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CRIME AND IMMIGRATION: EVIDENCE FROM LARGE IMMIGRANT WAVES

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Abstract—This paper focuses on empirical connections between crime and immigration, studying two large waves of recent U.K. immigration (the late 1990s/early 2000s asylum seekers and the post-2004 inflow from EU accession countries). The first wave led to a modest but significant rise in property crime, while the second wave had a small negative impact. There was no effect on violent crime; arrest rates were not different, and changes in crime cannot be ascribed to crimes against immigrants. The findings are consistent with the notion that differences in labor market opportunities of different migrant groups shape their potential impact on crime.

I. Introduction

MANY media and social commentators posit there to be a direct connection between immigration and crime. However, this is a key issue on which there is only a sparse academic literature (for notable exceptions, see the U.S. papers by Butcher & Piehl, 1998a, 1998b, 2005, and the Italian paper by Bianchi, Buonanno, & Pinotti, 2012).[1] This contrasts starkly with the by now very large literature on the labor market effects of immigration (see Borjas, 1999, or Card, 2005).

In this paper, we study possible crime effects from two recent large flows of immigrants entering the U.K. economy. These large flows offer an opportunity for careful appraisal as to whether the populist view that immigrants cause crime is borne out by rigorous evidence. We are able to exploit the fact that the two flows were very different in nature, in particular in their incentive to engage in criminal activities.[2]

The first immigrant flow we consider is the late 1990s and early 2000s wave of asylum seekers, which we refer to as the asylum wave. The second is the large inflow of workers from EU accession countries—the A8 wave—that occurred from 2004 onward. As we will demonstrate, connections of these two flows to the labor market are very different. As labor market opportunities on offer are a key determinant of criminal behavior in the standard economic model of crime (Becker, 1968; Ehrlich, 1973), we develop our empirical tests in this light. In particular, labor market opportunities available to the asylum wave are much worse than for both natives and the A8 wave, making the net returns to criminal activity likely to be different. We therefore hypothesize that crime effects are more likely in the case of the former.

Our evidence supports this way of analyzing the crime-immigration relationship. For the asylum wave, we report evidence of a higher incidence of property crime induced by the immigration flow. The A8 wave sees the opposite effect. There is also no observable impact on violent crime for either wave. Evidence from victimization data suggests that the changes in crime rates that occurred during the immigrant waves cannot be ascribed to crimes against immigrants, while data on incarceration corroborate the view that any immigrant-induced rise in crime is associated only with the first wave. This leads us to an overall conclusion that focusing on the limited labor market opportunities of asylum seekers could have a beneficial crime reduction effect.[3]

The rest of the paper is structured as follows. Section II describes the two migration waves in more detail and presents some summary statistics on their characteristics relative to both natives and other immigrants. Section III presents our main results. We exploit local area-level data on crime rates and migrants to estimate panel models of the relationship between recorded crime and the immigration waves. Section IV compares arrest rates for the A8 immigrant group with natives, gives evidence on immigrant-native differences in rates of incarceration, and presents findings from the victimization analysis. Section V offers an interpretation of the results, connecting them to the standard Becker/Ehrlich economics of crime model. Finally, section VI offers some conclusions.

II. Immigration to the United Kingdom since 1997: A Tale of Two Waves

We begin by describing the evolution of immigration in the United Kingdom over the past few decades, paying particular attention to the large flows since 1997, a period notable for the vast inflow of migrants relative to previous experience. We show that two particular waves of immigration into the United Kingdom since this date have been major contributors to the overall rise. Interestingly, they have very different characteristics and motivations for migrations. This makes them a natural focal point for analysis and for testing whether immigrant flows have an impact on crime.

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A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00337.

[1] Indeed, in the United Kingdom, the context we study, there is no evidence at all. The only quantitative evidence of which we are aware is contained in the unpublished MSc dissertation by Pearse (2009).

[2] Heterogeneity in migration flows from refugees and economic migrants to the United States is stressed in Cortes (2004), who demonstrates significant variation in labor market attachment and earnings, and assimilation, of these groups.

[3] See Mastrobuoni and Pinotti (2010) for evidence that granting legal status to migrants—by opening up better labor market opportunities for them—reduces their recidivism rate.

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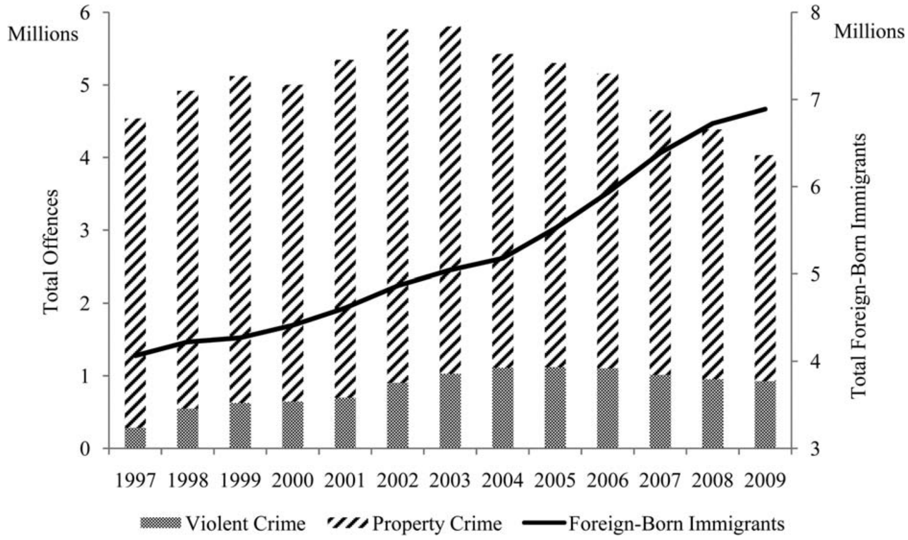
FIGURE 1.—IMMIGRATION STOCK AND CRIME TRENDS, ENGLAND AND WALES, 1997–2009



The pattern of immigration over the recent past is shown in figure 1. This plots the stock of immigrants each year over the period 1997 to 2009, together with the number of reported violent and property crimes. In 1981, the stock of immigrants was 3.2 million, this rose only to 4.1 million by 1997. Since then, the stock has risen to 6.9 million. The figure shows a sharp rise in immigration flows since 1997. In other words, fully three-quarters of the rise in the stock of immigrants over the past thirty years has occurred since 1997, and this is the only period during which the change in migration overwhelmed the natural change in the population. We think this gives us a credible setting for empirically studying the crime-immigration relationship. To see how, we turn to a closer examination of the immigration flows since 1997.

The first flow we concentrate on is the large rise in the number of asylum seekers arriving in the United Kingdom. Asylum flows to industrialized countries rose in the 1990s and early 2000s, with peaks in 1992 and 2001 (Hatton, 2009). The first peak was associated with the fall of the Berlin Wall and civil war in the former Yugoslavia; and Germany was the principal destination country. The second peak, which we focus on in this paper (as flows to the United Kingdom were much larger), was associated with wars and country breakdowns such as in Iraq, Afghanistan, and Somalia.

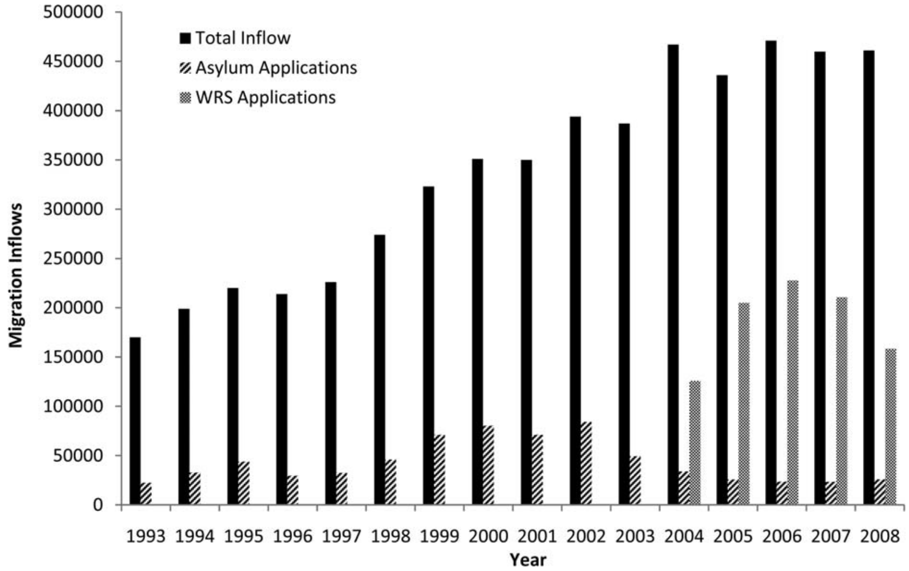
While the increased flow of asylum seekers occurred in many industrialized countries, the numbers seeking asylum in the United Kingdom were very large relative to both previous application trends and other forms of immigration. The United Kingdom was the second-highest recipient in the world of asylum seekers over this period, for instance, receiving almost twice as many as the United States. Figure 2 plots the number of applications for asylum in each year from 1993 to 2008. The sharp increase after 1997 is clear, as is the subsequent deceleration after 2002. The average number of new applications for asylum in the five years prior to 1997 was 31,000. In the five years after 1997, this rose to 71,000. At their peak, asylum seekers accounted for over 20% of all non-British migrants entering the United Kingdom.[4]

Most of the migrants associated with the first flow are ultimately denied leave to remain in the United Kingdom. On average during this period, around 70% of asylum seekers had their claim rejected or withdrawn. In this paper, we focus on the stock of asylum seekers rather than the subsequent smaller stock of successful asylum applicants. We do so for three reasons. First, as most asylum applicants are eventually denied, it would make little sense to focus only on the subset of successful applicants. Second, as a practical matter, we have data on the geographical location of asylum seekers only while their claim is being assessed or appealed. Third, the identification strategy we use relies on the dispersal policy adopted for asylum seekers. Successful applicants are no longer subject to these restrictions. It is a subject for future research to examine the performance of successful asylum seekers in the labor market and their impact on crime.[5]

[4] A detailed discussion of the causes of the rise and fall of asylum flows is provided by Hatton (2009).

[5] Edin, Fredriksson, and Åslund (2003) examine the economic success of refugee immigrants in Sweden, where a dispersal policy similar to that used in the United Kingdom was used. Their data do not identify refugee immigrants separately from other immigrants, so their identification relies on country of origin and year of arrival. Such an empirical strategy for the United Kingdom would be ineffective. Suppose we take all identified countries of origin that contributed asylum seekers between 1997 and 2003. Over the period, 412,000 asylum applications were made from these countries (95% of the total). We know that the ultimate acceptance rate was around 30%, implying around 125,000 applicants would be allowed to remain permanently in the United Kingdom. If we assume that all of these successful applicants remained in the United Kingdom, we can compare this figure to the size of the immigrant population in 2008 for these countries of origin who arrived as adults between 1997 and 2003. The Annual Population Survey gives an estimate of 634,000. So using country of origin and year of arrival to try and identify asylum immigrants would falsely identify around 80% of cases. Even if we restrict the sample to the largest five countries of origin, the error rate would still be around 50%. This highlights the fact that the majority of foreign migrants to the United Kingdom do not arrive as asylum seekers, even from countries that generate many asylum applicants.

FIGURE 2.—ASYLUM APPLICATIONS AND WORKER REGISTRATION SCHEME REGISTRATIONS, 1993–2008



The second flow we consider is rather different. This big inflow occurred because of the opening up of the U.K. labor market to citizens of eight countries that joined the EU in 2004. These accession countries (the so-called A8) were Poland, Hungary, Czech Republic, Slovakia, Slovenia, Latvia, Lithuania, and Estonia. At the time of accession, current EU members were allowed to decide whether to grant immediate access to their labor markets or maintain barriers to the free movement of labor. The United Kingdom, along with Ireland and Sweden, chose to open up the labor market. The impact on the labor market has been comprehensively analyzed by Blanchflower and Shadforth (2009). Our focus is simply on the size of the subsequent immigrant flow. Figure 2 shows the number of Worker Registration Scheme (WRS) applications from A8 migrants for each year since 2004.[6] Clearly the flows associated with this immigrant wave dominate the inflows of migrants over the period, accounting for almost 50% of such inflows at their peak.

The characteristics of the two immigrant waves are very different (a feature we return to in section V when considering the interpretation of the results we report and their theoretical underpinning). To provide some illustration of the characteristics of the two waves, tables 1A and 1B report some summary statistics from cross-section surveys for the two waves and for all other immigrants and for natives. Few data sets in the United Kingdom explicitly identify asylum seekers. For table 1A, we use the 2004 New Deal for Communities Evaluation Survey, which asks all respondents whether they entered the United Kingdom as refugees. The sample for this survey covers disadvantaged areas around the United Kingdom, so the data tend to show higher unemployment rates and lower wages than would be true for the whole country, but with these data, we are able to compare asylum seekers with natives and nonasylum immigrants within the same areas. The data for the A8 wave come from the nationally representative Labour Force Survey.

TABLE 1.—SUMMARY STATISTICS

A. Asylum Wave Statistics			
	British	Immigrant Non-Asylum	Immigrant Asylum
% Male	49.6	53.9	60.4
Age	40.9	37.7	35.2
% with Children	40.4	43.5	52.7
% Single Person	21.9	15.9	18.4
% No Qual	38.4	32.2	51.7
% Degree	3.6	6.5	4.1
% Poor English	-	9.8	32.3
Participation rate	60.4	62.3	48.6
Unemployment rate	14.7	17.7	32.7
Annual Mean wage (£)	16,267	15,543	12,672
Annual Median wage (£)	14,300	13,000	10,400
Sample size	8,063	3,385	514
B. A8 Wave Statistics			
	British	Immigrant Non-A8 Wave	Immigrant A8 Wave
% Male	49.6	49.3	54.6
Age	41.3	38.0	28.7
% White	93.1	65.0	93.7
% Married	52.3	53.2	35.7
% No Children	59.7	59.3	70.5
% Degree	15.3	16.1	7.2
Years of School	12.5	13.8	14.8
Participation rate	77.6	71.9	89.0
Employment rate	73.9	66.8	83.5
Mean weekly wage	£423	£432	£268
Median weekly wage	£350	£346	£242
Sample size	398,113	42,551	2,045

Table 1A: Data are tabulated from the 2004 Household Survey Data of the National Evaluation of the New Deal for Communities Programme. British are all those who identify themselves as British, and asylum are those who entered the United Kingdom as refugees. Sample are all heads of household aged 18 to 65, and all results are weighted to reflect the population in the selected areas.

Table 1B: Data are tabulated from the Labour Force Survey, spring quarters 2004–2009. British are all British citizens, A8 wave are all observations where country of birth is one of the A8 countries and year of arrival in the United Kingdom was 2004 or later, and non-A8 wave are all other non-British. Sample are all aged 18 to 65 and results are weighted using population weights.

[6] Workers coming to the United Kingdom from A8 countries were required to register on the WRS. More details are provided in the online appendix.

A number of observations can be made regarding the characteristics of the two waves. First, immigrants in both waves were younger and more likely to be male than natives. Both immigrant waves tend to have lower educational qualifications than natives.[7] Second, individuals in the A8 wave were much more likely to be single and have no dependent children compared to natives, other immigrants, and the asylum wave. This is consistent with the general impression that the A8 wave was dominated by young people coming to take up employment rather than for family relocation. Further support for this is shown by the participation and employment rates for this wave, which are higher than for natives. In contrast, the asylum wave has low participation rates and unemployment rates that are twice as high as for natives.[8] It is clear that the first wave has experienced very poor employment outcomes, while the second wave has the opposite experience. Wages tend to be low for both waves, though some of the wage disadvantage for the A8 wave can be explained by the lower average age of this group.[9]

Two broad conclusions follow from the discussion in this section. First, the rate of immigration into the United Kingdom was relatively smooth in the decades prior to 1997. Since then, the flows have been much more rapid. They were dominated first by the flow of asylum seekers, then by the flow of A8 workers. Second, the characteristics and outcomes, particularly in the labor market, of these two waves are starkly different. These differences will be crucial in examining whether there are links between immigration and crime.

III. Longitudinal Models of Crime and Immigration

In this section, we report results from estimating panel data models of the relationship between immigrant shares and recorded crime.[10] Our basic estimating equation takes the form

$$\Delta(Crime/Pop)_{it} = \beta_1 \Delta(Migrants/Pop)_{it} + \beta_2 \Delta \ln(Pop)_{it} + \beta_3 \Delta X_{it} + T_t + \varepsilon_{it}, \quad (1)$$

where *Crime* is the number of notified offenses, *Pop* is the resident adult population, *Migrants* is either the number of asylum seekers or the number of A8 immigrants, X denotes possible local area control variables such as the percentage of the population claiming welfare benefits and the share of young adults in the population, and T denotes a set of time dummies. Standard errors are clustered at the local authority level in the reported tables of results. In some specifications, we include dummies for each of the 43 police force areas (PFA). Since we are estimating a first-difference model, this controls for area-specific time trends. Since decisions on policing priorities, staffing, and so on are decided at the PFA level, the inclusion of such dummies controls for variations over time in the effect of such decisions on crime trends. In all cases, we also report results without the inclusion of such dummies.

For the immigrant waves, we have administrative data measured at the local authority (LA) level across England and Wales. We have 371 LAs that can be consistently identified over our sample period, with an average adult population of roughly 120,000. Annual crime rates are split into two broad categories: violent and property offenses. The crime data are measured consistently across LAs only from 2002, which therefore defines the starting date of our analysis. Full details of all data and sources are provided in the online Appendix.

For both waves, we can measure the number of immigrants using administrative data that cover the entire population of interest rather than rely on sample surveys. For the asylum wave, we have annual data on the stock of asylum applicants in each LA from 2001. The data begin in 2001, the first year that a national dispersal policy for asylum applicants was implemented and data at the local authority level were collected. The flow of immigrants associated with the A8 accession is measured using administrative data from the WRS. A8 migrants registered on the WRS when they first arrived in the United Kingdom. The WRS measures only the inflow of workers and so is not the stock of A8 workers at any point in time. Thus, we cumulate the data over time to approximate the stock.[11] The data are available at the LA level from May 2004 on an annual basis. Figures 3A and 3B show the distribution of the two

[7] Closer inspection of the numbers in table 1B reveals that the A8 migrants are less likely to have a university degree than natives, but they have more reported years of schooling. This latter result is simply a function of a later compulsory school-leaving age. Given the average age of the A8 migrants, many are likely to return to higher education in the future.

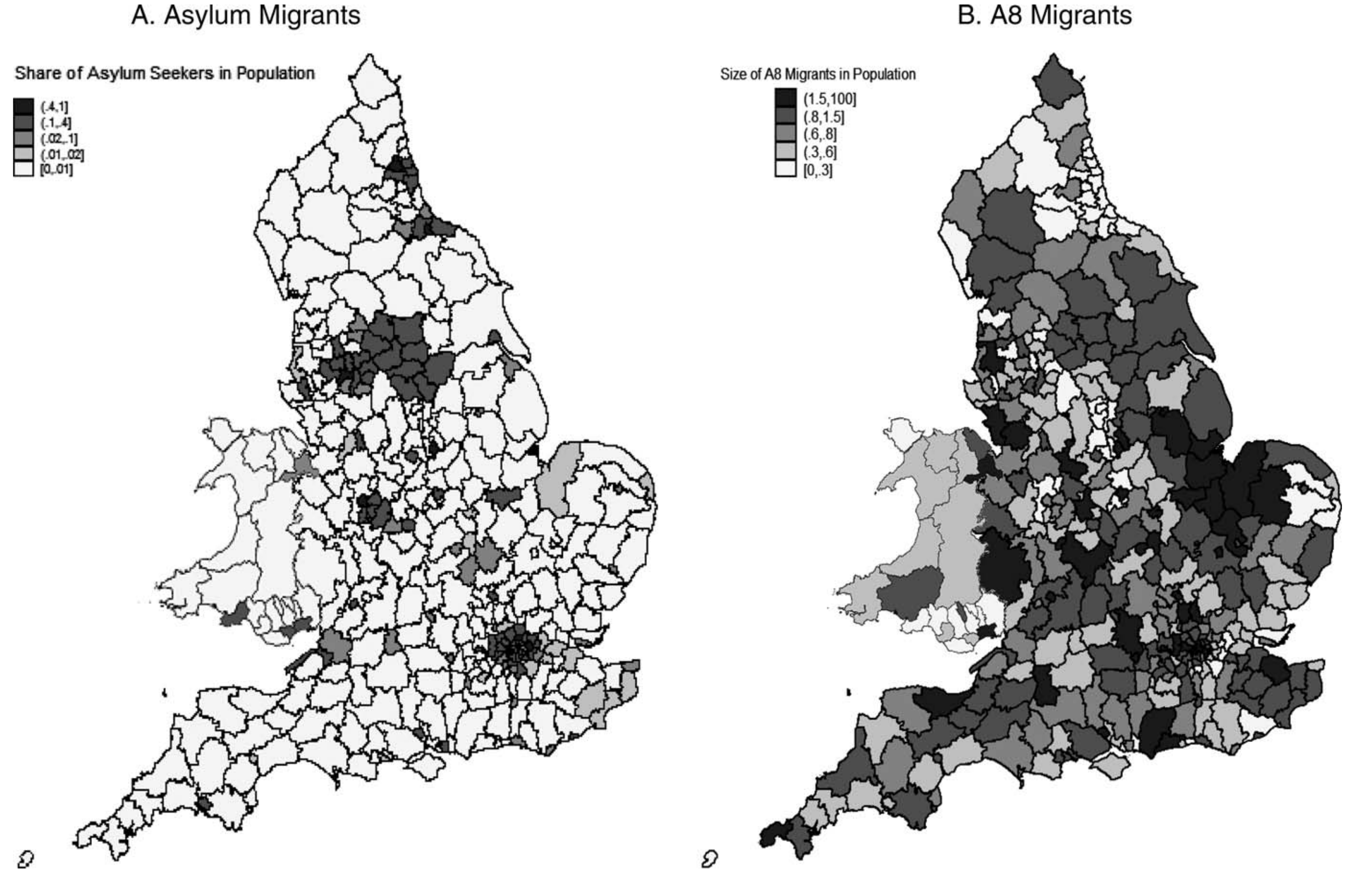
[8] Poor labor market performance relative to natives is a feature of asylum seekers who were relocated to other countries. For example, the Edin at al. (2003) analysis of refugee immigrants in Sweden shows them to have significantly lower employment rates as compared to Swedish-born individuals.

[9] Half of the wage difference between A8 migrants and natives is explained by age, educational qualifications, and sex in a standard wage regression. The low levels of wages for A8 migrants observed in the LFS are consistent with the self-reported wage rates in WRS registrations. In 2008, 93% reported earning an hourly wage below £8.

[10] In an earlier version of the paper, we used survey data (Labour Force Survey and Annual Population Survey) aggregated to area level to consider the relationship between the total immigrant population and crime; we found no significant effect. However, using survey data to estimate the stock of immigrants at lower-level geographies, such as local authorities, may introduce substantial attenuation bias (see Aydemir & Borjas, 2011). This reinforces the benefit of focusing on the two immigrant waves for which we have accurate administrative data on migrant stocks.

[11] There is a natural concern that differential rates of out-migration across local authorities by A8 immigrants would result in the cumulated inflow measure having a poor relationship to the true stock. To examine this, we have compared the flows from the WRS data with the change in the stock estimates from the Annual Population Survey. To achieve reasonable sample sizes of A8 citizens, we estimate APS stocks at the level of Police Force Area (42 areas) and aggregate the WRS data to the same level. We then regress the WRS flows on the change in APS stocks over the period 2004–2008 with time dummies included. The coefficient on the APS stocks is 0.97 with a t-statistic of 10 and an R^2 of 0.77, suggesting a fairly tight correspondence between the *WRS* flows and the stock changes.

FIGURE 3.—DISTRIBUTION OF MIGRANTS ACROSS ENGLAND AND WALES



immigrant waves across England and Wales. The asylum wave migrants are very unevenly distributed because of the dispersal policy that operated (which we discuss in more detail below), and a large number of local authorities had no exposure. In contrast, the A8 wave is more evenly distributed, though with pockets of larger concentrations.

Table 2 reports the results of estimating equation (1) for both waves.[12] For violent crime, we find no significant relationship for either immigrant wave. The estimated coefficients are always small, and the picture is unchanged whether we include a set of local control variables (column 2) or whether we also include a set of PFA dummies to control for time trends at the level of police force areas (column 3).

The results for property crime are very different. Column 4 shows a significant positive relationship between the asylum wave and property crime rates. In contrast, the coefficient on the A8 wave is negative, though small and insignificant. Adding local controls (column 5) marginally sharpens these estimates, though they remain essentially the same. There is a positive effect on property crime from having more welfare benefit claimants in the area and a surprisingly negative effect from a rising youth share. Finally, in column 6, we include PFA dummies to control for PFA-level time trends in property crime. This marginally reduces the size of the coefficient on the asylum wave, but it remains positive and significant. Interestingly, the coefficient on the A8 wave now becomes slightly more negative and significant (but is still an order of magnitude smaller than the coefficient on the asylum wave). The negative effect of the youth share loses its significance in this final specification. Thus, the broad conclusion from these results is that neither wave was associated with any significant change in violent crime, while the asylum wave was associated with a rise in property crime and the A8 wave with a small fall. As we shall discuss in section V, these differential responses are consistent with the theoretical predictions of a standard crime decision model.

As a robustness check, online appendix table 1 reports the full set of results from table 2 but with equation (1) reestimated as a within-group fixed-effect panel model rather than in first differences. We again find that with local controls, there is no significant relationship between either immigrant wave and violent crime rates, though the point estimate for the asylum wave switches signs but remains close to 0. For the property crime models, we again find a

[12] We report results controlling for population, welfare benefit claimants, and the share of young adults in the population. We have experimented with various other controls such as the local unemployment rate and local wages, but these were always less significant than the reported controls, and their inclusion did not affect the coefficients on the immigrant variables.

TABLE 2.—PANEL REGRESSIONS FOR IMMIGRANT WAVES

	Violent (1)	Violent (2)	Violent (3)	Property (4)	Property (5)	Property (6)
Δ(Asylum/Pop)	0.027	0.029	−0.090	1.141***	1.221***	0.930***
	(0.162)	(0.164)	(0.191)	(0.330)	(0.302)	(0.325)
Δ(A8/Pop)	−0.010	−0.003	−0.007	−0.034	−0.043	−0.061**
	(0.014)	(0.012)	(0.015)	(0.025)	(0.025)	(0.025)
Δln(Pop)		−0.019***	−0.029***		−0.029***	−0.032***
		(0.006)	(0.007)		(0.011)	(0.011)
Δ(Benefit Rate)		−0.004	−0.054		0.141***	0.131***
		(0.025)	(0.029)		(0.035)	(0.036)
Δ(Young Share)		0.026	0.035		−0.112***	−0.062
		(0.020)	(0.021)		(0.039)	(0.033)
Year dummies	x	x	x	x	x	x
PFA dummies			x			x
Sample size	2,591	2,591	2,591	2,591	2,591	2,591
p(Asylum = A8)	0.817	0.84	0.660	0.001	0.000	0.003
R^2	0.239	0.242	0.276	0.179	0.209	0.288

Regressions are run over the period 2002–2009. The dependent variable is Δ(Number of Crimes Recorded/Adult Population). All regressions are weighted by adult population. Standard errors in parentheses are clustered at the local authority level. Significant at **5% and ***1%.

significant positive effect for the asylum wave, which is somewhat larger than in the first-difference model. Again, the A8 wave is associated with a smaller but still significant fall in property crime. Thus, our broad conclusion is robust to consideration of this alternative econometric specification.

We now turn to the fact that so far, we have treated the migrant location of the two waves as exogenous. This will of course potentially bias our estimates of the coefficient of interest. For example, if immigrants choose to locate in areas experiencing low crime growth, this would bias down estimates of the causal effect of immigrants on crime. Such an effect might work directly—immigrants find out where low crime areas are—or indirectly—immigrants move to areas with good employment prospects that also produce lower crime rates. A bias in the opposite direction instead would be expected if migrants move to areas with increasing crime rates (because, for instance, they are attracted by falling housing prices). The recent literature on the impact of immigration on receiving countries has generally addressed this identification issue by either devising suitable instruments (Card, 2001) or exploiting some natural experiment where immigrants were forcibly allocated to areas they had not chosen (Edin, Fredriksson, & Åslund, 2003; Gould, Lavy, & Paserman, 2004; Glitz, 2012; Damm, 2009). We exploit a dispersal policy for the asylum seekers wave and will employ an instrumental variable strategy based on the past settlement of immigrants for the A8 wave.

Asylum seekers requiring accommodation are allocated to a location by the National Asylum Support Service (NASS). The NASS sought local authorities that were willing to provide accommodation, possibly because they had spare social housing, and also used private sector accommodation. NASS operated a dispersal policy that sought to locate asylum seekers across the country in a large number of locations and explicitly excluded London. The asylum seeker had no choice as to the destination to which he or she was sent and would often have no ties of any type to the area.[13] The evidence shows that the sample of local authorities that received asylum seekers under the dispersal policy were more deprived than average. There were 148 local authorities that had some asylum seekers provided with accommodation by NASS at some point since 2001 and 223 with no dispersal allocations.[14] Table 3 provides some summary statistics on the differences between the two groups. For our purposes, the level of crime in a local authority is not relevant since we estimate first-difference models. Therefore, the simple fact that asylum seekers were disproportionately sent to deprived areas with higher crime rates does not mechanically produce a positive relationship between changes in asylum stocks and changes in crime rates. Of more concern would be if we found that the growth rate in crime before the dispersal policy began was different between those areas that were designated by NASS and those that were not. As the final rows of table 3 show, there is no evidence to suggest that this is the case.

We can therefore directly exploit this exogenous variation in location by instrumenting the total number of asylum seekers in each local area by the number of those in dispersal accommodation. Columns 1 to 3 of table 4 report the instrumental variable (IV) results.[15] The violent crime effect remains insignificant and close to 0. For property crime, the results are very similar to the OLS results in table 2. In our preferred specification, where we control for PFA dummies

[13] The 1999 act required that in providing accommodation to asylum seekers, the secretary of state must have regard to the "desirability, in general, of providing accommodation in areas in which there is a ready supply of accommodation." Furthermore, the act explicitly states that regard may not be given to "any preference that the supported person or his dependents (if any) may have as to the locality in which the accommodation is to be provided" (s97).

[14] We also experimented with defining an asylum dispersal area as any local authority that accommodated more than five asylum applicants under the dispersal program at any point between 2001 and 2008 to remove very small allocations. This would result in 31 local authorities being redefined as nondispersal areas. Our results are robust if we adopt this alternative definition.

[15] Online appendix table A2 reports the IV first-stage regressions.

TABLE 3.—SUMMARY STATISTICS FOR DISPERSAL AND NONDISPERSAL AREAS, 2001

	All Areas	Dispersal Areas	Nondispersal Areas	t-Test of Difference in Means
Unemployment rate	3.6	3.9	2.6	9.9***
Benefit claimant rate	11.0	12.6	8.7	7.9***
Youth share	15.0	16.3	13.3	11.3***
Vacant housing rate	3.2	3.4	3.0	1.8
Social housing rate	19.2	22.6	14.6	9.0***
Immigrant share	9.1	12.2	4.8	8.7***
% with no qualifications	29.1	30.0	27.9	2.4**
Total crime rate	5.2	6.7	3.2	14.4***
Violent crime rate	1.5	1.9	1.1	9.6***
Property crime rate	3.6	4.8	2.1	14.5***
Prior Δ total crime rate	−0.02	−0.01	−0.02	0.8
Prior Δ violent crime rate	0.13	0.12	0.14	1.3
Prior Δ property crime rate	−0.14	−0.13	−0.16	0.1
Sample size	371	148	223	

The change in crime rates is the two-year change between 1999 and 2001. All figures are weighted by adult population in the local authority. Dispersal areas as defined as those that accommodated any asylum seekers under the dispersal program between 2001 and 2009. Significant at **5% and ***1%.

TABLE 4.—IV PANEL REGRESSIONS FOR IMMIGRANT WAVES

	Violent (1)	Property (2)	Property (3)	Violent (4)	Property (5)	Property (6)
Δ(Asylum/Pop)	0.026	1.776***	1.089**			
	(0.263)	(0.454)	(0.459)			
Δ(A8/Pop)				−0.074	−0.215**	−0.386***
				(0.096)	(0.102)	(0.081)
Δln(Pop)	−0.019***	−0.032***	−0.033***	−0.015**	−0.038***	−0.049***
	(0.006)	(0.011)	(0.012)	(0.006)	(0.011)	(0.010)
Δ(Benefit Rate)	−0.004	0.133***	0.130***	−0.002	0.048	0.020
	(0.024)	(0.034)	(0.036)	(0.028)	(0.037)	(0.033)
Δ(Young Share)	0.026	−0.116***	−0.060	−0.021	−0.040	−0.021
	(0.020)	(0.039)	(0.033)	(0.018)	(0.024)	(0.024)
Year dummies	x	x	x	x	x	x
PFA dummies			x			x
Sample size	2,591	2,591	2,591	1,849	1,849	1,849
R^2	0.242	0.203	0.286	0.073	0.068	0.093

Regressions are run over the period 2002–2009 for the asylum wave and 2004–2009 for the A8 wave. The dependent variable is Δ(Number of Crimes Recorded/Adult Population). All regressions are weighted by adult population. The instrumental variables are the number of asylum seekers in dispersal accommodation for the asylum wave and the supply-push instrument for the A8 wave. The F-statistic on the first stage IV is 1,522 ($p = 0.000$) in the asylum regression with PFA dummies and 12.8 ($p = 0.000$) in the A8 regressions with PFA dummies (see online appendix table A2). Standard errors in parentheses are clustered at the local authority level. Significant at **5% and ***1%.

(column 3), the coefficient on the asylum wave is 1.089. This compares with 0.930 in the OLS specification. It is natural to wonder why the IV and OLS estimates are so similar. The simple reason is that during the period considered, over 80% of the new asylum seekers were dispersed, so the OLS estimates essentially already incorporate much of the exogeneity generated by the dispersal program. This can be seen by both the strength of the first-stage regression and the coefficient on the dispersal share, which is almost exactly 1.[16]

Analyzing the results of the IV regressions separately for male and female asylum seekers (table 5) provides further confirmation that selective choice of dispersal locations by the authorities does not mechanically lead to our findings. If it were the case that the authorities had chosen, by accident or design, dispersal locations that were about to experience a relative increase in crime, we should see the coefficient of the female asylum stock also being positive. There is no evidence to suggest that male and female asylum seekers were systematically sent to very different dispersal locations, with the cross-section correlation between numbers of male and female migrants at each location being 0.84, and females account for around 45% of the total stock. However, we find no significant effect from the female asylum stock on crime in any specification, while a significantly positive effect on property crime is always obtained if we focus on male asylum seekers only.

In contrast to the asylum wave, the A8 migrants could choose to live and work anywhere in the United Kingdom. Thus, for them, we are not able to as precisely control for endogenous location choice as with the asylum wave. Following Altonji and Card (1991), spatial correlation analyses

[16] Our findings are substantially unaffected if we restrict our estimating sample to the asylum dispersal areas. Moreover, we have explored the robustness of our results when we explicitly control for the pretreatment differences between asylum dispersal and nondispersal areas. We estimate propensity score models to predict whether a local authority is a dispersal area based on 2001 local area characteristics. These characteristics include information on the housing stock, economic activity, welfare benefits, education, and population. We then reestimate our models on either the subset of local authorities for which there is common support in the propensity score or matched local authorities. Over various specifications of the propensity score model, we find that the coefficient on the asylum wave remains the same sign and order of magnitude as in the IV regressions of table 4, though significance in the property crime regression at the 5% level depends on the exact set of variables included in the propensity score model.

Table 5.—OLS and IV Panel Regressions for Male and Female Asylum Wave

	Violent OLS (1)	Violent IV (2)	Violent OLS (3)	Violent IV (4)	Property OLS (5)	Property IV (6)	Property OLS (7)	Property IV (8)
Δ(Female Asylum/Pop)	0.726	1.103			0.135	−0.669		
	(0.473)	(0.563)			(0.788)	(0.950)		
Δ(Male Asylum/Pop)			−0.343	−0.529			1.537***	2.106***
			(0.247)	(0.373)			(0.374)	(0.510)
Δln(Pop)	−0.028***	−0.027***	−0.028***	−0.027***	−0.031***	−0.032***	−0.036***	−0.037***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.012)
Δ(Benefit Rate)	−0.053	−0.053	−0.053	−0.052	0.133***	0.131***	0.127***	0.125***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.036)	(0.035)	(0.036)	(0.036)
Δ(Young Share)	0.030	0.028	0.035	0.034	−0.054	−0.049	−0.052	−0.051
	(0.021)	(0.020)	(0.021)	(0.021)	(0.030)	(0.029)	(0.034)	(0.034)
Year dummies	x	x	x	x	x	x	x	x
PFA dummies	x	x	x	x	x	x	x	x
Sample size	2,591	2,591	2,591	2,591	2,591	2,591	2,591	2,591
R^2	0.278	0.277	0.277	0.277	0.275	0.274	0.292	0.290

Regressions are run over the period 2002–2009. The dependent variable is Δ(Number of Crimes Recorded/Adult Population). All regressions are weighted by adult population. The instrumental variables are the number of asylum seekers in dispersal accommodation for the asylum wave (by gender). The F-statistic on the first-stage IV in the asylum regression is 5,476 ($p = 0.000$) for female asylum seekers and 1,345 for male asylum seekers ($p = 0.000$) (see Table A2). Standard errors in parentheses are clustered at the local authority level. Significant at **5% and ***1%.

of migrant impact on different host country outcomes have often made use of a supply-push component instrument.[17] The instrument is based on the persistence of location choices of immigrants in host countries: the initial distribution of migrants (by country of origin) across different areas and the current national inflows are used to obtain an exogenous predicted migrant share, which is then used to instrument the actual one. In our case, the instrument is generated using the distribution of each A8 nationality in each local authority in 2001 (using the full 100% Census sample) and the subsequent national flow of A8 migrants by nationality.

Columns 4 to 6 of table 4 show the IV results for the A8 wave. The effect on violent crime remains close to 0 and insignificant. When we look at property crime, the coefficient becomes substantially more negative and significant. This remains the case even when we control for police force area trends in property crime. So in sharp contrast to the asylum wave, the A8 wave if anything tended to generate falls in property crime. The first-stage regression shows that the instrument is positively correlated with changes in the A8 stock, with an F-statistic of 13 (see online appendix table A2).[18]

Our conclusions from this analysis are straightforward. There appears to be a significant positive effect from the asylum wave on property crime. In contrast, the evidence points to a negative effect from the A8 wave. The effect on violent crime is indistinguishable from 0 for both waves. It is natural to ask about the size of the property crime effects we find for the asylum and A8 wave. To give a sense of the magnitude on crime rates, consider the estimated coefficients from columns 3 and 6 of table 4. These give values of 1.09 and –0.39 on the migrant/population variable in the property crime regressions. Given the definitions of the variables, this implies that raising the percentage share of the local population who are asylum seekers (A8 migrants) by x% increases (reduces) the property crime rate by 1.09x% (0.39x%). The size of the asylum population in the average local authority was of course very low over our sample period. Across all England and Wales, it averaged 0.1% of the local adult population, so the average property crime rate might be 0.11% higher as a result—only around 4% of the average property crime rate of around 2.7%. Of course, some authorities had appreciably more asylum seekers located in the area, though shares larger than 1% of the local population were extremely rare. For the A8 migrants, the average share was 0.6%, so the average property crime rate might be 0.23% lower as a result—around 8% of the average property crime rate.

IV. Arrests, Incarceration, and Victimization

In this section we provide a range of supporting evidence to the conclusion reached in the previous section regarding the crime effects of the two immigrant waves. We begin with some specially collected data on arrests by nationality that shed some light on the likelihood that A8 immigrants interact with the police. We then turn to some national evidence on incarceration that is consistent with the conclusion that any rise in crime occurred as a result of the asylum wave rather than the A8 wave. Finally, we present evidence on immigrant victimization to ensure that any crime effects are not a result of increased crime against immigrants. There appears to be no evidence for such a conclusion.

[17] See, among others, Card (2001), Ottaviano and Peri (2006), Bianchi et al. (2012), Dustmann, Frattini, and Preston (2013), Cortes (2008), and González and Ortega (2011).

[18] If we simply split the local authorities into two equal groups based on the proportion of A8 migrants in the local population and examine the change in property crime rates over the period, we find that rates declined by 1.0 point (from 2.8 to1.8) in the low-A8 group and 1.4 points (from 3.6 to 2.2) in the high-A8 group. The A8 shares of the population in the two groups in 2008 were 0.7% and 2.5%, respectively. On most other metrics, the two groups had similar prewave characteristics so it would be hard to believe that A8 migrants generated a rise in property crime rates.

TABLE 6.—ARREST RATES BY NATIONALITY, A8 WAVE

	(1)	(2)	(3)	(4)
A8 share in population	1.250**	1.040**	1.148**	1.026**
	(0.099)	(0.243)	(0.162)	(0.266)
All crimes	x		x	
Property crimes		x		x
Clean sample			x	x
Sample size	90	57	71	50
R^2	0.684	0.460	0.709	0.476

Regressions are run over the period 2004–2008. The dependent variable is the share in total arrests of A8 citizens. Standard errors in parentheses, clustered at the PFA level. Significant at **5% and ***1%.

A. Arrests

Data on arrests by nationality are not collected or published in the United Kingdom. However, we can provide a little more evidence on the A8 wave by comparing arrest rates by nationality that were specially collected by us from every police force in the country (see the online appendix for more details). These data are available only from 2004 at the level of police force area and for a subsample of police forces. In table 6, we pool the data for all years and police forces and estimate the relationship between the share of A8 arrests in total arrests and the share of A8 citizens in the local population. A coefficient of 1 would be consistent with no differential effect of A8 citizens on local arrest rates. However, this is not a strong test, since any estimate is consistent with some pattern of differential arrest propensities across natives and A8 citizens irrespective of criminal activity. The results are, however, consistent with this neutrality. In column 1 we estimate a slightly larger coefficient than 1, but in column 3, we restrict the sample to data points that are consistently reported, and the coefficient is insignificantly different from 1.[19] Similar results are obtained when we focus on the smaller sample that isolates arrests for property crimes.

B. Incarceration

An alternative approach is to focus on incarceration rather than reported crime. The main advantage of this approach is that we have data on the nationality of prisoners so that we can more directly link the immigration flows from particular countries to incarceration rates. Unfortunately, such data are available only at the national level, so we will be identifying the link between the asylum and A8 waves and imprisonment by comparing the evolution of incarceration rates for the set of countries providing the flows to the incarceration rates of natives and of citizens of countries not involved in the two waves we focus on. In consequence, this analysis is susceptible to the criticism that we identify the asylum wave effect using nationality even though the majority of such nationals were unlikely to be asylum seekers. To mitigate this, we focus on only the five largest asylum seeker nationalities but recognize that this analysis can at best only be considered supportive of the previous results. The A8 results are less prone to this criticism as the wave that arrived after the 2004 enlargement dominates the stock of A8 citizens in the United Kingdom.

We can graphically illustrate the results for our two immigrant waves of interest. We generate an asylum and an A8 incarceration rate by weighting each nationality's incarceration rate each year by the share of that nationality in the flow associated with the two immigrant waves. These flow shares are average estimates for the period 1997 to 2002 for the asylum wave[20] and 2004 to 2007 for the A8 wave. We then examine the trend in these incarceration rates before and after the waves occur relative to both the native incarceration rate and the incarceration rate of all immigrants from countries not included in the asylum or A8 wave.

Because we have data from 1993 to 2008, we are able in both cases to examine prewave trends to ensure that our results are not driven by differential trends that existed before the large flows occurred. Figures 4A and 4B show the trends for the two immigrant waves. It is clear that the incarceration rates for the asylum wave rose rapidly as the size of the group expanded in the late 1990s and early 2000s in absolute terms and relative to the incarceration rates of both foreigners from nonasylum countries and British citizens. The rise began to tail off toward the end of the sample period. In contrast, the trend in incarceration rates for the A8 nationals almost exactly mirrored the trend for British citizens from 2004, suggesting no obvious impact of this wave on prison populations.

More formally, we can estimate the following model of incarceration:

$$IncarcerationRate_{it} = I_i + T_t + \theta WaveDummy_{it} + \mu_{it}. \tag{2}$$

In equation (2), the *WaveDummy* variable takes the value 1 for the immigrant wave observations for all years from the start of the relevant immigration wave (1997 for the asylum wave and 2004 for the A8 wave) and is 0 for the earlier years and for the comparison group. We also control for the group fixed effect and time fixed effects. A positive coefficient θ indicates a relative rise in incarceration rates following the immigrant wave. Results are given in table 7. Consistent with the evidence from the charts, we find a significant jump in the incarceration rates of the asylum wave nationalities after 1997, with rates 0.15 percentage

[19] To identify the clean sample, we make use of information provided from the relevant police force. For example, a number of forces report that some of the data, particularly in the first two years of our sample, were collected on only an ad hoc basis and that many arrest records have no nationality recorded. Such data points are excluded from the clean sample.

[20] For the asylum wave, we focus on only the largest five countries in terms of flow. For the period 1997–2002, these are, in order of contribution, Serbia and Montenegro, Somalia, Iraq, Afghanistan, and Sri Lanka. They represent 40% of applications over the period.

FIGURE 4.—INCARCERATION RATES, 1993–2008

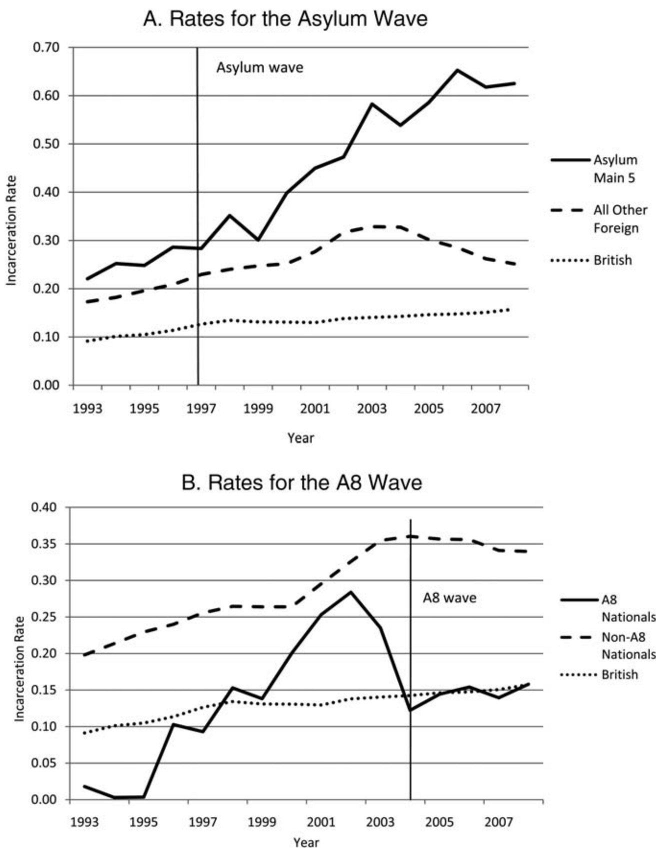


TABLE 7.—DIFFERENCE-IN-DIFFERENCE ESTIMATES OF INCARCERATION RATES

	Asylum Wave		A8 Wave	
	Comparison Group		Comparison Group	
	Nonasylum Foreign Nationals	British	Non-A8 Foreign Nationals	British
Wave dummy	0.150**	0.200***	−0.078***	−0.018
	(0.059)	(0.063)	(0.029)	(0.040)
Group dummy	0.062	0.149**	−0.129***	0.013
	(0.051)	(0.055)	(0.016)	(0.022)
R^2	0.744	0.829	0.865	0.227

Regressions are run over the period 1993–2008. Wave dummy equals 1 for the asylum/A8 group after the relevant wave begins and 0 before. Group dummy equals 1 for the asylum/A8 group and 0 for the comparison group. All regressions include the full set of time dummies. Standard errors in parentheses. Significant at **5% and ***1%.

points higher than the nonasylum immigrant control group. This is in addition to an average 0.06 percentage point higher incarceration rate. The estimated effects for the A8 group are insignificantly different from 0 when compared to the British control group and are actually negative compared to the non-A8 immigrant control group. We conclude that the asylum wave led to a rise in incarceration rates for nationals of countries who were disproportionately represented in the asylum wave relative to both natives and other immigrants, whereas the A8 wave had no discernible effect on the prison population. To the extent that there are more people in prison from A8 countries, this is simply a result of the massive rise in the size of those populations in the United Kingdom rather than evidence of increased incarceration rates.[21]

C. *Victimization*

As discussed in section III, we are also able to consider whether there is any evidence of higher crime victimization for the two immigrant waves. We use data from both the British Crime Surveys from 2004 to 2008 and the New Deal for Communities Surveys from 2002 and 2004. The former is used for official victimization statistics and is a large representative sample of the U.K. population. The identification of the immigrant waves is by country of birth and year of arrival in the United Kingdom. This is not problematic for the A8 wave, but the measurement of the asylum wave has the problems of misidentification discussed in section II. To address this issue we use the second data set, which can explicitly identify asylum applicants from other non-British immigrants. Fortunately, the data contain similar questions on victimization as those used in the British Crime Survey. Neither data set is sufficiently large to enable analysis to be conducted at the local authority level.

Table 8 shows the percent of individuals reporting that they have been a victim of crime in the twelve months up to the survey date. Victimization rates are reported for U.K.-born natives, the asylum wave, the five largest asylum countries, the A8 wave, and other non-U.K.-born individuals. Reassuringly, the data from both sources provide a similar picture, with both asylum and A8 waves having lower crime victimization rates than natives.

Table 9 shows statistical models of the probability of being victimized that condition on additional survey variables. For the British Crime Survey, the key finding of table 8 remains intact: crime victimization is significantly lower for the two migrant waves we consider. For the New Deal Survey, we find that lower victimization rates for asylum seekers in the raw data are eliminated when controls are added, such that rates appear to be essentially the same as those for natives.[22]

In summary, the results seem to suggest that differential changes in crime rates during the immigrant waves cannot be ascribed to crimes against immigrants. There is little empirical work on the factors affecting rates of crime and victimization against immigrants. For example, Krueger and Pischke (1997) find little evidence that crimes against immigrants in Germany can be explained by either economic variables or the relative number of immigrants within a locality. They do, however, find substantial differ-

[21] The number of prisoners from A8 countries rose from 145 in 2003 to 906 in 2008. This still represents only about 1% of the prison population. It should also be noted that the A8 prison population in years prior to the A8 wave was very small, which explains the volatility in incarceration rates for this group in the early years of the sample, as shown in figure 4B.

[22] It should be noted that we have fewer control variables available in the second data set.

Table 8.—Victimization Descriptive Statistics

	A. British Crime Survey, 2004–2008					
	United Kingdom	Asylum Wave	Asylum Wave, Largest Five Countries	A8 Wave	Other Non-United Kingdom	Sample Size
Crime Victim in last year (%)	31.6	22.5	22.4	25.5	29.8	141,164

	B. New Deal Evaluation, 2002–2004			
	United Kingdom	Asylum	Nonasylum	Sample Size
Crime Victim in Last Year (%)	35.4	31.0	29.6	23,725

Panel A from pooled British Crime Survey data (2004–2005 to 2007–2008 waves). The Asylum Wave percentages are weighted to reflect asylum shares as with earlier tables. The largest five asylum wave countries are Afghanistan, Iraq, Serbia and Montenegro, Somalia, and Sri Lanka. Panel B from pooled National Evaluation of the New Deal for Communities data (2002 and 2004 waves).

Table 9.—Victimization Equations, Pr(Crime Victim in Last Year)

	British Crime Survey, 2004–2008			New Deal Evaluation, 2002–2004		
Asylum				−0.142***	0.047	0.032
				(0.044)	(0.054)	(0.054)
Asylum wave largest five	−0.054**	−0.073***	−0.076***			
	(0.024)	(0.024)	(0.024)			
A8	−0.077***	−0.152***	−0.155***			
	(0.019)	(0.019)	(0.019)			
Other	−0.005	−0.020***	−0.021***	−0.178***	−0.005	−0.016
	(0.006)	(0.006)	(0.006)	(0.019)	(0.031)	(0.031)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Police force area	No	No	Yes	No	No	Yes
Sample size	141,164	141,164	141,164	23,725	23,725	23,725

Marginal effects reported. Standard errors in parentheses. Control variables for the BCS regressions are age, gender, student, education (nine categories), urban/rural (eight categories), housing tenure (eight categories), number of children (ten categories), household income (fifteen categories), marital status (five categories), years at accommodation (five categories), ethnicity (five categories), and nationality within the United Kingdom (five categories). Years run from 2004 to 2008, and there are 42 police force areas. Control variables for the New Deal regressions are age, gender, education (six categories), region (nine categories), household income (nine categories), housing tenure (three categories), years at accommodation (six categories), household size (five categories), household composition (four categories), ethnicity (three categories), employment status (three categories), and English language ability. Significant at **5% and ***1%.

ences between West and East Germany in the rate of crimes against foreigners.

V. Interpretation and Discussion

The reported results very much highlight the importance for crime participation of the different labor market prospects of the two migration waves we study. A natural interpretation of these results is in terms of the orthodox economic model of crime participation introduced by Becker (1968) and further developed by Ehrlich (1973) and others (see Freeman, 1999, for a review). In this model, individuals rationally choose between crime and legal labor market work depending on the potential returns each offers. The "returns" from crime are calculated relative to the probability of getting caught and the expected sanction if caught and compared to labor market earnings from employment. If the former outweighs the latter, an individual will engage in crime.

Formally, individuals choose between criminal and legal activity by comparing the expected utility from each. If $U(W)$ is the utility from working at a legal wage W, $U(W_C)$ the utility from a successful (that is, not caught) crime where p is the probability of being caught, and S the monetary-equivalent sanction if caught,[23] then an individual decides to engage in criminal activity if

$$(1-p)U(W_c) - pU(S) > U(W). \tag{3}$$

The usefulness of this framework for interpreting our results comes from the key prediction that relative labor market opportunities matter (there is good evidence from elsewhere supporting this; see Gould, Weinberg, & Mustard, 2002, and Machin & Meghir, 2004). People without a job (where $W = 0$) are more likely to participate in crime. So are those where the formal wage W is low relative to W_C.

It is evident from the discussion in section II (about tables 1A and 1B) that these crime-predicting features (low

[23] One might wonder about the severity of sanctions on migrants. In general, migrants receive the same penalties as natives. However after a sentence has been served, migrants are liable to deportation from the United Kingdom. Section 32 of the 2007 U.K. Borders Act requires the secretary of state to issue a deportation order against any foreign national convicted of a criminal offense and imprisoned for at least twelve months. However, section 33 makes clear that such an order cannot be given if doing so would violate U.K. obligations under the UN Refugee Convention or the European Convention on Human Rights. In other words, if an asylum seeker was eventually determined to be a legitimate claimant, he or she would also be protected from deportation if he or she were sent to prison.

employment rates, high unemployment rates, and low wages) are more marked for the asylum wave. Thus, it follows that to the extent that the model is relevant, this is the group most likely to be connected to higher crime. The difference between the legal labor market opportunities of asylum seekers and both natives and the A8 wave are actually more extreme than suggested by table 1. Asylum seekers are forbidden from working during the first six (extended to twelve in 2002) months of their claim being initiated. After this point, they can apply for permission to work until their case is decided. Evidence from the Refugee Council (2005) suggests that only about 10% of asylum seekers had been waiting less than six months for their asylum decision, while a third had been waiting over two years. Hence, the stock of asylum seekers is made up of a combination of those with no permission to work and claiming assistance from the state and those who are entitled to work because of the delays in reaching a final decision on their asylum claim. In addition, the level of benefits paid to asylum seekers is very low relative to other welfare benefits. For example, the weekly subsistence payment made to single adult asylum seekers in 2009 was £35.52 compared to £65.45 for those receiving unemployment benefits.[24]

What about the findings for different sorts of crimes? People usually associate the Becker-Ehrlich model with property crimes, and so the prediction of increased crime for the asylum wave due to less favorable labor market opportunities should be more strongly connected to this kind of crime. Intuitively, violent crime seems less sensible to consider in this way, especially in the context of immigration waves. While a small literature (for example, Grogger, 2000) does extend the Becker-Ehrlich model to violent crime through violence being complementary to drug crimes in the United States, this seems less appropriate to the context we study where economic differences are likely to be central to the crime-work decision. This is indeed what our results show, with there being no violent crime effects and the property crime effects for the asylum wave being associated with low labor force participation rates, high unemployment, and low wage levels.

Using the economic model of crime to understand the links between immigrant inflows and crime also helps us to understand the evidence from the United States and how it connects to our findings.[25] Butcher and Piehl (1998a, 1998b) show that city-specific crime rates do not rise in response to immigrant inflows and that immigrants have lower rates of incarceration than natives in the United States. Since nearly all immigrants in the United States come to work, they are perhaps most similar to the A8 migrants that we consider. Spenkuch (2011) shows that for a panel of U.S. counties, there is an economically meaningful impact of immigration on crime. Crucially, however, and consistent with our results, these effects are present only for immigrants who are likely to have poor labor market opportunities.

VI. Conclusion

There is much popular commentary on the supposed links between immigration and crime but a notable paucity of credible empirical evidence about the relationship. This paper has sought to fill some of this gap with an analysis on the response of crime rates to two very different immigration waves that hit the United Kingdom over the past ten to fifteen years. Our view is that the scale of these waves, their timing, and their very different characteristics make them suitable for the empirical analysis of crime and immigration.

We report results from an array of data sources and empirical methods that we argue are in line with key predictions from the canonical Becker/Ehrlich model of crime participation. For property crime, we find that crime rates are significantly higher in areas in which asylum seekers are located but that they are lower for the A8 wave. This conclusion is robust when we control for the endogeneity of location choice and for local crime trends within the police force area. In contrast, for both waves, we can find no significant relationship between immigrants and violent crime. The same picture emerges when we explore the time series evolution of incarceration rates, which suggests a rise in the rate of incarceration of foreigners from asylum seeker countries as the asylum wave arrived in the United Kingdom, but no such rise for A8 foreigners as that wave arrived. Finally, we show that the results are hard to explain on the basis that the rise in crime may be a result of crime against immigrants. Interestingly we find that victimization rates are in fact lower against the two waves than for natives in general.

Though we find consistently positive effects from the asylum wave on property crime, the average size of the effect is not substantial. However, some areas received substantial inflows of asylum seekers and were therefore likely to have experienced more significant property crime rises. From a policy perspective, this suggests that more attention should perhaps have been focused on the potential localized crime risks involved in the concentrated dispersal policy adopted by the authorities but that national crime rates were unlikely to have been strongly influenced by the arrival of the asylum wave.

Our results also suggest that focusing on improving the limited labor market opportunities of asylum seekers has

[24] Clearly, differences in policy treatment once in the destination country may not be the whole story. Criminal behavior between the two waves may also differ because the selection process that led these immigrants to the United Kingdom is not necessarily similar. Due to the endogeneity of the migration decision (Borjas, 1987), the two groups may substantially differ in their unobservables (the "quality" of migrants) and therefore in their potential returns in both legal and criminal labor markets. We do not speculate on the nature of these selection processes. When interpreting the findings of this paper, one needs to bear in mind that a differential criminal behavior between members of the two waves may have been observed even if they had been subject to an identical policy regime.

[25] See Bell and Machin (2012) for a comprehensive review of the empirical evidence on the link between crime and immigration.

scope to generate crime reductions, in addition to generating potential cost savings in terms of benefits. Since we are (rightly) obliged to consider all applications for asylum, it makes sense to allow applicants to seek work while their applications are being considered, particularly given the long duration that final decisions on such applications can take. In addition, job training and language courses are likely to be particularly beneficial for such migrants. Such an approach could potentially significantly tilt the labor market opportunities of migrants relative to illegal activities. The disadvantage of such an approach is the risk that it signals to potential migrants that asylum application could be used as a method of seeking work in the United Kingdom rather than as a route for those fleeing persecution.

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