The World Bank Economic Review, 32(1), 2018, 183–202
doi: 10.1093/wber/lhx010
Article

How and Why Does Immigration Affect Crime? Evidence from Malaysia

Caglar Ozden, Mauro Testaverde, and Mathis Wagner

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. The IV estimates suggest that immigration decreases crime rates, with an elasticity of around −0.97 for property and -1.8 violent crimes. 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.

JEL classification: F22, K42
Key words: crime, immigration, labor markets

Increased crime is among the main fears voiced in public opinion surveys on immigration.[1] Crime even surpasses economic concerns such as ”immigrants take jobs away from natives” as the main reason for public demands for more restrictive immigration policies in many destination 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 survey of the literature). This paper makes three main contributions to this literature. First, it provides causal estimates of the overall impact of immigration on different types of crime. Second, the paper presents evidence on the mechanisms that underlie this impact. 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.

Caglar Ozden is Lead Economist in the Development Research Group at the World Bank; his email is cozden@worldbank.org. Mauro Testaverde is Economist in the Social Protection and Labor Practice at the World Bank; his email address is mtestaverde@worldbank.org. Mathis Wagner (corresponding author) is a professor at Boston College, Boston, MA, USA; his email address is mathis.wagner@bc.edu. The authors thank Michel Beine, David McKenzie, Chris Parsons, Giovanni Peri, and participants at the Migration and Development Conference for comments and discussion. They are grateful to Ximena Del Carpio who led the technical advisory project that forms the basis for this paper and provided invaluable guidance. The findings, conclusions, and views expressed are entirely those of the authors and should not be attributed to the World Bank, its executive directors, and the countries they represent. A supplemental appendix to this article is available at https://academic.oup.com/wber.

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

The paper uses variation in crime rates and immigrant stocks across Malaysian states for the period 2003–10 to identify the impact of immigration on crime.[2] The 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 0.16 percent, calculated at the average immigration and crime levels for 2010.

The empirical approach adopted in this paper is most closely related to recent area panel studies on Italy (Bianchi, Pinotti, and Buonanno 2012), the United States (Spenkuch 2014; 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 of Mexican immigrants in the United States on property crime. For the United Kingdom, Bell, Fasani, and Machin (2013) find that economic migration, from the new member states entering the European Union in 2004, caused a decrease in property crimes. In contrast, 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, the estimates presented on the overall impact of immigration on crime rates are consistent with the evidence from economically motivated Eastern European migration to the United Kingdom and Mexican migration to the United States.

There are numerous plausible channels through which immigration affects crime rates, but evidence on their relative importance is 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. A change in their share in the population will lead to a direct change in crime rates. Second, the arrival of immigrants may change the economic outcomes and prospects, such as employment and wages, of the existing native population. This, in turn, changes the relative attractiveness of criminal activities for natives. Third, 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 and, maybe, induced to move to or from other regions of the country. As a result, each region will face inflows and outflows of different types of natives, further affecting the crime rates. The empirical strategy in the paper is designed with these different channels in mind. After identifying the causal relationship between immigration and crime, the empirical approach uses the decomposition of Gelbach (2016) to determine the relative importance of the various channels that underlie this relationship.

The empirical literature on the economics of crime suggests that the most important (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, the main results in the paper 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

2 The identifying variation of the 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 this instrument is that it provides both exogenous time-series and cross-sectional variation.

3 Further evidence comes 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 (Papadopoulos 2011, Nunziata 2015), and evidence from imprisonment rates (Butcher and Piehl 2007).

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).

of young males, as measured by the wages of the 25th percentile in the earnings distribution, and their employment rates are negatively correlated with property crime rates, though they are uncorrelated with violent crime rates. 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 rates. The implication is that immigration improves labor market conditions for people who are at high-risk of unemployment which, in turn, 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. It is less clear though why immigration also decreases violent crime rates.[5]

Malaysia is an important setting in which to explore the relationship between low-skilled immigration and crime. It is a major destination country with over ten percent of the population composed of foreign-born people according to the official numbers.[6] As in most non-OECD countries, these migrants are primarily from countries in the same region, with neighboring Indonesia as the largest source country. However, like in OECD destinations, immigration to Malaysia is primarily economically motivated and should have similar labor market effects (Docquier, Ozden, and Peri 2014). As a consequence, economic migrants are expected to have a negative impact on crime rates, adding to the evidence from Bell, Fasani, and Machin (2010). In another contrast to OECD countries, however, immigrants in Malaysia are overwhelmingly low skilled. Furthermore, there are almost no pathways to permanent residency or citizenship for such immigrants. Most migrant workers in Malaysia are on fixed-term employment visas or have overstayed them.[7] As the demand for and the share of migrant workers rose rapidly in Malaysia over the last two decades, a widespread public belief emerged on the role of migrants in explaining rising incidence of violent crimes during the same period.[8]

The remainder of the paper proceeds as follows: Section I provides a description of the data. Section II describes the empirical strategy and instrument, and section III presents the results. Section IV concludes.

I. Data and Descriptive Statistics

The 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 and federal territories in the analysis as Putrajaya and Labuan are included in Kuala Lumpur and Sabah, respectively. Data on economic and

5 A possibility is that migrants are less likely to both commit crimes and report being victimized. A lower propensity of immigrants to be involved in violent crimes cannot, however, fully explain the estimated reduction in violent crimes.

6 The true number may be over 20 percent of the workforce according to some estimates.

7 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).

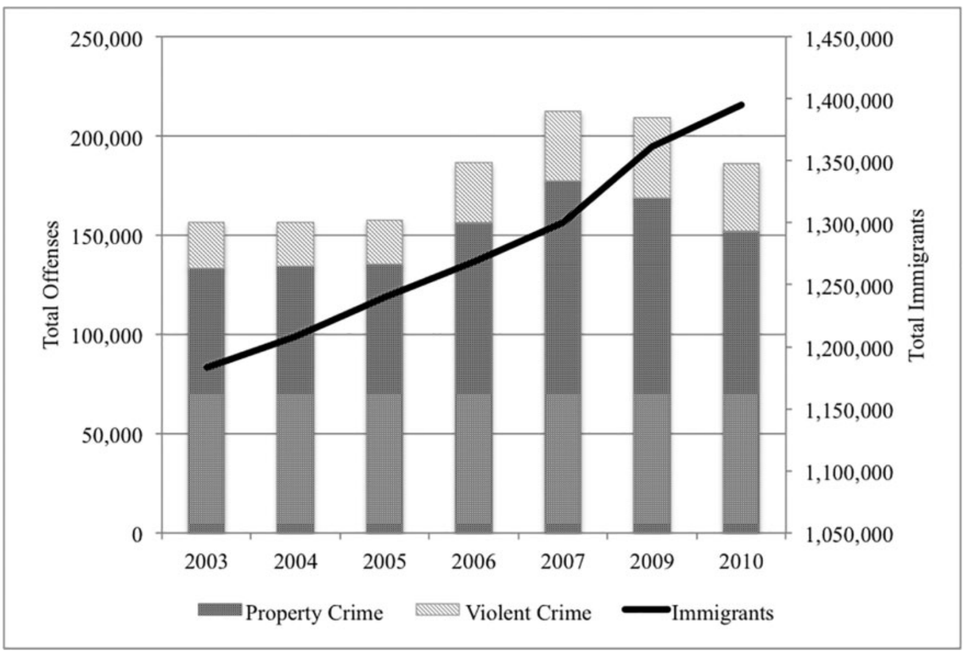
8 Free Malaysia Today, "Foreign migrants pushing up crime rates" published on November 20, 2014. Malaysian concerns about immigration and crime have made it as far as the New York Times, "Malaysia's Immigrant Worker Debate" published March 28, 2016. See also New Strait Times, "Illegal workers a threat 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 February 20, 2016.

demographic variables and the number of immigrants come from the annual Labour Force Survey (LFS) of Malaysia, which is available for the period 1990 to 2010.[9] 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 one percent of the population. The variables for this paper are constructed from the underlying micro-level data, 300-400 thousand observations per year. The micro-level data are aggregated to the state-year level since the data on crime is only available by state and year.

Crime in Malaysia

The main crime measures are based on total crime and its components: property and violent crime. Property crimes include house break-ins and theft, vehicle 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 graph of both property and violent crime together with the immigrant stock. Table 1 reports these numbers and their more detailed breakdown for the years 2003 and 2010.[10] 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

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



Note: Data from the Malaysian Labor Force Survey and the Malaysian Social Statistics Bulletin.

9 The exceptions are 1991 and 1994 when the survey was not conducted and 2008 for which the survey weights are not available.

10 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.

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).

bodily injuries. Violent crime rates 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 two percent from 851 to 827 incidences per 100,000 people.

There are large variations in property and violent crime rates across states (Supplemental appendix figure S.1 presents property and violent crimes rates per 100,000, inhabitants by state in 2010, available at https://academic.oup.com/wber). For example, crime is particularly high in the main city Kuala Lumpur (2,555 total offenses per 100,000 inhabitants) and particularly low in Sabah in northern Borneo (351 offenses per 100,000 inhabitants). Violent and property crime rates 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.

Immigrants in Malaysia

The share of immigrants in the Malaysian population has increased from 3.6 to 10.6 percent between 1990 and 2010, according to the Malaysian LFS. In 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. Supplemental appendix figure S.2 presents the immigrant share in the working-age population in each 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 eight percent in Kuala Lumpur.[11]

Migrants come to Malaysia overwhelmingly for economic reasons.[12] Table 2 provides basic descriptive statistics for the native and immigrant populations in 2010. Immigrant labor force participation is 79 percent, compared to 61 percent for natives, and the unemployment rate only 1.8 percent, compared to 3.5 percent for natives. Immigrants are primarily in Malaysia for work and are highly integrated in the labor market.[13] Immigrants are very low-skilled with 66 percent of the employed immigrants having at most completed primary school and only 4.3 percent are educated beyond high school. The same

11 Sabah is a clear outlier in terms of the share of immigrants in the working-age population due to its proximity to Indonesia and the high demand for migrant workers in plantations. All of the results are robust to dropping Sabah from the analysis.

12 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.

13 The other main reason for immigration is for marriage reasons with primarily southern Filipino women marrying Malaysian men.

Table 2. Native and Immigrant Characteristics (2010)

	Natives	Immigrants
Labor Force Participation rate (%)	61.5	78.9
Unemployment Rate (%)	3.5	1.8
	Among Employed (in %)	
Fraction Female in Labor Force	36.6	31.7
At most primary	20.5	66.0
Lower secondary	13.8	15.1
Upper secondary	43.3	14.6
Diploma/Certificate	11.6	1.2
Degree	10.7	3.1
Ages 15–19	3.2	5.1
Ages 20–29	30.7	19.3
Ages 30–39	27.0	39.5
Ages 40+	39.1	36.0
Agriculture and Mining	11.9	32.5
Manufacturing	17.1	17.9
Construction	8.6	14.0
Services	42.5	33.6
Public Admin, Health, Education	19.8	2.0
	Mean Monthly Wages by Educational Attainment (in US Dollars, Purchasing Power Parity)	
At most primary	763	550
Lower secondary	862	620
Upper secondary	1044	828
Diploma/Certificate	1758	2250
Degree	2845	5253
Number of Observations	242,276	16,224
Total	16,980,672	1,394,177

Notes: Data is from the Labour Force Survey of Malaysia. 1 US dollar is around 1.44 Malaysian Ringgit (RM) in purchasing power parity.

numbers are 20 and 22 percent, respectively, for the Malaysian citizens. Immigrants are over-represented in the 30-39 age group and underrepresented in the 20-29 age group. Nearly one-third of all immigrants work in agriculture and mining as compared to only 12 percent of Malaysians. At the low-end of the educational distribution, Malaysians earn significantly more than immigrants. For example, among those with at most primary school education, average monthly earnings for natives are $763 and for immigrants $550, a 28 percent difference. The native wage premium diminishes at higher levels of educational attainment, and immigrants with more than high school completion actually earn more than natives on average.

There are two types of formally registered immigrants in Malaysia: expatriates and foreign workers. Expatriates are highly-skilled or educated professionals and make up only two percent of the total immigrant stock in 2010. The remaining 98 percent of the immigrant population enter Malaysia with temporary work permits, which are generally valid for 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. It is almost impossible for this group to obtain permanent residency or citizenship. 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 in the labor markets.

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 visas. Precise estimates are not available, but a 1996/97 regularization program resulted in almost one million unregistered migrants being legalized. Another 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 there is no discontinuous increase in the estimated number of immigrants during the 1996/97 regularization.

The LFS is, of course, unlikely to obtain a fully representative sample of undocumented migrants in practice.[14] This creates measurement errors and general undercounting of immigrants in the data. The instrumental variable strategy, as discussed below, aims to ensure that this measurement error does not bias the estimates.

Variable Descriptions

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

The main demographic variable is the number of males aged 15–29, since this group is the most prone to engaging in criminal activities.[15] Consistent with economic models of crime (Becker 1968; Ehrlich 1973), several economic variables that proxy the expected costs and benefits of criminal activities are included. First variable is the 25th percentile of young, male earnings to proxy the returns to legal income opportunities available to the key demographic group likely to commit crimes.[16] Second variable is the total number of employed people (ages 15–64), as a general proxy for employment opportunities in a region. [17] Third is 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). It is not possible to access regional household poverty rates, so instead, a measure of the working poor at the state level is used. Specifically, the main metric is the number of employed people with earnings below the 50 percent of the median monthly earnings by state and year.[18] Note that there are two main ways how this measure may change over time. People might become poorer, and poor people might obtain jobs. Hence, it is unclear how the poverty measure will be related to crime. Fourth is a measure of the opportunities for criminal activity, such as theft. For this, the 75th percentile of earnings in a state and year is used as a proxy.

14 Note that, for example, the LFS does not survey those in communal housing. There are estimates that place the true immigrant to population rate at over 20 percent.

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

16 See Grogger (1998); Gould, Mustard, and Weinberg (2002); and Machin and Meghir (2004) on the connection between wages and crime. The 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.

17 More commonly, the literature uses the unemployment rate to proxy for employment opportunities. See, for example, Raphael and Winter-Ember (2001); Fougere, Kramarz, and Pouget (2009); Bianchi, Pinotti, and Buonanno (2012); Gronqvist (2013); and Spenkuch (2014). However, Malaysia has a particularly low unemployment rate—only 2.2 percent of the native working-age population—which, given the relatively small size of the LFS, is subject to a lot of measurement error. Hence, instead the number of employed in a given state in a given year is used, which is far more precisely measured.

18 In 2014 only 0.6 percent of Malaysians 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, a standard, relative poverty measure for the working poor using the Malaysian LFS is constructed.

The role of deterrence on criminal behavior is another critical issue in the literature. The number of police employed by year in each state is used in this paper as a potential measure of deterrence.[19] Finally, all of the specifications include the log of population (ages 15-64) as a covariate. This variable implicitly controls for population density, another key determinant of the level of criminal activity (Glaeser and Sacerdote 1999), since all of the estimating equations include state fixed effects. There are numerous alternative measures that could be included in these specifications. Most importantly, there is extensive work on the impact of education on crime.[20] The results are robust to using low educated men and their earnings as explanatory variables instead of young males.[21]

Table 3 presents summary statistics for the main explanatory variables used in the analysis. The data are for 2003 and 2010, except for variables based on earnings that are for 2007 and 2010, since the LFS started collecting wage and salary information only 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 slightly above two percent. The number of police increased by 42 percent between 2003 and 2010. The number of working poor also increased rapidly, from ten 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.[22]

Table 3. 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

Notes: 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.

19 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 is calculated from the Malaysian LFS using occupation codes (MASCO 5142). These are not official police numbers.

20 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).

21 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.

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

III. Empirical Strategy

The Impact of Immigration on Crime

The first step of the empirical strategy aims to identify the total effect of immigration on crime. The baseline specification takes the following standard form:

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

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.[23] All specifications include state δ_r and year fixed effects δ_t. Hence, the identifying 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. In contrast, if $\beta^B < 0$, then immigration decreases the crime rate.

In equation (1) all variables are aggregated at the state by year level. That is also the level of variation of the 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. The results are also robust to clustering standard errors by state. However, there are only 14 states of very different sizes, which is likely too few to make clustering advisable with unbalanced clusters (Angrist and Pischke 2009; Cameron and Miller 2015; MacKinnon and Webb 2017).

Channels and Decomposition

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

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

where all variables are specific to a state r and year t. ln *young* is the number of men between the ages of 15 and 29; ln *earnings25th* is the 25th percentile of the log 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 75th percentile of the log earnings among all employed people, and ln *police* is the log number of police. Section 1, above, provides a discussion of the economic justification for the inclusion of each of these covariates.

A common strategy for identifying how much of the relationship between the outcome and an explanatory variable of interest, such as between crime and immigration, 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 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).

Sequential covariate expansion exercises are not, however, necessarily very informative about the true impact of a covariate, as Gelbach (2016) argues. This is because their interpretation often crucially

23 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 the log-log specification, the results are identical if the dependent variable is the log of the crime rate or the log of the number of crimes.

depends on the *sequence* in which covariates are added to the regression. To put it differently, altering the order of the covariate expansion changes the difference in the estimated coefficients that will be attributed to each new 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 that 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 equation (1) is interpreted in this way, standard omitted variable bias formula can be applied.

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 in equation (2), and ln$M$ is the only explanatory variable.[24] Then the relationship between the coefficient on immigration in the baseline and full model is given by the following expression:

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

where θ_j is the coefficient on ln M in the regression j of the auxiliary model 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. It should be added that the decomposition relies on correctly identifying β^B and β^F as defined above. 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 detailed discussion).

Instrument

The central challenge in estimating equations (1) and (2) is the possible endogeneity of immigrant location decisions, a problem common to almost all migration-related papers. Migrants may choose to 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 stock of immigrants in a state, the main explanatory variable.

A valid instrument for immigration patterns across states needs to be uncorrelated with shocks that may deter or encourage crime. These shocks may be caused by changes in demographics, labor market opportunities, or policing. In order to construct such an instrument, changes in the population and age structure of immigrant source countries over time are used. 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, the number of individuals in each of seven age-groups in each of these source countries in every year during 2003-2010 are calculated.[25] These populations form the potential pool of immigrants to Malaysia by the likelihood of migration varies by age group, country of origin, and year. This is the measure of the supply of 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, the measure of the supply of immigrants for all other countries are aggregated into a single category. Hence, there are effectively three source countries: Indonesia, the Philippines, and Other.[26]

24 These covariates are ln *young*, ln *earnings25th*, ln *emp*, ln *workingpoor*, ln *earnings75th*, and ln *police*.

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

26 The population numbers of each source country are multiplied 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%, Laos 0.01%, Myanmar 2.18%, Sri Lanka 0.16%, Thailand 0.22%, Vietnam 0.78%, Indonesia 5.56%, and Philippines 0.38%.

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

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

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:

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

The main instrument is constructed by summing over the age-specific instruments by source country and over source countries (and take the natural logarithm). The instrument varies by state and year:

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

The results are also robust to allowing for three separate instruments by source country: $lnIV_{rt}^c = ln \sum_a \gamma_r^{ac} * S_t^{ac}$ for Indonesians, Filipinos, and all other nationalities.

The identifying variation comes from the interaction of γ_r^{ac} and S_t^{ac}, and is conditional on the included fixed effects. The variation in the instrument generated by the differential propensity of immigrant groups (defined by nationality and age) to work in different states in Malaysia 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). The instrument takes advantage of both exogenous time-series and cross-sectional variation.[27]

The supply of potential migrants to Malaysia from different source countries (S_t^{ac}) is determined by the demographic factors that were relevant 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 (γ_r^{ac}) in this earlier pre-period depends on permanent differences in the levels of labor demand across local labor markets. This is why state-specific fixed effects are included in all of the 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 period (2003-10) demand shocks. By allowing for a ten-year lag between these two periods to construct (γ_r^{ac}), that concern is minimized.[28]

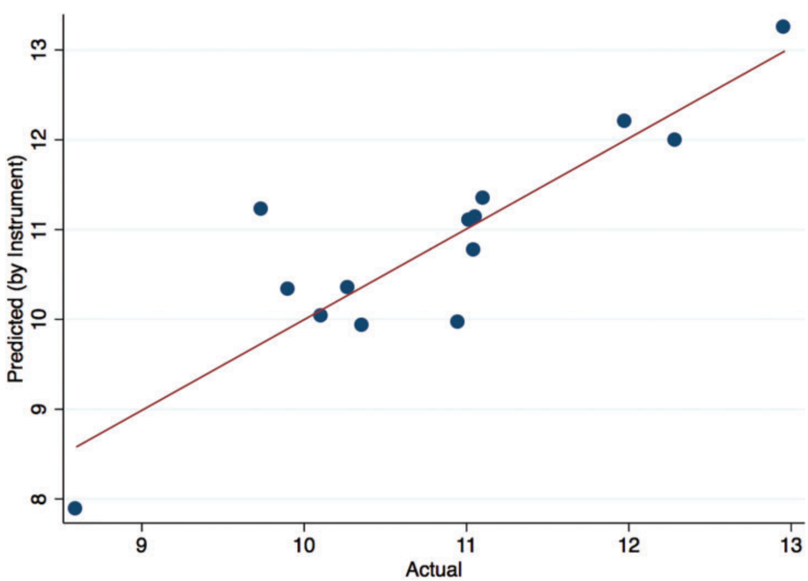
27 Other work that adds a plausibly exogenous time-series dimension to the Altonji-Card shift-share instrument includes Chalfin (2015) and Chalfin and Levy (2015), who follow a similar idea to develop an IV strategy based on fertility shocks in source areas of Mexico. Other related papers are Pugatch and Yang (2012) and Chalfin (2014), who use rainfall shocks in source areas as exogenous determinants of migrant outflows. The instrumenting strategy is very similar to that in Del Carpio et al. (2015) and Ozden and Wagner (2016).

28 Using the same data but a longer time period, Del Carpio et al. (2015) and Ozden and Wagner (2016) are able to show that, at the level of Malaysian states, there do not seem to be persistent underlying labor market trends that are correlated with immigration.

An additional important advantage of an instrumental variable approach is that it helps to address classical measurement problems. The Malaysian LFS attempts to survey undocumented immigrants in Malaysia, yet the survey is unlikely to obtain a fully representative sample. This creates measurement errors and general undercounting of immigrants in the data. All of the specifications include year fixed effects, which will control for general undercounting of immigrants over time. State fixed effects are also included, which will control for state-specific differences in the propensity of immigrants to be surveyed by the Malaysian LFS. These will be fully absorbed by the fixed effects in the (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).[29] In addition, there is likely to be idiosyncratic measurement errors (e.g., 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 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. It is unlikely for the instrument to be systematically correlated with measurement error in the period 2003–10.

Figure 2 plots the actual and predicted log number of immigrants for all 14 Malaysian states in 2010. Clearly, there is a close fit between instrumented and actual immigration numbers, suggesting the instrument is highly predictive of actual immigrant numbers.

Figure 2. Actual and Predicted Log Immigrant Numbers in 2010



Notes: Predictions are based solely on the instrument, having controlled for a full set of covariates and state and region fixed effects. Data are from the Malaysian LFS and based on authors' estimates.

29 The model of measurement error we have in mind is that the observed number of immigrants *MObs* is equal to the actual number of immigrants *MTrue* scaled by a state-specific factor τr and a year-specific factor τt, such that $M_{rt}^{Obs} = \tau_r \tau_t M_{rt}^{True}$

III. Results

The Impact of Immigration on Crime

Table 4 reports the results for the baseline equation (1), with (log) total, property and violent crimes as the dependent variable in each column, respectively. OLS estimates and IV estimates are presented in panel A and panel B, respectively. The crime rate is negatively correlated with the number of immigrants in a state's population. The OLS point estimates imply an elasticity of around −0.47 for all types of crime.

Table 4. 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

Notes: The baseline specification includes log total population as a covariate and state and year fixed effects. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the ten, five, one percent significance level.

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 slightly below -1 for both total and property crimes.[30] The implication is that an increase in the fraction of immigrants in a state's population from ten 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. The instrument is statistically significant in the first-stage, with a coefficient of 5.65 and t-statistic of 2.5.[31]

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, Bianchi, Pinotti, and Buonanno (2012), Spenkuch (2014), and Chalfin (2014) do 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 cannot rule out an effect. Consistent with these 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.[32]

30 Recall that over 80 percent of crimes in Malaysia are property crimes; hence, the estimates for total and property crimes are always very similar.

31 Since the 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 the first-stage t-statistic and not the F-statistic is reported as would be the case if there were multiple instruments.

32 Appendix table S.3 presents estimates of the causal impact of immigration on further disaggregated crime rates. Specifically, property crimes are disaggregated into vehicle thefts and other property crime, and violent crimes into robberies and other violent crimes.

Table 5 shows that the causal relationship between immigration and crime rates is highly robust to several different specifications. Panel A presents the results with the same point estimates but with standard errors that are clustered by state to account for serial correlation. All of the 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 sample. The point estimates and standard errors are almost identical to those in table 4. Analysis in panel C uses three instruments based on nationality, (for Indonesians, Filipinos, and Other, please see section 3.3 for details on the construction of the instruments). The point estimates somewhat increase and remain statistically significant.[33] In panel D, the independent variable is the number of employed immigrants, as opposed to all immigrants. The point estimates are almost identical to the main estimates in table 4 and the standard errors are slightly larger. All estimates remain statistically significant. This finding reinforces the idea that the estimates reflect the impact of economically active migrants as opposed to all migrants. They also likely 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 and the standard errors increase slightly when compared to the main estimates, though all estimates remain statistically significant.

Table 5. 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-statistic	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-statistic	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-statistic	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-statistic	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-statistic	2.18	2.18	2.18
Observations	98	98	98

Notes: 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 ten, five, one percent significance level.

Determinants of Crime Rates

Section I presented a detailed discussion of various demographic and economic variables that the literature identifies as likely factors to influence crime rates. These are included in the full specification given by equation (2), and table 6 reports these estimates. Panel A presents OLS estimates, and panel B

33 The t-statistic for the instrument in the first-stage is only 1.6 though.

Table 6. 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**	−0.292*	−0.347	−0.253	−1.464***
	(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 Income 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 Income 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

Notes: All specifications 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 ten, five, one percent significance level.

presents the IV estimates.[34] Clearly, the negative correlation between immigration and crime rates is robust to the inclusion of these additional covariates. The instrument continues to be statistically significant in the first-stage, with a coefficient of 5.73 and t-statistic of 3.2 when the covariates are added.

The most important change due to the inclusion of the covariates is the decrease in the magnitude of the estimated impact on property crimes. Specifically, the coefficient declines by three-quarters, from an elasticity of −0.97 to −0.25 (in the IV specification), and it is no longer statistically significant. In contrast, the inclusion of covariates changes 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 conditions for natives. It is less clear, though, why immigration also decreases violent crime rates. A plausible answer is that immigrants commit (or report) fewer violent crimes.[35] However, the magnitude of the estimated impact is too large to be simply explained by immigrants' lower propensity for committing violent crime.

The estimated impact of the covariates on crime rates are very similar in panels A and B. Interestingly, the population variable, reflecting the correlation between population density and crime, is not statistically significant in explaining crime rates.[36] Instead, consistent with the literature, the most important and robust variable explaining changes in crime rates is the fraction of young men (ages 15–

34 Appendix table S.1 reports standard errors clustered by state. For the OLS estimates these are near identical. For the IV estimates they are somewhat larger, but not sufficiently so as to invalidate any of the conclusions from the baseline results.

35 "Parliament: Only 1% of crimes are committed by foreigners, says Wan Junaidi," The Star, published on Tuesday, July 9, 2013.

36 Glaeser and Sacerdote (1999) find a positive correlation between city density and crime. These results suggest that this correlation may be the result of the demographics of cities rather than their density *per se*.

29) in the population. The impact is large with an elasticity of around 0.8 for property crimes and 1.2 for violent crimes. Consistent with economic theories of crime, the earnings potential of young males, as reflected by the 25th percentile of their (log) earnings, is negatively correlated with property crime rates. The elasticity is around -0.3 and statistically significant. In contrast, this variable is uncorrelated with violent crime rates. Similarly, the earnings potential from illegal activities, as proxied by 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; 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.

Decomposing the Immigration-Crime Relationship

The remaining question is how each of the covariates in the full specification in equation (2) explain the relationship between immigration and crime identified in the baseline equation (1). Table 7 reports the results of the Gelbach (2016) decomposition for the IV estimates for all property and violent crimes.[37] For convenience, the estimates reported in tables 4 and 6 in the rows 'immigrant - baseline' and 'immigration full', respectively, are presented again. The total change in the coefficient (β^B - β^F) is statistically

Table 7. 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	−1.464***
	(0.294)	(0.327)	(0.499)
Total Change in Coefficient	−0.642**	−0.717**	−0.346
	(0.287)	(0.320)	(0.224)
Fraction of Change in Immigrant Coefficient (Baseline - Full) Explained by:			
Young-Male Population	56%	49%	151%
Young-Male 25th Income Pctl.	8%	6%	−10%
Total Employed	32%	34%	−14%
Number Working Poor	43%	51%	−9%
75th Income Pctl.	−39%	−40%	−17%
Number Police	0%	0%	−2%

Notes: The Baseline specifications is identical to that in table 4, Panel B. The Full specification is identical to that in table 6, Panel B. Standard errors are robust to heteroscedasticity. *, **, *** denote significance at the ten, five, one percent significance level.

37 Since the inclusion of covariates has, as discussed, very little impact on the crime-immigration correlation in the OLS estimates, a further decomposition is not informative.

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.[38]

Table 7 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. In contrast, these 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 7 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 6 and 7, the underlying causal relationships can be inferred. The implication of these 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 further 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 (2016). Those papers find that all except the very least educated (without primary school education) Malaysians benefit from immigration. As a result of immigration, most native wages increase and states with an inflow of immigrants also experience an inflow of natives.

Supplemental appendix *TABLES S.4 AND S.5* show that the results are robust to alternative choices of covariates. In panel A of each table, all covariates are defined for the Malaysian population as a whole, such that none of the variables are specific to males. In panel B, all variables are defined exclusively for male Malaysians.[39] While there are some differences in the salience of particular covariates, the estimated impact of immigration on crime is near identical to that in the baseline results.[40]

IV. Conclusion

The perception that immigration fuels crime is an important source of anti-immigrant sentiment in almost every destination country. 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 socioeconomic changes among the native population. The results suggest that immigration decreases

38 Appendix table S.2 reports standard errors clustered by state. This increases standard errors sufficiently such that the change in the immigration coefficient due to the inclusion of covariates is no longer statistically significant.

39 The data does not allow distinguishing between crimes by the gender of the perpetrator or victim. Consequently, the dependent variable in these regressions is the same as in the main regressions.

40 The decompositions presented in appendix table S.5 are also very similar regardless of how the covariates are constructed. In addition, the decompositions are robust to the previous specifications of excluding Sabah from the analysis, using three instruments by nationality and using employed immigrants or male immigrants as the independent variable of interest. Finally, appendix table S.3 presents the Gelbach (2016) decomposition for further disaggregated types of crime.

property crime rates primarily because it changes economic conditions for natives, while the decrease in violent crimes is harder to explain. 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 fewer crimes than natives. A potential explanation is that 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 is 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, the findings in this paper may overstate the degree to which the actual number of crimes, specifically targeting foreign 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 in Malaysia.

Conflict of interest: none declared.

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