NORFACE MIGRATION Discussion Paper No. 2012-06

Spending more is spending less: on the desirability of enforcing migration

Alessandra Casarico, Giovanni Facchini and Tommaso Frattini

www.norface-migration.org

Spending more is spending less:
on the desirability of enforcing migration policies*

Alessandra Casarico† Giovanni Facchini‡ Tommaso Frattini§

December 29, 2011

Abstract

We study the migration policy set by a welfare maximizing government in a model where immigrant workers differ in their skills and are imperfectly matched with heterogenous occupations. The policy fixes a minimum skill level for legal migrants, and foreign workers that fall below it can only enter the country illegally. We start by analyzing under which conditions an amnesty is desirable compared to tolerating undocumented immigrants. Next, we study when it is preferable to have ex-ante lax enforcement, rather than to carry out costly enforcement. We show that three channels play an important role in this decision: an amnesty is more likely the larger are the output gains brought about by the legalization, the less redistributive is the welfare state and the higher is the expected cost of criminal activities carried out by illegal immigrants. Importantly, we also find that, when an amnesty is desirable, the destination country would reach an even higher welfare level investing in enforcement ex-ante. Empirical evidence based on a novel panel dataset of legalization programs carried out by a group of OECD countries between 1980-2007 broadly supports the role played by the channels identified in our theoretical model.

JEL classification: F22, J61.

Keywords: Illegal immigration, Immigration Policy, Amnesties.

*This paper is produced as part of the CEPR project "Temporary Migration, Integration and the role of Policies" (TEMPO) funded by the NORFACE Research Programme: "Migration in Europe - Social, Economic, Cultural and Policy Dynamics." We wish to thank for their comments and suggestions Peter Egger, Tim Hatton, Assaf Razin and seminar participants at the NORFACE Migration conference in London and at the CEPR Conference on the Economics and Politics of migration in Turin, Italy.

†Università Bocconi, CES-Ifo, Econpubblica and LdA; email: alessandra.casarico@unibocconi.it

‡Erasmus University Rotterdam, Universita' degli Studi di Milano, CEPR, CES-Ifo, CReAM, IZA and LdA; facchini@ese.eur.nl.

§Universita' degli Studi di Milano, CReAM, IZA, and LdA; tommaso.frattini@unimi.it.

1 Introduction

Growing migration pressures in the presence of restrictive immigration policies have lead to the emergence of illegal immigration as a widespread phenomenon, and most rich destination countries harbor today large populations of undocumented foreigners. Yet, there is substantial heterogeneity in terms of both the stocks (and flows) of illegal migrants, and the policies which are adopted to handle illegal immigrants once they are in the country. Table 1, based on Fasani (2009) and our own calculations, provides information on a selected group of destination countries.

As it can be seen, in 2008 the US hosted 12 millions illegals, representing one third of the total foreign born population. In the other countries included in the table, the absolute levels are much smaller, but illegal immigrants still represent an important fraction of total immigrants. For instance, in 2007 almost one of two foreigners in Greece was without proper documents, and in Italy the same situation held in 2008 for more than one out five immigrants.

The legal status of migrants clearly reflects the policy stance of the destination country, both in terms of the ex–ante controls introduced to discipline the flows, and the ex–post measures taken to grant legal status to existing illegal immigrants. Amnesties have been the focus of much attention, and much controversy. From Table 1 we can see that some countries have never resorted to general amnesties (e.g. Germany and the United Kingdom), whereas some others have made it a very frequently used instrument. For instance, this has been the case of Spain, which has introduced six times a broad legalization program between 1980 and 2008. This of course has a direct impact on the estimated stocks of illegals, which is greatly reduced right after a legalization. For instance, the 1986 amnesty introduced in the U.S. with the IRCA lead to approximately 3.5 million legalizations (Facchini and Testa 2010), and Dolado (2007) has convincingly argued that in the case of Spain during the nineties, about 98% of the legal foreign residents had been illegally living in the country at some point.

The purpose of this paper is to develop and empirically assess a general model of legal and illegal immigration, which can help us understanding the basic tradeoffs faced by a government between a costly enforcement of the official target, and a lax enforcement ex–ante, combined with an ex–post legalization program. To that end, we consider a two–period setting, in which heterogeneous domestic firms and foreign workers are randomly matched. The quality of the match is higher for legal than for illegal immigrants, and illegal immigrants might end up being involved in criminal activities. A redistributive welfare state is in place,

which for simplicity covers only agents in the formal sector. In the first period, the destination country government sets its official migration policy which involves the determination of a minimum skill requirement. Immigration then takes place, and foreign workers enter the destination country's labor market. In the second period, immigration no longer occurs.

We analyze the setting of the policy under three different scenarios. We start by considering the case in which migration policy enforcement is costless and the government can implement its minimum skill requirement by simply announcing it. This will serve as a useful benchmark for our subsequent discussion. In the second environment, implementing the desired policy is costly, but the enforcement activity is underfunded. The result is that illegal immigration can emerge in equilibrium. In this case, at the beginning of the second period, the government decides whether to introduce an amnesty program to legalize undocumented migrants or not. In the third scenario, the government uses instead a costly enforcement technology which allows it to obtain the desired minimum skill level in the immigrant population, and illegal immigration does not occur.

We show that an amnesty is more likely to be desirable the bigger is the gain to the natives' aggregate income brought about by an improvement in the labor market matching technology following a legalization, and the higher is the expected cost of criminal activities. On the contrary, a redistributive welfare state makes an amnesty less desirable, as it entitles low–skilled foreign workers to welfare state benefits. Importantly, we find that, when an amnesty is preferable to tolerating illegal migrants, the destination country would enjoy a higher level of welfare investing ex–ante in migration policy enforcement. Thus, the labor market matching technology, the extent of redistribution carried out by the welfare state and the degree of involvement in criminal activities by illegal immigrants can inform a government on the desirability of investing resources to control migration flows. On the other hand, when an amnesty is not desirable, the destination country might be better off by not devoting any resource to policy enforcement and by letting some foreign workers enter and stay illegally.

To assess the relevance of our theoretical model, we construct a novel panel dataset covering a large group of OECD countries over the period 1980-2007, and study the determinants of the introduction of immigration amnesties. We match the time of the introduction of a general legalization program with a wealth of characteristics of the country, that capture the working of the channels identified in our model. We proxy for the role of the labor market matching technology using a micro–based measure of the dispersion of educational attainment by occupation within each country. The extent of redistribution carried out by the welfare state is captured by social transfers, whereas the involvement of illegal immigrants

in criminal activities is proxied by the incidence of crime in a given country. Furthermore, we include a set of additional drivers that might influence the introduction of a legalization program. In particular, we control for the business cycle dynamics and the demographic structure in the immigrant destination country, for the pressure exercised by asylum seekers and for the ideological orientation of the government. We find broad support for the role played by the labor market matching and the welfare state channels in shaping the probability of an amnesty. This result is robust to alternative definitions of our key control variables.

This paper contributes to the small but growing literature on immigration amnesties. Chau (2001) shows that granting an amnesty to illegal workers can be part of an optimal migration policy package – together with internal and border controls — when there is a time inconsistency problem because the government cannot commit to implement the ex-ante optimal frequency of internal controls. Importantly, in her model all workers share the same skill level and immigrants are ex–ante all undocumented. They can become legal only as a result of an amnesty. In our model, besides considering heterogeneous workers and firms, we explicitly solve instead for the optimal migration policy of the destination country's government. This policy involves setting a minimum skill requirement for legal immigrants and as a result, it endogenizes the presence of illegal immigrants as those individuals whose skill level falls below the critical threshold chosen by the government.[1]

Karlson and Katz (2003) consider instead the role of amnesties as a tool for governments to induce immigrants to self–select based on ability. Similarly to our model, they also consider migrants that differ in their skill level, and emphasize that an amnesty will offer better labor market opportunities to more skilled workers. As a result, the latter might be enticed to migrate even as illegals, in the hope that an ex–post legalization will improve their income opportunities. Differently from us, in Karlson and Katz's (2003) model and in their companion paper (Karlson and Katz 2010) legal immigration is not explicitly modeled together with illegal immigration.

Epstein and Weiss (2011) also study the desirability of legalization programs. In their setting, immigrants can only enter the country illegally, and can become legal as a result of an amnesty. Immigration is always costly from the destination country's point of view, both when the migrants are illegal, as well as when they are ex–post legalized. Such cost depends only on the total number of immigrants, and not on their skill level. Moreover, the legalization program does not affect the labor market opportunities of the legalized

[1] Alternatively, the illegal status could be the result of an official quota which has been exceeded, as in the case of Facchini and Testa (2010).

migrant in the sense that he continues to earn the same wage before and after the amnesty. Empirical evidence has instead pointed out that labor market outcomes of legalized migrants do improve following an amnesty (Kossoudji and Cobb–Clark 2002). More generally, the skill level of the illegal migrant is likely to be a key determinant of the welfare consequences of a legalization program, and modeling this is at the heart of our analysis.

The remainder of the paper is organized as follows. Section 2 introduces the basic setup, whereas section 3 introduces the three policy setting scenarios. Section 4 characterizes the optimal policy. Section 5 describes the data we have used and section 37 develops our empirical analysis. Section 7 concludes the paper.

2 The model

To analyze the optimal choice of migration policy, we develop a two–period model. In the first period the destination country government sets its official migration policy which involves the determination of a minimum skill requirement. Immigration then takes place, and foreign workers enter the destination country's labor market. In the second period, immigration no longer occurs.

We analyze the setting of the policy under three different scenarios. In the benchmark setup, enforcement[2] is costless and the government can implement its minimum skill requirement by simply announcing it. In the second environment, implementing the desired policy is costly, but the enforcement activity is underfunded. The result is that illegal immigration can emerge in equilibrium. In this case, at the beginning of the second period, the government will decide whether to introduce an amnesty program to legalize undocumented migrants or not. In the third scenario, the government uses instead a costly enforcement technology which allows it to obtain the desired minimum skill level in the immigrant population and no illegal immigration occurs.

For simplicity, we assume that agents do not discount the future. In what follows we start by characterizing the destination country's economy, and introduce then the immigrants' decision to leave.

[2]We do not explicitly distinguish between domestic and border enforcement, even if both tools might play a role. In the U.S. for example, border enforcement is by far the most commonly used instrument. In fact, as Hanson (2006) has argued, between 1992–2004 "...93 percent of deportable aliens were located by the Border Patrol, rather than by ICE or INS agents in the U.S. interior."

2.1 The destination country

In each of the two periods, there is a set of $\mathscr{I}$ potentially active firms in the host country, each one of them indexed by i, with i distributed according to the density function $n(i)$ on the interval $[0, 1]$. Firms can be ranked according to their skill intensity and we will assume that a higher i indicates a higher skill requirement, with 1 being the most skill intensive firm. The firms active in the host country are owned by native individuals, and the mass of the domestic population is given by N, where $\mathscr{I} \geq N$.

Potential immigrants differ in their ability, and are indexed by j, with j distributed according to the density function $m(j)$ on the interval $[0, 1]$, with 1 being the highest skill level. The number of immigrants in the destination country is given by M, and it will be determined endogenously. The labor market in the host country is imperfect, in the sense that individual abilities and a vacancy's skill requirement are not necessarily perfectly matched.[3] If a migrant is employed in the host country, a match of value $v(i, j)$ is created, where

$$v(i,j) = \begin{cases} [1-(j-i)]v(j) & \text{if } j \geq i \\ 0 & \text{if } j < i \end{cases}$$

In other words, the value of the match is maximized if a vacancy of type j is occupied by an individual with skill type j. At the same time, the value of the match is zero, if the migrant's skill level is lower than the one required by the vacancy. Finally, if the individual ends up in a job for which he is over–qualified, then the value of the match is still positive, but smaller than the one which could be achieved if $i = j$. Finally, since individual ability increases with j, it is reasonable to assume that $v(j)$ increases with j. The probability that individual j is matched to vacancy i is described by the joint density function $f(i, j)$.

Let α be the share of the value of the match which is appropriated by each firm's owner, whereas $(1 - \alpha)$ is the share of the value of the match which goes to the immigrant worker. With $\mathscr{I}$ potentially active firms the average income of the firm's owners – that is the natives in the destination country – in each period is given by

$$Y^N = \alpha \frac{\int_{j_{min}}^1 \int_0^1 v(i,j) f(i,j) di dj}{N} \tag{1}$$

[3] See Petrongolo and Pissarides (2001).

whereas the average income of the immigrant is given by

$$Y^M = (1-\alpha)\frac{\int_{j_{min}}^{1}\int_{0}^{1} v(i,j)f(i,j)didj}{M} \tag{2}$$

where j_{min} represents the minimum skill requirement which will be endogenously determined in the model. Notice that j_{min} will differ according to the scenarios we will be considering.

In the destination country there is a redistributive welfare state, characterized by a proportional income tax τ and a lump–sum transfer b. All natives and legal immigrants contribute to the welfare system and are entitled to receive its benefits. To capture the existence of a fiscal leakage from the natives to the immigrants,[4] we assume that the average income of the natives is higher than the average income of the immigrants. In other words,

$$\frac{\alpha}{1-\alpha} > \frac{N}{M} \tag{3}$$

for any possible M. Notice that this assumption implies that *on average* natives will be net contributors to the welfare state, whereas immigrants will be net receivers. At the same time, it might well be that some natives end up on the receiving end of the welfare state, whereas some migrants are net contributors to it.

2.2 The source country

The source country is populated by $\mathscr{M}$ individuals, each one of them characterized by a skill level j. Let $\overline{v}$ be the reservation income the native earns in each period in the source country, which for simplicity is assumed to be equal across citizens. The decision to migrate is based on the comparison between the expected income in the destination country and the reservation income in the source. Note that the former depends on the migration policy enacted by the destination country's government. For this reason, we specify the details of this decision after introducing the various policy regimes.

[4]See for instance Razin, Sadka, and Swagel (2002) and Facchini, Razin, and Willmann (2004).

3 The setting of migration policy

3.1 Costless enforcement

As a benchmark, we start from the case in which the destination country government can carry out its optimal policy at no cost. In other words, in this scenario, the government can implement the desired migration quota, without facing any enforcement cost. The immigrants entering the country in this regime are legal and enjoy/contribute to the welfare state as all natives do.

Consider now a migrant's decision to relocate. An individual with skill level j, will move abroad if and only if

$$2[(1-\alpha)(1-\tau)\int_0^1 v(i,j)f(i,j)di + b_{ce}] - \kappa \geq 2\overline{v} \tag{4}$$

The term on the left hand side of the inequality captures the expected payoff of a potential migrant over the two periods if he decides to relocate abroad, where $\kappa > 0$ is an exogenously given migration cost. The first term in square brackets captures the net expected income appropriated by the migrant and b_{ce} is the lump–sum transfer he will receive from the destination country's welfare state. Remember that if a migrant j is matched with a firm requiring a higher skill intensity, the value of the match is set equal to zero. The above equation can be rewritten as follows:

$$v(j) \geq \frac{\overline{v} + \kappa/2 - b_{ce}}{(1-\tau)(1-\alpha)\left\{\int_0^1 [1-(j-i)]f(i,j)di\right\}} \tag{5}$$

Notice that the left hand side of equation 5 is increasing with j, whereas the right hand side is decreasing. The latter is true because as an individual becomes more skilled, the set of vacancies available to him strictly increases. Let $\overline{j}_{ce}$ be the individual which is indifferent between migrating and staying put. Then, all individuals for which $j \geq \overline{j}_{ce}$ will prefer to migrate, whereas all those individuals for which $j < \overline{j}_{ce}$ will stay behind.

As for the decision of the government, the policy will take the form of a minimum skill requirement which will be imposed upon the immigrant. The skill requirement will be set by maximizing the natives' aggregate welfare, which in our case is just aggregate income.[5] To simplify notation, we define $V(j,1) = \int_j^1 \int_0^1 v(i,j)f(i,j)didj$ which represents the total

[5]In this model we abstract from political economy considerations, that might affect the government's objective function. For an example of a political economy model of illegal immigration, see Facchini and Testa (2010).

expected value created by legal migrants whose minimum skill level is given by j, and let $M(j,1) = \int_j^1 m(j)dj$ be the total number of legal immigrants entering the country. Thus, the objective function of the government is given by

$$W = 2[\alpha(1-\tau)V(j,1) + b_{ce}N] \tag{6}$$

where j is the minimum skill requirement to be determined through the welfare maximization process. The government's budget is balanced in each period and is given by

$$\tau V(j,1) = b_{ce}\left[N + M(j,1)\right] \tag{7}$$

Maximizing 6 subject to 7, we obtain the following first order condition, which implicitly defines the skill requirement $\hat{j}$ that maximizes the destination country's welfare:

$$B_{ce}[.,\hat{j}(.)] = 2\frac{\partial V(\hat{j},1)}{\partial j}\left[\alpha(1-\tau) + \frac{N\tau}{N + M(\hat{j},1)}\right] - \frac{2\tau V(\hat{j},1)N}{[N + M(\hat{j},1)]^2}\frac{\partial M(\hat{j},1)}{\partial j} = 0 \tag{8}$$

where

$$\frac{\partial M(\hat{j},1)}{\partial j} = -m(\hat{j}) \tag{9}$$

indicates the change in the number of immigrants as the minimum skill required increases and

$$\frac{\partial V(\hat{j},1)}{\partial j} = -\int_0^1 v(\hat{j})[1 - (\hat{j}-1)]f(i,j)di < 0 \tag{10}$$

captures the change in aggregate income brought about by a marginal increase in the skill level of the last migrant to be admitted in the country. The first term on the right hand side of equation 8 represents the negative impact of an increase in the skill requirement on the aggregate income and therefore on the tax base, whereas the second term represents the positive effect of a more restrictive migration policy on the per capita benefits brought about by a reduction in the number of recipients.

It is interesting to study the effects of a change in the distribution of the surplus between natives and immigrants on the optimal number of immigrants to be admitted in the destination country. This is done in the following:

Lemma 1 *An increase in the share of output appropriated by the natives leads to a decrease in the minimum skill level required to the migrant.*

Proof. Using equation 8, applying the implicit function theorem, we have that

$$\frac{\partial \hat{j}}{\partial \alpha} = -\frac{B_{\alpha}[.,\hat{j}(.)]}{B_{\hat{j}}[.,\hat{j}(.)]} \tag{11}$$

where $B_{\alpha} = \frac{\partial B[.,\hat{j}(.)]}{\partial \alpha} = (1-\tau)\frac{\partial V(\hat{j},1)}{\partial j} < 0$, and $B_{\hat{j}} = \frac{\partial B[.,\hat{j}(.)]}{\partial \hat{j}} < 0$ from the assumption of concavity of the objective function. Thus, $\frac{\partial \hat{j}}{\partial \alpha} < 0$. ■

Similarly, we can also study the effect of an increase in the size of the welfare state on the optimal migration policy. This is done in the following:

Lemma 2 *An increase in τ leads to an increase in the minimum skill level required to the migrant.*

Proof. Using the implicit function theorem, the effect of an increase in τ on the optimal minimum skill threshold can be rewritten as

$$\frac{\partial \hat{j}}{\partial \tau} = -\frac{B_{\tau}[.,\hat{j}(.)]}{B_{\hat{j}}[.,\hat{j}(.)]} \tag{12}$$

where $B_{\tau}[.,\hat{j}(.)] = \frac{\partial V(\hat{j},1)}{\partial j}\left[-\alpha + \frac{N}{N+M(\hat{j},1)}\right] - \frac{V(\hat{j},1)N}{[N+M(\hat{j},1)]^2}\frac{\partial M(\hat{j},1)}{\partial j} > 0$ if $\frac{\alpha}{1-\alpha} > \frac{N}{M(\hat{j},1)}$ as assumed above. Thus, recalling that the objective function is concave, the result follows immediately. ■

Notice that, for the problem to be interesting, the government's policy needs to be binding, that is $\hat{j} > \overline{j}_{ce}$, i.e. the minimum skill requirement by the destination country must be higher than the minimum skill level of the marginal foreign worker, who is interested in moving abroad. We will retain this assumption throughout the remainder of the paper.

3.2 Underfunded government

We turn now to examine an alternative scenario, where implementing a restrictive migration policy is costly, but the government does not have a budget at its disposal to this end. In the first period, the policy maker announces a minimum skill requirement j^*, knowing that in the absence of a sufficient enforcement budget, it might see workers of lower skill levels settling in the country as *illegals*.[6] Such migrants can work in the formal sector. If they do

[6]In fact, in the recent debate on how to curb illegal immigration in the U.S., much emphasis has been placed on increasing funding for migration policy enforcement. This is for instance at the center of the proposal by senator Reid, Durbin, Schumer, Feinstein, Leahy, and Menendez (2010). Besides this channel, the literature has also emphasized the role played by shocks in the immigrant supply as a driver of illegal

so, the probability that individual j is matched to vacancy i is described by the joint density function $g(i,j)$. Alternatively, they can engage in criminal activities. In either case, they will neither contribute nor have access to the welfare state in the destination country.[7] To simplify the analysis, we assume that the selection into the sector of employment is random, i.e. with probability h an illegal immigrant will end up working in the formal sector, whereas with probability $(1-h)$ he will end up working in the criminal sector.

In the second period, if undocumented migrants are present in the country, the government can decide whether to grant an amnesty, or continue to keep them as illegals.[8] Granting an amnesty leads to an improvement in the labor market matching of the previously illegal workers and to their full involvement in the welfare state.

For all those foreign born individuals characterized by a skill level $j < j^*$, the only possible option is to enter the country illegally. However, when deciding whether to migrate or not, the migrant assigns a subjective probability q to the event that in the second period the host country government will not grant an amnesty, and correspondingly $(1-q)$ to the event that it will actually do so. Thus, we can write the condition determining whether an individual $j < j^*$ decides to migrate illegally or not as follows

$$\begin{aligned}(1+q)(1-\alpha)\left[h\int_0^1 v(i,j)g(i,j)di+(1-h)v^0\right]-\kappa+\\ +(1-q)\left[(1-\alpha)(1-\tau)\int_0^1 v(i,j)f(i,j)di+b_l\right] \geq 2\overline{v}\end{aligned} \tag{13}$$

where v^0 denotes the income from engaging in criminal activities. By assumption this does not depend upon the skill profile of the worker and furthermore we maintain that there is no minimum skill required to engage in such activities. We also assume that natives in the destination country can appropriate a share α of the income generated by these activities, whereas the migrants will receive the share $(1-\alpha)$ – i.e. the same sharing rule applies as for the formal sector.

To capture the more limited search opportunities available to an illegal immigrant than to a legal one we focus on the case in which $(1-\alpha)\int_0^1 v(i,j)f(i,j)di \geq (1-\alpha)\int_0^1 v(i,j)g(i,j)di$, for all $j \in [0,1]$ i.e. the expected income of working in the formal sector legally is higher

immigration when the government sets its official policy before the occurrence of the shock. See Facchini and Testa (2010).

[7]Of course this is a simplifying assumption, but it has been argued that legal and illegal migrants differ in their net position towards the welfare state. See for instance Camarota (2004).

[8]We are abstracting from considering the deportation of illegal immigrants. This is of course a relevant policy option, but in the context of our model, since illegal immigration is brought about by the lack of funds to carry out policy enforcement, we assume away the possibility of implementing costly deportations.

than the expected income of working in the formal sector as an illegal.[9] Finally, to make our problem interesting, we will also assume that the total expected income of a legal immigrant is higher than that of an illegal one, i.e.

$$(1-\tau)\int_0^1 v(i,j)f(i,j)di + b_l > h\int_0^1 v(i,j)g(i,j)di + (1-h)v^0$$

Equation 13 can be rewritten as

$$v(j) \geq \frac{2\overline{v} - b(1-q) + c - (1+q)(1-\alpha)(1-h)v^0}{\left\{(1+q)h\int_0^1[1-(j-i)]g(i,j)di + (1-q)(1-\tau)\int_0^1[1-(j-i)]f(i,j)di\right\}(1-\alpha)}$$

which leads to the identification of the threshold skill level $\overline{j}_{ill}$ such that a migrant will find it desirable to migrate as an illegal. Applying the same argument as for equation 5, it follows immediately that any individual with a skill level $j \geq \overline{j}_{ill}$ will also find it desirable to migrate. Recall that all individuals with $j > j^*$ will enter the country legally. Notice also that a more open official migration policy will not affect the incentives of the marginal individual to migrate illegally, as long as $\overline{j}_{ill} < j^*$. This is because the marginal illegal immigrant $\overline{j}_{ill}$ does not have access to occupations characterized by a skill intensity level $j \geq \overline{j}_{ill}$. Let $M(\overline{j}_{ill}, j^*) = \int_{\overline{j}_{ill}}^{j^*} m(j)dj$ be the number of illegal migrants entering the country.

Notice also that, from equation 13, we have that an increase in the probability of legalization in the second period leads to an increase in the number of illegal immigrants entering in the first period $M(\overline{j}_{ill}, j^*)$ by reducing the minimum skill threshold $\overline{j}_{ill}$ to find it optimal to emigrate.[10]

In order to determine the skill requirement chosen by an underfunded government, we need to maximize the following welfare function with respect to j:

$$\begin{aligned} W_{un} &= (1+\eta)\left[\alpha(1-\tau)V(j,1) + b_{un}N + \alpha h\mathscr{V}(\overline{j}_{ill}, j) - (1-h)(x-\alpha v^0)M(\overline{j}_{ill}, j)\right] + \\ &+ (1-\eta)\left[\alpha(1-\tau)V(\overline{j}_{ill}, 1) + b_l N\right] \end{aligned} \tag{14}$$

where $\mathscr{V} = \int_{\overline{j}_{ill}}^{j}\int_0^1 v(i,j)g(i,j)didj$ indicates the total expected value created by illegal migrants with skill levels comprised between $\overline{j}_{ill}$ and j and $\eta > 0$ is the likelihood that the government will not carry out an amnesty in the second period. The first row represents the destination country's expected welfare over the two periods when both legal and illegal

[9] See for instance Rivera Batiz (1999) and Kossoudji and Cobb–Clark (2002) for studies of the effect of legal status on immigrant wages.

[10] This is true as long as the effect of a change in q on the second period benefit has a second order impact on the immigrant's well being.

migration take place and no amnesty is granted with probability η. The first term in square brackets is the net aggregate income appropriated by natives when the official migration policy sets a minimum threshold j. The second term represents the welfare transfer to the natives when the government is underfunded and illegal immigrants do not have access to the welfare state benefits. The demogrant b_{un} is determined by

$$b_{un} = \frac{\tau V(j,1)}{N + M(j,1)} \tag{15}$$

The third term captures the native's share of the expected income generated by illegal immigrants working in the informal sector, whereas the fourth represents the expected net cost to the natives from illegal immigrants engaged in criminal activities, with $x > 0$ indicating the social burden induced by those activities. The second row captures instead the expected welfare in the second period when an amnesty takes place with probability $1 - \eta$. The first term captures the net aggregate income appropriated by natives when undocumented migrants have been legalized and the second term captures the welfare transfers to the natives when an amnesty has been introduced, and b_l is given by:

$$b_l = \frac{\tau V(\bar{j}_{ill},1)}{N + M(\bar{j}_{ill},1)} \tag{16}$$

Notice that if an amnesty takes place all immigrants are fully engaged in the welfare state and thus pay taxes and receive benefits. As a result, $b_{un} > b_l$.

The first order condition corresponding to the maximization of equation 14 is given by

$$\begin{aligned} B_{un}[.,j^*(.)] &= (1+\eta)\{\frac{\partial V(j^*,1)}{\partial j}\left[\alpha(1-\tau) + \frac{\tau N}{N+M(j^*,1)}\right] - \frac{\tau N V(j^*,1)}{[N+M(j^*,1)]^2}\frac{\partial M(j^*,1)}{\partial j} \\ &+ \alpha h \frac{\partial \mathscr{V}(\bar{j}_{ill},j^*)}{\partial j} - (1-h)(x-\alpha v^0)\frac{\partial M(\bar{j}_{ill},j^*)}{\partial j}\} = 0 \end{aligned} \tag{17}$$

Equation 17 implicitly defines j^*.

3.3 Costly enforcement

We now turn to an alternative scenario, in which the government uses the revenues raised not only to finance the welfare benefit, but also to carry out an enforcement policy. The cost of implementing this policy is given by $c(j)$, which is an increasing function of the minimum skill level required to the migrant. Throughout this section, as we have already done in our previous analysis, we assume that the minimum skill requirement introduced by the costly

migration policy is binding, i.e. there are more workers willing to come than those officially admitted. For this reason we do not explicitly model once again the migration choice of the natives in the sending country. The government's objective function thus becomes

$$W_c = 2\alpha(1-\tau)V(j,1) + (b_c + b)N \tag{18}$$

where the first term on the right hand side has the same interpretation as in equation 14, and b_c and b are respectively the demogrant paid in period 1, when a costly enforcement is carried out, and in period 2, when no further migration flows take place and therefore no enforcement is needed. Formally, they are defined by the following budget constraints:

$$b_c = \frac{\tau V(j,1) - c(j)}{N + M(j,1)} \tag{19}$$

$$b = \frac{\tau V(j,1)}{N + M(j,1)} \tag{20}$$

Maximizing 18 subject to equations 19 and 20, we obtain the following first order condition which implicitly defines the skill requirement $\tilde{j}$ that maximizes the destination country's welfare:

$$\begin{aligned} B_c[.,\tilde{j}(.)] &= 2\frac{\partial V(\tilde{j},1)}{\partial j}\left[\alpha(1-\tau) + \frac{\tau N}{N + M(\tilde{j},1)}\right] - 2\frac{\tau N V(\tilde{j},1)}{[N + M(\tilde{j},1)]^2}\frac{\partial M(\tilde{j},1)}{\partial j} \\ &- \frac{N\frac{\partial c(\tilde{j})}{\partial j}}{N + M(\tilde{j},1)} + \frac{N c(\tilde{j})}{[N + M(\tilde{j},1)]^2}\frac{\partial M(\tilde{j},1)}{\partial j} = 0 \end{aligned} \tag{21}$$

3.4 The optimal minimum skill requirement across regimes

We turn now to compare the minimum skill requirements chosen under the three different regimes we have considered so far. We start by comparing $\hat{j}$ and $\tilde{j}$, i.e. the ability threshold levels chosen respectively under costless and costly enforcement. This is done in the following

Lemma 3 *The minimum ability level $\hat{j}$ chosen by the government under the costless enforcement regime is higher than the minimum ability level $\tilde{j}$ chosen under the costly enforcement one.*

Proof. Combining equations 8 with 21, it follows immediately that equation 21 evaluated at $\hat{j}$ is negative. Since W_{un} is concave, $\tilde{j} < \hat{j}$. ■

The intuition for this result is that the presence of a migration policy enforcement cost leads to a decrease in the minimum skill level chosen by the government, i.e. to a less

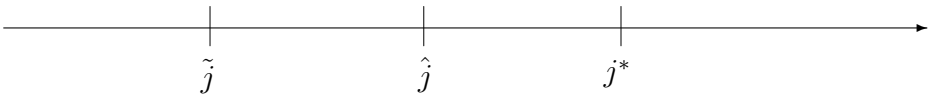

Figure 1: Minimum skill thresholds

restrictive migration policy. We can now compare the minimum skill requirement under costless enforcement and in the presence of an underfunded regime.

Lemma 4 *The minimum ability level j^* chosen by an underfunded government is greater or equal to the minimum ability level $\hat{j}$ chosen under costless enforcement as long as $\alpha h \frac{\partial \mathscr{V}(\bar{j}_{ill},\hat{j})}{\partial j} \geq (1-h)(x-\alpha v^0)\frac{\partial M(\bar{j}_{ill},\hat{j})}{\partial j}$.*

Proof. To carry out the comparison, we evaluate equation 17 at $j = \hat{j}$. Given that $\hat{j}$ satisfies equation 8 with equality, equation 17 simplifies to

$$B_{un}[.,\hat{j}(.)] = \alpha h \frac{\partial \mathscr{V}(\bar{j}_{ill},\hat{j})}{\partial j} - (1-h)(x-\alpha v^0)\frac{\partial M(\bar{j}_{ill},\hat{j})}{\partial j} \tag{22}$$

which is non negative iff $\alpha h \frac{\partial \mathscr{V}(\bar{j}_{ill},\hat{j})}{\partial j} \geq (1-h)(x-\alpha v^0)\frac{\partial M(\bar{j}_{ill},\hat{j})}{\partial j}$. Since W_{un} is concave, $j^* > \hat{j}$. ■

Thus, if the marginal contribution of an illegal immigrant to expected domestic income at $\hat{j}$ is greater than the expected cost of his criminal activities, the minimum skill requirement is at least as restrictive in the presence of an underfunded government as it is with costless enforcement. Summarizing our results, the following ordering emerges

$$\tilde{j} < \hat{j} < j^* \tag{23}$$

This is illustrated in Figure 1.

4 Choosing the optimal migration policy

In this section, we determine the optimal migration policy for the destination country, by solving the government's problem which is illustrated in Figure 2. We start by comparing the levels of welfare which can be obtained by a government, which has introduced a minimum skill requirement, but has not devoted any resource to its enforcement. In this case illegal immigration takes place in the first period, and ex post the authorities must decide whether

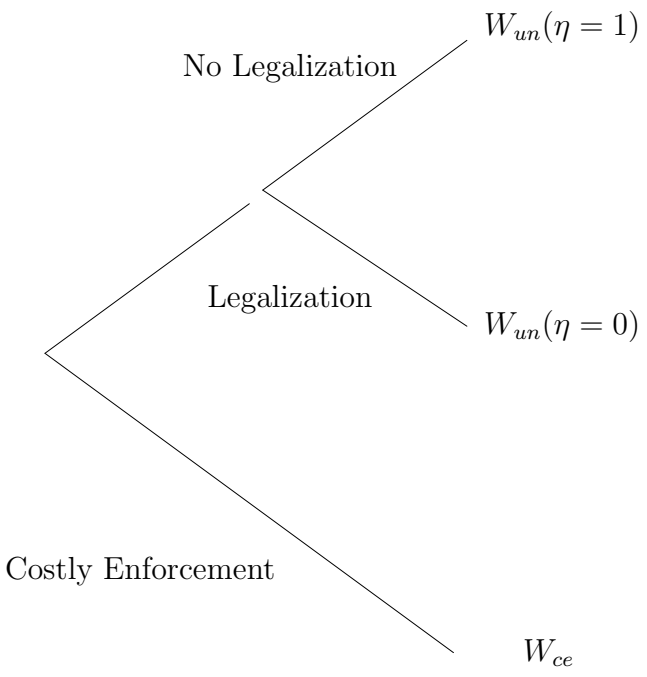

Figure 2: The government's decision problem

to legalize all illegal immigrants present in the country or to keep them in the informal economy. Next, we will compare the outcomes resulting from the choices of an underfunded government, with the costly enforcement option, in which the immigration authorities set an official policy ex–ante and invest resources to perfectly enforce it.

4.1 When is an amnesty desirable?

To decide whether to carry out an amnesty, the government compares aggregate welfare when undocumented migrants are kept illegal, i.e.

$$W_{un}(\eta = 1) = 2\left[\alpha(1-\tau)V(j^*,1) + b_{un}N + \alpha h\mathscr{V}(\overline{j}_{ill}, j^*) - (1-h)(x-\alpha v^0)M(\overline{j}_{ill}, j^*)\right] \tag{24}$$

to the welfare obtained by carrying out the legalization program, i.e.

$$\begin{aligned} W_{un}(\eta = 0) \;\; = &\left[\alpha(1-\tau)V(j^*,1) + b_{un}N + \alpha h\mathscr{V}(\overline{j}_{ill}, j^*) - (1-h)(x-\alpha v^0)M(\overline{j}_{ill}, j^*)\right] + \\ &+ \left[\alpha(1-\tau)V(\overline{j}_{ill},1) + b_l N\right] \end{aligned} \tag{25}$$

Subtracting equation 24 from equation 25 we obtain the following expression:

$$\begin{aligned} W_{un}(\eta=0) - W_{un}(\eta=1) &= \alpha\left[V(\bar{j}_{ill}, j^*) - h\mathscr{V}(\bar{j}_{ill}, j^*)\right] + \\ &+ N(b_l - b_{un}) - \tau V(\bar{j}_{ill}, j^*) + (1-h)(x - \alpha v^0) M(\bar{j}_{ill}, j^*) \end{aligned} \tag{26}$$

Equation 26 allows us to highlight three channels which shape the likelihood of carrying out a legalization program. The first is the labor market matching channel: the bigger is the gain to aggregate income induced by a better labor market matching process, the higher is the likelihood that a legalization will be carried out (see the first term on the right hand side). The second is the welfare state channel (see the second and third term on the right hand side). Recalling that $b_l < b_{un}$ this channel suggests that a legalization is not desirable. Notice also that

$$\frac{\partial[W_{un}(\eta=0) - W_{un}(\eta=1)]}{\partial\tau} = -\alpha V(\bar{j}_{ill}, j^*) - \left[\frac{V(j^*,1)}{N + M(j^*,1)} - \frac{V(\bar{j}_{ill},1)}{N + M(\bar{j}_{ill},1)}\right] < 0 \tag{27}$$

In other words, a more redistributive welfare state will make an amnesty even less desirable, as it makes the welfare leakage to the migrants more severe. The third channel is represented by the expected social cost of criminal activities. The bigger is the net cost of crime, the more likely will be an amnesty.

4.2 When should migration be restricted?

Let us start by assuming that $W_{un}(\eta = 0) - W_{un}(\eta = 1) > 0$, that is, a legalization is desirable whenever a government's migration policy is underfunded. We want to determine under which conditions the well being of natives is higher when the government carries out a costly enforcement strategy, rather than allowing undocumented immigrants in the country and then legalizing them.

This is done in the following

Proposition 1 *If $W_{un}(\eta = 0) - W_{un}(\eta = 1) > 0$, then $W_c > W_{un}(\eta = 0)$, that is costly enforcement is always preferable to an ex-post legalization.*

Proof. Subtract equation 25 evaluated at j^* from equation 18 evaluated at $\tilde{j}$. After a few manipulations, we obtain

$$\begin{aligned} W_c - W_{un}(\eta=0) &= \alpha\left[(1-\tau)V(\tilde{j}, j^*) - h\mathscr{V}(\tilde{j}, j^*)\right] + (1-h)[(x - \alpha v^0) M(\bar{j}_{ill}, j^*)] + \\ &- \alpha\left[(1-\tau)V(\bar{j}_{ill}, \tilde{j}) + h\mathscr{V}(\bar{j}_{ill}, \tilde{j})\right] + (b_c - b_{un} + b - b_l)\, N \end{aligned} \tag{28}$$

To sign the left hand side of equation 28, we use our assumption that $W_{un}(\eta=0)-W_{un}(\eta=1)>0$. This is equivalent to assume that

$$\begin{aligned}\alpha\left[(1-\tau)V(\tilde{j},j^*)-h\mathscr{V}(\tilde{j},j^*)\right]+(1-h)[(x-\alpha v^0)M(\overline{j}_{ill},j^*)] \;\; > \\ -\alpha\left[(1-\tau)V(\overline{j}_{ill},\tilde{j})-h\mathscr{V}(\overline{j}_{ill},\tilde{j})\right]-N(b_l-b_{un})\end{aligned} \tag{29}$$

We use the inequality in equation 29, to rewrite equation 28 as follows

$$\begin{aligned}W_c-W_{un}(\eta=0) \;\; > \;\; & -\alpha\left[(1-\tau)V(\overline{j}_{ill},\tilde{j})-h\mathscr{V}(\overline{j}_{ill},\tilde{j})\right]-N(b_l-b_{un})+ \\ - \;\; & \alpha\left[(1-\tau)V(\overline{j}_{ill},\tilde{j})+h\mathscr{V}(\overline{j}_{ill},\tilde{j})\right]+(b_c-b_{un}+b-b_l)\,N\end{aligned} \tag{30}$$

This is equivalent to

$$W_c-W_{un}(\eta=0)>N(b_c+b-2b_l)-2\alpha(1-\tau)V(\overline{j}_{ill},\tilde{j}) \tag{31}$$

Let the term on the right hand side of equation 31 be denoted by $\mathscr{A}$. This can be expressed also as

$$\mathscr{A}=2N(b-b_l)-2\alpha(1-\tau)V(\overline{j}_{ill},\tilde{j})-\frac{c(\tilde{j})N}{N+M(\tilde{j},1)} \tag{32}$$

The first term captures the gain in the per capita benefit arising from restricting immigration using costly enforcement compared to allowing all potential immigrants up to $\overline{j}_{ill}$ to enter the destination country legally, and thus giving them access to the welfare state. The second term represents the net income loss for natives due to the restriction in the inflow of immigrants. The third is the direct cost of limiting the inflow of foreign workers in the first period. Alternatively, $\mathscr{A}$ can be thought of as the difference between the welfare in the destination country when a restrictive policy is implemented and that when no enforcement cost is incurred and all immigrants up to $\overline{j}_{ill}$ are admitted as legals. Under our assumption that the government's welfare maximization in the presence of costly enforcement admits an interior solution, $\mathscr{A}>0$ as the government's objective is maximized at $\tilde{j}$ rather than at $\overline{j}_{ill}$. ■

Let us now turn to the case where $W_{un}(\eta=0)-W_{un}(\eta=1)<0$, that is, whenever the government is underfunded, it is desirable to keep the undocumented immigrants as illegal. We are still interested in studying whether carrying out a costly enforcement strategy in the first period is preferable to allowing illegal immigrants to remain. This is done in the following

Proposition 2 *If $W_{un}(\eta=0)-W_{un}(\eta=1)<0$, then the comparison between the level of*

welfare achievable under a costly enforcement regime and that achievable when undocumented immigrants are kept illegal is ambiguous.

Proof. Subtract equation 24 evaluated at j^* from equation 18 evaluated at $\tilde{j}$. After a few manipulations we obtain

$$\begin{aligned} W_c - W_{un}(\eta=1) &= 2\alpha\left[(1-\tau)V(\tilde{j},j^*) - h\mathscr{V}(\tilde{j},j^*)\right] + 2(1-h)[(x-\alpha v^0)M(\bar{j}_{ill},j^*)] + \\ &- 2\alpha h V(\bar{j}_{ill},\tilde{j}) + (b_c - 2b_{un} + b)\,N \end{aligned} \tag{33}$$

To sign the left hand side of equation 33, we use our assumption that $W_{un}(\eta=0) - W_{un}(\eta=1) < 0$. This is equivalent to assume that

$$\begin{aligned} \alpha\left[(1-\tau)V(\tilde{j},j^*) - h\mathscr{V}(\tilde{j},j^*)\right] + (1-h)[(x-\alpha v^0)M(\bar{j}_{ill},j^*)] &< \\ -\alpha\left[(1-\tau)V(\bar{j}_{ill},\tilde{j}) - h\mathscr{V}(\bar{j}_{ill},\tilde{j})\right] - N(b_l - b_{un}) \end{aligned} \tag{34}$$

We use the inequality in equation 34, to rewrite equation 33 as follows

$$\begin{aligned} W_c - W_{un}(\eta=1) &< -\alpha\left[(1-\tau)V(\bar{j}_{ill},\tilde{j}) - h\mathscr{V}(\bar{j}_{ill},\tilde{j})\right] - N(b_l - b_{un}) + \\ &- \alpha\left[(1-\tau)V(\bar{j}_{ill},\tilde{j}) + h\mathscr{V}(\bar{j}_{ill},\tilde{j})\right] + (b_c - b_{un} + b - b_l)\,N \end{aligned} \tag{35}$$

This can be expressed as

$$W_c - W_{un}(\eta=1) < 2N(b-b_l) - 2\alpha(1-\tau)V(\bar{j}_{ill},\tilde{j}) - \frac{c(\tilde{j})N}{N + M(\tilde{j},1)} = \mathscr{A} \tag{36}$$

As we have argued above, $\mathscr{A} > 0$, and thus $W_c \gtreqless W_{un}(\eta=1)$. ■

Summarizing, we have shown that an amnesty is more likely to be desirable the bigger is the gain to aggregate income brought about by an improvement in the labor market matching technology following a legalization, and the higher is the expected cost of criminal activities. On the contrary, a redistributive welfare state makes an amnesty less desirable, as it entitles low–skilled foreign workers to welfare state benefits. Importantly, we find that, when an amnesty is preferable to tolerating illegal migrants, the destination country would enjoy a higher level of welfare investing ex–ante in migration policy enforcement. Thus, the labor market matching technology, the extent of redistribution carried out by the welfare state and the degree of involvement in criminal activities by illegal immigrants can inform a government on the desirability of investing resources to control migration flows. On the

other hand, when an amnesty is not desirable, the destination country might be better off by not devoting any resource to policy enforcement and by letting some foreign workers enter and stay illegally. We next investigate the role of these three channels in explaining the likelihood of the introduction of a legalization program.

5 Data

To assess the role played by the labor market channel, the welfare state channel and the social cost of criminal activities in shaping the incentives to carry out an amnesty, we construct a novel dataset covering 17 OECD countries[11] spanning the period 1980-2007. In this section we describe the variables we have used in our analysis.

5.1 Amnesties

For each of the countries in our sample we have started by collecting information on immigrants' legalization programs (amnesties). We define an amnesty as a procedure that allows immigrants who are already in the country of destination in violation of its immigration law (i.e. undocumented immigrants) to obtain a legal residence and work permit. To qualify as an amnesty, a regularization program must also satisfy the following requisites: a) it does not form part of the regular migration policy framework; b) it runs for a limited period of time; c) it is not specific to certain categories of immigrants alone. Note that a legalization program may well be conditional on some individual characteristics: typically, a minimum period of residence in the country of destination is required and/or having a job.

Our main sources of information are the annual reports of the OECD Continuous Reporting System on Migration, now known as the OECD International Migration Outlook (SOPEMI 2011). These reports contain detailed country notes on developments in migration policy in member states that are compiled annually by country experts. We cross-check and supplement that information with the Final Report and Appendices A and B of the European Commission-funded Regularizations in the European Union (REGINE) research program, conducted by the International Centre for Migration Policy Development[12] (Baldwin–Edwards and Kraler 2009). The REGINE report provides information on immigrant regularization practices in the EU member states as well as in Switzerland and the

[11] We include: Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, France, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Sweden, the UK, and the US.

[12] http//www.icmpd.org.

United States.

The REGINE project identifies five additional legalization episodes, that are not mentioned in the SOPEMI reports. Furthermore, in up to three instances we do not have enough information to determine whether a regularization satisfies all the criteria set out above to be considered a general amnesty. In our empirical specification we check the robustness of our results to the source of our information and to the exclusion of those legalizations whose nature is ambiguous. As a result, in our benchmark specification, we use *Amnesty 1*, which records all amnesties listed in SOPEMI. In addition, we also use *Amnesty 2*, which includes all programs listed in REGINE or SOPEMI, *Amnesty 3*, which excludes from the SOPEMI list the ambiguous cases and *Amnesty 4* which excludes from the REGINE or SOPEMI list the ambiguous cases.

In Table 2 we report for each country the sample period covered in our analysis, and the years in which we observe an amnesty. We provide a detailed description of the amnesties included in our study in table A1.

5.2 Mismatch in the labor market

Our model highlights the role played by a legalization on the quality of the labor market match for migrants. Ideally, we would like to be able to construct a measure for both legal and illegal migrants. Unfortunately, standard sources cover only small samples of immigrants. Furthermore, no information is available on the legal status of foreign workers and as a result, we will need to use a proxy for this important driving force.

We build an index measuring the quality of the match between workers' qualifications and their occupations. To that end we consider the distribution of educational attainment for each occupation. Employees who depart from a centrality index by at least one standard deviation are classified as either over– or under–educated. We then base our index of the extent of mismatch on the share of workers that are under- or over- educated (for a discussion of this type of indices see e.g. Chevalier 2003, Verdugo and Verdugo 1988, Mendes de Oliveira, Santos, and Kiker 2000 and Hartog 2000).

We construct these indicators for every country using annual microdata (Labor Force Surveys for most European countries and Canada, and the March extract of the Current Population Survey for the US). For European countries from 1998 onwards we use the European Union Labor Force Survey (EULFS), which provides a homogeneous source of information. The EULFS does not contain data on educational qualifications in any country before 1998, so we have to rely on country-specific data for earlier years, where available. We

provide details on the source of the data used in every year and country in the Appendix. We proceed as follows. First, we transform the variable on educational qualification into years of education, using UNESCO conversion tables or experts' evaluations. Second, we compute for every sub-major occupation group (two–digit ISCO88 categories or equivalent) the mode, median and standard deviation of years of education. Third, for each occupation group we calculate the percentage of workers with a level of education that is more than one standard deviation above or below the mode (median). Fourth, we compute the (weighted) average across all occupations of the above indices to have two alternative country-wide measures of job market educational mismatch. Our preferred index is based on deviations from the mode. The mode is less sensitive to the presence of outliers in the data and seems therefore more appropriate as a centrality measure for a discrete distribution (like that of educational qualifications).[13] We check the robustness of our results to the choice of the median as an alternative measure.

5.3 Social expenditure

We proxy the extent of redistribution carried out by the welfare state with public expenditure on unemployment benefits as a share of GDP, taken from the OECD Social Expenditure Database for all years 1980-2007. As Boeri, Hanson, and McCormick (2002) show, unemployment benefits are one of the transfer programs that are used most by immigrants. We also check the robustness of our results to the inclusion of broader measures of public expenditure encompassing also family benefits as a share of GDP, and housing expenditure as a share of GDP, as both these programs are disproportionately used by immigrants (see also Boeri 2010).

5.4 Crime data

In our theoretical analysis, a legalization has the effect of reducing the incidence of crime among migrants. To exactly capture the working of this channel, we would need data on the incidence of crime by the legal status of the perpetrator. Unfortunately, this information is not consistently available for all the countries and years included in our study. As a result we had to limit ourselves to broad measures of criminal activities, which do not allow a breakdown based on the nationality of the offender. Our working hypothesis is that the crime rate among illegal immigrants is higher in countries where the overall crime rate is

[13] See also Mendes de Oliveira, Santos, and Kiker (2000) for a discussion.

higher. In particular, we have collected information using waves 2 to 11 of the United Nations Surveys on Crime Trends and the Operations of Criminal Justice Systems (UN–CTS),[14] and supplemented it with information taken from the four editions of the European Sourcebook on Crime and Criminal Justice Statistics (ESCCJS, see Killias et al. 2010). Data for the UN–CTS are collected through questionnaires sent by the United Nations Office on Drugs and Crime (UNODC) to all member states, which are asked to report information on the incidence of police-reported crime and on the operation of criminal justice systems in every country. The ESCCJS is a data collection initiative that started in 1993 under the umbrella of the Council of Europe which contains, among other things, data on crime reported to the police for European countries for the years 1990-2007. Data are collected through a network of national correspondents who base their reports on a plurality of national and international data sources. Importantly, at each new edition, data from past years are validated and updated (see Killias et al. (2010) for details).

Our final variables express each type of crime as a rate per 100 thousand people. Our preferred indicator is the number of robberies, as this is the series with the fewest missing values. We check the robustness of our results using alternative measures where we both interpolate and extrapolate missing observations. In particular, we use data on intentional homicides, thefts and rapes reported to the authorities.

5.5 Further controls

In all our regressions we include a number of additional variables that might be correlated with the probability of having an amnesty. First, we are concerned that the stock and flows of illegal immigrants might be an important driver of a government's decision to undertake a legalization. As noticed before, no reliable estimates exist of the number of these figures over time and across countries. For this reason, we have decided to proxy the flow of illegal immigrants with the number of applications for asylum in every year. We believe this to be a reasonable strategy, as in many Western destination countries popular opinion tends to identify asylum seekers with illegal immigrants (see Hatton 2011).[15] We obtain data on the annual number of asylum applications by country from the UNHCR Statistical Database, and normalize them by the size (in thousand) of the country population, retrieved from the 2010 revision of the World Population Prospects prepared by the Population Division, Department

[14] www.unodc.org/unodc/en/data-and-analysis/United-Nations-Surveys-on-Crime-Trends-and-the-Operations-of-Criminal-Justice-Systems.html

[15] There is also some direct evidence suggesting that a large proportion of failed asylum seekers do simply stay as illegals. See Hatton (2009).

of Economic and Social Affairs of the United Nations. Additionally, we control for business cycle dynamics in the receiving country by including the growth rate of the GDP per head, expressed at constant prices and exchange rate, which we construct from the OECD National Accounts. We also include the old-age dependency ratio, i.e. the ratio of people older than 64 to the working age (16-64) population, from the World Bank World Development Indicators database, to capture the demographic characteristics of the receiving country. In particular it has been argued that migration might be a tool to relieve the financial sustainability problem of pay as you go social security systems in destination countries and as a result we might expect that an aging population might increase the probability of an amnesty that would allow young immigrants to contribute to the social security system. Finally, we control for the political orientation of the government in each country. We use data from the 2010 edition of the World Bank's Database of Political Institutions (DPI)[16] to construct an indicator variable that takes a value of one if the main party in the government's coalition is right–wing. Summary statistics for all the variables used in the analysis are reported in Table A2 in the Appendix.

6 Empirical analysis

Our model has identified three channels that play a role in shaping the decision to introduce an amnesty. Our predictions are that the larger is the improvement in the labor market matching, the more likely is the introduction of a legalization program, as this increases the natives' welfare. At the same time, the more redistributive is the welfare state, the less likely is the introduction of the amnesty, as the fiscal leakage to migrants becomes more severe. Finally, the more likely it is that an illegal immigrant is involved in criminal activities (compared to legals), the higher is the probability of a legalization.

As we have already mentioned, we cannot directly capture the effect of the legalization on the quality of the match for the migrants. Therefore we proxy for our key explanatory variable with a mismatch index for the overall labor force. Assuming that a change in the mismatch index for the entire labor force is positively correlated with that in the mismatch index in the informal labor market, to establish a link between our theoretical model and the index we construct, we need to consider two possible scenarios. On the one hand, if the change in the mismatch index is larger for the informal sector than for the overall economy, we expect a positive relationship between a change in our labor market mismatch index

[16]See Beck, Clarke, Groff, Keefer, and Walsh (2001) for a description of this dataset.

and the probability of a legalization. Alternatively, if the change is smaller for the informal sector, this relationship is ambiguous.[17] The sign of the relationship between our measure of the quality of the match in the labor market and the likelihood of an amnesty is thus an empirical question.

We estimate the following empirical model:

$$A_{ct} = \beta \text{mis}_{ct} + \gamma \text{welfare}_{ct} + \delta \text{crime}_{ct} + \mathbf{X}\theta + \zeta \text{eulfs}_{ct} + \sum_{w=wave} \chi_w \text{uncts}^w_{ct} + D_t + D_c + u_{ct} \quad (37)$$

where A_{ct} is a dummy variable indicating whether country c has implemented an amnesty in year t, mis_{ct} is the labor market mismatch index described in section 5.2, $welfare_{ct}$ is the measure of the size of the welfare state described in section 5.3, $crime_{ct}$ is our crime measure described in section 5.4, $\mathbf{X}$ is a vector of control variables which includes the number of asylum applications, per capita GDP growth, the old age dependency ratio, and a dummy for the government's political orientation, as described in section 5.5. $eulfs_{ct}$ is a dummy variable indicating whether the mismatch index is computed using EULFS data, $uncts^w_{ct}$ is an indicator variable denoting the UN–CTS wave w from which the data have been obtained. Finally, D_t and D_c are respectively year and country indicators to account for unobserved time and country–specific effects. The error term u_{ct} is a mean zero error term, which we assume to be uncorrelated with the explanatory variables. We allow for serial correlation within country over time and cluster the standard errors at the country level.

We report results from our basic specification in Table 3, where we use as dependent variable *Amnesty 1*, i.e. the indicator of amnesties based on SOPEMI (see section 5.1). In all specifications we include the vector of control variables $\mathbf{X}$, year and country dummies, while we gradually add our regressors of interest. We standardize all the continuous variables, with

[17] To see this point, consider a simple discrete example with two firms, 1 and 2, and focus on an individual of skill level $j = 2$. Abstracting from the other channels considered in the model and focusing only on the labor market, the gain in aggregate income from a legalization at time t can be expressed as $gain_t = v(2,2)p^{22} + v(2,1)p^{21} - v(2,2)\pi^{22} - v(2,1)\pi^{21}$, where p^{22} and π^{22} are respectively the probability of a good match for legal and illegal workers, and $p^{22} > \pi^{22}$. Furthermore, $p^{21} = 1 - p^{22}$ and $\pi^{21} = 1 - \pi^{22}$ are the probabilities of a bad match for legal and illegal workers. Consider now the gain in aggregate income from legalizing worker $j = 2$ at $t + 1$, that is $gain_{t+1} = v(2,2)p^{22}_{t+1} + v(2,1)p^{21}_{t+1} - v(2,2)\pi^{22}_{t+1} - v(2,1)\pi^{21}_{t+1}$ where we assume that $p^{21}_{t+1} = \alpha p^{21}$ with $\alpha > 1$ and that $\pi^{21}_{t+1} = \beta\pi^{21}$ with $\beta > 1$. $\alpha, \beta > 1$ imply a positive correlation in the mismatch indeces between the two sectors. Consider now the effect of changes in the mismatch indeces on the change in the gain from legalization from t to $t + 1$. This is given by $\Delta gain = gain_{t+1} - gain_t = (v^{21} - v^{22})(\alpha p^{21} - p^{21} - \beta\pi^{21} + \pi^{21})$, where $v^{21} - v^{22} < 0$. If $(\alpha p^{21} - p^{21} - \beta\pi^{21} + \pi^{21}) < 0$, an increase in the mismatch indeces determines an increase in the gain from legalization, i.e. $\Delta gain > 0$. Notice that $(\alpha p^{21} - p^{21} - \beta\pi^{21} + \pi^{21}) < 0$ is equivalent to assuming $\frac{p^{21}}{\pi^{21}} < \frac{\beta - 1}{\alpha - 1}$. If $\beta \geq \alpha$, that is if the change in the mismatch index for the informal than for the formal sector, $\Delta gain > 0$. On the other hand, if $\beta < \alpha$, $\Delta gain \gtreqless 0$.

the exception of the per capita GDP growth rate, by the within-country standard deviation. Each coefficient can thus be interpreted as the percentage points increase in the probability of having an amnesty brought about by a one standard deviation increase in the regressor.

In column (1) we start with a parsimonious specification, that includes only the mismatch index based on deviations from the mode. We find that there exists a strongly positive and statistically significant relationship between the value of the mismatch index and the probability of having an amnesty, which is compatible with the idea that an increase in the mismatch index for the formal labor market is smaller than the increase in the same indicator for the informal labor market. In terms of the magnitude of the effect, an increase by one standard deviation in the share of workers that are imperfectly matched to their job increases the probability of an amnesty by 2.5 percentage points or approximately by about one ninth of the standard deviation. Among our controls, only the number of asylum applications has a significant effect. As it turns out, an increase in this variable is associated with a decrease in the likelihood of an amnesty. This is consistent with the view that – if asylum seekers are perceived to be likely to become illegals – receiving countries try to reduce their own attractiveness towards them by carrying out fewer amnesties. In column (2) we also include a dummy variable to control for whether our mismatch index has been constructed using the EULFS or national labor force surveys, and we retain it throughout the remainder of the table. The sign and significance of our results are unaffected. In column (3) we account also for the extent of redistribution carried out by the welfare state by including public spending on unemployment as a share of GDP. As suggested by our theoretical model, a higher level of spending is negatively and significantly correlated with the probability of an amnesty. An increase by one standard deviation in the level of this variable decreases the probability of a legalization by 2.2 percentage points, without affecting the sign and significance of the other drivers included in the model. In column (4) we introduce also our preferred measure of the incidence of criminal activities, namely the number of robberies per 100 thousand inhabitants, which however does not have a significant impact. Finally, in column (5) we add controls for the source of our data on crime, by including dummy variables for the different waves of the UN–CTS. We will use the specification in column (5) as our benchmark when carrying out our extensive series of robustness checks. Notice that our results in Table 3 are remarkably robust across specifications.

Much of our efforts have been devoted to the collection of a comprehensive dataset on general immigration amnesties. As we have mentioned in section 5.1, two main sources have been used, i.e. the SOPEMI reports and the Regine project output. The overlap between

the two sources is substantial, yet not complete, as shown in Table A.1 in the Appendix. Furthermore, there are a few instances for which we do not have enough information to determine whether the legalization program satisfies the definition introduced in section **??**. We assess the robustness of our analysis by experimenting with different definitions of our dependent variable. Table 4 reports our results. As we can see, even if the number of legalization episodes considered changes, our results are remarkably robust. Neither the sign nor the significance of our proxies for the labor market channel, the welfare state channel or the criminality channel are affected.

We are also concerned that some of our results might be driven by the choice of our key explanatory variables. To assess the robustness of our findings, in Table 5 we experiment with alternative definitions of the mismatch index, our measure of the welfare state generosity and of the incidence of criminal activities. For comparison purposes, column (1) reports our benchmark specification, i.e. column (5) of Table 3. In column (2) we use the mismatch index based on the median value of education within occupations. Results with this alternative index are virtually identical to the benchmark. In column (3) and (4) we instead use a more comprehensive measure of the extent of redistribution by adding to the expenditures on unemployment benefits public spending on family in column (3) and public spending on family and housing in column (4). In the latter case, our estimates are based on a lower number of observations as we have no data on public expenditure for housing in the US in any year, and in Belgium until 1999. Changing the measure of public expenditure has no effect on our estimates, even when they are based on fewer observations. Finally, we check the robustness of our results to the choice of different measures of the incidence of criminal activities: intentional homicides (column 5), thefts (column 6) and rapes (column 7). Also in this case, our results are not affected.

Our data include 17 countries over a period of 28 years. We are worried that some of our findings might be driven by a particular country. For this reason in Table 6 we replicate the estimates from our basic specification (column (5) of Table 3) excluding one country at a time from our sample. Our results are qualitatively unaffected, with the estimated coefficient on the mismatch index ranging between 0.22 and 0.3, the coefficient on the generosity of the welfare state ranging between -0.18 and -0.25, and no significant effect of crime.

Some of the countries in our sample have never implemented an immigration amnesty over the period we study them. We are therefore concerned that by including them we might bias our parameter estimates. This is because in these countries changes in our explanatory variables might not carry any useful information on the likelihood of an amnesty.

In Table 7, we therefore replicate our benchmark specification using the four definitions of amnesties described above, but restricting the sample to those countries that implemented at least one legalization over the sample period. Although the number of observations shrinks dramatically, especially for *Amnesty 1* and *Amnesty 3*, our parameter estimates in all specifications, have the expected sign and are larger in magnitude relative to those obtained with the full sample, even though they are less precisely estimated.[18]

7 Conclusions

In this paper we have developed a model of legal and illegal immigration, which has helped us understanding the basic tradeoffs faced by a government between a costly enforcement of the official immigration target and a lax enforcement ex–ante, combined with an ex–post legalization program. We have started by analyzing under which conditions an amnesty is preferable to tolerating undocumented immigrants. Next, we have considered when it is desirable to have ex–ante lax enforcement, rather than carrying out costly enforcement, and we have shown that three channels play an important role in this decision. An amnesty is more likely the larger are the output gains brought about by the legalization, the less redistributive is the welfare state and the higher is the expected cost of the criminal activities carried out by undocumented immigrants. Importantly, we have shown that, when an amnesty is desirable from the point of view of the destination country, the latter could have reached an even higher welfare level by investing in enforcement ex–ante. On the other hand, when an amnesty is not desirable, the destination country might be better off by not devoting any resource to policy enforcement, and by letting some foreign workers enter and stay illegally.

We have then assessed the relevance of the channels identified by our theoretical model by constructing a novel panel dataset covering a large group of OECD countries over the period 1980-2007 to study the determinants of the introduction of immigration amnesties. We have found broad support for both the role played by the labor market matching and the welfare state channels, obtaining results that are robust to a variety of alternative specifications.

We can think of several avenues along which our analysis could be extended. First, in our model the government acts as a pure welfare maximizer. We made this assumption to keep the analysis tractable, but a more realistic setting would involve taking explicitly into account political economy forces that do play an important role in shaping immigration policy and

[18]It should also be noted that we have only six countries in the sample for *Amnesty 3*, and seven countries for *Amnesty 1*. With such a small number of countries, cluster-robust standard errors are not very reliable. Standard errors should therefore be interpreted with due caution.

its enforcement (see Facchini and Testa 2010). While we have highlighted the effect that an increase in the probability of an amnesty has on the incentives to migrate illegally, a more comprehensive analysis of the dynamic implications of immigration amnesties could be developed.[19]On the one hand, this would allow us to explore issues related to the credibility of migration policy, and on the other it would enable us to take into account the long run effects of legalization programs on the descendants of current immigrants. While both these extensions are important, they are left for further research.

References

Baldwin–Edwards, M. and A. Kraler (2009). *REGINE: Regularisations in Europe*. Amsterdam: Pallas Publications.

Beck, T., G. Clarke, A. Groff, P. Keefer, and P. Walsh (2001). New tools in comparative political economy: The database of political institutions. *World Bank Economic Review 15*, 167–190.

Boeri, T. (2010). Immigration to the land of redistribution. *Economica 77*, 651–687.

Boeri, T., G. Hanson, and B. McCormick (2002). *Immigration policy and the welfare system*. Oxford OX2, 6DP: Oxford University Press.

Camarota, S. A. (2004). The high cost of cheap labor: Illegal immigration and the federal budget. Mimeo, Center for Immigration Studies.

Chau, N. H. (2001). Strategic amnesty and credible immigration reform. *Journal of Labor Economics 19*, 604–634.

Chevalier, A. (2003). Measuring over-education. *Economica 70*, 509–531.

Dolado, J. J. (2007). The spanish approach to immigration. *Vox EU*.

Epstein, G. S. and A. Weiss (2011). The why, when, and how of immigration amnesties. *Journal of Population Economics 24*, 285–316.

Facchini, G., A. Razin, and G. Willmann (2004). Welfare leakage and immigration policy. *CES Ifo Economic Studies 50*, 627–645.

Facchini, G. and C. Testa (2010). The rhetoric of closed borders: quotas, lax enforcement and illegal immigration. CEPR discussion paper 8245, London.

[19]For an empirical study on the long run effects of the legalization program introduced by IRCA, see Orrenius and Zavodny (2003).

Hanson, G. (2006). Illegal migration from Mexico to the United States. *Journal of Economic Literature 44*, 869–924.

Hartog, J. (2000). Over-education and earnings: where are we, where should we go? *Economics of Education Review 19*, 131–147.

Hatton, T. J. (2009). The rise and fall of asylum: What happened and why? *Economic Journal 119*, F183–F213.

Hatton, T. J. (2011). *Seeking Asylum: Trends and policies in the OECD countries*. London: CEPR.

Jacobs, J., P. Michon, and K. Tijdens (2007). State of the art report. mimeo Erasmus University Rotterdam, Rotterdam, The Netherlands.

Karlson, S. H. and E. Katz (2003). A positive theory of immigration amnesties. *Economic Letters 78*, 231–239.

Karlson, S. H. and E. Katz (2010). Immigration amnesties. *Applied Economics 42*, 2299–2315.

Killias, M., M. F. Aebi, K. A. B. Aubusson de Cavarlay, G. Barclay, B. Gruszczyska, H. von Hofer, V. Hysi, J. M. Jehle, P. Smit, and C. Tavares (2010). *European Sourcebook of Crime and Criminal Justice Statistics* (Fourth ed.). Meppel, The Netherlands: van Boom.

Kossoudji, S. A. and D. Cobb–Clark (2002). Coming out of the shadows: Learning about legal status and wages from the legalized population. *Journal of Labor Economics 20*, 598–628.

Mendes de Oliveira, M., M. C. Santos, and B. F. Kiker (2000). The role of human capital and technological change in overeducation. *Economics of Education Review 19*, 199–206.

Orrenius, P. and M. Zavodny (2003). Do amnsety programs reduce undocumented immigration? Evidence from IRCA. *Demography 40*, 437–450.

Petrongolo, B. and C. Pissarides (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature 39*, 390–431.

Razin, A., E. Sadka, and P. Swagel (2002). Tax burden and migration: A political economy theory and evidence. *Journal of Public Economics 85*, 167–190.

Reid, H., R. Durbin, C. Schumer, D. Feinstein, P. Leahy, and R. Menendez (2010). Real enforcement with practical answers for immigration reform (REPAIR) proposal. mimeo.

Rivera Batiz, F. (1999). Undocumented workers in the labor market: An analysis of legal and illegal immigrants in the United States. *Journal of Population Economics 12*, 91–116.

SOPEMI (2011). *International Migration Outlook 2011*. Paris: OECD.

Verdugo, R. R. and N. T. Verdugo (1988). Overeducation and the earnings of black, hispanic, and white male workers. *Sociological Perspectives 3*, 190–212.

Appendix

We provide here details on the data source and construction of each of the variables used in our analysis.

A Labor Market Data

We construct indicators of labor market mismatch using annual country-specific microdata. For European countries from year 1998 onwards we use the European Union Labor Force Survey (EULFS), which provides a homogeneous source of information. The EULFS does not contain information on educational qualifications in any country before 1998, so we have to rely on country-specific microdata for earlier years, where available. Here we describe the data used for each country, and the occupational and educational classification adopted in each of them.

Austria: *Dataset*: Microcensus; *Years*: 1980 – 1997; *Occupational Classification*: 1980-1983: OeBS (Oesterreichische Berufssystematik), 2–digit (84 categories); 1984–1993: OeBS 3–digit available in dataset; 1994-1997: ISCO88, 2–digit; *Education*: National qualifications.

No official crosswalk available between OeBS and ISCO88 2 digit. We use our best judgement to group OeBS 2–digit categories into 27 macro–categories for years 1980–1993. We transform the national educational classification into years of education based on Eurostat conversion tables provided by Statistics Austria.

Belgium: *Dataset*: Aggregate tables on education by occupation based on Belgian LFS, provided by Statistics Belgium. *Years*: 1986 – 1997; *Occupational Classification*: 1986–1992: INS (Institut National Statistiques) rev. 1981 2–digit ; 1993–1996: INS rev. 1991 2–digit ; 1997: ISCO88, 2–digit; *Education*: National qualifications.

We transform INS codes into ISCO88 2–digit and educational classifications into years of education based on crosswalks provided by Statistics Belgium.

Canada: *Dataset*: Canadian Labour Force Survey; *Years*: 1980 – 2007; *Occupational Classification*: 1980–1986: SOC (Standard occupational classification) rev. 1980, 2–digit (21 categories); 1987–2007: NOC-S (National Occupational Classification– Statistics) rev. 2001, 2–digit (25 categories); *Education*: National qualifications.

We transform national qualifications into years of education using the table available at: *www.uis.unesco.org/Education/ISCEDMappings/*

France: *Dataset*: French Labour Force Survey; *Years*: 1980 – 1997; *Occupational Classi-*

fication: 1980–1981: CPS (Catégories socioprofessionnelles), 2–digit; 1982–1997: ISCO88, CPS 4–digit. *Education*: National qualifications.

No crosswalk between CPS 2–digit and ISCO88 2–digit: we use original occupational classification for years 1980-1981. For years 1982 onwards we use the crosswalk provided by Jacobs, Michon, and Tijdens (2007). We transform national qualifications into years of education using the table available at: *www.uis.unesco.org/Education/ISCEDMappings/*

Germany: *Dataset*: IAB employment sample (IABS); *Years*: 1980 – 2001; *Occupational Classification*: KldB (Klassifizierung der Berufe) rev. 1988, *Education*: National qualifications.

We group occupation into 20 categories.

Italy: *Datasets*: Bank of Italy's Household Budget Survey (Indagine sui Bilanci delle Famiglie – IBF) for years 1980–1991 (no data available for the years 1985, 1988 and 1990); Italian Labor Force Survey (ILFS) for the years 1992–1997; *Occupational Classification*: 1977–1990: IBF professional classification (Ripartizione per condizione professionale), 1–digit (7 categories); 1991: IBF new professional classification, 1–digit (7 different categories); 1992-1997: CP1991 (1991 professional classification – Classificazione delle Professioni 1991), 2–digit; *Education*: National qualifications for years 1980–1991; years of education and national qualifications for years 1992–1997.

We use original occupational classifications for years 1980–1991. For years 1992 onwards we convert CP1991 into 2–digit ISCO88 based on the tables available at: *www.ilo.org* and *www*3.*istat.it*. For the years 1980–1991 we transform national qualifications into years of education based on the conversion adopted in the ILFS for years 1992–1997.

Netherlands: *Dataset*: Dutch Labour Force Survey; *Years*: 1990 – 1997; *Occupational Classification*: 1991–1992: CBS-Beroepenclassificatie rev. 1984, 1–digit; 1990 and 1993–1997: CBS-Beroepenclassificatie 1992, 1–digit; *Education*: National qualifications.

We use original occupational classification at 1–digit, as there is no mapping between CPS and ISCO88. We transform national qualifications into years of education based on country experts' advice.

Norway: *Dataset*: Norwegian Labor Force Survey; *Years*: 1980 – 1999 and 2005; *Occupational Classification*: 1980–1995: NYK (Nordic Classification of Occupation), 1–digit; 1996–2009: NOC (Norwegian Classification of Occupation), 4–digit; *Education*: National qualifications.

We use original 1–digit occupational classification for years 1980–1995. From year 1996 we use 2–digit NOC, which closely follows 2–digit ISCO88. We transform national qualifications

in years of education using a crosswalk provided by the Norwegian Statistical Institute and the table available at: *www.uis.unesco.org/Education/*. Note that in 1991 the variable indicating interviewees' occupation is not provided, hence, it is not possible to compute the mismatch index for that year.

Spain: *Dataset*: Spanish Labor Force Survey (Encuesta de Poblacion Activa, EPA); *Years*: 1983 – 1997; *Occupational Classification*: 1992–Q1 1994: CNO (National Occupational Classification) rev. 1979, 3–digit; Q2 1994 –1997: CNO (National Occupational Classification) rev. 1994, 3–digit; *Education*: National qualifications.

We transform CNO rev. 1979 into CNO rev. 1994 in all years. We then transform CNO rev. 1994 into ISCO88 2–digit. Conversions are based on tables provided by the National Statistics Institute at: *www.ine.es/*. We transform national qualifications into years of education based on country experts' advice.

Switzerland: *Dataset*: Swiss Labor Force Survey; *Years*: 1991 – 2007; *Occupational Classification*: ISCO88 2–digit; *Education*: 1991–2000: National qualifications; 2001–2007: ISCED (International Standard Classification of Education) rev. 1997. We transform national qualifications and ISCED categories into years of education based on the information available at: *www.swissworld.org/en/education/compulsory_schooling/overview/* and *www.uis.unesco.org/Education/ISCEDMappings/*.

UK: *Dataset*: UK Labor Force Survey; *Years*: 1984–1997; *Occupational Classification*: years 1984–1990: KODOT; years 1991-1997 SOC (Standard Occupational Classification) rev. 1990; *Education*: age at which individuals left full time education.

We transform KODOT into SOC rev. 1990 using conversion tables provided by the Office of National Statistics Classifications and Harmonisation Unit. We then group 2–digit SOC rev. 1990 categories into sub–major occupation groups based on the SOC90 structure. We obtain years of education from the variable "Age at which left full time education", assuming for everyone a school starting age of 5.

USA: *Dataset*: IPUMS-Current Population Survey (CPS); *Years*: 1980–2007; *Occupational Classification*: 1990 Occupation codes, 21 macrocategories; *Education*: National qualifications.

We have no country-specific microdata for Denmark, Greece, Ireland, Portugal and Sweden. For these countries, we therefore only use years 1998 onwards, based on the EULFS.

B Crime Data

Our main source of information on crime are the United Nations Surveys on Crime Trends and the Operations of Criminal Justice Systems (UN–CTS). In particular, we use wave 2 and 3, covering years 1975 – 1986, wave 4, covering years 1986 – 1990, wave 5, covering years 1990 – 1994, wave 6, covering years 1995 – 1997, wave 8, covering years 2001 – 2002, wave 9 2003 – 2004, wave 10, covering years 2005 – 2006, and wave 11, covering years 2007 – 2008. The UN–CTS is a survey conducted by the United Nations Office on Drugs and Crime on crime levels and criminal justice trends in member states. Information from participating countries is collected through questionnaires sent to one reference person/institution in each country (the so called "focal point") who is responsible for coordinating the country's responses. Frequency and homogeneity of data collection has improved in recent years. Data are now collected annually, and series from 2003 onwards are homogeneous. We account for potential discontinuities in the crime series in our empirical analysis with dummy variables to indicate the wave from which the data are obtained.

Some years are covered in two different waves of the UN-CTS: 1986 is covered in both wave 3 and wave 4 and 1990 is covered in both wave 4 and wave 5. In these cases we keep data from the earlier wave available for each country. For instance, if a country reports the number of crimes in 1986 both in wave 3 and in wave 4, we keep information from wave 3 only; if a country does not report data wave 3 but does report it in the wave 4, we use the latter. We use data on police reported crime for robberies, intentional homicides, thefts and rapes. We do not have data for each of these crimes in all countries in every year. We use robberies as the main crime indicator because it is the series with the fewest missing values, and we replace missing observations with linearly interpolated values, in an effort to maximize the number of data points available in the regression analysis. In our robustness checks, we also use data on intentional homicides, thefts and rapes, where we both interpolate and extrapolate missing values, to keep the sample size constant.

The UN–CTS does not report crime data for the UK as a whole in all years. Instead, it reports consistently data for England and Wales, with the exception of years 2001 and 2002 (UN–CTS wave 8) where we only have aggregate UK data. We therefore use crime rates for England and Wales as a proxy for crime rates in the entire UK with the exception of years 2001 and 2002.

Our final variables express crime as rates per 100 thousand individuals. To construct these figures, we use data on the size of a country's population from the United Nations,

Department of Economic and Social Affairs, World Population Prospects, 2010 Revision.

We have also checked the reliability of our measures of crime from the UN–CTS, with figures from the European Sourcebook on Crime and Criminal Justice Statistics (ESCCJS), a data collection initiative that started in 1993 under the umbrella of the Council of Europe. This source covers European countries only, over the period 1990-2007: data from this independent data source match closely those from the UN-CTS. Based on a comparison with information from the ESCCJS, we have concluded that in the UN–CTS robbery rates for Belgium starting from 2003, and for Spain before 1990 and after 1997 are one order of magnitude too big, and in Belgium in 1994 one order of magnitude too small. We have manually corrected this recording mistakes. All our results are robust to the use of the unadjusted original figures.

Table 1. Illegal immigrants in thousands and number of amnesties

Country	Year	Stock	Share in foreign population	Year	Inflow	Amnesties (1980-2007)
USA	2008	12000	32.4	2008	500	2
Austria	2003	100	10.8	2001	50	1
Italy	2008	650	22.1	2001	100	5
Germany	2005	500	7.4	2001	90	0
Greece	2007	250	43.8	2001	80	2
Spain	2008	570	10.9	2001	40	6
UK	2007	725	11.1	2001	95	0

The table reports for each country the estimated stock of undocumented immigrants in the corresponding year, expressed in thousands and as a percentage of the foreign population. It also reports the estimated inflow of undocumented migrants (in thousands) in selected years. The last column reports the number of immigration amnesties adopted by each country over the period 1980-2007.

Source: our elaboration on Fasani (2009)

Table 2. Sample years and amnesties by country

Country	First year	Last year	Amnesty 1	Amnesty 2	Amnesty 3	Amnesty 4
Austria	1980	2006	1990	1990	1990	1990
Belgium	1986	2007	0	0	0	0
Canada	1980	2007	0	0	0	0
Switzerland	1991	2007	0	0	0	0
Germany	1980	2007	0	0	0	0
Denmark	1998	2007	0	0	0	0
Spain	1983	2007	1985, 1991, 1996, 2000, 2001, 2004	1985, 1991, 1996, 2000, 2001, 2004	1985, 1991, 1996, 2000, 2001, 2004	1985, 1991, 1996, 2000, 2001, 2004
Greece	1998	2007	2001, 2005	2001, 2005	2001, 2005	2001, 2005
Ireland	1999	2006	0	0	0	0
Italy	1980	2006	1986, 1990, 1995, 1998, 2002	1982, 1986, 1990, 1995, 1998, 2002, 2006	1986, 1990, 1995, 1998, 2002	1982, 1986, 1990, 1995, 1998, 2002
Netherlands	1990	2006	0	1991	0	1991
Norway	1980	2007	0	0	0	0
Portugal	1998	2007	2001	2001	0	0
Sweden	1998	2007	0	0	0	0
UK	1984	2007	0	2003	0	2003
USA	1980	2007	1986, 2000	1986, 2000	1986	1986
Total			*19*	*24*	*17*	*21*

The table reports, for each country, the first and the last year in which the country enters the sample. Columns Amnesty 1 - Amnesty 4 report the years in which each amnesty occurs. The last row reports the total number of occurrences of each amnesty in our study.

Amnesty 1: all amnesties listed in SOPEMI. Amnesty 2: all amnesties listed in REGINE or SOPEMI. Amnesty 3: amnesties listed in SOPEMI, excluding ambiguous cases. Amnesty 4: amnesties listed in REGINE or SOPEMI excluding the ambiguous cases.

Table 3. Main results: Dependent variable Amnesty 1

	1	2	3	4	5
Mismatch index (mode)	0.025**	0.027**	0.029**	0.029**	0.028***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.008)
Public spending unemployment			-0.022***	-0.022***	-0.023***
			(0.007)	(0.007)	(0.008)
Robberies				0.003	0.003
				(0.010)	(0.011)
Asylum applications	-0.022**	-0.020**	-0.022**	-0.022**	-0.024**
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
GDP per head growth rate	0.234	0.189	0.087	0.117	0.061
	(0.469)	(0.463)	(0.434)	(0.433)	(0.425)
Old age dependency ratio	0.003	0.004	0.002	0.002	0.002
	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
Right-wing government	0.046	0.048	0.048	0.049	0.045
	(0.032)	(0.033)	(0.031)	(0.031)	(0.033)
EULFS	No	Yes	Yes	Yes	Yes
Crime survey dummies	No	No	No	No	Yes
N	347	347	347	347	347
R-squared	0.11	0.111	0.118	0.118	0.135

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country had an immigration amnesty in that year. All specifications include country fixed effects and year dummies. All continuous variables except GDP growth are standardized by their within-country standard deviation. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. Crime survey dummies are a series of dummy variables indicating the UN-CTS wave from which the data have been obtained. Standard errors in parenthesis are clustered at the country level.

* denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 4. Robustness check: Alternative definitions of amnesty

	Dependent variable		
	Amnesty 2	**Amnesty 3**	**Amnesty 4**
Mismatch index (mode)	0.033***	0.021**	0.032**
	(0.008)	(0.009)	(0.012)
Public spending unemployment	-0.026**	-0.018**	-0.018*
	(0.010)	(0.008)	(0.010)
Robberies	0.006	0.007	0.001
	(0.014)	(0.011)	(0.014)
Asylum applications	-0.021**	-0.019**	-0.017**
	(0.008)	(0.008)	(0.008)
GDP per head growth rate	0.666	0.12	0.76
	(0.810)	(0.428)	(0.842)
Old age dependency ratio	-0.002	0.006	-0.002
	(0.013)	(0.008)	(0.012)
Right-wing government	0.061	0.052	0.06
	(0.050)	(0.031)	(0.046)
EULFS	Yes	Yes	Yes
Crime survey	Yes	Yes	Yes
N	347	347	347
R-squared	0.12	0.127	0.123

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country had an immigration amnesty in that year. Each column reports results with a different definition of amnesty (see Table 2 for details). All specifications include country fixed effects and year dummies. All continuous variables except GDP growth are standardized by their within-country standard deviation. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. Crime survey dummies are a series of dummy variables indicating the UN-CTS wave from which the data have been obtained. Standard errors in parenthesis are clustered at the country level.

* denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 5. Robustness check: Alternative definitions of main regressors.

	1	2	3	4	5	6	7
Mismatch index (mode)	0.028***		0.026***	0.026***	0.028***	0.028***	0.027***
	(0.008)		(0.008)	(0.007)	(0.009)	(0.009)	(0.009)
Mismatch index (median)		0.027**					
		(0.012)					
Public spending unemployment	-0.023***	-0.021**			-0.022**	-0.022**	-0.022***
	(0.008)	(0.008)			(0.008)	(0.008)	(0.008)
Public spending unemployment and family			-0.020**				
			(0.008)				
Public spending unemployment, family and housing				-0.021**			
				(0.009)			
Robberies	0.003	0.004	0.001	-0.001			
	(0.011)	(0.011)	(0.011)	(0.014)			
Homicides					0		
					(0.006)		
Thefts						-0.002	
						(0.011)	
Rapes							0.011
							(0.018)
Asylum applications	-0.024**	-0.022**	-0.022**	-0.020*	-0.024**	-0.024**	-0.024***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
GDP per head growth rate	0.061	0.072	0.01	0.006	0.029	0.012	0.06
	(0.425)	(0.428)	(0.389)	(0.540)	(0.449)	(0.504)	(0.468)
Old age dependency ratio	0.002	0.003	0.001	0.003	0.002	0.002	0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Right-wing government	0.045	0.045	0.044	0.051	0.045	0.045	0.046
	(0.033)	(0.033)	(0.034)	(0.035)	(0.033)	(0.035)	(0.031)
EU LFS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crime survey	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	347	347	347	305	347	347	347
R-squared	0.135	0.135	0.134	0.141	0.135	0.135	0.136

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country had an immigration amnesty in that year. Amnesty definition: Amnesty 1. All specifications include country fixed effects and year dummies. All continuous variables except GDP growth are standardized by their within-country standard deviation. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. Crime survey dummies are a series of dummy variables indicating the UN-CTS wave from which the data have been obtained. Standard errors in parenthesis are clustered at the country level.

* denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 6. Robustness check: Excluding one country at a time

	Austria	Belgium	Canada	Switzerland	Germany	Denmark	Spain	France	Greece	Ireland	Italy	Netherlands	Norway	Portugal	Sweden	UK	USA
Mismatch index (mode)	0.028***	0.028***	0.030***	0.029***	0.028***	0.028***	0.022**	0.032***	0.025**	0.028***	0.023**	0.030***	0.027***	0.026***	0.028***	0.030***	0.027***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.011)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Public spending unemployment	-0.019**	-0.023**	-0.023**	-0.025***	-0.025**	-0.024***	-0.023**	-0.019**	-0.022**	-0.024***	-0.018**	-0.025***	-0.025***	-0.019**	-0.024**	-0.023**	-0.023**
	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Robberies	0.005	0.001	0.003	0.003	0.005	0.004	-0.007	0.002	0.006	0.005	0.002	0.005	0.007	0.003	0.004	0.003	0.002
	(0.013)	(0.011)	(0.013)	(0.012)	(0.012)	(0.012)	(0.008)	(0.010)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.014)
Asylum applications	-0.027**	-0.024**	-0.026**	-0.026**	-0.026**	-0.024**	-0.022**	-0.019	-0.027**	-0.023**	-0.018*	-0.028***	-0.025**	-0.025**	-0.023**	-0.024**	-0.019*
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
GDP per head growth rate	-0.102	0.025	-0.032	0.063	0.183	0.073	0.201	0.168	0.185	0.15	-0.053	0.041	0.213	-0.153	0.045	0.008	0.056
	(0.424)	(0.461)	(0.499)	(0.442)	(0.511)	(0.418)	(0.485)	(0.440)	(0.420)	(0.439)	(0.491)	(0.456)	(0.457)	(0.424)	(0.427)	(0.495)	(0.514)
Old age dependency ratio	0.002	0.002	0	0.003	0.001	0.002	0	-0.004	-0.002	0.005	0.005	0.002	0.001	0.006	0	0.005	0.004
	(0.010)	(0.010)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.014)	(0.009)	(0.008)	(0.010)	(0.008)
Right-wing government	0.057*	0.045	0.05	0.044	0.047	0.046	0.04	0.016	0.039	0.046	0.031	0.045	0.058	0.049	0.045	0.052	0.053
	(0.032)	(0.033)	(0.035)	(0.034)	(0.036)	(0.034)	(0.038)	(0.025)	(0.032)	(0.034)	(0.030)	(0.034)	(0.036)	(0.033)	(0.033)	(0.036)	(0.034)
EULFS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crime survey	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	320	325	319	330	319	337	322	319	337	339	320	330	319	337	337	323	319
R-squared	0.152	0.143	0.145	0.139	0.146	0.136	0.143	0.157	0.135	0.139	0.141	0.14	0.149	0.132	0.137	0.144	0.137

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country had an immigration amnesty in that year. All specifications include country fixed effects and year dummies. All continuous variables except GDP growth are standardized by their within-country standard deviation. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. Crime survey dummies are a series of dummy variables indicating the UN-CTS wave from which the data have been obtained. Standard errors in parenthesis are clustered at the country level.

Each column reports results from a regression where the country in the column header has been excluded from the sample.

* denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 7. Robustness check: Excluding countries which never had an amnesty

	Amnesty 1	Amnesty 2	Amnesty 3	Amnesty 4
Mismatch index (mode)	0.033*	0.038***	0.025	0.040**
	(0.015)	(0.010)	(0.014)	(0.014)
Public spending unemployment	-0.054***	-0.061***	-0.044***	-0.051**
	(0.011)	(0.013)	(0.009)	(0.019)
Robberies	0.032	0.029	0.018	0.01
	(0.028)	(0.023)	(0.042)	(0.034)
Asylum applications	-0.031*	-0.018	-0.032	-0.015
	(0.015)	(0.012)	(0.026)	(0.017)
GDP per head growth rate	-0.039	1.381	-0.142	1.555
	(0.963)	(1.618)	(1.261)	(1.515)
Old age dependency ratio	0.015	-0.031	0.011	-0.037
	(0.034)	(0.045)	(0.049)	(0.045)
Right-wing government	0.111	0.115	0.154*	0.118
	(0.077)	(0.075)	(0.065)	(0.068)
EULFS	Yes	Yes	Yes	Yes
Crime survey	Yes	Yes	Yes	Yes
N	155	196	145	186
R-squared	0.284	0.201	0.279	0.209

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country had an immigration amnesty in that year. Each column reports results with a different definition of amnesty (see Table 2 for details). All specifications include country fixed effects and year dummies. All continuous variables except GDP growth are standardized by their within-country standard deviation. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. Crime survey dummies are a series of dummy variables indicating the UN-CTS wave from which the data have been obtained. Standard errors in parenthesis are clustered at the country level.

The sample is restricted to countries that have had at least one amnesty during the observation period.

* denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table A1. List of immigration amnesties

Country	Year	SOPEMI	REGINE	Ambigous	Details on amnesty
Austria	1990	Yes	Yes	No	Sanierungsaktion: aimed at legalizing irregular employment, especially with regard to asylum seekers.
France	1980	No	Yes	No	Administrative regularization
	1981	Yes	Yes	No	Administrative regularization; open to anyone with stable labour markey integration, stable family relations, or *de facto* refugees.
	1997	Yes	Yes	No	Administrative regularization started in June 1997 and terminated in May 1998, aimed at rejected asylum seekers and *de facto* refugees, partners and families, long-term present immigrants. These categories were trapped in irregular situations by the "Pasqua Law", yet protected from expulsion by law.
Greece	2001	Yes	Yes	No	Law 2910/ 2001; open to holders of expired residence permits and to anyone who had resided, legally or illegally, in Greece for one year immediately prior to the entry into force of the 2001 law.
	2005	Yes	Yes	No	Immigration Law 3386/2005; open to migrants who had lost their legal status because of the expiry of their residence permit before August 23, 2005 and who did not have it renewed, and to migrants who had never resided in the country legally, provided they could prove their presence in Greece before January 1, 2005.
Italy	1982	No	Yes	No	Administrative regularization, promoted by the Ministry for Labor Memoranda dated 17.12.1979, 08.03.1980, 02.03.1982, 09.09.1982; open to anyone with two months of continuous residence in Italy over the preceding two months, and with an employment offer.
	1986	Yes	No	No	Legislative regularization (Law no. 943 of 1986), passed in 1986, originally meant to last 3 months but then extended three times. Program covered the period January 27, 1987 - September 30, 1988; open to anyone in Italy as of the end of April 1987.
	1990	Yes	Yes	No	Legislative regularization (Law no. 39 of 1990, so-called "Martelli"), open to anyone who was present in Italy on December 1, 1990.
	1995	Yes	Yes	No	Legislative regularization (Law Decree no. 489 of 1995). Open to anyone in the country at the date the bill came into force who either had a job for the last six months, or had legally resident family members.
	1998	Yes	Yes	No	Regularization programme (Prime Minister Decree 16.10.1998 and Leg. Decree 113/1999) approved together with the immigration reform introduced by Law no. 40 of 1998 (so-called "Turco-Napolitano" law). Open to anyone who was in the country, and employed, at the time the amnesty was introduced.
	2002	Yes	Yes	No	Legislative regularization which came into force on September 9, 2002, that is 15 days after the publication of the new immigration law (Law no. 189 of 30 July 2002, also known as the "Bossi-Fini" law and law 222/2002). Initially targeted to housekeepers and domestic care workers, then extended to any worker who had been in continuous employment for at least three months prior to the introduction of the amnesty.
	2006	No	Yes	Yes	"*De facto*", ex-post regularization programme: March 2006 law decree on migration flows enforced by the Berlusconi Cabinet; April 2006 the new Italian centre-left government elected in April immediately announced the adoption of a second decree providing for a number of "entriy permits" roughly equivalent to the number of unsuccessful applications in the framework of the previous decree on flows.

Table continues on next page

Country	Year	SOPEMI	REGINE	Ambigous	Details on amnesty
Netherlands	1991	No	Yes	No	Regularization program open to anyone who could prove lengthy stay and work in the Netherlands, including payment of taxes and social benefits.
Portugal	2001	Yes	Yes	Yes	Art. 55 Decree 4/2001, regularization programme ran from January until November 2001, targeted to immigrants already working in the country.
Spain	1985	Yes	Yes	No	Open to anyone resident and employed in Spain as of July 24, 1985.
	1991	Yes	Yes	No	Program running from June to December, open to immigrants with expired residence permits, who had worked in the previous two years for at least 9 months, with employment contract or self employed.
	1996	Yes	Yes	No	Regularization programme under the New Aliens Act of September 1996. Open to irregular workers and relatives.
	2000	Yes	Yes	No	Organic Law 4/2000 of 11th January, Royal Decree 239/2000 of 18th of February, program ran from March to July 2000. Open to irregular workers, irregular residents, relatives, and rejected asylum seekers.
	2001	Yes	Yes	No	Royal Decree 142/2001 of 16 February, open to foreigner present in Spain before January 23 , 2001, integrated in the labor market or with family ties in Spain.
	2004	Yes	Yes	No	Royal Decree 2393/2004 of 30 December, open to irregular workers with employment contract for at least six months.
UK	2003	No	Yes	No	Family indefinite leave to remain exercise, open to certain asylum-seeking families who have been in the UK for at least four years.
USA	1986	Yes	Yes	No	Immigration Reform and Control Act (IRCA), open to anyone continuosly resident since 1982, and some categories of seasonal agricultural workers.
	2000	Yes	Yes	Yes	Legal Immigration and Family Equity Act (LIFEA), enabling almost 400 thousand undocumented migrants to apply for regularisation provided they entered the US before 1992.

For each country we report the year in which amnesties occurred, based on SOPEMI and/or REGINE. Column SOPEMI indicates whether the amnesty is listed in SOPEMI. Column REGINE indicates whether the amnesty is listed in REGINE. Column Ambigous indicates whether there are doubts as to whether the amnesty satisfies the criteria to be included in our analysis.

Table A2. Summary statistics for variables used in main regressions

	Amnesty 1		*Mismatch index (mode)*		*Robberies per 100k individuals*		*Public spend unemployment as a % of GDP*		*Asylum applications per 1000 population*		*GDP per head growth rate*		*Old age dependency ratio*		*Right-wing party in government*	
	mean	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***
Austria	0.04	*0.19*	0.25	*0.04*	28.82	*13.20*	0.99	*0.23*	2.06	*1.28*	0.02	*0.01*	22.55	*0.89*	0.26	*0.45*
Belgium	0.00	*0.00*	0.38	*0.04*	121.60	*46.70*	3.08	*0.20*	1.63	*0.91*	0.02	*0.01*	24.18	*1.90*	1.00	*0.00*
Canada	0.00	*0.00*	0.39	*0.03*	98.58	*8.85*	1.35	*0.58*	0.86	*0.41*	0.02	*0.02*	16.96	*1.72*	0.39	*0.50*
Switzerland	0.00	*0.00*	0.26	*0.07*	38.88	*10.86*	0.89	*0.31*	3.13	*1.60*	0.01	*0.02*	22.47	*0.77*	0.29	*0.47*
Germany	0.00	*0.00*	0.29	*0.05*	57.30	*17.74*	1.30	*0.38*	1.38	*1.20*	0.02	*0.01*	23.53	*2.62*	0.64	*0.49*
Denmark	0.00	*0.00*	0.33	*0.02*	55.19	*4.27*	2.91	*0.48*	1.05	*0.70*	0.02	*0.01*	22.57	*0.44*	0.60	*0.52*
Spain	0.24	*0.44*	0.33	*0.05*	133.12	*38.26*	2.63	*0.72*	0.15	*0.08*	0.03	*0.01*	22.17	*2.37*	0.32	*0.48*
France	0.07	*0.26*	0.35	*0.07*	111.53	*50.08*	1.44	*0.72*	0.59	*0.23*	0.02	*0.01*	22.68	*2.03*	0.46	*0.51*
Greece	0.20	*0.42*	0.35	*0.01*	18.75	*5.37*	0.40	*0.03*	0.70	*0.61*	0.04	*0.01*	25.97	*1.35*	0.30	*0.48*
Ireland	0.00	*0.00*	0.38	*0.03*	52.06	*9.15*	0.88	*0.11*	1.97	*0.82*	0.04	*0.02*	16.43	*0.29*	0.00	*0.00*
Italy	0.19	*0.40*	0.39	*0.04*	57.70	*23.48*	0.75	*0.30*	0.14	*0.14*	0.02	*0.01*	23.84	*3.55*	0.26	*0.45*
Netherlands	0.00	*0.00*	0.39	*0.05*	102.37	*17.08*	2.04	*0.64*	1.78	*0.84*	0.02	*0.01*	19.71	*0.75*	0.53	*0.51*
Norway	0.00	*0.00*	0.41	*0.09*	23.41	*9.14*	0.66	*0.34*	1.31	*1.12*	0.02	*0.02*	23.97	*0.99*	0.50	*0.51*
Portugal	0.10	*0.32*	0.32	*0.06*	173.07	*23.65*	0.89	*0.23*	0.02	*0.01*	0.02	*0.02*	24.64	*0.89*	0.30	*0.48*
Sweden	0.00	*0.00*	0.45	*0.20*	93.86	*6.90*	1.23	*0.33*	2.56	*0.94*	0.03	*0.01*	26.61	*0.22*	0.10	*0.32*
UK	0.00	*0.00*	0.34	*0.10*	126.47	*52.98*	0.83	*0.59*	0.59	*0.41*	0.02	*0.01*	24.05	*0.47*	0.58	*0.50*
USA	0.07	*0.26*	0.29	*0.01*	201.17	*45.65*	0.45	*0.17*	0.22	*0.15*	0.02	*0.02*	18.49	*0.64*	0.64	*0.49*
Total	0.05	*0.23*	0.34	*0.08*	90.42	*60.10*	1.32	*0.90*	1.09	*1.15*	0.02	*0.02*	22.25	*3.10*	0.46	*0.50*

The table reports mean and standard deviation of all the variables used in our main regressions of Table 3.

See Table 2 for the definition of Amnesty 1. Mismatch index (mode)is the proportion of workers with a number of yers of schooling at least one standard deviation above or below the mode of years of schooling in their occupation, measured at the sub-major occupation group level (ISCO88 2-digit or equivalent). Robberies per 100k individuals is the ratio of police-reported robberies (from UN-CTS) to the country population, expressed in hundreds of thousands. Public spend unemployment as a % of GDP is the public expenditure on unemployment benefits as a share of GDP, from the OECD Social Expenditure Database. Asylum applications per 1000 population is the ratio of the number of applications for asylum in every year (from the UNHCR Statistical Database) to the country population, expressed in thousands. GDP per head growth rate is the growth rate of the GDP per head, expressed at constant prices and exchange rate, constructed from the OECD National Accounts. Old age dependency ratio is the ratio of people older than 64 to the working age (16-64) population, from the World Bank World Development Indicators database. Right-wing party in government is a dummy variable indicating whether the main party in the government's coalition is right-wing, constructed from the 2010 edition of the World Bank's Database of Political Institutions (DPI).

Table A2 (cont.). Summary statistics for variables used in the robustness checks

	Amnesty 2		*Amnesty 3*		*Amnesty 4*		*Mismatch index (median)*		*Homicides per 100k individuals*		*Thefts per 100k individuals*		*Rapes per 100k individuals*		*Public spending unemployment and family as a % of GDP*		*Public spending unemployment, family and housing as a % of GDP*	
	mean	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***	**mean**	***st. dev.***
Austria	0.04	*0.19*	0.04	*0.19*	0.04	*0.19*	0.23	*0.03*	1.44	*0.65*	1894.68	*267.77*	8.37	*2.25*	3.83	*0.30*	3.93	*0.28*
Belgium	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.36	*0.04*	1.89	*0.47*	2591.97	*574.10*	16.09	*8.81*	5.55	*0.31*	5.84	*0.20*
Canada	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.36	*0.03*	2.62	*1.39*	3373.66	*1159.87*	64.39	*41.57*	2.16	*0.46*	2.76	*0.54*
Switzerland	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.25	*0.07*	1.31	*0.56*	2297.89	*526.42*	6.13	*1.58*	2.14	*0.33*	2.28	*0.33*
Germany	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.29	*0.05*	2.24	*1.12*	3586.27	*580.57*	8.32	*1.35*	3.21	*0.59*	3.49	*0.69*
Denmark	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.33	*0.02*	0.92	*0.20*	3358.61	*179.21*	9.13	*0.65*	6.29	*0.52*	6.97	*0.53*
Spain	0.24	*0.44*	0.24	*0.44*	0.24	*0.44*	0.30	*0.05*	1.29	*0.47*	964.19	*482.44*	6.80	*4.00*	3.23	*0.66*	3.37	*0.67*
France	0.11	*0.31*	0.07	*0.26*	0.11	*0.31*	0.34	*0.08*	2.71	*1.21*	2407.48	*1645.54*	10.48	*4.67*	4.22	*0.75*	5.00	*0.85*
Greece	0.20	*0.42*	0.20	*0.42*	0.20	*0.42*	0.35	*0.03*	1.08	*0.26*	516.66	*136.50*	1.89	*0.41*	1.47	*0.06*	2.04	*0.05*
Ireland	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.36	*0.05*	1.17	*0.27*	1129.90	*214.37*	8.95	*2.36*	3.15	*0.33*	3.51	*0.33*
Italy	0.26	*0.45*	0.19	*0.40*	0.22	*0.42*	0.38	*0.04*	2.71	*1.56*	2055.98	*487.88*	2.78	*1.87*	1.69	*0.35*	1.70	*0.35*
Netherlands	0.06	*0.24*	0.00	*0.00*	0.06	*0.24*	0.39	*0.04*	3.75	*4.41*	4264.60	*591.32*	9.82	*0.92*	3.56	*0.57*	3.93	*0.56*
Norway	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.38	*0.10*	1.18	*0.53*	3530.26	*671.64*	9.71	*4.66*	3.45	*0.87*	3.64	*0.85*
Portugal	0.10	*0.32*	0.00	*0.00*	0.00	*0.00*	0.32	*0.06*	1.96	*0.70*	965.55	*221.45*	3.57	*0.38*	2.02	*0.36*	2.02	*0.36*
Sweden	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.44	*0.21*	1.50	*0.53*	5553.20	*1323.10*	27.97	*9.91*	4.45	*0.32*	5.04	*0.39*
UK	0.04	*0.20*	0.00	*0.00*	0.04	*0.20*	0.31	*0.09*	1.57	*0.13*	4225.74	*834.24*	13.34	*8.01*	3.32	*0.44*	4.73	*0.43*
USA	0.07	*0.26*	0.04	*0.19*	0.04	*0.19*	0.27	*0.01*	7.25	*1.57*	3500.22	*1029.84*	35.53	*3.49*	1.08	*0.21*		
Total	0.07	*0.25*	0.05	*0.22*	0.06	*0.24*	0.33	*0.08*	2.37	*2.09*	2803.74	*1403.19*	15.88	*20.79*	3.15	*1.36*	3.63	*1.35*

The table reports mean and standard deviation of variables used in the robustness checks, overall and by country.

See Table 2 for the definition of Amnesty 3 - Amnesty 4. Mismatch index (median) is the proportion of workers with a number of yers of schooling at least one standard deviation above or below the median years of schooling in their occupation, measured at the sub-major occupation group level (ISCO88 2-digit or equivalent). Homicides per 100k individuals is the ratio of police-reported intentional homicides (from UN-CTS) to the country population, expressed in hundreds of thousands. Thefts per 100k individuals is the ratio of police-reported thefts (from UN-CTS) to the country population, expressed in hundreds of thousands. Rapes per 100k individuals is the ratio of police-reported rapes (from UN-CTS) to the country population, expressed in hundreds of thousands. Public spending unemployment and family as a % of GDP is the public expenditure on unemployment and family benefits as a share of GDP, from the OECD Social Expenditure Database. Public spending unemployment, family and housing as a % of GDP is the public expenditure on unemployment, family and housing benefits as a share of GDP, from the OECD Social Expenditure Database.