CESifo Working Papers
www.cesifo.org/wp

What Drives Immigration Amnesties?

Alessandra Casarico
Giovanni Facchini
Tommaso Frattini

CESIFO WORKING PAPER NO. 3981
CATEGORY 1: PUBLIC FINANCE
OCTOBER 2012

Presented at CESifo Area Conference on Public Sector Economics, April 2012

CESifo *Working Paper No. 3981*

What Drives Immigration Amnesties?

Abstract

We develop a general model of legal and illegal immigration to understand the basic tradeoffs faced by a government in the decision to implement an immigration amnesty in the presence of a selective immigration policy. We show that two channels play an important role: an amnesty is more likely the more restricted are the occupational opportunities of undocumented immigrants and the less redistributive is the welfare state. Empirical evidence based on a novel panel dataset of legalizations 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-Code: F220, J610.

Keywords: illegal immigration, amnesties, labor market mismatch, welfare state.

Alessandra Casarico
Bocconi University
Milan / Italy
alessandra.casarico@unibocconi.it

Giovanni Facchini
University of Nottingham
Nottingham / UK
Giovanni.Facchini@nottingham.ac.uk

Tommaso Frattini
Università degli Studi di Milano
Milan / Italy
tommaso.frattini@unimi.it

October 1, 2012
This paper is a revised version of the manuscript circulated as “Spending more is spending less: Policy dilemmas on illegal immigration” and has been 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.” Cecilia Caliandro and Mauro Testaverde provided excellent research assistance in the construction of the dataset on amnesties and in working on several Labour Force Survey datasets. We are also indebted to many people who helped us navigating through the institutional features of different labor markets, including Suzanne Bijkerk, Sara de la Rica, Lidia Farré, Libertad Gonzalez, Sauro Mocetti, Mariola Pytlikova, Max Steinhardt. We wish to thank for their comments and suggestions Peter Egger, Francesco Fasani, Tim Hatton, Eivind Hoffmann, Fabio Mariani, Karin Mayr, Luca Nunziata, Assaf Razin, Ioana Schiopu, Cecilia Testa and seminar participants at the NORFACE Migration conference in London, the CEPR Conference on the Economics and Politics of migration in Turin, the CES–Ifo Area Conference on Public Sector Economics, the Fafo–Frisch Center conference on “Moving for Work” in Oslo, the CHOICES Workshop in Den Haag, the ESPE Conference in Bern, the Fifth Migration and Development Conference in Paris and the workshop on “Legal, illegal and criminal migration” at Collegio Carlo Alberto. All remaining errors are ours.

1 Introduction

Growing migration pressures in the presence of restrictive immigration policies have made illegal immigration widespread, and most rich destination countries harbor today large populations of undocumented foreigners.[1] Yet, there is substantial heterogeneity in terms of both the stocks of illegal migrants, and the policies which are adopted to handle illegal immigrants once they are in the country. Table 1, based on Dustmann and Frattini (2011) and our own calculations, provides information on a group of destination countries.[2]

The best available estimates suggest that in 2008, 3.5% of the total population in the United States was made up by irregular migrants. In Europe the figures are on average much lower, but there is substantial variation across countries. The phenomenon is virtually absent in Denmark or Sweden, very small in countries like Austria and Germany, while it is instead sizeable in Greece, Belgium, Portugal and the United Kingdom. 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 led to over three million legalizations (Kossoudji and Cobb–Clark 2002), 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 in the decision to implement an immigration amnesty and how this choice interacts with the setting of the regular migration policy framework. When does a policy maker find it optimal to resort to the introduction of an amnesty? How does the availability of this policy tool affect the restrictiveness of the policy towards legal immigrants?

To address these questions, we consider a two-period setting in which heterogeneous domestic firms and foreign workers are randomly matched, generating an output which is shared between natives and immigrants. A formal and an informal sector coexist in the economy, and differ in their skill intensity. In the first period, the destination country's government sets its official migration policy involving the determination of a minimum skill requirement, which cannot be

[1] Throughout the paper we will use "irregular", "illegal" and "undocumented" immigrants as synonyms.

[2] See also Fasani (2009) for estimates of the stocks and flows of illegal immigrants.

perfectly enforced. A one-off immigration flow then occurs, and foreign workers enter the domestic labor market. Those whose skill level falls below the official threshold are illegal and can only find gainful employment in the informal sector, whereas legal migrants can be employed by all firms. The host country has a redistributive welfare system in place, which is financed through proportional taxation levied on the formal sector. All natives and legal migrants are entitled to the lump-sum transfer paid out by the system, whereas illegal immigrants are excluded from it. At the beginning of the second period a shock might take place affecting the distribution of expected output between natives and migrants in the formal sector. Having observed the realization of the shock, the government can then decide whether to carry out an amnesty or not. Such a program will legalize all illegal foreigners, granting them access to the full set of labor market opportunities and to the welfare state benefits.

We show that an amnesty is more desirable the bigger is the gain to aggregate income induced by granting legalized workers access to all the available employment opportunities. On the contrary, a more redistributive welfare state makes an amnesty less desirable, as low-skilled legalized foreign workers will gain access to benefits. We also find that the introduction of a legalization program can only be optimal if there is a positive shock affecting the income received by the natives. In this case, the legalization allows the government to mitigate the adverse effects of an excessively restrictive policy implemented in the first period.

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 approval 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 the output gains from granting migrants access to the full set of labor market opportunities 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 instead captured by public social expenditure. Furthermore, we include a set of additional drivers that might influence the introduction of a legalization program. In particular, we control for the incidence of crime, 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 and the welfare state channels in shaping the probability of an amnesty. This result is robust to the use of alternative definitions of both dependent and control variables and to the implementation of different estimation methodologies.

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 all immigrants are ex–ante undocumented. They can become legal only as a result of an amnesty. In our model, besides considering heterogeneous workers and firms, we endogenize the migration policy choice. The latter defines a minimum skill requirement for legal immigrants and as a result, illegal immigrants are defined as those individuals whose skill level falls below the critical threshold chosen by the government.[3]

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. In particular, they emphasize that a legalization will offer skilled workers better labor market opportunities. 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 considered 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, migrants earn the same wages irrespective of their status. Empirical evidence has instead pointed out that the wages 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 characterizes the optimal policy. Section 4 describes the data we have used and section 5 develops our empirical analysis, while section 6 assesses the robustness of our results. Section 7 concludes the paper.

2 The model

To analyze the optimal choice of migration policy, we develop a two–period model. For simplicity, we assume that agents do not discount the future. In each of the two periods, there are $\mathscr{I}$ potentially active firms in the host country, each one of them indexed by i, with i distributed

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

according to the density function $n(i)$ on the interval $[0, 1]$. Firms can be ranked according to their skill intensity and a higher value of 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 $\mathscr{I} \geq N$. We model the existence of two sectors. Firms with skill intensity above a given threshold $\tilde{i}$ represent the "formal" economy, whereas firms with skill intensity below $\tilde{i}$ constitute the "informal" economy.

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 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.[4] 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 for worker j is maximized if he occupies a vacancy offered by a firm of type j. At the same time, the value of the match is zero if a migrant of skill level j ends up in a job i for which he is under–qualified (i.e. $j < i$). 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 that could be achieved if $i = j$. Since individual ability increases with j, it is reasonable to assume that $v(j)$ increases with j.[5] The probability that individual j is matched to vacancy i is described by the joint density function $f(i, j)$.

In the first period the government of the destination country sets its migration policy which involves the determination of a minimum skill requirement j^*: all foreign workers whose skill level is above this threshold will enter as legals.[6] Implementing migration policy is however costly, and we assume that the host country government cannot perfectly enforce its minimum skill requirement. This could happen because the enforcement technology is very demanding and sealing the borders is prohibitively expensive; alternatively, it could be the result of a fiscal consolidation in the destination country, which makes a government's budget constraint particularly tight.[7] The result

[4] See Petrongolo and Pissarides (2001) for a survey of the labor market matching literature.

[5] Notice though that our assumptions on $v(i, j)$ do not rule out the possibility that the value created by a highly skilled individual, if he is matched to a low–skill job, could be higher than the value created by a low skilled individual for whom that job represents the ideal match. Formally, this means that $v(j, j+1) \gtreqless v(j, j)$.

[6] As it will become clear later in the paper, this modeling choice will enable us to distinguish legal and illegal migrants based on their skill level. Alternatively, we could have described the migration policy as involving a quota determining the number of legal migrants. In this case, illegal and legal migrants would share on average the same skill level, but existing empirical evidence suggests instead that on average illegal immigrants tend to be less skilled than legal ones.

[7] 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 senators Reid, Durbin, Schumer, Feinstein, Leahy, and Menendez (2010).

is that illegal immigration will emerge.[8] The number of legal migrants, i.e. those whose skill level is above the threshold j to be set by the government, is given by $M(j,1) = \int_j^1 m(j)dj$, whereas the number of illegal immigrants is given by $M(\bar{j}, j) = \int_{\bar{j}}^{j} m(j)dj$, where $\bar{j}_{ill}$ is the exogenously given minimum skill level of an illegal immigrant. In each period, if legal migrants are employed in the formal sector, they generate a total expected income denoted by

$$V(j,1;\tilde{i},1) = \int_j^1 \int_{\tilde{i}}^1 v(i,j)f(i,j)didj \tag{1}$$

whereas if they end up in the informal sector, they generate a total expected income given by

$$V(j,1;0,\tilde{i}) = \int_j^1 \int_0^{\tilde{i}} v(i,j)f(i,j)didj. \tag{2}$$

Illegal migrants can work only in the informal sector and generate in each period an expected income given by

$$V(\bar{j}_{ill}, j; 0, \tilde{i}) = \int_{\bar{j}_{ill}}^{j} \int_0^{\tilde{i}} v(i,j)f(i,j)didj \tag{3}$$

Our assumption that immigration policy is always binding results in $\bar{j}_{ill} < j^*$, i.e. illegal immigration always takes place. Moreover, to make the problem interesting, we impose that $\bar{j}_{ill} < \tilde{i} < j^*$, i.e that at least some illegal migrants are sufficiently skilled that in the absence of restrictions to their employment opportunities, they could have been employed in the formal sector. The relationship between the legal status of the migrants and their sector of employment is illustrated in figure 1. Notice that in our model, by being constrained to the informal sector, illegal migrants have fewer opportunities to be employed and to generate a positive level of output than if they were legal. For instance, while a legal foreign national holding a high school degree could find employment as a bank teller or as a public employee, a similarly educated illegal migrant could not be gainfully employed in such jobs. More generally, the illegal status prevents the emergence of some labor market matches that could be economically viable.

In the destination country there is a redistributive welfare state, characterized by an exogenously given proportional income tax τ and a lump-sum transfer b, which adjusts in order to keep the budget balanced.[9] All natives and legal immigrants in the formal sector contribute to the welfare system, whereas both natives and migrants active in the informal sector do not.[10] All natives

[8]Note that, for simplicity, we do not explicitly model the emigration decision, and we assume that the destination country's policy is always binding, i.e. there are always more migrants willing to enter than those the destination country is willing to accept as legals.

[9]Our theoretical analysis focuses on intra–generational redistribution, even though inter–generational considerations are important. We will account for these in our empirical implementation.

[10]This assumption captures the stylized fact that in many destination countries the informal sector is characterized by widespread tax evasion.

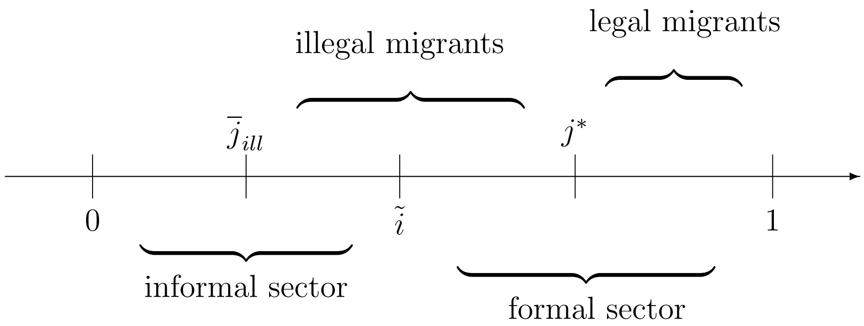

Figure 1: The distribution of migrants and firms

and legal migrants are entitled to receive the welfare state benefits, whereas illegal migrants are not.[11] The government's budget is thus given by

$$\tau V(j, 1; \tilde{i}, 1) = b\,[N + M(j, 1)] \tag{4}$$

Equation 4 reflects our assumption that the government's enforcement activities are underfunded, and in particular we have normalized the resources devoted to the implementation of migration policy to zero.

To capture the existence of a fiscal leakage from the natives to the legal immigrants,[12] we assume that the average taxable income of the natives is higher than the average taxable income of the immigrants. 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. The average taxable income of the natives is then given by

$$Y^N = \alpha \frac{V(j^*, 1; \tilde{i}, 1)}{N} \tag{5}$$

whereas the average taxable income of the legal immigrants is

$$Y^M = (1-\alpha)\frac{V(j^*, 1; \tilde{i}, 1)}{M(j^*, 1)} \tag{6}$$

where j^* is the minimum skill requirement for legal migrants which will be determined in the model. The condition for the presence of a fiscal leakage can then be rewritten as

$$\frac{\alpha}{1-\alpha} > \frac{N}{M(j^*, 1)} \tag{7}$$

[11] Of course these are simplifying assumptions, but they capture the stylized fact that legal and illegal migrants differ in their net position towards the welfare state. See Camarota (2004).

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

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

In the second period immigration no longer occurs and the economy might be hit by a shock affecting the distribution of output produced in the formal sector between firms' owners and employees. Following the realization of the shock, the government will decide whether to introduce an amnesty program to legalize undocumented migrants.[13] For simplicity we consider only two states of the world, $k \in \{H, L\}$. With probability p the natives' share of domestic output produced in the formal sector increases to $\alpha_H > \alpha$, whereas with probability $(1-p)$ it is unchanged, i.e. $\alpha_L = \alpha$. The distribution of output in the informal sector is instead not affected. Importantly, as we will show in the next section, the presence of this shock might make the minimum skill threshold fixed in the first period suboptimal.

3 The setting of migration policy

In this section we characterize the optimal migration policy from the point of view of the destination country's government. To fix ideas, we start by analyzing a benchmark scenario in which there is no uncertainty. In other words, the government knows for sure whether the shock will occur or not when setting the minimum skill threshold in the first period. We then consider a scenario with uncertainty, in which the government relies on expectations on the realization of the shock when setting the minimum skill requirement ex–ante, and investigate whether it is desirable to carry out a legalization ex–post.

3.1 No uncertainty

In deciding the optimal policy we assume that the government maximizes the natives' aggregate welfare over the two periods, which in our model is simply aggregate income, subject to its budget constraint.[14] If there is no uncertainty, the objective function of the government is given by

$$\begin{aligned} W_k &= \alpha(1-\tau)V(j,1;\tilde{i},1) + \alpha V(j,1;0,\tilde{i}) + \alpha V(\bar{j}_{ill},j;0,\tilde{i}) + bN + \\ &+ \alpha_k(1-\tau)V(j,1;\tilde{i},1) + \alpha V(j,1;0,\tilde{i}) + \alpha V(\bar{j}_{ill},j;0,\tilde{i}) + bN \end{aligned} \tag{8}$$

[13]Introducing uncertainty on the share of output between natives and migrants is analytically convenient, and can be rationalized for instance by an increase in the bargaining power of the natives induced by a policy change in a foreign market which opens up new investment opportunities. Alternatively, it could be the result of the unexpected availability of new technologies that increase the bargaining power of domestic firms' owners.

[14]For simplicity, we assume no discounting also for the government. Furthermore, 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).

where $k \in \{H, L\}$. The first and second line denote respectively the first and second period welfare. The first term on the right hand side of the equation represents the expected net income appropriated by the natives from activities carried out in the formal sector. The second and third terms respectively capture the share of expected income generated by the employment of legal and illegal migrants in the informal sector, which is appropriated by the natives and escapes taxation. The last term captures the lump-sum benefit received by natives through the welfare state. The only difference between the first and the second period is given by the possible presence of a shock on the share of output received by the natives in the formal sector.

Equation 8 can be rewritten as

$$W_k = (\alpha + \alpha_k)(1 - \tau)V(j, 1; \tilde{i}, 1) + 2\alpha V(\overline{j}_{ill}, 1; 0, \tilde{i}) + 2bN. \tag{9}$$

Maximizing equation 9 subject to the constraint given by equation 4[15] results in the following first order condition which implicitly defines j_k^*, i.e. the optimal skill requirement under certainty over the state of the world k:

$$B_k[., j_k^*(.)] = \frac{\partial V(j_k^*, 1; \tilde{i}, 1)}{\partial j}\left[(\alpha + \alpha_k)(1 - \tau) + \frac{2\tau N}{N + M(j_k^*, 1)}\right] - \frac{2\tau N V(j_k^*, 1; \tilde{i}, 1)}{[N + M(j_k^*, 1)]^2}\frac{\partial M(j_k^*, 1)}{\partial j} = 0. \tag{10}$$

We can now state our first result:

Lemma 1 *In the absence of uncertainty, an increase in the share of output accruing to the natives leads to a higher number of legal migrants admitted by the government.*

Proof. To establish this result, we need to compare j_L^* and j_H^*. To do so, we start by considering the first order condition in equation 10 when $\alpha_k = \alpha_L = \alpha$. We compute then the first order condition with $\alpha_k = \alpha_H$ and evaluate it at $\alpha_k = \alpha_L = \alpha$. We can immediately show that $B_H[., j_H^*(.)] \mid_{j=j_L^*} < 0$. The concavity of the government's objective function implies then that $j_L^* \geq j_H^*$. ■

3.2 Uncertainty

Let us now turn to the more realistic situation in which the government formulates its policy in the first period, without knowing which state of the world will materialize in the second. Once the uncertainty is resolved, the government may want to adjust its policy and a legalization is the tool which can be employed to this end. If an amnesty is introduced, it involves all illegal immigrants present in the country, and will have the following effects. First, legalized migrants will have access

[15]Notice that the government budget does not directly depend upon the particular realization of the state of the world, as the sharing rule does not affect the tax base.

to the full set of occupations, i.e. those in the formal and those in the informal sector. At the same time, they will receive benefits from the welfare state, while they will contribute to it only if they work in the formal sector. In other words, legalized migrants share the same rights and obligations with the natives.

In order to determine the optimal skill threshold j^* in the first period we proceed backwards, starting from the second period when the uncertainty is resolved. Assume that the true state of the world is k. The second period welfare of the destination country is denoted by w_k^z, with $z \in \{\text{A, NA}\}$, where A stands for amnesty and NA for the lack of it. If no legalization is implemented we have

$$w_k^{NA}(j^*) = \alpha_k(1-\tau)V(j^*, 1; \tilde{i}, 1) + \alpha V(\bar{j}_{ill}, 1; 0, \tilde{i}) + b^{NA}N \tag{11}$$

with b^{NA} determined from equation 4 evaluated at $j = j^*$. Thus, the second period welfare depends on the net income accruing to the natives from the employment of migrants in the formal sector (first term on the right hand side), in the informal sector (second term) and on the lump-sum transfer the natives receive from the government (third term). If an amnesty is introduced we have instead

$$w_k^{A} = \alpha_k(1-\tau)V(\bar{j}_{ill}, 1; \tilde{i}, 1) + \alpha V(\bar{j}_{ill}, 1; 0, \tilde{i}) + b^{A}N \tag{12}$$

with

$$b^A = \frac{\tau V(\bar{j}_{ill}, 1; \tilde{i}, 1)}{N + M(\bar{j}_{ill}, 1)}. \tag{13}$$

Note that when a legalization is implemented (see equation 12) all migrants present in the country can be employed in the formal sector. Moreover $b^A < b^{NA}$ because all immigrants working in the formal sector are fully engaged in the welfare state and their taxable income is on average lower than that of natives.[16] Subtracting equation 11 from equation 12 we obtain the following expression, which captures the incentives faced by the government to implement or not an amnesty:

$$w_k^A - w_k^{NA}(j^*) = \alpha_k V(\bar{j}_{ill}, j^*; \tilde{i}, 1) + N(b^A - b^{NA}) - \alpha_k \tau V(\bar{j}_{ill}, j^*; \tilde{i}, 1). \tag{14}$$

Equation 14 allows us to highlight the two important drivers of a legalization. The first is the labor market matching channel: the bigger is the gain to aggregate income induced by the fact that legalized workers can have access to a broader range of occupations, 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) which indicates

[16] To simplify the notation, in the remainder of this section we will simply refer to w_k^{NA}, without explicit reference to its dependence on j^*.

Payoffs	Optimal Action
$w_k^A - w_k^{NA} > 0$ for all k	Always Amnesty (AA)
$w_H^A - w_H^{NA} > 0$ and $w_L^A - w_L^{NA} < 0$	Amnesty only if state of the world is high (AH)
$w_k^A - w_k^{NA} < 0$ for all k	Never Amnesty (AN)

Table 1: Second period payoffs and actions

instead that a legalization is not desirable. Notice also that

$$\frac{\partial[w_k^A - w_k^{NA}]}{\partial\tau} = -N\left[\frac{V(j^*,1;\tilde{i},1)}{N+M(j^*,1)} - \frac{V(\bar{j}_{ill},1;\tilde{i},1)}{N+M(\bar{j}_{ill},1)}\right] - \alpha_k V(\bar{j}_{ill},j^*;\tilde{i},1) < 0. \tag{15}$$

In other words, a more redistributive welfare state will make an amnesty less desirable, as it increases the welfare leakage to the migrants.

The following result will be useful in the remainder of the analysis.

Lemma 2 *The change in second period welfare induced by a legalization is larger in the high than in the low state of the world. In other words, $w_H^A - w_H^{NA} > w_L^A - w_L^{NA}$.*

Proof. Using equation 14, it follows immediately that

$$w_H^A - w_H^{NA} - (w_L^A - w_L^{NA}) = (\alpha_H - \alpha)(1-\tau)V(\bar{j}_{ill},j^*;\tilde{i},1) > 0. \tag{16}$$

■

In the second period the government faces the following alternatives. It could decide to legalize always, no matter what the state of the world is. This would occur if $w_k^A - w_k^{NA} > 0$ for any k. Alternatively, it could decide never to introduce an amnesty. This would occur if $w_k^A - w_k^{NA} < 0$ for any k. Finally, it could decide to legalize in one state of the world, but not in the other. From lemma 2 we know that it will never be optimal to legalize in the low state of the world, but not in the high one. We can thus rule out this possibility from our subsequent analysis, and focus only on the case in which it is optimal to legalize in the high state of the world, and not in the low one, i.e. $w_H^A - w_H^{NA} > 0$ and $w_L^A - w_L^{NA} < 0$. The three possible relevant scenarios are illustrated in Table 1.

Taking into account the second period optimal actions, we can move to the first period and solve for the equilibrium policy. Remembering that in the first period the policy maker is uncertain about the future realization of the shock, the objective function of the government under the

"Always Amnesty" scenario (the AA case in Table 1) is given by:

$$\begin{aligned} W_{AA} &= \alpha(1-\tau)V(j,1;\tilde{i},1)+\alpha V(\overline{j}_{ill},1;0,\tilde{i})+bN+ \\ &+ p\left[\alpha_H(1-\tau)V(\overline{j}_{ill},1;\tilde{i},1)+\alpha V(\overline{j}_{ill},1;0,\tilde{i})+b^A N\right]+ \\ &+ (1-p)\left[\alpha(1-\tau)V(\overline{j}_{ill},1;\tilde{i},1)+\alpha V(\overline{j}_{ill},1;0,\tilde{i})+b^A N\right]. \end{aligned} \tag{17}$$

The first line represents the first period welfare, while the second and third lines describe the expected second period welfare if the government implements an amnesty respectively in the high and low states of the world. It follows immediately that

Proposition 1 *The minimum skill requirement chosen by the government in the first period is* $j^*_{AA}=j^*_L$. *As a result, in the second period it is never optimal to introduce an amnesty if the state of the world is low.*

Proof. We start by calculating the first order condition resulting from the maximization of equation 17 subject to the budget constraints given by equations 4 and 13. We find

$$B_{AA}[.,j^*_{AA}(.)]=\frac{\partial V(j^*_{AA},1;\tilde{i},1)}{\partial j}\left[\alpha(1-\tau)+\frac{\tau N}{N+M(j^*_{AA},1)}\right]-\frac{\tau N V(j^*_{AA},1;\tilde{i},1)}{[N+M(j^*_{AA},1)]^2}\frac{\partial M(j^*_{AA},1)}{\partial j}=0 \tag{18}$$

which implicitly defines j^*_{AA}, i.e. the optimal minimum skill requirement set in the first period under the assumption that is always optimal to grant an amnesty in the second, irrespective of the state of the world. Notice that equation 18 is identical to equation 10 evaluated at $k=L$. Therefore $j^*_{AA}=j^*_L$, i.e. the optimal immigration policy threshold determined in this scenario is identical to the first best solution obtained under no uncertainty, if no shock occurs. So, if ex–post the government finds out that the share of output accruing to the natives in the formal sector is equal to α, it will never find it optimal to legalize foreign immigrants. This is because it did not admit more of them legally in the first best. ∎

Note that Proposition 1 shows that always implementing an amnesty in the second period can never be part of an equilibrium. We therefore turn to consider a scenario in which in the second period a legalization might be optimal only if the shock occurs (AH in Table 1). The government's objective function in this case is given by:

$$\begin{aligned} W_{AH} &= \alpha(1-\tau)V(j,1;\tilde{i},1)+\alpha V(\overline{j}_{ill},1;0,\tilde{i})+bN+ \\ &+ p\left[\alpha_H(1-\tau)V(\overline{j}_{ill},1;\tilde{i},1)+\alpha V(\overline{j}_{ill},1;0,\tilde{i})+b^A N\right]+ \\ &+ (1-p)\left[\alpha(1-\tau)V(j,1;\tilde{i},1)+\alpha V(\overline{j}_{ill},1;0,\tilde{i})+bN\right] \end{aligned} \tag{19}$$

where the second and third lines describe the expected second period welfare if the government implements an amnesty only in the high state of the world. We can now establish the following result:

Proposition 2 *The minimum skill requirement chosen by the government in the first period is* $j^*_{AH} = j^*_L$*. Furthermore, given that* $w^A_H - w^{NA}_H(j^*_L) > 0$*, an amnesty will be implemented in the second period if there is a positive shock to the share of output accruing to the natives in the formal sector.*

Proof. The maximization of equation 19 subject to the budget constraints given by equations 4 and 13 requires

$$B_{AH}[., j^*_{AH}(.)] = \frac{\partial V(j^*_{AH}, 1; \tilde{i}, 1)}{\partial j}\left[\alpha(1-\tau) + \frac{\tau N}{N + M(j^*_{AH}, 1)}\right] - \frac{\tau N V(j^*_{AH}, 1; \tilde{i}, 1)}{[N + M(j^*_{AH}, 1)]^2}\frac{\partial M(j^*_{AH}, 1)}{\partial j} = 0 \tag{20}$$

which implicitly defines j^*_{AH}, i.e. the optimal minimum skill requirement set in the first period under the assumption that it is optimal to grant an amnesty only if the state of the world is high. It is straightforward to notice that the first order condition for the maximization of equation 19 is identical to that described in equation 10 evaluated at $k = L$, from which it follows that the optimal minimum skill threshold in this scenario is still given by $j^*_{AH} = j^*_L$. Remember that if the true state of world is H and there is no uncertainty over it, the government choose $j^*_H < j^*_L$. Since the government under uncertainty admits a lower number of legal migrants than it would in the presence of a positive shock known in advance, a legalization gives the policy maker the opportunity to increase their number, easing the excessive restrictiveness of the original policy. ■

Last, we consider the case in which it might never be optimal for the government to carry out a legalization (AN in Table 1). In this scenario, the objective function of the government is given by:

$$\begin{aligned} W_{AN} &= \alpha(1-\tau)V(j, 1; \tilde{i}, 1) + \alpha V(\bar{j}_{ill}, 1; 0, \tilde{i}) + bN + \\ &+ p\left[\alpha_H(1-\tau)V(j, 1; \tilde{i}, 1) + \alpha V(\bar{j}_{ill}, 1; 0, \tilde{i}) + bN\right] + \\ &+ (1-p)\left[\alpha(1-\tau)V(j, 1; \tilde{i}, 1) + \alpha V(\bar{j}_{ill}, 1; 0, \tilde{i}) + bN\right]. \end{aligned} \tag{21}$$

where the second and third lines describe the expected second period welfare if the government does not implement an amnesty in either state of the world. The first order condition for the maximization of equation 21 subject to 4 is given by

$$\begin{aligned} B_{AN}[., j^*_{AN}(.)] &= \frac{\partial V(j^*_{AN}, 1; \tilde{i}, 1)}{\partial j}\left\{[\alpha + p\alpha_H + (1-p)\alpha](1-\tau) + \frac{2\tau N}{N + M(j^*_{AN}, 1)}\right\} + \\ &- \frac{2\tau N V(j^*_{AN}, 1; \tilde{i}, 1)}{[N + M(j^*_{AN}, 1)]^2}\frac{\partial M(j^*_{AN}, 1)}{\partial j} = 0 \end{aligned} \tag{22}$$

which implicitly determines the optimal policy j^*_{AN}, i.e. the minimum skill requirement set in the first period when it is never optimal to grant an amnesty in the second period. We can show that

Proposition 3 *The minimum skill requirement chosen by the government in the first period is* $j^*_{AN} \in (j^*_H, j^*_L)$. *Given that* $w^A_H - w^{NA}_H(j^*_{AN}) < 0$, *a legalization does not take place.*

Proof. To establish this result, we need to compare the first order condition given by equation 22 with the first order condition given by equation 10, evaluated respectively at $k = H$ and $k = L$. Given the concavity of the government's objective function, the conclusion follows immediately. ■

Proposition 3 highlights that if the government never finds it optimal to carry out a legalization ex-post, it chooses a minimum skill requirement in the first period that is intermediate between those selected in the absence of uncertainty. Since the policy maker under incomplete information knows that an amnesty is not optimal ex-post, it will try to undo the effects of the uncertainty by choosing an average of the optimal state-contingent measures.

Summarizing, our theoretical model has shown that the introduction of a legalization program can only be optimal if there is a positive shock affecting the share of income received by the natives. Such a measure might be introduced as it allows the government to mitigate the adverse effects of an excessively restrictive policy implemented in the first period. Furthermore, we have also established that a legalization is more likely to occur the bigger is the gain to aggregate income brought about by granting legalized workers access to all the available employment opportunities. On the contrary, a more redistributive welfare state makes an amnesty less desirable, as it entitles lower–skilled legalized foreign workers to benefits. In the remainder of the paper, we investigate the empirical relevance of these channels in explaining the likelihood of the introduction of a legalization program.

4 Data

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

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

4.1 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 legal residence and a 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: for example, a minimum period of residence in the country of destination and/or having a job are typical requirements.

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[18] (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 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 the 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 the robustness checks, 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 an amnesty has been approved.[19] We provide a detailed description of the amnesties included in our study in table A1.

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

[19] We have chosen the approval date as the criterion to assign an amnesty to a given year as this is consistent with the framework of our model. Notice though that the year of approval of the legalization measure does not necessarily coincide with the period covered by the amnesty.

4.2 The labor market channel

Our model highlights the role played by the illegal status on the set of labor market matches that are available to migrants. Ceteris paribus, the larger is the group of individuals whose labor market opportunities are restricted because of their illegal status,[20] the larger will be the expected output gain associated to the legalization. Ideally, we would like to be able to construct a measure of the quality of the match for illegal migrants. Unfortunately, standard sources cover only small samples of immigrants. Furthermore, no information is available on their legal status and, as a result, we will need to rely on a proxy.

We build an index measuring the quality of the match between workers' qualifications and their occupations. To this 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 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).[21] We check the robustness of our results to the choice of the median as an alternative measure.

[20] More precisely, these are individuals with a skill level j such that $\tilde{i} < j < j^*$.

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

4.3 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).

4.4 Additional controls

In all our regressions we include a number of additional variables that might be correlated with the probability of having an amnesty. First, as illegal immigrants are often perceived to be involved in criminal activities, ideally we would like to control for the incidence of crime among them. Unfortunately, this information is not consistently available for most of the countries and years included in our study. As a result we limit ourselves to broad measures of criminal activities, which do not allow a breakdown based on the nationality and legal status of the offender. 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),[22] 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).[23] As an indicator of the incidence of crime we use the number of robberies per one hundred thousand individuals.[24]

Second, 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 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

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

[23] 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).

[24] This is the type of crime for which we have the most complete data. We have also checked the robustness of our results using alternative measures such as data on intentional homicides, thefts and rapes reported to the authorities. The results are available upon request and do not affect our findings.

tends to identify asylum seekers with illegal immigrants (see Hatton 2011).[25] 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 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. 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)[26] 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.

5 Empirical analysis

Our model has identified two channels that play a role in shaping the decision to introduce an amnesty. Our predictions are that the larger is the group of individuals whose labor market opportunities are restricted because of their illegal status, the larger will be the expected output gain associated to the legalization and the more likely is therefore its implementation. 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.

As we have already mentioned, we cannot directly measure the increase in output induced by the legalization. Since this depends on the size of the group whose labor market opportunities are restricted, we proxy the dimension of this group with our mismatch index. In particular, a higher value of the mismatch index suggests a worse allocation of skills across occupations and therefore the possibility of larger output gains which make a legalization more likely to be implemented. We estimate the following empirical model:

$$A_{ct} = \beta \text{mis}_{ct} + \gamma \text{welfare}_{ct} + \mathbf{X}_{ct}\theta + D_t + D_c + u_{ct} \tag{23}$$

where A_{ct} is a dummy variable indicating whether country c has approved an amnesty in year t, mis_{ct} is the labor market mismatch index described in section 4.2, $welfare_{ct}$ is the measure of the

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

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

size of the welfare state described in section 4.3, $\mathbf{X}_{ct}$ is a vector of control variables which includes our measure of the crime rate, the number of asylum applications, per capita GDP growth, the old-age dependency ratio, a dummy for the government's political orientation, as described in section 4.4, indicator variables denoting the UN–CTS wave from which the crime data have been obtained and in some specifications a dummy variable indicating whether the mismatch index is computed using EULFS data. Finally, D_t and D_c are respectively year and country indicators to account for unobserved time and country–specific effects. 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 4.1). We standardize all the continuous variables by the within-country standard deviation. Each coefficient can thus be interpreted as the percentage point 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 specification that includes only the mismatch index based on deviations from the mode and the controls. 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 consistent with the idea that amnesties are more likely the larger the output gains from giving migrants access to the full set of jobs. 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.[27] 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 indicating whether our mismatch index has been constructed using the EULFS or national labor force surveys, and we retain it in 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

[27] One might be concerned that granting an amnesty is likely to reduce the extent of mismatch in the labor market, and thus that reverse causality might bias our results. The way we have constructed our amnesty indicator as capturing the year of approval of the measure rather than the period over which it has actually been in place, alleviates this concern. More importantly, even in the presence of a reverse causality bias, our estimated coefficient would still represent a lower bound for the true effect of the labor market mismatch on the probability of a legalization.

legalization by 2.3 percentage points, without affecting the sign and significance of the coefficient of the labor market mismatch index and of the other controls.

6 Robustness Checks

In this section we perform a series of robustness checks involving both the definition of our dependent and explanatory variables and the econometric methodology we have implemented in our main analysis.

To carry out the former, we use the specification in column (3) of Table 3 as our benchmark. Most of our efforts have been devoted to the collection of a comprehensive dataset on general immigration amnesties. As we have mentioned in section 4.1, 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 A1 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 4.1. 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 and the welfare state 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 and our measure of the welfare state generosity. For comparison purposes, column (1) of Table 5 reports our benchmark specification, i.e. column (3) 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.

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 (3) 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, and the coefficient on the generosity of the welfare state ranging between -0.18 and -0.25.

Some of the countries in our sample have never implemented an immigration amnesty over the period we consider. 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.[28] We have also carried out a series of additional checks whose results are available upon request. First, following the 2004 EU Eastern enlargement, the EU 15 member states had the choice to restrict access by citizens of the new entrants to their labor market for a period up to seven years. Only three countries (Ireland, Sweden and the United Kingdom) immediately opened up their labor market, whereas the remaining ones granted access progressively over the subsequent years.[29] As this worked as a de–facto regularization for citizens of the new EU member states that were irregularly resident in EU 15 countries, we have augmented our baseline amnesty variables by including the year in which each country granted full access to its labor market. Second, to further explore the role of inter-generational redistribution in shaping the likelihood of an amnesty, we have replaced the old-age dependency ratio with the GDP share of public spending on old-age benefits. Third, as illegal migrants are primarily employed in the shadow economy, we have additionally included among our control variables estimates of the size of the shadow economy as a share of GDP, based on Feld and Schneider (2010). Finally, to account for different immigration dynamics across countries, we have also controlled for the stock of immigrants as a share of the total population in the receiving country. All of these exercises do not significantly affect the sign and significance of the labor market and welfare state channels.

Last, we have assessed the robustness of our main findings to the choice of a different econometric methodology. Rather than estimating a linear probability model, we have modeled the occurrence of amnesties using survival analysis. The advantage of using this approach is that we are able to account for the role played, in each year, by the time elapsed since the introduction of the most recent amnesty in determining the occurrence of a new one, something we cannot do using a simple linear probability model.

[28]It should also be noted that we have only six countries in the sample for *Amnesty 3*, and seven countries for *Amnesty 1*, and as a result the standard errors of our coefficients should be interpreted with caution. Stata corrects though for the small number of clusters by calculating the critical values using a t distribution with a number of degrees of freedom equal to the number of clusters minus one.

[29]In particular among the countries in our sample, Greece, Italy, Portugal and Spain opened up in 2006, and the Netherlands in 2007.

We fit multiple-spell proportional Cox hazard models to our data and we account for within-country correlation by clustering standard errors at the country level. In particular, we estimate the following specification:

$$h_c(t) = h_0(t)exp(\beta \text{mis}_{ct} + \gamma \text{welfare}_{ct} + \mathbf{X}_{ct}\theta + D_t + D_c) \tag{24}$$

In every year t the hazard function $h_c(t)$ gives the probability of an amnesty, provided that an amnesty has not been granted until that year. We assume that the baseline hazard rate $h_0(t)$ remains unchanged over time, except that time t is reset to zero after each amnesty. We display the results of our analysis in table 8, in which we report a series of specifications using alternative definitions of amnesty. In the table we show estimates of the exponentiated coefficients, so that all entries can be interpreted as hazard ratios: a value of one indicates that an increase of one standard deviation in the variable of interest does not significantly affect the hazard rate relative to the baseline, while values higher (lower) than one indicate that a one standard deviation increase in the variable significantly increases (decreases) the probability of an amnesty relative to the baseline. Our estimates suggest that a one standard deviation increase in the labor market mismatch index is associated with an increase in the hazard rate of between 10% (*Amnesty 2*) and 20% (*Amnesty 3*), while a one standard deviation increase in the welfare state generosity is associated with a 18% (*Amnesty 1*) to 25% (*Amnesty 4*) decrease in the hazard. This broadly confirms the results we have obtained with the linear probability model.

7 Conclusions

We develop a general model of legal and illegal immigration to understand the basic tradeoffs faced by a government in the decision to implement an immigration amnesty in the presence of a selective immigration policy.

We have shown that an amnesty is more desirable the bigger is the gain to aggregate income induced by granting legalized workers access to all the available employment opportunities. On the contrary, a more redistributive welfare state makes an amnesty less desirable, as it entitles lower–skilled legalized foreign workers to benefits. Finally, we have shown that a legalization is optimal only if it allows the government to mitigate the adverse welfare effects of an excessively restrictive policy implemented ex-ante.

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 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. An alternative would involve taking explicitly into account political economy forces that do play an important role in shaping immigration policy and its enforcement. Second, the decision to migrate is exogenous in our model. While we are interested in analyzing a world where the policy set by the destination country's government is binding and the number of potential immigrants is always larger than the one the destination country is willing to admit, a more comprehensive analysis of the dynamic implications of immigration amnesties would call for the endogenization of the migration decision.[30] 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*.

Dustmann, C. and T. Frattini (2011). Immigration: The European experience. Dp 326 Centro Studi Luca d'Agliano, Milan, Italy.

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

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

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.

Fasani, F. (2009). Deporting undocumented immigrants: The role of labor demand shocks. mimeo, University College London.

Feld, L. P. and F. Schneider (2010). Survey on the shadow economy and undeclared earnings in OECD countries. *German Economic Review 11*, 109–149.

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 amnesty 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.

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 Classification*: 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 occupations 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 *www3.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/* 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 in wave 3 but does report it in 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: Estimates of undocumented immigrants and number of amnesties

	As a % of total population		As a % of immigrant population		Amnesties (1980-2008)
	Min	Max	Min	Max	
Austria	0.22%	0.65%	2.20%	6.50%	1
Belgium*	0.82%	1.24%	9.40%	14.20%	0
Denmark*	0.02%	0.09%	0.30%	1.70%	0
France*	0.28%	0.63%	4.90%	11.00%	2
Germany	0.24%	0.56%	2.70%	6.30%	0
Greece	1.53%	1.86%	9.10%	19.20%	3
Ireland*	0.68%	1.41%	6.70%	13.80%	0
Italy	0.47%	0.77%	9.50%	15.70%	5
Netherlands*	0.38%	0.80%	9.10%	19.20%	0
Norway°	0.22%	0.68%	2.75%	8.39%	0
Portugal*	0.75%	0.94%	18.40%	23.00%	1
Spain	0.62%	0.78%	6.10%	7.70%	6
Sweden*	0.09%	0.13%	1.60%	2.40%	0
UK	0.68%	1.41%	11.40%	23.60%	0
EU 15*	0.46%	0.83%	6.60%	11.90%	
USA	3.50%		28.40%		2

The table reports minimum and maximum estimates of the size of the undocumented immigrant population for each country in 2008, expressed a share of the total country population or as a share of the total immigrant population. The last column reports the number of immigration amnesties approved by each country over the period 1980-2008.

* denotes low-quality estimates

° data refer to 1 January 2006, "Min" and "Max" represent the lower and upper bounds of a 95% confidence interval.

Source: our elaboration on Dustmann and Frattini (2011) for undocumented immigration in all countries except Norway; Norway: our elaboration on data in Zhang (2008) and on the OECD International Migration Database; SOPEMI (variuos years) for amnesties.

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
Denmark	1998	2007	0	0	0	0
France	1980	2007	1981, 1997	1980, 1981,1997	1981, 1997	1980, 1981,1997
Germany	1980	2007	0	0	0	0
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
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
Sweden	1998	2007	0	0	0	0
Switzerland	1991	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 is approved. 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
Mismatch index (mode)	0.025***	0.026***	0.028***
	(0.008)	(0.008)	(0.008)
Public spending on unemployment			-0.023***
			(0.008)
Robberies	-0.003	-0.001	0.003
	(0.010)	(0.011)	(0.011)
Asylum applications	-0.023**	-0.022**	-0.024**
	(0.010)	(0.009)	(0.009)
GDP per head growth rate	0.003	0.003	0.003
	(0.008)	(0.008)	(0.008)
Old-age dependency ratio	0.005	0.005	0.002
	(0.008)	(0.009)	(0.008)
Right-wing government	0.043	0.045	0.045
	(0.034)	(0.035)	(0.033)
EULFS	No	Yes	Yes
N	347	347	347
R-squared	0.127	0.127	0.135

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country approved an immigration amnesty in that year. All specifications include country fixed effects, year dummies and dummies indicating the UN-CTS wave from which crime data have been obtained. All continuous variables 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. 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**	0.033**
	(0.008)	(0.009)	(0.012)
Public spending on unemployment	-0.026**	-0.018**	-0.018*
	(0.011)	(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	0.009	0.004	0.011
	(0.012)	(0.008)	(0.013)
Old-age dependency ratio	-0.002	0.006	-0.001
	(0.012)	(0.007)	(0.012)
Right-wing government	0.061	0.052	0.06
	(0.049)	(0.031)	(0.046)
EULFS	Yes	Yes	Yes
N	347	347	347
R-squared	0.119	0.128	0.122

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country approved an immigration amnesty in that year. All specifications include country fixed effects, year dummies and dummies indicating the UN-CTS wave from which crime data have been obtained. All continuous variables 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. 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
Mismatch index (mode)	0.028***		0.026***	0.026***
	(0.008)		(0.008)	(0.007)
Mismatch index (median)		0.027**		
		(0.012)		
Public spending on unemployment	-0.023***	-0.021**		
	(0.008)	(0.008)		
Public spending on unemployment and family			-0.020**	
			(0.008)	
Public spending on unemployment, family and				-0.021**
				(0.010)
Robberies	0.003	0.005	0.001	0
	(0.011)	(0.010)	(0.010)	(0.013)
Asylum applications	-0.024**	-0.022**	-0.022**	-0.020*
	(0.009)	(0.009)	(0.009)	(0.009)
GDP per head growth rate	0.003	0.003	0.002	0.004
	(0.008)	(0.008)	(0.007)	(0.010)
Old-age dependency ratio	0.002	0.003	0.001	0.003
	(0.008)	(0.009)	(0.009)	(0.009)
Right-wing government	0.045	0.045	0.044	0.051
	(0.033)	(0.033)	(0.034)	(0.035)
EULFS	Yes	Yes	Yes	Yes
N	347	347	347	305
R-squared	0.135	0.135	0.134	0.141

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country approved an immigration amnesty in that year. Amnesty definition: Amnesty 1. All specifications include country fixed effects, year dummies and dummies indicating the UN-CTS wave from which crime data have been obtained. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. 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	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	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 on unemployment	-0.019**	-0.023**	-0.023**	-0.025***	-0.025**	-0.024***	-0.023**	-0.019**	-0.023**	-0.025***	-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)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Robberies	0.004	0.001	0.004	0.003	0.006	0.004	-0.007	0.003	0.006	0.005	0.002	0.005	0.008	0.004	0.004	0.003	0.002
	(0.013)	(0.011)	(0.013)	(0.012)	(0.012)	(0.012)	(0.008)	(0.009)	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)
Asylum applications	-0.027**	-0.024**	-0.026**	-0.026**	-0.026**	-0.024**	-0.022**	-0.018	-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)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
GDP per head growth rate	-0.002	0.002	0.002	0.003	0.005	0.003	0.004	0.005	0.005	0.003	0.001	0.002	0.005	-0.001	0.003	0.002	0.004
	(0.007)	(0.009)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
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	0.005	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)	(0.013)	(0.008)	(0.008)	(0.010)	(0.008)
Right-wing government	0.057*	0.045	0.05	0.045	0.047	0.046	0.04	0.016	0.04	0.046	0.031	0.045	0.058	0.049	0.045	0.053	0.053
	(0.032)	(0.033)	(0.035)	(0.034)	(0.037)	(0.034)	(0.038)	(0.025)	(0.032)	(0.033)	(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
N	320	325	319	330	319	337	322	319	337	339	320	330	319	337	337	323	319
R-squared	0.152	0.143	0.146	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 approved an immigration amnesty in that year. All specifications include country fixed effects, year dummies and dummies indicating the UN-CTS wave from which crime data have been obtained. All continuous variables 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. 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*	0.028*	0.034*	0.027
	(0.015)	(0.014)	(0.015)	(0.014)
Public spending on unemployment	-0.053***	-0.051***	-0.043***	-0.047**
	(0.010)	(0.009)	(0.009)	(0.015)
Robberies	0.033	0.023	0.035	0.028
	(0.028)	(0.021)	(0.037)	(0.025)
Asylum applications	-0.031*	-0.024	-0.038	-0.026
	(0.015)	(0.014)	(0.021)	(0.015)
GDP per head growth rate	0.005	0.012	-0.001	0.01
	(0.013)	(0.014)	(0.013)	(0.014)
Old-age dependency ratio	0.014	-0.007	0.026	-0.006
	(0.033)	(0.019)	(0.041)	(0.027)
Right-wing government	0.111	0.089	0.132	0.097
	(0.077)	(0.051)	(0.082)	(0.054)
EULFS	Yes	Yes	Yes	Yes
N	155	196	145	186
R-squared	0.284	0.228	0.284	0.225

The table reports results from linear probability models where the dependent variable is a dummy indicating whether the country approved 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, year dummies and dummies indicating the UN-CTS wave from which crime data have been obtained. All continuous variables 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. 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 8. Robustness check: Proportional Cox hazard model, different amnesty definitions

	Amnesty 1	**Amnesty 2**	**Amnesty 3**	**Amnesty 4**
Mismatch index (mode)	1.129**	1.098*	1.202***	1.131**
	(0.064)	(0.058)	(0.071)	(0.054)
Public spending on unemployment	0.819***	0.797***	0.781***	0.754***
	(0.047)	(0.046)	(0.054)	(0.049)
Robberies	0.867	0.874	0.758*	0.809
	(0.125)	(0.108)	(0.121)	(0.110)
Asylum applications	0.736	0.729	0.909	0.818
	(0.234)	(0.174)	(0.222)	(0.169)
GDP per head growth rate	1.08	1.393	1.499	2.327**
	(0.414)	(0.298)	(0.550)	(0.856)
Old-age dependency ratio	0.903***	0.933***	0.871***	0.923***
	(0.034)	(0.023)	(0.045)	(0.023)
Right-wing government	1.209	1.603	2.287	3.231
	(0.750)	(1.094)	(1.579)	(2.697)
EULFS	Yes	Yes	Yes	Yes
N	347	347	347	347

The table reports hazard ratios from multiple spells Cox proportional hazard models where failure occurs when a country approves an immigration amnesty. Each column reports results with a different definition of amnesty (see Table 2 for details). All continuous variables are standardized by their within-country standard deviation. All specifications include country fixed effects, year dummies and dummies indicating the UN-CTS wave from which crime data have been obtained. EULFS is a dummy variable indicating whether the labor market mismatch index is computed on EULFS data or on national datasets. Standard errors in parenthesis are clustered at the country level.

* 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 market 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 “entry 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 January 11, 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 February 16 , 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 December 30, 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 were approved, 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)*		*Public spending on unemployment as a % of GDP*		*Robberies per 100k individuals*		*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*	0.99	*0.23*	28.82	*13.20*	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*	3.08	*0.20*	121.60	*46.70*	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*	1.35	*0.58*	98.58	*8.85*	0.86	*0.41*	0.02	*0.02*	16.96	*1.72*	0.39	*0.50*
Denmark	0.00	*0.00*	0.33	*0.02*	2.91	*0.48*	55.19	*4.27*	1.05	*0.70*	0.02	*0.01*	22.57	*0.44*	0.60	*0.52*
France	0.07	*0.26*	0.35	*0.07*	1.44	*0.72*	111.53	*50.08*	0.59	*0.23*	0.02	*0.01*	22.68	*2.03*	0.46	*0.51*
Germany	0.00	*0.00*	0.29	*0.05*	1.30	*0.38*	57.30	*17.74*	1.38	*1.20*	0.02	*0.01*	23.53	*2.62*	0.64	*0.49*
Greece	0.20	*0.42*	0.35	*0.01*	0.40	*0.03*	18.75	*5.37*	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*	0.88	*0.11*	52.06	*9.15*	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*	0.75	*0.30*	57.70	*23.48*	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*	2.04	*0.64*	102.37	*17.08*	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*	0.66	*0.34*	23.41	*9.14*	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*	0.89	*0.23*	173.07	*23.65*	0.02	*0.01*	0.02	*0.02*	24.64	*0.89*	0.30	*0.48*
Spain	0.24	*0.44*	0.33	*0.05*	2.63	*0.72*	133.12	*38.26*	0.15	*0.08*	0.03	*0.01*	22.17	*2.37*	0.32	*0.48*
Sweden	0.00	*0.00*	0.45	*0.20*	1.23	*0.33*	93.86	*6.90*	2.56	*0.94*	0.03	*0.01*	26.61	*0.22*	0.10	*0.32*
Switzerland	0.00	*0.00*	0.26	*0.07*	0.89	*0.31*	38.88	*10.86*	3.13	*1.60*	0.01	*0.02*	22.47	*0.77*	0.29	*0.47*
UK	0.00	*0.00*	0.34	*0.10*	0.83	*0.59*	126.47	*52.98*	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*	0.45	*0.17*	201.17	*45.65*	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*	1.32	*0.90*	90.42	*60.10*	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 years 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). Public spending on unemployment as a % of GDP is the public expenditure on unemployment benefits as a share of GDP, from the OECD Social Expenditure Database. Robberies per 100k individuals is the ratio of police-reported robberies (from UN-CTS) to the country population, expressed in hundreds of thousands. 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 A3. Summary statistics for variables used in robustness checks

	Amnesty 2		*Amnesty 3*		*Amnesty 4*		*Mismatch index (median)*		*Public spending on unemployment and family as a % of GDP*		*Public spending on 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.***
Austria	0.04	*0.19*	0.04	*0.19*	0.04	*0.19*	0.23	*0.03*	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*	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*	2.16	*0.46*	2.76	*0.54*
Denmark	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.33	*0.02*	6.29	*0.52*	6.97	*0.53*
France	0.11	*0.31*	0.07	*0.26*	0.11	*0.31*	0.34	*0.08*	4.22	*0.75*	5.00	*0.85*
Germany	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.29	*0.05*	3.21	*0.59*	3.49	*0.69*
Greece	0.20	*0.42*	0.20	*0.42*	0.20	*0.42*	0.35	*0.03*	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*	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*	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*	3.56	*0.57*	3.93	*0.56*
Norway	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.38	*0.10*	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*	2.02	*0.36*	2.02	*0.36*
Spain	0.24	*0.44*	0.24	*0.44*	0.24	*0.44*	0.30	*0.05*	3.23	*0.66*	3.37	*0.67*
Sweden	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.44	*0.21*	4.45	*0.32*	5.04	*0.39*
Switzerland	0.00	*0.00*	0.00	*0.00*	0.00	*0.00*	0.25	*0.07*	2.14	*0.33*	2.28	*0.33*
UK	0.04	*0.20*	0.00	*0.00*	0.04	*0.20*	0.31	*0.09*	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*	1.08	*0.21*		
Total	0.07	*0.25*	0.05	*0.22*	0.06	*0.24*	0.33	*0.08*	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 2 - 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). Public spending on 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 on 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.