How and Why Does Immigration Affect Crime?

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Abstract

The perception that immigration fuels crime is an important source of anti-immigrant sentiment. Using Malaysian data for 2003-10, this paper provides estimates of the overall impact of economic immigration on crime and evidence on different socio-economic mechanisms underpinning this relationship. Our IV estimates suggest that immigration decreases crime rates, with an elasticity of around -0.97 for property and -1.8 violent crime. Three-quarters of the negative causal relationship between immigration and property crime rates can be explained by the impact of immigration on the underlying economic environment faced by natives. The reduction in violent crime rates is less readily explained by these factors, and is plausibly due to a lower propensity of immigrants to commit violent crimes.

Keywords: crime, immigration.

JEL Classification: F22, K42.

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1 Introduction

Increased crime is among the main fears voiced in public opinion surveys on immigration.[1] Crime even surpasses other concerns such as 'immigrants take jobs away from natives' as the main reason for public demands for more restrictive immigration policies in many countries (Mayda 2006; Bianchi, Pinotti and Buonanno 2012). Despite its prominence in the public narrative, the academic literature on the linkages between immigration and crime is still sparse and often inconclusive (see Bell and Machin 2013 for a comprehensive survey). This paper makes three main contributions to this literature. First, it provides causal estimates of the impact of immigration on different types of crime. Second, the paper presents evidence on the mechanisms that underlie the impact of immigration on crime. Third, while previous work has focused almost entirely on high-income OECD destination countries, the paper provides analysis for Malaysia, a major middle-income destination where there is considerable public concern about the impact of immigration on crime.

The paper uses variation in crime rates and immigration flows across Malaysian states for the period 2003-10 to identify the impact of immigration on crime.[2] Our instrumental variable estimates show that immigration results in a significant reduction in crime rates. The IV estimates of the elasticity of the crime rate with respect to immigration are large and statistically significant, -0.97 for property crime rates and -1.8 for violent crime rates. The implication is that an increase in immigrants in a state's population from 10 to 11 percent decreases the property crime rate from 0.83 to 0.75 percent, and the violent crime rate from 0.19 to 0.17 percent, calculated at the average immigration and crime levels for 2010.

Our empirical approach is most closely related to recent cross-area panel studies on Italy (Bianchi, Pinotti and Buonanno 2012), the United States (Spenkuch 2014, and

[1] See, for example, Duffy and Frere-Smith (2013).

[2] The identifying variation of our novel instrument comes from changes in the population and age structure of the main migrant source countries and the differential historic propensity of these groups to migrate to particular regions in Malaysia. The instrument combines the demographic variation used in, for example, Hanson and McIntosh (2010) with the typical Altonji-Card instrument. The major advantage of our instrument is that it provides both exogenous time-series and cross-sectional variation.

Chalfin 2014, 2015) and the United Kingdom (Bell, Fasani and Machin 2013).[3] The evidence for the United States and Italy is, on the whole, inconclusive on whether there is a causal relationship between immigration and crime (property or violent). Among the papers that find significant effects, Chalfin (2015) shows there is a negative impact on property crime of Mexican immigrants to the United States. Also, Bell, Fasani and Machin (2013) find that economic migrants, from the new member states entering the European Union in 2004, caused a decrease in property crimes in the United Kingdom; while asylum seekers, mostly without access to the formal labor market, caused an increase. The vast majority of immigration to Malaysia is based on economic motivations. Hence, our estimates on the overall impact on crime rates are consistent with the evidence from economically motivated Eastern European migration to the United Kingdom and Mexican immigration to the United States.

There are numerous plausible channels through which immigration affects crime rates, but evidence on these is even more scarce. First, there is a direct impact. Immigrants may have a different propensity than natives to commit or be victimized by crime due to their different economic, social and cultural profiles. Second, immigration might induce a change in the size and composition of the local population in a region. Natives with different propensities to commit crimes may be differentially affected by immigration. As a result, each region will face inflows and outflows of different types of natives, depending on the degree of their complementarity and substitutability with the migrants. Third, the arrival of immigrants may change the economic outcomes, such as employment and wages, of the existing native population. This in turn changes the relative attractiveness of and incentives for criminal activities for natives. Our empirical strategy is designed with these different channels in mind. After identifying the relationship between immigration and crime, we use the decomposition of Gelbach (2016) to determine the relative importance of the various channels which underlie this causal relationship.

The empirical literature on the economics of crime suggests that the most important

[3] Further evidence come from Alonso, Garoupa, Perera and Vazquez (2008) for Spain and Butcher and Piehl (1998) for the US. Other approaches include individual-level studies of criminal behavior (Butcher and Piehl 1998, Papadopoulos 2011, Nunziata 2011), and evidence from imprisonment rates (Butcher and Piehl 2007).

(and robust) variables explaining crime rates are related to the number and economic prospects of young (ages 15 - 29) males in a region's population.[4] Fully consistent with this evidence, our results show that around 50 percent of the estimated impact of immigration on property crime can be accounted for by the immigration-induced change in the fraction of young males in a state. Also, the earnings potential of young males, as measured by the 25th percentile of their earnings distribution, and their employment rates are negatively correlated with property crime rates (though uncorrelated with violent crime). Changes in the number of police in a state are uncorrelated with both property and violent crimes. The fraction of working poor among the employed, those below 50 percent of the median earnings in a state and year, is negatively correlated with property crimes rates (and uncorrelated with violent crime). The implication is that improved labor market conditions for people who are at high-risk of unemployment reduces their incentives to engage in property crimes.

Controlling for these covariates decreases the magnitude of the estimated causal impact of immigration on property crimes by three-quarters, from an elasticity of -0.97 to an elasticity of -0.25. It is also no longer statistically significant. In contrast, the inclusion of covariates decreases the estimated magnitude of the impact of immigration on violent crime by only 20 percent, and the estimated elasticity of -1.5 remains statistically significant. These results suggest that immigration decreases property crime rates primarily because it changes various economic conditions for natives. On the other hand, immigration decreases violent crime rates directly because immigrants plausibly commit less violent crimes.[5]

Malaysia is an important setting in which to explore the relationship between low-skilled immigration and crime. It is a major destination for migrants; officially, over 10 percent of the population is composed of foreign-born people. As in most developing countries, these migrants are primarily from countries in the same region, with Indonesia as the largest source country. Like in OECD destinations, immigration to Malaysia is

[4]See, for example, Gottfredson and Hirschi (1983), Farrington (1986), Levitt (1997), Grogger (1998), Freeman (1999), Gould, Mustard and Weinberg (2002), Machin and Meghir (2004), and Dills, Miron and Summers (2010).

[5]Another possibility is that migrants are less likely to report being victimized.

primarily economically motivated and should have similar labor market effects (Docquier, Ozden and Peri 2014). As a consequence, we expect economic migrants to have a negative impact on crime rates, adding to the evidence from Bell, Fasani and Machin (2010). In contrast to OECD countries, however, immigrants in Malaysia are overwhelmingly low skilled. Furthermore, there are only very limited pathways to permanent residency or citizenship for immigrants. Most immigrants in Malaysia are on fixed-term employment visas or have overstayed them.[6] Over this period there was also prominent public concern in Malaysia about the rising incidence of violent crimes, which has increased by nearly 30 percent between 2003 and 2010, and the role of immigrants in explaining this rapid change. For example, Deputy Home Minister Wan Junaidi Tuanku Jaafar in 2014 suggested that "The influx of foreign migrants is among the contributing factors to the rise in crime rates in the country."[7]

The remainder of the paper proceeds as follows. Section 2 provides a description of the data. Section 3 describes our empirical strategy and instrument, and Section 4 presents the results. Section 5 concludes.

2 Data and Descriptive Statistics

2.1 Data Sources

Our analysis relies on two main data sources. The crime data for the years 2003 to 2010, by type and state, come from the Department of Statistics publication, titled *Social Statistics Bulletin* and are based on the Royal Malaysian Police crime database. There are 14 states in our analysis as we include Putrajaya in Kuala Lumpur and Labuan in Sabah. Data on economic and demographic variables, and the number of immigrants, come from the annual Labour Force Survey (LFS) of Malaysia, which is available for the period 1990

[6]The role of legal status of migrants and the permanency of migration on the propensity to commit crime is explored in recent work by Baker (2015) and Mastrobuoni and Pinotti (2015).

[7]Free Malaysia Today, "Foreign migrants pushing up crime rates" published on November 20, 2014. Malaysian concerns about immigration and crime have made it as far as the New York Times, "Malaysia's Immigrant Worker Debate" published March 28, 2016. See also New Strait Times, "Illegal workers a threat to security" published on February 16, 2016; The Star, "Deputy IGP: Locals, not migrant workers, are major perpetrators of crime" published February 19, 2016; and The Straits Times, "In Malaysia: 'No' to having more foreign workers" published on February 20, 2016.

to 2010.[8] Information on wages, salaries and overtime pay, as well as days and hours worked is collected as part of a supplement to the main LFS since 2007. The main survey samples, on average, around 1 percent of the population. The variables for this paper are constructed from the underlying micro-level data, 300-400 thousand observation per year, and aggregated to the state-year level. We aggregate our micro-level data to the state-year level since the data on crime is only available by state and year.

2.2 Crime and Immigration

Our main crime measures are total crime, and its components - property and violent crime. Property crimes include house break-ins and theft, vehicles thefts, snatch theft and other thefts. Violent crimes include murder, rape, robbery (with and without a firearm) and offenses causing bodily injuries. Figure 1 presents a time-series of both property and violent crime, together with the immigrant stock. Table 1 reports these, and a more detailed breakdown, for the years 2003 and 2010.[9] Property crimes are far more prevalent than violent crimes, with respectively 827 and 186 incidences per 100,000 (working-age population of 15-64 year olds) in 2010. Vehicle thefts make up nearly half of all property crimes, followed by house break-ins (around 20 percent). The large majority of violent crimes are robberies (around two-thirds), though there has been a marked increase in (reported) rapes and bodily injuries. Violent crime rates in general have increased by almost 30 percent between 2003 and 2010, from 145 to 186 per 100,000 people. Annual property crime rates in contrast have fallen by about 2 percent from 851 to 827 incidences per 100,000 people.

Figure 2 present property and violent crime rates per 100,000 inhabitants by state in 2010. There are clearly large variations in property and violent crime rates. For example, crime is particularly high in the main city Kuala Lumpur (2555 total offense per

[8] The exceptions are 1991 and 1994 when the survey was not conducted and 2008 when the survey weights were not available.

[9] Note that Malaysia has quite low violent crime rates by international standards. The homicide rate per 100,000 inhabitants is 2.3, compared to 4.8 in the United States. Other South East Asian countries have much higher homicide rates, with 8.1 in Indonesia, 8.8 in the Philippines and 5.0 in Thailand. Statistics are from the United Nations Office on Drugs and Crime for the latest year available, see https://data.unodc.org.

100,000 inhabitants) and particularly low in Sabah in northern Borneo (351 offenses per 100,000 inhabitants). Violent and property crimes are highly correlated, with a correlation coefficient of 0.93. However, there is still considerable variation in the relative prevalence of property and violent crimes across states. The fraction of all offenses that are violent crimes ranges from 25 percent in Negeri Sembilan, in Peninsular Malaysia south of Kuala Lumpur, to 12 percent in Sarawak in northern Borneo.

Figure 3 presents the immigrant share in the working-age population by state in 2010. This share varies from 1.8 percent in Perlis, in the northwest of Peninsular Malaysia bordering Thailand, to 26 percent in Sabah and 8 percent in Kuala Lumpur.[10] Over a longer period, the share of immigrants in the population has increased from 3.6 to 10.6 percent between 1990 and 2010. Over the sample period about 55 percent of all immigrants come from Indonesia, 20 percent from the Philippines and the remainder from other Asian countries such as Bangladesh, Cambodia, India, Laos, Myanmar, Sri Lanka, Thailand, and Vietnam. Overwhelmingly migration to Malaysia is for economic reasons.[11] There are two types of formally registered immigrants in Malaysia: expatriates and foreign workers. Expatriates are highly-skilled or educated professionals and made up only 2 percent of the total immigrant stock in 2010. The remaining 98 percent of immigrant population receive temporary work permits, which are valid for generally a year and renewable for at most five years. These workers are not allowed to bring any dependents and are required to exit Malaysia upon termination of their contract. There are very limited pathways to permanent residency or citizenship for this group. Formal employment of foreign workers is regulated by quotas assigned to specific sectors, which are adjusted annually if there are extraordinary changes in underlying demand conditions.

There are a substantial number of irregular or undocumented foreign workers in the labor force due to the restrictions on formal employment. Many of the undocumented migrants have entered Malaysia legally but overstayed their permits. Precise estimates are not available, but a 1996/97 regularization program resulted in almost one million un-

[10]Sabah is a clear outlier in terms of the share of immigrants in the working-age population. We show that all our results are robust to dropping Sabah from the analysis

[11]UNHCR data shows that in 2003 there were less than 10,000 refugees in Malaysia, by 2010 that number had increased to around 80,000 primarily due to refugees from Myanmar.

registered migrants being legalized. Another new program, labelled the 6P, implemented in 2011 also registered over one million undocumented foreign workers. This evidence suggests that as many as half of migrant workers might be employed without proper documentation. In principle, the Malaysian LFS attempts to survey these undocumented immigrants as well. It is, for example, reassuring that we do not observe a discontinuous increase in the estimated number of immigrants during the 1996/97 regularization. In practice, of course the LFS is unlikely to obtain a fully representative sample of undocumented migrants.[12] This creates measurement error and general undercounting of immigrants in our data. Our instrumental variable strategy, as discussed below, aims to ensure that this measurement error does not bias our estimates.

2.3 Variable Descriptions

There are a number of demographic and economic variables that the crime and economics literature has identified as important determinants of crime rates. Our main specifications include seven variables that arguably proxy for most of the major explanations for crime: demographics, legal earning opportunities for potential criminals, general economic conditions, poverty, the economic benefits of crime, deterrence (police), and population density.

Our main demographic variable used to explain crime rates is the number of males aged 15 - 29, since young men compose the group that is most prone to engaging in criminal activities.[13] Consistent with economic models of crime (Becker 1968, Ehrlich 1973), we include several variables that proxy the expected costs and benefits of illegal activity. First, the 25th percentile of the earnings of young men, to proxy the returns to legal activity available to the key demographic likely to commit crimes.[14] Second, the total number of employed (ages 15 - 64), a general proxy for employment opportunities.

[12] Note that, for example, the LFS does not survey those in communal housing.

[13] See Gottfredson and Hirschi (1983), Farrington (1986), Levitt (1997), Grogger (1998), Freeman (1999), Dills, Miron and Summers (2010). Our results are robust to varying definitions of who counts as young, specifically using ages 15-24 or ages 15-34.

[14] See Grogger (1998), Gould, Mustard and Weinberg (2002) and Machin and Meghir (2004) on the connection between wages and crime. Our monthly earnings measure reflects both the hourly wage and the hours worked per month. It is a broader measure of earnings than simply the hourly wage. Wage and salary information is available for all private and public sector employees starting in 2007.

More commonly, the literature uses the unemployment rate to proxy for employment opportunities.[15] However, Malaysia does not have a proper unemployment insurance system and informal employment is quite prevalent. So the reported unemployment rates are low and poor proxies of labor market conditions. Instead we use the number of employed in a given state in a given year. Third, we include a poverty measure. The connection between poverty and crime is a heatedly debated topic, and the linkages are far from clear (see, for example, Heller, Jacob and Ludwig 2011). We do not have access to regional household poverty rates, so instead we construct a measure of the working poor. Specifically, our metric is the number of employed with earnings below the 50 percent of the median monthly earnings by state and year.[16] Note that there are two main reasons why this measure may vary over time. People might become poorer and poor people might obtain jobs. Hence, it is unclear how this measure will be related to crime. Fourth, we include a measure of the opportunities for criminal activity, such as theft. For this, we use the 75th percentile of earnings in a state and year as a proxy.

The role of deterrence on criminal behavior is an another critical issue in the literature. We include the number of police by state and year as our measure of deterrence.[17] Finally, all our specifications include the log of population (ages 15 - 64) as a covariate. This implicitly controls for population density, another key determinant of the level of criminal activity (Glaeser and Sacerdote 1999), since all our estimating equations include state fixed effects. There are numerous alternative measures that could be included in our specifications. Most importantly, there is extensive work on the impact of education on crime.[18] Our results are robust to using low educated men and their earnings as

[15] Raphael and Winter-Ember (2001), Fougere, Kramarz and Pouget (2009), Bianchi, Pinotti and Buonanno (2012), Gronqvist (2013) and Spenkuch (2014).

[16] In 2014 only 0.6 percent of Malaysian fell below the official national poverty line (RM930 in the peninsula, RM1,170 in Sabah and Labuan and RM990 in Sarawak). Given the small incidence of absolute poverty in Malaysia, we construct a standard, relative poverty measure for the working poor using the Malaysian LFS.

[17] For evidence that police reduces crime see Levitt (1997) or Draca, Machin and Witt (2011). Kessler and Levitt (1999) consider whether longer mandated sentence lengths reduce crime. Similarly, Langan and Farrington (1998), building on a large body of cross-national studies, find substantial negative correlations between the likelihood of conviction and crime rates. The number of police are calculated from the Malaysian LFS using the occupation codes (MASCO 5142), they are not official police numbers.

[18] There is evidence showing a causal crime reducing impact of education. For the US see Lochner and Moretti (2004), and for England and Wales see Machin, Marie and Vujic (2011).

explanatory variables instead of young males.[19]

Table 2 presents summary statistics for the main explanatory variables used in the analysis. The data is for 2003 and 2010, except for variables based on earnings which are for 2007 and 2010, since the LFS only started collecting wage and salary information at this date. The number of immigrants increased by 18 percent over this period. The fraction of young males in the working-age population is stable at 22 percent and equally split between men and women. The fraction employed fell from 61 to 59 percent, while unemployment remained stable at 2 percent. The number of police increased by 42 percent between 2003 and 2010. The number of working poor also increased rapidly, from 10 to 14 percent. The 25th percentile of monthly earnings for young males increased from 714 to 764 Malaysian Ringgit. The 75th percentile of the overall earnings distribution increased more rapidly from 1908 to 2296 Malaysian Ringgit.[20]

3 Empirical Strategy

3.1 The Impact of Immigration on Crime

The first step of our empirical strategy is identifying the total effect of immigration on crime. Our baseline specification takes the following form:

$$\ln C_{rt} = \beta^B \ln M_{rt} + \alpha_1 \ln pop_{rt} + \delta_r + \delta_t + \varepsilon_{rt}, \quad (1)$$

where $\ln C_{rt}$ is the natural log of the number of crimes, $\ln M_{rt}$ is the log of the number of immigrants, and $\ln pop_{rt}$ is the log of the total population of state r in a particular year t.[21] All specifications include state δ_r and year fixed effects δ_t. Hence, the identifying

[19] When including both sets of variables the estimates become a lot less precise and only those based on age remain significant. The likely reason is that in Malaysia educational attainment has been increasing rapidly, and thus age and education are highly correlated. This makes it hard to disentangle the impact of education from that of age.

[20] Monthly earnings have been adjusted for changes in the consumer price index and are in 2010 Malaysian Ringgit. 1 US dollar is around 1.44 Malaysian Ringgit (RM) in purchasing power parity.

[21] The log-log specification is common in this literature, see for example Bianchi, Pinotti and Buonanno (2012) and Spenkuch (2014). Bell, Fasani and Machin (2013) estimate the effect of immigration ratios on crime rates in levels. Chalfin (2014, 2015) regresses the log crime rate on the immigrant share. Given our log-log specification the results are identical if our dependent variable is the log of the crime rate or

variation comes from state-level deviations of changes in immigration and crime rates over time from the national average. The inclusion of the natural logarithm of population implies that the main coefficient of interest, β^B, is the elasticity of the crime rate with respect to the immigrant share in a given state and year. If $\beta^B > 0$ then the total impact of immigration is to increase the crime rate in a Malaysian region, if $\beta^B < 0$ immigration decreases the crime rate.

In estimating equation (1) all variables are aggregated at the state by year level. That is also the level of variation of our instrumented immigration numbers. Remaining concerns pertain to the possible heteroscedasticity of standard errors and serial correlation within a state, (see Bertrand, Duflo and Mullainathan 2004). All reported standard errors are robust to heteroscedasticity. One option for dealing with serial correlation is to cluster standard errors by state. In a robustness check, we show that our main results are robust to clustering standard errors by state. However, there are only 14 states, which is likely too few to make clustering advisable (Angrist and Pischke 2009, Cameron and Miller 2015). Hence, following Donald and Lang (2006) and Cameron and Miller (2015), we instead adjust the degrees of freedom of our t-tests in all our main specifications. Specifically, the degrees of freedom for our tests are based on the number of clusters (14) minus the number of regressors that are invariant within cluster (2) for a total of only 12 degrees of freedom for each t-test.

3.2 Channels and Decomposition

The next step in the analysis is to understand the channels through which immigration affects crime. In order to do so, we specify a full regression, denoted by superscript "F" , with a full set of covariates:

$$\begin{aligned}\ln C_{rt} =& \beta^F \ln M_{rt} + \alpha_1 \ln pop_{rt} + \alpha_2 \ln young_{rt} + \alpha_3 \ln earnings25th_{rt} + \alpha_4 \ln emp_{rt} \\ &+ \alpha_5 \ln workingpoor_{rt} + \alpha_6 \ln earnings75th_{rt} + \alpha_7 \ln police_{rt} + v_{rt},\end{aligned} \tag{2}$$

the log of the number of crimes.

where all variables are specific to a state r and year t. $\ln young$ is the number of men ages 15 - 29, $\ln earnings25th$ is the log 25th percentile of the earnings of young men, $\ln emp$ is the log of the number of employed people, $\ln workingpoor$ is the log number of employed with earnings below the 50 percent of the median monthly earnings, $\ln earnings75th$ is the log 75th percentile of earnings among all employed, and $\ln police$ is the log number of police. Section 2.3, above, provides the discussion of the economic justification for the inclusion of each of these covariates.

A common strategy for evaluating how much of the relationship between an outcome and the explanatory variable of interest, such as the immigration-crime relationship, can be attributed to various factors is to sequentially add covariates to a baseline specification. The change in the estimated coefficient of the immigration variable $\ln M$ is then interpreted as being due to variation in the most recently added set of variables. In the literature on crime, for example, this is the strategy pursued by Donohue and Levitt (2001) and Lee and McCrary (2005).

Gelbach (2016) argues that the sequential covariate expansion exercises are not particularly informative since their interpretation crucially depends on the *sequence* in which covariates are added to the regression. To put it differently, altering the order of the covariates changes the difference in the estimated coefficients that will be attributed to each covariate. As long as covariates are correlated with each other, only the full specification is truly informative about the impact of these covariates. In order to overcome this issue, Gelbach (2016) develops a different decomposition. The key result relies on the following insight: equation (2) is the complete model whereas equation (1) is a model with the variables $\ln young$, $\ln earnings25th$, $\ln emp$, $\ln workingpoor$, $\ln earnings75th$, and $\ln police$ omitted. If we think of equation (1) in this way, the well known omitted variable bias formula applies.

Consider an auxiliary model with six regressions where the dependent variable in each regression, X_j, is one of the covariates of the full specification, equation (2), and $\ln M$ is the explanatory variable.[22] Then the relationship between the coefficient on immigration

[22] These covariates are $\ln young$, $\ln earnings25th$, $\ln emp$, $\ln workingpoor$, $\ln earnings75th$, and $\ln police$.

in the baseline and full model is given by:

$$\beta^B = \beta^F + \sum_{j=2}^{7} \theta_j \alpha_j, \tag{3}$$

where θ_j is the coefficient on $\ln M$ in the auxiliary model j with X_j as the dependent variable. Note that $\theta_j \alpha_j$ is the contribution of covariate j in explaining the immigration-crime relationship. We apply this decomposition to the immigration-crime relationship. We should note that the decomposition relies on correctly identifying β^B and β^F. Potential endogeneity concerns require immigration to be instrumented using two-stage least squares. However, it is not necessary that the causal impact of additional covariates is correctly identified, and thus these variables do not need to be instrumented (see Gelbach 2016 for a more extensive discussion).

3.3 Instrument

The central challenge in estimating equations (1) and (2) is the endogeneity of immigrant location decisions, a problem common to almost all migration related papers. Migrants may locate in states that experience unobserved (positive or negative) shocks to factors that also affect the crime rate. The likelihood of biased OLS estimates makes it important to instrument for the inflow of immigrants to a state.

A valid instrument for immigration patterns across states needs to be uncorrelated with shocks, caused by changes in demographics, labor market opportunities, policing, that may deter or encourage crime. In order to construct such an instrument, we use changes in the population and age structure of immigrant source countries over time. The main source countries are Indonesia, the Philippines, Bangladesh, Cambodia, India, Laos, Myanmar, Sri Lanka, Thailand, and Vietnam. Using the data from the United Nations Population Division, we calculate the number of individuals in each of 7 age-groups in each of these source countries in every year during 2003-2010.[23] These population numbers form the potential source of immigrants to Malaysia, where the likelihood of migration varies by age group, country of origin and year. This is our measure of the supply of

[23] The age groups are 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, and 45 and above.

immigrants S_t^{ac} to Malaysia from source country c in age-group a and year t. Since the Malaysian LFS consistently categorizes immigrants' nationality only as Indonesians, Filipinos and the rest of the world, we add our measure of the supply of immigrants for all other countries into a single category. Hence, we effectively have three source countries: Indonesia, the Philippines and Other.[24]

What remains to be determined are the states within Malaysia in which the immigrants choose to live. In order to construct this variable, we use the LFS for the years 1990 to 1993, ten years before the start of our analysis, to calculate the probability of individuals from a source country and age group to be employed in a certain state :

$$\lambda_r^{ac} = \frac{\frac{1}{T}\sum_{t=1990}^{1993} M_{rt}^{ac}}{\frac{1}{T}\sum_{t=1990}^{1993} M_t^{ac}}, \tag{4}$$

where M_{rt}^{ac} is the number of immigrants from a source country in an age group, state and year. M_t^{ac} is the total number of immigrants in Malaysia from a source country and in a given age group.

The source country and age-group specific instrument for the immigration flows in a certain, region and year is then given by:

$$IV_{rt}^{ac} = \lambda_r^{ac} * S_t^{ac}. \tag{5}$$

We sum over the age-specific instruments by source country and over source countries (and take the natural logarithm) to construct our main instrument. The instrument varies by state and year:

$$\ln IV_{rt} = \ln \sum_c \sum_a \lambda_r^{ac} * S_t^{ac}$$

We should add that our results are also robust to allowing for three separate instruments by source country: $\ln IV_{rt}^c = \ln \sum_a \lambda_r^{ac} * S_t^{ac}$ for Indonesians, Filipinos and all other nationalities.

[24]We multiply the population numbers of each source country by the average propensity of people from that country to migrate to Malaysia. These propensities are calculated from data provided by the Ministry of Home Affairs of Malaysia and are: Bangladesh 1.96%, Cambodia 1.03%, India 0.11%, Lao 0.01%, Myanmar 2.18%, Sri Lanka 0.16%, Thailand 0.22%, Vietnam 0.78%, Indonesia 5.56% and Philippines 0.38%.

The identifying variation comes from the interaction of λ_r^{ac} and S_t^{ac}, and is conditional on the included fixed effects. It is due to changes in the size of cohorts in source countries, which are experiencing their demographic transition at different rates, and their differential propensity to be employed in different states in Malaysia. The variation in the instrument generated by the differential propensity of immigrant groups (defined by nationality and age) to work in different local labor markets is similar to the commonly used Altonji-Card instrument (Altonji and Card 1991, Card 2001). The variation induced by the demographic changes in source countries is similar to the instrument constructed by Hanson and McIntosh (2010, 2012). Our instrument relies on both exogenous time-series and cross-sectional variation.[25]

The supply of potential migrants to Malaysia from different source countries (S_t^{ac}) is determined by the demographic patterns and transition that occurred in those countries several decades earlier. These are most likely to be exogenous with respect to contemporaneous labor market shocks in Malaysia. The average propensity of an immigrant from a source country to be employed in a certain state (λ_r^{ac}), in the pre-period, depends on permanent differences in the levels of demand across local labor markets. This is why we include state specific fixed effects in all of our regression specifications. It is of course independent of any transitory shocks that may affect demand for natives and immigrants in a particular year. However, the concern is that persistent demand shocks, i.e. long periods of decline or growth in certain states, would result in a correlation between the average distribution of immigrants in the pre-period (1990-93) and current (2003-10) demand shocks. By allowing for a ten-year lag between the data used to construct (λ_r^{ac}) and the period of analysis we minimize that concern.

An additional important advantage of an instrumental variable approach is that it helps deal with classical measurement problems. The Malaysian LFS attempts to survey undocumented immigrants in Malaysia, yet the survey is unlikely to obtain a fully

[25]Other work that adds a plausibly exogenous time-series dimension to the Altonji-Card shift-share instrument includes Chalfin (2015) and Chalfin and Levy (2015), who follow a similar idea to develop an IV strategy based on fertility shocks in source areas of Mexico. Other related papers are Pugatch and Yang (2012) and Chalfin (2014) who use rainfall shocks in source areas as exogenous determinants of migrant outflows. Our instrumenting strategy is very similar to that in Del Carpio et al. (2015) and Ozden and Wagner (2015).

representative sample. This creates measurement errors and general undercounting of immigrants in our data. All our specifications include year fixed effects, which will control for general undercounting of immigrants over time. They also include state fixed effects, which will control for state-specific differences in the propensity of immigrants to be surveyed by the Malaysian LFS. In our log-log specifications, as long as the measurement error is proportional to the true number of immigrants (where that proportion can vary by state and year) it will be fully absorbed by our fixed effects.[26] In addition, there is likely idiosyncratic measurement error, for example sampling error, that will attenuate the OLS estimates but not the IV estimates. If there is an even more complicated form of measurement error then the OLS estimates will be biased but not necessarily attenuated, even though we think proportional measurement error seems reasonable to assume. However, for the IV estimates to be biased that residual measurement error (controlling for the fixed effects) would have to be somehow correlated with the instrument. The identifying variation in the instrument relies on the interaction between the demographic transition in migrant source countries and the 1990-93 distribution of immigrants. We would argue that it is unlikely for the instrument to be systematically correlated with measurement error in the period 2003-10.

In Figure 4 we plot the actual and predicted log number of immigrants for all 14 Malaysian states in 2010. The figure only the presents the residual identifying variation from the instrument, not the covariates or fixed effects. Clearly, there is a close fit between instrumented and actual immigration numbers, suggesting our instrument is highly predictive of actual immigrant numbers.

[26]The model of measurement error we have in mind is that the observed number of immigrants M^{Obs} is equal to the actual number of immigrants M^{True} scaled by a state-specific factor τ_r and a year-specific factor τ_t, such that $M_{rt}^{Obs} = \tau_r \tau_t M_{rt}^{True}$.

4 Results

4.1 The Impact of Immigration on Crime

We report results for the baseline equation (1) in Table 3, with total, property and violent crimes as the dependent variable in each column, respectively. OLS estimates are presented in Panel A and IV estimates in Panel B. Standard errors are robust to heteroscedasticity and critical values for the t-tests are based on 12 degrees of freedom as discussed above. The crime rate is negatively correlated with the share of immigrants in a state's population. The OLS point estimates imply an elasticity of around -0.47 for all types of crime.

The IV estimates suggest that this negative relationship between immigration and crime is causal. The point estimates show that immigration causes a decrease in crime rates, with an elasticity close to -1 for both total and property crimes.[27] The implication is that an increase in the fraction of immigrants in a state's population from 10 to 11 percent decreases the property crime rate from 0.83 to 0.75 percent (calculations are for average immigration and crime levels in 2010). The impact on violent crime is even greater, with an elasticity of -1.8. Since the standard errors are also larger for violent crime, the difference between the estimates for property and violent crimes are not statistically significant. All estimates are significant at the 5 percent significance level despite having only 12 degrees of freedom for the t-tests. The instrument is statistically significant in the first-stage, with a coefficient of 5.65 and t-statistic of 2.5.[28]

The fact that the IV estimates are more negative than the OLS estimates suggests that immigrants are more likely to migrate to states that, for other reasons, are experiencing a decrease in crime rates. It may also of course be that the OLS estimates are simply attenuated due to measurement error in the number of immigrants. Finally, we should note that Bianchi, Pinotti and Buonanno (2012), Spenkuch (2014) and Chalfin (2014) do

[27]Recall that over 80 percent of crimes in Malaysia are property crimes, hence our estimates for total and property crimes are always very similar.

[28]Since our two-stage least squares estimates are just-identified (a single instrument and endogenous variable) they are "approximately unbiased" (Angrist and Pischke 2009). Hence, the key issue is only whether the instrument is statistically significant in the first-stage. Thus we report the first-stage t-statistic and not the F-statistic as we would if there were multiple instruments.

not find conclusive evidence on the causal relationship between immigration and crime. Their estimates are mostly not significantly different from zero, and the standard errors of their IV estimates are sufficiently large that they can not rule out an effect. Consistent with our findings Bell, Fasani and Machin (2013) and Chalfin (2015) find a negative impact on property crime of immigrants coming to the United Kingdom for work from Eastern European accession countries and for Mexican immigrants to the United States, though no effect on violent crime.[29]

In Table 4 we show that the causal relationship between immigration and crime rates is highly robust to several different specifications. Panel A presents results with standard errors that are clustered by state to account for serial correlation. All our estimates remain statistically significant, despite only having 14 clusters. Panel B shows estimates when Sabah, which is an outlier with immigrants accounting for around one-quarter of the working-age population, is dropped from the analysis. The point estimates and standard errors are almost identical to those in Table 3. In Panel C we use three instruments based on nationality, for Indonesians, Filipinos and Other (see Section 3.3 for details on the construction of the instruments). The point estimates increase somewhat and remain statistically significant.[30] In Panel D the independent variable is the number of employed immigrants, as opposed to all immigrants. The point estimates are almost identical to our main estimates in Table 3 and the standard errors are slightly larger, though all estimates remain statistically significant. This finding reinforces the idea that our estimates reflect the impact of economic migrants as opposed to refugees. They are also likely to reflect some combination of impacts from both documented and undocumented immigrants. Panel E presents results using male migrants as the independent variable of interest. The point estimates increase slightly when compared to our main estimates. The standard errors also increase slightly, though all estimates remain statistically significant.

[29] In Appendix Table A we present estimates of the causal impact of immigration on further disaggregated crime rates. Specifically, we disaggregate property crimes into vehicle thefts and other property crime, and violent crimes into robberies and other violent crimes.

[30] The F-test for the first-stage is only 1.6, suggesting there may be weak instrument problems. However, the point estimates are very close to our baseline estimates, especially for property crimes.

4.2 Determinants of Crime Rates

Section 2.3 presented a detailed discussion of various demographic and economic variables that the literature identifies as likely correlates of crime rates. These are included in our full specification, given by equation (2) and Table 5 reports the estimates for that full specification. Panel A presents OLS estimates and Panel B presents the IV estimates. Clearly, the negative correlation between immigration and crime rates is robust to the inclusion of additional covariates. The instrument continues to be statistically significant in the first-stage when we add covariates, with a coefficient of 5.73 and t-statistic of 3.0.

The most important difference due to the inclusion of covariates is the decrease in the magnitude of the estimated causal impact on property crimes. More specifically, the coefficient declines by three-quarters, from an elasticity of -0.97 to -0.25, and it is no longer statistically significant. In contrast, the inclusion of covariates decreases the estimated magnitude of the impact of immigration on violent crimes by only 20 percent, from -1.81 to -1.46. The estimated elasticity also remains statistically significant. The included covariates clearly have a far greater role in explaining the relationship between immigration and property crime, than between immigration and violent crime. More importantly, the results suggest that immigration decreases property crime rates mainly because it changes economic conditions for natives. Meanwhile, it plausibly decreases violent crime rates simply because immigrants commit (or report) fewer violent crimes.[31]

The estimated impact of the covariates on crime rates are very similar in Panels A and B. Interestingly, population, reflecting the correlation between population density and crime, is not statistically significant in explaining crime rates, in contrast to the findings of Glaeser and Sacerdote (1999) on city density and crime. Instead, consistent with the literature, the most important and robust variable explaining changes in crime rates is the fraction of young men (ages 15 - 29) in the population. The impact is large; the elasticity with respect to young males is around 0.8 for property crimes and about 1.2 for violent crimes. Consistent with economic theories of crime, the earnings potential of young males,

[31] The Deputy Home Minister of Malaysia recently claimed that only one percent of all crimes in Malaysia were committed by foreigners, suggesting a dramatically lower propensity to commit crimes. Reported in The Star, "Parliament: Only 1% of crimes are committed by foreigners, says Wan Junaidi" published on Tuesday, 9 July 2013

as reflected by the 25th percentile of their earnings distribution, is negatively correlated with property crime rates. The elasticity is around -0.3 and statistically significant. In contrast, the variable is uncorrelated with violent crime rates. Similarly, the earnings potential from illegal activities, as proxied by the the 75th percentile of the earnings distribution in a state, is positively correlated with property crimes, with an elasticity of around 0.65. This variable is also uncorrelated with violent crime rates. The employment rate is consistently negatively correlated with crime rates, as expected, but the impact is never statistically significant. This finding mirrors the literature's general difficulties in identifying a relationship between employment opportunities, typically proxied by the unemployment rate, and crime (see, for example, Freeman 1999 and Gould, Mustard and Weinberg 2002). Perhaps most surprisingly, the fraction of working poor among the employed, those below 50 percent of the median earnings in a state and year, is negatively correlated with property crimes rates and uncorrelated with violent crime. This result suggests that the variable is actually picking up labor market conditions for people who are at a high-risk of being unemployed. Improved labor market conditions for these people reduces their incentives to engage in property crimes and also increases the measured number of working poor. Finally, changes in the number of police in a state are uncorrelated with both property and violent crimes. This is, of course, not a causal relationship. In sum, variables reflecting the costs and benefits of engaging in illegal activity play an important role in explaining property crimes but not violent crimes. The fraction of young males in the population explains both property and violent crimes.

4.3 Decomposing the Immigration-Crime Relationship

The remaining question is how each of the covariates in the full specification, equation (2), explain the relationship between immigration and crime identified in the baseline equation (1). Table 6 reports the results of the Gelbach (2016) decomposition for the IV estimates for all, property and violent crimes.[32] For convenience, we present again the estimates reported in Tables 3 and 5 in the rows 'immigrant - baseline' and 'immigration -

[32]Since the inclusion of covariates has, as discussed, very little impact on the crime-immigration correlation given by the OLS estimates, a further decomposition is not informative.

full', respectively. The total change in the coefficient ($\beta^B - \beta^F$) is statistically significant for total and property crimes but not for violent crime. In sum, additional covariates explain two-thirds of the causal relationship between immigration and total crime rates and three-quarters of the causal relationship with property crime rates.

Table 6 also reports, in percentage terms, how important each covariate is in explaining the immigration-crime relationship. The immigration induced changes in the fraction of young males and the number of working poor explain around 50 percent of the overall immigration - property crime relationship. The impact on total employment explains around one-third of the relationship. In contrast, the induced change in the 75th percentile of the earnings distribution goes against explaining the observed relationship (-40 percent). Changes in the earnings of young males and the number of police have no explanatory power. Covariates do not significantly explain the causal impact of immigration on violent crime. The only variable that has any explanatory power is the fraction of young males in the population of a state.

The decomposition presented in Table 6 reflects two distinct relationships. First, immigration causes changes in each of the covariates. Second, the change in each covariate then affects crime rates. The decomposition only reports the total impact, but using Tables 5 and 6 we can infer the underlying causal relationships. The implication of our estimates is that immigration decreases the fraction of young males in a state and thereby decreases property and violent crimes. This is consistent with the pattern of population movements in response to immigration in Malaysia identified by Del Carpio et al. (2015). Immigration also increases the 25th earnings percentile of young males, the fraction of people employed and the fraction of working poor thereby decreasing property crime rates. In addition, it increases the 75th earnings percentile in the general population, however, that results in higher crime rates. The implication that immigration has a positive impact on the earnings and employment of Malaysians in a state is consistent with the findings in Del Carpio et al. (2015) and Ozden and Wagner (2015).

Tables 7a and 7b show that the results of our decomposition are robust to excluding Sabah from the analysis (Panel A), using three instruments by nationality (Panel B), and using employed immigrants (Panel C) or male immigrants (Panel D) as the independent variable of interest. Table 8 shows that our results are robust to an important variation in the included covariates. Specifically, replacing the variables the number of young men and the 25th percentile of their earnings distribution by the equivalent variables for young, low education (primary or less) males does not change the results.[33]

5 Conclusion

The perception that immigration fuels crime is an important source of anti-immigrant sentiment. This paper makes three important contributions to this debate. First, it finds a sizable and statistically significant negative causal impact of economic immigration on property and violent crime rates. Second, it decomposes the impact into those attributable to immigration induced socio-economic changes among the native population. The results suggest that immigration decreases property crime rates primarily because it changes economic conditions for natives, while it decreases violent crime rates because immigrants commit fewer violent crimes. Third, it provides some of the first evidence for non-OECD destinations, where around half of all migrants in the world live.

An important question raised by the findings in this paper is why immigrants in Malaysia seem to commit less crimes than natives, in particular violent crimes. Immigrants in Malaysia are mainly economic migrants and a considerable fraction is undocumented. Such economic migrants are distinct from other migrants, notably refugees, on a number of dimensions. First, their access to the labor market reduces the benefits and increases the costs of engaging in criminal activities. Second, they self-select into migrating for work and their underlying propensity to commit crimes are likely to be quite different from that of non-migrants. The fact that a large fraction of foreign workers in Malaysia are undocumented may be salient as well. Undocumented workers may be more likely to be victimized by crime, but also less likely to report crime due to their fear of deportation. If immigration results in a drop in the reporting of crimes our findings may overstate the degree to which the actual number of crimes, specifically targeting foreign

[33]In Appendix Table A we also present the Gelbach (2016) decomposition for further disaggregated types of crime.

workers, declines with immigration. Undocumented workers' wariness of the police and the judicial system may also act as a deterrent to committing crimes, not just reporting them. As such, the availability of more detailed data on undocumented immigrants would be crucial to better understand the impact of immigration on crime.

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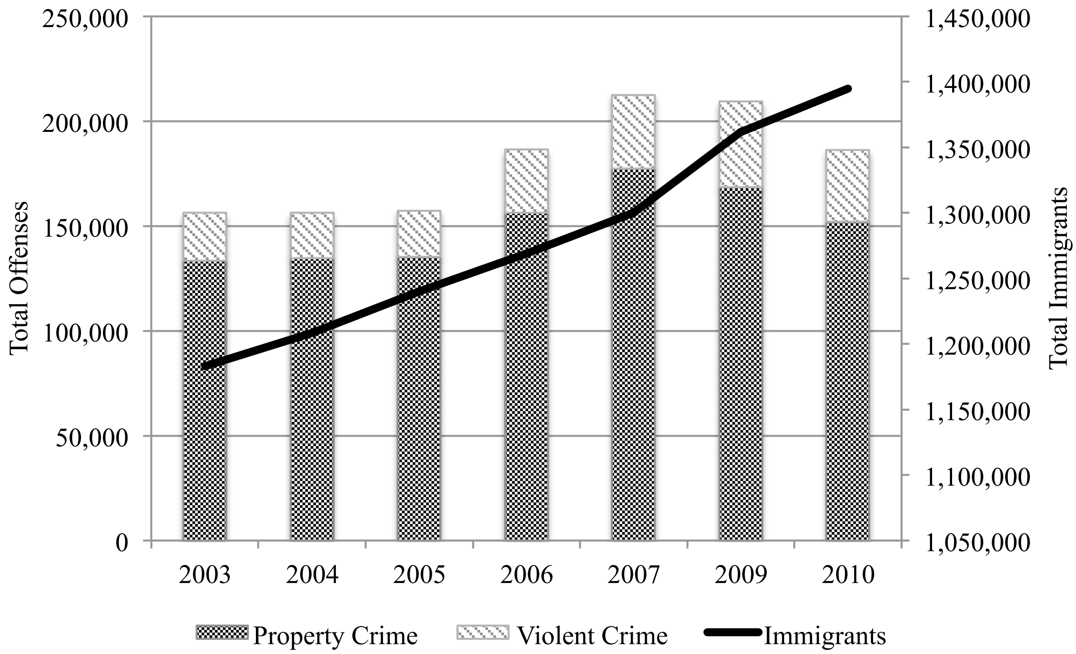
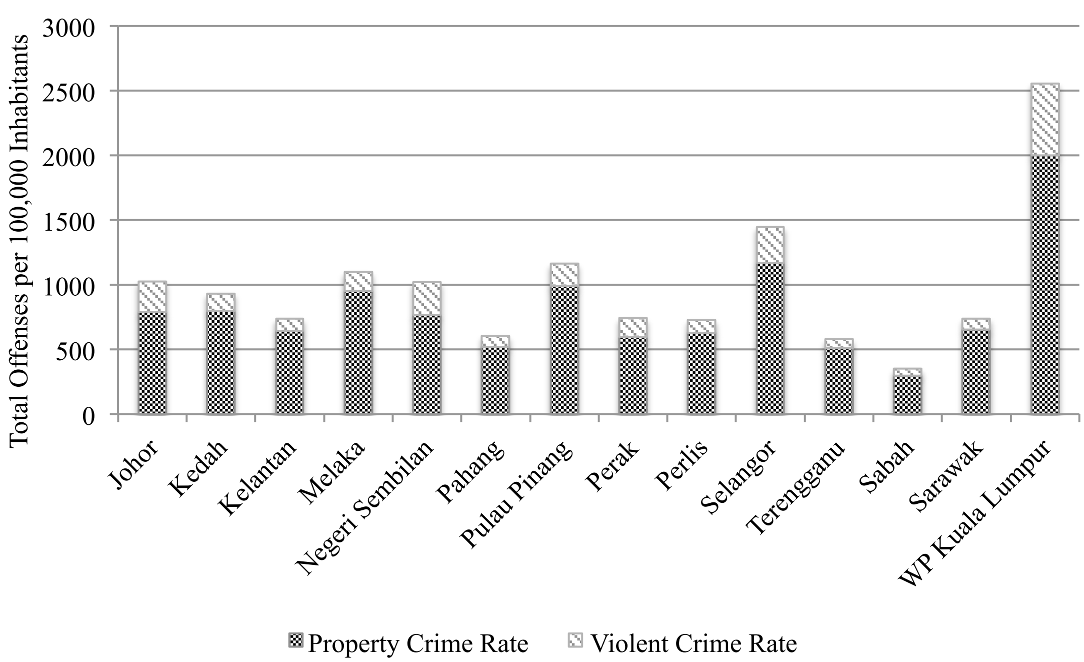
Figure 1. Immigrant Stock and Crime Trends, Malaysia, 2003-10



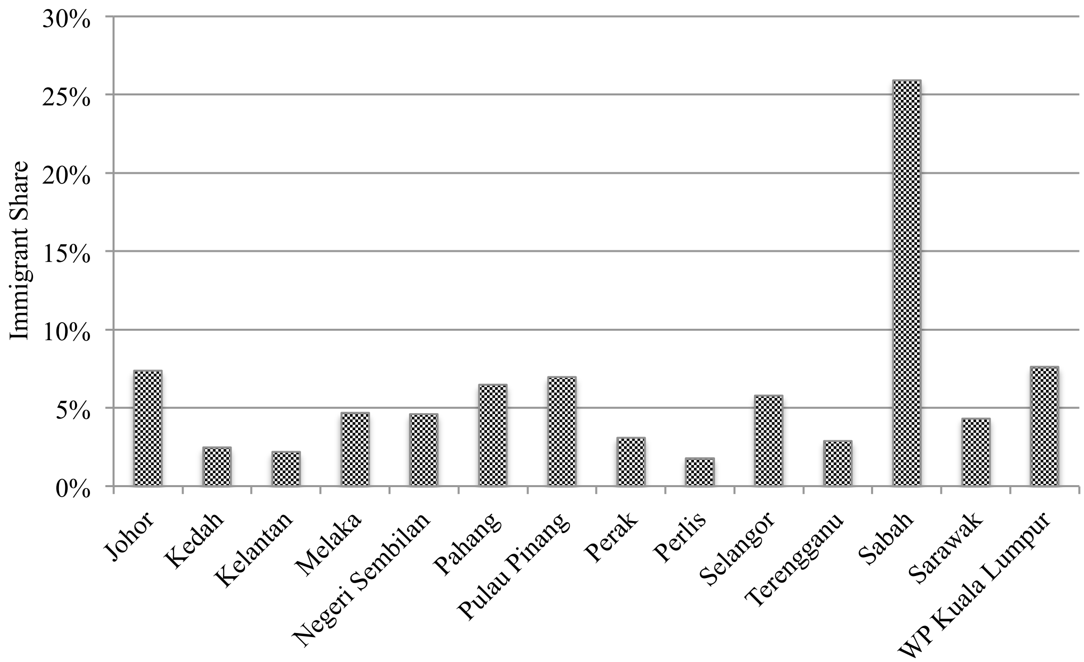
Note: based on the Malaysian Labor Force Survey and the Malaysian Social Statistics Bulletin.

Figure 2. Property and Violent Crime Rates by State, 2010



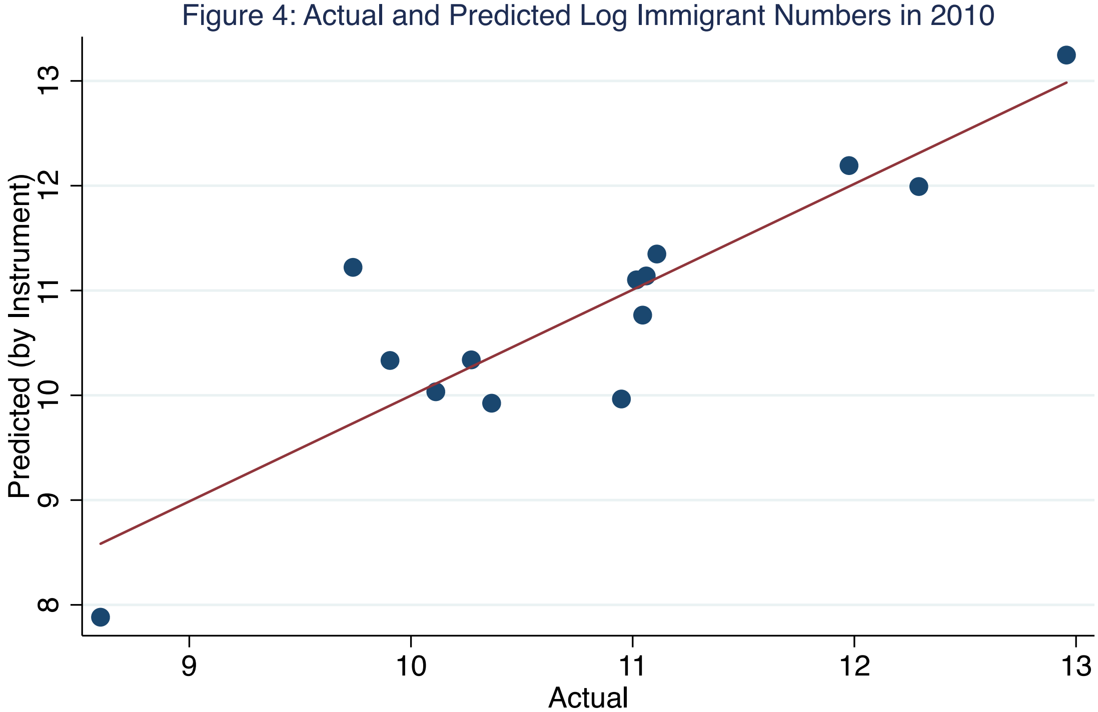
Note: based on the Malaysian Social Statistics Bulletin.

Figure 3. Immigrant Share by State, 2010



Note: based on the Malaysian Labor Force Survey.

Figure 4: Actual and Predicted Log Immigrant Numbers in 2010



Note: predictions are based solely on the instrument, having controlled for a full set of covariates and state and region fixed effects

Table 1: Property and Violent Crime Statistics for Malaysia

	Property Crimes			Violent Crimes	
	2003	2010		2003	2010
Total Number	133,525	152,029		22,713	34,133
Rate	0.85%	0.83%		0.14%	0.19%
Breakdown:			Breakdown:		
House Breaking	19%	23%	Murder	2%	2%
Vehicles Theft	48%	49%	Rape	6%	11%
Snatch	12%	4%	Robbery	72%	64%
Other	21%	24%	Body Injuries	19%	24%

Note: Data from the Malaysian Social Statistics Bulletin (based on Royal Malaysian Police crime data).

Table 2: Descriptive Statistics for Working-Age Population (15 - 64)

	2003	2010
Native Population (ages 15 - 64)	14,514,910	16,979,767
Immigrant Population (ages 15 - 64)	1,182,995	1,395,003
Demographics of Malaysians		
Fraction Aged 15 - 29	21.6%	21.7%
Fraction Employed	61.3%	58.9%
Fraction Unemployed	2.5%	2.2%
Number Police	71,896	101,898
	2007	2010
Earnings Indicators		
Working Poor	10.3%	13.6%
Earnings Male, Ages 15 - 29, 25th pctl.	RM 714	RM 764
Earnings, 75th pctl.	RM 1908	RM 2296
LFS Observations	279,224	397,467

Note: Data is from the Malaysian LFS, earnings information available beginning in 2007. Monthly earnings have been adjusted for changes in the consumer price index and are in 2010 Malaysian Ringgit (RM). 1 US dollar is around 1.44 RM in purchasing power parity.

Table 3: Impact of Immigration on Crime, OLS and IV, Baseline Specification

	Crime	Property	Violent
		Panel A. OLS	
Log Immigrants	-0.479**	-0.470*	-0.465**
	(0.211)	(0.224)	(0.168)
		Panel B. IV	
Log Immigrants	-0.988**	-0.970**	-1.810**
	(0.372)	(0.398)	(0.599)
First-stage T-stat	2.5	2.5	2.5
Observations	98	98	98

Note: Estimates are for the baseline specification including log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state).

Table 4: Impact of Immigration, Robustness Checks, IV Estimates, Baseline Specification

	Crime	Property	Violent
	Panel A. Standard Errors Clustered by State		
Log Immigrants	-0.988**	-0.970*	-1.811***
	(0.480)	(0.528)	(0.555)
First-stage T-stat	2.33	2.33	2.33
	Panel B. Excluding Sabah		
Log Immigrants	-1.002**	-0.994**	-1.759**
	(0.381)	(0.407)	(0.592)
First-stage T-stat	2.41	2.41	2.41
	Panel C. Three Instruments by Nationality		
Log Immigrants	-1.266***	-1.257***	-2.521**
	(0.338)	(0.359)	(0.949)
First-stage T-stat	1.60	1.60	1.60
	Panel D. Employed Migrants		
Log Immigrants	-1.074**	-1.055**	-1.968**
	(0.434)	(0.460)	(0.681)
First-stage T-stat	2.64	2.64	2.64
	Panel E. Male Migrants		
Log Immigrants	-1.223*	-1.201*	-2.241**
	(0.572)	(0.594)	(0.906)
First-stage T-stat	2.18	2.18	2.18
Observations	98	98	98

Note: Estimates are for the baseline specification including log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity and in Panel A clustered by state. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests in Panels B to E are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state), except in Panel B where we use 11 degrees of freedom and there are 91 observations.

Table 5. The Impact of Immigration and Covariates on Crime, OLS and IV Estimates

	Panel A: OLS Estimates			Panel B: IV Estimates		
	Crime	Property	Violent	Crime	Property	Violent
Log Immigrants	-0.342**	-0.343*	-0.29*	-0.347	-0.253	-1.460**
	(0.148)	(0.164)	(0.152)	(0.294)	(0.327)	(0.499)
Log Total Population	0.476	0.300	0.991	0.471	0.397	-0.279
	(1.220)	(1.290)	(1.360)	(1.130)	(1.220)	(1.500)
Log Young-Male Pop.	0.814*	0.815**	0.970*	0.815**	0.780**	1.195*
	(0.379)	(0.406)	(0.426)	(0.332)	(0.367)	(0.620)
Log Young-Male 25th Earnings Pctl.	-0.227	-0.289*	-0.068	-0.227**	-0.296**	0.024
	(0.128)	(0.147)	(0.150)	(0.115)	(0.132)	(0.140)
Log Total Employed	-0.779	-0.526	-1.716	-0.770	-0.695	0.504
	(0.892)	(0.949)	(1.020)	(1.010)	(1.090)	(1.230)
Log Working Poor	-0.085**	-0.099**	-0.018	-0.085**	-0.101**	0.020
	(0.038)	(0.041)	(0.043)	(0.034)	(0.036)	(0.042)
Log 75th Earnings Pctl.	0.569**	0.644**	0.233	0.568**	0.651**	0.134
	(0.230)	(0.254)	(0.238)	(0.199)	(0.220)	(0.231)
Log Police	0.010	0.009	0.026	0.010	0.009	0.025
	(0.041)	(0.044)	(0.057)	(0.035)	(0.037)	(0.061)
Observations	98	98	98	98	98	98

Note: All specifications include log total population as a covariate and state and year fixed effects. In Panel B the first-stage t-statistic for the instrument is 3.2. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state).

Table 6: Decomposition of the Impact of Immigration on Crime, IV Estimates

Dependent crime variable:	Crime	Property	Violent
Immigrants - Baseline	-0.988**	-0.970**	-1.810**
	(0.372)	(0.398)	(0.599)
Immigrants - Full	-0.347	-0.253	-1.460**
	(0.294)	(0.327)	(0.499)
Total Change in Coefficient	-0.642*	-0.717*	-0.346
	(0.341)	(0.375)	(0.348)
Fraction of Change in Immigrant Coefficient (Baseline - Full) Explained By:			
Young-Male Population	56%	49%	151%
Young-Male 25th Earnings Pctl.	8%	6%	-10%
Total Employed	32%	34%	-14%
Number Working Poor	43%	51%	-9%
75th Earnings Pctl.	-39%	-40%	-17%
Number Police	0%	0%	-2%
Observations	98	98	98

Note: All specifications include log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state).

Table 7a: Impact of Immigration and Decomposition, Robustness Checks, IV Estimates

	Panel A. Excluding Sabah			Panel B. Three Instruments by Nationality		
	Crime	Property	Violent	Crime	Property	Violent
Immigrants - Baseline	-1.002**	-0.994**	-1.759**	-1.27***	-1.26***	-2.522**
	(0.381)	(0.407)	(0.592)	(0.338)	(0.359)	(0.949)
Immigrants - Full	-0.357	-0.263	-1.655**	-0.363	-0.282	-1.783**
	(0.336)	(0.390)	(0.685)	(0.344)	(0.390)	(0.763)
Change in Coefficient	-0.945**	-1.068**	-0.646	-0.942**	-1.046**	-0.547
	(0.425)	(0.478)	(0.579)	(0.391)	(0.431)	(0.594)
Fraction of Change in Immigrant Coefficient (Baseline - Full) Explained By:						
Young-Male Population	65%	55%	139%	63%	56%	167%
Young-Male 25th Earnings Pctl.	3%	3%	-9%	5%	4%	-13%
Total Employed	28%	29%	-18%	34%	37%	-21%
Number Working Poor	44%	53%	18%	41%	48%	-15%
75th Earnings Pctl.	-39%	-40%	-24%	-42%	-44%	-14%
Number Police	-1%	-1%	-4%	-1%	-1%	-4%
Observations	91	91	91	98	98	98

Note: All specifications include log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state), except for Panel A where we use 11 degrees of freedom.

Table 7b: Impact of Immigration and Decomposition, Robustness Checks, IV Estimates

	Panel C. Employed Migrants			Panel D. Male Migrants		
	Crime	Property	Violent	Crime	Property	Violent
Immigrants - Baseline	-1.074**	-1.055**	-1.968**	-1.22*	-1.201*	-2.241**
	(0.434)	(0.460)	(0.681)	(0.572)	(0.594)	(0.906)
Immigrants - Full	-0.383	-0.279	-1.616**	-0.385	-0.281	-1.629**
	(0.397)	(0.434)	(0.740)	(0.400)	(0.437)	(0.695)
Change in Coefficient	-0.692*	-0.776*	-0.352	-0.84*	-0.919	-0.612
	(0.377)	(0.415)	(0.353)	(0.497)	(0.535)	(0.551)
Fraction of Change in Immigrant Coefficient (Baseline - Full) Explained By:						
Young-Male Population	55%	48%	153%	57%	50%	132%
Young-Male 25th Earnings Pctl.	8%	7%	-8%	5%	5%	-20%
Total Employed	31%	34%	-27%	35%	36%	14%
Number Working Poor	45%	52%	0%	43%	50%	4%
75th Earnings Pctl.	-39%	-40%	-17%	-40%	-40%	-29%
Number Police	0%	0%	-1%	-1%	0%	-2%
Observations	98	98	98	98	98	98

Note: All specifications include log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state).

Table 8: Immigration-Crime Relationship Decomposition, Alternative Covariates, IV Estimates

Dependent crime variable:	Crime	Property	Violent
Immigrants - Baseline	-0.988**	-0.970**	-1.810**
	(0.372)	(0.398)	(0.599)
Immigrants - Full	-0.582	-0.482	-1.709**
	(0.367)	(0.400)	(0.689)
Total Change in Coefficient	-0.406	-0.487	-0.101
	(0.267)	(0.299)	(0.262)
Fraction of Change in Immigrant Coefficient (Baseline - Full) Explained By:			
Young-Male Low Educated Pop.	36%	30%	37%
Young-Male Low Educ. 25th Earnings Pctl.	17%	14%	-3%
Total Employed	42%	42%	-3%
Number Working Poor	24%	34%	29%
75th Earnings Pctl.	-20%	-21%	42%
Number Police	0%	0%	-2%
Observations	98	98	98

Note: All specifications include log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state).

Appendix Table A: Impact of Immigration by Type of Crime and Decomposition, IV Estimates

Dependent crime variable:	Vehicles	Other Property	Robbery	Murder, Rape
Immigrants - Baseline	-0.791	-1.115*	-2.65**	-1.724**
	(0.485)	(0.621)	(0.923)	(0.604)
Immigrants - Full	0.016	-0.437	-2.02**	-1.563***
	(0.494)	(0.487)	(0.830)	(0.499)
Total Change in Coefficient	-0.806	-0.678	-0.627	-0.161
	(0.470)	(0.516)	(0.489)	(0.372)
Fraction of Change in Immigrant Coefficient (Baseline - Full) Explained By:				
Young-Male Population	71%	36%	81%	351%
Young-Male 25th Income Pctl.	-6%	22%	5%	-95%
Total Employed	21%	43%	34%	-164%
Number Working Poor	38%	57%	6%	11%
75th Income Pctl.	-23%	-58%	-25%	7%
Number Police	-1%	0%	-1%	-10%
Observations	98	98	98	98

Note: All specifications include log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the 10, 5, 1 percent significance level. Critical values for the t-tests are for 12 degrees of freedom (the number of states minus the number of regressors invariant within state).