headed households. The evidence so far yields to conclude that trade may be a costly and slowly process and, furthermore, it may be not beneficial for some local labour markets.[11] It comes natural to ask whether this increasing exposure to Chinese competitiveness has indirectly contributed to the propensity of committing crimes through the displacement of workers.

Legal labour market opportunities represent an important factors of committing crimes or not. As Becker (1968) and Ehrlich (1973) emphasize in their seminal works, a declining economy

[10] Balsvik et al. (2015), Donoso et al. (2015) and Autor et al. (2013a) come to similar conclusions.

[11] Recently, Autor et al. (2016) study whether the rise in trade integration between the US and China has an effect on the polarization of US politics. They find that congressional districts which are more exposed to larger increases in import competition removed moderate representatives from office in the 2000s.

provides higher incentives for the individuals to switch into illegal sector. It is clear that from a theoretical point of view, declining labour market opportunities, which are manifested by an increasing unemployment rate, worsen legal income opportunities and therefore make crime more attractive and profitable.[12] Consistent with this hypothesis, trade-induced supply shocks may have a negative effect on labour market opportunities especially for those LLMs that more exposed to the increase Chinese competitiveness. The increase of unemployment rate is often associated with changing opportunity costs that determine the propensity to commit crime. Nevertheless, the crime empirical results fail to show a consistent and strong association between downturns and crime, as highlighted by Mustard (2010).

On the one hand, the majority of the early works which have analysed the relationship between unemployment and crime rates tend to find small and positive effect of unemployment on economic-related crimes but not on violent crime (Freeman, 1983; Piehl, 1998). Chiricos (1987) reviews more than 60 studies on the crime-unemployment relationship and concludes that the evidence appears "inconsistent" and "weak". This relates to the fact that there was no attempt to tackle the endogeneity issue between crime rate and unemployment. On the other hand, recent literature has generally found a stronger, positive and significant effect on property (but not violent) crimes (Lin, 2008). This significant change in the estimated effect of unemployment on crime has to be attributed to a more appropriate list of controls or sub-group analyses of individual who can be considered at "risk" of committing crimes (Gould et al., 2002). Additionally the recent need to control for endogeneity caused by omitted variables, reverse causation and measurement error issues determined a notable improvement in the estimation process (Raphael and Winter-Ember, 2001; Lin, 2008).

Raphael and Winter-Ember (2001) represent the first attempt in providing an instrumental variable estimates of the link between unemployment and crime. The authors exploit an arguably exogenous variation across States in unemployment due to the closing of military bases and the shocks to oil prices. They discuss the validity of both sets of instruments, which are unrelated to crime, once other observable factors such as the imprisonment rate, demographic composition and percentage in poverty have been controlled for. In their IV findings a one percentage point increase in unemployment leads to an increase in property crime between 2.8% and 5%. Similarly Gould et al. (2002), using a US panel of counties from 1979 to 1997, find a significant and positive effect. They focus on those individuals at the margin of committing crime: young, unskilled, and low-educated males. Their findings show that a one percentage point increase in the unemployment rate of the group "at risk" group would increase property crime rate by 1-2%.[13] Lin (2008) analyses the same association using a panel of US States from 1974 to 2000. In order to instrument unemployment, the author exploits the changes in the real annual exchange rates times the percentage of State manufacturing sectors employees as an exogenous shock. In 2SLS estimates, one percentage point

[12] Other scholars focus on the idea of time allocation between legal and illegal activities and its influence on the decision whether or not to participate in criminal activities (Grogger, 1998).

[13] Also Grönqvist (2011) examines the relation between youth unemployment and crime. His results suggest that joblessness explain a meaningful portion of why male youths are overrepresented among criminal offenders.

rise in unemployment leads to a rise in crime rate by about 4% to 6%, which is about three times larger than the OLS estimate.

Some authors demonstrate that the recessions may lead to substantial and persistently higher rates of crime (de Blasio and Menon, 2013). Using a range of US and UK data to document a more disturbing the effect of recessions, Bell et al. (2015) conclude recessions lead to short-term job loss, lower levels of happiness and decreasing income levels. Others focused on the effect of exposure to plant closure on crime using an individual-level panel data set containing criminal charges for all unmarried and employed Norwegian men below 40 years old. Men originally employed in plants that subsequently closed are fourteen per cent more likely to be charged of a crime than comparable men in stable plants (Rege et al., 2009). Using detailed employer-employee Danish data, Bennett and Ouazad (2015) study the impact of job loss on an individual's probability to commit crime, i.e. job losses in firms losing a substantial share of their workers, for workers with at least three years of tenure. Displaced workers are more likely to commit offenses leading to conviction for property crimes and for alcohol-related traffic violations in the two years following displacement. Recently, Bindler (2015) provides evidence on the relationship between downturn and crime in the light of increasing unemployment durations and temporary benefit extensions in the United States. It is interesting to note that most of the crime papers analised above employ State level data, which suffers from the problem of aggregation bias that has been discussed in the crime literature since Cornwell and Trumbull (1994) and more recently stressed by Levitt (2001).

3 Identification and Empirical Specification

3.1 Local labour market geographical units

Looking at long-term change relationship between crime and unemployment requires a time-consistent definition of the US LLM economy. Hypothetically, in this area both the employers and workers interact within a space bounded by places of work and places of residence (Topel, 1986). The ideal geographical definition should be determined by strong commuting ties within the LLM, and weak commuting ties across LLM in order to, for instance, alleviate any migration spillovers and mobility. Often, given the lack of precise geographical information or of data sources, empirical studies on crime-unemployment consider the 50 States of the United States as labour market area (Raphael and Winter-Ember, 2001, is a notable example). However, this broad definition presents several drawbacks. To start with, there is no credible economic reason why the LLM dynamics should coincide with State boundaries which, indeed, appear too large for being considered a single LLM.[14] On top of this, the unit of observation migh be characterised by large within-state heterogeneity which may confound the relationship between crime and unemployment rates. Gould et al. (2002), using the counties as LLM, made a considerable improvement in the crime literature, although this geographic structure presents similar methodological concerns as the States. In fact, counties represent a too small geographical unit and they suffer from migration spillovers. In recent studies, the Metropolitan Statistical Areas (hereafter MSA) have been believed to be the natural location in identifing a LLMs (Card, 2001; Mazzolari and Ragusa, 2013). On the one hand, MSAs have a more economic appeal in the sense that they typically cover areas with commutable distances and they may overlap State boundaries so they fit for studying the relationship between labour market condition and crime. On the other hand, they do not cover rural areas and their geographical definition differs over time which prevents to map the crime-unemployment relationship.

For all the above reasons, I pursue an alternative approach for the definition of LLM based on the concept of Commuting Zones (CZs) which have been created with the explicit aim of capturing the economic notion of LLMs and they do not reflect any political boundaries.[15] This feature is extremely relevant because it limits to a large extent the possibility of spillovers across market areas including, among the others, commuting from other counties, short range county-to-county migration and firms location choices. Tolbert and Sizer (1996) divide the United States in 741 clusters of counties and I focus on the 722 mainland CZs which include both metropolitan and rural areas.[16] CZs are particular suitable to measure the job opportunities because they cover the entire area and workforce of the United States where employers, workers and residents are located within commutable distances. Finally, for the aim of this study, it is plausible that the effects of

[14] In particular, there are many urban areas overlapping with State lines (e.g. , New York City/Jersey City, Washington D.C./Arlington, Kansas City MO/Kansas City KS), notably because cities developed on both sides of rivers that serve as State boundaries (Dorn, 2009).

[15] By taking this regional economies as the unit of analysis, I circumvent the degrees of freedom problem endemic to estimate the labour market consequences of trade (Autor et al., 2013a).

[16] Figure A.2 shows the 722 US CZs that cover the 48 mainland States. I follow Tolbert and Sizer (1996) who define the CZs based on commuting patterns in the 1990 Census which are not fully matched with the 1980 definitions (Tolbert and Killian, 1987). The crosswalk is generously obtained from David Dorn in *http://www.ddorn.net/data.htm*.

Chinese imports will vary across CZ because there is considerable geographic variation in industry specialisation across different economic structure.[17] CZ specialized in industries whose outputs compete with Chinese imports should react more strongly to the growth of these imports, inducing structural changes in the labour market opportunities; these, in turn, trigger a rise in crime rate through the displacement of workers in the most exposed sectors.

3.2 First-difference specification

In order to wipe out the time-invariant heterogeneity, I initially focus on the relationship between crime and unemployment rates estimating a first-difference model for the long-term change interval between 1990 and 2007. I then stack the ten-year equivalent first differences for the two periods, 1990 to 2000 and 2000 to 2007 including separate time dummies for each decade. Due to the fact that the model is estimated in first difference, the decade-specific model is directly comparable to fixed effects regressions, while the stacked first difference models are similar to a three-period fixed effects model with slightly less restrictive assumptions made on the error. This should remove any concern related to the time-invariant unobserved heterogeneity between crime and unemployment. For instance, if cultural characteristics across the sampled CZs systematically affect crime and LLM behaviour, one CZ may display higher crime rates and worse LLM conditions independent of the effect of interest for this analysis. Hence, I rule out all the variation in crime rates caused by factors that vary within CZs and are constant over time, while the inclusion of time effects eliminates the influence of factors that cause time-to-time changes in crime rates common to all CZs. Using the full sample of 722 CZs, I fit models in first-difference of the following form:

$$\Delta Crime^{k}_{c,t} = \beta_1 \Delta Unemployment_{c,t} + \gamma_t + \Delta X^{'}_{c,t}\beta_2 + \Delta\varepsilon_{c,t} \qquad (1)$$

where Δ is the (decade) first-difference operator.[18] $Crime^{k}_{c,t}$ is the crime rate, measured as the number of arrests and offenses over working-age population, in Commuting Zone c, for the category of crime k and in the decade t, which is equal to 0 and 1 over the period 1990-2000 and 2000-2007, respectively. Additionally, γ_t indicates the dummies for each time decade and $\varepsilon_{c,t}$ is the residual. Standard errors are clustered at the State level to account for spatial correlations across CZs.[19] The main regressor is $Unemployment_{c,t}$ which measures the ratio of the unemployed to the working-age population. Furthermore, the vector X contains a rich set of economic and demographic controls at CZ level with the aim of capturing any time-varying confounding factors in the crime-unemployment

[17] The largest export growth has been in machinery, and within this broad category, telecoms, electrical machinery, and office machines have experienced the highest growth and make up the largest shares within machinery (Amiti and Freund, 2010). Differently from Rodrik (2006), the export growth was accompanied by increasing specialisation and it was mainly accounted for by high export growth of existing products rather than in new varieties (Amiti and Freund, 2010).

[18] Following Autor et al. (2013a), the 2000-2007 change in import growth is multiplied by 10/7 to place it in ten-year equivalent terms. I consider the period 1990-2007 because data on trade are available from 1991 and I explicitly not analyse the period of Great Recession in order to avoid possible confoundings to the identification.

[19] Estimating the model as a fixed-effects regression assumes that the errors are serially uncorrelated, while the first-differenced specification is more efficient if the errors are a random walk (Wooldridge, 2010). I cluster the standard errors at US State level in all models and I run some sensitivity at CZ level. The estimates are robust.

relationship (Cook and Zarkin, 1985).[20]

First, in order to control for changes in demographic or racial structure composition, I include to the main specification three distinct age-group categories: the share of people in 15-34, 35-49, 50-64 age bands which are meant to measure the change in age distribution at the CZ level (Fougere et al., 2009). Second, for each age category, I define the proportion of CZ residents that are White, Black, Indian or Asian, which are included to pick the decade differences across race distributions for the population subgroup with higher offending rates relative to other Americans (Levitt, 2001). Third, I control for the share of individuals with low, medium and high level of educational attainment defined as less than high school diploma, high school diploma or higher but no bachelor degree and finally with bachelor degree or higher, respectively. The predicted influence of this variable on crime is hard to determine a priori. The level of education can affect crime through three main mechanisms namely an income effect, short-sightedness and self-incapacitation.

To begin with, education increases the payoff to legitimate work which, in turn, makes working more worthwhile than criminal activity. Nevertheless this relationship may also work in the other direction, as education can also increase the earnings from certain crimes (e.g. white-collar crime such as fraud). Furthermore, young people who leave education earlier tend to care more about today than they do about tomorrow so in other words they prioritise short-term gratification in favour of long-term benefits. This makes them more likely to undertake risky activities, such as crime. Finally, self-incapacitation: time spent in school means less time on the streets committing crime.[21] Following Lin (2008), I additionally characterize each local labour market including a measure of federal income assistance, which comprises SSI (Supplemental Security Income), $TANF$ (Temporary Assistance for Needy Families) and $SNAP$ (Supplemental Nutrition Assistance), the share of Democratic and Republican voters in each presidential election over the period 1990-2007 and police force rate.

In the robustness analysis I further control for the share of non-participating individuals in the labour force. Nevertheless, the bulk of this category comprises full-time homemakers, retirees, students who have no other occupation and people permanently unable to work, all of which are in principle less likely to commit a crime. Following Levitt (1996, 1997), I also consider the prison population rate, which affects crime rates negatively through the deterrence effect. A positive effect of unemployment on crime is likely to lead to a positive correlation between unemployment and prison populations (assuming that some offenders are caught and sent to prison). Incarceration rates would downwardly bias the main results if they reduced crime rates via incapacitation and deterrence. A last set of covariates encompasses the average wage at commuting zone level and the

[20] I do not apply any logarithm to count crime data as it is detailedly explained in Silva and Tenreyro (2006). Moreover, using this smaller geographical unit, I may risk to drop the CZs which show zero event for a particular crime category. On top of this, the estimates using the logarithm of crime rate produce similar results but with smaller sample size.

[21] The literature on the relationship between education and crime is growing fast and Machin et al. (2011); Fella and Gallipoli (2014) represent a notable example. As discussed by Lochner (2004) and Lochner and Moretti (2004), human capital increases the opportunity cost of crime from foregone work and expected costs associated with incarceration. In the other contribution, Lochner and Moretti (2004), using Census and FBI data, find that schooling significantly reduces the probability of incarceration and arrest.

results are unaltered.[22] A complete list of the variables with the correspondent sources is shown in Subsection 3.4.

3.3 IV approach and the role of trade shock

As previously discussed, the relationship between these two phenomena may be biased by omitted variables, simultaneity or simply measurement error. Then, the estimated correlation between the LLM condition and crime might be flawed so that, *ex ante*, the causation of unemployment on crime is not obvious, often leading to reverse causality concerns. For instance, individuals commit crimes based on unobservable characteristics, which may be associated with ones determining unemployment. If the unobservables are positively (negatively) correlated with the unemployment and they are also positively (negatively) correlated with participation in the illegal market, the estimated effect is downward biased. Additionally, reversed causation (i.e. that criminal activity reduces the employability of offenders, or that economic growth is harmed by a high crime rate in the region) may also bias the unemployment effect on crime. Recent research using instrumental variable techniques shows that this relationship is underestimated due to endogeneity between unemployment and crime (Raphael and Winter-Ember, 2001; Fougere et al., 2009; Lin, 2008).

Since the results may contain bias coming from simultaneity or simple measurement error, and knowing that the list of potential omissions is never complete, it gets complicated to correctly identify the effect of unemployment on crime. Hence, to obtain a consistent estimator, an instrumental variable Z is necessary. For this reason, in order to capture the effect of a long-term change in unemployment on crime at the local labour market level, an exogenous source of variation, which will only affect crime rate through a change in labour market opportunity is needed. This measure should not be determined by endogenous factors that contemporaneously affect the outcome variable (crime). A credible exogenous variation, which may impact the unemployment dynamic is essential and this can be identified in the trade literature. I exploit the "unprecedented" rise in the Chinese exports across the world to instrument the unemployment rate. The interest of scholars in China is due to both by its large quantitative importance as the main exporter of goods, and by the scarceness of an exogenous variation for labour market conditions, especially when the aim is to look at a long-term change effects.

Three peculiarities of China's experience are useful to overcome the challenges in identifying the casual effects of trade shocks on LLM conditions. First, China's export growth was completely unexpected and it caught academics and economists by surprise (Autor et al., 2015). Second, the isolation under Mao created generous opportunities for successive catch up (Zhu, 2012). A final important key feature of China's rise is its distinctive and overwhelmingly comparative advantage

[22] The wages are in nominal and not real terms. Since I lack complete data on prices at the CZ level, I leave consideration of regional variation in price changes out of the empirical analysis. Nevertheless, when wages of workers in a labour market decrease, the price of local services also decrease, and since non-traded services have a large expenditure share, the real wages changes have a very weak association with nominal wages changes. As discussed by Monte (2014), there is basically no difference in the distribution of gains of exposed and unexposed locations. To conclude, if price decreases, the natural consequence is the increase of purchasing, making crime relatively more costly.

in producing industrial goods. This trade concentration means that China's growth has represented a large positive net global supply shock and the impact of its rise are consequently likely to vary across regional and national economies according to their initial patterns of industry specialisation.

The identification strategy in fact relates to changes in exposure to international trade shock to US CZs with the growth in US imports from China between 1990 and 2007, exploiting a cross-market variation in import exposure stemming from initial differences in industry specialisation.[23] Hence, I concentrate on the trade with China because it is responsible for nearly all of the expansion in US imports from low-income countries since the beginning of the 90's. As described by Chen et al. (2010), China's spectacular increase in exports has been primarily determined by its internal reforms, which triggered the transition to a market-oriented economy and that involved a migration from rural to urban areas of around 150 million workers.[24] This radical change came together with its accession to the World Trade Organization in the early 2000's. These transformations have determined China leadership in the exports to the US especially among the low-income countries. In the globalization context, trade with middle-income nations may also matter and this can be used as an alternative unexpected shock to the LLMs. An evident case, for instance, is Mexico, which can be historically considered as one of the most notable exporter to the US economy. In this case, finding a credible exogenous source of variation in Mexico's export growth is complicated. For example, the rise of US import from Mexico may be caused by changes in US bilateral trade policy, which could be influenced by economic conditions in the United States rather than an unusual increase in Mexican productivity. Moreover, a recent contribution by McLaren and Hakobyan (2010) shows no evidence of North American Free Trade Agreement (NAFTA) effects on US LLMs. In a different manner, China experienced an incredible productivity growth over the period 1990-2007 and arguably, the simultaneity in the joint determination of trade barriers, trade itself and investment flows are less of an issue.

In this framework, it is problematic to justify how a trade shock can impact the economy at the CZ level because trade shocks may play out in general equilibrium context so one needs to empirically map many industry-specific shocks into a small number of aggregate outcomes. Using (national) labour market unit at annual frequencies, it is possible to have very few observations left and many confounding factors. Using CZ as the unit of analysis, I bypass the degrees-of-freedom problem endemic of estimating the labour market consequences of trade. Therefore, it is then possible to identify the labour market consequences of trade as far as (i) CZs differ in their pattern of industry specialisation, and (ii) frictions in labour markets allow regional differences in the LLM conditions to persist over the medium run. A greater exposure to trade with China affects local labour market structure increasing the unemployment rate in those CZs most exposed to foreign competition.

Following the trade literature, I then define a general measure of trade shock coming from

[23] The identification strategy is related to that used by Autor et al. (2013a), who consider the relationship between imports from China and different labour market outcomes in the US.

[24] Autor et al. (2014) report some other important channels through which China had this incredibly penetration in the world market gaining access to long-run banned foreign technologies, capital goods and intermediate inputs being permitted to operate in the country.

the increase in Chinese competitiveness. This indicator measures the LLM exposure to import competition which is the change in Chinese import exposure per worker in a CZ, where imports are apportioned to each region according to its share of national industry employment:

$$\Delta import_{uit} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\Delta M_{ucjt}}{L_{it}} \tag{2}$$

In this expression L_{it} is the start of period employment (year t) in CZ i and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period. In detail, I need to allocate to each CZ a share of total national import growth and divide this import value by a CZ's total employment. Hence equation (2) yields a measure of "import growth per worker" (in \$1,000's of US dollar). The variation arises from two sources: differential concentration of employment in manufacturing versus non-manufacturing activities and specialisation in import-intensive industries within CZ. Local economies that are specialised in industries whose outputs compete with Chinese imports react more strongly to the growth of these imports.[25] The variable $\Delta import_{uit}$ measures overall trade exposure experience. Furthermore, it is relevant to mention that the CZ exposure variable is by nature a proxy of imports and they are not shipped to import competing CZs for redistribution but rather are distributed broadly to wholesalers, retailers, and consumers (Autor et al., 2013a).

A concern may be related to the fact that US imports from China may be affected by US demand shocks rather than just China's growing productivity and falling trade costs, which may be correlated with unemployment rate. To correctly identify only the *supply-driven* component of Chinese imports, which should cause the job displacement at CZ level, I use the contemporaneous composition and growth of Chinese imports in eight other developed countries and ten year lagged employment levels to rule out or at least mitigate simultaneity bias.[26]

$$\Delta import_{oit} = \sum_j \frac{L_{ijt-10}}{L_{jt-10}} \frac{\Delta M_{ocjt}}{L_{it-10}} \tag{3}$$

Equation (3) is similar to (2) and it only differs in two aspects. First, I use the realized imports from China to other high-income markets (ΔM_{ocjt}), which substitutes the previous ΔM_{ucjt} and, second, in place of start-of-period employment levels by industry and region, I lag the variable by ten years to avoid any simultaneity.[27]

[25] Information on industry employment structure by CZs, including employment in 397 manufacturing industries L_{ijt}, is derived from the County Business Patterns data following Autor et al. (2013a).

[26] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland are the eight other high-income countries with comparable trade data over the period 1990-2007.

[27] In Subsection 4.3, I run some robustness checks keeping the propensity to import fixed at the beginning of the first decade. The results are similar.

3.4 Data and summary statistics

In the following, I describe the data sources and discuss some descriptive statistics over the period 1990-2007. I aggregate the county data at the CZ level to estimate the link between unemployment and criminal rate at the same (geographical) unit. In order to match the geographic information contained in the IPUMS data to Commuting Zones I use the crosswalk developed by Autor et al. (2013a).[28]

Crime data come from the master file of the Uniform Crime Reporting program, UCR hereafter. Since 1930, law enforcement agencies in the United States have been participating in gathering crime statistics through the UCR program. The FBI administers the program and the participation, which is voluntary for all agencies at county level. The county-level crime data consider both less serious and more frequent property criminal activities and more serious and less frequent violent crimes. Using the "standard" definition in UCR program, I split the *total* crime category into two main components: (i) *violent*, which includes murders, rapes, robberies and aggravated assaults; (ii) *property*, which covers burglaries, larcenies, motor vehicle thefts and arson. Vandalism, fraud, stolen property and weapons violations are *other* crimes I look at because they are very closely related to property delinquency. Arrest rates are calculated as the number of arrests, aggregated at CZ level, divided by the working-age population in the observational unit and scaled by 100 for the ease of interpretation. Illegality is often measured by arrests but not all of the felonies are detected by the police and, for this reason, I also collect data on the offenses, which are divided into similar standard categories as I previously defined. From the same source of data, I additionally collect information on police force and the total number of prisoners.

Trade data are recovered from the UN Comtrade Database on US imports at the six-digit Harmonized System (HS) product level and then aggregate up to four-digit SIC industries.[29] Due to delays in countries implementing the HS classification, 1991 is the first year for which I can obtain data across many high-income economies (Autor et al., 2013a). The annual value of US imports for the years 1991, 2000, and 2007 (with all values in 2007 US$) is reported in Table 1, Panel A. The import value has exponentially increased over the period 1990-2007, as it jumped from $26 to $121 billions in 2000 and it reached its peak in 2007 ($330 billion). In the second column I show the value of annual US exports to China in 1992, 2000, and 2007. Comparing the results, it is plausible to conclude that the main change in trade between China and the United States (over the period) is due to an astounding increase of US imports rather than exports to China.[30]

Panel B shows the trade flows from the same exporters to a group of eight high-income countries located in Europe, Asia, and the Pacific (Australia, Denmark, Finland, Germany, Japan, New

[28] In order to group the counties into a single CZ, I use the crosswalk available in the Integrated Public Use Microdata Series projects (IPUMS) at this url: *https://usa.ipums.org/usa/volii/1990lma.shtml*.

[29] The data are available at *http://comtrade.un.org/db/default.aspx* and in order to concord these data to four-digit SIC I use both the crosswalk in Pierce and Schott (2012) and in Autor et al. (2013a).

[30] In order to put the two periods on a comparable decadal scale, trade growth during 1991 to 2000 and during 2000 to 2007 has been multiplied with the factors 10/9 and 10/7, respectively as it has been done by Autor et al. (2013a).

Table 1: Value of the trade with China for the US and other high-income countries

	Trade with China (in billions 2007 US$)			
	Panel A: United States		**Panel B**: Other developed countries	
	Imports from China	Exports to China	Imports from China	Exports to China
1991-1992	26.3	10.3	28.2	26.6
2000	121.6	23.0	94.3	68.2
2007	330.0	57.4	262.8	196.9
Growth 1991-2007	1156%	456%	832%	639%

Notes: Trade data is reported for the years 1991, 2000, and 2007, except for exports to China, which are all first available in 1992. The set of "other developed countries" in panel B comprises Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Zealand, Spain, and Switzerland). Like the United States, these countries experienced a dramatic increase in imports from China between 1991 and 2007, especially after China's WTO accession, and a more modest growth of imports from other medium- or low-income countries.[31] The high-income regions are useful to isolate the foreign-supply-driven component of changes in Chinese import penetration. As showed by Autor et al. (2015), the annual US imports from China increased by 304 billion dollars between 1991 and 2007, while Chinese imports grew by 235 billion dollars across the eight other high-income countries offering comparable trade data for the full sample period. Moreover, the pattern of import growth across industries is highly correlated among the US and the other countries, with correlation coefficients ranging from 0.55 (Switzerland) to 0.96 (Australia). The fact that China made comparable gains in penetration by detailed sector across numerous countries in the same time interval suggests that China's falling prices and diminishing trade and tariff costs in these surging sectors are the basis for its success.[32] The potential exposure of Commuting Zones to Chinese import competition comes from a detailed information on local industry employment structure in the years 1980, 1990 and 2000, which is taken from the County Business Patterns (CBP) data.[33] CBP is an annual data series that provides information on employment, firm size distribution, and payroll by county and industry and it covers all US.

Unemployment, duration data, individuals not in the labour force (hereafter NILF) and population structure are recovered from the Census Integrated Public Use Micro Samples for the years 1990 and 2000 (Steven et al., 2010), and the American Community Survey (hereafter ACS) for 2006 through 2008.[34] The 1980, 1990 and 2000 Census samples include 5% of the US population, while the pooled ACS samples include 3% of the population. Federal income assistance comprises Unemployment Insurance benefits, Social Security Disability Insurance (SSDI) benefits, income assistance benefits from SSI (Supplemental Security Income), TANF (Temporary Assistance for

[31] As discussed in detail by Autor et al. (2013a), these countries have been selected because they are the richest nations for which disaggregated HS trade data are available back to early nineties.

[32] All imports are inflated to 2007 US$ using the Personal Consumption Expenditure deflator.

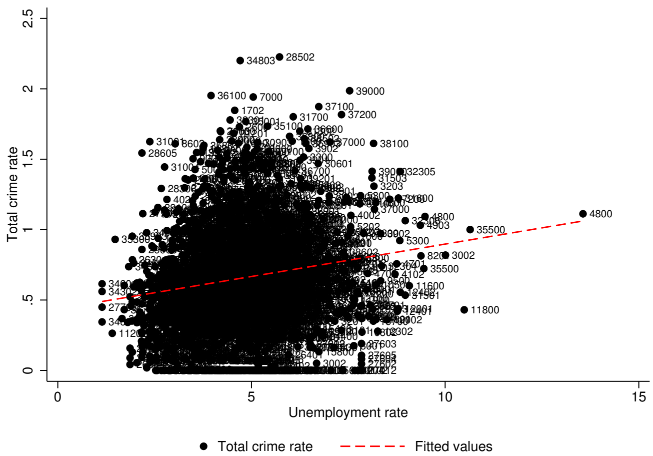
[33] CBP data is extracted from the Business Register, a file of all known US companies that is maintained by the US Census Bureau, and it is available for download in *http://www.census.gov/econ/cbp/index.html*. I follow the online material available in *http://www.ddorn.net/data.htm* and in Autor et al. (2013a) to build the propensity to import for each CZ.

[34] The CZs' sample is selected with the individuals aged between 16 and 64 and who were working in the year preceding the selected survey as in Autor et al. (2013a). The population composition comes from an excellent survey for recent 1969-on US population at the county level and by age, race, sex, and more recently Hispanic origin, which is available at *http://www.nber.org/data/seer_u.s._county_population_data.html*. Finally, the level of educational attainment at CZ level is derived from Eckhardt (2011) and is freely downloadable at *hdl.handle.net/1902.1/15351*.

Needy Families) are from Regional Economic Accounts of the Bureau of Economic Analysis (hereafter REA). The REA data provides the exact amount of annual transfers by county and transfer type unless the transfer is very small (i.e. positive amounts of transfers that are below 50,000 dollars in a given county and year). All transfer amounts are inflated to 2007 US$ using the Personal Consumption Expenditure deflator. Finally, the share of Democrats and Republicans are collected from American National Election Studies. I select the presidential elections in 1988, 1996 and 2004 which proxy 1990, 2000 and 2007 respectively.

The summary statistics provided in Table B.1 show that, approximately, 6.5 crimes per 1000 residents were committed over the period 1990-2007 in the United States, albeit these are property crimes in the great majority of cases (5 crimes). As expected the number of offenses is higher with respect to the arrests. The Table also shows that there are approximately 400 prisoners and 790 police force per capita (100,000 residents).[35] The average unemployment rate is around 4.6 per cent and the national trend over the periodo is decreasing. Understanding how crime rates respond to variations in economic labour conditions is a relevant task for economists and policy-makers but it is generally difficult to have a clear picture, especially in the case of aggregated data (for instance at the State level).

Figure 1: Correlation between crime rate and unemployment rate, 1990-2007

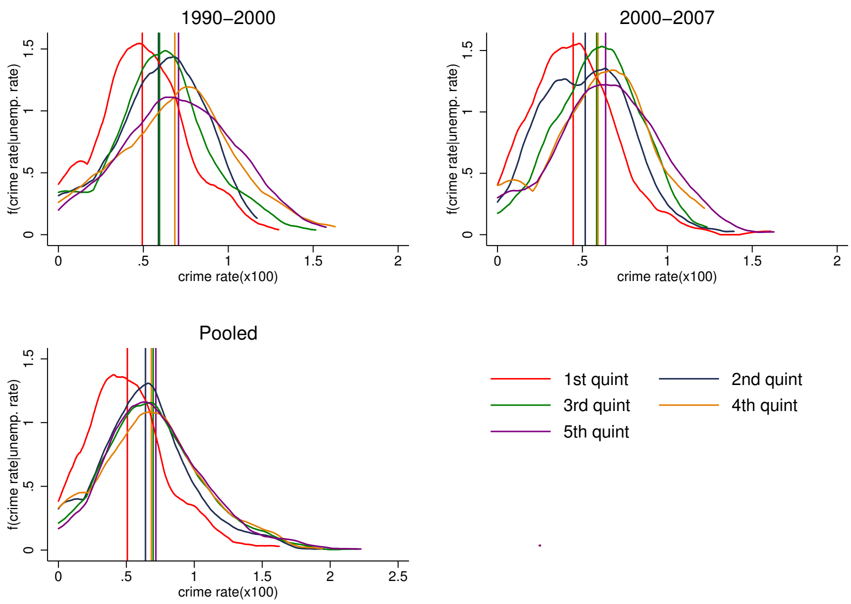


When looking at the raw data, as Figure 1 shows, higher unemployment rates are associated with higher total crime rates at CZ level. This mere correlation hightlights a positive relationship between these two phenomena. Obviously, there are numerous factors that could potentially change the nature of this correlation but it is still informative on the expected results. This correlation explains the reasons why economists typically conclude that unemployment or a decline in labour market conditions may lead to an increase in crime due to the worsening opportunities in the legal employment sectors, which make committing crimes more attractive activities (Ehrlich, 1973).

Figure 2 helps to clarify how the crime distribution depends on the specific unemployment rate quantile. Looking at the distribution of crime rate conditioning on the unemployment rate by

[35] Differently from the crime rate and the unemployment rate, these two variables are not expressed in per cent.

Figure 2: Crime rate distribution and unemployment rate by quintiles



quintile, I observe a positive propensity to commit more illegal activities moving from the lowest to the highest quintiles albeit this does not always hold across groups (obviously less crime in the bottom distribution). The vertical line, which indicates the average crime rate for each quintile, moves to the right supporting the general idea that a higher crime rate is associated with higher unemployment rate. I separately analyse the two decades and then I pool the data. The final result, even less evident than before, is a positive link between crime and unemployment rate also across distributions.

Finally, Figure A.3 and A.4 provide a general picture of the crime-unemployment relationship and the instrument, namely the exposure to China products. In particular, these figures show the geographical distribution of crime rate, unemployment rate and Chinese import exposure. Each map describes the impact of these phenomena using warmer (colder) colours for relatively larger (smaller) effects. Figure A.3, which refers to the decade 1990-2000, shows the total crime rates (in the Top Panel), the unemployment rate (in the Middle Panel) and the import exposure from China to eight high income countries (in the Bottom Panel). Figure A.4 refer to the decade 2000-2007 and it shows similar correspondence between the crime rate, the unemployment rate and Chinese exposure, which became more clear in the following decade. I will deepen these initial findings in Subsection 4.2 with regard to the First-Stage and Reduced Form equation where I also condition on a rich set of covariates. This preliminary descriptive analysis shows a positive correlation between these three variables and the evidence suggests that higher unemployment rates are associated with larger increases in Chinese import competition and, then, crime rates act accordingly.

4 Results: the Effect of Unemployment on Crime

In this section, I empirically analyse the relationship between labour market conditions and criminal activities both in terms of arrest and offense rates. To the extent that the variables omitted from the regression are correlated with the measure of labour market condition, there is scope for omitted variable bias. A relevant development in mitigating the bias from unobserved variables is the use of panel data estimation technique that allows to control for the time-invariant heterogeneity. As long as the heterogeneity is constant over time, it is possible to wipe out the omitted variables through differencing, for example by taking the model in first difference (FD). In Subsection 4.1, I initially estimate the model in FD using the repeated observations over time (1990, 2000 and 2007). As I explain in Subsection 3.2, the decade-specific model in equation (1) is equivalent to time fixed effects regression, while the stacked first difference model is similar to a three-period fixed effects model with slightly less restrictive assumptions made on the error term (Wooldridge, 2010).

Still, *ex ante*, the direction of causality is not guaranteed due to potential time-varying unobservables, which may bias the results of the crime-unemployment relationship. Hence, in order to identify the effects of unemployment at the local labour market level an exogenous source of variation is needed. I exploit the cross-market variation in Chinese import exposure stemming from initial differences in industry specialisation. This identification strategy predicts that rises in Chinese imports within a given industry (e.g. , apparel, footwear, furniture, luggage, toys) that occurs simultaneously in the US and other high-income countries are predominantly driven by the surge in Chinese productivity that have accompanied its transition to a market economy (Brandt et al., 2012) and by the reduction of trade barriers resulting from China's accession to the World Trade Organization. As discussed by Autor et al. (2013b), since manufacturers within an industry tend to cluster geographically, China's rising penetration of specific industries results in sharp disparities in the change in import exposure across CZs. The following Subsections discuss the empirical findings and the main mechanism with some robustness checks.

4.1 First difference estimations

Table 2 presents the regressions in FD where the dependent variable is the total crime rate at CZ level, which includes both violent and property crime. In column (1), I show the main estimate, only controlling for the specific decade effects. The evidence is clearly in favour of a strong positive relationship between crime and unemployment rate once the time-invariant unobserved heterogeneity is considered. The effect is significant at the one per cent level of confidence and it suggests that one percentage point increase in the unemployment rate is associated with a rise in total crimes by 35 per 100,000 residents. In column (2) I add a long set of controls, which are meant to capture the US population structural changes. For each age class, I define the change in the proportion of White, Blacks, Asians and Indians (baseline) with the idea to capture the observable differences in age and racial composition, which may bias the results. As expected, the age-race profiles are relevant determinants of the crime-unemployment association and the resultant point estimate shrinks to 0.019 significant at the ten per cent level of confidence. Overall, the results are in line with the recent findings on ethnic minorities. Some authors interpret this decline as resulting from greater upward mobility and a better social standing among African Americans during the past two decades. Nevertheless "[...] there may be a growing affluent black middle class, but at the same time, the black underclass appears to have become even more disenfranchised and more segregated from the rest of society" as discussed by Steffensmeier et al. (2011). At last, in line with the expectations, Table 2 shows a negative effect of the elderly characteristics (50-64) on the propensity to commit a crime.

Table 2: Total Crime Rate and Unemployment Rate, First-Difference Regressions, 1990-2007

Arrests	Total Crime Rate				
	(1)	(2)	(3)	(4)	(5)
ΔUnemployment	0.035***	0.019*	0.023**	0.019*	0.018*
	(0.013)	(0.011)	(0.011)	(0.010)	(0.010)
[*Elasticity*]	[0.25]	[0.13]	[0.16]	[0.13]	[0.13]
γ_t	-0.071***	0.036	0.044	0.033	0.041
	(0.019)	(0.039)	(0.032)	(0.094)	(0.092)
ΔAge 15-34					
White		1.870***	2.909***	3.061***	3.161***
		(0.657)	(0.926)	(0.791)	(0.810)
Black		-4.775**	-3.566	-3.462	-3.604
		(2.350)	(2.688)	(2.632)	(2.646)
Asian		-5.379	-5.949	-6.353	-5.494
		(8.148)	(9.395)	(8.607)	(8.586)
ΔAge 35-49					
White		-0.767	-1.999	-2.130	-2.320
		(1.198)	(1.354)	(1.400)	(1.436)
Black		2.779	-1.86	-1.643	-1.498
		(5.205)	(4.267)	(4.252)	(4.236)
Asian		-28.343*	-24.437	-23.473	-23.323
		(16.420)	(16.197)	(15.425)	(15.238)
ΔAge 50-64					
White		-1.501**	-2.213**	-2.335**	-2.519***
		(0.712)	(0.901)	(0.885)	(0.918)
Black		-3.757*	-5.645**	-6.045**	-5.957**
		(2.027)	(2.328)	(2.473)	(2.451)
Asian		-30.884	-19.234	-18.364	-19.069
		(22.426)	(23.001)	(21.731)	(21.249)
ΔNo Diploma			0.661	0.497	0.611
			(0.861)	(0.842)	(0.824)
ΔHigh School			2.241**	2.092**	2.127**
			(1.011)	(0.937)	(0.938)
ΔFederal Assistance				0.001	0.001
				(0.000)	(0.000)
ΔRepublicans				-0.071	-0.097
				(0.452)	(0.446)
ΔPolice Forces					-1.189
					(1.247)
Observations	1444	1444	1444	1444	1444
Clusters	48	48	48	48	48
R^2	0.03	0.151	0.179	0.182	0.184

Notes: N = 1444 (722 CZ x 2 time periods). The dependent variable is total crime rate which includes both violent and property crime. All the variables are expressed in first-difference (rates). Arrests are scaled by 100 for the ease of interpretation. All regressions include a dummy for the 2000-2007 period (γ_t). The reference category for the race profile, the level of education and the voters are Indians, individuals who obtained at least a bachelor degree and percentage of people who voted Democratic party, respectively. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

In column (3) I include other relevant controls such as educational attainment. As extensively discussed in the literature (Machin et al., 2011; Lochner and Moretti, 2004), there are a number of reasons to believe that education may affect subsequent crimes. Generally, the results are mildly affected and the coefficient of unemployment marginally increases to 0.023 significant at the five per cent level of confidence. Following Lin (2008) and Raphael and Winter-Ember (2001), I additionally include other relevant covariates, namely the change in percentage of Republican voters, which is used as a proxy of criminal-justice system, and the government expenditure in SSI, AFDC/TANF and SNAP programs. These controls include unemployment and social security disability insurance, income assistance benefits from supplemental security income and temporary assistance for needy families. These sets of variables are meant to pick any variation in the benefit claims, which may be associated with a decline in the economic conditions. As a consequence, it increases $defacto$ the relative payoff of criminal activity, thus inducing workers to substitute away from the legal sector towards the illegal sector. Both controls do not have any statistical significant impact on the outcome variable. Results are shown in columns (3) and (4).

Finally, in column (5), I include the (per capita) police force at CZ level as a measure of deterrence effects (Lin, 2008). Deterrence plays a crucial role in economic models of crime. Police forces deter crime by increasing the perception that criminals will be caught and punished. The variable is negatively correlated (not significant at the conventional level) with total crime rates. Another measure, frequently used in empirical analysis, of deterrence effects is the incarceration rate (Raphael and Winter-Ember, 2001). I further include the prison population in the robustness check and the results are invariant.

The total crime index is a combination of violent and property crimes. In Table B.2, I study the relationship between the unemployment and crime rate at CZ level focusing on the two main components: violent (Panel A) and property crime rates (Panel B). The former is the "more aggressive" component in which an offender uses or threatens force upon a victim. Violent crimes may, or may not, be committed with weapons. On top of this, some crimes, such as robberies, which are defined as violent, may depend on economic need: this relates to the action of taking or attempting to take anything of value from the care, custody, or control of a person. Violent crime rate, among others, includes burglary, larceny, theft, motor vehicle theft and arson. On the contrary, property crime involves the taking of property, and does not generally involve force or threat of force against a victim. Crimes against property are divided into two groups: destroyed property and stolen property. When property is destroyed, it would be called arson or vandalism. Examples of the act of stealing property is robbery. As expected, although unemployment has a positive effect on property crime, I do not find a clear link between worsening labour market conditions and violent crime rates. The magnitude of this effect is economically small and not statistically significant at any conventional level. By the same token, the evidence suggests an increase in property crime by 15 units.[36]

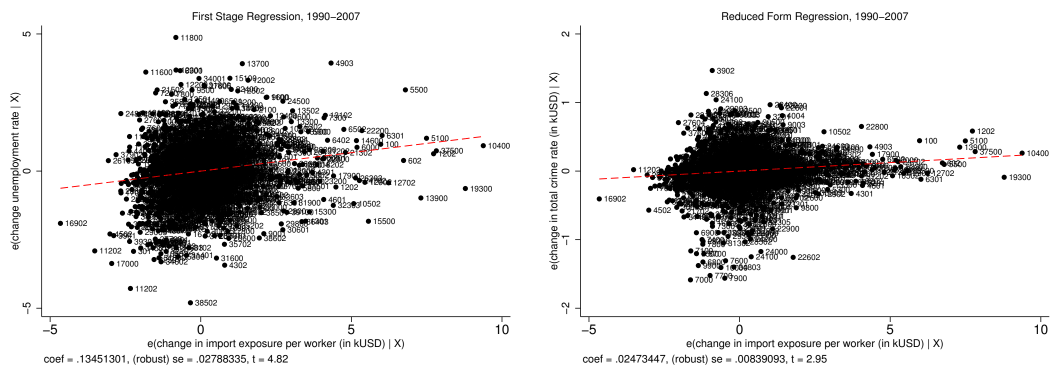
4.2 Impact of labour market trade shock on crime

The empirical findings of the previous section may still be plagued by omitted confounding factors that are not captured by the first-difference specification. As a consequence, an instrumental

[36]The correspondent elasticity for violent and property crime is 0.08 and 0.13, respectively, which is in line with the crime literature. Note that these results still suffer from downward bias.

variable approach is needed to tackle the endogeneity issue related to the crime-unemployment relationship. In order to identify the long-tem change effect of unemployment on crime rates, an exogenous source of variation is needed. Endogenous factors should not determine this change and I aim at describing the identification strategy I use, namely the effect of rising Chinese import competition between 1990 and 2007 on crime rate at CZ level passing through a change in the unemployment rate. The instrumental variable strategy, discussed in Subsection 3.3, identifies the component of US import growth that is due to Chinese productivity and trade costs, which affect local labour market conditions. Recall that if the model specifications leave out crime-determining factors, which are correlated with unemployment and that are not picked up by the fixed effects, the previous results in Subsection 4.1 will be possibly biased. Moreover, if crime rates reverse the direction of the causation with unemployment rates, OLS inference will not be appropriate.

Figure 3: 2SLS regression, 1990-2007



Notes: Added variable plots of First-stage and reduced form estimates: change in import exposure per worker (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) and total crime rate.

Using CZs level data it is possible to map the trade exposure from China. This approach is valid for identifying the labour market consequences of trade to the extent that CZs differ in their pattern of industry specialisation and frictions in labour markets allow regional differences to persist over the medium-long run. Therefore, before discussing the second-stage estimates of the unemployment effects on crime, an evaluation of the strength of the first-stage relationship is appropriate. Figure 3 sketches the estimation strategy. On the one hand, the left picture reveals the substantial predictive power of the high-income-country instrument for changes in US unemployment rate. A \$1,000 predicted increase in import exposure per CZ worker corresponds to a robust rise in unemployment rate by 0.13 percentage points. On the other hand, the right picture plots a reduced form (OLS) regression of the change in crime rate on the instrument. This figure shows a substantial increase in (total) crime in the CZs facing large increases in Chinese import exposure. The results suggest that there is indeed a reduced form effect of increase Chinese competition on crime rates. This evidence is itself striking and it demonstrates an intended and disturbing effect of trade shock.[37]

[37]For an easier visualization, Figure 3 shows the results without 4 Commuting Zones which are Calloway County,

Table 3: Total Crime and Unemployment Rate, 2SLS Regressions, 1990-2007

Arrests	Total Crime Rate	Violent Crime Rate	Property Crime Rate
Panel A: 2nd Stage	(1)	(2)	(3)
ΔUnemployment	0.120***	0.021	0.098***
	(0.043)	(0.013)	(0.032)
[*Elasticity*]	[0.78]	[0.59]	[0.85]
All controls	✓	✓	✓
Observations	1444	1444	1444
Clusters	48	48	48
R^2	0.013	0.001	0.041
RMSE	0.339	0.097	0.275
Panel B: 1st Stage			
ΔImports China-other		0.132***	
		(0.022)	
First-stage		26.93	
Kleibergen-Paap LM test (p-value)		0.000	
C.D.W. F-stat		63	

Notes: N = 1444 (722 CZ x 2 time periods). The dependent variable is total crime rate (over the working-age population), which includes both violent and property crime. All the variables are expressed in first-difference (rates). I rescale the outcome by 100 for the ease of interpretation. All regressions include a dummy for the 2000-2007 period (γ_t). The reference category for the race profile, the level of education and the voters are Indians, individuals who obtained at least a bachelor degree and percentage of people who voted Democratic party, respectively. First-stage estimates in Panel B also include the control variables that are indicated in the second-stage. The instrument in all the regressions is Chinese imports in eight developed countries. Robust standard errors in parentheses are clustered at the State level. * p<.10 ** p<.05 *** p<.01.

Table 3 presents the 2SLS estimates of the unemployment effects, induced by an increase in Chinese import competition, on total, violent and property crime rates at CZ level.[38] In Panel B, I report the first-stage statistics, which integrate the previous information found in Figure 3. The result from first-stage regression suggests that Δ*Imports China-other* is a strong predictor of US unemployment with an F-statistic around 27, larger than the rule-of-thumb threshold of 10 proposed by Staiger and Stock (1997). I reject the null hypothesis of weak instrument problem using both the Kleibergen-Paap LM test and Cragg-Donald Wald F statistic (Kleibergen and Paap, 2006). It is worth clarifying what the estimated model identifies and how the IV estimates should be interpreted. Following Imbens and Angrist (1994), the Local Average Treatment Effect (LATE) measures the effect for those whose unemployment status is affected by the instrument, though this requires a suitable monotonicity assumption. This means that, while the instrument may have no effect on some unemployed, all those who are affected are influenced in the same way. In this context, I identify the LATE for those whose unemployment status is affected by the change in exposure to China products. Hence, the compliers are those unemployed who are triggered by the increase in Chinese competitiveness at CZ level and they suffer more from these trade shocks inducing longer unemployment spells. I shed light on the main channel through which the rise in the Chinese import penetration affects the duration in unemployment in the Subsection 4.3. This interpretation would also reasonably motivate why I find the IV estimates to be larger, in magnitude, than the OLS ones. This is consistent with Imbens and Angrist (1994) who show that, in the presence of heterogeneous effects, the IV estimates may well exceed the OLS estimates.[39]

KY (25402), Edwards County, IL (14801), Chase County, KS (29402) and McLeod County, MN (21201). The main analysis includes the all sample of the 722 CZs.

[38]The estimation with the full set of covariates is shown in Table B.3, in Appendix.

[39]According to Imbens and Angrist (1994), the IV estimator is a weighted average of local average treatment effects with higher weights attributed to those parts of the support of the IV for which changes in the instrument

The evidence from Table 3 suggests a sizable impact of Chinese trade shocks, passing through a change in labour market conditions, on crime rate among US CZs. I find that a one percentage point increase in unemployment rate causes a rise of total arrests by 120 per 100,000 residents, which is to say that one standard deviation increase in the unemployment causes 165 more crimes. The 2SLS estimation then yields a 0.78 elasticity of the total arrest rate with respect to the unemployment rate, which is statistically significant at the 1% level. In column (2), the result for violent crime is not statistically significant at any conventional level. The effect implies that one percentage point increase in unemployment rate moves violent crimes by 21 units per 100,000 habitants. By the same token, the evidence suggests an increase of property crimes by 98.[40] The circumstance that IV estimates are higher than their OLS counterparts suggests that, among the sources of bias, those that deliver attenuation (such as the measurement error) are likely to play a prominent role.

Table 4: Different Crimes and Unemployment Rate, 2SLS Regressions, 1990-2007

Panel A: Violent Crimes	Murder	Rape	Robberies	Assaults
	(1)	(2)	(3)	(4)
ΔUnemployment	0.000	0.001	0.006***	0.013
	(0.000)	(0.001)	(0.002)	(0.011)
[*Elasticity*]	[0.08]	[0.50]	[1.42]	[0.49]
Panel B: Property Crimes	Burglaries	Larcenies	Vehicle thefts	Arson
	(1)	(2)	(3)	(4)
ΔUnemployment	0.023**	0.069***	0.007**	0.000
	(0.009)	(0.023)	(0.003)	(0.001)
[*Elasticity*]	[0.97]	[0.79]	[0.89]	[0.07]
Panel C: Other Crimes	Vandalism	Fraud	Property stolen	Weapons
	(1)	(2)	(3)	(4)
ΔUnemployment	0.005	0.005	0.003	0.005
	(0.006)	(0.025)	(0.002)	(0.003)
[*Elasticity*]	[0.23]	[0.23]	[0.43]	[0.50]
Observations	1444	1444	1444	1444
Clusters	48	48	48	48
All controls	√	√	√	√

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 3. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

I further investigate the effect of unemployment on crime rate distinguishing by types focusing on a variety of violent, property and the other crimes. Table 4 shows a clear and strong association between the worsening of LLM opportunities and the economic crimes. In Panel A, violent crimes are not responsive and the only exception is the highly statistical significance of the robberies. On the one hand, they imply the use of the force and this is the main reason why it is generally categorized under the violent group. On the other hand, UCR defines robbery as the taking or attempting to take anything of value from a person. It appears clear that robbery is mostly driven by economic needs, which are triggered by worsening labour conditions, namely increasing unemployment rate, exacerbated by the increase of Chinese competition. The effect shows an elasticity of 1.42 suggesting a more than proportional effect. This result is new in the literature and it implies that one per cent increase in unemployment causes almost 1.5 per cent rise in the

have greater effects on the endogenous variable.

[40] The 2SLS estimations for violent and property crime yield a 0.59 and 0.85 elasticity with respect to the unemployment rate, respectively.

arrests for robberies.

The findings concerning property crimes are fairly substantial, with the exception of arson, which is not statistically significant. The reasoning seems opposite to the previous case of robberies. UCR defines arson as any willful or malicious burning or attempting to burn, with or without intent to defraud, a personal or public property. Consequently, it is legitimate to believe that the increase in unemployment essentially triggers those crimes related with the need to satisfy economic needs. As expected, jobloss, induced by Chinese trade shocks, forces the unemployed to switch to the illegal sector. This is especially true for those who register longer unemployment duration spells.

For the burglary rate, the 2SLS results are positive and significant at five per cent, while for larceny the evidence is positive and significant at a one per cent confidence interval. Again, when significant, instrumenting, yields stronger unemployment effects relative to the previous results in Table 2. Finally, Panel C provides some further evidence using other relevant criminal activities. Vandalism and weapons possession, which primarily involve the use of violence, do not seem responsive to changes in unemployment rate stemming from an increase in Chinese competitiveness. Conversely, the property stolen and the fraud rates are not significant at any conventional level. The reason behind this evidence relates to the fact that these illegal activities need more "criminal ability" than, for instance, a simple larceny-theft. In fact property stolen crime is defined as the buying, receiving, possessing, selling, concealing, or transporting any property with the knowledge that it has been unlawfully taken (by burglary, larceny or robbery for example). The case of fraud requires an intentional perversion of inducing another person or other entity in reliance upon it to part with something of value or to surrender a legal right. Fraudulent conversion and appropriation of money or property by false pretenses involve a high level of criminal "technicality" both in terms of resources and organization. The marginal unemployed, who will be more likely to commit a (property) crime, is the one who at some point switches to the illegal sector in order to satisfy monetary needs. I expect to find weak effect for the category of crimes, which involves violence or high "criminal" skills, which implies to have a sort of criminal career. It seems clear that, so far, evidence shows larger effects for crimes related with an economic need.[41]

The results for non-economic related crimes can be seen as a further reinforcement of the idea that displaced workers - due to a rise in China competitiveness - may commit crime to primary satisfy their economic needs. On top of this, some violent crimes are anyway weakly correlated on economic conditions; secondly, violent crimes, such as murders or sexual abuses (which I do not show here), are generally associated with some criminal skills (e.g. the ability to use a weapon), which are unlikely to be developed in the short term. Therefore, if I find that the measure of economic activity is also related to crimes for which no link is expected, I should suspect that I am mistakenly capturing something else (for instance, a surge in crime due to cultural factors that have nothing to do with the concomitant downturn). This does not appear to be the case. The empirical evidence finds that the economy does not have any role in murders and sexual crimes.

[41] All these results are confirmed when I focus on the offenses rates in Table B.4. As expected the effects are larger with respect to the ones in Table 4.

4.3 The main mechanism

To the best of my knowledge, this is the first study that estimates the effect of a long-term change in trade-induced unemployment on crime rate at US CZ level. Differently from the previous literature, the 2SLS empirical evidence in this paper yields a larger elasticity of total crime rate with respect to the unemployment rate, which is statistically significant at the 1% level. The most recent studies, listed in Table 5, try to account for the endogeneity concern in the crime-unemployment relationship and estimate a property crime elasticity of about 0.3 (Lin, 2008; Raphael and Winter-Ember, 2001), that is considerably smaller than 0.85, which I find in this paper. This strategy highlights the long-term change variation in the crime and LLM structure. Given the consequences of criminal activity, including human capital investments specific to the illegal sector and the potential for extended periods of incarceration, crime should be more responsive to low-frequency changes in CZs' conditions. Due to the measurement error in the independent variables, especially when measured at state-level, the changes may suffer less from attenuation bias than the estimates based on annual data, as it has been recently discussed by Gould et al. (2002).

Table 5: Recent literature on crime-unemployment relationship

Authors	Analysis	IV Instruments	Elasticity of Property Crime
Raphael and Winter-Ebmer 2001	State-level panel 1971-97	State military contracts	OLS: 0.11
		Exposure to oil shocks	IV: 0.35
Lin 2008	State-level panel 1974-2000	Δ in exchange rates and oil prices	OLS: 0.15
		% State union membership	IV: 0.28
		% State manufacturing	

Although the comparison with previous contributions is not obvious, mainly due to a lack of general consensus about the crime-unemployment elasticity, I further discuss the implication of the results presented in Section 4.2. In cases where response to treatment varies across CZs, Imbens and Angrist (1994) point out that using linear IV gives an estimate of the local average treatment effects for "compliers" (those induced to get treatment by assignment to the treatment group). Following Imbens and Angrist's (1994) LATE interpretation, the subpopulation of compliers would reveal the causal effect of being unemployed for the marginal individuals whose likelihood of being unemployed is affected by changes in exposure to Chinese products. This is likely to be an unemployed in the sector of greater exposure, with relatively higher difficulty to migrate to other CZs and then facing longer unemployment spells. This interpretation would also reasonably motivate why the IV results are larger, in magnitude, than OLS ones, which also suffer from well-known attenuation bias.[42] shortly (with respect to what)

Additionally, as argued by Becker (1968), the probability of engaging in criminal activities depends on how long an individual takes to exit from unemployment. At the margin, an individual that remains in unemployment is more likely to become a criminal than her re-employed hypothetical counterpart. Local labour market conditions become more severe the longer an individual is unemployed and human capital depreciation further decreases expected future employability and

[42] It is indeed difficult to fully compare the results in here with the ones generally found in the literature, principally, because of different period, geographical units and subpopulation of compliers.

potential legal returns. In this study, the instrument is likely to pick up the marginal individual who will dramatically decrease her employability due to longer unemployment duration.

Table 6: Unemployment Duration and Imports from China, 1990-2007

	Unemployment Duration (weeks)			
	Average	Short-term (≤ 14)	Medium-term (15-26)	Long-term (≥ 27)
	(1)	(2)	(3)	(4)
ΔImport China-other	0.065***	0.0004	0.0004***	0.0007***
	(0.019)	(0.0003)	(0.0001)	(0.0001)
All controls	√	√	√	√
Observations	1444	1444	1444	1444
R^2	0.512	0.177	0.207	0.644

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 3. The dependent variable in column (1) is average duration at CZ level. From Columns (2) to (4), the dependent variables are the (change of) percentage of individuals in short, medium and long-term unemployment. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table 6 corroborates this hypothesis. The evidence in column (1) suggests a positive correlation between the change in average unemployment duration and the change in exposure from Chinese products. It is clearly showed that an increase in import competition from China is associated with a rise in the average unemployment duration at CZ level. Think of two almost identical US CZs, which assumably look homogeneous with respect to the most relevant socio-economic and demographic characteristics such as GDP per capita, population and density, e.g., once again, Buffalo, NY and Orlando, FL, which hypothetically only differ in their initial industry specialisation. Rising imports correspond to higher unemployment duration. Thus in this example, Buffalo, NY is likely to face, *ceteris paribus*, a larger increase in the average unemployment duration due to a worsening of LLM opportunities. This may happen as a result of the dramatic structural changes due to the rise in Chinese exports that are likely to be associated with longer unemployment spells, and that may constantly decrease the return to legal market and determine an (expected) increase in their risk to undertake criminal activities. Following this line of reasoning, I would *ex ante* expect a stronger association with the CZs characterised by longer unemployment spells. Table 6 shows the results for short, medium and long-term duration (Krueger et al., 2014).[43] On the one hand, there is not evidence of association between the instrument and the (change in the) share of individuals in short-term unemployment, as it is displayed in column (2), suggesting no effect for the individuals who are temporarily unemployed. On the other hand, the exposure to Chinese competion is statistically significant and correlated with medium and long-term unemployed at 5% and 1% level, respectively: the larger the import from China the higher the duration in unemployment both in the medium and the long-term.

The arguments made above are valid in the case of weak migration responses. In order to correctly identify the effect of unemployment rate on crime rate, I need to avoid any significant change in the working-age population in each decade. Undoubtedly, a serious concern for the identification relates to the fact that if labour is highly mobile across regions, trade may affect workers without its consequences being identifiable at the regional level. Nevertheless, the literature on regional adjustment to labour-market shocks suggests that mobility responses to labour demand

[43]The separate results in column (2), (3) and (4) are similar to estimate seemingly unrelated regressions (SUR) conditioning on the same set of covariates.

shocks across US cities and States are slow and incomplete (Topel, 1986; Autor et al., 2013a).

Table 7: Imports from China and Change of Working-Age Population, 1990-2007

	ΔLn Pop$_{it}$		
	(1)	(2)	(3)
ΔUnemployment	-0.0039	0.0209	
	(0.0104)	(0.0138)	
ΔImports China-other			0.0037
			(0.0027)
γ_t		$\checkmark$	$\checkmark$
Observations	1444	1444	1444

Notes: N = 1444 (722 CZ x 2 time periods). Columns (1) and (2) show the 2SLS estimations. Column (3) shows the direct impact of import from China on the change in population. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

It is therefore plausible that the effects of trade shocks on regional labour markets will be evident over the medium term; indeed, the analysis does not find significant population adjustments for local labour markets with substantial exposure to imports. The sluggish response of regional labour supply to import exposure may be related to the costly mobility of labour between sectors, as documented by Artur et al. (2010) in the United States. In columns (1) and (2) I control whether the change in import competition, passing through an increase in unemployment, has any impact on the change of (logarithm) working-age population. Including the decade dummy the coefficient turns positive but there is no statistical significant evidence that shocks to local labour market lead to substantial changes in population (Table 7). Moreover, there is no significant direct impact of increasing exposure from Chinese products and the change in population. These results are in line with the literature, which underline that mobility responses are slow.

4.4 Robustness checks and further results

In the following Subsection, I conduct some robustness checks to the main specification. I start by including the prison population rate at CZ level. This is a different measure of deterrence used in the literature, for example by Raphael and Winter-Ember (2001), and it plays a crucial role in economic models of crime. The results are shown in column (1) and do not suggest any difference with respect to the baseline evidence. The coefficient of the change in prison population is significant at 1% level and it has the expected negative sign. In column (2), I include as a new covariate, namely the mean log weekly earnings in a CZ. If, plausibly, workers with lower ability and earnings are more likely to lose their job in the face of an adverse shock (which has been established with the First-stage), the inclusion should capture a possible wage effect (Gould et al., 2002). The effect of unemployment on crime rate marginally increases and the "potential" wage confounding is not at work, as the variable is not significant at any conventional levels. In the last column, I further control for the share of non-participating individuals in the labour force. The evidence illustrates a slight increase of the main effect and is still positive and highly significant. The NILF rate is negatively correlated with the total crime rate, suggesting that the individuals out of the labour force are less likely to engage in criminal activities. This is a resonable conclusion considering the fact that, as I explained before, the bulk of this category is comprised of full-time homemakers, retirees, students who have no other occupation and people permanently unable to work, which are in principle less likely to commit a crime.[44]

Another concern relates to the fact that US exposure to Chinese products may be correlated with pre-existing trends in the outcome of interest. For this reason, I introduce the initial crime level for each decade as a new independent variable to rule out that the estimated effects were driven by a (coincidental) correlation between pre-existing trends and (future) US imports from China. The result showes that pre-trends had no effect on our estimates of interest, indicating that pre-existing trends are not likely to be a challenge to the identification strategy, Column (4) in Table 8 shows the results. Moreover, I conduct a placebo exercise where I regress the changes in crime rates on future US exposure to Chinese products. In case of pre-existing trends, the regression would yield statistically significant results. I replicate the specifications in Table 3. Results are presented in Table B.6. All coefficients are very small in magnitude, with opposite signs to those from Table 3, and none is statistically significant both for the 2SLS specifications and reduced forms, in Column (1)-(2) and (3)-(4), respectively. Indeed, pre-existing trends do not seem to be a challenge to the identification strategy. As a further robustness check, I estimate the main regression including all the controls at the beginning of each decade. The results are in Table B.5 and they are similar to the baseline.

Table 8: Robustness Check I, 2SLS Regressions, 1990-2007

Arrests	Total Crime Rate				
	Baseline	(1)	(2)	(3)	(4)
ΔUnemployment	0.120***	0.120***	0.148***	0.171***	0.118***
	(0.043)	(0.043)	(0.059)	(0.063)	(0.049)
ΔPrisoners pc		-0.343***			
		(0.147)			
ΔAverage wage (log)			0.008		
			(0.006)		
ΔNILF				-0.019**	
				(0.009)	
Total Crime (at the initial t)					-0.591***
					(0.050)
All controls	√	√	√	√	√
Observations	1444	1444	1444	1444	1444
1st Stage (F-stat)	26.93	26.76	18.23	18.91	26.55

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 3. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

In this part, I argue that the main empirical evidence is not driven by any outlier in the distribution of change in trade shock, crime and unemployment rate. Thus I control whether an extraordinary decade change in one of these variables may have deteriorated the main conclusions. To do so, I drop from the sample the top and bottom 1 (5) percentile of their distributions. The results are still similar to the baseline as it is shown in Table B.7, columns (1) to (6).

An additional exploration relates to the heterogeneous effects across macro local economies. This study helps to shed some light on the nature of the phenomenon I analyse. Concerning the geographic areas, I split the sample into South-Atlantic versus Central-West zone roughly around

[44] I also redefine the endogenous variable of interest as the sum of the unemployed individuals and the people not in labour forces. The results (not shown here) are similar, though the magnitude of the coefficient appears slightly weaker due to the inclusion of individuals out of the labour forces.

the Mississippi river as a dividing line between Eastern and Western 'halves' of the U.S., which also represents the only way to balance the trade-off between number of observations and capturing the heterogeneous effects across CZ. In Table 9 there is some evidence of heterogeneous responses across geographic regions in fact the point estimate is larger for South-Atlantic zone and (smaller) not significant in the other case, column (1) and (2), respectively. A further evidence, shown in the last two columns, points in the direction that trade-induced unemployment-crime is larger in the metropolitan than the rural areas which is in line with the IV strategy.

Table 9: Robustness Check II, 2SLS Regressions, 1990-2007

Arrests			Total Crime Rate		
	Baseline	(1)	(2)	(3)	(4)
ΔUnemployment	0.120***	0.162***	0.040	0.182*	0.091***
	(0.043)	(0.039)	(0.039)	(0.103)	(0.031)
All controls	✓	✓	✓	✓	✓
Sample	All	South-Atlantic	Central-West	Metropolitan	Small-town/Rural
Observations	1444	664	780	616	828
1st Stage (F-stat)	26.93	30.71	13.9	11.87	32.3

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 3. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

To conclude I replicate the main analysis running some sensitivity both on the propensity to import from China and on the method of estimate. I redefine equation (4) as the Chinese import exposure per worker in a CZ keeping the propensity to import fixed at the beginning of the first decade (1990).[45] The alternative instrument follows:

$$Import_{uit} = \sum_j \frac{L_{ij1990}}{L_{j1990}} \frac{\Delta M_{uct}}{L_{i1990}} \tag{4}$$

In this expression L_{i1990} is the employment in the 1990 in CZ i and ΔM_{ucjt} is the observed change in US imports from China in industry j between the start and end of the period. I then estimate the model in fixed-effects (FE) assuming that the errors are serially uncorrelated, while the first-difference specification (Subsection 4.2) is more efficient in case of random walk errors. Since before I apply errors clustered on US State the first set of estimates are more robust. The empirical evidence from column (1) to (3) is similar to the baseline model and the effect of unemployment rate on crime is larger than the effects in Table 3. Futhermore in columns (4) to (6), I also consider the use of population weights and, following the recent discussion on the topic (Solon et al., 2015; Durlauf et al., 2014), I weigh the regression by the share of CZ population. According to Durlauf et al. (2014), the use of population weights to control for heteroskedasticity in crime rates has almost little evidentiary support in many model specifications. The past literature justifies the use of the weights with different assumptions, which range from the specification of the nature of the policy effect to choices of control variables; from heteroskedasticity corrections to formulations of potential parameter heterogeneity and the choices of instrumental variables. The use of population weights has become standard practice in empirical crime studies (Raphael and Winter-Ember, 2001; Lin, 2008). There are various reasons for including weights, but the usual argument is based on concerns

[45]Table B.8 (Panel B) shows the results using a slightly different version of equation (4) in which I compute the exposure to Chinese product per-capita instead of per-worker.

regarding heteroskedasticity of the residuals. However, it ignores the possibility that location-time-specific unobservables, such as unmeasured demographic and socio-economic factors, are present (Durlauf et al., 2014). Consequently, the use of population weights will overweight observations from more populous counties, leading to invalid confidence intervals, and potentially misleading point estimates. In other words, models with weights are more likely to find larger effects on crime. The results in Table B.8, although similar to the baseline (Table 3), may confirm this possibility. In sum, the analysis in this section supports the previous endings that worsening labour market conditions, triggered by an unexpected rise in Chinese competition, affect the long-run change propensity to commit a crime at CZ level.

5 Conclusions

To the best of my knowledge, this is the first analysis that offers empirical evidence on the effect of a long-term change in trade-induced unemployment on crime rate triggered by the increase in the exposure to Chinese trade at US CZ levels. I provide new evidence on the causal effect of unemployment on crime exploiting the exogenous variation in import exposure to China products by CZ. Rising import competition has a large LLM effect in terms of increased unemployment rate. The results presented here consistently indicate that unemployment is a relevant determinant of the rise in crime rates.

For the first time, an empirical study provides a coherent narrative for the impact of labour market trade shocks on crime rate through a displacement effect using CZ data. Adverse shocks to local employment opportunities, stemming from rising competition from China, increase the propensity to commit economic related crimes. The central finding of the paper, however, is that trade shocks to labour market outcomes have strikingly and surprisingly parallel impacts on crimes both in terms of arrests and offenses. Another unique feature of this study relates to the possibility to map the crime phenomenon for the US mainland including both metropolitan and rural areas.

Although the comparison with previous contributions is not straightforward, mainly because of the different LATE interpretations, I generally estimate greater elasticity leading to almost one-to-one relationship between crime and unemployment, which is likely to be induced by longer duration in unemployment. Trade has significant distributional costs, which are tangible at local level: Chinese imports determine a sharp increase of unemployment in more trade-exposed labour markets. Here the focus is on the relationship between crime and unemployment. Thus, I study another possible collateral effect of import competition which should be a priority in the research agenda for labour economists.

Additionally, as argued by Becker (1968), the probability of engaging in criminal activities depends on the length of the individual exit from unemployment. At the margin, the still unemployed individual is more likely to engage in criminal activities than her re-employed counterpart. An increase in import competition from China is also associated with a fair rise in the average unemployment duration at CZ level. Two almost identical US CZs, which are hypothetically homogeneous in the socio-economic aspects, e.g., once again, Buffalo, NY and Orlando, FL, and only differ in their initial industry specialisation, are differently affected. Furthermore, additionally to what has been found in the literature by Autor et al. (2013a), rising imports correspond to higher unemployment duration. Thus, Buffalo, NY is likely to face, *ceteris paribus*, a major increase in the average unemployment duration due to a worsening of LLM opportunities. This interpretation would also suggest the motivation why the IV results are larger, in magnitude, than OLS. The evidence and arguments made above are valid in the case of weak migration responses, which are not significant at any conventional level. The robustness checks confirm the main results.

Possibly, the policy-makers should also consider the collateral cost of trade shocks associated with job displacement. A possibility would be to develope effective tools in order to limit the chances that the individuals stay out-of-work for long. A potential solution would point in the direction of vocational courses which should be designed to help the unemployed to learn, in a practical way, how to change the specific industry sector. In this way, the individuals who work in the sectors most exposed to Chinese products, may reduced the probability to be fired, increasing the mobility across-sectors (less exposed) and avoid *de facto* to engage in criminal activity to satify their economic needs.

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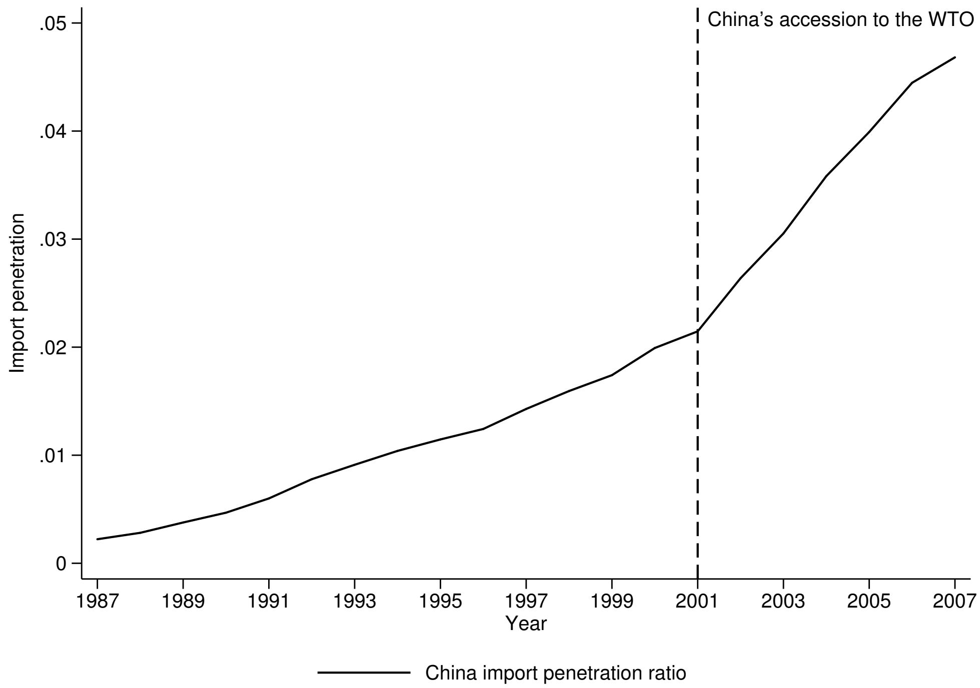
Appendix A: Figures

Figure A.1: Import Penetration Ratio for US-China



Notes: Import penetration is computed as US imports from China divided by total US expenditure on goods, measured as US gross output plus US imports minus US exports (Autor et al., 2013a).

Figure A.2: 722 US Commuting Zones, by Interstate Regions

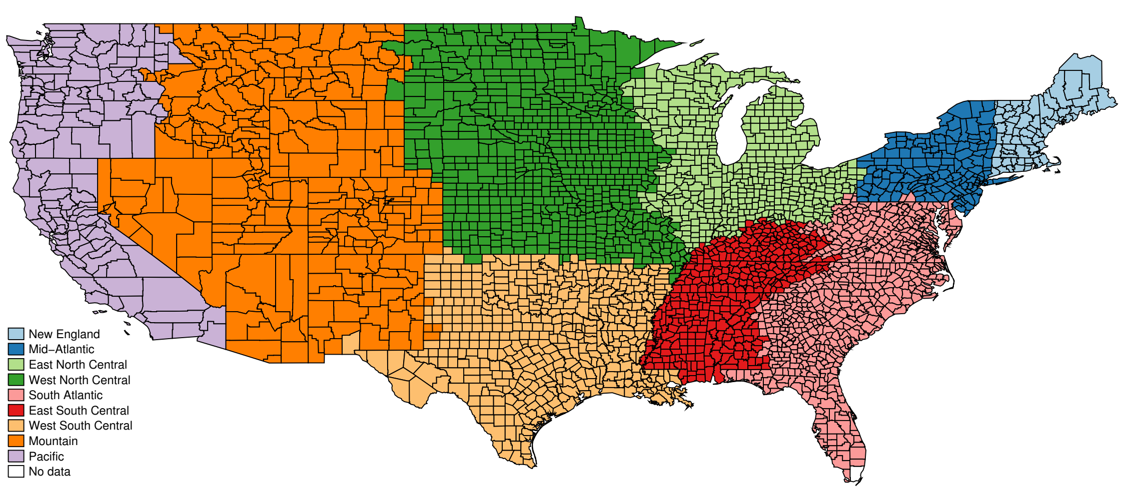
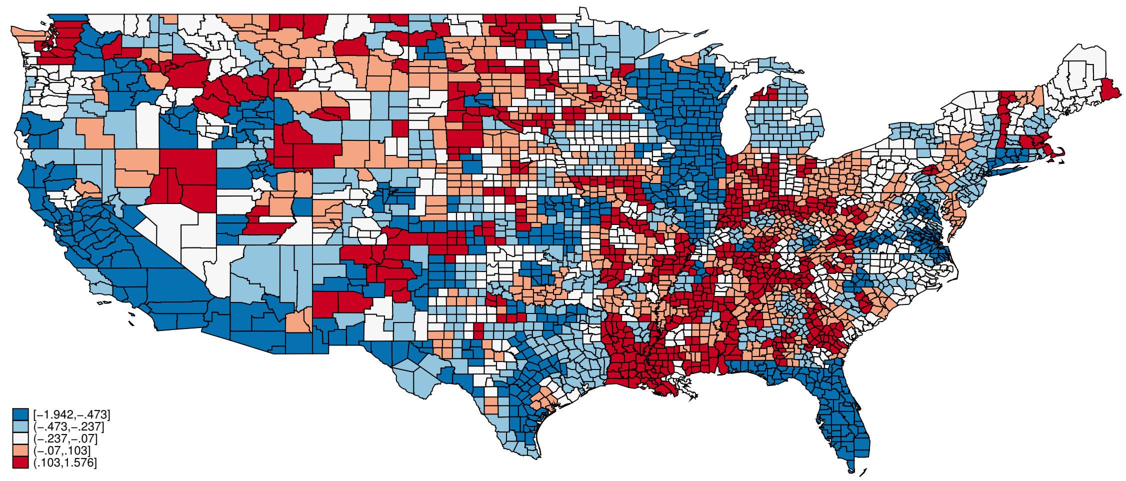
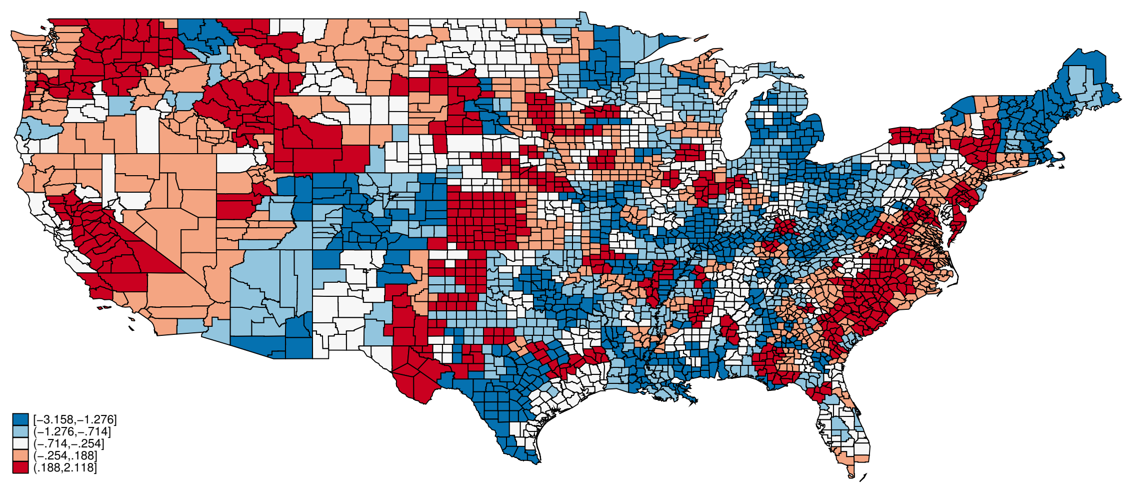


Figure A.3: United States Maps at CZ Level, over the Period 1990-2000

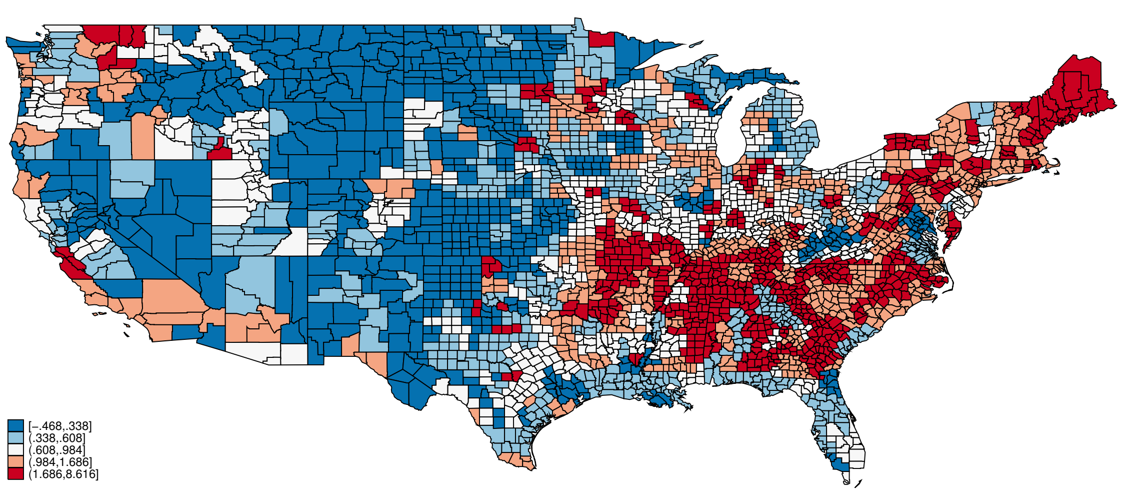
Top Panel: Average Δ Total Crime Rate



Middle Panel: Average Δ Unemployment rate



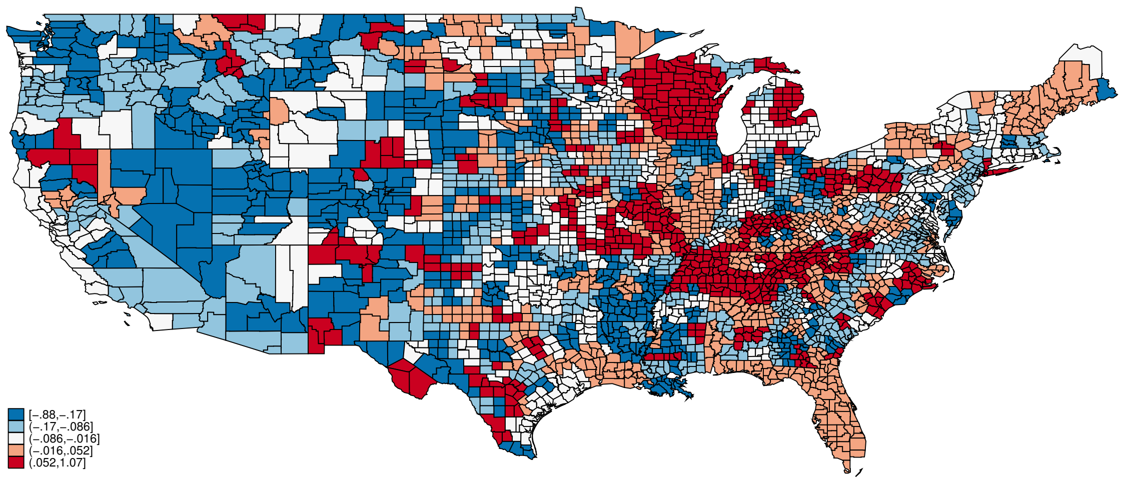
Bottom Panel: Average Δ Import Exposure per worker (in kUSD)



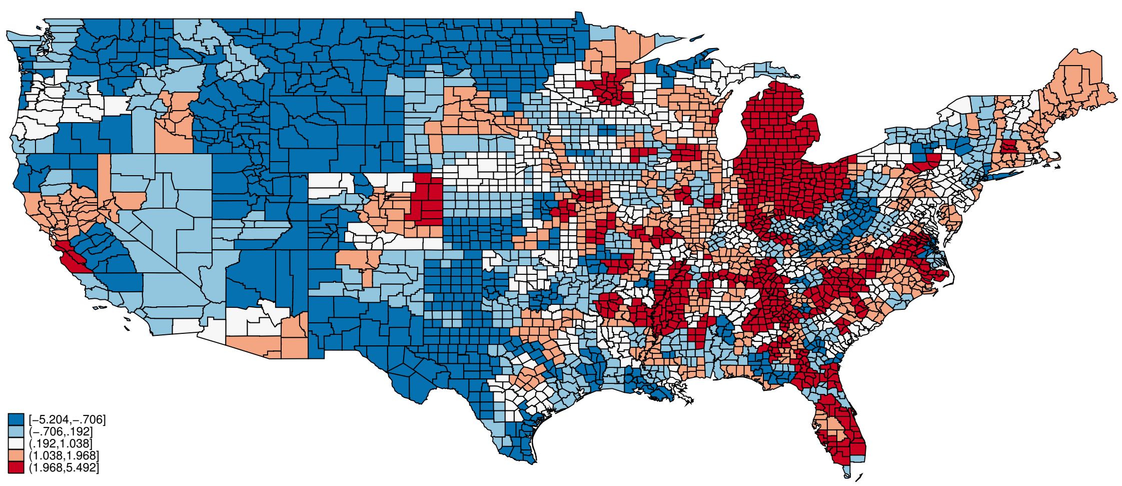
Notes: All the variables are ten-year equivalent changes between 1990-2000. Total crime is the sum of violent and property crimes. Import exposure per worker (in kUSD) is the instrument and it relates to the import from China to eight high income countries, namely Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Figure A.4: United States Maps at CZ Level, over the Period 2000-2007

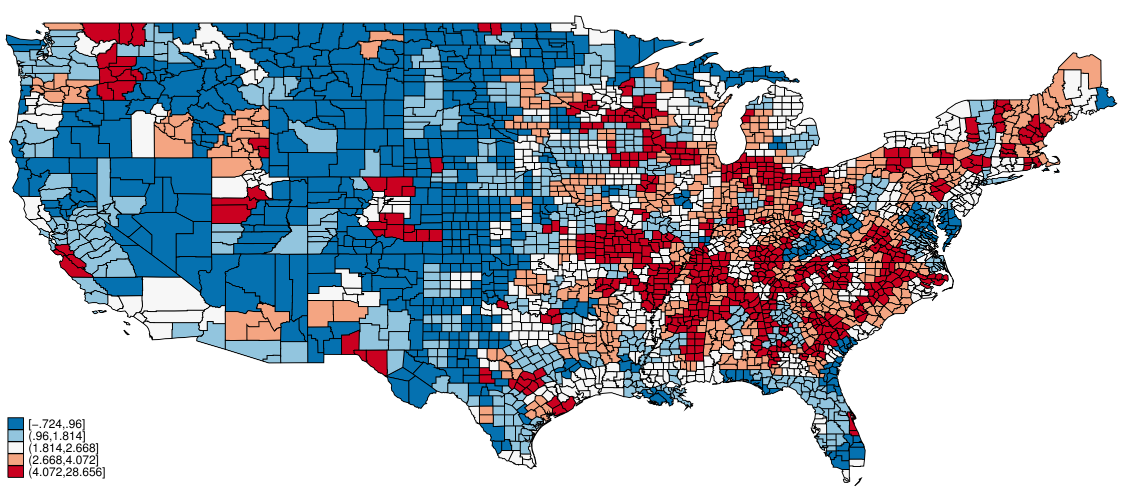
Top Panel: Average Δ Total Crime Rate



Middle Panel: Average Δ Unemployment rate



Bottom Panel: Average Δ Import Exposure per worker (in kUSD)



Notes: All the variables are ten-year equivalent changes between 2000-2007. Total crime is the sum of violent and property crimes. Import exposure per worker (in kUSD) is the instrument and it relates to the import from China to eight high income countries, namely Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Appendix B: Tables

Table B.1: Summary statistics, 1990-2007

	Levels				Differences			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Arrests								
Total crime (A+B)	0.649	0.365	0.000	2.226	-0.112	0.341	-1.942	1.576
Violent crime (A)	0.143	0.110	0.000	1.006	-0.011	0.097	-0.867	0.429
Property crime (B)	0.506	0.292	0.000	1.774	-0.101	0.280	-1.461	1.268
A. Violent								
Murder	0.004	0.005	0.000	0.075	-0.001	0.006	-0.064	0.031
Rape	0.008	0.008	0.000	0.107	-0.002	0.009	-0.058	0.087
Robberies	0.018	0.021	0.000	0.284	0.000	0.016	-0.165	0.112
Aggravated Assault	0.112	0.093	0.000	0.967	-0.008	0.086	-0.927	0.429
B. Property								
Burglaries	0.100	0.066	0.000	0.519	-0.022	0.068	-0.416	0.401
Larcenies	0.367	0.228	0.000	1.490	-0.069	0.216	-1.128	0.977
Vehicle thefts	0.033	0.031	0.000	0.610	-0.009	0.033	-0.543	0.177
Arson	0.005	0.010	0.000	0.354	-0.001	0.012	-0.100	0.347
C. Others								
Vandalism	0.092	0.070	0.000	0.809	-0.010	0.067	-0.518	0.809
Fraud	0.143	0.209	0.000	2.408	-0.030	0.197	-2.398	1.468
Stolen property	0.030	0.034	0.000	0.640	-0.004	0.031	-0.631	0.241
Weapons possession	0.043	0.035	0.000	0.234	-0.006	0.030	-0.182	0.205
Offenses								
A. Violent								
Murder	0.004	0.005	0.000	0.087	-0.001	0.006	-0.087	0.047
Rape	0.025	0.019	0.000	0.150	0.000	0.018	-0.090	0.122
Robberies	0.053	0.075	0.000	0.971	-0.005	0.047	-0.731	0.439
Aggravated Assault	0.068	0.130	0.000	1.168	0.102	0.148	0.000	1.168
B. Property								
Burglaries	0.643	0.402	0.000	2.594	-0.123	0.309	-2.250	1.103
Larcenies	1.875	1.045	0.000	8.219	-0.280	0.717	-4.554	3.419
Vehicle thefts	0.185	0.181	0.000	1.599	-0.022	0.117	-1.235	0.371
Arson	0.019	0.019	0.000	0.237	-0.004	0.020	-0.213	0.134
Unemployment	4.610	1.375	1.143	13.559	-0.096	1.362	-5.204	5.491
Unemployment duration†	16.590	1.340	12.419	21.619	-0.373	1.232	-4.432	3.982
Import China-others (kUS$)⋆	1.058	0.700	0.311	1.990	1.755	2.085	-0.723	28.655
Age: 15-34								
White	0.231	0.052	0.035	0.445	-0.022	0.020	-0.096	0.106
Black	0.027	0.039	0.000	0.219	0.000	0.005	-0.026	0.055
Asian	0.004	0.006	0.000	0.075	0.001	0.001	-0.003	0.016
Age: 35-49								
White	0.183	0.033	0.032	0.283	-0.002	0.024	-0.084	0.098
Black	0.016	0.024	0.000	0.136	0.002	0.006	-0.028	0.042
Asian	0.002	0.004	0.000	0.064	0.001	0.001	-0.002	0.021
Age: 50-64								
White	0.148	0.035	0.038	0.311	0.023	0.015	-0.022	0.095
Black	0.010	0.016	0.000	0.117	0.002	0.005	-0.008	0.041
Asian	0.001	0.002	0.000	0.041	0.001	0.001	-0.002	0.012
No college	0.220	0.099	0.033	0.643	-0.065	0.063	-0.210	0.073
High school degree	0.617	0.073	0.283	0.767	0.039	0.053	-0.068	0.190
Federal assistance pc (kUS$)‡	269.498	158.485	24.860	1237.341	20.136	69.476	-237.047	361.914
Republicans (share)	0.541	0.118	0.159	0.901	0.027	0.144	-0.276	0.348
Police force pc	0.008	0.014	0.000	0.196	-0.007	0.016	-0.191	0.009
Prisoners pc	0.004	0.027	0.000	0.911	0.001	0.026	-0.907	0.110
Average wage (log)					8.117	6.652	-10.631	37.523
NILF§	26.003	5.520	13.140	48.717	-0.925	2.714	-14.701	7.988

Notes: All the variables are rates so they are divided by the working-age population at CZ level. Arrests and Offenses are scaled by 100 for the ease of interpretation. † Average duration of an unemployment spell in weeks. ⋆ The import China-others is divided by the workers in 1980, 1990 and 2000 following the construction of the instrument. ‡ Federal income assistance includes the SSI, AFDC/TANF, and SNAP programs. § Individuals not in labour force. The commuting zones are 722 so the observations in levels are 2166 (1444 in differences).

Table B.2: Violent, Property Crime and Unemployment, First-Difference Regressions, 1990-2007

Arrests	Panel A: Total Violent Crime Rate					Panel B: Total Property Crime Rate				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
ΔUnemployment	0.001	0.001	0.002	0.003	0.003	0.033***	0.019*	0.021**	0.016*	0.015*
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)
[*Elasticity*]	[0.03]	[0.03]	[0.06]	[0.08]	[0.08]	[0.28]	[0.16]	[0.18]	[0.14]	[0.13]
γ_t	-0.012**	0.008	0.009	0.018	0.020	-0.059***	0.029	0.036	0.016	0.021
	(0.005)	(0.010)	(0.010)	(0.027)	(0.026)	(0.016)	(0.035)	(0.029)	(0.073)	(0.072)
ΔAge 15-34										
White		0.223	0.535**	0.492**	0.523***		1.642***	2.367***	2.563***	2.634***
		(0.193)	(0.250)	(0.196)	(0.195)		(0.532)	(0.744)	(0.658)	(0.675)
Black		-0.383	-0.101	-0.148	-0.192		-4.393**	-3.463*	-3.313*	-3.415*
		(0.992)	(1.047)	(1.042)	(1.054)		(1.672)	(1.923)	(1.857)	(1.860)
Asian		-2.974	-3.613	-3.514	-3.245		-2.423	-2.343	-2.848	-2.232
		(2.386)	(2.748)	(2.576)	(2.544)		(6.508)	(7.196)	(6.602)	(6.581)
ΔAge 35-49										
White		0.264	-0.085	-0.033	-0.093		-1.017	-1.900	-2.082*	-2.218*
		(0.195)	(0.259)	(0.265)	(0.284)		(1.069)	(1.174)	(1.212)	(1.231)
Black		0.126	-0.942	-1.037	-0.991		2.647	-0.929	-0.619	-0.515
		(1.417)	(1.322)	(1.230)	(1.224)		(3.897)	(3.119)	(3.191)	(3.187)
Asian		-3.957	-2.803	-3.124	-3.077		-24.470*	-21.719	-20.434	-20.327
		(4.883)	(4.856)	(4.765)	(4.809)		(13.459)	(13.439)	(12.906)	(12.704)
ΔAge 50-64										
White		-0.010	-0.235	-0.210	-0.267		-1.502**	-1.990**	-2.137***	-2.269***
		(0.183)	(0.224)	(0.230)	(0.224)		(0.631)	(0.769)	(0.730)	(0.768)
Black		-1.008*	-1.459**	-1.356*	-1.328*		-2.774	-4.213**	-4.718**	-4.655**
		(0.507)	(0.669)	(0.783)	(0.771)		(1.922)	(1.997)	(2.076)	(2.066)
Asian		-3.822	-1.960	-2.573	-2.794		-26.946	-17.124	-15.651	-16.155
		(3.998)	(4.533)	(3.874)	(3.802)		(20.378)	(20.280)	(20.156)	(19.795)
ΔNo Diploma			-0.031	0.040	0.076			0.697	0.462	0.544
			(0.221)	(0.230)	(0.228)			(0.686)	(0.664)	(0.655)
ΔHigh School			0.320	0.379*	0.390*			1.929**	1.720**	1.746**
			(0.241)	(0.226)	(0.223)			(0.829)	(0.772)	(0.775)
ΔFederal assistance				0.000	0.000				0.001	0.001
				(0.000)	(0.000)				(0.000)	(0.000)
ΔRepublicans				0.008	0.000				-0.079	-0.098
				(0.129)	(0.127)				(0.334)	(0.330)
ΔPolice forces					-0.373					-0.851
					(0.383)					(0.949)
Observations	1444	1444	1444	1444	1444	1444	1444	1444	1444	1444
Clusters	48	48	48	48	48	48	48	48	48	48
R-squared	0.007	0.035	0.052	0.058	0.061	0.036	0.175	0.200	0.208	0.210

Notes: N = 1444 (722 CZ x 2 time periods). The dependent variable is total crime rate which includes both violent and property crime. All the variables are expressed in first-difference (rates). Arrests are scaled by 100 for the ease of interpretation. All regressions include a dummy for the 2000-2007 period (γ_t). The reference category for the race profile, the level of education and the voters are Indians, individuals who obtained at least a bachelor degree and percentage of people who voted Democratic party, respectively. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table B.3: Total Crime and Unemployment Rate, 2SLS Regressions, 1990-2007

Arrests	Total Crime Rate	Violent Crime Rate	Property Crime Rate
Panel A: 2nd Stage	(1)	(2)	(3)
ΔUnemployment	0.120***	0.021	0.098***
	(0.043)	(0.013)	(0.032)
γ_t	0.389***	0.033	0.358***
	(0.133)	(0.036)	(0.106)
ΔAge 15-34			
White	0.897	0.381*	0.506
	(0.785)	(0.205)	(0.649)
Black	-3.224	-0.149	-3.079
	(2.833)	(1.076)	(2.090)
Asian	2.600	-2.171	4.783
	(8.655)	(2.375)	(6.849)
ΔAge 35-49			
White	-0.557	-0.080	-0.458
	(1.411)	(0.344)	(1.138)
Black	1.729	-0.736	2.464
	(3.827)	(1.125)	(2.949)
Asian	-36.996**	-5.868	-31.149***
	(15.293)	(5.110)	(11.850)
ΔAge 50-64			
White	0.827	0.112	0.699
	(1.061)	(0.295)	(0.866)
Black	-10.400***	-2.145***	-8.267***
	(2.601)	(0.832)	(2.118)
Asian	-5.225	-1.523	-3.563
	(17.040)	(3.956)	(15.233)
ΔNo Diploma	-2.327*	-0.190	-2.133**
	(1.280)	(0.353)	(0.997)
ΔHigh School	0.970	0.275	0.703
	(1.164)	(0.273)	(0.939)
ΔFederal assistance	0.000	-0.000*	0.000
	(0.001)	(0.000)	(0.000)
ΔRepublicans	-0.110	0.014	-0.126
	(0.463)	(0.134)	(0.341)
ΔPolice forces	-1.874	-0.342	-1.572
	(1.284)	(0.371)	(0.990)
Constant	-0.437***	-0.026	-0.412***
	(0.082)	(0.021)	(0.072)
Observations	1444	1444	1444
Clusters	48	48	48
R^2	0.013	0.001	0.041
RMSE	0.339	0.097	0.275
Panel B: 1st Stage			
ΔImports China-other		0.132***	
		(0.022)	
First-stage		26.93	
Kleibergen-Paap LM test (p-value)		0.000	
C.D.W. F-stat		63	

Notes: N = 1444 (722 CZ x 2 time periods). The dependent variables are total, violent and property crime in column (1), (2) and (3), respectively. All the variables are expressed in first-difference (rates). Arrests are scaled by 100 for the ease of interpretation. All regressions include a dummy for the 2000-2007 period (γ_t). The reference category for the race profile, the level of education and the voters are Indians, individuals who obtained at least a bachelor degree and percentage of people who voted Democratic party, respectively. First-stage estimates in Panel B also include the control variables that are indicated in the second-stage. The instrument in all the regressions is Chinese imports in eight developed countries. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table B.4: Offenses and Unemployment Rate, 2SLS Regressions, 1990-2007

Panel A: Violent Crime	Murder	Rape	Robberies	Assaults
	(1)	(2)	(3)	(4)
ΔUnemployment	0.000	0.004*	0.010***	-0.021
	(0.000)	(0.002)	(0.003)	(0.021)
[*Elasticity*]	[0.00]	[0.67]	[0.80]	[−1.30]
Panel B: Property Crime	Burglaries	Larcenies	Vehicle thefts	Arson
	(1)	(2)	(3)	(4)
ΔUnemployment	0.116***	0.367***	0.033***	0.004*
	(0.035)	(0.083)	(0.011)	(0.002)
[*Elasticity*]	[0.76]	[0.83]	[0.75]	[0.88]
Observations	1444	1444	1444	1444
Clusters	48	48	48	48
All controls	√	√	√	√

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 3. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table B.5: Total Crime and Unemployment Rate, 2SLS Regressions, 1990-2007 (initial decade)

Arrests	Total Crime Rate	Violent Crime Rate	Property Crime Rate
Panel A: 2nd Stage	(1)	(2)	(3)
ΔUnemployment	0.125***	0.035***	0.090***
	(0.039)	(0.013)	(0.028)
	0.208***	0.038*	0.171***
γ_t	(0.069)	(0.022)	(0.053)
ΔAge 15-34			
White	-0.775*	-0.063	-0.710*
	(0.466)	(0.112)	(0.390)
Black	4.455**	0.861*	3.590**
	(1.975)	(0.494)	(1.556)
Asian	6.407	-0.269	6.665
	(6.498)	(1.238)	(5.904)
ΔAge 35-49			
White	1.673	0.264	1.403
	(1.126)	(0.272)	(0.914)
Black	-10.793*	-0.97	-9.810**
	(6.091)	(1.476)	(4.829)
Asian	-32.309*	-9.989**	-22.223
	(19.431)	(5.077)	(16.078)
ΔAge 50-64			
White	0.472	-0.174	0.65
	(0.780)	(0.239)	(0.614)
Black	5.984	-1.308	7.279
	(6.907)	(1.865)	(5.518)
Asian	32.905	13.618*	19.142
	(33.553)	(7.695)	(27.889)
ΔNo Diploma	1.225***	0.202*	1.022***
	(0.410)	(0.115)	(0.309)
ΔHigh School	-0.274	-0.089	-0.186
	(0.318)	(0.089)	(0.248)
ΔFederal assistance	-0.001	-0.000**	0
	(0.001)	(0.000)	(0.000)
ΔRepublicans	0.025	0.009	0.018
	(0.176)	(0.052)	(0.130)
ΔPolice forces	1.047	0.116	0.968
	(1.210)	(0.334)	(0.966)
Constant	-0.029	0.022	-0.051
	(0.048)	(0.016)	(0.036)
Regions	√	√	√
Observations	1444	1444	1444
Clusters	48	48	48
Panel B: 1st Stage			
ΔImports China-other		0.131***	
		(0.023)	
First-stage		29.81	
Kleibergen-Paap LM test (p-value)		0.000	
C.D.W. F-stat		59.2	

Notes: N = 1444 (722 CZ x 2 time periods). All the controls are the same as in Table 3 but the variables are set at the beginning of each decade. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table B.6: Placebo tests

	Total Crime			
	2SLS estimates		OLS estimates	
	(1)	(2)	(3)	(4)
ΔUnemployment	-0.025	-0.044		
	(0.024)	(0.032)		
ΔImports China-other			-0.004	-0.006
			(0.004)	(0.004)
All controls		√		√
Observations	1444	1444	1444	1444

Notes: N = 1444 (722 CZ x 2 time periods). Total crime rate is computed between 1975-1980 and 1980-1990. Controls are the same as in Table 3. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table B.7: Robustness Check III, 2SLS Regressions, 1990-2007

Arrests		Panel A: drop p1/p99			Panel B: drop p5/p95		
Total Crime Rate	Baseline	(1)	(2)	(3)	(4)	(5)	(6)
ΔUnemployment	0.120***	0.118**	0.113***	0.136***	0.127*	0.083***	0.158**
	(0.043)	(0.053)	(0.032)	(0.052)	(0.067)	(0.026)	(0.062)
Drop in import from China		√			√		
Drop in total crime			√			√	
Drop in unemployment				√			√
All controls	√	√	√	√	√	√	√
Observations	1444	1415	1416	1413	1300	1298	1297
1st Stage (F-stat)	26.93	40.76	26.92	27.62	24.16	24.85	33.42

Notes: N = 1444 (722 CZ x 2 time periods). Controls are the same as in Table 3. Robust standard errors in parentheses are clustered at the state level. * p<.10 ** p<.05 *** p<.01.

Table B.8: Robustness Check IV, 2SLS Regressions, 1990-2007

	Panel A: the instrument is per-worker Chinese exposure (in 1990)					
	Total Crime	Violent Crime	Property Crime	Total Crime	Violent Crime	Property Crime
	(1)	(2)	(3)	(4)	(5)	(6)
ΔUnemployment	0.201***	0.038**	0.163***	0.431**	0.036	0.396**
	(0.042)	(0.011)	(0.035)	(0.201)	(0.040)	(0.174)
All controls	√	√	√	√	√	√
Observations	2166	2166	2166	2166	2166	2166
1st Stage (F-stat)	18.94	18.94	18.94	6.43	6.43	6.43
Weights				√	√	√
	Panel B: the instrument is per-capita Chinese exposure (in 1990)					
	Total Crime	Violent Crime	Property Crime	Total Crime	Violent Crime	Property Crime
	(1)	(2)	(3)	(4)	(5)	(6)
ΔUnemployment	0.173***	0.029**	0.145***	0.300**	0.016	0.284***
	(0.032)	(0.008)	(0.027)	(0.123)	(0.027)	(0.105)
All controls	√	√	√	√	√	√
Observations	2166	2166	2166	2166	2166	2166
1st Stage (F-stat)	23.17	23.17	23.17	13.7	13.7	13.7
Weights				√	√	√

Notes: N = 2166 (722 CZ x 3 time periods). Controls are the same as in Table 3. In parentheses the robust standard errors. * Models (4), (5) and (6) are weighted by the CZ share of working-age population. * p<.10 ** p<.05 *** p<.01.