The China Syndrome in US: Import Competition, Crime, and Government Transfer

Che, Yi and Xu, Xun

November 2015

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Yi Che and Xun Xu

Antai College of Economics and Management

Shanghai Jiao Tong University

This Version, November 2015

Abstract

In this paper, we exploit the exogenous rise of Chinese imports in US to investigate the effect of import competition on crime at county level. Our results indicate that counties with high exposure to Chinese import competition are with high crime rates while the exposure effect on property crime is much larger than that for violent crime: one standard deviation increase of exposure will increase 2.1 more violent crimes in the county while such increase of exposure will cause 26.5 more property crimes. Interestingly, we find that the crime impact of exposure to Chinese import competition disappears in counties with high government transfer.

Keywords: Chinese Import Competition; US Crime; Government Transfer

JEL Codes: F14; F16; K42

1 Introduction

Chinese imports account for a dominant portion of US imports from low-income countries. For example, during 2000-2007, China accounts for 89 percent of the import growth of US from low-income countries. Noticeably, this increase of Chinese imports happened within a short time horizon, see, Figure 1. This sharp increase of imports from China is usually explained by China's own institutional reform and its accession into WTO, i.e., supply driven. Using this supply shock as a source of exogenous variation, several studies have documented that Chinese import competition cause higher unemployment, lower labor force participation, earnings losses, and explain a large part of employment sag in U.S. during 2000s (see, e.g., Autor, Dorn, and Hanson, 2013; Autor, Dorn, Hanson, and Song, 2014; Acemoglu, Autor, Dorn, Hanson, and Price, forthcoming; Pierce and Schott, 2015).[1] Most saliently, Autor, Dorn, and Hanson (2013) consider unemployment, wage reduction, and rising labor adjustment costs, caused by Chinese import competition, as "Syndrome" in US.

In this paper, following the logic of Autor, Dorn, and Hanson (2013), we consider another aspect of "Syndrome" caused by Chinese import competition, US crime. Crime is considered to be a major issue in US, which costs victims $200 billion per year while the cost in reducing it is equally large (Miller, Cohen, and Rossman, 1993; Levitt, 1997). Figure 2 presents time series of seven crime categories in US. We see that over 1990-2010 period, there is an accelerated decrease of crime in all of seven crime categories.[2] However, we find that around 2001, the speed of decrease slows down which coincide with China's accession to WTO. Combined with data pattern shown in Figure 1, it seems that the movement of Chinese imports and the trend of crime rate tracked each other after 2000.

To ensure that the seemly positive time series correlation between US crime and Chinese import competition is indeed causal, we employ the identification strategy developed by Autor, Dorn, and Hanson (2013) to investigate, i.e., Two-Stage Least Squares (2SLS). First, our key independent variable, county exposure to Chinese import competition, is constructed using

[1]These empirical evidences are consistent with the prediction of specific factor model that groups who are "stuck" in import- competing sector loss after trade liberalization.

[2]Donohue and Levitt (2001) provide evidences showing that legalized abortion could be an important reason behind the sharp decline of crime during 1990s.

county industry structure obtained from County Business Patterns (CBP) and industry specific Chinese imports of U.S. from UN Comtrade for 2000-2010 period. Second, to isolate the exogenous variation of county exposure to Chinese import competition, we use lag one decade county industry structure and Chinese imports of other eight developed countries to construct our instrument. The underlying logic is that the rising Chinese imports of US is driven by the economic rise of China due to its internal institutional reforms and WTO accession in 2001. Arguably, this is a supply shock to US domestic demand market and can be regarded as an exogenous phenomenon.

Combining county exposure to Chinese import competition measure with crime data obtained from FBI and other covariates found to be important in affecting crime, we find that there exists positive and significant effect of county exposure to Chinese import competition on both violent- and property- crime. Perhaps more important, we find that the exposure effect on property crime is about 11 times larger than that for violent crime. One standard deviation increase of exposure will increase 2.1 more violent crimes in the county while such increase of exposure will cause 26.5 more property crimes.

The exclusion restriction implied by our 2SLS estimation is that, conditional on the covariates included in the regression, our instrument does not have a direct impact on US county crime rates, other than its influence through county exposure to Chinese import competition. The major concern with this condition is that developed countries during our sample periods may experience demand shocks that coincide with Chinese goods supply shock, in which case we could overestimate the coefficient of our interest. We find that controlling for the two major demand shocks in developed countries during our sample period, i.e., housing booms and technological change, our main results remain robust. To further corroborate the condition of exclusion restriction, we conduct a falsification test by regressing current county crime on future county exposure to Chinese import competition in various periods. For example, we expect that counties that only became strongly exposed to Chinese import competition in 2000s should not have seen differential increases in crimes in the 1990s. In all cases, we did not detect any positive exposure impacts on crime.

We document that our results are not affected by the specific sample period in consideration and industries in which China have a comparative advantage. Also, our results are robust by controlling for the US exports to China. Cross-category analysis on crime indicates that our baseline results are mainly driven by exposure effects on Burglary and Larceny.

Additional analysis on heterogeneous response suggests that government transfer in counties with high Chinese import competition could effectively reduce the propensity of crime of citizens with high life pressure. For example, our subsample analysis show that effect of county exposure to Chinese import competition on crime remain positive for counties below government transfer sample mean while exposure effect disappears for counties above government transfer sample mean.

Our paper is related to recent studies on the effect of Chinese import competition and unemployment (Acemoglu, Autor, Dorn, Hanson, and Price, forthcoming; Autor, Dorn, and Hanson, 2013; Autor, Dorn, Hanson, and Song, 2014; ; Pierce and Schott, 2015). However, our paper goes one step further by considering the behavior of these affected workers, i.e., crime.

The causal link between Chinese import competition and crime detected in this study complements the literature examining the effect of unemployment on crime (see, e.g., Gould, Weinberg, and Mustard, 2002; Deiana, 2015). However, we focus on the life pressure imposed by Chinese import competition rather than unemployment. In this regard, our paper is more related to Dix-Carneiro, Soares, and Ulyssea (2015) who also emphasize the exposure effect on crime, but use a different source of exogenous variation and Brazil as the empirical setting.

Broadly, our work is related to public finance literature on redistribution (see, e.g., Autor, Dorn, and Hanson, 2013). In particular, we provide evidences showing that redistribution policies could be an effective way in alleviating adverse effects caused by import competition.

The paper proceeds as follows. Section 2 outlines our identification strategy following Autor, Dorn, and Hanson (2013). Section 3 describes the data sets and variable used in the paper. Section 4 presents our empirical results, and Section 5 concludes.

2 Identification Strategy

2.1 Constructing County Exposure to Chinese Import Competition (Key Independent Variable)

Our regressor of interest concerns each US county's exposure to Chinese imports. However, as the data of Chinese imports do not have the breakdown for each county's consumption, we follow Autor, Dorn, and Hanson (2013)'s approach, which extracts information of regional import exposure from the total Chinese imports through the use of regional variations in industry employment structure. More specifically, the change in the county-level exposure to Chinese import competition is expressed as follows,

$$\Delta Exposure_c = \ln \left[\sum_j \frac{L_{jc2000}}{L_{j2000}} \frac{\Delta import_j^{US\_China}}{L_{c2000}} \right]$$

where L_{jc2000} is the total employment of industry j in county c in 2000; L_{j2000} is the national total employment of industry j in 2000; L_{c2000} is the total employment in county c in 2000; $\Delta import_{j2000\_2010}^{US\_China} \equiv import_{j2010}^{US\_China} - import_{j2000}^{US\_China}$ is the change of U.S. imports from China in industry j from 2000 to 2010. A higher value of $\Delta Exposure_c$[3] indicates greater exposure to Chinese import competition.

For robustness checks, we experiment two alternative measures of trade exposure, that is, net imports exposure and exposure to imports from other low-income countries. The first alternative measure is to take into account the fact that U.S. exports to China bring job opportunities and tax revenues, which in turn influence citizen's welfare, $\Delta US\ Net\ Imports_c^{China} = \Delta US\ Imports_j^{China} - \Delta US\ Exports_j^{China}$. The second alternative measure is to find out whether the effect of US exposure to Chinese import competition is different from imports from other low-income countries, $\Delta US\ Imports_j^{LowWage}$.

[3] Please note that to mitigate the influence of extreme exposure at county level, we take a log for country exposure. However, our result remains robust without the log transformation.

2.2 Estimating Equation

To examine the impact of county exposure to Chinese import competition on crime, our baseline estimating equation is

$$\Delta crime_c = \beta_0 + \beta \Delta Exposure_c + \zeta y_c^0 + \mathbf{X_c^0}'\boldsymbol{\theta} + \Delta\varepsilon_c, \tag{1}$$

where $\Delta crime_c$ denotes the difference of crime for county c between 2000 and 2010. $\Delta Exposure_c$ captures the change in exposure of county c to Chinese import competition over 2000-2010 period. The coefficient of our interest is β. If county exposure to Chinese import competition do trigger large life pressure for citizens living in the county, we should see a positive and significant estimate of β, i.e., counties with higher exposure to Chinese import competition experienced an increase of crime during 2000-2010 period.

y_c^0 is the initial level of crime in county c, which is included to capture persistence in crime and also possible mean-reverting dynamics, i.e., regions with high crime rate in the initial period are less likely to have high crime rate increase during the period (e.g., Barro, 1991; Higgins, Levy, Young, 2006). To alleviate the concern of omitted variable bias in estimating β, we control for a vector county attributes $\mathbf{X_c^0}$ that may be correlated with both county exposure and crime, including number of police officers (Levitt, 1997; Chalfin and McCrary, forthcoming), unemployment rate (see, e.g., Gould, Weinberg, and Mustard, 2002; Deiana, 2015; Dix-Carneiro, Soares, and Ulyssea, 2015), percentage of population aged between 18-25, percentage of black population (Levitt, 1997), percentage of population with bachelor degree, income per capita, government welfare spending (Levitt, 1997), and total population (Levitt, 2002). For details on all the relevant variables, please refer to Appendix Table A. $\Delta\varepsilon_c$ indicates the error term, containing all the unobserved factors..

In the baseline analysis, we investigate the effect of change in county exposure to Chinese import competition between 2000 and 2010, a period with significant increases in Chinese imports largely due to China's accession into WTO. In subsequent specifications, we experiment several alternate time period intervals to investigate the robustness of our baseline results, e.g., 2000 to 2006 and 2000 to 2008.

Here, we choose a long period, 2000-2010, for our baseline analysis mainly motivated by Barro-type equation (Barro, 1991) and the construction of county exposure to Chinese import competition (Autor, Dorn, and Hanson, 2013).

2.3 Identification

Our identification of β requires that county exposure to Chinese import competition is exogenous, conditional on other controls y_{cs}^0, $\mathbf{X_{cs}^{0\prime}}\boldsymbol{\theta}$, in equation (1). This is plausible, since the main variation of county exposure to Chinese import competition comes from the growth of US imports from China, which is largely driven by the unexpected sharp growth of Chinese economy (triggered by internal institutional reform rather than the influence of other economies) and the change of trade policies (China's accession into WTO). In other words, conditional on county industry structure, $\Delta Exposure_{cs}$ is exogenous if US imports from China are largely driven by supply shocks.

However, if regions with larger crime growth potential experience more exposure to Chinese import competition (reverse causality), our estimate of β would be biased upwards. Perhaps more important, if there are some unobserved factors that affect US's demand on Chinese products, our estimate of β could be contaminated (e.g., productivity shocks that positively affect manufacturers' demand on intermediate goods or the change of consumers' preferences). To resolve these problems, we utilize the plausible instrument developed by (Autor, Dorn, and Hanson, 2013) to isolate the exogenous variation of county exposure to Chinese import competition.

More specifically, to the extent that the rise in U.S. imports from China is driven by the supply side (i.e., China's internal institutional reform or falling global trade barriers), US imports from China should be highly correlated with imports of other developed countries[4] from China but uncorrelated with internal crime of US. More specifically, our first instrument is constructed as

[4]Following Autor, Dorn, and Hanson (2013), we select Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland as our other eight other developed countries.

$$IV_c = \ln\left[\sum_j \frac{L_{jc}^{1990}}{L_j^{1990}} \frac{\Delta Imports_j^{Other\_China}}{L_c^{1990}}\right]$$

where L_{jc}^{1990} denotes total employment of industry j in county c in 1990; L_j^{1990} represents the national total employment of industry j in 1990; L_c^{1990} is the total employment in county c in 1990; $\Delta import_j^{Other\_China} \equiv import_{j2010}^{Other\_China} - import_{j2000}^{Other\_China}$ is the change of U.S. imports from China in industry j from 2000 to 2010. Here, we use ten-year-lagged county employment structure to mitigate the concern that county industry structure could be affected by the aticipation of US-China trade (i.e., simultaneity bias).

This instrument is less effective if the increase in U.S. and other countries' imports from China are driven by the same demand shocks across developed countries. We mitigate this concern in two ways: first, we recomputed $\Delta import_j^{US\_China}$ and $\Delta Imports_j^{Other\_China}$ by excluding steel, flat glass, and cement industries which were in large demand affected by developed countries' housing booms during 2000-2010 period; second, to excluding the influence of technology shocks in developed countries, we construct $\Delta Exposure_{cs}$ and IV_c without industry computer. As an additional robustness test, we drops three industries in which China has a strong comparative advantage: apparel, footwear and textiles.

The validity of our instrumental-variables strategy depends on two assumptions. First, our instruments should be correlated with $\Delta Exposure_{cs}$. Figures 3A and 3B display correlations between our instruments and the potential endogenous variable $\Delta Exposure_{cs}$. The positive correlation between IV_c^1 and $\Delta Exposure_{cs}$ shown in Figure 3A suggests that supply-driven imports from China in US is correlated with imports from China in other developed countries. This correlation is in line with our intuition. We will test the significance of these relationships in section 4.1. Though significant, if our instruments can only explain a small portion of the variation of $\Delta Exposure_{cs}$, our estimate of β could be biased toward OLS estimate. We thus reply on Kleibergen-Paap rk Wald F statistic, Shea Partial R Square, and Stock-Yogo test to check whether our instrument suffers from weak instrument problem (Bound, Jaeger, and Baker, 1995, Staiger and Stock, 1997; Stock, Wright, and Yogo, 2002). Second, the exclusion restriction implied by our instrumental-variables strategy is that, conditional on the covariates included in the regression, our instruments should have no direct effect on county crime rate, other than through county exposure to Chinese import competition. Since this instrument has been widely recognized and used in the literature (see, e.g., Feigenbaum and Hall, 2015; Balsvik, Jensen, and Salvanes, 2015; Dippel, Gold, and Heblich, 2015) and the economic rise of China is mainly via internal institutional reforms, it is plausible that it does isolate the exogenous variation of county exposure. As a final experiment, we will conduct Durbin-Wu-Hausman test to check whether difference between 2SLS and OLS estimate are statistically significant enough to state the endogeneity of $\Delta Exposure_{cs}$.

Throughout the paper, white's standard errors are reported to control for arbitrary heteroskedasticity.

3 Data Sets

To construct the regressor of our interest (county exposure to Chinese import competition), we need to get information on county industry structure and Chinese imports by industry. We obtain number of employees by industry-county cell from County Business Pattern (CBP, http://www.census.gov/econ/cbp/download/index.htm). Although CBP provides such data since 1986, we select 2000-2010 as our sample period[5] which corresponds to the major era of economic rise of China. Since Office of Management and Budget (OMB) switches industry codes on recording USA business economy every five years (i.e., years that end with "2" or "7"), following Autor, Dorn, and Hansen (2013), we convert industry-county employment coded by NASIC to SIC.[6] During our sample period, county boundary rarely changes, therefore, we do not need to make any adjustment for Census Bureau county id.[7] With these information

[5]However, we use other sample periods to conduct robustness checks and find that our baseline results are preserved.

[6]In CBP, SIC87 industry code is used for 1992-1997 period; NAICS97 industry code is used for 1998-2002 period; NAICS02 is used for 2003-2006 period. We need to have a common industry code, which is achieved with the following two steps: step 1, we convert NAICS07 to NAICS02 and NAICS02 to NAICS97 using concordance table provided by Census Bureau (http://www.census.gov/eos/www/naics/concordances). For example, if one NAICS02 code is split into two or more NAICS97 codes, we assume the employment for the 02 code is split equally among the 97 codes; step 2, we convert NAICS97 to SIC87 using cross walk provided by Autor, Dorn, and Hanson (2013). Autor, Dorn, and Hanson uses 1997 census "bridge" file to create a weight for NAICS97 code to be split into two or more SIC87 codes (http://www.census.gov/epcd/ec97brdg/). In this way, we have a consistent industry code SIC87 across years. For details, please refer to Autor, Dorn, and Hansen (2013).

[7]Dade county, Florida (FL): in 1997, Dade county changes name to Miami-Dade. FIPS code is changed from 12025 to 12086. Skagway-Yakutat-Angoon Census Area, Alaska (AK): after Yakutat was incorporated as a unified city-borough on September 22, 1992, it was renamed as Skagway-Hoonah-Angoon Census Area. When Skagway followed suit on June 20, 2007, the census area assumed its current name, Hoonah–Angoon

at hand, we can construct county industry structure for the regressor of our interest, i.e., $\Delta Exposure_c$.

We obtain US imports from China on UN Comtrade (http://comtrade.un.org/), which provides bilateral imports at HS-6 digit level. Following Pierce and Schott (2015) and Autor, Dorn, and Hanson (2013), we convert HS codes used to classify imported products to SIC industry codes used to classify domestic economic activity. Here, all imports are inflated to 2007 USD using Personal Consumption Expenditure deflator from Bureau of Economic Analysis (BEA, http://www.bea.gov/). In UN Comtrade, we also extract imports of other eight developed countries[8] from China, imports of US from other low income countries[9], and imports of US from Mexico. Combining these information with county industry structure, we can construct regressors of our interest and the related instrument.

Our key dependent variable, country crime rate, is extracted from Uniform Crime Reports (UCR) issued by the Federal Bureau of Investigation (FBI). The crime data includes seven types of crime: murder and nonnegligent manslaughter, forcible rape, assault, robbery, burglary, larceny, and motor vehicle theft. Following Levitt (1997), we consider first four types crime as violent crime while the last three as property crime. The raw crime data is available at U.S. reporting agency level. To match up with the county exposure and other control variables, we aggregate the original agency level crime to county level, from 1991 to 2010. Finally, following Levitt (1997), we use category specific crime per 100,000 populations in the county for standardization.

In the regression, we include a variety of controls that are found to be important in ex-

Census Area. South Boston city, Virginia (VA): in 1960, it became an independent city by court order. South Boston became a town again and rejoined Halifax County on July 1, 1995. Yakutat Borough, Alaska (AK): it is incorporated as a non-unified Home Rule Borough on September 22, 1992. Yakutat was previously a city in the Skagway-Yakutat-Angoon Census Area. Clifton Forge city, Virginia (VA): this independent city becomes a town of in Alleghany County in 2001. Broomfield County, Colorado (CO): it becomes a county in On November 15, 2001.

[8]Following Autor, Dorn, and Hanson (2013), they are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[9]Following Autor, Dorn, and Hanson (2013), low-income countries are: Afghanistan, Albania, Angola, Armenia, Azerbaijan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Burma, Cambodia, Central African Republic, Chad, China, Comoros, Republic of the Congo, Equatorial Guinea, Eritrea, Ethiopia, The Gambia, Georgia, Ghana, Guinea, Guinea-Bissau, Guyana, Haiti, India, Kenya, Laos, Lesotho, Madagascar, Maldives, Mali, Malawi, Mauritania, Moldova, Mozambique, Nepal, Niger, Pakistan, Rwanda, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Sierra Leone, Somalia, Sri Lanka, Sudan, Togo, Uganda, Vietnam, and Yemen.

plaining US crime rates in the literature. Previous studies have uncovered that police hiring is an effective way in reducing crime in US (see, e.g., McCrary, 2002; Chalfin and McCrary, forthcoming). To control this, we include police per capita (both sworn and civilian officers) in the regression, where the data is also from FBI UCR. Following Levitt (1997), we also control for percentage of population aged between 18 and 25, black, and citizens with bachelor degree, where these controls are from US Census Bureau. Unemployment has been proved to be an important determinant of crime in the literature (e.g., Gould, Weinberg, and Mustard, 2002). We control for this by constructing unemployment rate[10] from US Bureau of Labor Statistics (BLS). To mitigate simultaneous police hiring due to electoral cycles, we control for government welfare spending following Levitt (1997). Following Levitt (2002), we construct income per capita at county level using total income and population obtained from Bureau of Economic Analysis (BEA). Finally, total population is included in the regression to mitigate the influence of the size of the county (Levitt, 2002).

Figure 2 illustrates the intensity of county exposure to Chinese import competition between 2000 and 2010, with a darker shade corresponding to greater exposure. It is apparent that there is a large variation of county exposure to Chinese import competition at the county level. Moreover, we find that east of US suffer more from Chinese import competition, possible due to its concentration on labor intensive industries, e.g., toys, clothes, furniture.

Table 1 documents summary statistics of variables used in the baseline regression. In Table 1A, observations, mean, standard deviation, min and max are provided for all variables. Totally, we have 3059 out of 3141 counties in the sample and missing counties are either due to the change of county boundary during 2000-2010 period or missing values on crime rate or county exposure. We find that average county crime rate change during 2000-2010 period is -0.98, with a standard deviation of 21.55 for violent crime and -9.98 with a standard deviation of 107.12 for property crime, suggesting that crime rate is decreasing in the whole country during our sample period. To ease the illustration of estimated coefficients, log of county exposure is multiplied by 100. Here, we are more interested in the association between county exposure to Chinese import completion and county crime. To explore this, we report subsamples with

[10] Ratio of unemployed to labor forces in the county.

top and bottom 20% of county exposure to Chinese import competition in Tables 1B and 1C, respectively. Obviously, the decreasing rate of crime is significantly lower for countries with high exposure to Chinese import competition (0.43 for violent crime and -3.33 for property crime) than those for counties with lower exposure (-1.52 for violent crime and -15.57 for property crime). This observation is consistent with the story that Chinese import competition exert significant life and work pressure on citizens in counties with large exposure, which in turn leads to higher crime rate in these counties. We would test this relationship formally in the next section.

4 Empirical Results

4.1 First Stage Estimates

Before presenting 2SLS estimates, we first report our first stage estimation results in Table 2 and check the validity of our instruments.

Columns 1 and 2 report first stage estimates for violent and property crime respectively. In both columns, we include all the relevant controls in the second stage regression. Note that the only difference between controls in columns 1 and 2 is the initial period crime. We find that the estimate of IV_c is positive and significant in both columns, 0.230 with standard error of 0.013. According to this estimate, one standard deviation increase of other developed countries' imports from China will cause 0.44 standard deviation increase of county exposure to Chinese import competition in U.S. This results suggests that Chinese imports of other eight developed countries is positively related to Chinese imports of U.S., suggesting the usefulness of this instrument (Autor, Dorn, and Hanson, 2013; Autor, Dorn, Hanson, and Song, 2014; Acemoglu, Autor, Dorn, Hanson, and Price, Forthcoming).

Does our instrument have high predictive power to $\Delta Exposure_c$? The Shea Partial R square reported in both columns indicate that IV_c account for 19 percent of the variation of $\Delta Exposure_c$, which seem to be not trivial (Acemoglu, Johnson, and Robinson, 2001). This result suggests that our instrument do explain a large variation of the endogenous variable. Also, Kleibergen-Paap rk LM statistic implies that we can reject the null hypothesis of underidentification of our equation at 1 percent level. By allowing 10% percent bias of our IV estimates, Kleibergen-Paap rk Wald F statistic safely pass the critical value suggested by Stock and Yogo (2005). All in all, our first stage estimate suggest that, there exists positive and significant correlation between IV and exposure and this estimate does not suffer from weak instrument problem.[11]

4.2 Second Stage Estimation Results (Baseline Results)

Estimates of equation (1), with dependent variable being either violent crime or property crime, are reported in Table 3. The first three columns are results for violent crime while the remaining columns report estimation results for property crime. In column 1 and 4, we report univariate regression by including only exposure in the estimating equation. Column 2 and 5 further add initial period crime while column 3 and 6 contain all of our baseline covariates.

In column 1, the estimated coefficient for county exposure to Chinese import competition is positive and significant, 0.057 with a standard error of 0.029. This is consistent with our hypothesis that due to the work and life pressure imposed by competition, counties with high Chinese import competition during our sample period are more likely to have high violent crime rate. According to this estimate, a one standard deviation increase of exposure will increase 0.1 standard deviation of violent crime on average in US counties. If we look at the result in column 4, we get the same message: counties with high exposure to Chinese import competition experienced an increase of property crime. However, we find that the effect of exposure is 10 times larger for property crime than for violent crime, 0.631 vs. 0.057. This result is intuitive because once unemployment rate is controlled for, citizens' pressure due to Chinese import competition are mainly from financial side, e.g., lower cumulative earnings, job relocation, and facing elevated risk of obtaining public disability benefits (Autor, Dorn, and Hanson, 2013; Autor, Dorn, Hanson, and Song, 2014). Although murder, rape, and other violent crimes are not impossible due to financial pressure, property crime is main channel through which citizens temporarily getting relief. In section 4.5, we will see that in the violent

[11] We also use weak-instrument-robust estimator, Limited-Information Maximum Likelihood (LIML), to check the robustness of our results. We actually find that our estimates are not influenced by weak instrument problem. These results are available upon request.

crime regression, robbery is the main category driving the significant effect of exposure.

In columns 2 and 5, initial period crime rate is further added as control. The estimates of β for both violent crime and property crime become larger, but they are still positive and significant at 1 percent level. In columns 3 and 6, all of our baseline controls is added in the regression. We find that exposure still exert positive and significant effect on both types of crime and its impact on property crime is much larger than on violent crime: one standard deviation increase of exposure will increase 2.1 violent crime in the county while such increase of exposure will cause 26.5 more property crime, which is 11.6 times larger.

Is the instrumental-variables estimation necessary? To check this, we examine the null hypothesis of indifference between OLS and 2SLS estimates using Durbin-Wu-Hausman test (DWH). The results in columns 3 and 6 show that we can reject the null hypothesis at 1 percent level, suggesting that it is necessary to employ our identification strategy. In later parts of the paper, we consider specifications in columns 3 and 6 as our baseline model speciation.

4.3 Falsification Test

Our interpretation of estimate of β is causation running from exposure to crime rate. However, if there are some underlying factors trending crime rate, exposure as well as our instrument together, our key estimate could be biased upwards. To alleviate this concerns, following Autor, Dorn, and Hanson (2013), we conduct a falsification exercise by regressing crime rate change on future change of county exposure to Chinese import competition.

The estimation results are reported in Table 4. The key independent variable is county exposure to Chinese import competition between 2000 and 2010 while dependent variable in columns 1-2, 3-4, and 5-6 are change of crime rate for 1992-2010, 1994-2000, and 1996-2000 period, respectively. In all cases, we do not find any significant positive effect of future exposure on Chinese import competition on crime rates. This falsification test alleviates our concern that omitted factors, if any, may invalidate our identification strategy.

4.4 Checks on IV Validity

Key to the validity of our instrument is that Chinese imports of other eight developed countries are also Chinese supply driven. However, if there are some demand shocks occurring in all developed countries, our estimate of β could be biased. To alleviate this concern, following Autor, Dorn, and Hanson (2013), we drop industries that may be causing this problem. First, since many rich countries during our sample period experienced housing booms, which induces large demand for construction material, we drop steel, flat glass, and cement industries in our regression. The estimation results are reported in columns 1-2 of Table 5. We find that this exercise does not affect our main results qualitatively. Another industry that is causing similar demand structure of developed countries is computer. During the past 15 years, processing trade has render China become the world manufacturing factory, where computer industry accounts for a large portion (assembly). If technology advancement increases demand for computers in developed countries, computer industry could bias our estimates upwards. Estimation results by dropping computer industry are reported in columns 3-4. It shows that there still exist positive and significant effect of county exposure to Chinese import competition on crime and its impact is much larger for property crime than for violent crime. There two sets of results combined show that our instrument plausibly isolates the exogenous variation of county exposure and our baseline estimates are reliable.

4.5 Robustness Checks

In this subsection, we check the robustness of our baseline results and address a variety of concerns to our baseline specification.

Alternative Sample Periods: in our main results, we take a long difference for 2000-2010 period following Autor, Dorn, and Hanson (2013). One may be worried that if the short- or median- run effect of county exposure to Chinese import competition evolve in a non-monotonic way, our estimates may mask this feature (Griliches and Hausman, 1986). To check for this, we report estimation results for other alternative sample periods in Table 6. The first two columns report estimation result for 2000-2008 period while columns 3-4, column 5-6, and columns 7-

8 are results for 2000-2006, 2000-2004, and 2000-2002 respectively. We find that in all cases, there exists positive and significant effect of exposure to both types of crime and exposure effect on violent crime is significantly smaller than on property crime, which is consistent with our baseline result. Interestingly, the shorter the period in consideration, the smaller the exposure effect on crime. This suggests that the effect of exposure on crime cumulative monopolistically over time during the sample period.

Controlling US Exports to China: one potential concern to our baseline estimate is that counties suffering much from Chinese import competition could also benefit from exporting heavily to China (e.g., jobs in exporting sectors). If exporting industries to China negatively correlated with import competing industries across counties, then we may over estimate the effect of county exposure to Chinese import competition on crime. Following Autor, Dorn, and Hanson (2013), to tackle this concern, we construct the following county net exposure to Chinese import competition[12] as our key independent variable,

$$\mathbf{\Delta N}_{c2000\_2010} = \ln\left[\sum_j \frac{L_{jc2000}}{L_{j2000}} \frac{\Delta import^{US\_China}_{j2000\_2010} - \Delta export^{US\_China}_{j2000\_2010}}{L_{c2000}}\right] \tag{2}$$

where $\Delta export^{US\_China}_{j2000\_2010}$ is the change of US exports to China for industry j during the 2000-2010 period. The estimation results using the newly constructed net exposure are reported in the first two columns of Table 7. We find that the exposure effect disappear for violent crime once exporting to China is controlled for. However, we still observe a significant and positive effect of Chinese import competition on property crime and its magnitude is much larger than that for violent crime, 0.771 vs. 0.041.

Comparison to Other Low-income Countries: in order to check the difference of import competition between China and other low-income countries, we report estimation results for the effect of county exposure to other low-income countries on crime in columns 3-4 of Table 7. Interestingly, we find that county exposure to import competition from low-income countries does not have statistically significant impact on crime, though the estimate has a positive sign. This result is consistent with the fact that Chinese imports account for 89% of total imports

[12] Please refer to Autor, Dorn, and Hanson (2013) why incorporating exporting is confusing due to China and US occupying different positions in global value chain.

from low-income countries (Autor, Dorn, and Hanson, 2013) and thus county exposure to increased import competition in 2000-2010 period mainly stems from sudden increase of Chinese imports.

Excluding Dominant Industries: during our sample period, labor-intensive product exports play an dominant role in Chinese exports (Khandelwal, Schott, and Wei, 2013). One may be worried that our main result is totally driven by these labor-intensive product imports. To exclude this possibility, we run regressions by excluding apparel, footwear, and textiles following Autor, Dorn, and Hanson (2013). The results shown in the last two columns of Table 7 indicate that both estimates for violent- and property- crime become smaller (0.069 vs. 0.082; 0.593 vs. 1.035), suggesting the basic intuition that labor-intensive good imports play an important role is right. Albeit, both estimates remain positive and highly significant and the exposure impact on property crime is still much larger than that on violent crime.

Individual Crime Categories: although we find robust positive effect of exposure to Chinese import competition on two broadly defined crime categories, one may be interested in looking at crime categories individually. To explore this, we re-estimate equation (1) by changing the dependent variable to seven crime categories obtained from the original data. The corresponding estimation results are reported in Table 8. The first four columns correspond to results of violent crime for Murder, Rape, Robbery and Assault respectively while the last three columns are for property crime, i.e., Burglary, larceny, and motor theft. We find that within violent crime, robbery and assault are affected more by Chinese import competition (0.019 and 0.054) while rape are not affected and the magnitude of estimate for murder is relatively small, 0.002. This is understandable and consistent with our conjecture that the main motive for crime caused by Chinese import competition are from financial considerations. Looking at results within property crime, we find that the magnitude of estimate for Burglary and Larceny is much larger than that for Motor vehicle theft, 0.251, 0.769 vs. 0.023. Again, if the assumption of aggravated financial pressure caused by Chinese import competition is plausible (Autor, Dorn, Hanson, and , 2014), this result is intuitive too because the "profit" of Burglary and Larceny is modestly higher than motor vehicle theft (at least for expectation before the action).

4.6 Heterogeneous Response: Government Transfer

Theoretically, gains from trade outweigh the losses, i.e., although trade may hurt low-income workers in various ways, the gains from trade to consumers and producers due to lower price of imported goods and greater variety of inputs will insure that the net impact of trade to a country is positive. In this case, to ensure a pareto improvement of trade liberalization on all groups in the society, adoption of redistribution policies is critical. For example, if workers suffering from Chinese import competition could be compensated by government redistribution policies, the life pressure on them could be greatly alleviated which in turn will significantly decrease their motivations on crime.

To check this conjecture empirically, we expect that in counties with high level of government transfer, the exposure effect on crime should be significantly lower than that in counties with low government transfer.[13] The corresponding estimation results are reported in Table 9, with the first two columns corresponding to a subsample of counties below government transfer sample mean while the last two columns are results for a subsample of counties above government transfer sample mean. We find that there is no effect of exposure on both violent- and property- crime in the first two columns. However, we detect a positive and significant effect of exposure on crime in the last two columns; moreover, consistent with our baseline results, the effect of exposure on property crime is much larger than that for violent crime. These results suggest that consistent with trade theory, redistribution is an effect way in alleviating the adverse impact of trade liberalization.

5 Conclusion

Recent studies have uncovered that import competition has significant and negative effect on employment and wage of manufacture workers (see, e.g., Autor, Dorn, and Hanson, 2013; Balsvik, Jensen, and Salvanes, 2015). In this paper, we go one step further by examining the effect of county exposure to Chinese import competition on Crime in US. Following the same identification strategy of Autor, Dorn, and Hanson (2013), our empirical results indicate

[13] Government transfer data is obtained from BEA.

that counties with high import competition from China suffer from high crime rates. We conduct various robustness checks showing that our results are not influenced by assumption in the exclusion assumption, alternate sample periods, outliers, and US exports to China. Interestingly, we find that counties with large government transfer are less likely to be influenced by Chinese import competition.

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Table 1A: Summary Statistics

Variable	Observations	Mean	S.D.	Min	Max
Violent Crime Change	3059	-0.98	21.55	-629.46	140.21
Property Crime Change	3059	-9.98	107.12	-1571.43	488.03
Exposure	3068	357.08	25.58	0	606.06
Police	3059	30.21	83.08	0	3486.32
Unemployment Rate	3067	4.34	1.64	1.39	17.43
Pct 18_25	3066	8.85	3.45	2.5	41.7
Pct Black	3066	8.66	14.48	0	86.1
Pct Bachelor	3066	10.94	4.92	0	40
Per Capita Income	3023	0.34	1.24	0.001	49.72
Government Transfer	3031	0.35	1.17	0.0002	36.60
Population	3068	0.89	2.90	0	95.19

Notes: this table provides summary statistics for variables used in the baseline regression. Violent Crime Change and Property Crime Change are defined as the difference of relevant variables between 2000 and 2010 while Exposure denotes county exposure to Chinese import competition during the same period. Police, Pct 18_25, Pct Black, Pct Bachelor, Per Capita Income, Government Welfare, and Population are at the initial period level (2000).

Table 1B: Summary Statistics, Sample for Top 20% of County Exposure

Variable	Observations	Mean	S.D.	Min	Max
Violent Crime Change	616	0.43	18.04	-78.64	140.21
Property Crime Change	616	-3.33	94.78	-302.07	488.03
Exposure	621	392.27	28.58	370.26	606.06
Police	616	26.29	25.44	2.81	524.74
Unemployment Rate	620	4.34	1.63	1.41	17.43
Pct 18_25	620	9.20	3.57	4	34
Pct Black	620	10.17	15.05	0	84.7
Pct Bachelor	620	11.47	5.65	3.1	32.8
Per Capita Income	603	0.35	0.89	0.003	16.14
Government Transfer	607	0.66	2.24	0.003	36.60
Population	621	1.54	5.38	0	95.19

Notes: this table provides summary statistics for sample of top 20% of county exposure. Violent Crime Change and Property Crime Change are defined as the difference of relevant variables between 2000 and 2010 while Exposure denotes county exposure to Chinese import competition during the same period. Police, Pct 18_25, Pct Black, Pct Bachelor, Per Capita Income, Government Welfare, and Population are at the initial period level (2000).

Table 1C: Summary Statistics, Sample for Bottom 20% of County Exposure

Variable	Observations	Mean	S.D.	Min	Max
Violent Crime Change	610	-1.52	18.90	-130.25	128.23
Property Crime Change	610	-15.57	102.28	-597.02	349.03
Exposure	611	332.26	18.45	0	339.43
Police	610	28.54	31.63	2.21	498.66
Unemployment Rate	611	4.55	1.96	1.48	16.82
Pct 18_25	610	7.77	2.73	2.5	41.7
Pct Black	610	6.54	14.10	0	84.3
Pct Bachelor	610	10.23	4.30	0	36.6
Per Capita Income	604	0.22	0.17	0.002	2.22
Government Transfer	605	0.07	0.16	0.0002	3.59
Population	611	0.20	0.51	0	8.44

Notes: this table provides summary statistics for sample of bottom 20% of county exposure. Violent Crime Change and Property Crime Change are defined as the difference of relevant variables between 2000 and 2010 while Exposure denotes county exposure to Chinese import competition during the same period. Police, Pct 18_25, Pct Black, Pct Bachelor, Per Capita Income, Government Welfare, and Population are at the initial period level (2000).

Table 2: First Stage Estimates, 2000-2010

VARIABLES	(1)	(2)
	Dependent variable is county exposure to Chinese import competition	
Variable of Interest		
IV	0.230***	0.230***
	(0.013)	(0.013)
Initial Crime	-0.012	-0.001
	(0.014)	(0.003)
Police	-0.004*	-0.004*
	(0.002)	(0.002)
Unemployment Rate	0.400	0.395
	(0.297)	(0.297)
Pct 18_25	0.137	0.141
	(0.119)	(0.120)
Black	0.031	0.027
	(0.034)	(0.032)
Education	0.360***	0.367***
	(0.109)	(0.111)
Per Capita Income	0.194	0.186
	(0.257)	(0.255)
Population	-0.484	-0.507
	(0.553)	(0.552)
Kleibergen-Paap rk LM statistic	223.969***	224.219***
Shea Partial R Square	0.191	0.191
Kleibergen-Paap rk Wald F statistic	335.631*	335.773*
R-Square	0.211	0.211
Observations	3,022	3,022

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3: Country Exposure to Chinese Import Competition and Crime, 2SLS

VARIABLES	(1) Dependent variable is change of violent crime, 2000-2010	(2)	(3)	(4) Dependent variables is change of property crime, 2000-2010	(5)	(6)
Variable of Interest						
Exposure	0.057**	0.130***	0.082***	0.631***	1.221***	1.035***
	(0.029)	(0.027)	(0.026)	(0.157)	(0.146)	(0.144)
Initial Crime		-0.541***	-0.606***		-0.436***	-0.457***
		(0.083)	(0.087)		(0.021)	(0.025)
Unemployment Rate			0.005**			0.010
			(0.002)			(0.012)
Police			0.742***			1.019
			(0.226)			(1.071)
Pct 18_25			0.365***			2.588***
			(0.088)			(0.515)
Black			0.226***			0.679***
			(0.062)			(0.153)
Education			0.016			-1.520***
			(0.080)			(0.433)
Per Capita Income			-0.467			-1.888
			(0.397)			(2.301)
Population			0.609*			1.954**
			(0.313)			(0.966)
DWH-Test (p)	1.05	13.85***	3.96**	10.25***	57.20***	38.70***
R-Square	0.002	0.44	0.49	0.003	0.35	0.39
F Statistic	4.01**	23.93***	20.52***	16.20***	214.26***	95.12***
Observations	3,059	3,059	3,022	3,059	3,059	3,022

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 4: Falsification Tests, 2SLS

VARIABLES	(1) Period: 1992-2000 Violent crime	(2) Property crime	(3) Period: 1994-2000 Violent crime	(4) Property crime	(5) Period: 1996-2000 Violent crime	(6) Property crime
Variable of Interest						
Exposure (2000-2010)	-0.002	0.282	-0.010*	0.156	-0.006	0.214
	(0.006)	(0.173)	(0.006)	(0.167)	(0.006)	(0.161)
Initial Crime	-0.475***	-0.394***	-0.435***	-0.404***	-0.365***	-0.371***
	(0.021)	(0.016)	(0.017)	(0.018)	(0.026)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.54	0.42	0.49	0.37	0.32	0.32
F Statistic	106.93***	122.36***	106.61***	87.84***	34.22***	59.05***
Observations	3,018	3,018	3,019	3,019	3,021	3,021

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: Check for IV Validity, 2SLS

VARIABLES	(1) Violent crime	(2) Property crime	(3) Violent crime	(4) Property crime
	Subsample: excluding steel, flat glass, and cement		Subsample: excluding computers	
Variable of Interest				
Exposure	0.076***	1.018***	0.018***	0.250***
	(0.026)	(0.145)	(0.006)	(0.033)
Initial Crime	-0.604***	-0.456***	-0.607***	-0.464***
	(0.087)	(0.025)	(0.087)	(0.025)
Controls	Yes	Yes	Yes	Yes
DWH-Test (p)	4.00**	37.45***	2.84*	35.79***
R-Square	0.49	0.40	0.49	0.40
F Statistic	363.22***	264.18***	363.83***	265.35***
Observations	3,022	3,022	2,995	2,995

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6: Alternative Sample Periods, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2000-2008 period		2000-2006 period		2000-2004 period		2000-2002 period	
VARIABLES	Violent crime	Property crime	Violent crime	Property crime	Violent crime	Property crime	Violent crime	Property crime
Variable of Interest								
Exposure	0.013**	0.637***	0.019***	0.585***	0.018***	0.383**	0.015**	0.238*
	(0.006)	(0.148)	(0.005)	(0.113)	(0.006)	(0.158)	(0.006)	(0.139)
Initial Crime	-0.343***	-0.358***	-0.330***	-0.308***	-0.352***	-0.230***	-0.303***	-0.172***
	(0.109)	(0.039)	(0.111)	(0.039)	(0.107)	(0.043)	(0.114)	(0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	4.37***	43.87***	5.21***	24.7***	5.80***	17.07***	3.63***	5.76***
F Statistic	0.19	0.26	0.16	0.21	0.21	0.15	0.21	0.12
Observations	3,022	3,022	3,022	3,022	3,022	3,022	3,022	3,022

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: Other Robustness Checks, 2SLS

VARIABLES	(1) Accounting for county exports to China: Violent Crime	(2) Accounting for county exports to China: Property Crime	(3) Import Competition from low-income countries: Violent Crime	(4) Import Competition from low-income countries: Property Crime	(5) Excluding apparel, footwear, and textiles: Violent Crime	(6) Excluding apparel, footwear, and textiles: Property Crime
Net Exposure	0.041	0.771***				
	(0.037)	(0.205)				
Exposure			0.185	1.240	0.069***	0.593***
			(0.205)	(1.638)	(0.016)	(0.086)
Initial Crime	-0.607***	-0.454***	-0.608***	-0.455***	-0.608***	-0.462***
	(0.087)	(0.025)	(0.087)	(0.025)	(0.087)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.49	0.41	0.48	0.40	0.41	0.49
F Statistic	17.71***	86.52***	17.36***	85.84***	86.04***	18.68***
Observations	3,022	3,022	3,022	3,022	3,022	3,022

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: Individual Crime Categories, 2SLS

VARIABLES	(1) Murder	(2) Rape	(3) Robbery	(4) Assault	(5) Burglary	(6) Larceny	(7) Motor Theft
Variable of Interest							
Exposure	0.002**	0.006	0.019***	0.054**	0.251***	0.769***	0.023**
	(0.001)	(0.003)	(0.004)	(0.023)	(0.047)	(0.102)	(0.011)
Initial Crime	-0.853***	-0.589***	-0.472***	-0.638***	-0.408***	-0.484***	-0.547***
	(0.048)	(0.028)	(0.121)	(0.072)	(0.032)	(0.024)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Square	0.59	0.31	0.44	0.49	0.23	0.44	0.66
F Statistic	40.55***	73.72***	11.38***	20.46***	37.94***	92.64***	173.68***
Observations	3,022	3,022	3,022	3,022	3,022	3,022	3,022

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 9: Role of Government Transfer

VARIABLES	(1) Above Sample Mean Violent Crime	(2) Property Crime	(3) Below Sample Mean Violent Crime	(4) Property Crime
Variable of Interest				
Exposure	0.011	0.056	0.073**	1.070***
	(0.052)	(0.295)	(0.030)	(0.164)
Initial Crime	-0.445***	-0.502***	-0.668***	-0.489***
	(0.031)	(0.032)	(0.090)	(0.031)
Controls	Yes	Yes	Yes	Yes
R-Square	0.48	0.61	0.52	0.37
F Statistic	27.85***	36.61***	13.81***	67.79***
Observations	542	542	2,480	2,480

Notes: white's standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 1: Chinese Imports in U.S., 1991-2011

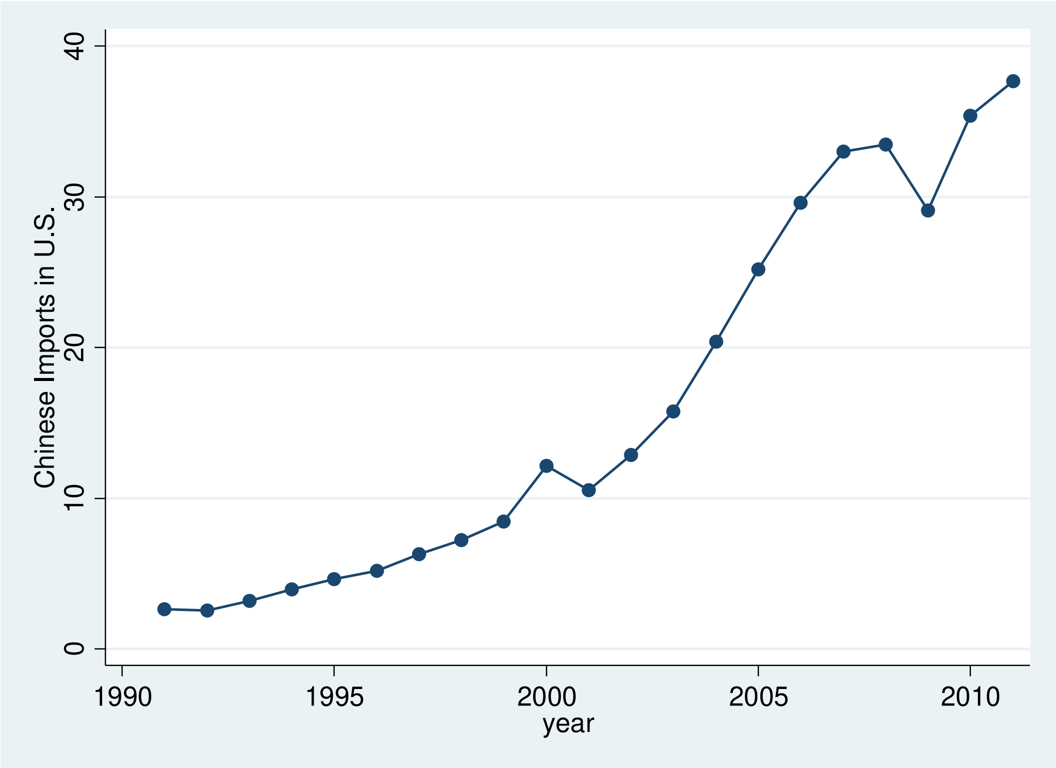

Figure 2A: Times Series of Murder

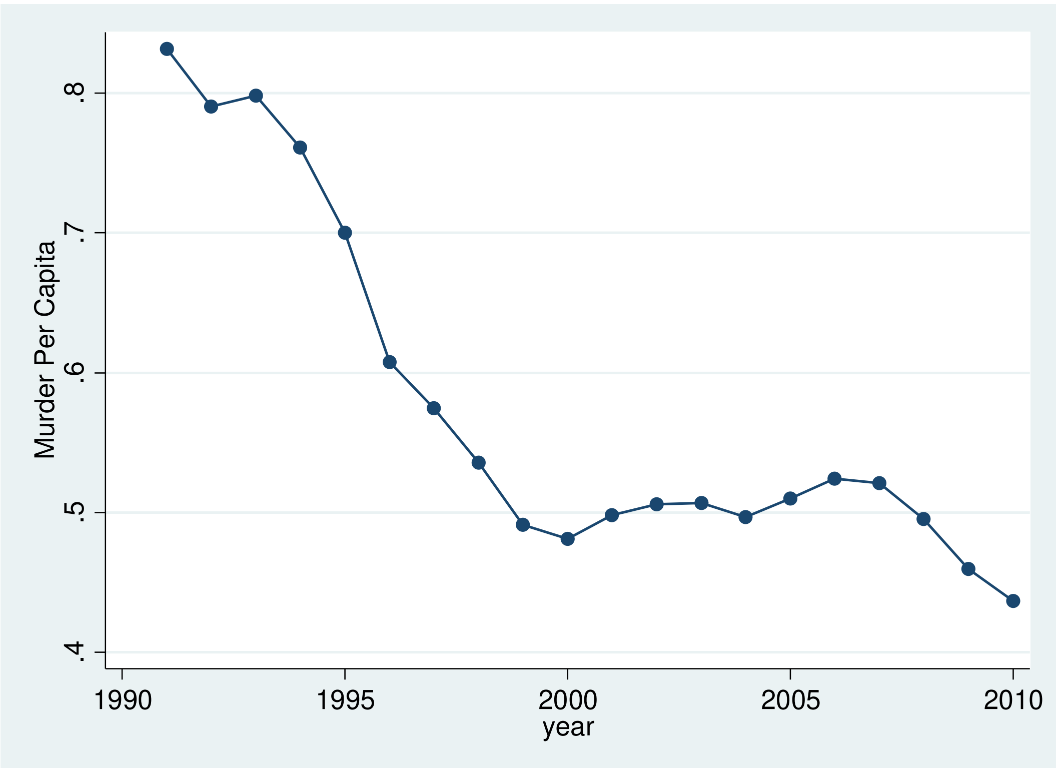

Figure 2B: Time Series of Rape

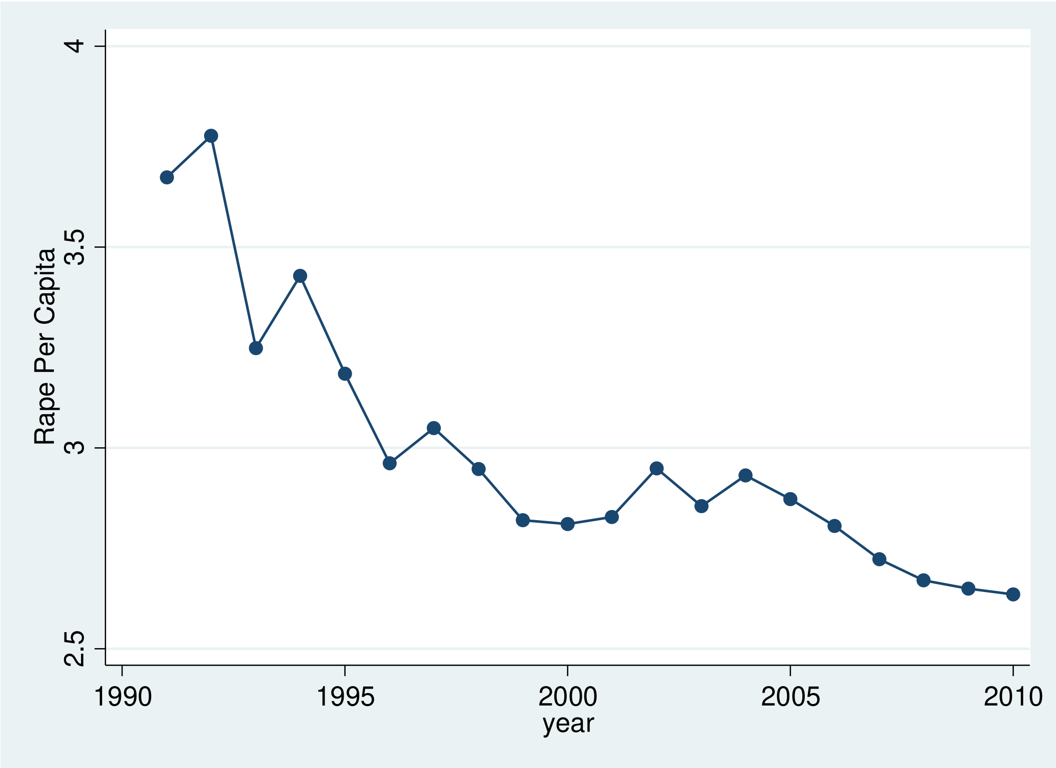

Table 2C: Time Series of Robbery

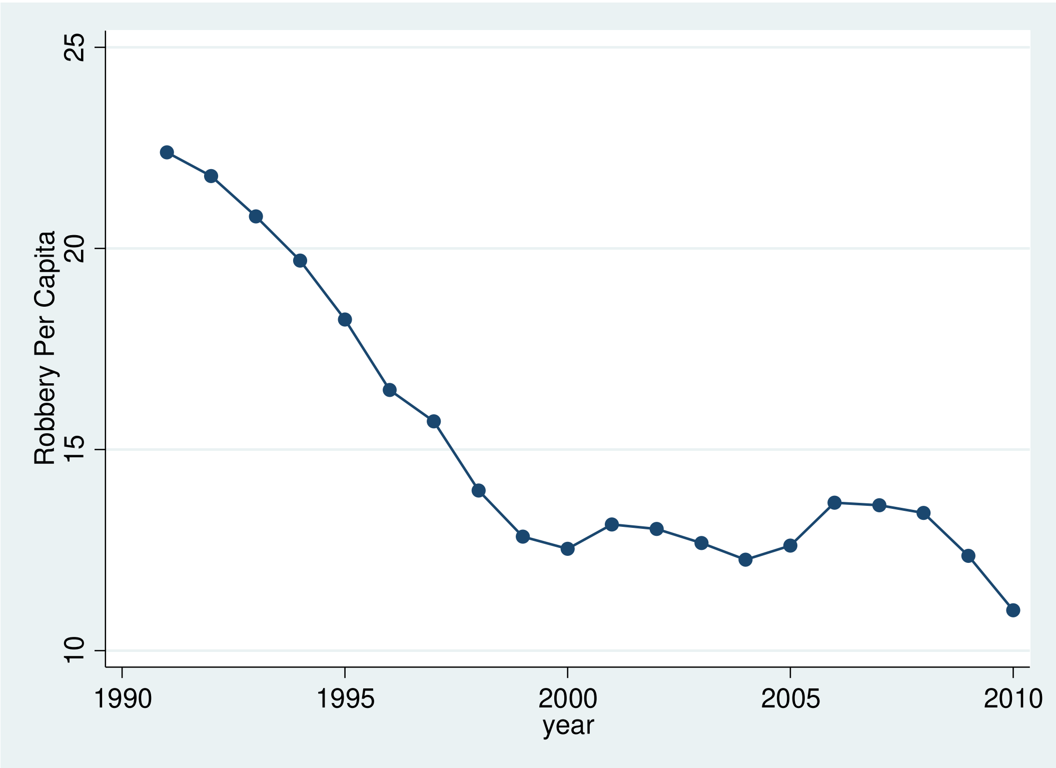

Figure 2D: Time Series of Assault

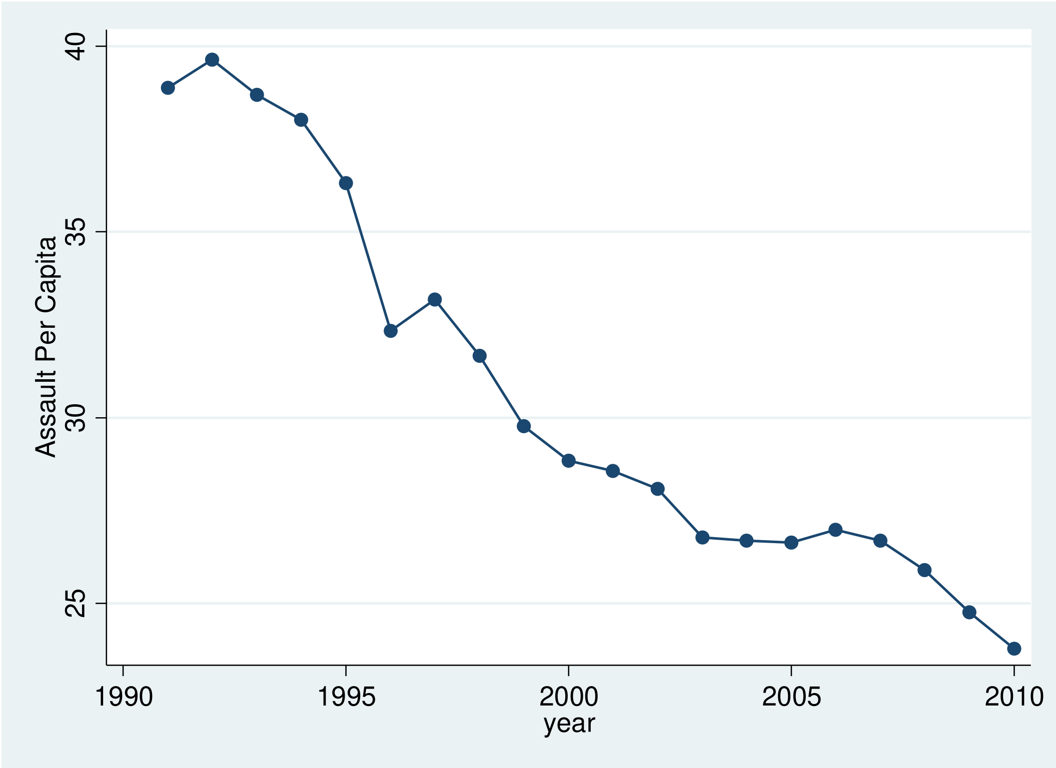

Figure 2E: Time Series of Burglary

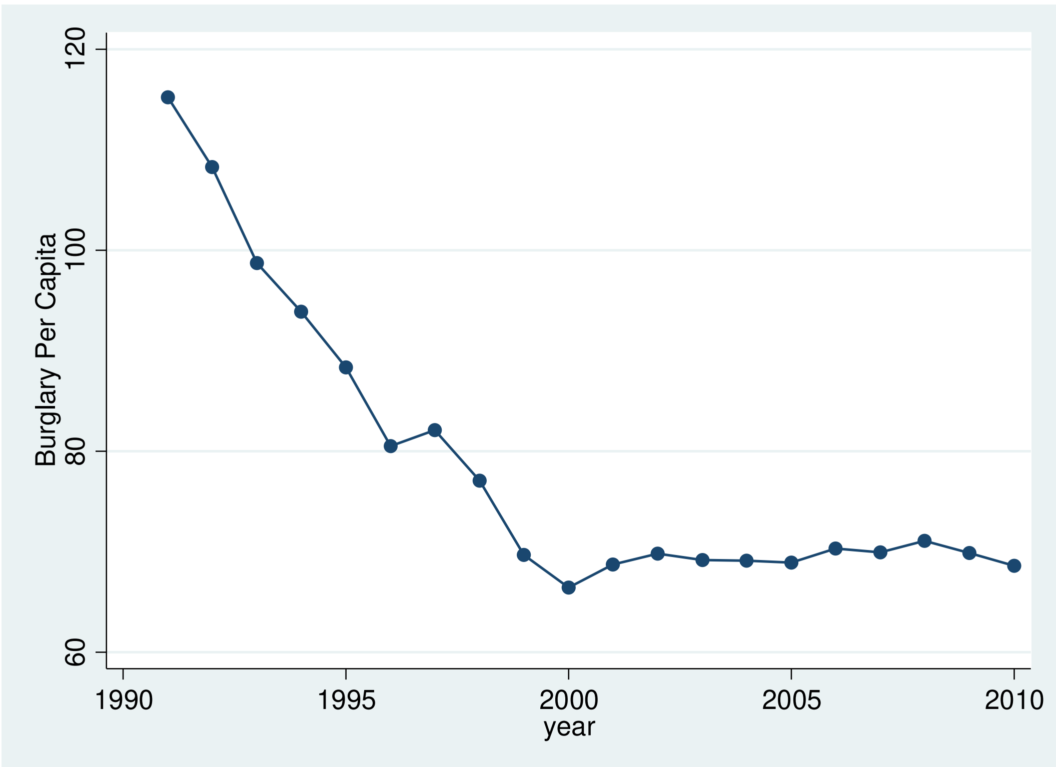

Figure 2F: Time Series of Larceny

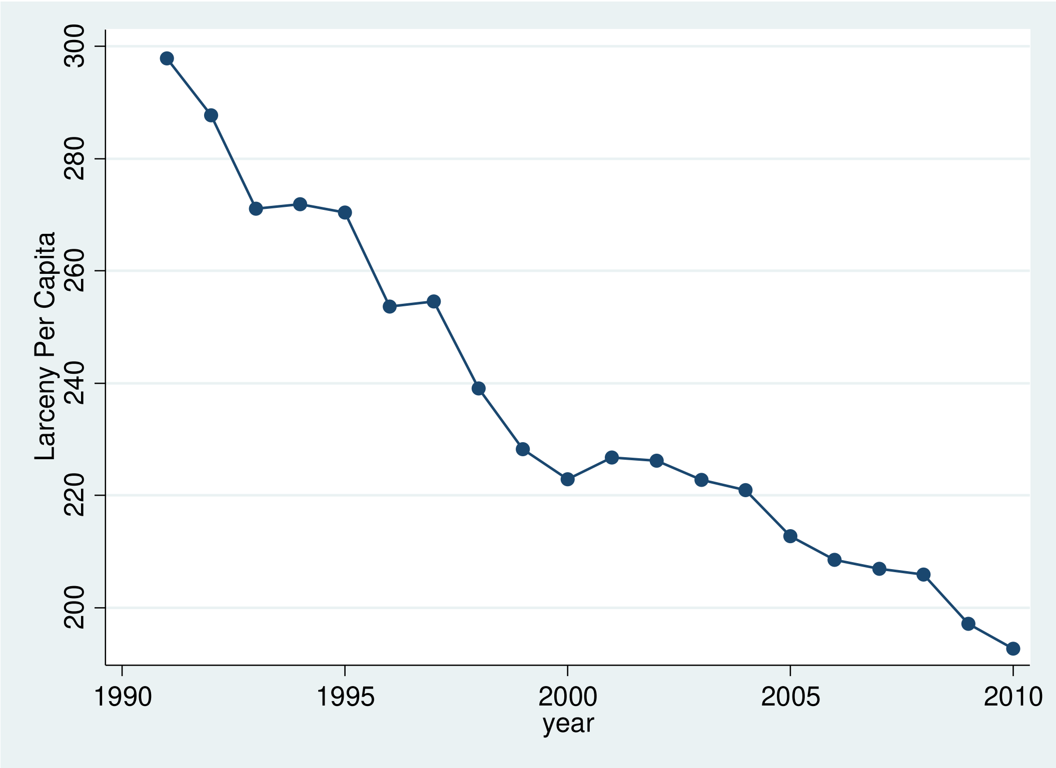

Figure 2G: Time Series of Motor Theft

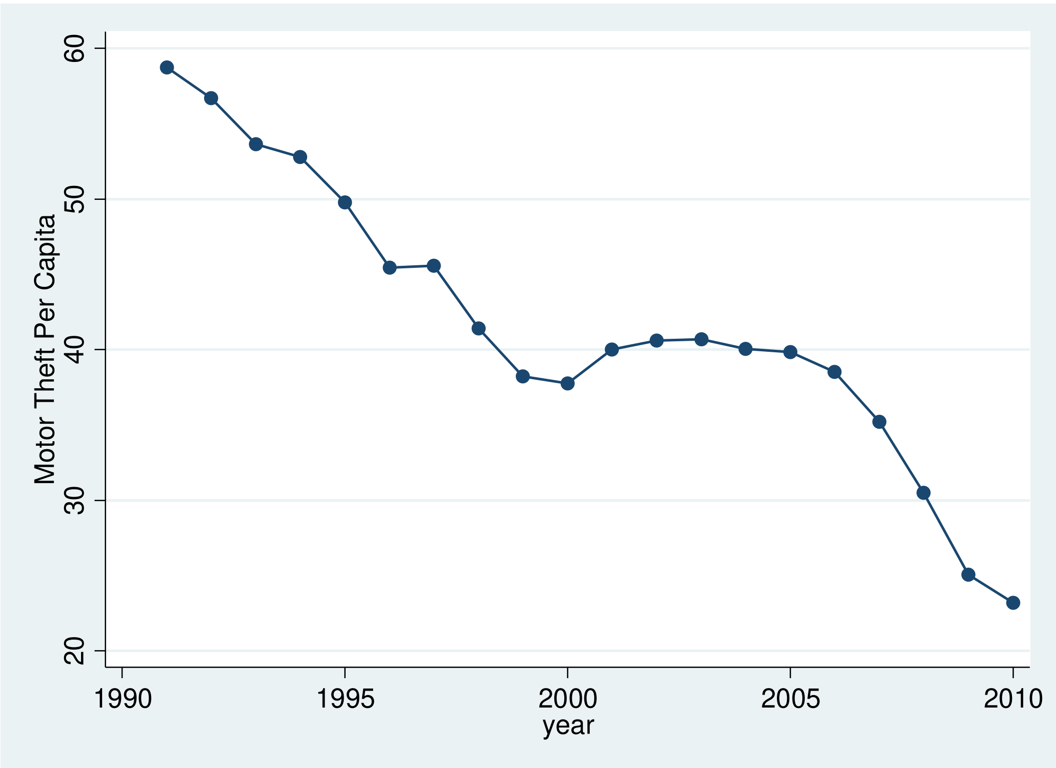

Figure 2: Country Exposure to Chinese Import Competition, 2000-2010

Notes: this figure shows the intensity of county exposure to Chinese import competition between 2000 and 2010. A darker shade corresponds to greater exposure.