Emigration & Education: Separating Remittance from Wage Premium Effects

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Abstract

Remittances to developing countries are a large source of income but come at the cost of losing workers to destination countries. Fears of "brain drain" abound when migrants are positively selected, but may be assuaged by "brain gains" at home. These effects are usually motivated by an increased wage premium for skill but can also arise if enough constrained households use remittances to finance education investments. I argue dominance of the premium channel can make short-run gains transitory, while dominance of the remittance channel is necessary for persistent increases in origin skills. To infer their relative contributions to reduced form estimates, I show that remittances are more dominant whenever emigration increases education rates and closes skill gaps between constrained and unconstrained households. I then study Romania since the fall of Communism in 1990, where over 20% of the population (six million people) has emigrated. In 2002, Schengen visa requirements were waived for all Romanians, which generated heterogeneous opportunities for emigration that I capture with a continuous measure of foreign migrant networks. Difference-in-differences estimates show increases in enrollment and graduation rates, but no resulting increase in the stock of educated. Urban-rural skill gaps do not shrink in response to the shock, which implies changing perceptions of the skill premium generated most of the short-run education gains. These subsequently disappeared with Romania's continued European integration and higher skilled emigration rates.

JEL codes: F22, I25, O15.

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1 Introduction

Remittances are a large source of international capital in developing countries. Empirical studies estimate sizable gains to origin areas (Khanna et al., 2022; Ambler et al., 2015; Yang, 2008), while other work emphasizes a major cost of obtaining remittances is the loss of emigrants themselves. When they are positively selected, this leads to "brain drain" (Docquier & Schiff, 2021; Anelli et al., 2020; Schiff, 2005; Radu, 2004; Bhagwati & Hamada, 1974). Despite this, in many settings the loss of skilled emigrants leads to an increase in the share of skilled workers at origin. Whenever this overcomes the initial loss, the perceived cost at home is reinterpreted as a "brain gain" (Fernandez-Sanchez, 2020; Chand & Clemens, 2019; Theoharides, 2018; Shrestha, 2015; Gibson & McKenzie, 2012; Batista et al., 2012; Beine et al., 2001; Stark et al., 1998).[1] Since higher skilled people emigrate more (Bütikofer & Peri, 2021; Weiss, 2015; Grogger & Hanson, 2011), this raises the question: how long do brain gains associated with emigration last for origin areas?

I develop a framework to answer this question as a function of two mechanisms which encourage non-migrants to increase their education in response to emigration. On one hand, remittances relieve credit constraints and enable people to get more schooling. Alternatively, if emigration is associated with a higher perceived skill premium, then individuals may increase education absent any constraints. I argue that dominance of the remittance mechanism is necessary for persistent gains in skill rates to origin areas, while dominance of the premium channel can result in long run losses. The main idea is that absent enduring caps on overall immigration, newly educated non-migrants are more likely to eventually leave if their investments were primarily motivated by conditions in destination countries. These investments would not be worthwhile without migration, so individuals will leave at rates greater than those predicted only by their new skill level.

To infer the relative contributions of the remittances and premium channels to reduced form estimates, I construct a model where emigration and education simultaneously respond to emigration opportunity shocks. On one hand, all households respond to changes the perceived premium for skill implied by on-going migration. For example,

[1] See Table 1 for an overview of results and identification strategies in the brain gain empirical literature.

if most jobs abroad are in high skilled occupations that require college, the premium goes up. Alternatively, only constrained households with inefficiently low levels of accumulated schooling will respond via the remittance channel. If remittance flows are large enough to relax existing constraints, those individuals gain the possibility to finance higher levels of education. The premium channel is like an ”intensive” margin, while remittance channel is an ”extensive” margin in the education responses.

I use the model to study Romania during the post-Communist era since 1990, when over 20% of the population (six million people) emigrated. Continuous measures of migrant networks induced plausibly exogenous variation in emigration across Romanian counties given the removal of Schengen visas in 2002. People were more easily able to explore destination labor markets and secure both formal and informal employment (Baldwin-Edwards, 2005; Radu, 2004). One way to measure local exposure to this opportunity is via access to foreign nationals with knowledge about jobs, housing, and schooling opportunities abroad. I define treatment as the number of Italian residents in a Romanian county in a baseline period, in line with previous work suggesting that Italian investors were key facilitators of emigration experiences (Iara, 2006; Lazioriu 2003).

To identify reduced form effects on emigration and education, I implement a continuous treatment difference-in-differences (DD) design. However, the measure of exposure I specify has no “pure controls”, or units with zero exposure, which is common in the networks literature that uses historical migration to instrument for current flows (Munshi, 2020; McKenzie and Rapoport, 2011). Common two-way fixed effects (TWFE) estimators must restrict treatment effect heterogeneity substantially in the absence of pure controls (Callaway, Goodman-Bacon, and Sant’Anna, 2021). I use the framework in Haxhiu and Helgerman (2022) to illustrate these identification issues, and target the effects of above-median treatment exposure under mininal assumptions (parallel trends only) relative to a Mean Square Error-optimal researcher-defined control group (“donut” estimator).

Current results are based on standard TWFE specifications and maintain the ”strong” parallel trends assumption (Callaway, Goodman-Bacon, and Sant’Ana, 2021) required to properly identify slope effects. Estimates with administrative data imply a one standard deviation increase in exposure (roughly 10 more Italian residents) leads to an average increase of 100 permanent emigrants across Romanian counties. The same increase in exposure leads to a 5 percentage point increase in college enrollment and 2 percentage point increase in college graduation. These short-run ”brain gains” are transitory, as Census data estimates on the stock of college educated Romanians at home does not respond to exposure. This implies most of the short-run gains in schooling were driven by increased perceptions of the skill premium, as those newly educated Romanians were able to leave with Romania's continued European integration later that decade. The skill gap between urban and rural areas does not shrink (but grows slightly), confirming the comparatively smaller role for remittances in supporting educational investments at home.

This paper makes four contributions. First, there is large and growing literature using natural experiments to study the effects of emigration in origin countries (Khanna et al., 2022; Chand and Clemens, 2019; Shrestha, 2015; Yang, 2008). While most of these studies use household level data with rich information on migration experiences, I follow Theoharides (2018) in studying variation in emigration at the local level to better capture effects on non-migrant households. Additionally, most papers in this area isolate plausibly exogenous variation in either the remittances channel (Khanna et al., 2022; Yang, 2008) or wage premium channel (Batista et al., 2012) separately. Theoharides (2018) considers shocks to overall emigration, as I do, that inherently involve both mechanisms, and provides suggestive evidence that remittances were more important by rejecting differential effects of gender-specific shocks across genders.

Second, I illustrate how to apply the framework in Haxhiu and Helgerman (2022) for causal inference in continuous treatment difference-in-differences research designs with no pure control units. The advantages of this approach are that researchers can properly identify average treatment effect on the treated (ATT)-type parameters under usual assumptions on the counterfactual evolution treated outcomes (that they are well proxied by the observed evolution in some control group). Otherwise, dose regressions without pure control units rely exclusively on comparing the evolution in outcomes of units at ”adjacent” levels of the treatment. Callaway, Goodman-Bacon, and Sant'Ana (2021) show these comparisons only identify the slope effect of treatment under "strong" parallel trends (that counterfactual evolution in outcomes at one dose level for units at *all other* dose levels are well proxied by units at that dose level). This restriction on counterfactual heterogeneity is stronger than usual parallel trends, and can be eschewed with access to a pure control group or by using the methods in Haxhiu and Helgerman (2022).

Third, the model I specify clarifies the competing roles of remittances and wage premium effects in generating short-run brain gains by non-migrants in origin areas. Following Lochner and Monge-Naranjo (2012), I augment a two-period model of human capital to include emigration as a separate investment vehicle. As avenues for improving human productivity, education and emigration can be viewed either as complements or substitutes (Clemens, 2022; Bilal and Rossi-Hansberg, 2021; Hines and Park, 2019) and this relationship can vary with time and sending-receiving country dynamics. If increased returns (or diminished costs) in one lead to more investment in the other, they are complementary; otherwise, they are substitutes. This shows how the wage premium channel can even decrease schooling directly, if opportunities abroad are only in low skilled jobs (McKenzie and Rapoport, 2011). The model also shows that rising schooling at home combined with persistent gaps between urban and rural areas identifies the relative dominance of premium effects over remittances in driving (possibly transitory) brain gains.

Finally, the empirical results contribute to an on-going debate among economists about whether emigration is a net good or bad for sending countries, especially in cases of positive selection that drive brain drain (Schiff, 2005; Bhagwati and Hamada, 1974). The growing empirical papers estimating brain gains suggest concerns over drains are overblown, but many rely on wage premium effects driving short-run causal estimates (Shrestha, 2015; Chand and Clemens, 2019). I show that when immigration barriers do not endure, these brain gains at home will be transitory as newly skilled people leave to where those skills are valued most. This may especially true if education choices are made with increased integration being imminent, as I document in Romania. This argument implies a higher burden of proof regarding negative externalities for economists advocating more migration to capture Clemens' (2011) trillion-dollar bills on the sidewalk: they must show that not all gains are premium-driven, as these are less likely to endure than remittance-driven ones (Khanna et al., 2022; Thoeharides, 2018; Yang, 2008). Moreover, newly acquired skills at home may be a better match for destination labor markets than local ones if they are driven primarily by incentive effects. This could contribute to an international missallocation of labor (Spirovska, 2022; Abarcar and Theoharides 2021) that harms high-emigration developing countries, in addition to inhibiting them from adequately replacing those who left, exacerbating labor shortages.

Rather than discouraging people from leaving (Bhagwatti and Hamada, 1974) or trying to bring them back (Romania Diaspora Ministry), source countries should focus on channeling remittances to as many non-migrants as possible (Pritchett, 2006; McKenzie and Yang, 2015). The more skilled emigrants they can replace with previously-constrained non-migrants (versus unconstrained ones with changing incentives), the likelier it is that any short-run brain gains will persist. They should encourage more low skilled migration, reaping the gains from remittances and embracing "virtuous cycles" of up-skilled mobility across generations (Khanna et al., 2022). In destination countries, selective immigration policies clearly exacerbate brain drain by mechanically inflating the perceived wage premium (Chand and Clemens, 2019). They should stop discriminating on skill, and instead focus on domestic labor market needs. Recognizing current and looming demographic pressures in their labor markets, rich countries should also embrace greater levels of low skilled immigration and focus efforts on dealing with the real, but marginal, distributional consequences on natives who would compete directly.

2 Romania since Fall of Communism

2.1 Background

After decades behind the brutal and repressive iron curtain, Romania emerged from Communist dictatorship in the waning days of 1989 with ambitions to liberalize and integrate with the West. They joined the North Atlantic Treaty Organization (NATO) in 2004 and ascended to the European Union (EU) in 2007. This integration also came with economic transformations, and Romania turned into a service economy and net exporter of machines and durable goods. Income per capita in purchasing power parity terms grew from $14,000 in 2007 to $28,000 in 2018. Despite this rapid modernization, about a quarter of all workers are still employed in agriculture (mostly private family farming) while half of the population lives in rural areas, where most employment is in private agriculture.

Today, Romania confronts the growing pains of a recently democratized, middle income country. Accusations of corruption in the public sector are pervasive. This inefficient use of public funds contributes to a deteriorating national infrastructure, as well as chronically underfunded education (Iara, 2008). Both of these problems are more severe in rural areas of Romania, that receive less public support in general and where many rural students drop out after middle school during this time, since there are no high schools in Romania in villages and it can be too prohibitive to travel to urban areas (Bleahu, 2004). In addition to limited employment, corruption and underfunded public services are the most common reasons Romanians give for leaving, or wanting to leave, in survey data (Suciu et al., 2017). This encouraged six million emigrants since 1990, and explains projections that Romania's population will fall to 10 million in 2050 (from 23 million in 1989).

2.2 Data

I gather and synthesize data from three main sources. First, the National Institute of Statistics (NIS) in Romania provides administrative data on educational enrollment and graduation by level, as well as permanent emigration. This data is annual and spans from 1995 to 2017, with information on each of the 42 counties in Romania. A key strength of this dataset is the geographic granularity with which I can measure local emigration, facilitating causal inference for questions that could typically only be answered by cross-country comparisons. This advantage comes at a cost, however, as only permanent emigrants are recorded by NIS. These individuals are defined as leaving their residence in Romania without intention to return, which they convey by changing their permanent address with government authorities in their local county. These flows generally comprise 15% of all emigration from Romania, with the remaining temporary emigrants being ones that leave for at least a year, but do not state to authorities intentions for return.

Confining attention to permanent emigrants is thus a limitation of this paper, but I present aggregate data to suggest these series move together, so that local comparisons based on one measure likely would not differ greatly from those based on the other. Additionally, permanent emigrants are more likely to represent an enduring loss for Romania, making them the ideal sub-population of emigrants to study competing narratives of brain drain or gain. These data challenges are even more severe when measuring remittances, which are only available at the national level in Romania, and likely represent a major underestimate of total flows (Baldwin-Edwards, 2005; Anghel, 2016).

The second source of data is the Romanian census in 1977, 1992, 2002, and 2011, provided by the IPUMS. Whereas the administrative panel contain information on local flows of enrollment and graduation in a given year, the census is the only place I can measure the overall stock of skilled people in an area. This measure is crucial to assessing whether any short-run estimated gains to enrollment and graduation led to persistently higher skill rates. Moreover, the census contains information on whether individuals live in rural or urban areas, allowing an assessment of whether the gaps in overall education rates shrink, grow, or remain constant in response to the on-going emigration. Finally, the census allows me to construct individual network measures connecting people in one county to other counties, whose emigrants may share remittances with them, representing cross-county spillovers associated with emigration.

Finally, I combine data on Romanian emigrants abroad from numerous sources. Immigration data from the Organization for Economic Cooperation and Development (OECD) allows me to verify the emigration levels reported by Romania and paints a picture of the ever-growing Romanian diaspora, now the fifth highest in the world, as well as its distribution among rich countries. The IAB Brain Drain database measures the education levels of Romanian migrants over time in OECD countries, facilitating an aggregate assessment of the brain drain, brain gain question, while also documenting heterogeneity by destination country. A key feature of Romanian emigration is its polarization on skill, which is apparent in this dataset. Finally, I obtain more detailed demographic and labor market information of Romanian emigrants abroad with census data from Spain and the United States and labor force surveys from Italy, all provided by IPUMS.

2.3 Trends

Romanian emigrants can be grouped into three eras, each representing different legal migration regimes (Baldwin-Edwards, 2005; Radu, 2006). The first era was before the fall of Communism, and exhibited extremely small migration flows as the government placed tight restrictions on who could leave. These constraints gave way to huge numbers of permanent emigrants immediately following the collapse of the political regime, who were mostly ethnic Hungarians and Germans fleeing to reunite with family abroad. These flows continued throughout the decade, but diminished every year, generating heterogeneous trends among Romanian counties in the departure of permanent emigrants (see Figure 4). This is important to properly specifying the reduced form estimating equation of emigration of my measure of opportunity shocks, as treatment effects are only revealed as deviations from these pre-existing trends.

The next phase of Romanian emigration starts in 2002, with the removal of Schengen visa requirements, and ends in 2007 with ascension to the EU. During this period, most migrants were temporary, low skilled workers going to Italy and Spain (see Figures 1 and 5) and working disproportionately in construction, for males, and service sector jobs, for females (see Figure 8). Previous work showed how this increased access to destination labor market led to a surge in emigration by allowing Romanians to explore job opportunities, both regular and undocumented (Sandu, 2006; Iara, 2008; Baldwin-Edwards, 2005). The new opportunities to explore European labor markets on a tourist visa also facilitated creative job sharing in Italy and Spain. In order to respect the 3-month visa rule and for fear of sanctions by both Romanian and destination country authorities, a group of three or more individuals would share a job over possibly non-overlapping trips (Anghel, 2016; Iara, 2008; Baldwin-Edwards, 2005). In addition, the new ease of travel allowed previously established emigrants in Italy and Spain to reunite with their spouses and children.

The final phase of migration is after Romania joined the EU in 2007, although full and unfettered access to incumbent state labor markets did not occur until 2014, when the last transitional agreements expired. This gradual opening up to the EU was associated with continued large flows to Italy and Spain, and a subsequent emergence of Germany as a new major destination (see Figures 2 and 3). Migration during this period is highly polarized, with Italian, Spanish and many German emigrants being low skilled (see Figures 8 and 9) and emigrants to the United Kingdom, France, and the United States being disproportionately high skilled (see Figures 6 and 7). In addition to emigration, education rates at home increased rapidly over the sample period in Romania (see Figures 10 and 11).

3 Theory of Emigration and Education

The following model describes dynamic consumption and human capital investment choices a la Lochner and Monge-Naranjo (2012), who study education in the presence of credit constraints. I augment their model first by endogenizing emigration decisions and casting them as an alternative investment in human capital, in line with recent theoretical advances (Clemens, 2022; Bilal and Rosi-Hansberg, 2021). Second, I allow pre-established emigrant networks to affect individual emigration costs as in Dai et al. (2019) and Munshi (2020), as well as the stock of foreign born nationals in some baseline period. Previous work has shown that in Romania, willingness and ability to facilitate the mobility of future cohorts wanes with time abroad (Anghel, 2016; Baldwin-Edwards, 2005). This implies that traditional historical measures of networks may lack power, but also that foreign nationals can substitute for them. This is motivated by Barsbai et al. (2021) who experimentally show that emigrants rely less on traditional networks when provided information about destination prospects.

The purpose of the model is three-fold. First, it illustrates the simultaneity inherent in emigration and education decisions. Second, it motivates the reduced form relationships to my measure of exposure to emigration opportunities. Finally, the model motivates estimating effects of emigration opportunities on the gap in skills between rural and urban areas as an avenue to discern whether remittance or wage premium effects drive most of the observed variation. The following section describes the environment.

3.1 Environment

Individuals live for two periods, and make human capital and savings decisions to maximize their lifetime utility. They are defined by their individual ability and migration costs (A_i, K_i) drawn from the joint distribution $F_{AK}(a, k)$, their connections to other Romanians G_i, as well as their county of residence o. They choose savings (or borrowing) levels $s_{io} \in \mathbb{R}$ between periods, a level of education $h_{io} \geq 0$ and whether or not to emigrate in the second period $e_{io} \in \{0, 1\}$. They do not work in the first period, but receive remittances R_{io} from current emigrants, which they use to eat and pay convex schooling costs $C(h_{io}, a_i)$. In the second period, they supply a single unit of labor inelastically, using their wages and any funds saved in the first period to consume. State utility is given by a neoclassical utility function $u(\cdot)$ over consumption c each period, discounted by $\beta \in (0, 1)$.

Each county inside Romania is defined by a level of wages for low skilled work $\overline{w}_o^{LS}$, a premium for skill Δ_o^{HS}, an exogenous shifter of migration costs Z_o corresponding to the number of Italian residents who may confer help or information about emigration opportunities abroad to peers, and the endogenous cumulative stock of emigrants

$$N_{ot} := \sum_{\tau<t} \sum_{i \in o} 1\{e^*_{io\tau} = 1\}$$

Destination countries d are defined by the level of wages for low skilled Romanian emigrants $\overline{w}_d^{LS,RO}$ as well as their premium for skill $\Delta_d^{HS,RO}$.

3.2 Optimization Problem

An individual's lifetime maximization problem defines indirect utility

$$\begin{aligned} V^e_{io} = \max_{\substack{s_{io} \in \mathbb{R} \\ h_{io} \geq 0 \\ e_{io} \in \{0,1\}}} \quad & u(c^1_{io}) + \beta \cdot u(c^2_{io}) \\ \text{s.t.} \quad & c^1_{io} + s_{io} = R_{io} - C(h_{io}, a_i) \\ & c^2_{io} = w(h_{io}, e_{io}) + (1 + r)s_{io} \\ & s_{io} \geq -\bar{b}_{io} \end{aligned}$$

where wages are a function of human capital accumulated via education and emigration

$$w(h_{io}, e_{io}) := (1 - e_{io}) \left[\overline{w}_o^{LS} + h_{io} \cdot \Delta_o^{HS}\right] + e_{io} E_i \left[w^F | h_{io}, \tilde{e}_{iod}\right]$$

Since I do not observe where emigrants go $\tilde{e}_{oid} \in \{1, ..., D\}$, only whether they leave $e_{io} \in \{0, 1\}$, I model individual expectations of where they may end up by specifying

$$E_i[w^F | h_{io}, \tilde{e}_{iod}] := \sum_d \frac{P[\tilde{e}^*_{iod} = d | e^*_{io} = 1]}{\sum_{d'} P[\tilde{e}^*_{iod} = d' | e^*_{io} = 1]} \cdot (1 - \tau_{iod}) \left[\overline{w}_d^{LS,RO} + h_{io} \cdot \Delta_d^{HS,RO}\right]$$

where $\tau_{iod} = \tau(K_i, N_o, Z_o)$ denotes migration costs. The same data limitations that require modeling individual expectations over foreign wages also means that the weights $\sum_d P[\tilde{e}^*_{iod} = d | e^*_{io} = 1] / \{\sum_{d'} P[\tilde{e}^*_{iod} = d' | e^*_{io} = 1]\}$ are unobserved. To connect these quantities to observable data, I proxy these weights by $\tilde{\omega}_d^{RO}$ or the fraction of aggregate Romanian emigrants that go to destination d. Wages are then given by

$$w(h_{io}, e_{io}) := (1 - e_{io}) \left[\overline{w}_o^{LS} + h_{io} \cdot \Delta_o^{HS}\right] + e_{io} \sum_d \tilde{\omega}_d^{RO} (1 - \tau_{iod}) \left[\overline{w}_d^{LS,RO} + h_{io} \cdot \Delta_d^{HS,RO}\right]$$

Since I do not observe remittances directly, but do know flows and stocks of emigrants, I specify them as proportional to N_o, so that $R_{io} = \gamma_o N_o$. To see how remittances cause spillover effects from emigration in one county onto education in another, note that

$$R_{io} = \gamma_o N_o + \sum_{c \neq o} G_{i,c(j)} \gamma_c N_c$$

3.3 Human Capital Decisions

To characterize optimal education and emigration decisions, first consider individuals who are not constrained. Assume there is fraction $\delta \in (0, 1)$ of unconstrained individuals with s^*_{io} satisfying the Euler equation

$$\frac{u'(c^{1*}_{io})}{u'(c^{2*}_{io})} = \beta(1 + r)$$

After substituting the period budget constrains into the lifetime utility function and taking a first-order condition with respect to education, I find that

$$h^*_{io} = \frac{a_i}{p_o(1+r)}\left[(1-e^*_{io})\Delta_o^{HS} + e^*_{io}\sum_d \tilde{\omega}_d(1-\tau_{iod})\Delta_d^{HS,RO}\right]$$

under linear emigration costs $\tau_{iod} := K_i - \gamma_o N_o - \pi Z_o 1\{t \geq 2002\}$ and quadratic education costs $C_{io} := \frac{p_o}{2a_i}h^2_{io}$. This solution implies that education is increasing in the migration-probability-weighted average of the high skill wage premium and ability, but decreasing in direct costs p_o. Since unconstrained individuals can always finance their optimal education decisions, these choices do not depend on remittances or previous flows of emigration. The only dependence on emigration is given by the individual's own probability of leaving, which places more or less weight on the set of premia abroad.

In contrast, constrained individuals will always have lower levels of education than the unconstrained, so that their education decisions depending on their overall wealth levels, and hence remittances. For the share $(1-\delta) \in (0,1)$ who are constrained, optimal borrowing $s^{**}_{io} = \bar{b}$ is right at the boundary, and implies large returns to schooling so that

$$\frac{u'(c^{1**}_{io})}{u'(c^{2**}_{io})} > \beta(1+r)$$

Solving the resulting first-order conditional, I find that

$$h^{**}_{io} = \frac{a_i}{p_o}\left[(1-e^{**}_{io})\Delta_o^{HS} + e^{**}_{io}\sum_d \tilde{\omega}_d(1-\tau_{iod})\Delta_d^{HS,RO}\right]\left[\frac{u'(R_{io} - C(h^{**}_{io}, a_i) - \bar{b})}{\beta \cdot u'(w(h^{**}_{io}, e^{**}_{io}) + (1+r)\bar{b})}\right]^{-1}$$

which shows that schooling levels for constrained individuals respond not only wage premium effects and own migration probabilities, but also to overall emigration rates from their local county (and other counties, if spillovers are included) via R_{io}.

3.4 Inferring Mechanisms

Given optimal constrained education decisions above, let

$$\begin{aligned}
\text{REM}(R_{io}, e_{io}^{**}) &:= \frac{u'(R_{io} - C(h_{io}^{**}, a_i) - \bar{b})}{\beta \cdot u'(w(h_{io}^{**}, e_{io}^{**}) + (1+r)\bar{b})} \\
\text{PREM}(\tau_{iod}, e_{io}^{**}) &:= (1 - e_{io}^{**})\Delta_o^{HS} + e_{io}^{**} \sum_d \tilde{\omega}_d (1 - \tau_{iod}) \Delta_d^{HS,RO}
\end{aligned}$$

with a similar definition for $\text{PREM}(\tau_{iod}, e_{io}^{*})$. Then the gap in average education between constrained and unconstrained individuals in this model can be expressed as

$$\text{Gap}(H_o) \quad := \quad h_{io}^{*} - h_{io}^{**} = \frac{a_i}{p_o}\left[\frac{1}{1+r}\text{PREM}(\tau_{iod}, e_{io}^{*}) - \text{PREM}(\tau_{iod}, e_{io}^{**}) \cdot \text{REM}(R_{io}, e_{io}^{**})\right]$$

which shows that we can infer the relative size of remittance effect by the extent to which gaps in education shrink in response to the emigration opportunity shock Z_o in τ_{iod}, as long as wage premium effects are similar between constrained and unconstrained. If the gap does not move, or grows after the shock, then premium effects must have been dominant. In addition to reduced-form effects on average local education

$$\text{Mean}(H_o) := \delta h_{io}^{*} + (1 - \delta) h_{io}^{**}$$

I estimate the effect of exposure on the urban rural education gap, where I assume that there are relatively more constrained people in rural areas of Romania.

4 Inference without Pure Controls

I measure a Romanian county's individual exposure to the emigration opportunity generated by visa-free travel to Schengen countries by computing the number of Italian residents in 2001 per 100,000 in the working age population (see Figure 12 for its geographic distribution). This variable is continuous but does not contain "pure control" counties with zero exposure, so it is unclear how to use traditional parallel trends assumptions to conduct inference with difference-in-differences. I present two options for proper identification in this setting. First, I specify the target estimand as the average causal response (ACR), or the average effect of incrementing the exposure, across all observed values. I can then use "strong" parallel trends in Callaway, Goodman-Bacon, and Sant'Ana (2021) to identify this average slope effect from a standard TWFE regression, which aggregates the set of "adjacent" differences in outcomes across the exposure distribution.

Alternatively, I target ATT-type estimands under traditional parallel trends assumptions by using the methods in Haxhiu and Helgerman (2022) to construct an optimal, data-driven control group using information on exposure. The key argument is that although no pure controls exist, there may be units in the sample with *low enough* levels of the exposure that we can assume they do not exhibit treatment effects. This section derives both estimators using the framework in Haxhiu and Helgerman (2022).

4.1 Potential Outcomes

Suppose there are two time periods $t \in \{\tau - 1, \tau\}$ and N units $i \in \{1, ..., N\}$, all exposed at $t = \tau$. The continuous dose treatment is given by $Z_o \in [Z_L, Z_U] \subset \mathbb{R}_+$ and the true cutoff is $Z^* \in (Z_L, Z_U)$. This means we can denote the treated group by $T_o := 1\{Z_o \geq Z^*\}$ and the treatment period by $P_t := 1\{t = \tau\}$. Let $Y_{ot} = Y_{ot}(Z_o, T_o)$ denote potential outcomes. The following section lists the main identification assumptions for inference in this setting.

4.2 Assumptions

The first three assumptions define a two-period dataset of observations on outcomes and exposure for a set of units, incorporating no-anticipation in treatment effects prior to exposure (common in the DD literature). Assumptions [A4] and [A5] define weak and strong parallel trends, respectively, while [A6] and [A7] define homogeneity (of dose responses) or exogeneity (of dose assignments) that are equivalent to strong parallel trends.

A1 Random sampling: Data $\{Y_{o,\tau}, Y_{o,\tau-1}, Z_o\}_{o=1}^{O}$ is iid

A2 Dose distribution: $Z_o \sim F_Z(z)$ over $\text{supp}\{Z_o\} := [Z_L, Z_U] \subset \mathbb{R}_+$

A3 No anticipation: $Y_{o,\tau-1} = Y_{o,\tau-1}(Z_o, 0)$ and observed outcomes

$$Y_{o\tau} = T_o Y_{o\tau}(Z_o, 1) + (1 - T_o) Y_{o\tau}(Z_o, 0) \quad \forall o$$

A4 W-PTA(z, Z^*): Weak parallel trends *across* dose distribution

$$E[\Delta Y_{ot}(Z_o, 0) | T_o = 1, Z_o = z] \;\;=\;\; E[\Delta Y_{ot}(Z_o, 0) | T_o = 0, Z_o = z']$$

for all pairs $(z, z') \in [Z_L, Z^*) \times (Z^*, Z_U]$, or the equivalent parametric version that $Y_{ot}(Z_o, 0) = \alpha_o + \theta_t + \varepsilon_{ot}$ whenever $T_o = 0$ or $t = \tau - 1$, where $\alpha_o, \theta_t, \varepsilon_{ot}$ denote unit, time, and idiosyncratic effects respectively.

A5 S-PTA(z): Strong parallel trends from CGS (2021)

$$E[Y_{ot}(Z_o, 1) - Y_{o,t-1}(Z_o, 0)] \;\;=\;\; E[Y_{ot}(Z_o, 1) - Y_{o,t-1}(Z_o, 0) | Z_o = z] \qquad \forall z \in (Z_L, Z_U)$$

A6 Dose response function (DRF) homogeneity $\mu_o(Z_o) = \mu(Z_o)$ and parameterizations

$$\begin{array}{rrcl} \text{A6.1 (Binary)} & \mu(Z_o) & = & \beta_1 \\ \text{A6.2 (Jump linear)} & \mu(Z_o) & = & \beta_1 + \beta_2(Z_o - Z^*) \\ \text{A6.2' (Connected linear)} & \mu(Z_o) & = & \beta_2(Z_o - Z^*) \\ \text{A6.3 (Smoothness)} & \mu''(Z_o) & \neq & 0 \end{array}$$

A7 Conditional independence of dose assignment: $Z_o \perp \mu_o | \alpha_o$

4.3 Estimands

The main estimands I target are conditional averages of the dose response functions, or their slopes across the support of the exposure variable

$$\mu(a|d) \;\;:=\;\; E[Y_{ot}(a, 1) - Y_{ot}(a, 0) | Z_o = d]$$

$$\mu'(a|d) \quad := \quad E\left[\frac{\partial}{\partial a}\mu_o(a)\middle| Z_o = d\right]$$

The $\mu(\cdot|\cdot)$ functions are ATTs at hypothetical doses (for each dose). Note that the $\mu'(\cdot|\cdot)$ represent average causal responses (ACR) only under a boundedness condition on the derivatives of the individual μ_i functions. Additionally, I define the binned ATT

$$\begin{aligned}
\text{BATT}(r) \quad &:= \quad E[Y_{ot}(Z_o, 1) - Y_{ot}(Z_o, 0)|Z_o \geq r] = E[\mu_o(Z_o)|Z_o \geq r] \\
\text{BATT}(r, k) \quad &:= \quad E[Y_{ot}(Z_o, 1) - Y_{ot}(Z_o, 0)|Z_o \in (r, k)]
\end{aligned}$$

which are meaningful estimands even when the true cutoff Z^* is unknown.

4.4 Estimators

Under assumptions [A1], [A2], and [A3], I can always write observed outcomes as

$$\begin{aligned}
Y_{ot} \quad &= \quad (1 - P_t)Y_{ot}(Z_o, 0) + P_t\left[T_o Y_{ot}(Z_o, 1) + (1 - T_o)Y_{ot}(Z_o, 0)\right] \\
&= \quad Y_{ot}(Z_o, 0) + P_t T_o \underbrace{[Y_{ot}(Z_o, 1) - Y_{ot}(Z_o, 0)]}_{:=\mu_o(Z_o)} \\
&= \quad Y_{ot}(Z_o, 0) + \mu_o(Z_o) \cdot P_t T_o
\end{aligned}$$

where $\mu_o(Z_o)$ is the county-specific dose response function (DRF). Adding the usual parllel trends assumption [A4] delivers the familiar TWFE specification

$$\begin{aligned}
Y_{ot} \quad &= \quad Y_{ot}(Z_o, 0) + \mu_o(Z_o) \cdot P_t T_o \\
&= \quad \alpha_o + \theta_t + \mu_o(Z_o) \cdot P_t T_o + \varepsilon_{ot}
\end{aligned}$$

Then under suitable restrictions on the DRFs, I obtain estimating equations I can take directly to the data. For example, under assumption [A7.2'] we get linear TWFE model

$$Y_{ot} = \alpha_o + \theta_t + \beta_2 \cdot P_t T_o + \varepsilon_{ot}$$

where $\beta_2 \in \mathbb{R}$ represents variance-weighted average of differences in outcomes between units at "adjacent" levels of the dose. This estimand is the ACR under a range of assumptions. Callaway, Goodman-Bacon, and Sant'Ana (2021) show that [A5] strong parallel trends is sufficient, but likely to be quite strong in practice (though it is not implied by nor implies usual weak parallel trends). Haxhiu and Helgerman (2022) further clarify the strength of the assumptions needed to interpret typical linear TWFE estimators as properly targeting slope effects, by showing that [A5] is equivalent to either [A6] DRF homogeneity or [A7] conditional independence of dose assignment. All of these assumptions rule out any selection bias across different levels of the treatment, but are considered "strong" because they essentially assume selection effects away, either via the assignment process through [A7] or suitable restrictions on response heterogeneity [A6].

To conduct inference under traditional parallel trends assumptions only, there needs to be a well-defined group of units who do not experience any treatment so that their evolution in outcomes can proxy the counterfactual evolution of treated units. Ideally, researchers have access to pure control units in the data, and can follow the reccomendations in Callaway, Goodman-Bacon, and Sant'Ana (2021) to conduct proper causal inference. They should partition all treated units into groups according to dose level, and estimate individual ATT effects at each dose. Differences in these ATT estimtes will not generally recover ACRs, but can be estimated for different subpopulations to infer selection bias.

If no pure control units are available to do this, researchers can still conduct inference under minimal assumptions by using information on the exposure to optimally determine the cutoff below which units can be approximately treated as controls. The procedure first involves a concession that "the true" set of ATTs is generally impossible to identify without knowing the true cutoff Z^*. Haxhiu and Helgerman (2022) recommend that researchers instead target the BATT estimands, which represent meaningful causal parameters regardless of the true cutoff. In general, binarizing the dose at a percentile and comparing units above to those below results in bias of unknown sign. However, with closed form expressions for the bias and variance of this estimator, we can define a Mean Square Error (MSE) optimal estimator by selectively removing high dose units in the researcherspecified control group to balance bias reduction (throwing them out refines the control group) with variance gains (keeping them results in a more robust control group). The objective function that exhibits this tradeoff also depends on the unknown Z^* parameter, and we are currently working on completing a proof for the implied minimax estimator.

5 Results

5.1 Administrative Panel

Current results are based on estimating a single slope parameter from a linear TWFE specification, maintaining some version of ”strong” parallel trends assumption. Additionally, I present estimates as deviations from unit-specific trends to reflect the fact the permanent emigration from Romania was trending down leading up 2002 given early ethnic migration by Hungarians and Germans. I modify weak parallel trends assumption [A4]

$$Y_{ot}(Z_o, 0) = \alpha_o + \theta_t + \delta_o \cdot t + \varepsilon_{ot}$$

whenever $T_o = 0$ or $t = \tau - 1$, where δ_o is the estimate of the county-specific linear pre-trend in the pre-period. Effects of treatment are identified as deviations from these estimated pre-existing trends across the dose distribution. Confidence intervals are based on $\alpha = 0.05$ false rejection rate, with standard errors are clustered at the county level. Event study estimates for the effect of exposure Z_o on the permanent emigration rate, college enrollment rate, and college graduation rate are in Figures 13,14, and 15 respectively. These estimates suggest that a one standard deviation increase in the number of Italian residents of a Romanian county (about 10 more people) leads to 100 more permanent emigrants on average relative to the pre-shock period. Additionally, the same increase leads to a 5 percentage point higher college enrollment and 2 percentage points higher college graduation rates on average. These estimated short-run brain gains peak in 2007 when Romania joined the EU, and dissipate in the following years.

5.2 Origin Census

The first column in Table 2 replicates the positive short-run brain gains estimated in administrative data, with the same measure of exposure. However, we cannot reject the hypothesis that all the observed increases in the stock of educated people in a given county are due to pre-existing differential trends given exposure (column 2). The increases in college enrollment and graduation at the local level do not correspond to a greater fraction of skilled people in the long-run, relative to pre-existing trends. This is explained by most of the observed effects in administrative data arising from changing perceptions of the skill premium, rather than constrained individuals using remittances to finance previously unaffordable schooling. The last two columns of Table 1 estimate the differential response in rural versus urban areas, and confirms that premium effects are likely dominant over remittance effects as the gap between them grows. Although the amount is small, even a constant gap with short-run brain gains implies premium effects dominate.

5.3 Destination Census

What did Romanian emigrants do once they arrived at their destination? I present descriptive statistics using census data from Romania (on non-migrants), Spain, the United States, and Italy (labor force survey) in Table 3 (early 2000s period) and Table 4 (early 2010s period). Polarization by skill is apparent, as emigrants to Spain and Italy are about three times as likely to be working in low skilled occupations (relative to non-migrants), whereas emigrants to the US are disproportionately high skilled. Over time, there is an increase in the fraction of Romanians employed in low skilled occupations, both at home and abroad in Spain (and likely Italy as well). There is also an overall increase in the fraction of college educated Romanians both at home (matching the NIS administrative data) and in the United States (matching the IAB Brain Drain database).

How much does having a college degree reduce the likelihood of working in a low skilled occupation? Table 5 estimates the "Low Skill Occupation-Education" elasticity in census data and labor force surveys, comparing Romanians abroad to natives and other immigrants. One takeaway is that for Spain in the late 2010s, there is no reduction in likelihood of working on low skilled occupation for Romanian emigrants who are skilled! However, emigrants to the US exhibit the opposite effect, where a college degree lowers the likelihood of working in a low skill occupations by more than natives! These patterns confirm the trends in aggregate data: most Romanian emigrants in Spain, Italy, and Germany work in low skilled occupations, while those that go to America are skilled and receive a premium for their education. Although high skilled Romanian emigrants represent a small fraction of all emigrants (see Figures 7-9), they increasingly represent a large share of all educated Romanians (see Figure 6 from the IAB brain drain database showing the fraction of skilled Romanians in OECD countries increase from 5% in 1980 to 20% in 2010).

5.4 Additional Evidence

I present two additional arguments that the brain gains in Romania were likely premium-driven, and hence transitory. The first is the total number of the number of high school students in Romania enrolled in English language classes (see Figure 18). There is an increase in this measure until 2011, when it levels off. Given the gradual nature of integration with incumbent EU states after ascension in 2007, it is possible this trend was driven by young Romanians preparing for employment or education in destination countries other than Spain, Italy, and Germany. In other words, students disproportionately selected into English language classes looking ahead to future emigration possibilities. These numbers dropped once the doors to English-speaking countries opened.

The second relates to aggregate trends in private colleges (see Figure 16) and private enrollment in Romania (see Figure 17). Both measures rise and fall, matching other aggregate series in the data, with private schools peaking in 2000 and private enrollment peaking in 2009. In subsequent years, enrollment in private colleges in Romania falls to similar rates in the 1990s. There was a documented increase in private colleges during this time period in Romania (Stanciu, 2014; Nicolescu, 2005). However, many of these schools failed to obtain accreditation as Romania harmonized its higher education standards with other countries in Europe during this time (Stanciu, 2014). It is possible that some of the increased demand for higher education from people motivated by higher wage premia abroad was satisfied by the private sector, which subsequently diminished once more employment (and better educational) opportunities in Europe became available.

6 Conclusion

The short-run brain gains in Romania since 2000 were likely transitory. Increases in schooling were tied more to the future possibility of emigrating (perhaps to the EU) than the remittance effects of previous emigrants. This is implied by a growing urban rural skill gap given the shock, as well as aggregate trends (Figure 6 shows that 20% of all skilled Romanians live in OECD countries in 2010, compared to just 5% in 1980). Moreover, the fact that administrative level estimates drop after 2007 provides more suggestive evidence that the gains were transitory, as many would go on to emigrate themselves. These findings have numerous implications for migration policy around the world. Sending countries should not try and stop their ”best and brightest” from leaving, but instead focus resources and efforts on training their replacement at home! Some of those resources could come from previous waves of emigrants in the form of remittances, but these need to be better channeled to constrained individuals who could and would use the funds to increase their human capital via education.

On the other hand, receiving countries should be cautious with skill selective immigration policies, as these mechanically inflate the wage premium channel and contribute to illusory brain gains for developing countries. They should also work together with sending countries to streamline the process of sending remittances home, reducing overall fees that leak out in the process but amount to billions of dollars in income every year among all migrants. Finally, policy-makers in destination countries face looming demographic pressures in their labor markets. They should also embrace greater levels of low skilled immigration. As with the realized gains to globalization via increased trade in recent decades, economists should focus efforts on dealing with the real, but marginal, distributional consequences on natives who would compete directly with immigrants.

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8 Figures

Figure 1: Romanian Immigration Flows (thousands). Source: OECD Migration Database.

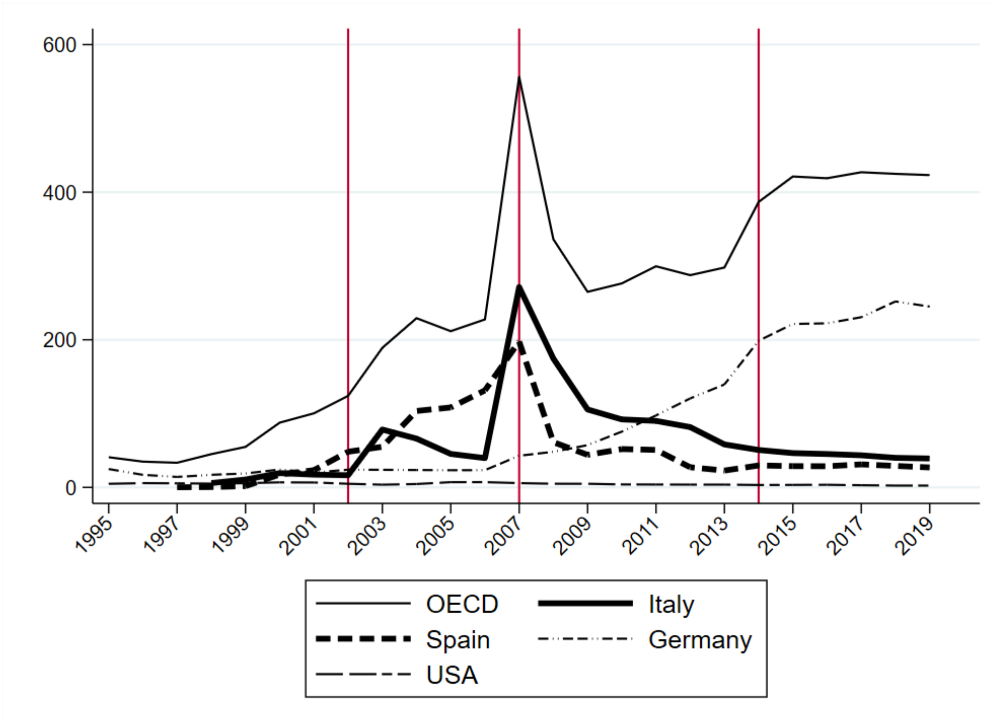

Figure 2: Romanian Outmigration Flows (thousands). Source: OECD Migration Data.

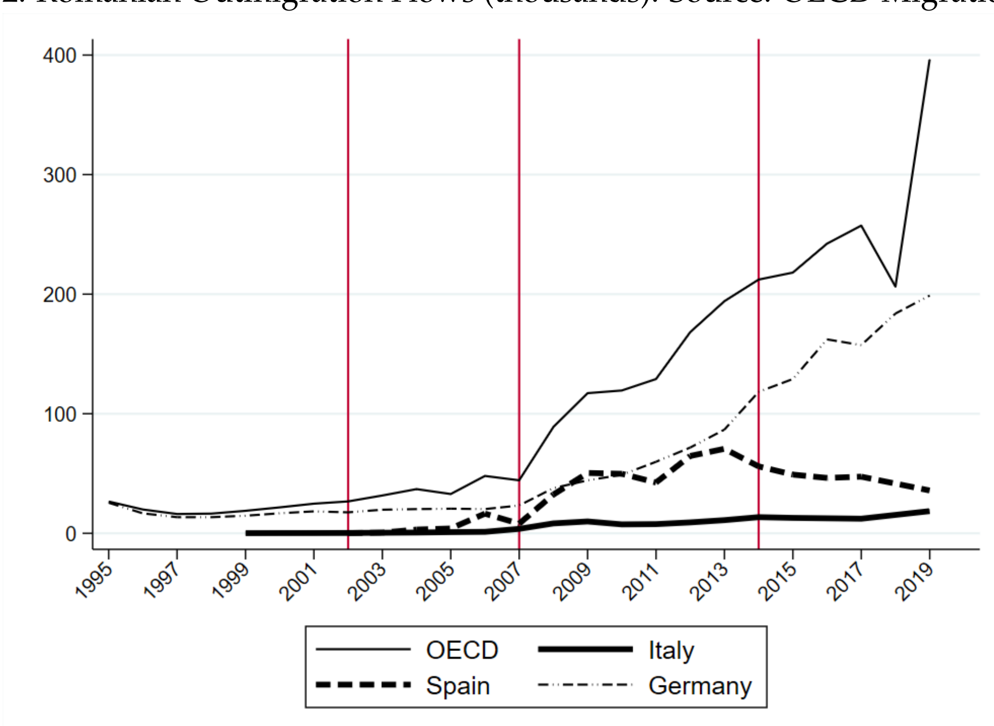

Figure 3: Romanians Living Abroad (thousands). Source: OECD Migration Database.

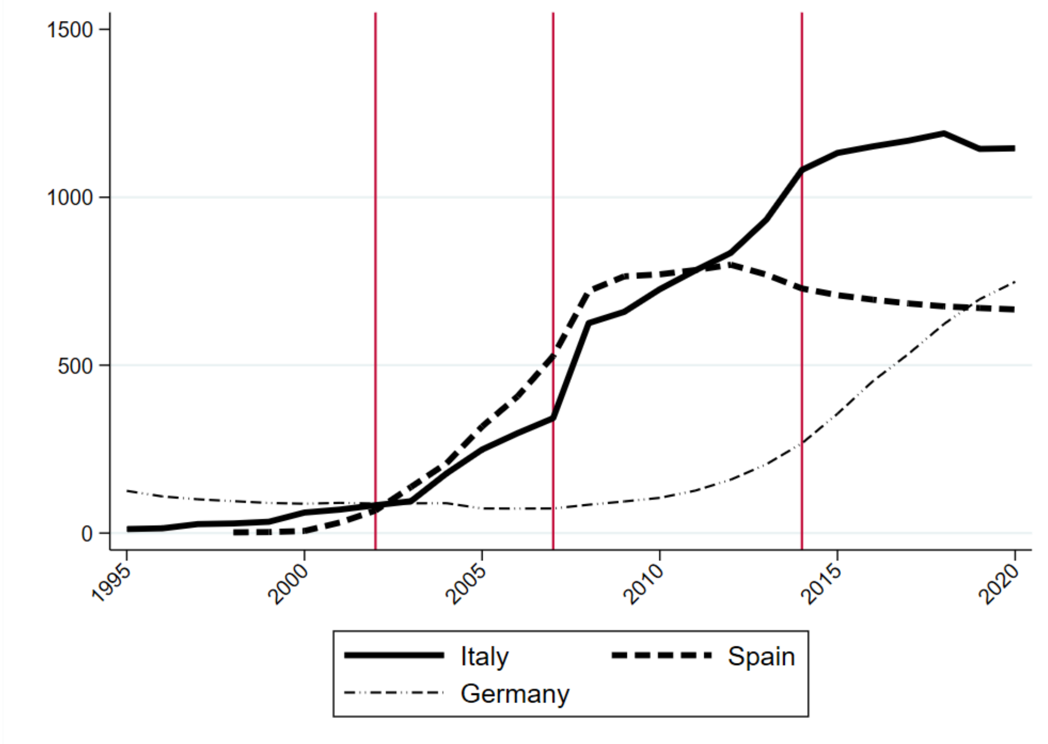

Figure 4: Permanent Emigrants (thousands). Source: NIS Romania Administrative panel.

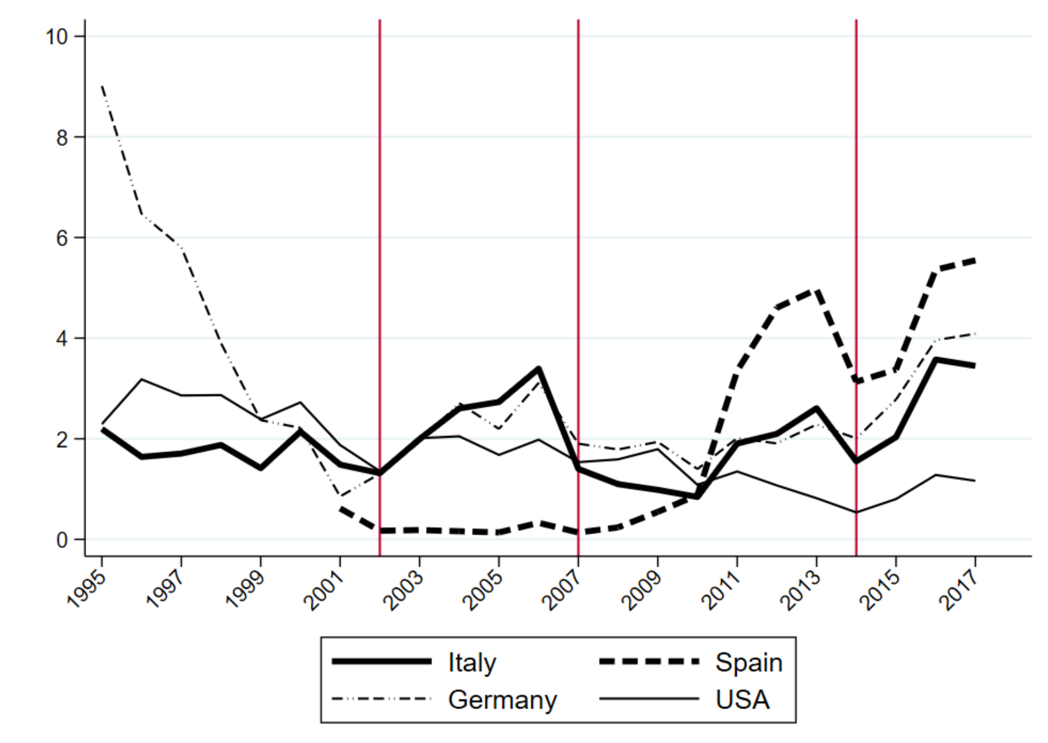

Figure 5: Temporary Emigrants (thousands). Source: NIS Romania Administrative panel.

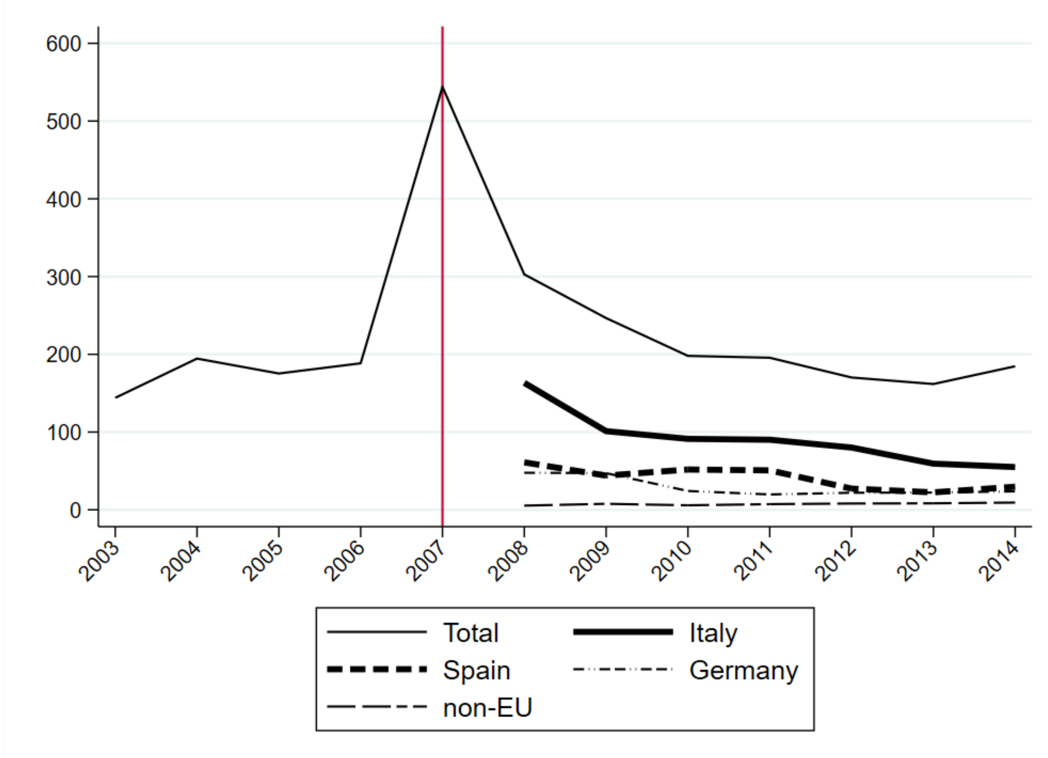

Figure 6: Romanian emigrants in OECD by Education level, as a fraction of all Romanians with given education level (percent). Source: IAB Brain Drain database.

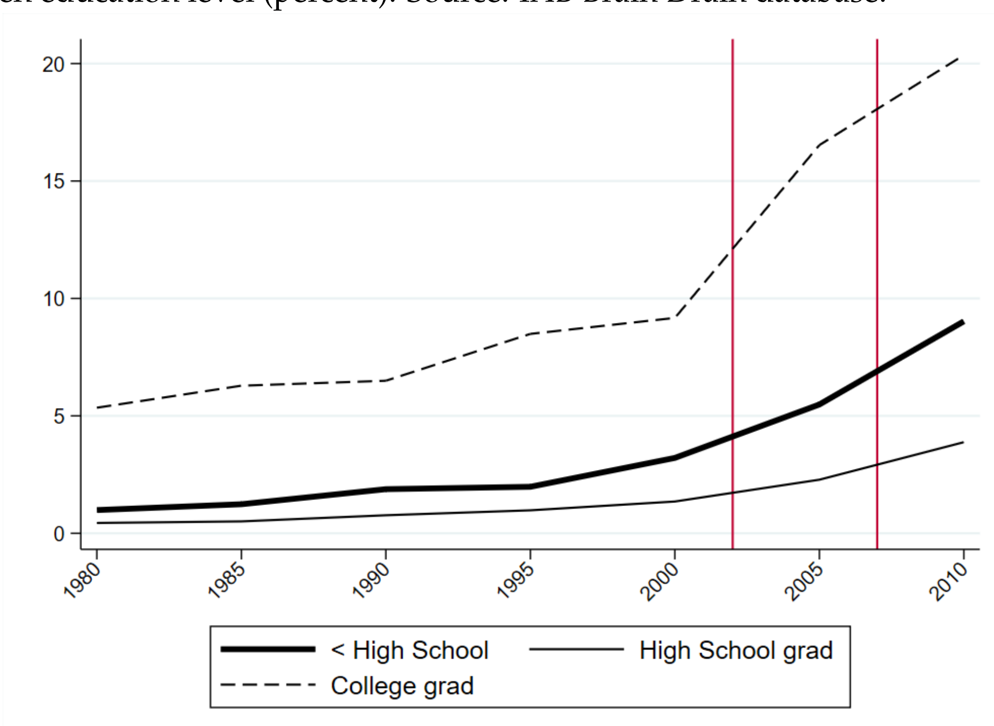

Figure 7: Romanians living in OECD by Education level, excluding Italy and Spain (percent). Source: IAB Brain Drain database.

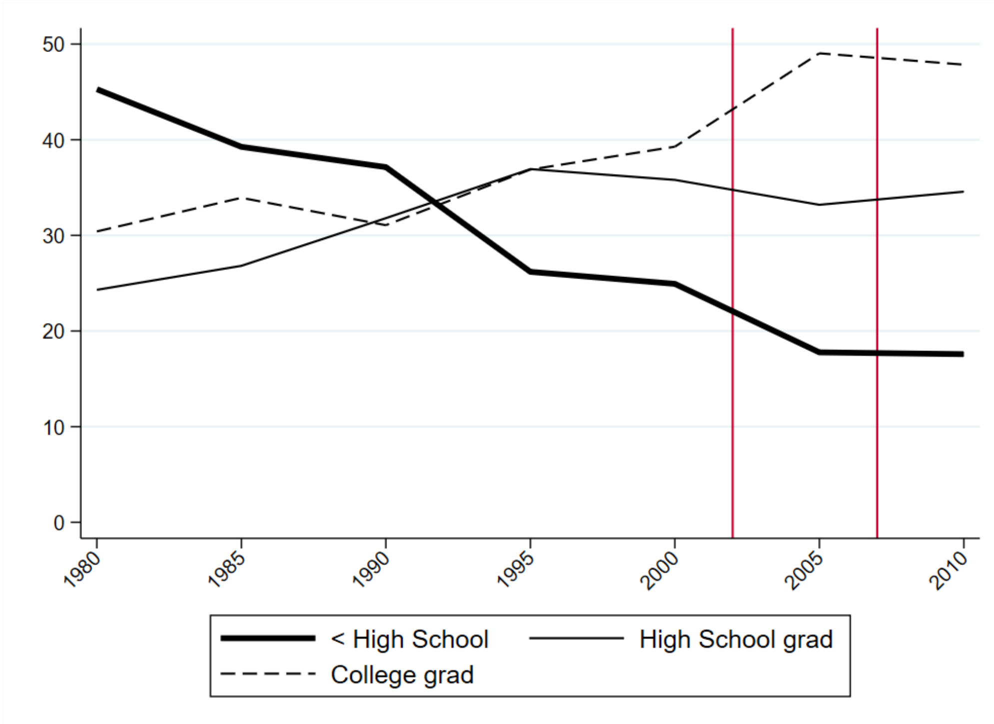

Figure 8: Romanian Males living in Spain by Education (percent). Source: IAB Brain Drain database.

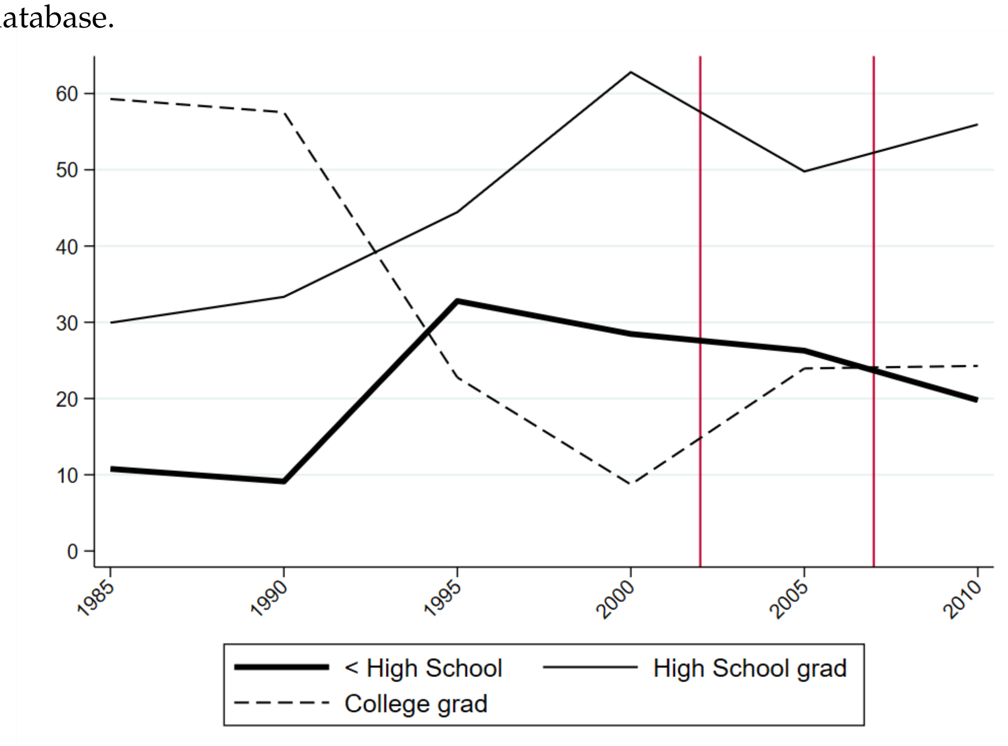

Figure 9: Romanians in Germany by Education (pct). Source: IAB Brain Drain database.

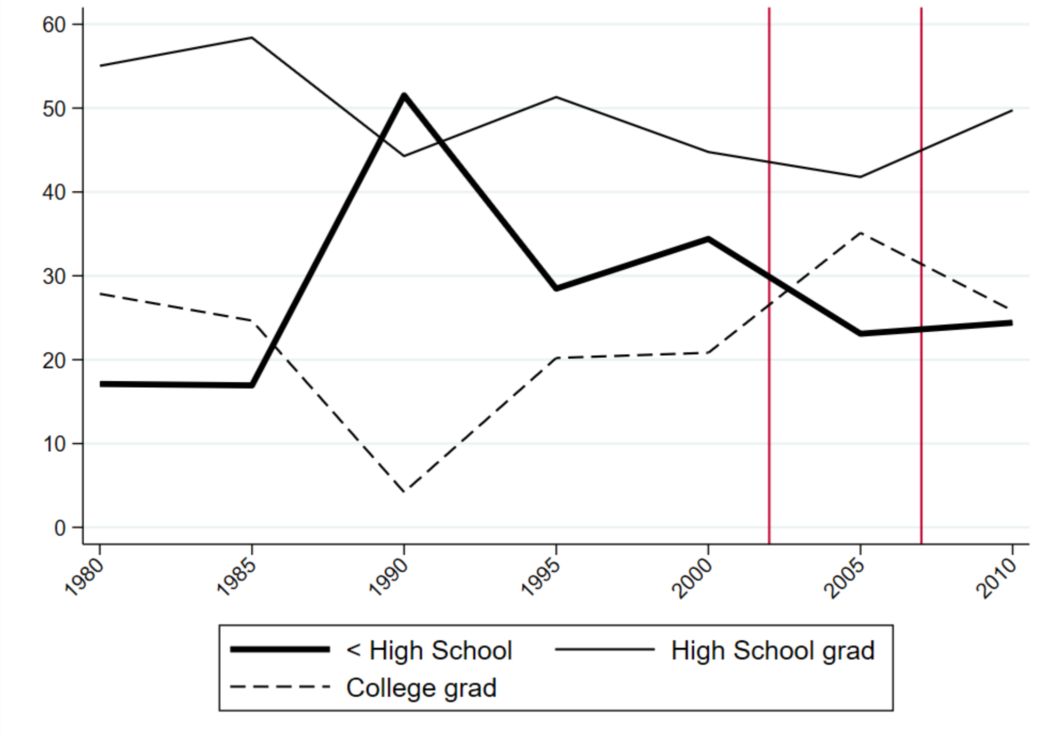

Figure 10: Enrollment Rates (percent). Source: NIS Romania Administrative panel.

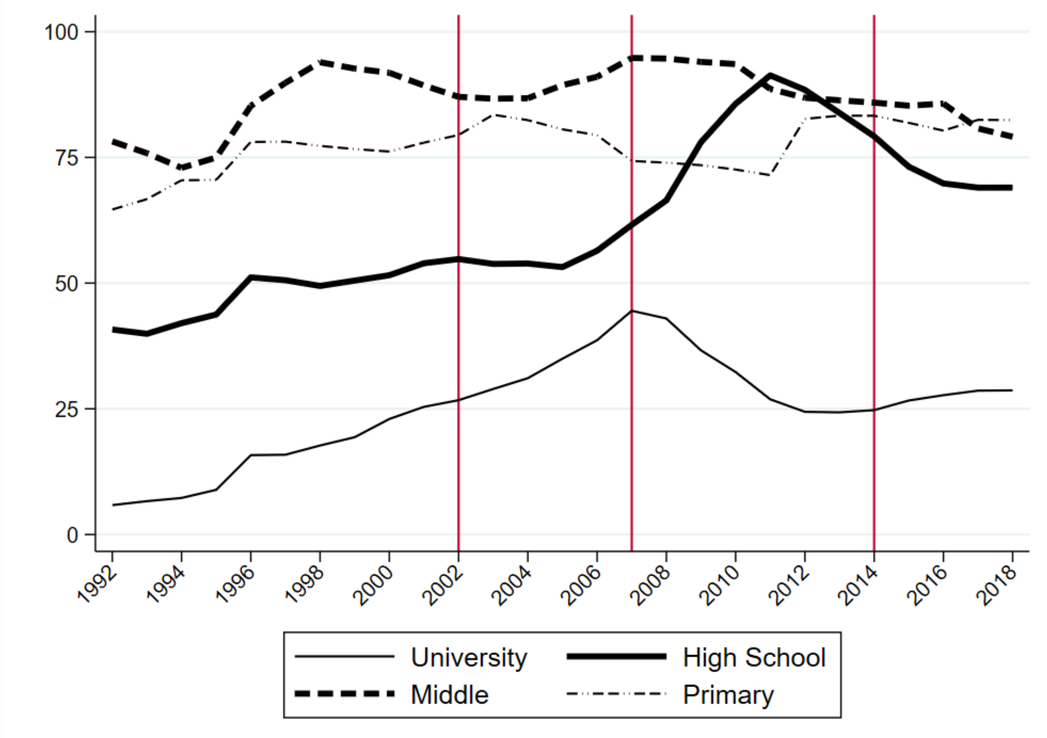

Figure 11: Graduation Rates (percent). Source: NIS Romania Administrative panel.

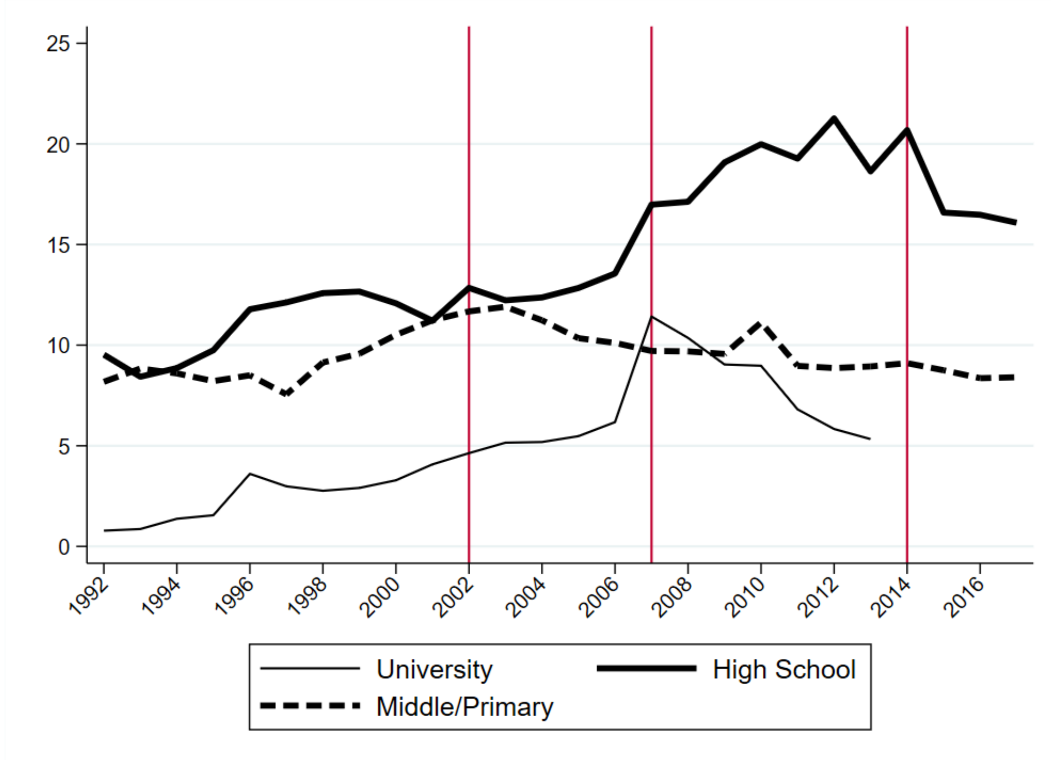

Figure 12: Italian Residents in 2001 (per 100k population). Source: NIS Romania data.

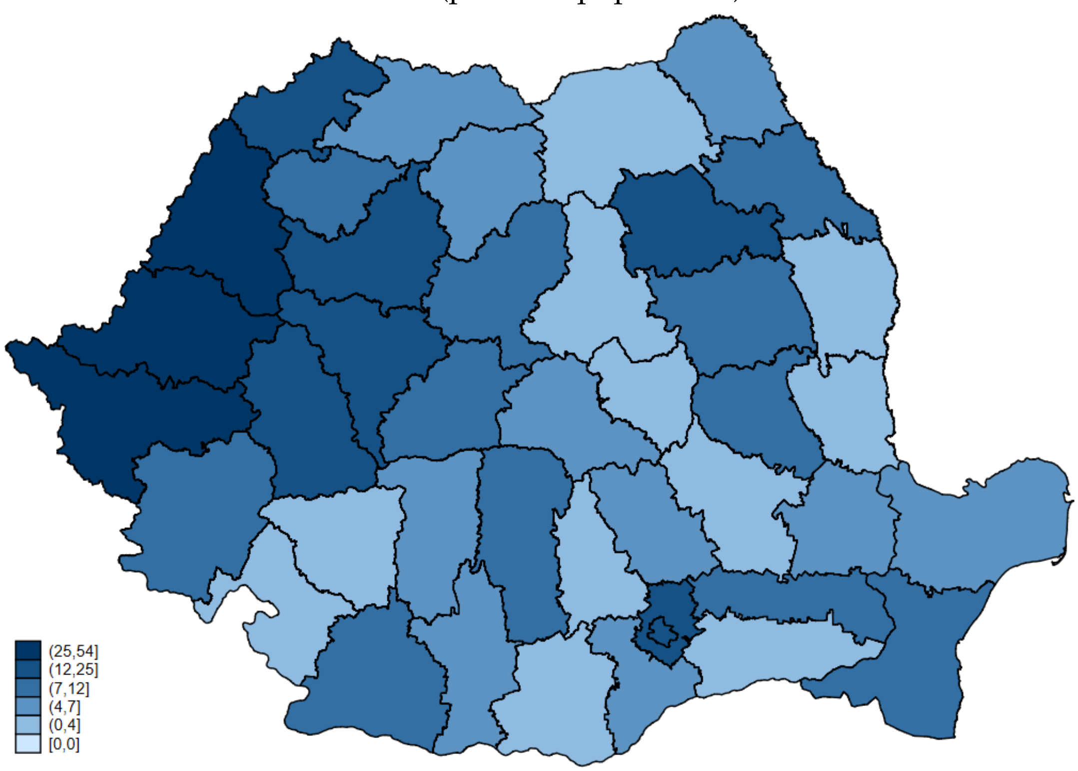

Figure 13: Permanent Emigration Rate on Exposure. Estimates represent event study coefficients from TWFE regression of permanent emigration on continuous exposure Z_o. Confidence intervals are 95% and based on standard errors clustered at the county-level.

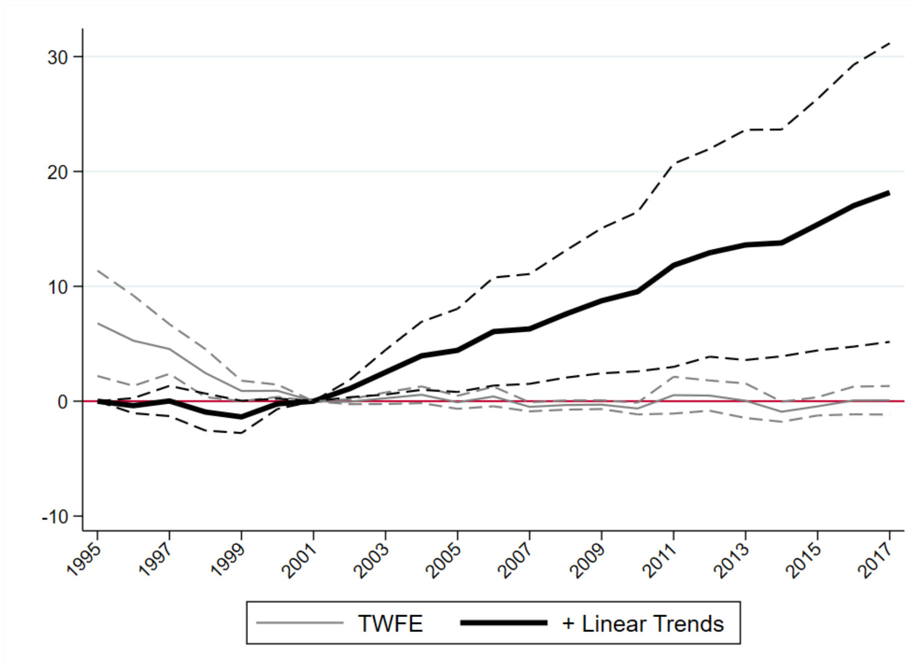

Figure 14: College Enrollment Rate on Exposure. Estimates represent event study coefficients from TWFE regression of college enrollment on continuous exposure Z_o. Confidence intervals are 95% and based on standard errors clustered at the county-level.

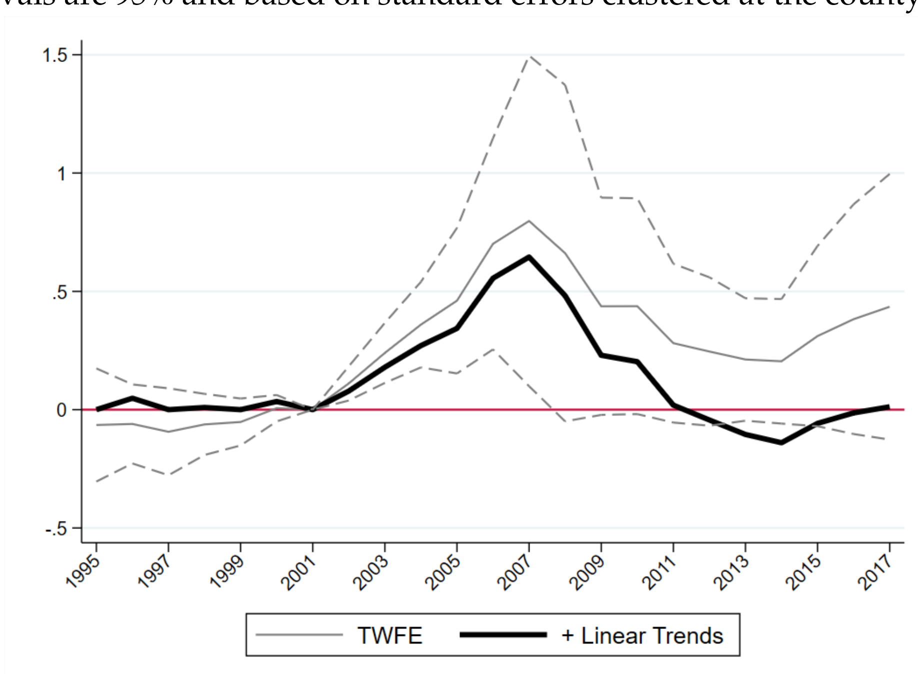

Figure 15: College Graduation Rate on Exposure. Estimates represent event study coefficients from TWFE regression of college graduation on continuous exposure Z_o. Confidence intervals are 95% and based on standard errors clustered at the county-level.

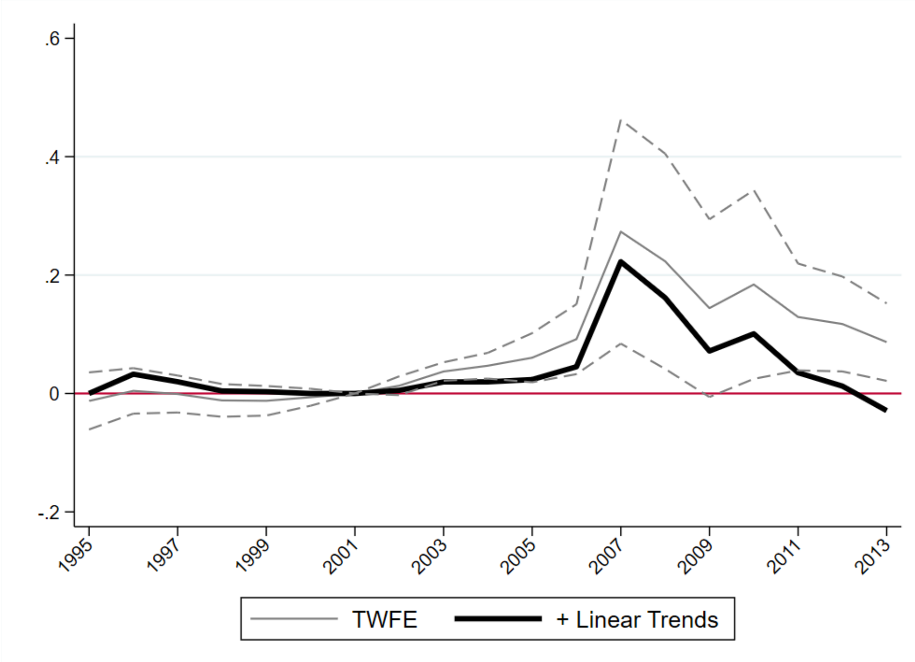

Figure 16: College Enrollment rate (percent). Source: NIS Romania Administrative panel.

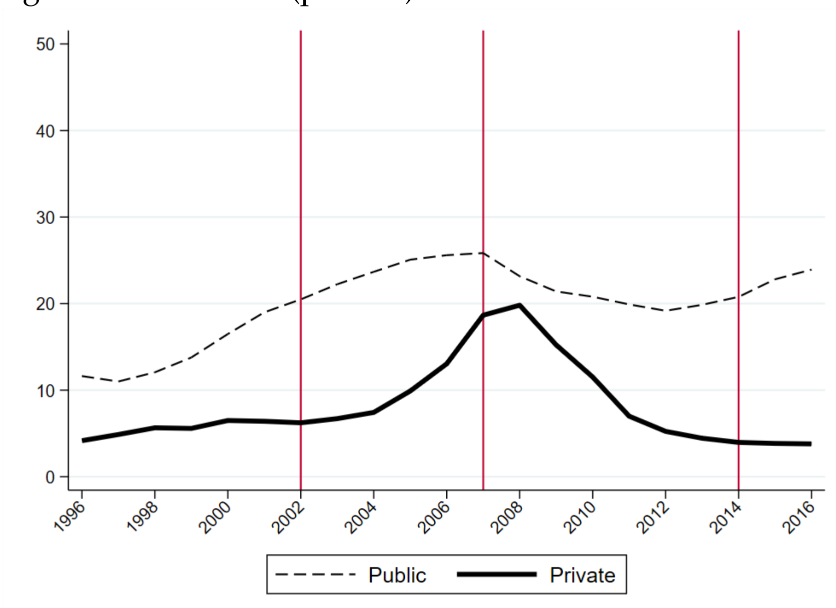

Figure 17: Number of Universities. Source: NIS Romania Administrative panel.

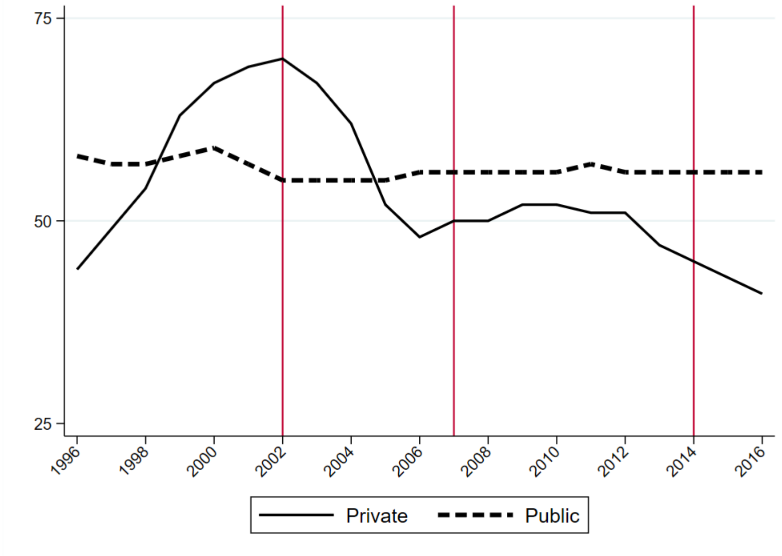

Figure 18: High School Enrollment in English Language classes (thousands). Source: NIS Romania Administrative panel.

9 Tables

Table 1: Overview of Empirical Estimates of Emigration on Origin Education.

Identification Strategy	Positive Effect	Negative Effect
IV: Networks	Hanson & Woodruff (2003) *Abarcar & Theoharides (2017)* Beine et al. (2011)	McKenzie & Rapoport (2011) de Brauw & Giles (2006) Lara (2015)
IV: Shocks	**Theoharides (2018)** **Theoharides & Yang (2018)** **Khanna & Morales (2018)** **Fernandez-Sanchez (2020)** Yang (2008)	Ameuendo-Dorantes & Pozo (2010) Antman (2011)
Diff-in-Diff	**Dinkelman & Mariotti (2016)** ***Chand & Clemens (2019)*** Shrestha (2015)	
Other	Antman (2012) **Adukia et al. (2018)** Cox-Edwards & Ureta (2003)	Pan (2017) Giannelli and Mangiavacchi (2010)

Note: The unit of analysis in the bold papers is at some aggregate level while italicized papers have tertiary education as their main outcome variable.

Table 2: Romanian Census Results. Source: IPUMS Census data.

	1{in school}	1{college grad}	1{in school}	1{college grad}
$Z_c \times 1\{t = 2011\}$	0.002***	0.002**	0.003***	0.003***
	(0.0008)	(0.0008)	(0.001)	(0.009)
$Z_c \times 1\{t = 2002\}$	0.002**	0.0005***	0.004***	0.007**
	(0.0009)	(0.0002)	(0.009)	(0.0003)
$Z_c \times 1\{t = 1977\}$	-0.001	-0.001***	-0.0008	-0.002***
	(0.0006)	(0.008)	(0.007)	(0.0006)
1{rural}			-0.13***	-0.08***
			(0.01)	(0.005)
$1\{\text{rural}\} \times Z_c \times 1\{t = 2011\}$			-0.0035***	-0.0038***
			(0.001)	(0.01)
$1\{\text{rural}\} \times Z_c \times 1\{t = 2002\}$			-0.006***	-0.0007
			(0.0016)	(0.0004)
$1\{\text{rural}\} \times Z_c \times 1\{t = 1977\}$			0.006	0.003***
			(0.0007)	(0.0008)
Other Variables				
1. Region Fixed Effects	✓	✓	✓	✓
2. Year Effects	✓	✓	✓	✓
4. "Stayers" only	✓	✓	✓	✓
3. Controls	✓	✓	✓	✓
Statistics				
Age group	18-24	≥ 25	18-24	≥ 25
Observations	849,583	5,349,339	849,583	5,349,339
Adjusted-R^2	0.07	0.27	0.39	0.26

Standard errors in parentheses

Standard errors are clustered at the county level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Descriptive Statistics on Romanians (2000-2010). Source: IPUMS Census data.

	RO native 2002	ES: RO immig 2001	USA: RO immig 2000-2010	ES native 2001	USA native 2000-2010
Low-Skilled Occ	0.17	0.48	0.11	0.22	0.11
College Grad	0.06	0.04	0.37	0.06	0.19
In Labor Force	0.82	0.86	0.59	0.85	0.49
Employed	0.36	0.58	0.55	0.36	0.45
Unemployed	0.05	0.12	0.04	0.06	0.03
Self-employed	0.05	0.04	0.11	0.07	0.06
Age	37.34	28.41	44.64	39.70	38.45
Male	0.49	0.58	0.47	0.49	0.48
Married	0.49	0.48	0.62	0.47	0.43

Table 4: Descriptive Statistics on Romanians (2011-2018). Source: IPUMS Census data.

	RO native 2011	ES: RO immig 2011	IT: RO immig 2011-2018	ES native 2011	IT native 2011-2018
Low-Skilled Occ	0.20	0.51	0.47	0.28	0.17
College Grad	0.13	0.05	0.04	0.08	0.08
In Labor Force	0.84	0.88	0.94	0.85	0.87
Employed	0.43	0.42	0.55	0.36	0.32
Unemployed	0.03	0.28	0.19	0.14	0.07
Self-employed	0.08	0.05	0.05	0.08	0.08
Age	40.24	32.42	35.83	43.70	46.43
Male	0.49	0.46	0.41	0.49	0.48
Married	0.52	0.50	0.46	0.48	0.48

Table 5: Occupation Returns to College
Dependent Variable = $1\{$Low Skill Occuppation$\}$
Source: IPUMS Census data.

	RO 2002	ES 2001	USA 2000s	RO 2011	ES 2011	USA 2010s	IT 2011-2018
1{College Grad}	-0.161***	-0.127***	-0.0770***	-0.110***	-0.118***	-0.0916***	-0.106***
	(0.000690)	(0.00104)	(0.000169)	(0.000744)	(0.000922)	(0.000199)	(0.00165)
1{RO Immig}		0.219***	0.00428		0.194***	0.0329***	0.289***
		(0.00931)	(0.00424)		(0.00440)	(0.00570)	(0.00556)
1{RO} × 1{College}		-0.0223	0.00440		0.0849***	-0.0263***	-0.0122
		(0.0462)	(0.00571)		(0.0185)	(0.00727)	(0.0287)
1{Other Immig}		0.121***	0.0472***		0.137***	0.0682***	0.206***
		(0.00157)	(0.000336)		(0.00154)	(0.000375)	(0.00275)
1{Other} × 1{College}		-0.0772***	-0.0303***		-0.0421***	-0.0520***	0.0262***
		(0.00442)	(0.000517)		(0.00384)	(0.000542)	(0.00892)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FEs			✓			✓	✓
Observations	2,137,967	2,039,274	22,963,594	1,991,924	4,107,385	25,198,523	968,149
Adjusted-R^2	0.06	0.042	0.054	0.049	0.039	0.019	0.047

Heteroskedasticity-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$