# UNIVERSITÀ DEGLI STUDI DI TORINO

Dipartimento di Scienze Economico-Sociali e Matematico-Statistiche


## PhD in Economics "Vilfredo Pareto"

XXXII Cycle

# Three Essays on Applied Economics


Phd Candidate: Davide Bellucci

Supervisor: Prof. Pierluigi Conzo


2016-2019

# Childhood exposure to the Second World War and financial risk taking in adult life

Pierluigi Conzo[§]

Davide Bellucci[*]

Giulia Fuochi[†]

This version: *July 2019*

**Abstract**

Adverse childhood experiences might have long-lasting effects on decisions under uncertainty in adult life. Merging the European Survey on Health, Ageing and Retirement with data on conflict events during the Second World War, and relying on region-by-cohort variation in war exposure, we show that warfare exposure during childhood is associated with lower financial risk taking in later life. Individuals who experienced war episodes as children hold less – and are less likely to hold – stocks, but are more likely to hold life insurance, compared to non-exposed individuals. Effects are robust to the inclusion of potential mediating factors, and are tested for nonlinearity and heterogeneity. Moreover, we provide evidence of hedonic adaptation to war, as high and low intensity of war exposure have comparable long-term effects. We also document that war exposure in childhood increases sensitivity to financial uncertainty since exposed-to-war individuals are less likely to hold stocks after periods of high volatility.  Finally, we shed light on the most likely mechanism in the relationship between war exposure and financial risk taking – i.e., enhanced sensitivity to uncertainty – and we show that preferences, and not beliefs, channel this relationship.

**Keywords:** financial risk taking; risk aversion; stocks; life insurance; life experiences; WW2

**JEL codes:** D14 D81 D91 G01 G11
**PsycINFO codes:** 3920 2840

[§] *Corresponding author* - Dept. of Economics and Statistics "S. Cognetti de Martiis", University of Turin – Campus Luigi Einaudi, Lungo Dora Siena 100A, 10153, Turin, ITALY. Email: pierluigi.conzo@unito.it

[*] University of Turin & Collegio Carlo Alberto

[†] Dept. FISPPA – Applied Psychology, University of Padua

## 1. Introduction

Most financial decisions involve the individual's propensity to take risks, and this propensity depends on several factors. Assuming that one has the cognitive abilities and income or wealth to invest in the financial market, financial literacy is key: low levels of financial knowledge are still very common, and negatively associated with stock holding (Guiso & Jappelli, 2005; van Rooij, Lusardi, & Alessie, 2011). Other individual characteristics limiting financial investments by most European and US households include: a low level of education of the investor (Guiso, Haliassos, & Jappelli, 2003); genetic endowment, explaining approximately 25% of individual variation in investment portfolio risk (Cesarini, Johannesson, Lichtenstein, Sandewall, & Wallace, 2010); and being female (Sapienza, Zingales, & Maestripieri, 2009).

Yet there are also relevant individual factors around personality, attitudes and beliefs: lower extraversion and higher openness to experiences are associated with greater financial assets (Brown & Taylor, 2014); individualism is related to a stronger willingness to take financial risks (Breuer et al., 2014); participation in the stock market is associated with more social activities (Christelis, Jappelli, & Padula, 2010) and with generalized trust (Guiso, Sapienza, & Zingales, 2008).

All these individual characteristics have something in common: they interact with – and are partially driven by – the environment (e.g., Gottlieb, 1997, 1998), i.e., the places, contexts, and experiences that have shaped one's life. Research has shown that the formation of risk attitudes and the propensity to take financial risks are influenced by important negative life experiences, such as: the loss of a child; being the victim of physical attack (Bucciol & Zarri, 2015); and having been exposed to natural calamities (Cameron & Shah, 2013); conflicts (Kim & Lee, 2014; Callen et al. 2014; Cassar et al. 2017); and macroeconomic shocks (Malmendier & Nagel, 2011).

These studies established the role of traumatic experiences in the formation of risk attitudes by means of lab-experiments in developing countries (Cameron & Shah, 2013; Callen et al. 2014; Cassar et al. 2017) or life-course analysis in more developed societies (Bucciol & Zarri, 2015; Malmendier & Nagel, 2011). However, endogeneity issues, due to non-random exposure to shocks and concerns about the external validity of single-country results, leave open the question of whether early-life hardships shape risk-based decisions over the long run.

We aim to provide an answer to this question by testing whether strong negative childhood experiences have a role in financial choices in adulthood. In particular, we examine whether exposure to World War II (WW2) during infancy affects financial risk taking (stock ownership and stocks' share) and financial choices buffering individuals and families from life events (life insurance).

The region-by-cohort variation induced by WW2 events in Europe provides us with an ideal natural experiment for identifying the impact of childhood hardships on risk attitudes in later life. In addition, since WW2 caused shocks in a variety of European regions, at different developmental stages, our results benefit from a larger degree of external validity than those in previous studies based on a single, developing country.

We exploit retrospective data about childhood conditions (hunger periods, parental absence, dispossession, the health and socio-economic status of the family); adulthood characteristics (income, education, job status, physical and mental health); positive expectations about future outcomes; and (current and past) macro-level characteristics to test whether these factors affect relations between war exposure and financial risk preferences. This allows us to investigate – and possibly to rule out – their mediating role in the link between war and risk taking.

Our results show that exposure to WW2 negatively impacts on stock-ownership and share of stock in financial portfolio, and simultaneously a positive effect on the probability of having life insurance. We find no room for mediating effects of the aforementioned adulthood and childhood characteristics, cognitive abilities, war-related hardships, and macro-level factors interacting with war-exposure and risk preferences.

To enhance the novelty of the contribution, we provide evidence of hedonic adaptation, by showing that a more prolonged or more intense exposure to war has the same long-term effects on financial risk taking as low levels of exposure. We also document that war exposure in childhood increases sensitivity to financial uncertainty, as war-exposed individuals are less likely to hold stocks after periods of high volatility. A series of tests allows us to shed light on the most likely mechanism in the relationship between war exposure and financial risk taking – i.e., enhanced sensitivity to uncertainty – and to understand that preferences, and not (optimistic or pessimistic) beliefs, channel this relationship.

## 2. Background

### *2.1. Life shocks and risk preferences*

Research on the effects of shocking life experiences on risk preferences has thrown up sometimes contradictory findings. Some studies have documented an increase in risk-seeking attitudes and behavior after dreadful life experiences. These include: large losses in property values after the 2011 Australian floods (Page, Savage, & Torgler, 2014); community deaths due to civil conflict in Burundi (Voors et al., 2012); and evacuation immediately after Hurricane Katrina (Eckel, El-Gamal, & Wilson, 2009).

On the other hand, a greater number of studies reported an increase in risk aversion after negative life shocks, for instance, recent exposure to floods and earthquakes in Indonesia (Cameron

& Shah, 2015); the 2004 Asian tsunami (Cassar, Healy, & Kessler, 2017); health shocks – measured by extreme losses in hand grip strength – (Decker & Schmitz, 2016); and being four to eight years old during the peak of Korean war (Kim & Lee, 2014). Malmendier and Nagel (2011) showed that the willingness to take financial risks was lower for people who experienced adverse financial market conditions in the early stages of their lives. Callen, Isaqzadeh, Long, & Sprenger (2014) found that individuals exposed to violence in Afghanistan, when primed to recall fear, exhibited an increased preference for certainty. Particularly relevant to this paper is the work of Bucciol and Zarri (2015), showing that individuals who lost a child or experienced a physical attack were less likely to hold stocks, and had a lower share of stocks. As in the present paper, both outcomes were considered, by Bucciol and Zarri, as two measures of risk taking in financial choices.

Concluding that risk tolerance is decreased by life shocks may be too simplistic: first, the association between risk taking and life shocks may depend on the domain of risky choices, for instance, gain vs. losses. In two studies, Li, Li, Wang, Rao, and Liu (2011) found that people living in areas devastated by heavy snowstorms or a major earthquake in China were more likely – than people living in non-devastated areas – to prefer a sure loss to a larger loss with low probability. They were also more likely to prefer a low-probability associated gain to a sure smaller gain. The experience of a natural disaster increased both risk aversion in the domain of losses and risk propensity in the domain of gains.

Second, the association between risk taking and life shocks may depend on the severity of the shocks. For instance, CEOs who have experienced the extreme downsides of natural disasters tend to lead firms in a more conservative and less risky way compared to CEOs who have experienced disasters without extremely negative consequences (Bernile, Bhagwat, & Rau, 2017). One possible channel may be the accessibility of events in memory: the more shocking, the more salient events are, and events that are more accessible in memory are associated with increased risk aversion (Kusev, van Schaik, Ayton, Dent, & Chater, 2009).

Third, the same life shock may be more or less influential depending on the person's age when the shock occurred: memory and the stage of brain development play a huge role. Infants (one to 18-24 months) are aware of their surroundings and possess a rudimentary form of episodic memory, but they do not have the ability to consciously *remember* (Bauer & Dow, 1994). Long-term ordered recall emerges after around twelve months of life (Carver & Bauer, 2001). Between three to six years children become able to remember events as experienced (Perner & Ruffman, 1995). Moreover, neural circuits develop during sensitive periods of one's life: in sensitive periods experiences have a major influence on brain development, including structures and functions (Fox, Levitt, & Nelson, 2010; Knudsen, 2004). Thus, life shocks occurring during the sensitive period of a certain brain area or neural circuit may affect the functions pertaining to that area or circuit. Consistent with this reasoning, Kim and Lee (2014) found that the Korean War affected risk aversion particularly for respondents who had lived in the provinces where conflict was more intense and who had been four to eight years old during the conflict. Those who had been younger or older were not significantly affected. The authors explained these results with the fact that the prefrontal cortex, which is the main brain region managing risky decision-making, has a strong development at that age (4-8).

As life shocks experienced before adulthood may have a long-term impact, the next section focuses on early life (infancy and childhood) major experiences and their associations with human capital outcomes.

### *2.2. Major early life experiences and adulthood outcomes*

A growing number of economic, psychological and demographic results, based on the life-course approach, have shown that the type of childhood one has had well predicts the adult (s)he will be (e.g. Elder, 2018; Giuliano & Spilimbergo, 2014). A frequent finding in this literature is that exposure to warfare in early life accounts for a large proportion of the variation in health and economic outcomes found in adult life.

Experiencing WW2-related episodes in childhood have been shown to have detrimental effects on the health, education and income of Europeans aged 50 or more (Kesternich, Siflinger, Smith, & Winter, 2014; Havari & Peracchi, 2016). Similarly, Ichino and Winter-Ebmer (2004) provided causal evidence that Germans or Austrians who were ten years old during WW2 had worse educational outcomes than their counterparts in Switzerland and Sweden (neutral countries). Akbulut-Yuksel (2014) exploited region-by-cohort variation in WW2 intensity to document that the war produced negative consequences on human capital and labour market outcomes for those Germans who were children during the war. In Nigeria and Burundi as well, civil war negatively impacted long-term health outcomes (Akresh, Bhalotra, Leone, & Osili, 2012; Bundervoet, Verwimp, & Akresh, 2009).

Early-life exposure to conflict shapes human capital outcomes in later life, and also affects social preferences in a persistent way: Conzo and Salustri (2017) and Grosjean (2014) found that WW2 made exposed individuals less trusting. Hörl, Kesternich, Smith, and Winter (2016) found hunger episodes in German cohorts born after WW2 to have a similar effect on trust. Lab-in-the-field experiments showed short-term effects of conflict on social preferences, with either positive or negative signs, depending on the context. Some studies documented lower cooperation and trust among conflict victims (e.g. Cassar et al., 2013; Becchetti et al., 2014), while others reported increased prosociality in the aftermath of a civil war (e.g. Voors et al., 2012; Bauer et al., 2017).

Children experience, in war, hunger, poverty, family separation, a lack of resources, but especially a large increase in the perceived probability of risk and unexpected danger. This leads to general uncertainty in both present and future life (Barenbaum, Ruchkin, & Schwab-Stone, 2004; Jensen & Shaw, 1993). To assess the role of all these factors in explaining the association between WW2 and financial risk taking, we consider, in the empirical models, childhood characteristics and adult outcomes stemming from war exposure.

## 3. Method

### *3.1. Data and variables*

The dataset we use in our study combines four different data sources. The main database is based on five waves (from 2004 to 2015) of the "Survey on Health, Ageing and Retirement" (SHARE)[3]: to investigate the effect of early life shocks on later socio-economic outcomes, we merge such longitudinal data with retrospective information on past life events from the "SHARELIFE" survey. Due to the high number of missing values, we impute, when possible, socio-economic variables and adulthood controls with information extracted from previous (or subsequent) waves or with the median value at country level[4].

SHARE contains an entire section on financial and real assets. More specifically, it provides information about the amount of directly held stocks and the composition of mutual funds and third-party managed accounts. When such information is not available, we impute the missing values as in Christelis et al. (2010), based on the answer's range as indicated by each respondent. We reconstruct the monetary value of directly held stocks, resources invested in mutual funds and individual retirement account (IRA), and compute the composition of mutual funds and IRA using the self-reported fraction of accounts that are mostly invested in bond, stocks, or equally split (for which we assign value of 75%, 25% or 50%-50%).

We consider four different financial outcomes in our regressions. Three of them are dichotomous variables taking value one if the respondent respectively holds direct stocks, life insurance, and direct or indirect stocks. The fourth outcome is the share of directly held stocks with respect to the total amount of stocks, including those indirectly held through mutual funds and IRA. As stocks represent the riskiest financial instrument in SHARE, we use stock ownership and stocks' share as proxies for financial risk taking (Love & Smith, 2007)[5]. This practice, well established in the

[3] The SHARE project (SHARE website) is the main longitudinal cross-national survey on European individuals aged 50 or older.
[4] More details on the imputation strategy are available in the Electronic Supplementary Material (ESM) 1.
[5] The use of a dichotomous measure of stock market participation has two advantages. First, it mitigates potential measurement errors in reporting the exact portfolio share allocated to stocks. Second, it is less sensitive to market

economic literature, was first adopted by Cohn, Lewellen, Lease, and Schlarbaum (1975) and Friend and Blume (1975), and more recently by Malmendier and Nagel (2011) and Bucciol and Zarri (2015). Life insurance is, instead, mostly a financial tool to protect against unexpected negative life events. It can, thus, be considered as a financial by-product of risk aversion regarding life (Browne & Kim, 1993; Yaari, 1965).

As shown in Figure 1, panel A and panel B, stockowners in Europe are quite rare, except in Denmark and Switzerland, in which two countries 15-20% of total household financial wealth is held in stocks. Life insurance is more common across Europe, with Italy and Greece at the bottom of the ranking. Netting out country, cohort and period effects, individuals who were not exposed to WW2 tend to hold more – or are more likely to hold – stocks, compared to their exposed counterparts (Figure 2, panel A to C). On the other hand, individuals exposed to war are more likely to have life insurance than their non-exposed counterparts.

The second source of data is an original database we created about WW2 events. It collects information on the number of traumatic war episodes including battles, attacks, bombings, invasions, and occupations as reported by Ellis (1993), Davies (2006) and Collier (2004). In particular, for each war episode during WW2 (September 1939 - July 1945) we registered the date (month and year) and the region in which it occurred (NUTS2 level), collecting a total of 1,512 war episodes. To determine respondents' war exposure, we first computed the number of war episodes that occurred in each region in each month during the war years. We then classified each region as exposed to war within a given month of the year, as long as at least one war episode occurred in that time-space window. In this way, each region within each country can be considered to have been either exposed or not-exposed in the same year, depending on the timing of the war episode. For example, Paris Basin region (FR2) was a war-exposed region in 1940 for four months since it suffered episodes in May, June, July and August of that year, but it was not a war-exposed region in March, April or September of the same year. We therefore had the number of war months (months with at least one war episode) for each region in each year of WW2. We, next, combined this data with the information about year of birth and region of residence during WW2 for our respondents. This was done to calculate the number of months of war exposure for each respondent in each year of WW2. More specifically, at an extensive margin, we considered each respondent as being exposed if he/she was living in the war region when the episode occurred. In this way, our war-exposed (treatment) group includes all individuals born after 1929 who experienced at least one month of war events. The non-exposed (control) group, was composed of individuals born after 1929 who did not suffer war episodes in the

dynamics, which – since individuals might not promptly adjust their portfolio – could make it hard to disentangle whether the observed changes in shares are merely due to changes in stock prices or to risk preferences (Bucciol & Zarri, 2015).

region where they were living during WW2, together with those born after the end of the war. At an intensive margin, we compute the overall median of months of war exposure across the European countries in our sample. We classify individuals as being highly exposed if the number of months of war that they experienced is above that median (we consider also tertiles of exposure in additional tests). Figure 3A shows the geographical distribution of months of war across European regions. On average, war exposure was 3 months of war and the most affected region was North Rhine-Westphalia in western Germany, with 35 months of war exposure. Accordingly, respondents who on average suffered most in WW2 lived in north-western Germany (Figure 3B).

Given our focus on childhood experiences, we decided to exclude individuals born before 1929, who might have actively participated to the war (e.g. because of conscription)[6]. This exclusion mitigates the confounding effect in our data of physical and mental injuries due to combat operations, which are not reported and that, hence, cannot be controlled for. We also exclude Spain from the sample as it had a Civil War in the years preceding WW2 and remained under Franco's military regime until 1975. Countries that did not experience war events within their territories, such as Sweden or Portugal, are not included in the analysis[7]. Finally, although we restrict our sample to native respondents, we decided not to exclude from the sample those who changed region of residence during WW2[8].

The third database contains information about the stock market volatility of the main European indices. The volatility indexes are extracted from the World Bank database and are calculated as the 360-day standard deviation of the return on the national stock market index[9]. We use this variable as an additional regressor in our model when we estimate the effect of increased uncertainty in the financial market, proxied for by high index volatility, on financial behaviour[10].

The fourth source of data is Eurostat, from which we take yearly measures of real GDP per inhabitant in purchasing power standard (PPS) and rate of unemployment of working-age population (i.e. from 15 to 74 years old) at country level, which we use as controls.

Eventually, as in Kesternich et al. (2014), we employ two war-related variables, proportion of deaths and sex ratio in 1945 and, relying on Maddison (2011), GDP in the years following WW2, each computed at country level. These are used to further control for historical macroeconomic shocks.

---

[6] Different sources report Calvin Graham as the youngest soldier in WW2. US born, he participated actively at the age of twelve. The Nazi army had Hitler Youth groups, with young males aged 10 to 14. Our exclusion limits the possibility of including young soldiers in our sample.
[7] Results are robust to the inclusion of Sweden, Portugal and Spain (available upon request).
[8] Less than 2% of the sample changed region during WW2. Our baseline findings are robust to the exclusion of individuals who moved to other regions during WW2 (see Section 4.5).
[9] World Bank financial database https://datacatalog.worldbank.org/dataset/global-financial-development .
[10] Figure SM1 in ESM 2 shows the index volatility for each country from 2004 to 2015.

All the variables employed in the models are described in the Variable legend in Table SM1, included in Electronic Supplementary Material (ESM) 2, together with their descriptive statistics (Table SM2).

### *3.2. Descriptive statistics*

Table SM2 reports the descriptive statistics (pooled over the waves) of the variables included in our econometric analyses. Around one third of respondents experienced at least one month of war exposure. About 55% of the sample respondents are women, the average age is 66, and more than 70% of the pooled sample has a partner.

In accordance with the age composition of our sample, on average each respondent suffers from at least one chronic disease, and memory capacity is quite low (5.2 out of 10), while numeracy and orientation are high. Average individual life expectancy, measured as the subjective probability of being alive in the ten years following the interview-date (independently from current age), is 64%. As to body mass index (BMI), most respondents are overweight (44%) or obese (20%), while a minority has normal BMI (35%). Respondents have, on average, eleven years of education, and most of them (58%) are retired. The average logarithm of income is 9.9 (slightly more than €20,000), while that of financial wealth is 2.6 (around €15,000).

As for the retrospective variables, SES is measured with the first extracted component (Childhood SES) from a factor analysis of four childhood characteristics at age 10: namely, the main occupation of the breadwinner; the number of books at home; the number of rooms *per capita*; and the number of bathrooms in their residence (Kesternich et al., 2014; Havari & Peracchi, 2017). We classify all respondents in the 75$^{th}$ percentile of the distribution of Childhood SES as “high SES”. Almost 40% reported living in rural areas at age 10, and almost the entire sample were inoculated during childhood. Fewer than 10% lived without their father, and slightly more than 3% suffered from dispossession episodes. As for cognitive abilities, average memory capacity is, as noted above, quite low (5.2/10), while numeracy and orientation record are respectively 3.88 over 5 and 3.86 over 4.

### *3.3. Empirical strategy*

Our baseline model captures the effect of war exposure (both at the intensive and extensive margin) on financial risk-taking. The estimating equation is reported below, for individual *i* at wave *t*.

$$Financial\ Instrument_{it} =$$

$$= \beta_0 + \beta_1 War_i + \beta_2 Log(Fin\ wealth)_{it} + \beta_3 Log(Income)_{it} + \beta_4 Gender_i + \sum_c \gamma_c\, Country_{it} + \sum_d \lambda_d\, Year\ of\ birth_i + \sum_f \theta_f\, Wave_{it} + \varepsilon_{it}$$

*Financial Instrument* represents one of the four aforementioned financial variables and *War* captures war exposure, either as a dummy variable or expressed in terms of intensity (median and tertiles of months of exposure, with results on tertiles reported in ESM 2). The two logarithmic regressors control for household wealth and income. All models include dummies for country of residence, as well as for year of birth and wave participation, which account for, respectively, cohorts and period effects[11].

We also investigate whether the effect of war on financial risk-taking is conveyed by other variables that may be both affected by exposure to WW2 and related to risk propensity. If this were the case, including them as controls in additional models would weaken the effects of war compared to the baseline model, and they would be channels – mediators – of the relationship (Baron & Kenny, 1986). The first two sets of potential mediators we include in the baseline model are adult-age socio-demographic characteristics (marital and employment status, years of education, number of children, number of chronic diseases, BMI, smoke and alcohol consumption) and childhood characteristics (SES at age 10, inoculation during infancy, and residence in rural areas). The other potential mediators we use as control variables are: cognitive abilities (memory, numeracy, orientation), mental health (EURO-D depression scale score), war-related hardships (absence of father at age 10, hunger episodes, dispossession), historical and current macro-economic factors (GDP, unemployment, demographic shocks), and optimistic beliefs (subjective life expectancy and health status, belief that life is full of opportunities, trust, and optimism). We include them one at a time, in models already containing adulthood and childhood controls.

As a third step, we investigate nonlinearity and heterogeneity in war effects. We test nonlinearity by measuring war with median and tertiles of months of exposure, and then with the number of months of war and its squared value, while we test heterogeneity with respect to gender and age.

Then, we explore how being exposed to WW2 during childhood affects reactions to periods of high stock-market volatility. Lastly, we perform a number of robustness checks on the results.

[11] Results without adulthood and childhood controls are available upon request.

Due to the panel structure of the dataset, we conduct random-effects probit (with binary financial outcomes) and random-effects OLS (with share of stocks) regressions with robust standard errors[12]. To facilitate the interpretation of the results, we report average marginal effects.

## 4. Results

### *4.1. The effect of exposure to war, controlling for adulthood and childhood characteristics*

Table 1 reports the results of the model on (dichotomous) war exposure, while controlling for adulthood and childhood characteristics together (models with adulthood and childhood controls included separately are, respectively, in Table SM3 and Table SM4 in ESM 2). Having suffered at least one month of war during infancy significantly affects all the financial outcomes considered in our study. War exposure has a negative impact on risky assets holding and share, while positively affecting the probability of holding life insurance, which is considered as a safe asset. The riskier the financial instrument (direct stocks ownership compared to indirect participation), the larger the effect of war. In particular, we find that individuals exposed to war during childhood, are 1.8 percentage points less likely to hold stocks in adult age (column 1 Table 1), and 3.3 percentage points more likely to hold life insurance (column 3 Table 1) than those who were not exposed. The share of financial wealth owned in stocks of exposed individuals is on average 1.5 percentage points lower than the one of non-exposed individuals. In line with previous findings in the economic literature (Croson & Gneezy, 2009; Sapienza et al., 2009), we find significant gender differences in risk-taking behavior. On average women are less likely to hold both risky and safe assets, confirming generalized higher risk aversion compared to men. The two controls for household wealth show effects in line with our predictions. Higher available resources are positively related to the probability of holding financial instruments.

As for marital status (living with a partner is the omitted benchmark), we find that being divorced or separated is negatively associated with the probability of holding risky assets, and the effect is similar for the number of children. Health status, measured by the number of chronic diseases respondents suffer from, does not yield statistically significant results. As to job status (being retired is the omitted benchmark), we find that being employed is the only category that increases the probability of a respondent holding life insurance. Better educated individuals are more likely to hold financial instruments, either risky (stocks) or risk-free (life insurance) assets. Previous research showed that risky behaviour correlates positively with financial risk tolerance (Dave & Saffer, 2008). We find, though, that all categories of alcohol consumption (no consumption omitted category) are

[12] Results are robust to random-effect panel OLS estimations with standard errors clustered by country of residence and by year of birth (available upon request).

positively associated with financial risk propensity, and that smoking habits are negatively associated with risky assets ownership, though the effect is not robust in all specifications.

Moving to childhood controls, findings are in line with the literature on parental transmission of risk preferences (Dohmen, Falk, Huffman, & Sunde, 2011). Those who had relatively higher socio-economic status in childhood are more likely to invest in risky instruments in adult age, and those who received vaccination are more prone to invest in life insurance (Table SM4 in ESM 2). The former result is not robust in the full specification model, when we jointly control for child and adulthood characteristics. This suggests that the effect of SES at the age of 10 may be absorbed by adulthood socio-demographic characteristics[13].

### *4.2. Investigating alternative explanations*

#### *4.2.1 Mental health and cognitive abilities*

As alternative explanations, we first consider cognitive abilities (Table SM5 in ESM 2) and depression status (Table SM6 in ESM 2). We do so to rule out the possibility that the detrimental effect of war on financial risk taking is due to impaired cognitive abilities and mental health. Table SM5 shows that numeracy positively predicts financial risk taking, as in Christelis et al. (2010). However, we do not find evidence that cognitive abilities play a mediating role: the marginal effect of war exposure does not change in magnitude in comparison with the baseline specification with adult and childhood controls. In the same vein, mental health is not able to explain variations in investments in risky assets (Table SM6 in ESM 2).

Despite having controlled for numeracy, orientation, and memory, it is important to acknowledge that war-related trauma could induce a more general cognitive strain in exposed individuals, in turn restraining their financial risk taking. To test this channel, we first compared the different effects of war exposure on the likelihood of holding stock, mutual funds, bonds, Individual Retirement Account (IRA), and contractual savings, both without and when controlling for cognitive abilities, and we found that exposure to war was negatively related to the probability of holding stocks, but not to the probability of holding other financial instruments. This suggests that enhanced risk aversion, rather than cognitive strain, is more likely to be the main mechanism underlying our results (Table SM7 in ESM 2). Secondly, we tested whether exposure to war affected financial asset allocations, characterized by different levels of risk and direct vs. indirect participation (Table SM8 in ESM 2). War exposure was positively related to the "share of low-risk assets" (the ratio between the sum of directly held bonds, indirectly held bonds, life insurance and contractual savings and total

[13] We do not find a statistically significant effect of the interaction term between war exposure and SES at the age of 10 (results available upon request). This rules out a moderating role of the familiar environment in childhood.

financial wealth). It was, instead, unrelated to the ratio of directly vs. indirectly held stocks. These results suggest that war exposure is associated with risk aversion in financial choices, and that cognitive strain – keeping risk aversion constant – is not a relevant mechanism. If it were so, individuals exposed to war would choose indirectly – over directly-held stocks, as indirect participation reduces the amount of cognitive resources needed to manage the chosen financial instrument(s).

*4.2.2 Hunger, dispossession and parental absence*

Results in Table 2 show that the absence of a father at age 10 is positively related to the ownership of life insurance. As the magnitude of the marginal effects of war exposure remains unaltered and statistically significant with respect to each one of our four variables of interest, war-related hardships do not appear either to be channels of the effects of war exposure on financial risk taking. It is important to note that these hardships differ from simple exposure to WW2. Dispossession, hunger, and parental absence are household-related consequences of the war that affect the individual from a practical point of view. When we control for these variables, together with childhood controls, the effect of exposure to war is separated from the effect of household-based conditions during war. As such, it can be interpreted as a pure effect of the context. We argue that this context effect involves the horrors of the war: for instance, seeing dead bodies lying in the streets and destroyed houses, the sound of air raid sirens, bombings, the Holocaust, witnessing murders or other violent acts, family separation. These mean fear, and this is likely to affect sensitivity to uncertainty, simultaneously fostering a preference for safe environments. Hence the lower likelihood that the exposed respondent, in later life, takes financial risks, and the higher likelihood of holding life insurance.

*4.2.3 Macro-level factors*

There is an additional advantage of assessing the long-term effects of a global shock on the behavior of respondents residing in different countries: we can exploit the cross-country dynamics of the war, and check how these interact with war exposure and risk taking. First, controlling for country dummies in the aforementioned estimates is not a trivial matter; it allows us to check whether exposure to a worldwide conflict has a long-term impact on preferences independently from time invariant, country-specific characteristics such as institutions and geography. These characteristics might, indeed, interact with the dynamics of WW2, the recovery after said war and risk preferences.

Our results that show that exposure to war has a significant effect, even controlling for country dummies, implies that country time-invariant characteristics do not matter[14].

To disentangle the effect of WW2 from the effects of macro-economic conditions related to – and brought along by – the same war, we re-estimate models in Table 1, by adding controls for past and current macro events likely to be related to risk preferences (one separate model for each control). Concerning past macro events, we controlled for the GDP of the country in which the respondent lived at age 10 (GDP in the year in which the respondent was 10, divided by *per capita* GDP in 2006, as in Kesternich et al., 2014), the country-specific proportion of deaths by 1945 (number of civilian and military deaths by 1945 over total population in 1939), and demographic shocks (sex ratio of women to men in 1945, taken from Kesternich et al., 2014). Concerning current macro events, we controlled for current GDP and country-specific unemployment rates. Results are reported in Table SM9 in ESM 2, and show that in all the models, the effect of exposure to WW2 is robust to the inclusion of current and past macro events, even the ones strongly related to the presence of war, such as the proportion of deaths in 1945. This finding suggests again that the horror and violence of a war witnessed while young might affect risk preferences independently of macro-level factors.

Finally, we run a check for heterogeneity of war exposure by WW2-coalitions in order to assess whether being on the side of the "winners" or of the "losers" played a role. Results are reported in Table SM10 in ESM 2 and show that there are no systematic differences in stock-market participation among exposed respondents from countries that won *vis-à-vis* those from countries that lost. This result provides evidence that "winning" or "losing" did not affect the development of risk preferences. It also suggests, together with former results, that the impact of war atrocities on financial risk taking is not mediated by macro-level factors.

#### *4.2.4 Optimistic beliefs and positive expectations about the future*

Experiencing macro-level events that have dramatic personal consequences may influence both risk preferences and beliefs – for instance, optimistic or pessimistic beliefs on future macroeconomic outcomes –, which in turn may affect financial risk taking (Das, Kuhnen, & Nagel, 2019; Malmendier & Nagel, 2011, 2015). In this study, pessimistic expectations about macroeconomic conditions could reduce stock investment, while pessimistic beliefs about future life events may increase life insurance holdings.

The results here suggest that sensitivity to uncertainty, and a preference for safe situations, are likely to convey the effect of war exposure on financial risk taking. To rule out the possibility that

[14] The lack of a mediating role of time-invariant socio-economic and institutional arrangements proxied for by country dummies survives the restriction to WW2-born cohorts and the control for region (instead of country) fixed characteristics that might interact both with exposure to war and risk-taking behavior (see Section 4.5).

this effect was, instead, driven by pessimistic beliefs about life and the environment, we repeated the models in Table 1 controlling for beliefs about one's life and health (subjective life expectancy, subjective health status and the belief that life is full of opportunities)[15], and beliefs about the behaviors of others (trust, and optimism).

Results (Table SM11) show that exposure to war was robust with the inclusion of these controls, offering support to the idea of the "preference" channel (sensitivity to uncertainty), rather than the "belief" channel.

### *4.3. Addressing nonlinearity and heterogeneity of effects*

As individuals tend to adapt to shocks (Lyubomirsky, 2010), we test whether the effect of the intensity or duration of war exposure on financial risk taking is nonlinear: the magnitude of that effect could increase with the intensity of exposure (linearity), or be similar at different (extreme) levels of exposure (hedonic adaptation).

We, therefore, estimate the impact of being above vs. below the median months of exposure relative to being non-exposed (omitted category); we also check for statistically significant differences between the estimated above- vs. below-median coefficients. Results in columns 1-2 of Table 3 and the test on equality of the coefficients of the above vs. below-median exposure (reported below Table 3) show that prolonged exposure to WW2 has the same (negative) effect on stock holding and stocks share as that of shorter exposure. There is apparently, then, a non-monotonic relationship. This result is also found when using tertiles of exposure (Table SM12 in ESM 2), whereby WW2 has about the same impact both for those exposed for a few months and for those exposed for a longer period.

As an additional test for nonlinearity, we use two discrete measures of exposure respectively capturing war duration (number of years) and war intensity (number of war events over the six years of the war). Results are reported in columns 3-4 for war duration and 5-6 for war intensity (Table 3), while graphs of quadratic predictions are in Figures SM2-3 (ESM 2). In both cases, we find a u-shaped relationship, with short and prolonged exposure producing similar effects, although the coefficient of the linear term of war intensity is not significant at the conventional 5% probability level (column 5 Table 3, $p = .077$).

Overall, results suggest hedonic adaptation. WW2-exposure reduces financial risk-taking, but up to a certain point: after a long series of war episodes, individuals adapt and become less sensitive to uncertainty.

[15] Relatedly, Arpino et al. (2019) show that WW2-exposure in childhood increases later life optimism in subjective evaluations of longevity. They argue that this might be due to the post-traumatic growth of exposed individuals.

Then, we explore heterogeneity in the effect of war by gender (Table SM13a-b in ESM 2) and age of exposure (Table SM14 in ESM 2). Women's higher risk aversion compared to men is a well-known finding in the economic literature. Table SM13a in ESM 2) shows that exposed women tend to participate less in the stock market than men; however, there are no significant differences in the other financial outcomes under consideration. To check for differential behaviour by gender at different levels of exposure, we compare coefficients of above- vs. below-median exposure, separately for men and women. Table SM13b (in ESM 2) shows that war exposure has a larger impact for men than for women. Considering stock-market participation and share of stocks, hedonic adaptation tends to occur mostly for men, while for women the detrimental effect of a war experience increases with the length of exposure. Specifically, with respect to stock ownership, the marginal effect of under-median exposure for men is almost 3 times as big as the marginal effects for women (-0.028 vs -0.011, p-value = 0.073; columns 1 and 5). The same result holds considering the share of stocks; the marginal effect of under-median exposure on men is higher than for women (-0.024 vs -0.007, p-value = 0.030; columns 2 and 6). As for life insurance, we find a similar pattern with marginal effects being relatively stronger for males, yet differences by gender are not statistically significant. Regarding total participation, coefficients of above- and below-median exposure for men seem to offset each other, though they are not statistically significant (column 8); for women, instead, the above- vs. below-median effects go in the same direction, but exposure matters only at low levels of exposure (column 8). Results for total participation show hedonic adaptation for women, as well; nevertheless, gender differences at different levels of exposure are not statistically significant.

Regarding age classes (Table SM8 in ESM 2), we find that being exposed to war at between nine and fifteen years of age has the most detrimental (and robust) effect on financial risk taking in adult age (columns 1 and 2), whereas it has a positive effect on the probability of holding life insurance. Moreover, having been zero to three years old during exposure to WW2, is negatively related to stock ownership and positively related to life-insurance ownership, while having been four to eight years old seems to have no effect. Wald tests between coefficients of the classes 0-3 and 9-15 reveal that the difference is statistically different from zero for stock ownership, share of stock, and life insurance. Thus, the effect of war on financial risk taking is heterogeneous for age, with stronger effects for respondents in the 9-15 age class during WW2. The effect is stronger for older children because during WW2 they would most likely be helping the family in adverse conditions, and they were more aware of hardships (Werner, 2000).

### *4.4. War exposure and reactions to high-volatility periods*

We proceed with our analysis by investigating the role of war exposure during childhood on financial decisions after periods of high stock-market volatility. Our hypothesis is that if war-exposed individuals are more sensitive to uncertainty, they would be more likely to rebalance their holdings than non-exposed individuals when the variance (and hence uncertainty) of returns, increases.

In order to study the effect of uncertainty in the stock market, we take information on the volatility of stock price index at country level. Each respondent has been matched with the volatility index, relative to the year preceding the interview, of his/her country of residence. Then, for each year, we ranked countries according to their stock volatility index and created a dummy with value one if the country is in the top 20% of the volatility index distribution (*high volatility*).

To test the heterogeneous effect of high past volatility on stock-market participation and share of directly owned stocks, we interact the high-volatility dummy with the war exposure dummy. High volatility is positively associated with participation in the stock market and, especially, with share of stocks (Table 4). Individuals exposed to war and to high volatility are 1.5 percentage points less likely to hold stocks than individuals that did not experienced high volatility (columns 3 and 5 Table 4). Similar results hold for stock shares. Individuals who both suffered war episodes during childhood and high volatility in adulthood, have a share of stock that is on average 0.4% lower (columns 4 and 6 Table 4). This result is probably driven by the most risk-loving individuals in the sample, who – attracted by the prospect of high gains – overinvest in risky assets as volatility increases.

However, with respect to heterogeneity by war-exposure, we find that war-exposed individuals tend to participate less in the stock market than non-exposed individuals after periods of high volatility, e.g. during the 2009 financial crisis (see Figure SM1 in Supplementary Materials 2). This result stays robust when we control for cognitive abilities (Table 4, columns 5-6), ruling out the possibility that higher sensitivity to volatility for the war-exposed is due to the impaired cognitive abilities of this group.

Overall these results are consistent with the hypothesis that the experience of WW2 in childhood increases sensitivity to uncertainty, driving exposed individuals to reduce stock holding later in life, especially when faced with the high uncertainty of stock-market returns.

### *4.5. Robustness checks*

Although SHARE informs us about the region of residence during each year of WW2 and permits us to track respondents' migration, it does not contain detailed information about the month in which respondents started living in their new place of residence[16]. Hence, we cannot be sure about whether respondents arrived in a war region before, or just after, the war episode occurred. We

[16] Migration within country during WW2 can be a concern because selective targeting of industrialized or dense regions would have pushed individuals to emigrate. Controlling for region fixed effects in the robustness check performed below permits us to mitigate potential endogeneity driven by non-random war targeting of regions and differential migration induced by war operations.

addressed this issue by re-estimating Table 1 models without individuals who migrated during the WW2 period. Furthermore, to rely on a control group that is more similar to our treatment group (made up of war-exposed respondents), we excluded individuals born after the end of WW2. The results of both these robustness checks (available upon request) are consistent with our previous findings (including the magnitude of coefficients), with war exposure negatively affecting financial risk taking. Consider that the fraction of migrants in our sample, though it may seem too low (2%), is in line with external data: the population in our sample countries was about 344 million in 1939[17], while the estimated number of refugees in Europe in 1945 was around seven million (Barnett 2002). Regarding out-of-sample migration, Kesternich et al. (2014) and Conzo and Salustri (2017) provide evidence that migration outside the countries in our sample during and after the war (1939-1947) was not easy. In addition, migration to the US from the 1920s to 1965 was at its minimum levels due to restrictions, imposing a ceiling on the number of immigrants accepted each year.

So far, we have relied on the *year* of birth and region of residence to merge retrospective information with WW2 data. To identify war exposure for each respondent more precisely, we exploit the within-region variation stemming from the *months* of respondents' birth and the *months* of war episodes. To this end, we restrict the sample to individuals born during WW2 (i.e. 1939-1945) and classified as "exposed" those who were born in a war region, at least one month before a war event occurred there[18]. By exploiting within-region variation in war exposure, we also net out the effects of time-invariant institutional, geographical, and macroeconomic features at the regional level, features which might affect both war exposure (and its intensity) and local recovery capacity. If, through this identification strategy, we gain in terms of the causal interpretation of results, we lose the generalizability of results to other cohorts. Results reported in Table SM15 in ESM 2 confirms our previous findings.

Selection on mortality might also be a threat to our identification strategy. Despite not being able to address this issue with the data at our disposal, we would argue that selection on mortality does not lead to a severe bias in our estimates. First, the previous analysis on the specific cohort of those born during WW2 might mitigate selective mortality induced by WW2. Compared with older cohorts, individuals born during WW2 are less subject to mortality and to the scarring effects of war exposure (Havari & Peracchi, 2017). Relying on the SHARE dataset, Havari and Peracchi (2017) provide evidence of low levels of childhood mortality during WW2 even in war countries; they also show that mortality at later ages was not systematically higher for those born during the war. Second,

---

[17] Data source: Lahmeyer 2006, Populstat [online]; available at http://www.populstat.info; own elaboration.

[18] Our control group, in this case, is composed of individuals who were born and grew up in no-war regions and by those who were born in war regions but at least a month after WW2 events occurring in those regions. See Conzo and Salustri (2017) for more details about this identification strategy.

Kesternich et al. (2014) – who also use SHARE – address the issue of differential mortality by war-induced SES. In our case, this source of selection would lead to an overestimation of the war effect if mortality was higher among low-SES respondents. The latter tend also to participate less in the stock market than high-SES respondents (Table SM4 in ESM 2). To assess the severity of selection, Kesternich et al. (2014) compare the age of death of the respondents' father by SES, by war vs. non-war countries, and by year of birth (before 1946 vs. after 1945). They find that both low- and high-SES respondents face almost the same reduction in the age of death of fathers, and conclude that this type of selection is not large enough to drive their findings.

Finally, the negative effect of war exposure on stocks share could be driven by the more exposed individuals investing less in direct and more in indirect forms of stock holding. In order to check whether this is the case, we rely on three tests. First, as shown in Section 4.2.1 (Table SM7 in ESM 2), exposed individuals do not seem to compensate lower stock-market participation with participation in other financial assets such as bonds, IRA, Mutual Funds and Contractual Savings. Second, exposed individuals tend to invest more in risk-free assets (columns 1 and 3, Table SM8 in ESM 2), but do not substitute direct with indirect participation when risk is kept constant, i.e. when we compare the share of directly vs. indirectly held stocks (columns 2 and 4, Table SM8 in ESM2). The last robustness check regards the definition of the "share of stock" variable: we compute the share of stock owned as a function of the total wealth as in Bucciol et al. (2015). Results are robust to this check, even when controlling for cognitive abilities (Table SM16 in ESM 2). All these estimates suggest that the observed reduction in the share of stocks is not due to a change in the denominator: exposed individuals do not seem to allocate relatively more to indirect stock holdings.

## 5. Discussion

This paper investigates the long-term effect of WW2 on financial risk taking (stock ownership and stocks' share) and on financial choices protecting respondents from life events (life insurance). It does so through a tight identification strategy based on region-by-cohort variation in war exposure. Results show that childhood exposure to WW2 decreases by about two percentage points the probability of holding direct and indirect stocks, and by about one percentage point and a half the share of stocks in later life. Exposure to WW2 also increases by three percentage points the probability of having life insurance in adulthood. The effects of war are almost unchanged when including classic socio-economic controls, childhood and adulthood characteristics, war-related hardships, past and current macro-level factors, proxies for optimistic beliefs about future outcomes, and cognitive abilities and mental health at the time of the interview. Thus, we may conclude that such effects are not conveyed by impaired cognitive abilities and mental health, or other individual and macro-level variables affected by war and potentially related to financial choices. Childhood exposure to war has a direct, persistent negative effect on financial risk taking.

With respect to the extant literature, we contribute in several different ways. We provide evidence of hedonic adaptation, since high intensity or duration of war exposure has the same impact as low levels of exposure; we show that war-exposed respondents are less likely to hold stocks after periods of high volatility, suggesting that they are more sensitive to uncertainty. Through a series of tests, we shed light on the most likely mechanism in the relationship between war exposure and financial risk taking – i.e. enhanced risk aversion and preference for safer environments – and we show that preferences, and not (optimistic or pessimistic) beliefs, channel this relationship.

The negative relationship between financial risk taking and exposure to WW2 is consistent with results from previous research (Bucciol & Zarri, 2015; Cameron & Shah, 2015; Kim & Lee, 2014). This suggests that life shocks may be able to change cognitive schemata in subtle ways, not captured by an individual’s physical, psychological, or socio-economic conditions. Cognitive schemata stem from the generalization of past experiences into cognitive structures that in turn guide the processing of new information and experiences (Stotland & Canon, 1972). Thus, schemata influence how reality is perceived, and because they are rigid, individuals tend to fit reality into schemata, rather than adapting them to new information.

In this perspective, the experience of WW2 during childhood would be a fundamental constituent of exposed individuals’ cognitive schemata. In particular, exposure to conflict might have increased the perception of uncertainty and lack of control over the environment (Barenbaum et al., 2004). This leads, in turn, to an increase in risk aversion and safer financial investments in exposed individuals, compared to non-exposed ones. Hence the lower propensity to invest in stocks, and the higher propensity to buy life insurance. The amount of risk characterizing stocks may be perceived to be unmanageable, whereas life insurance may be considered necessary to counteract life adverse conditions and negative events.

Our results are also consistent with Kim & Lee (2014) in showing that exposure to war during childhood reduces risk taking during adulthood. The effect of strong and negative early life experiences on risk propensity is enduring. This may occur because the shock alters the development of the prefrontal lobe (Kim & Lee, 2014), which is one of the main brain regions involved in risk-related decision-making (Figner et al., 2010). But it might also alter cognitive schemata, especially in ages beyond the sensitive period of the prefrontal lobe.

We also acknowledge the possible presence of war-related traumas captured neither by our childhood and adulthood controls, nor by mental health and cognitive skill variables. Adults who were exposed to war as children may suffer from Post-Traumatic Stress Disorder (PTSD) symptoms

(Macksoud & Aber, 1996) that are not fully captured by the depression scale in SHARE. WW2 caused an unprecedented amount of civilian losses and bombardments (Werner, 2000), which led people, even at a young age, to witness – and to remember – these events (Berntsen & Rubin, 2006). Such experiences may be the ones increasing the perception of risk (for instance, in stock holding), and the willingness to reduce or control life risks (stimulating the purchase of life insurance).

As these effects held when controlling for a number of individual and macro-level factors also related to the conflict, we may conclude that the main channel of the relationship is enhanced sensitivity to uncertainty and to risky circumstances. This sensitivity, the results suggest, was fostered by the unpredictable, fear-inducing horrors of the war.

We also have to acknowledge several limitations in this paper. First, when we measure the months of war of each region in each year of WW2, we do not distinguish between regions with one, five, or ten episodes of war in the same month. This approach overlooks the intensity, then, of conflict based on the number of war episodes, and the possible differences in the intensity of single war episodes. However, this does not appear to be a severe concern since results hold also when considering number of WW2 events instead of months of exposure. Second, there might be small inaccuracies in the number of months of exposure to war because we use the region of residence during WW2, but we cannot check when respondents started living in that region. This issue was partly addressed through a robustness check on the sample of individuals who did not relocate during WW2. Third, the estimated magnitude of the WW2-effect might appear negligible. However, it is very close to the effect of income and other important controls.

Despite these limitations, our paper finds robust effects of exposure to WW2 on financial risk taking. Exposed individuals prefer to avoid risky financial instruments, while purchasing life insurance. Increasing wealth by investing in stocks may not be alluring, compared to, for them, the more important task of defending what they already possess. The experience of war, with its dangers and uncertainty, might yield a strong willingness to protect life and avoid risk. Life, after all, will quite possibly be more valuable to those who once thought that they could lose everything.

## References


Agresti, A. (2010). *Analysis of ordinal categorical data* (Vol. 656). John Wiley & Sons.

Akbulut-Yuksel, M. (2014). Children of war the long-run effects of large-scale physical destruction and warfare on children. *Journal of Human resources, 49*(3), 634-662.

Akresh, R., Bhalotra, S., Leone, M., & Osili, U. O. (2012). War and stature: Growing up during the Nigerian civil war. *American Economic Review*, *102*(3), 273-77.

Arpino, B., Conzo, P., & Salustri, F. (2019). *I'm a survivor, keep on surviving: Early-life exposure to conflict and subjective survival probabilities in adult life*. University of Turin.

Barenbaum, J., Ruchkin, V., & Schwab-Stone, M. (2004). The psychosocial aspects of children exposed to war: practice and policy initiatives. *Journal of Child Psychology and Psychiatry*, *45*(1), 41-62.

Barnett, L. (2002). Global governance and the evolution of the international refugee regime. *International Journal of Refugee Law*, *14*(2_and_3), 238-262.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology*, *51*, 1173-1182.

Bauer, M., Blattman, C., Chytilová, J., Henrich, J., Miguel, E., & Mitts, T. (2016). Can war foster cooperation?. *The Journal of Economic Perspectives*, *30*(3), 249-274.

Bauer, P. J., & Dow, G. A. (1994). Episodic memory in 16- and 20-month-old children: Specifics are generalized but not forgotten. *Developmental Psychology*, *30*(3), 403–417.

Becchetti, L., Conzo, P., & Romeo, A. (2014). Violence, trust, and trustworthiness: evidence from a Nairobi slum. *Oxford Economic Papers*, *66*(1).

Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *The Journal of Finance*, *72*(1), 167–206.

Breuer, W., Riesener, M., & Salzmann, A. J. (2012). Risk aversion vs. individualism: what drives risk taking in household finance? *The European Journal of Finance*, *20*(5), 446–462.

Brown, S., & Taylor, K. (2014). Household finances and the "Big Five" personality traits. *Journal of Economic Psychology*, *45*, 197–212.

Browne, M. J., & Kim, K. (1993). An international analysis of life insurance demand. *Journal of Risk and Insurance*, *60*(4), 616-634.

Bucciol, A., & Zarri, L. (2015). The shadow of the past: Financial risk taking and negative life events. *Journal of Economic Psychology*, *48*, 1–16.

Bundervoet T., Verwimp P., and Akresh R. (2009), Health and civil war in rural Burundi. *Journal of Human Resources*, *44*, 536–563.

Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and Risk Preference: Experimental Evidence from Afghanistan. *American Economic Review*, *104*(1), 123–148.

Cameron, L., & Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. *Journal of Human Resources*, *50*(2), 484-515.

Carver, L. J., & Bauer, P. J. (2001). The dawning of a past: The emergence of long-term explicit memory in infancy. *Journal of Experimental Psychology: General*, *130*(4), 726–745.

Cassar, A., Grosjean, P., & Whitt, S. (2013). Legacies of violence: trust and market development. *Journal of Economic Growth*, *18*(3), 285-318.

Cassar, A., Healy, A., & Von Kessler, C. (2017). Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. *World Development*, *94*, 90-105.

Cesarini, D., Johannesson, M., Lichtenstein, P., Sandewall, Ö., & Wallace, B. (2010). Genetic variation in financial decision-making. *The Journal of Finance*, *65*(5), 1725–1754.

Christelis, D., Jappelli, T., & Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, *54*(1), 18–38.

Cohn, R. A., Lewellen, W. G., Lease, R. C., & Schlarbaum, G. G. (1975). Individual investor risk aversion and investment portfolio composition. *Journal of Finance*, *30*, 605–620.

Collier, P. (2004). *The Second World War*. The Mediterranean 1940-1945 Oxford: Osprey Publishing.

Conzo, P., & Salustri, F. (2017). A war is forever: The long-run effects of early exposure to World War II on trust (No. 201735). University of Turin.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, *47*(2), 448-74.

Dave, D., & Saffer, H. (2008). Alcohol demand and risk preference. *Journal of Economic Psychology*, *29*(6), 810–831.

Das, S., Kuhnen, C. M., & Nagel, S. (2019). Socioeconomic status and macroeconomic expectations. *Review of Financial Studies*, forthcoming

Davies, N. (2006). *Europe at War 1939-1945: No simple victory*. Pan.

Decker, S., & Schmitz, H. (2016). Health shocks and risk aversion. *Journal of Health Economics*, *50*, 156–170.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2011). The intergenerational transmission of risk and trust attitudes. *The Review of Economic Studies*, *79*(2), 645-677.

Eckel, C. C., El-Gamal, M. A., & Wilson, R. K. (2009). Risk loving after the storm: A bayesian-network study of hurricane Katrina evacuees. *Journal of Economic Behavior and Organization*, *69*, 110–124.

Elder, G. H. (2018). *Children of the great depression*. Routledge.

Ellis, J. (1993). *World War II: A statistical survey: The essential facts and figures for all the combatants*. Facts on File.

Figner, B., Knoch, D., Johnson, E.J., Krosch, A.R., Lisanby, S.H., Fehr, E., & Weber, E.U. (2010). Lateral prefrontal cortex and self-control in intertemporal choice. *Nature Neuroscience*, *13*(5), 538–539.

Fox, S. E., Levitt, P., & Nelson III, C. A. (2010). How the timing and quality of early experiences influence the development of brain architecture. *Child Development*, *81*(1), 28–40.

Friend, I., & Blume, M. E. (1975). The demand for risky assets. *American Economic Review*, *65*, 900–922.

Giuliano, P., & Spilimbergo, A. (2014). Growing up in a Recession. *The Review of Economic Studies*, *81*(2 (287)), 787-817.

Gottlieb, G. (1997). *Synthesizing nature-nurture: Prenatal roots of instinctive behavior*. Mahwah, NJ: Erlbaum.

Gottlieb, G. (1998). Normally occurring environmental and behavioral influences on gene activity: From central dogma to probabilistic epigenesist. *Psychological Review*, *105*(4), 192-802.

Grosjean, P. (2014). Conflict and social and political preferences: Evidence from World War II and civil conflict in 35 European countries. *Comparative Economic Studies*, *56*(3), 424-451.

Guiso, L., & Jappelli, T. (2005). Awareness and stock market participation. *Review of Finance*, *9*(4), 537–567.

Guiso, L., Haliassos, M., and Jappelli, T. (2003) Household stockholding in Europe: Where do we stand and where do we go? *Economic Policy*, *18*, 123–170.

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *The Journal of Finance*, *63*(6), 2557–2600.

Havari, E., & Peracchi, F. (2017). Growing up in wartime: Evidence from the era of two world wars. *Economics & Human Biology*, *25*, 9-32.

Hörl, M., Kesternich, I., Smith, J. P., & Winter, J. (2016). Early-life circumstances predict measures of trust among adults: Evidence from hunger episodes in Post-War Germany (No. 6093). CESifo Group Munich.

Ichino, A., & Winter-Ebmer, R. (2004). The long-run educational cost of World War II. *Journal of Labor Economics*, *22*(1), 57-87.

Jensen, P. S., & Shaw, J. (1993). Children as victims of war: current knowledge and future research needs. *Journal of the American Academy of Child & Adolescent Psychiatry*, *32*(4), 697-708.

Kesternich, I., Siflinger, B., Smith, J. P., & Winter, J. K. (2014). The effects of World War II on economic and health outcomes across Europe. *Review of Economics and Statistics*, *96*(1), 103-118.

Kim, Y. I., & Lee, J. (2014). The long-run impact of a traumatic experience on risk aversion. *Journal of Economic Behavior & Organization*, *108*, 174-186.

Knudsen, E. I. (2004). Sensitive periods in the development of the brain and behavior. *Journal of Cognitive Neuroscience*, *16*(8), 1412–1425.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., & Chater, N. (2009). Exaggerated risk: Prospect theory and probability weighting in risky choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*(6), 1487–1505.

Lahmeyer, J. (2006), *Populstat* [online]. Available at http://www.populstat.info

Li, J.-Z., Li, S., Wang, W.-Z., Rao, L.-L., & Liu, H. (2011). Are people always more risk averse after disasters? Surveys after a heavy snow-hit and a major earthquake in China in 2008. *Applied Cognitive Psychology*, *25*(1), 104–111.

Love, D. A., & Smith, P. A. (2010). Does health affect portfolio choice?. *Health economics*, *19*(12), 1441-1460.

Lyubomirsky, S. (2010). Hedonic adaptation to positive and negative experiences. In S. Folkman (Ed.), *The Oxford handbook of stress, health, and coping*, 200-224. New York, NY, US: Oxford University Press.

Macksoud, M. S., & Aber, J. L. (1996). The war experiences and psychosocial development of children in Lebanon. *Child development*, *67*(1), 70-88.

Maddison A. (2008). Historical statistics: Statistics on world population, GDP and per capita GDP. http://www.ggdc.net/MADDISON/oriindex.htm.

Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk-taking? *Quarterly Journal of Economics*, *126*, 373–416.

Malmendier, U., & Nagel, S. (2015). Learning from inflation experiences. *The Quarterly Journal of Economics*, *131*, 53–87.

Page, L., Savage, D. A., & Torgler, B. (2014). Variation in risk seeking behaviour following large losses: A natural experiment. *European Economic Review*, *71*, 121-131.

Perner, J., & Ruffman, T. (1995). Episodic memory and autonoetic conciousness: Developmental evidence and a theory of childhood amnesia. *Journal of Experimental Child Psychology*, *59*(3), 516–548.

Sapienza, P., Zingales, L., & Maestripieri, D. (2009). Gender differences in financial risk aversion and career choices are affected by testosterone. *Proceedings of the National Academy of Sciences*, *106*(36), 15268–15273.

Stotland, E., & Canon, L. K. (1972). *Social psychology: A cognitive approach*. Saunders Limited.

Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, *101*(2), 449–472.

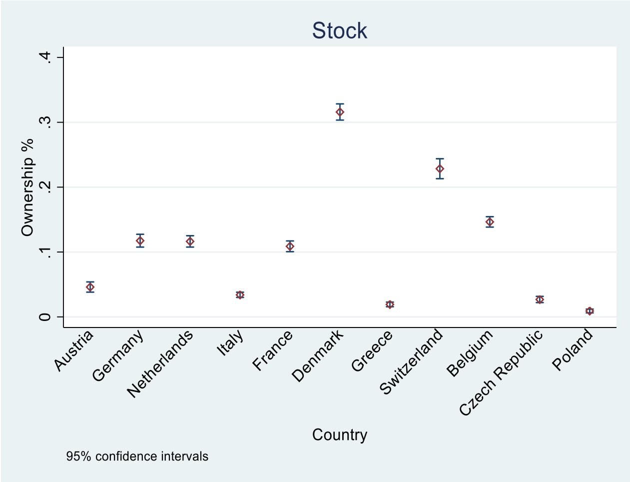
Voors, M. J., Nillesen, E. E. M., Verwimp, P., Bulte, E. H., Lensink, R., & Soest, D. P. V. (2012). Violent conflict and behavior: A field experiment in Burundi. *American Economic Review*, *102*(2), 941–964.

Werner, E. E. (2000). *Through the eyes of the innocents: Children witness World War II.* Boulder, CO: Westview Press.

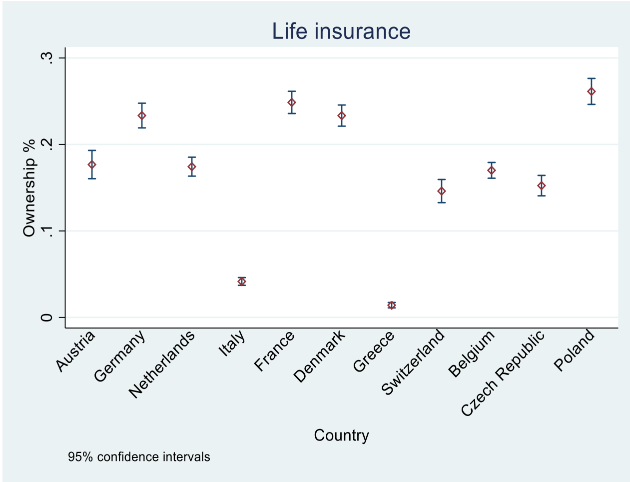
Yaari, M. E. (1965). Uncertain lifetime, life insurance, and the theory of the consumer. *Review of Economic Studies*, *32*, 137-150

## Figure 1. Financial risk taking by country

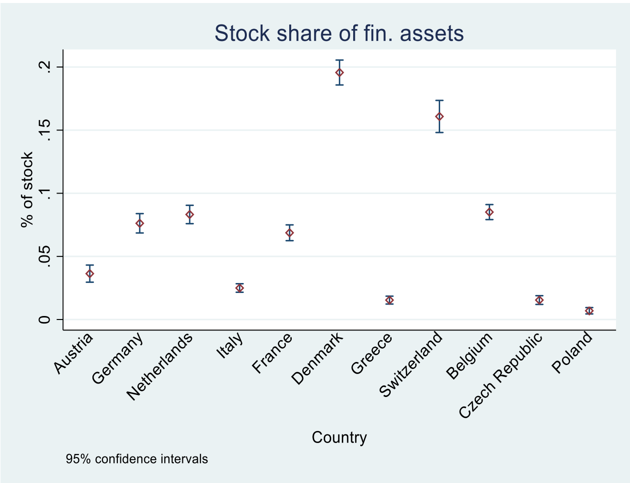
### Panel A



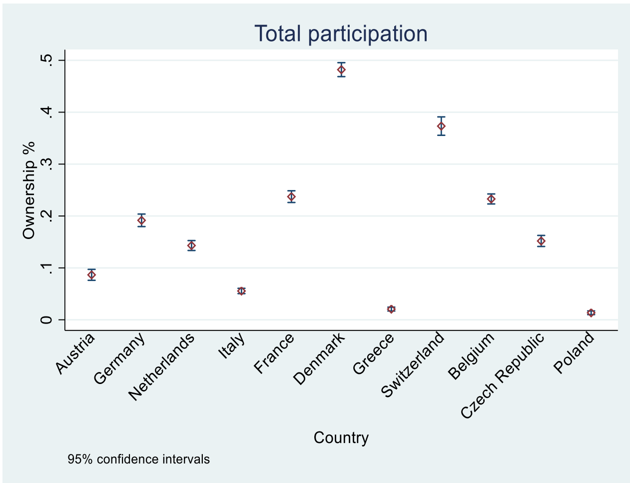

### Panel C




### Panel B



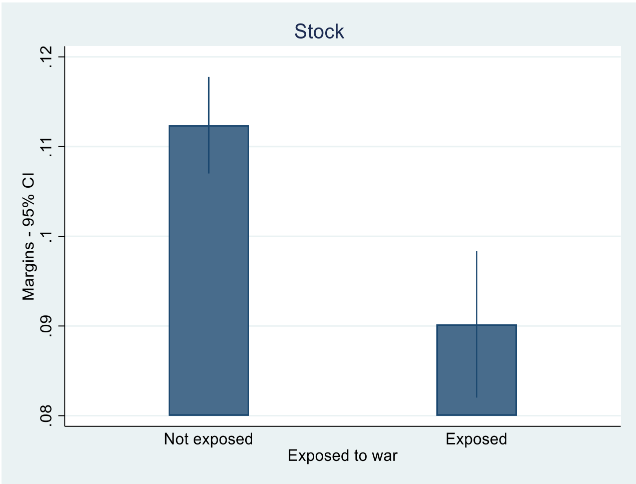

### Panel D



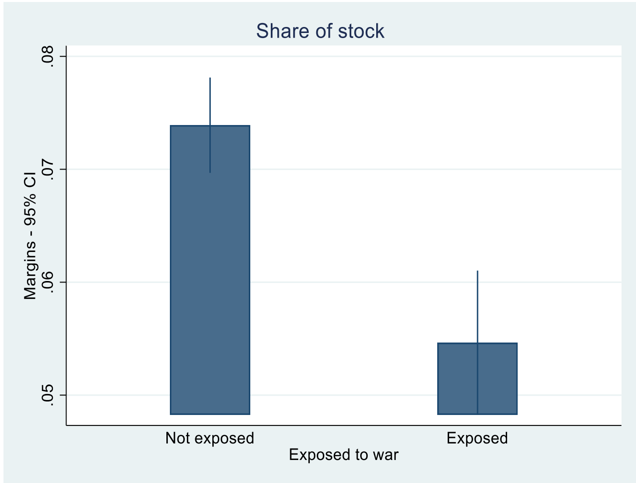

*Notes*: The figures report the percentage of stock and life insurance ownership and participation in the financial markets (Panels A, C and D), and average share of wealth held in stocks (panel D), across European countries that participated in the SHARE survey.

## Figure 2. Financial risk taking by war exposure

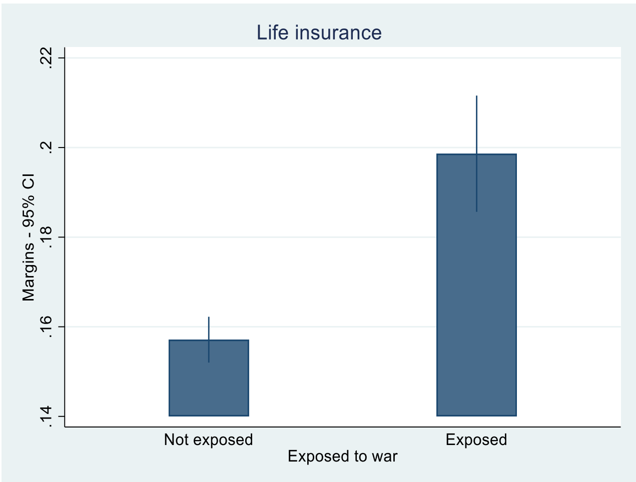
**Panel A**



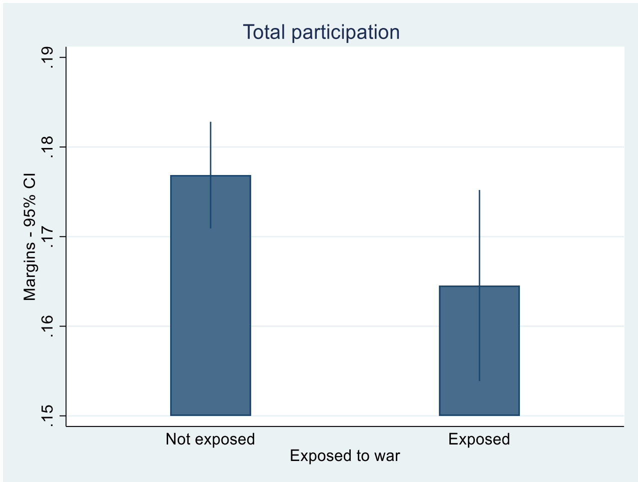

**Panel B**




**Panel C**



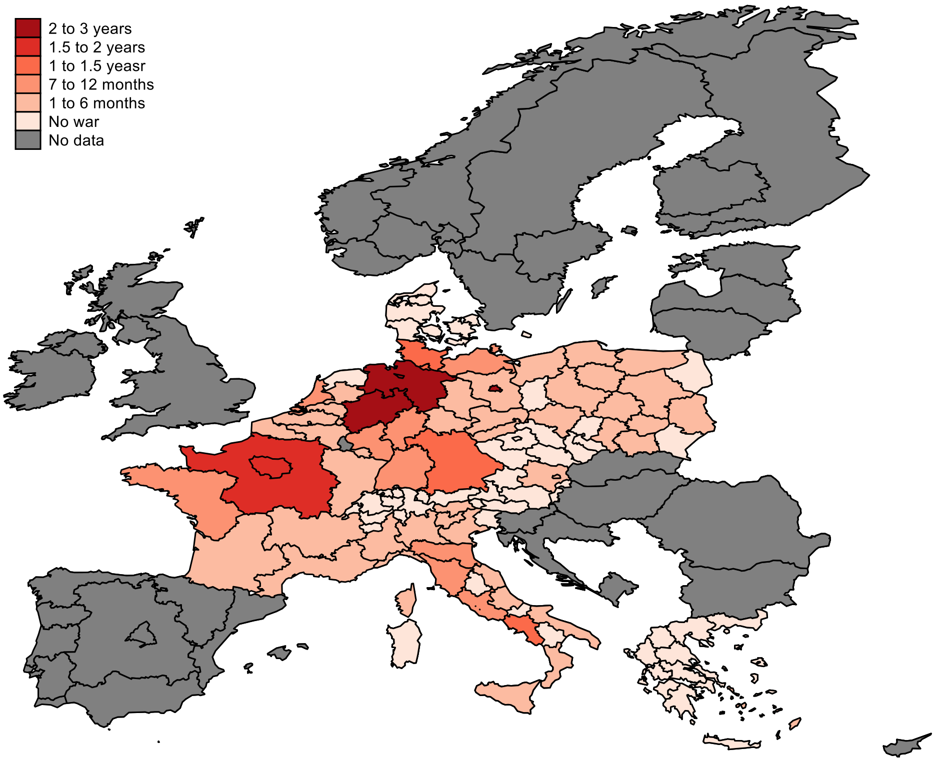

**Panel D**



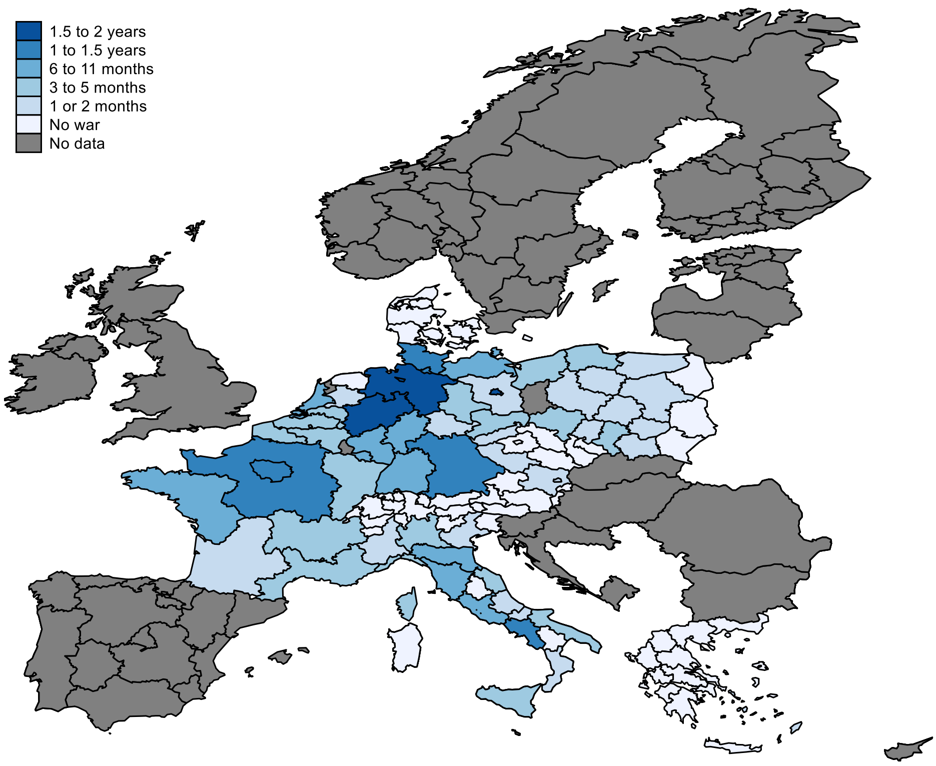

*Notes*: The figures report predictive margins from panel probit (Panels A, C and D) or OLS (Panel B) random-effects regressions controlling for wave, country and year of birth.

**Figure 3 – War exposure by NUTS2 regions**

*A – average months of war exposure across EU regions*




*B – Respondents' average months of war exposure*




*Notes*: The figures report the distribution of WW2 events in selected European countries. Figure A refers to European regions in our sample across the years 1939-1945. Figure B shows the average number of months of war exposure of our sample respondents.

**Table 1**. **The effect of war exposure on financial risk taking, controlling for adulthood and childhood characteristics**

| VARIABLES | (1) Stock | (2) Share Stock | (3) Life insurance | (4) Total Participation |
|---|---|---|---|---|
| Exposed to war | -0.018*** | -0.016*** | 0.033*** | -0.009*** |
| | (0.004) | (0.004) | (0.007) | (0.004) |
| Female | -0.013*** | -0.013*** | -0.006 | -0.006*** |
| | (0.003) | (0.003) | (0.004) | (0.002) |
| Log financial wealth | 0.015*** | 0.022*** | 0.020*** | 0.026*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Log Income | 0.013*** | 0.005*** | 0.009*** | 0.003** |
| | (0.001) | (0.001) | (0.002) | (0.001) |
| High SES at age 10 | 0.002 | 0.001 | 0.002 | 0.002 |
| | (0.003) | (0.003) | (0.004) | (0.002) |
| Lived in a rural area when child | 0.001 | 0.003 | -0.005 | -0.003 |
| | (0.003) | (0.002) | (0.004) | (0.002) |
| Received vaccination when child | 0.003 | 0.003 | 0.030*** | -0.014** |
| | (0.007) | (0.004) | (0.012) | (0.007) |
| Divorced or separated | -0.016*** | -0.012*** | 0.002 | -0.005 |
| | (0.004) | (0.004) | (0.006) | (0.003) |
| Never married | -0.001 | -0.001 | -0.020*** | -0.005 |
| | (0.006) | (0.006) | (0.008) | (0.005) |
| Widowed | 0.006 | 0.002 | 0.009 | 0.006** |
| | (0.004) | (0.003) | (0.006) | (0.003) |
| Employed or self-employed | 0.003 | 0.002 | 0.034*** | 0.004 |
| | (0.003) | (0.003) | (0.005) | (0.003) |
| Unemployed | -0.005 | -0.008 | 0.008 | 0.002 |
| | (0.006) | (0.006) | (0.009) | (0.006) |
| Permanently sick or disabled | 0.002 | 0.000 | 0.010 | -0.004 |
| | (0.007) | (0.005) | (0.008) | (0.006) |
| Homemaker | 0.001 | 0.003 | 0.002 | -0.000 |
| | (0.005) | (0.003) | (0.006) | (0.004) |
| Other | 0.005 | 0.003 | 0.061*** | -0.013 |
| | (0.008) | (0.007) | (0.012) | (0.008) |
| Number of children | -0.004*** | -0.001 | 0.002 | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Years of Education | 0.004*** | 0.002*** | 0.001** | 0.001*** |
| | (0.000) | (0.000) | (0.001) | (0.000) |
| N. of chronic diseases | -0.000 | 0.001 | 0.002 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Normal weight | 0.018 | 0.005 | 0.005 | 0.024** |
| | (0.010) | (0.009) | (0.015) | (0.010) |
| Overweight | 0.013 | 0.001 | 0.016 | 0.022** |
| | (0.010) | (0.009) | (0.015) | (0.010) |
| Obese | 0.011 | 0.001 | 0.023 | 0.020 |
| | (0.010) | (0.009) | (0.015) | (0.011) |
| Low alc. consumption | 0.013*** | 0.005** | 0.021*** | 0.011*** |
| | (0.004) | (0.002) | (0.004) | (0.003) |
| Medium alc. consumption | 0.015*** | -0.002 | 0.029*** | 0.012*** |
| | (0.003) | (0.003) | (0.004) | (0.003) |

| | | | | |
|---|---|---|---|---|
| High alc. consumption | 0.019*** | 0.012*** | 0.022*** | 0.014*** |
| | (0.004) | (0.003) | (0.005) | (0.003) |
| Smoke at the present time | -0.009*** | -0.005 | 0.009** | -0.004 |
| | (0.003) | (0.003) | (0.004) | (0.003) |
| | | | | |
| Observations | 53,336 | 52,610 | 51,396 | 56,931 |
| Dummy Country | Yes | Yes | Yes | Yes |
| Dummy wave | Yes | Yes | Yes | Yes |
| Year of birth | Yes | Yes | Yes | Yes |

*Note:* Marginal effects after probit panel estimation (columns 1, 3 and 4) and OLS panel estimation (column 2); Robust standard errors in parentheses; C.I. *** p<0.01, ** p<0.05.

**Table 2. The effect of war exposure on financial risk taking, controlling for war-related hardships**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | Stock | Share Stock | Life insurance | Total Participation |
| | | | | |
| Exposed to war | -0.018*** | -0.015*** | 0.033*** | -0.010*** |
| | (0.004) | (0.004) | (0.007) | (0.004) |
| Father absent at age 10 | -0.007 | -0.007 | 0.013** | 0.002 |
| | (0.005) | (0.004) | (0.006) | (0.004) |
| Hunger | -0.002 | 0.000 | 0.003 | 0.005 |
| | (0.006) | (0.004) | (0.008) | (0.005) |
| Dispossession | 0.012 | 0.006 | 0.003 | 0.006 |
| | (0.007) | (0.006) | (0.010) | (0.005) |
| | | | | |
| Observations | 53,309 | 52,584 | 51,367 | 56,901 |

*Note:* Marginal effects after probit panel estimation (columns 1, 3 and 4) and OLS panel estimation (column 2); Robust standard errors in parentheses; C.I. *** p<0.01, ** p<0.05; Columns (1) – (4) include adulthood and childhood controls, country, wave and year of birth dummies.

**Table 3. Testing nonlinearity in the effect of war exposure (median exposure, war duration, and war intensity) on financial risk taking**

| VARIABLES | (1) Has stock | (2) Share stock | (3) Has stock | (4) Share stock | (5) Has stock | (6) Share stock |
|---|---|---|---|---|---|---|
| Under median exposure (a) | -0.018*** | -0.016*** | | | | |
| | (0.004) | (0.004) | | | | |
| Above median exposure (b) | -0.018*** | -0.015*** | | | | |
| | (0.005) | (0.005) | | | | |
| N. of years of war | | | -0.027** | -0.025** | | |
| | | | (0.010) | (0.010) | | |
| N. of years of war^2 | | | 0.011** | 0.012** | | |
| | | | (0.005) | (0.005) | | |
| N. of war events | | | | | -0.024 | -0.024** |
| | | | | | (0.014) | (0.012) |
| N. of war events^2 | | | | | 0.016** | 0.019** |
| | | | | | (0.008) | (0.009) |
| Observations | 53,336 | 52,610 | 53,336 | 52,610 | 53,336 | 52,610 |
| Test | (a)-(b) | (a)-(b) | | | | |
| Chi squared | 0.02 | 0.03 | | | | |
| p-value | 0.896 | 0.860 | | | | |

*Note*: Marginal effects after probit panel estimation (columns 1, 3 and 4) and OLS panel estimation (column 2); Robust standard errors in parentheses; C.I. *** p<0.01, ** p<0.05; Omitted category columns (1) – (2): "Not Exposed". Columns (1) – (6) include adulthood and childhood controls, country, wave and year of birth dummies.

**Table 4. The combined effect of exposure to war and high stock volatility on financial risk taking**

| VARIABLES | (1) Stock | (2) Share stock | (3) Stock | (4) Share stock | (5) Stock | (6) Share stock |
|---|---|---|---|---|---|---|
| Exposed to war | -0.019*** | -0.015*** | -0.015*** | -0.012*** | -0.015*** | -0.012*** |
| | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) |
| High stock volatility | -0.002 | 0.002 | 0.005 | 0.006** | 0.005 | 0.006** |
| | (0.003) | (0.002) | (0.004) | (0.003) | (0.004) | (0.003) |
| Exposed*High stock volatility | | | -0.020*** | -0.010*** | -0.021*** | -0.011*** |
| | | | (0.006) | (0.004) | (0.006) | (0.004) |
| Observations | 42,979 | 43,039 | 42,979 | 43,039 | 42,494 | 42,524 |
| Cognitive abilities | No | No | No | No | Yes | Yes |

*Note:* Marginal effects after probit panel estimation (columns 1, 3 and 4) and OLS panel estimation (column 2); Robust standard errors in parentheses; C.I. *** p<0.01, ** p<0.05; Columns (1) – (6) include adulthood and childhood controls, country, wave and year of birth dummies.

# Slippers and Shirt: The Long-Term Effect of Inequality of Opportunity on Human Capital.

Davide Bellucci*

October 2019

**Abstract**

Human capital accumulation during adolescence is an essential factor for adult socio-economic status achievement. Yet, it requires effort and commitment. Parental background constitutes a valuable asset that facilitates human capital accumulation. Parents transmit to their children ability, knowledge or network connections and provide them with financial resources to afford better education. At the same time, social context affects children's decisions on human capital investment. Exploiting Italian data from the Survey on Household Income and Wealth (SHIW), we show that the interaction between parental background and social context may have counterintuitive effects on young adults' human capital investment. Respondents who at age 18 happened to live in wealthy families in highly nepotistic regions, display lower accumulation of human capital in adult age. We believe that these results are driven by the way children perceive the functioning of the job market. In nepotistic regions perceived return on parental background outweighs that on human capital. Results have strong implications in terms of redistribution of opportunities and welfare policy.

**Keywords:** inequality, parental background, return to education, human capital

**JEL codes:** I24, I26, J24

* Corresponding author. Dept. of Economics and Statistics "S. Cognetti de Martiis", University of Turin – Campus Luigi Einaudi, Lungo Dora Siena 100A. Email: davide.bellucci@unito.it

## Introduction

Among European countries, Italy is one of those with lower share of individuals aged 25 to 34 with tertiary education. As compared to European average (41%), Italy has only 28% of graduated in 2018. It is 16 percentage points behind France, and 14 points behind Spain (Figure 1 Panel A). Since the Bologna Process start in 2000 and the introduction of the "3+2" system, University in Italy is structured in two parts. After high school completion, which usually occurs at age 18, students can enroll in bachelor programs, lasting three years. With two years of additional education, a master degree can be obtained. On average, Italian master students complete their education carrier at age 27[2]. More than 40% of all the bachelor students do not graduate in time, i.e. within the natural completion term of 3 years after enrollment. The percentage remains high for masters, where one third of all the students takes more than 2 years to graduate[3]. Italy has also a very high share of young people (aged 20–34) neither in employment nor in education and training. Almost one third of the population in this age range does not engage in any studying or working activity after higher school. The percentage is almost double the European average (16.5%) and 17 p.p. higher than Germany (Figure 1 Panel B). Understanding the causes of such differences has relevant implication in terms of public policy and interventions on young adults' human capital (HC) accumulation. Using the Survey on Household Income and Wealth (SHIW) of the Bank of Italy we shed light on one of the mechanisms that determines such evidence. We study the effect of the interaction between parental background and social context on young adults' human capital accumulation. Economic literature long investigated the effect of parental background on individuals' education attainment and work participation (Becker, 1969, Checchi, 2006, Björklund an Jäntti, 2009). Using US census data and proxying parental background with income and household head education status, Masters (1969) found that students whose parents had little education or income were 20% more likely to fall behind and drop out from high school. Ermisch and Francesconi (2001) matching parents and young adult children data from the British Household Panel Study (BHPS) document the causal

2 Almalaurea, 2019

3 ANVUR report, 2018

relationship between parents' and children educational attainment. Similar results have been found in France and Germany (Lauer, 2003), Italy (Caroleo and Pastore, 2012, Aina, 2013) and Denmark (Bingley et al., 2008, McIntosh and Munk, 2007). Wealthier and better educated parents can transmit their assets to their children, either ability, knowledge, network connections or financial resources (for a review Björklund and Salvanes, 2011). They can spend more time with their children and invest more resources in culturally enriching activities, which in turn improve children educational success (Duncan and Murnane, 2016). On the other hand, social context has been found to affect substantially educational outcomes as well. Areas characterized by high levels of income inequality drive low-income young adult to perceive return on education as little profitable. These individuals react by reducing investment in their own human capital (Kearney and Levine, 2018). Using cross-country data, Perez-Alvarez and Strulik (2018) document strong and negative correlation between the extent to which students perceive the functioning of the job-market as nepotistic and PISA scores. Indeed, occupational sorting has been shown to be a determinant channel that may depress education outcomes, especially for children from less advantaged families (Piatek and Gensowski, 2016). Gevrek and Gevrek (2009), merging administrative and survey data from Turkey, study nepotism in the form of family firms employing their children. They show that self-employed's and entrepreneurs' children who foresee to work in their family firms, enjoy lower success in the educational carrier, either in terms of attainment and grades. In this respect, Italy has been documented to be characterized by high levels of nepotism in politics (Gagliarducci and Manacorda, 2016), academia (Allesina, 2011) and in the job market (Scoppa, 2009). Accordingly, Italy shows low levels of upward social mobility and return on education (Corak, 2013). Wide differences exist between north and south of Italy. Northern Italy, the richest area of the country, shows 3-4 times larger levels of upward mobility than the South. This regional variation is strongly correlated with local labor market conditions, indicators of family instability, and school quality (Acciari et al., 2019). The present research contributes to these two fields of study. We aim at investigating the long-term effects on human capital accumulation, of the interaction between nepotism and parental background. Using Italian SHIW data, we proxy the level of nepotism during '90s by the Inequality of Opportunity (IoP) at regional level, and parental background by household income. We show that children who grow up in regions characterized by highly nepotistic social context, and who at the same time enjoy high parental background, tend to accumulate less human capital in the long run. Individuals with strong parental background living in highly nepotistic areas may be induced to rely more on their parental background, rather than on personal effort, for the determination of their future socio-economic status (SES). Given that in these regions parental background constitutes a valuable asset for the determination of children future SES, investment in effort and human capital accumulation loses attractiveness. The rest of the paper is structured as follows. In section 2 we present the model we use to compute IoP. In section 3 we pose our research hypothesis. We then introduce the SHIW dataset and discuss the main variables of interest used to perform the analysis. In section 5 we present the descriptive statistics, while section 6 is dedicated to the econometric specification. We discuss our results in section 7 and 8. Finally we conclude in section 9.

**Inequality of Opportunity**

The concept of inequality of opportunity is at the root of any discussion about inequality, social and redistributive justice. The seminal contribution of philosophers as Dworkin (1981) and Cohen (1989), and economists as Roemer (1993, 1998) and Fleurbaey (1995, 2008) made clear the idea that within a "just society" a certain level of inequality is eventually acceptable. Differences in achievements that are generated by differences in individuals' level of commitment are deemed to be fair and also desirable, inasmuch they are intended to reward accordingly different levels of effort (rewarding principle). By contrast, inequalities due to circumstances, factors outside the sphere of individual control, are considered unfair, unethically acceptable, and ought to be compensated through public intervention, according to the compensation principle. According to the famous metaphor of "leveling the playing field"[4], any fair society should not be concerned about differences observed in the final outcomes, as long as the field

[4] "Our philosophy is that we have no problem competing with the mutual savings banks if they start from the level playing field," J. Bolger, 1977, lobbyist for the US Bankers Association.

has been leveled equally for everybody, and resources and initial endowment have been redistributed evenly across individuals. Inequality of opportunity emerges within a society whenever life achievements directly depend on circumstances or factors for which individuals could not be held responsible for (i.e. gender, ethnicity or parental background). Hence, seeking equality of opportunity does not imply the elimination of all differences in terms of final outcomes. It rather means that such differences in achievements reflect individuals' levels of effort, as well as differences in decision taken at different stages in life (Ferreira and Peragine, 2016).

The model used to compute IoP in Italy at regional level builds up the ex-ante non-parametric approach developed by Checchi and Peragine (2010). In general terms, a society is said to be characterized by equality of opportunity if the outcome variable does not depend on circumstances. In our paper we consider individual earnings as outcome variable and parental education as the unique circumstance outside individual control. The model develops as follows: within a given society each individual can be represented by a list of traits grouped in two broad classes: the first class includes traits beyond individual responsibility, called *circumstances (m)*, while the second embraces all other factors for which individuals are considered to be responsible for, grouped into a single variable called *effort (e)*, for simplicity. Each circumstance $m$ can assume a certain number of different values, denoted by $m_j$. The entire population ca be divided into groups of homogeneous individuals, called types $(t \in \{1, \dots, T\})$, according to their specific vector of circumstances, $c_i$[5]. Within the society, therefore, the number of types reflects the number of circumstances and the number of different values that each circumstance can have. For example, assuming as unique circumstances gender and race, taking values {Male, Female} and {Black, White}, respectively, the finite set of types would consists of four mutually exclusive combinations $T$: $(\{Male, White\}, \{Male, Black\}, \{Female, White\}, \{Female, Black\})$. Formally, $T = \prod_{j=1}^{J} m_j$. The second class that includes all the factors for which individuals are accounted to be responsible for is represented by a scalar variable, called effort for ease of understanding, $e \in E$. The effort variable is

[5] Where $c_i = (m_{1,i}, \dots, m_{j,i})$

assumed to be one-dimensional and by construction captures all the other factors that are not explicitly included in the list of circumstances. The outcome variable, individual earnings $y$, is generated by a deterministic function $f: M * E \rightarrow \mathbb{R}_+$ that combines effort and circumstances. Under this specification, for any initial set of circumstances, any variation in individual income is attributed to personal effort, that implies to consider individuals responsible for any random component beyond the personal control also, and to overestimate the part of the total inequality that is "ethically acceptable". However, the function $f$ is assumed to be identical for each individual, monotonically increasing in effort, and the conditional distribution of effort is assumed to be independent from circumstances. This last assumption might result particularly strong given the existence of a series of intermediate variables determined by the joint effect of effort and circumstances. This type of variables directly affects the determination of individual income. Attained education represents a clear example as discussed by Pistolesi (2009). Better circumstances may facilitate effort, which in turn determines final outcome. In such a case, the orthogonality assumption between effort and circumstances should be extended to all of these intermediate factors. However, assuming that the conditional distribution of effort is independent from circumstances constitutes the simplest version of the model, compatible with the empirical analysis performed in the paper. Given the individuals' income distribution, $Y$, the society results to be characterized by a certain degree of income inequality, denoted by $I(Y)$. The main idea of the model is to decompose the total heterogeneity in income into a "non-ethically acceptable" part, attributable to differences in initial circumstances, and a residual "ethically acceptable" component, that reflects differences in individual effort. Hence, the model needs to be coupled with a measure of inequality that is additively decomposable into subgroups by a path-independent decomposition. The mean logarithmic deviation, MLD, or Theil's L, defined as $MLD = \frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{\bar{y}}{y_i}\right)$, which belongs to the family of generalized entropy measures, represents a suitable candidate to operate such decomposition (Shorroks, 1980, Foster and Shneyrov, 2000).

The model proceeds considering a population of size $N$, represented by an income distribution $Y = (y_1, \ldots, y_N) \in \mathbb{R}_+^{\mathrm{N}}$, that can be divided into $T$ types of homogeneous individuals. The type income distribution can be interpreted as the opportunity set of outcomes that each individual can achieve, by exerting different level of effort, starting with the same set of circumstances. The same population can be also partitioned according to the level of effort exercised to achieve the final outcome. Because effort is not directly observable, it is proxied by the quantile in the income distribution by type. In this sense, independently from their type, all individuals in the $q^{th}$ quantile of their income distribution are assumed to have exercised effort to the same extent. Ideally, if circumstances do not matter for the determination of income, if effort is independent from circumstances and if it is equally distributed across the entire population, the mean incomes across types should be equal, and the relative inequality should tend to 0. Therefore, there is inequality of opportunity if all the types do not have the same mean income, and it lowers if inequality between the types incomes reduces. Now, considering all the individuals who share the same initial circumstances, an artificial distribution can be created to eliminate the inequality within types, by substituting to each individual the mean of the income distribution of their type, denoted by $\mu_i^t$. Therefore, thanks to this transformation, the population incomes vector can now be written as $\mu_i^t = (\mu_1^1, \dots, \mu_{n_1}^1, \dots, \mu_i^T, \dots, \mu_N^t)$. This artificially smoothed income distribution is characterized by a certain level of inequality, $I\{\mu_i^t\}$. By construction, the MLD applied to this smoothed vector captures only and fully the between-type inequality, and therefore the part of inequality that exclusively depends on circumstances. In the same fashion, a similar transformation can be applied to the original income distribution in order to obtain a standardized vector of incomes such that the inequality between types disappears. This time, the artificial distribution is obtained by proportionally rescaling each quantile distribution until it has the same mean as the original population distribution, that is $\tilde{Y}_q = (\tilde{y}_1, \dots, \tilde{y}_q)$. The relative level of inequality is denoted by $I\{\tilde{Y}_q\}$. This standardized distribution eliminates between quantiles inequality, while leaving unaffected inequality within quantiles. The MLD applied to this distribution captures the part of income inequality that is attributable to individual responsibility only. As said, MLD permits to decompose total inequality into these two additive parts. Therefore, for any income distribution, $Y$, total inequality, $I(Y)$, can be written as the sum of inequality due to individual responsibility $I\{\tilde{Y}_q\}$ and the part given by circumstances $I\{\mu_i^t\}$.

$$I(Y) = I\{\mu_i^t\} + I\{\tilde{Y}_q\}$$

Hence, for any initial income distribution, the part of "non-ethically acceptable" inequality that only depends on factors outside individual control, in relative terms, is given by $OI_B^C = \frac{I\{\mu_i^t\}}{I(Y)}$, which represents Inequality of Opportunity (IoP). In this paper we estimate IoP with respect to income, taking individual earnings as objective outcome, and consider household-head's education status as the unique circumstance. It takes five different mutually exclusive categories: i) no education, ii) primary school, iii) middle or secondary school, iv) high school, and v) tertiary education[6]. What we get is a relative measure of the relevance of parental education to explain total income inequality at regional level. We use this measure to proxy for regional nepotism in the labor market. Our estimate is extremely conservative as we do not include in the circumstances a set of factors that are clearly outside individual control, such as sex or ethnicity. If any, the effect of circumstances on total income inequality that we find represents, therefore, a lower bound.

**Outline of the hypothesis**

The transition from high school to academic or work carrier is a crucial decision-point for young adult individuals. The decision they face has long-term impact in many respects, and a substantial part of achievements in adult age depends on it (Chen et al, 1996, Sansone and Berg, 1993). Clearly, either keeping on with education and going straight to work are options that increase human capital but require effort and commitment. Our hypothesis is that young adult individuals take this decision with the objective of maximizing their future socio-economic status. We assume that future SES depends on individual effort, circumstances outside individual control, i.e. parental background (PB), and on the social context, proxied by regional IoP in our paper. We also assume that future SES is an increasing function with respect to effort and parental background. Each individual who is about to take the decision

[6] Estimations have been implemented using the user-written STATA command iop (Juárez and Soloaga, 2014).

perfectly recognizes his or her own PB, and has an idea about the level of IoP in the region where he or she lives in. In this framework, therefore, better SES is expected from higher level of effort and higher level of PB. From a young adult's perspective, investment in human capital is costly in terms of effort and time. PB on the other hand is given, and depending on the region where he or she lives in, it can be more or less exploited to for future SES achievements. We investigate whether under specific circumstances parental background can refrain individuals to invest in human capital. The idea behind is that young adult can perceive PB and effort either as complementary or substitute components for the determination of future SES. Perceived as complementary, for any level of PB, the optimal strategy would be to engage and accumulate human capital. Contrarily, perceived as substitute, young adults with high parental background would be more prone to substitute human capital accumulation with parental background to form future SES. In other words, in high nepotistic regions (high IoP), perceived return on circumstances may outweigh perceived return on effort, hence, crowding out human capital investment. In this respect, Aparicio-Fenoll (2016) using a novel identification strategy that exploits housing boom in Spain, shows that perceived return on human capital is a determinant driver for school enrollment decision and grade completion. Under this perspective, the decision about the level of effort can be seen as an unconstrained maximization problem in which each individual, taking as given IoP and PB, choses the optimal effort level. That is,

$$\max_{e}\{U_{i,t}\} = \max_{e}\{f(e_{i,t-1}, \overline{PB}_{i,t-1}, \overline{IoP}_{t-1})\}$$

Where,

$U_{i,t}$ represents the objective function that has to be maximized, i.e. future SES, $e$ is the level of effort that each individual $i$ decides to put before getting adult, $PB$ captures parental background during adolescence, and $IoP$ the social context in which they grow up, i.e. the regional level of inequality of opportunity. We test whether and how the interaction between PB and IoP affects young adults' investment decision on human capital.

In particular, we aim to test the following hypotheses:

Hp1: High inequality of opportunity, coupled with strong parental background, affects negatively the probability to obtain tertiary education.

Hp2: High inequality of opportunity, coupled with strong parental background, increases the probability to accumulate years of delay in the educational carrier.

Hp3: High inequality of opportunity, coupled with strong parental background, affects negatively work participation.

The mechanism supporting our research hypotheses is as follows. On the one hand, high parental background facilitates investment in effort and human capital accumulation. On the other, higher levels of IoP suggest that the job market and social context are characterized by high levels of nepotism and low return-on-effort and human capital. Young adults with high parental background in high IoP regions would neglect human capital accumulation, substituting effort with parental background. From a public perspective, understanding such dynamics has relevant implications in terms of youth education and work involvement policy.

**Source of data**

The Survey on Household Income and Wealth (SHIW) of the Bank of Italy constitutes the main body of our source of data. Conducted any two years since the 60's, SHIW collects detailed information on income and wealth of around 8,000 thousand households (20,000 individuals) across 300 municipalities each wave. The panel dimension covering almost one third of the interviewed makes SHIW dataset the ideal source of data to study intergenerational dynamics in Italy. SHIW provides us with a rich set of information on individual and household income, education attainment, work participation and parental background of each individual within the household. Particularly relevant for our analysis is the section dedicated to the collection of retrospective information on socio-economic status of respondents. Among other things, in this section respondents are asked to recall the education attained and the job occupation of their parents, when parents were the same age as respondent. We create the final dataset in two sequential steps. In the first step, we use surveys from the year 1993 to 2006 to compute annual IoP at regional level. As in Checchi and Peragine (2010), due to low reliability of earnings information, in this step we exclude from the sample self-employed individuals, those who reported non positive incomes, and respondents younger than 15 and older than 75 years old. As of the very low sample numerosity, we merge Valle d'Aosta with Piemonte region. We apply the model described in section 2 to this dataset, considering individual incomes as outcome variable, and education attained by the breadwinner as the unique circumstance outside individual control. Specifically, for each component within the household we directly observe the education level of the household-head, while for the household head himself or herself and for his/her spouse, we rely on retrospective information about their breadwinner's education attainment when the breadwinner was the same age. We obtain an estimation of the level of relative IoP at regional level for the years of the SHIW waves (i.e 1993, 1995, 1998, 2000, 2002, 2004 and 2006)[7]. Figure 2 maps regional IoP across the seven waves. In general, southern regions have higher values of IoP with respect to center and northern regions. Still, Lombardia, Trentino Alto Adige, Friuli Venezia Giulia or Umbria showed high levels of IoP quite frequently across the years. As described in section 2, this measure informs us on the relative weight that circumstances outside individual control (i.e. parental education) have in explaining regional income inequality. For example, Lombardia region registered an income inequality of 0.22 in 1993. The relative IoP of 0.061 tells us that parental education is responsible for the 6.1% of the total income inequality observed in Lombardia in that year. In this way, independently of the absolute value of income inequality, we are able to compute the relative weight attached to parental education[8]. To perform our analysis, we eventually divide Italian regions in high and low nepotistic area depending on the IoP level. Nepotistic are those areas which IoP value is in top 30% of the IoP distribution across waves, i.e. greater than 9% (Figure 3). In this way we are allowed to exploit the within region variation of the IoP level across years, and to

[7] To compute yearly IoP we consider always 3 waves together. For example, to compute IoP in 2000, we use data from 1998 to 2002.

[8] An example may clarify the identification. Consider two regions, A and B, that share the same (low) value of income inequality, be 0.1. In region A parental education explains the 20% of total inequality, while in region B it accounts only for the 5%. Consider two other regions, C and D, that share the same (high) value of income inequality, be 0.9. In region C, PB accounts for 20% of total inequality, while in D its weight is 5%. According to our identification, region A and C are high IoP regions. B and D are instead low IoP regions.

assign each region in either group, depending on the wave. For example, Lombardia region was a nepotistic area in the years 2002, 2004 and 2006, and not earlier. As already noted in Section 2, this measure of IoP constitutes a lower bound estimation. First, we only consider parental education as circumstance. Clearly, including parental occupation, gender or ethnicity among the list of circumstances outside individual control increases the share of the total inequality that can be explained by circumstances. Second, we exclude from the sample entrepreneurs and self-employed and consider after tax and transfer net incomes as outcome variable. Given that taxes and transfers are used to redistribute wealth in the population, relying on net incomes, we underestimate the level of income inequality. As a consequence, our circumstances are able to capture only a smaller fraction of the total inequality.

In the second step, we use SHIW data from the year 2004 to year 2016 and exploit the panel dimension of the database. In each wave we consider individuals aged 26 to 35 years old and, along with base demographic characteristics (age, gender, year and birth region), we draw information on their current socio-economic status (education attained and job status). Relying on the panel dimension, we are able to recollect information, relative to respondents' adolescence, about the region of residence, parental education and occupation, household income, household size and population size of the municipality of residence. Information about region of residence during adolescence permits us to assign to each individual the level of relative IoP of the region where he or she was living during that period[9]. We use information on household income to divide individuals in high and low parental background (high PB for household income in the top 30% of the yearly regional income distribution, low PB in bottom 70%). This two information, jointly considered, constitute the core our research hypothesis. Figure 4 shows the distribution across regions of the group of children who had high parental background and at the same time were living in high IoP regions at age 18. Most of them are from southern regions (74%), while the rest is distributed evenly between north and center (13% per area). As of outcomes of interest, we chose three different variables to capture effort exercised and human capital of each individual in the educational and working career. First, exploiting information on the level and the type

[9] We assign individuals the level of relative IoP of the year in which they were 18 years old. If not available we look at the value when they were 17 years old or, alternatively, 19 years old.

of education attained and year of completion, we are able to see whether respondents obtained a degree, either bachelor or master *(graduated)*. Second, we observe whether he or she accumulated years of delay in the study completion *(out of course)*. Third, using information on the age at which respondents started working, we compute the years of working experience (*experience)*. The second source of data is Italian Institute of Statistics (ISTAT) from which we collect information on the unemployment rate of the working age population and GDP growth rate at regional level from 1993 to 2016.

**Descriptive statistics**

Table 1 reports descriptive statistics of our sample. We have around 2,000 individuals aged 26 to 35 years (mean age 29 years), distributed across 7 waves. The sample is slightly unbalanced towards male (58.4%) and southern region representativeness. 47% of the sample lives in southern regions and islands (Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna). Central regions (Toscana, Umbria, Marche and Lazio) represent the 20% of our sample, while the remaining 33% is from the north (Val d'Aosta, Piemonte, Lombardia, Trentino Alto Adige, Veneto, Friuli Venezia Giulia, Liguria and Emilia Romagna). 30% obtained tertiary education, 45% accumulated years of delay to complete education and 13% of the sample results to be still in education. Our subjects have on average 7 years of work experience. 12.4% started to work before turning 20. In Figure 5 we report the descriptive statistics of our three outcome variables (*gradauate, out of course, work experience)* by high and low parental background. According to the existing literature, high PB children graduates more frequently (39% vs 25%, p-value 0.003) (Figure 5 Panel A). They also seem to accumulate more frequently years of delay to complete their studies. 49% of high PB children completed education with a delay, compared to the 42% of low PB (Figure 5 Panel B). The difference is statistically significant at 1% level. High PB individuals also accumulate less years of work experience. On average, wealthier children have 6.5 years of working experience, compared to 7.6 of less wealthy children (Figure 5 Panel C). 41% of the sample has educated household-head, i.e. completed high school, while slightly more than one third enjoyed high parental background during adolescence, i.e. household income on the top 30% of the yearly regional income distribution. Almost 10% of the sample changed region of residence during his or her life. Regarding parental job status, around one tenth of the sample had unemployed parents in adolescence. One fourth were blue collars' children and one third were white's. Almost 18% of the sample had self-employed household-head (of which 4.6% entrepreneurs). 16% of our respondents instead had retired parent in adolescence. For what concerns education attained, less than 1% results to be very little educated (primary or no education completed). Almost one fifth of the sample instead dropped out of school after secondary education, while 50% obtained higher education diploma (of which 7.6% from a professional school). The vast majority of respondents with tertiary education (30%) obtained a master degree (23%), 5% bachelor, and 2% kept on further after the master. As of the job status, around 44% declared not to have a job, 47% are employed and 9% are instead self-employed. Almost the totality of the sample never married (92%). Only 0.5% separated or divorced from partner, while 6.5% is married. The majority of our respondents during adolescence lived in a municipality with number of inhabitants between 40 and 500 thousand (47,4) and only 5.5 % come from big cities (i.e. with more than 500,000 inhabitants). The rest of the sample (47%) lived in municipalities with less than 40,000 individuals (27% of which in cities with up to 20,000 inhabitants). SHIW dataset also provides us with a set of variables that describe the house of residence during adolescence. In particular, we have information on house size (in squared meters), on the presence of heating and bathroom, type of house (a categorical variable with 6 options from luxury to popular house) and location (another categorical variable with 6 options, from city center to rural area). We exploit this information to perform a principal component analysis and use the decile distribution of the first extracted components to proxy for house characteristics during adolescence. Finally, regarding unemployment rate of the working age population at NUTS3 level, we have that during adolescence period the worst region was Sicily in 1998 (24.4%), while the best was Emilia-Romagna in 2002 (2.5%). At current period instead, the region with highest unemployment rate is Calabria in 2016 (23.2%), while the lowest is registered in Trentino Alto Adige (2.4% in 2004). As of GDP growth rate during adolescence, Friuli Venezia Giulia recorded the highest rate in 2000 (5.6%) and Liguria the lowest

(-1.95% in 2002). In current period, Lazio in 2004 is the region that performed the best (6.5% of GPD growth rate), while Basilicata the worst (-3.74% in 2014).

**Econometric model**

In order to assess the joint effect of IoP and PB on human capital accumulation in a long-run perspective we estimate the following model, by means of random effects panel regressions.

$$Y_{i,t} = \beta_0 + \beta_1 HighIoP_{j,t-1} + \beta_2 HighPB_{i,t-1} + \beta_3 HighIoP_{j,t-1} * HighPB_{i,t-1} + \sum_{\alpha} \gamma_{\alpha}\, Controls_{i,t-1} + \sum_{k} \delta_k\, Controls_{i,t} + \sum_{j} \theta_j\, DummyYear + \sum_{\varphi} \vartheta_{\varphi}\, DummyRegion + \varepsilon_{i,t}$$

Where,

$Y_{i,t}$, is alternatively one of the three variables of interest described in the previous section, of individual *i,* at time *t (present time)*. With respect to the two dummy variables of interest *(graduated,* and *out of course)* we use a panel logistic regression, while for the continuous variable *(years of work experience)* we perform a panel OLS. *High IoP* is a dummy variable that takes value 1 for nepotistic regions, i.e. if the IoP level of the region of residence during adolescence is in the top 30% of the annual IoP distribution. *High PB* is the dummy that captures strong parental background during adolescence *(time t-1)*. It is 1 if the subject's household income was in the top 30% of the regional yearly income distribution of incomes when he or she was aged 18. The interaction term between these two dummy variables *(High IoP*HighPB)* is the main variable of interest of the paper. It informs about the relationship between regional nepotism, parental background and young adult children human capital accumulation. The set of control variables referred to the adolescence period includes parental occupation, parental education, household size and characteristics of the house of residence (decile of pca score distribution), and a multinomial variable with 4 categories to capture for municipality population size. The inclusion of this variable permits us to limit errors due to the fact that in our dataset we are forced to consider cities within the same region, with different size and characteristics, as sharing the same level of IoP. As for current period control variables, apart from standard demographic characteristics as gender, marital status, age and age squared, we include in our econometric specification a dummy variable equal to 1 if respondent is still in education, a dummy variable equal to 1 if respondents has changed region of residence between adolescence and adult age, and a dummy variable equal to 1 if respondents worked under age 20. Region, year and cohort fixed effects are included in the regressions.

**Results**

Tables 2 reports regression results of the first variable of interest *(graduated)*. According to the literature, we find that parental background at age 18 affects positively and significantly the probability to graduate in adult age. Growing up in a highly nepotistic area *(high IoP)* does not play instead a crucial role in this respect in the long run (column 1). We also find that males are less likely to graduate than females. In column 2 we add the interaction term between parental background and IoP, and the set of adolescence period controls. Educated parents facilitate substantially the process of accumulation of human capital. None of the parental job status instead affects significantly the relationship. The effect of house characteristics pca score is relevant and in the expected direction. Interpreted as a proxy for household wealth, the higher the score, the higher the probability to be graduated in adult age. The two dummy variables capturing high parental background and regional IoP at age 18 do not affect significantly the probability to graduate, individually considered. According to our predictions, their joint effect instead influences negatively and significantly (at 5% level) the probability to have a degree in adulthood, and the size of the effect remains constant across all the specifications. Due to the possible presence of omitted variables bias, in column 3 we further control for additional factors that might be driving our results. We include a dummy variable equal to 1 if the respondent started to work early in life (i.e. under age 20), a dummy variable equal to 1 if respondent changed region of residence, and two categorical variables that capture current marital and job status. Having changed regions is positively correlated with the probability to graduate, while surprisingly, early starting work does not affect significantly the likelihood to graduate in adulthood. Never being married is the only marital status that correlates positively with the outcome variable. In the last two columns (4 and 5) we add two standard variables that describe the economic context of the region of residence *(GDP growth rate* and *unemployment rate of the working age population)* during young age and in adulthood, alternatively. As evidenced, the magnitude of the effect of the interaction term remains stable and significant. In Table 2.1 we report the marginal effects of models in columns 2 to 5 of Table 2. Individuals who happened to live in wealthy families and in a high IoP regions at age 18 are 16% less likely to have obtained a bachelor or a master degree years after, with respect to individuals who had strong parental background but did not grew up in high IoP regions. Results regarding *out of course* outcome variable are reported in Table 3. While high IoP dummy variable does not affect the probability to accumulate years of delay in study completion, high parental back seems to correlate positively with it. Older respondents are more likely to have gone out of course in their educational carrier than younger individuals (column 1). In column 2 we introduce the interaction term between parental background and regional IoP at age 18, as well as the set of adolescence control variables. The effect of parental background reduces sensibly and loses significance, while the interaction term itself does not show a relevant effect. As soon as we add controls for education attained and current period controls the interaction term turns to be sizeable, significant and in the expected directions (column 3). Having obtained a degree, either bachelor or master, increases the probability to have accumulated years of delay in the educational carrier (with respect to the omitted category of high school completion). Having started to work early, i.e. before turning 20, correlates positively with the probability to be out of course in adult age. Working individuals instead, either employed and self-employed, are less likely to have accumulated years of delay in the educational carrier than unemployed. Read together, these results might suggest that working students take more time to complete their studies after high school, if they decide to go for tertiary education. In following columns (4 and 5) we further control for the two standard economic variables, at adolescent period and at present time, respectively. The effect of the interaction term remains stable and significant across both specifications. To facilitate understanding of our results, in Table 3.1 we report marginal effects. Growing up in wealthy family and in highly nepotistic regions increases on average by a factor of 17-18% the likelihood to have accumulated years of delay in adulthood in the educational carrier. Finally, In Table 4 we investigate the effect of high PB and high IoP on the years of working experience, our last variable of interest used to proxy for human capital. We find that having high parental background at age 18 does not affect significantly the years of work experience accumulated in adult age, as soon as we add controls in the model (columns 2 to 5). Growing up in highly nepotistic regions instead seems to facilitate entry in the job market. The coefficient of *high IoP* is sizeable and significant across all specifications from column 2 to 5. Parental job status and house characteristics do not play a significant role in this respect. Parental education instead is negatively correlated with work experience. An explanation of this result might be that educated parents are more likely to push their children towards tertiary education, postponing job market entry. In line with this reasoning, individuals who worked under age 20 accumulate sensibly higher work experience, while higher level of education attained correlates negatively with the outcome variable in consideration (column 3). According to our hypothesis, we find that the interaction term between PB and IoP affects negatively and significantly with years of work experience (columns 3 to 5 Table 4 and Table 4.1). Respondents who at age 18 had high parental background and were living in high IoP regions, have on average 1 year less of work experience. Considering an average experience of 7.2 years, this result translates into a 14% lower working experience in adulthood. Taken together, these findings do not reject our research hypothesis.

**Alternative definition of parental background**

In this section we further proceed our analysis by changing the definition of parental background. Instead of considering household income at age 18, in this step we proxy parental background with parental education and parental occupation. First, we consider as high PB children those whose household-head obtained at least a higher education diploma. Second, we define as high PB those children whose household-head was employed as a white collar and those whose household-head was an entrepreneur or a professional self-employed (such as doctors and lawyers). Household income is highly correlated with household-head's education and occupation status. By changing definition of parental background, we check whether our results remain unchanged across these two different specifications, or whether children weight differently parental income, education and occupation. Results of this exercise are reported in Table 5. We find that the interaction term between *High IoP* and parental occupation or parental education produces strikingly different results with respect to our initial definition of parental background. In particular, only the interaction term between *High IoP* and parental occupation affects negatively and significantly the probability to graduate (column 1), although the magnitude of the marginal effects is sensibly smaller than our previous findings. We do not find any significant effect with respect to the two other variables of interest, i.e. *out of course* and *work experience.* According to the existing literature, this result suggests that entrepreneurs' and white collars' children who grow up in highly nepotistic area tend to neglect tertiary education. An explanation of this result can be that these children perceive return on education as less profitable than return on parental background and that they are likely to believe they inherit their job status from their parents. As of parental education (columns 4 to 6) we do not find any significant result of the interaction term with IoP. Read together, these results suggest that children in highly nepotistic area weight parental income much more than parental education and parental occupation when deciding about how to proceed after high school completion. In particular, we find that high parental income can offset human capital accumulation incentives. Contrarily, parental occupation and education do not produce the same evidence.

**Robustness checks**

In order to test the reliability of our results we perform a series of robustness checks. First, given that the majority of our sample is from southern regions, it might be that individuals in those regions constitute outlier observations and are driving our results. To that aim, following the approach of Frey and Stutzer (2000) and Otterbach (2010) we perform a DFBETA test. We consider the coefficient of the interaction term in column 3 of each outcome variable, (Tables 2, 3 and 4) and compare it with the coefficient estimated omitting one region at a time. According to the following formula, DFBETA are computed as the difference between regression coefficients, divided by the diminished regression standard error

$$DFBETA_{i,k} = \frac{\beta_k - \beta_{k(-i)}}{se_{k(-i)}}$$

where, $\beta_k$ is the coefficient of the model that includes all the regions, $\beta_{k(-i)}$ the coefficient of the regression without region *i*, and $se_{k(-i)}$ its standard error. Belseley, Kuh, and Welsh (1980) suggest that the significance of the considered regressor does not depend crucially from the omitted region if the value of the DFBETA is below the 1.96 threshold, in absolute value. Table 6 reports the results of the test and confirms that none of the region is driving our findings. These results are also confirmed in Figure 6. In panel A we draw the distribution of graduated individuals by parental background and IoP quartiles, on the left, and by parental background and macro-area, on the right. The picture we produce shows that the drop we observe in the share of high PB graduated is not driven by southern region and islands. In panel B, we display the same graph considering the distribution of the out of course students. Again, the graph clearly shows that our results are not entirely driven by regional differences. Panel C, dedicated to distribution of years of work experience is also in line with our previous findings.

In a second check, we test whether our results are robust when we depart from the normality assumption on our dependent variables of interest. We re-estimate the models in column 3 of Table 2, Table 3 and Table 4, performing bootstrap estimations with 500 repetitions, and compute marginal effects. Table 7 shows that our findings remain unchanged with bootstrapped estimates.

Finally, given the age composition of our sample, we check whether our results are robust to exclusion of younger and older individuals. To that aim, we re-estimate the models in column 3 of Table 2, Table 3 and Table 4 excluding individuals aged 26 and 27 years old, and individuals aged 35 and 36 years old. Also considering therefore only individuals aged from 28 to 34 years old, our results remain stable and coherent with our previous finding[10].

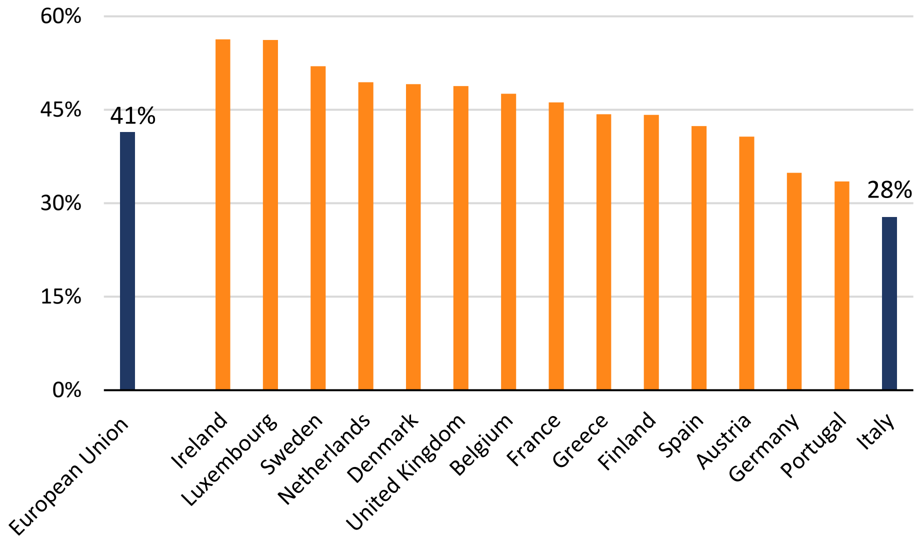
[10] Results table of this robustness check is available upon request.

**Conclusion**

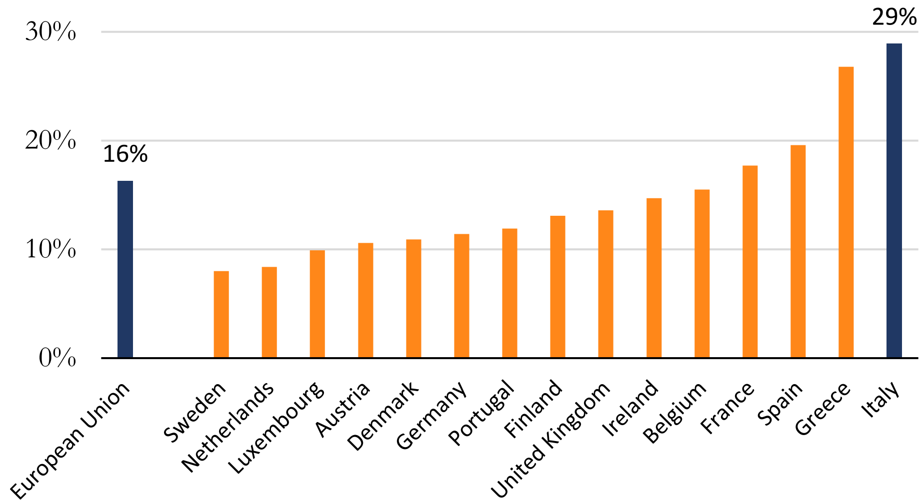
The main goal of this paper is to shed light on the determinants of the (poor) educational outcomes in Italy. Starting with the evidence that parental background and social context both affects the process of young adults' human capital accumulation, we provide new findings of their joint effect. Exploiting Italian data from the Survey on Household Income and Wealth (SHIW), we show that the interaction between parental background and social context may have counterintuitive effects on young adults' investment in human capital. We consider a specific aspect of the social context at regional level, i.e. nepotism. We proxy nepotism by the relative share of income inequality explained by parental education at regional level, i.e. Inequality of Opportunity. We consider highly nepotistic areas all those regions which level of IoP is in the top 30% of the distribution across years. In this way we are able to exploit within region variations of the level of Inequality of Opportunity. Parental background is instead captured by the percentile of the yearly household income distribution at regional level. Similarly, we consider high parental background all those individuals whose household income was in the top 30% of the distribution. Relying on the panel dimension of the database, we are able to reconstruct the initial condition of each respondents in terms of parental background and regional IoP at age 18. We assume that young adult individuals, when facing the decision on how to proceed with their carrier after high school, observe their parental background and form an idea on the extent to which the job market rewards effort and parental background. High level of IoP signals highly nepotistic job market functioning and relatively low return on effort. Therefore, concerned with the determination of their future SES, young adults evaluate these circumstances and decide on the accumulation of their human capital. We show that respondents who at age 18 happened to live in wealthy families in highly nepotistic regions, display lower human capital accumulation in adult age with respect to individuals with the same parental background in different regions or cohorts. We believe that these results are driven by the way children perceive the functioning of the job market. In nepotistic regions, perceived return on parental background outweighs that on human capital. This in turn affects human capital investments by the group of young adults who have high parental background, and at the same time live in region where it can be exploited as an asset. Although most of the nepotistic regions are from the south of Italy, we produce evidence to show that our results are not only capturing a "north vs south" effect. Our findings have relevant implications in terms of higher education and youth work participation policy.

**Figure 1. Tertiary education and NEET in EU 15**

*Panel A*

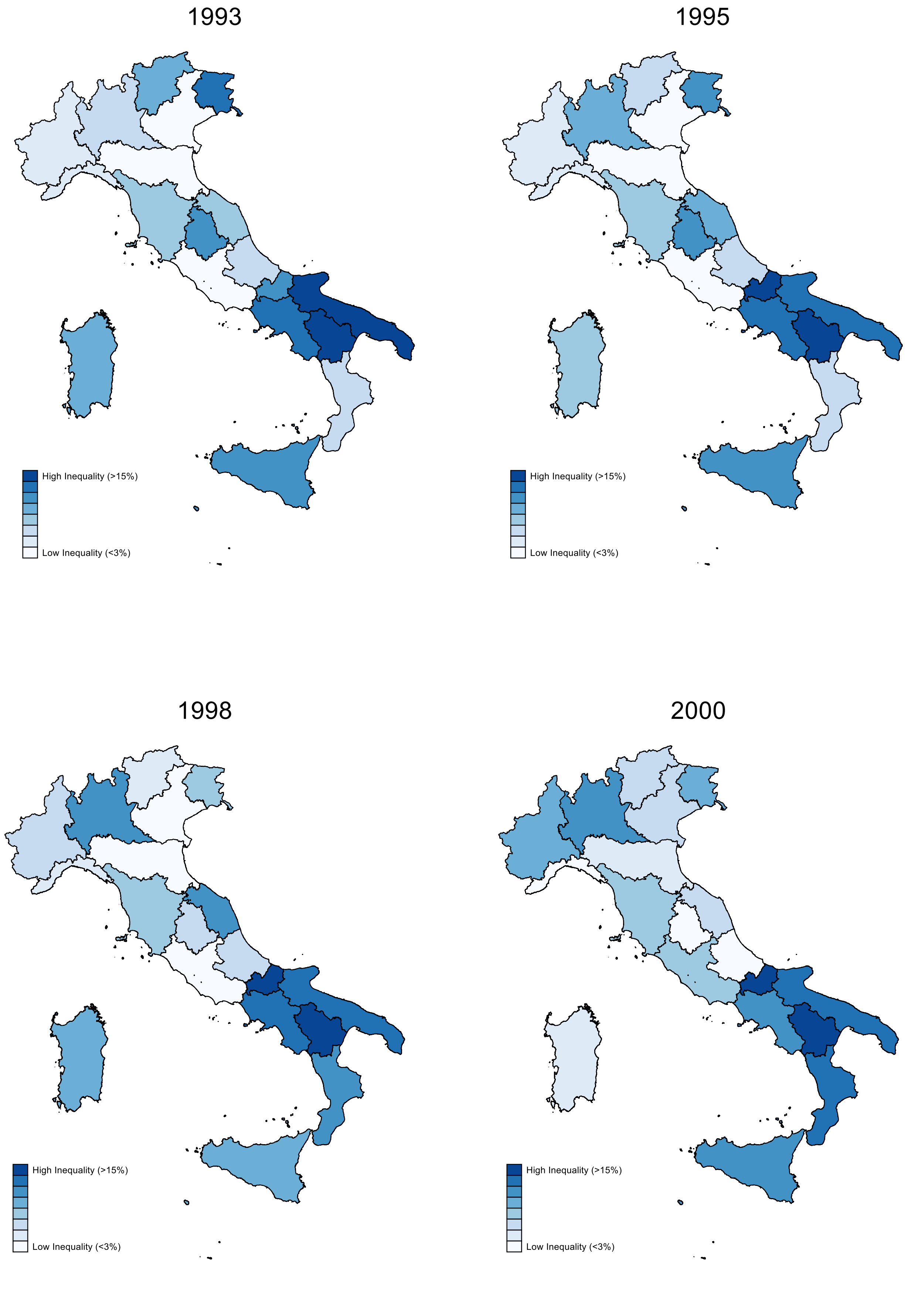


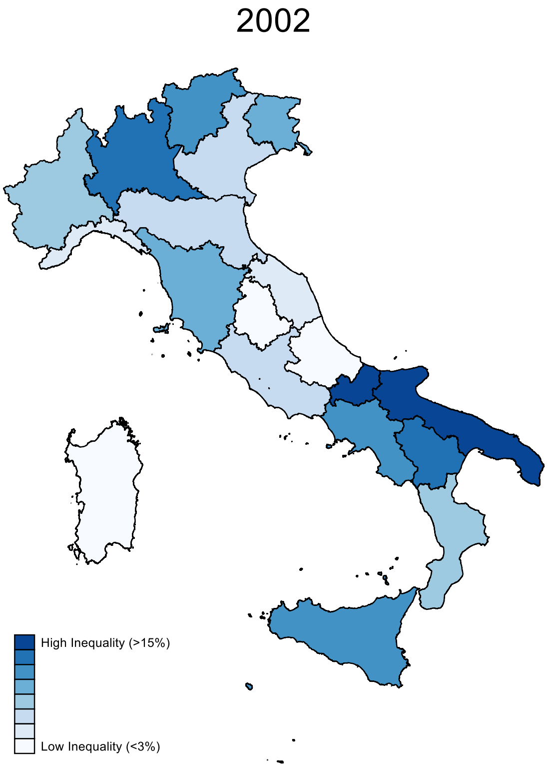

*Panel B*

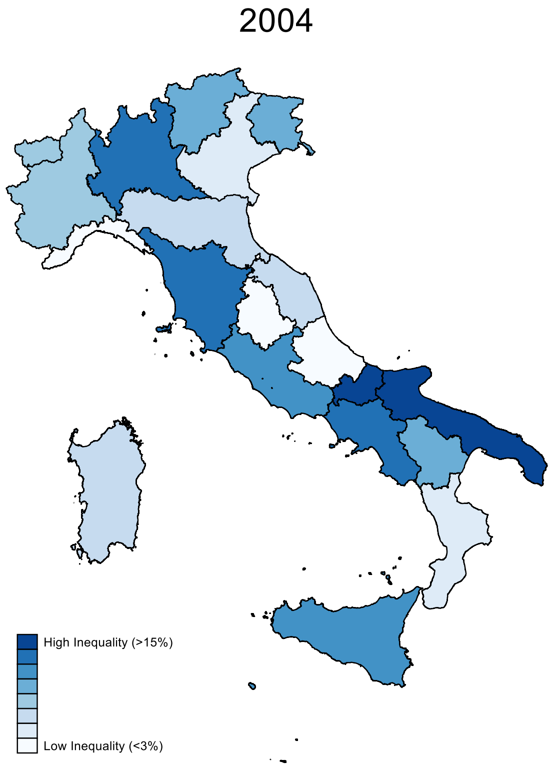


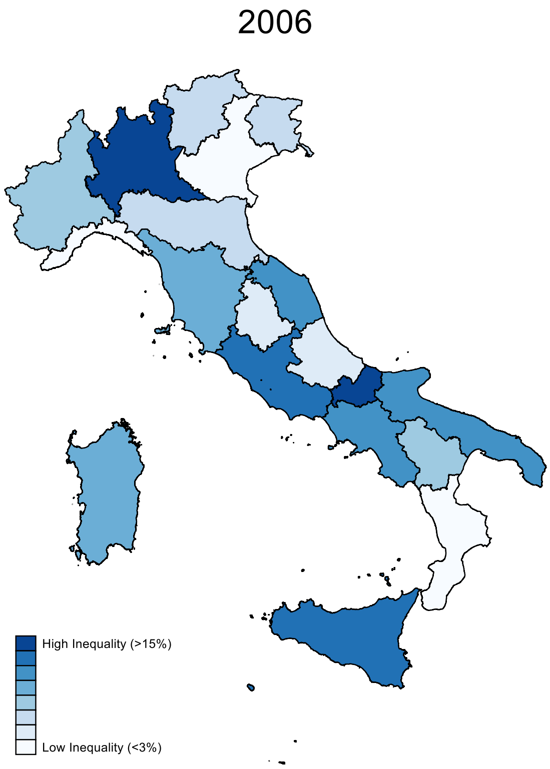

*Note:* Our elaboration based on Eurostat data, 2018. *Panel A*: percentage of individuals aged 30-34 with tertiary education (ISCED 5-8), by EU 15 countries. *Panel B:* percentage of individuals neither in employment nor in education and training (NEET) aged 20-34, by EU 15 countries.

**Figure 2. Inequality of Opportunity in Italy over the years 1993-2006.**





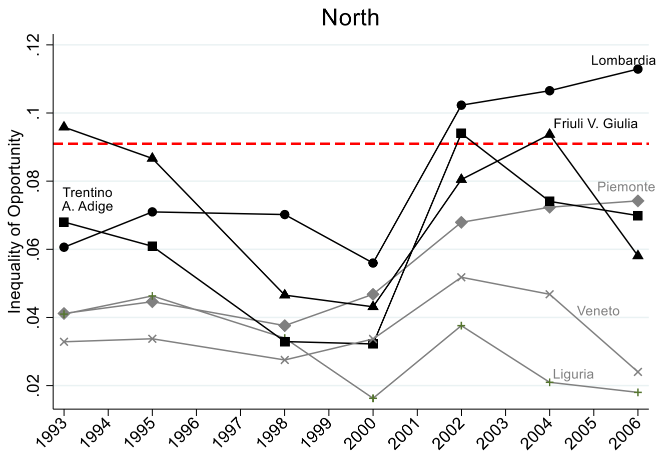



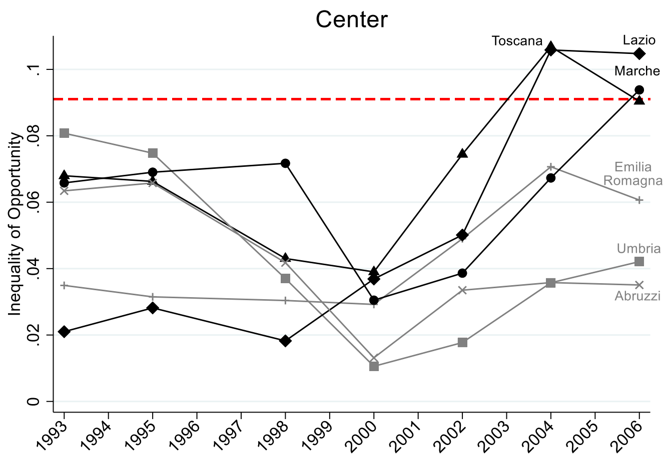

*Note:* Our elaboration based on SHIW data, 1993-2006. These graphs map regional IoP across regions and waves. Dark blue IoP>15%, Ligth blue IoP<3%.

**Figure 3. Regional IoP across waves.**

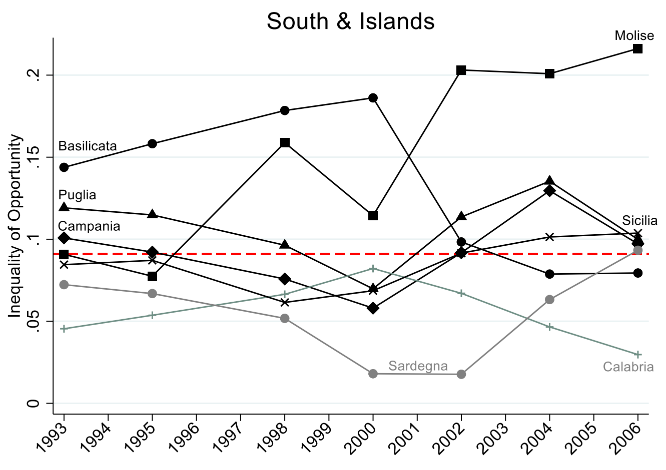
*Panel A*




*Panel B*

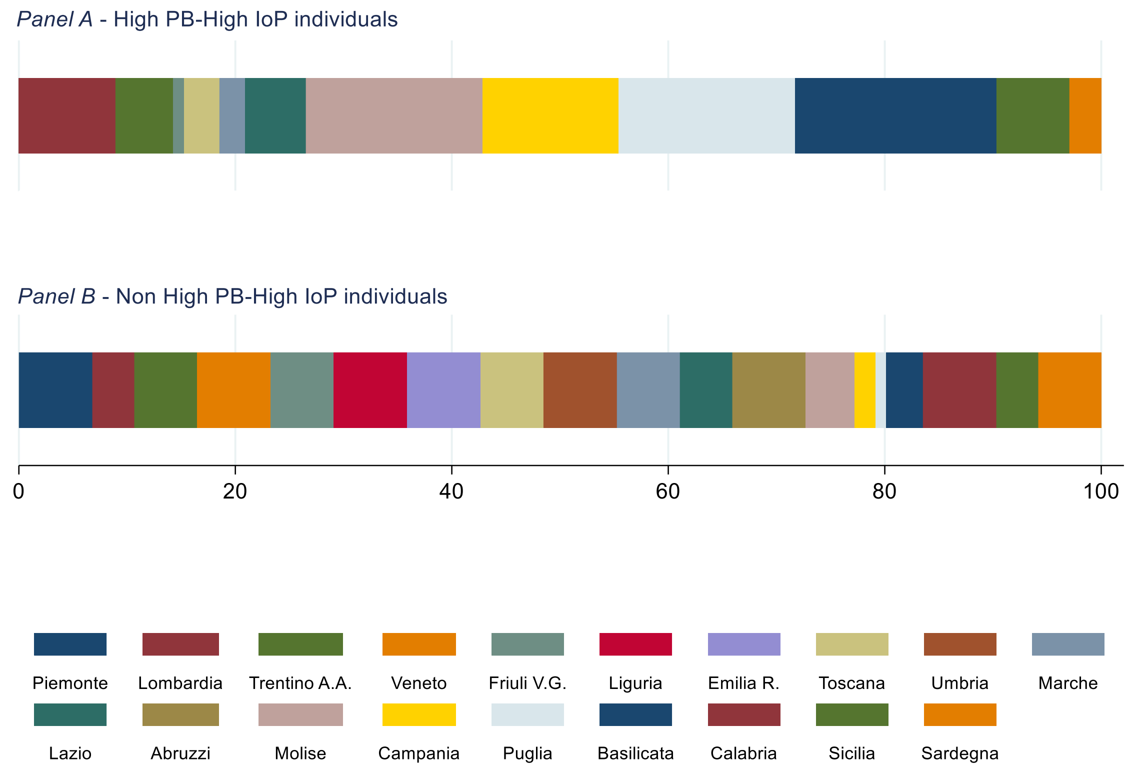



*Panel C*



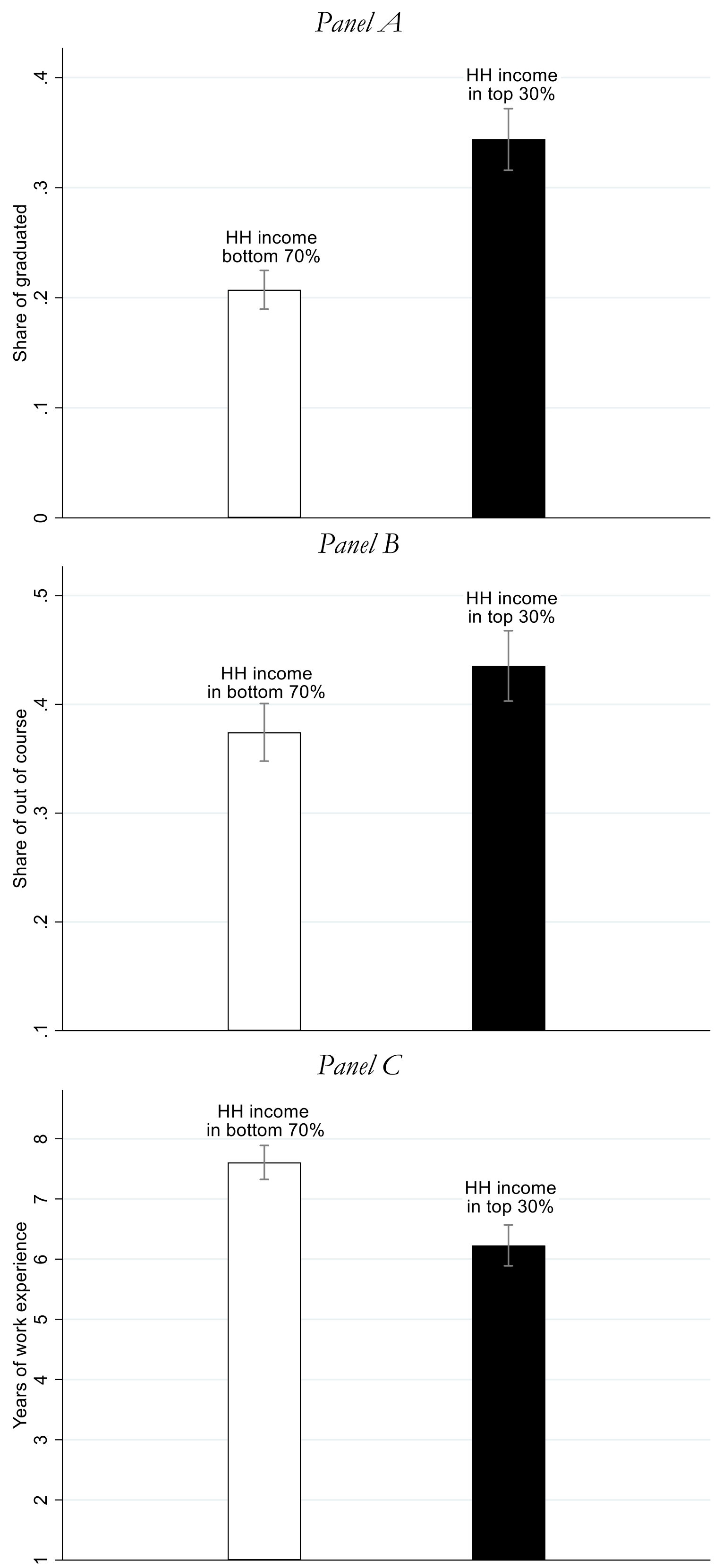

*Note:* Our elaboration based on SHIW data,1993-2006. These graphs report regional IoP across waves. *Panel A*: northern regions. *Panel B:* central regions. *Panel C:* southern regions and islands. The red dashed line represents the threshold for high IoP region (9%).

**Figure 4. Distribution of the High PB-High IoP individuals across regions.**




*Note:* Our elaboration based on SHIW data, 1993-2006. It reports the distribution of the group of high PB-high IoP (Panel A) and Non high PB-high IoP (Panel B) individuals across regions, over the years 1993-2006.

**Figure 5. Share of graduated, out of course, work experience, by parental background**




*Note:* Our elaboration based on SHIW data, 2004-2016. Household income in bottom 70% proxies low parental background; Household income in top 30% proxies high parental background; *Panel A:* share of graduated, bachelor or master, in the age range 26-35, by parental background at age 18. *Panel B:* share of out of course students, in the age range 26-35, by parental background at age 18. *Panel C:* average years of work experience in the age range 26-35, by by parental background at age 18

**Table 1. Descriptive statistics**

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Graduated | 1,961 | .304 | .460 | 0 | 1 |
| Out of course | 1,443 | .450 | .498 | 0 | 1 |
| Years of work experience | 1,318 | 7.193 | 4.317 | 0 | 21 |
| Inequality of Opportunity | 1,961 | .067 | .033 | .011 | .216 |
| High Inequality of Opportunity | 1,961 | .246 | .431 | 0 | 1 |
| Household income at age 18 | 1,961 | 46604.15 | 32753.48 | 607.5402 | 316969.8 |
| High Parental Background | 1,961 | .357 | .479 | 0 | 1 |
| Educated parents | 1,961 | .412 | .492 | 0 | 1 |
| Male | 1,961 | .584 | .493 | 0 | 1 |
| Age | 1,961 | 28.739 | 2.388 | 26 | 35 |
| Still in education | 1,961 | .130 | .336 | 0 | 1 |
| Worked under 20 | 1,961 | .124 | .330 | 0 | 1 |
| Migrated | 1,961 | .093 | .290 | 0 | 1 |
| *Parental Occupation* | | | | | |
| Unemployed | 1,929 | .090 | .287 | 0 | 1 |
| Blue collar | 1,929 | .237 | .426 | 0 | 1 |
| White collar | 1,929 | .331 | .471 | 0 | 1 |
| Self-employed | 1,929 | .137 | .344 | 0 | 1 |
| Entrepreneur | 1,929 | .046 | .209 | 0 | 1 |
| Retired | 1,929 | .160 | .367 | 0 | 1 |
| Decile of home characteristics (PCA) | 1,961 | 5.805 | 2.803 | 1 | 10 |
| Household size | 1,961 | 4.159 | .904 | 1 | 8 |
| *Education attained* | | | | | |
| Primary or no education | 1,961 | .008 | .090 | 0 | 1 |
| Secondary education | 1,961 | .180 | .384 | 0 | 1 |
| Professional education | 1,961 | .076 | .265 | 0 | 1 |
| High school | 1,961 | .432 | .495 | 0 | 1 |
| Bachelor degree | 1,961 | .056 | .230 | 0 | 1 |
| Master | 1,961 | .228 | .420 | 0 | 1 |
| Post-graduate | 1,961 | .019 | .138 | 0 | 1 |
| *Marital status* | | | | | |
| Married | 1,961 | .069 | .253 | 0 | 1 |
| Not Married | 1,961 | .927 | .260 | 0 | 1 |
| Separated/ divorced | 1,961 | .004 | .064 | 0 | 1 |
| *Job status* | | | | | |
| Unemployed | 1,960 | .437 | .496 | 0 | 1 |
| Employed | 1,960 | .474 | .499 | 0 | 1 |
| Self-employed | 1,960 | 0.89 | .284 | 0 | 1 |
| *Municipality population size* | | | | | |
| Less than 20,000 inhabitants | 1,961 | .274 | .446 | 0 | 1 |
| From 20,000 to 40,000 inhabitants | 1,961 | .197 | .398 | 0 | 1 |
| From 40,000 to 500,000 inhabitants | 1,961 | .474 | .499 | 0 | 1 |
| More than 500,000 inhabitants | 1,961 | .055 | .228 | 0 | 1 |
| Unemployment rate NUTS3 ($t_0$) | 1,858 | 10.672 | 5.653 | 2.4 | 23.2 |
| GDP growth rate NUTS3 ($t_0$) | 1,858 | 1.465 | 2.188 | -3.474 | 6.506 |
| Unemployment rate NUTS3 ($t_1$) | 1,961 | 11.099 | 6.15 | 2.5 | 24.4 |
| GDP growth rate NUTS3 ($t_1$) | 1,936 | 1.582 | 1.34 | -1.955 | 5.628 |
| *Wave* | | | | | |
| 2004 | 1,961 | .125 | .331 | 0 | 1 |
| 2006 | 1,961 | .139 | .346 | 0 | 1 |
| 2008 | 1,961 | .154 | .361 | 0 | 1 |
| 2010 | 1,961 | .153 | .361 | 0 | 1 |
| 2012 | 1,961 | .184 | .387 | 0 | 1 |
| 2014 | 1,961 | .138 | .345 | 0 | 1 |
| 2016 | 1,961 | .107 | .309 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| *Cohort* | | | | | |
| 1972-1975 | 1,961 | .088 | .283 | 0 | 1 |
| 1976-1979 | 1,961 | .273 | .446 | 0 | 1 |
| 1980-1983 | 1,961 | .313 | .464 | 0 | 1 |
| 1984-1987 | 1,961 | .261 | .439 | 0 | 1 |
| 1988-1990 | 1,961 | .065 | .247 | 0 | 1 |
| *Region* | | | | | |
| Piemonte & Val d'Aosta | 1,961 | .054 | .225 | 0 | 1 |
| Lombardia | 1,961 | .064 | .245 | 0 | 1 |
| Trentino Alto Adige | 1,961 | .016 | .125 | 0 | 1 |
| Veneto | 1,961 | .053 | .224 | 0 | 1 |
| Friuli Venezia Giulia | 1,961 | .030 | .171 | 0 | 1 |
| Liguria | 1,961 | .014 | .117 | 0 | 1 |
| Emilia Romagna | 1,961 | .105 | .307 | 0 | 1 |
| Toscana | 1,961 | .057 | .231 | 0 | 1 |
| Umbria | 1,961 | .035 | .183 | 0 | 1 |
| Marche | 1,961 | .043 | .204 | 0 | 1 |
| Lazio | 1,961 | .060 | .237 | 0 | 1 |
| Abruzzo | 1,961 | .035 | .184 | 0 | 1 |
| Molise | 1,961 | .009 | .095 | 0 | 1 |
| Campania | 1,961 | .076 | .265 | 0 | 1 |
| Puglia | 1,961 | .075 | .264 | 0 | 1 |
| Basilicata | 1,961 | .022 | .146 | 0 | 1 |
| Calabria | 1,961 | .055 | .227 | 0 | 1 |
| Sicilia | 1,961 | .122 | .328 | 0 | 1 |
| Sardegna | 1,961 | .075 | .263 | 0 | 1 |

**Table 2. The negative effect of IoP and PB on the probability to have a master degree.**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.394 | 1.918 | 2.499 | 2.277 | 2.601 |
| | (1.396) | (1.505) | (1.628) | (2.245) | (1.813) |
| High Parental Background (PB) | 2.477*** | 0.953 | 0.836 | 1.053 | 1.158 |
| | (0.907) | (1.321) | (1.222) | (1.320) | (1.329) |
| High IoP*High PB | | -4.800*** | -4.428** | -4.833** | -4.832** |
| | | (1.845) | (1.916) | (2.102) | (2.035) |
| Household head educated | | 7.220*** | 7.159*** | 7.501*** | 5.778*** |
| | | (1.200) | (1.051) | (1.097) | (0.780) |
| *Household head occupation* | | | | | |
| Blue collar | | 0.607 | 1.092 | 1.400 | 2.406 |
| | | (2.042) | (1.912) | (2.267) | (2.343) |
| White collar | | 3.759 | 3.988** | 4.452** | 5.240** |
| | | (2.364) | (1.829) | (2.261) | (2.145) |
| Self-employed | | -0.530 | -0.510 | 0.180 | 1.051 |
| | | (2.403) | (2.115) | (2.617) | (2.446) |
| Entrepreneur | | 3.064 | 2.004 | 3.639 | 3.334 |
| | | (2.422) | (3.838) | (2.727) | (3.090) |
| Retired | | 1.346 | 1.311 | 1.786 | 2.702 |
| | | (2.376) | (1.842) | (2.382) | (2.309) |
| *House PCA* | | | | | |
| Second decile | | 4.678* | 3.950* | 3.798* | 3.661 |
| | | (2.651) | (2.336) | (2.271) | (3.112) |
| Third decile | | 3.046 | 2.840 | 3.035 | 1.976 |
| | | (2.155) | (2.044) | (2.532) | (2.928) |
| Fourth decile | | 8.047*** | 7.434*** | 7.602*** | 7.340** |
| | | (2.262) | (2.095) | (2.149) | (3.117) |
| Fifth decile | | 5.409** | 4.597** | 5.309** | 3.640 |
| | | (2.256) | (2.300) | (2.199) | (3.178) |
| Sixth decile | | 8.510*** | 7.203*** | 7.470*** | 7.013** |
| | | (2.193) | (2.085) | (2.120) | (3.070) |
| Seventh decile | | 5.824*** | 4.832** | 5.060** | 5.113 |
| | | (2.184) | (2.162) | (2.107) | (3.193) |
| Eighth decile | | 9.004*** | 9.039*** | 8.489*** | 8.153*** |
| | | (2.394) | (2.056) | (2.391) | (3.111) |
| Ninth decile | | 8.620*** | 8.839*** | 8.674*** | 8.873*** |
| | | (2.038) | (2.069) | (2.248) | (3.011) |
| Tenth decile | | 11.904*** | 12.035*** | 11.952*** | 11.112*** |
| | | (2.439) | (2.246) | (2.631) | (3.281) |
| Household size | | -0.626 | -0.654* | -0.545 | -0.486 |
| | | (0.423) | (0.396) | (0.518) | (0.501) |
| *Municipality size* | | | | | |
| 20-40 thousand inhabitants | | 1.162 | 1.062 | 1.065 | 0.836 |
| | | (1.295) | (1.374) | (1.464) | (1.547) |
| 40-500 thousand inhabitants | | 3.620*** | 3.198*** | 3.337** | 3.310** |
| | | (1.150) | (1.191) | (1.531) | (1.550) |

| | | | | | |
|---|---|---|---|---|---|
| More than 500 thousand inhabitants | | 1.282 | 1.245 | 0.715 | -1.669 |
| | | (2.874) | (2.737) | (2.719) | (3.380) |
| Student | | | -2.855*** | -2.794*** | -2.977*** |
| | | | (0.677) | (0.702) | (0.725) |
| Worked under age 20 | | | -1.186 | -1.177 | -1.072 |
| | | | (0.956) | (0.970) | (1.050) |
| Migrated | | | 4.577*** | 4.909** | 5.066*** |
| | | | (1.593) | (2.109) | (1.845) |
| *Marital status* | | | | | |
| Not married | | | 2.650** | 2.557** | 2.704** |
| | | | (1.182) | (1.043) | (1.101) |
| Separated/divorced | | | -2.891 | -1.683 | -0.154 |
| | | | (7.629) | (4.710) | (5.619) |
| *Job status* | | | | | |
| Employed | | | -0.489 | -0.505 | -0.806 |
| | | | (0.633) | (0.621) | (0.675) |
| Self employed | | | -0.349 | -0.283 | -0.600 |
| | | | (0.882) | (0.835) | (0.903) |
| Unemployment (t0) | | | | 0.184 | |
| | | | | (0.218) | |
| GDP growth rate (t0) | | | | 0.000 | |
| | | | | (0.000) | |
| Unemployment (t1) | | | | | 0.023 |
| | | | | | (0.175) |
| GDP growth rate (t1) | | | | | 0.130 |
| | | | | | (0.177) |
| Male | -4.221*** | -4.435*** | -4.737*** | -4.453*** | -4.073*** |
| | (1.052) | (0.848) | (0.997) | (1.053) | (1.118) |
| Age | 6.074*** | 5.497*** | 5.913*** | 5.903*** | 6.312*** |
| | (1.826) | (1.725) | (1.893) | (1.884) | (2.037) |
| Age squared | -0.091*** | -0.084*** | -0.089*** | -0.091*** | -0.097*** |
| | (0.030) | (0.029) | (0.031) | (0.031) | (0.033) |
| Constant | -111.718*** | -107.592*** | -120.677*** | -125.243*** | -121.031*** |
| | (28.465) | (27.288) | (30.778) | (32.365) | (33.192) |
| Observations | 1,961 | 1,929 | 1,928 | 1,928 | 1,824 |
| Number of id | 918 | 907 | 907 | 907 | 854 |

Note: Dependent variable Dummy Graduated; RE panel logit estimation with robust standard errors in parentheses; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include year, birth region and cohort dummies; Omitted category for Household head occupation "unemployed", for House PCS "first decile", Municipality size "less than 20,000 inhabitants", Marital status "Married", Job status "Unemployed".

**Table 2.1. The negative effect of IoP and PB on the probability to have a master degree. Marginal effects**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.051 | 0.067 | 0.061 | 0.070 |
| | (0.039) | (0.042) | (0.058) | (0.048) |
| High Parental Background (PB) | 0.025 | 0.023 | 0.028 | 0.031 |
| | (0.035) | (0.033) | (0.035) | (0.036) |
| High IoP*High PB | -0.127*** | -0.119** | -0.129** | -0.129** |
| | (0.048) | (0.051) | (0.054) | (0.054) |
| Observations | 1,929 | 1,928 | 1,928 | 1,824 |
| Student, Work <20, Migrated | No | Yes | Yes | Yes |
| Job and Marital status | No | Yes | Yes | Yes |
| NUTS3 economic variables t-1 | No | No | Yes | No |
| NUTS3 economic variables t | No | No | No | Yes |

*Note:* Dependent variable Dummy Graduated; Marginal effects after RE panel logit estimation with robust standard errors in parentheses; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include Adolescence control variables and year, birth region and cohort dummies. Omitted category for Household head occupation "unemployed", for House PCA "first decile", Municipality size "less than 20,000 inhabitants", Marital status "Married", Job status "Unemployed".

**Table 3. The positive effect of IoP and PB on the probability to have be out of course.**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.251 | 0.389 | -0.017 | -0.173 | -0.028 |
| | (0.364) | (0.483) | (0.527) | (0.540) | (0.536) |
| High Parental Background (PB) | 0.712*** | -0.017 | 0.037 | 0.092 | 0.042 |
| | (0.229) | (0.330) | (0.361) | (0.369) | (0.375) |
| High IoP*High PB | | 0.815 | 1.688*** | 1.665*** | 1.720*** |
| | | (0.569) | (0.631) | (0.636) | (0.642) |
| Household head educated | | 0.918*** | 0.158 | 0.169 | 0.134 |
| | | (0.291) | (0.323) | (0.330) | (0.335) |
| *Household head occupation* | | | | | |
| Blue collar | | 0.996* | 0.940 | 0.873 | 1.107* |
| | | (0.576) | (0.623) | (0.630) | (0.654) |
| White collar | | 0.857 | 0.581 | 0.551 | 0.841 |
| | | (0.554) | (0.599) | (0.604) | (0.633) |
| Self-employed | | 0.606 | 0.793 | 0.775 | 1.030 |
| | | (0.607) | (0.656) | (0.664) | (0.689) |
| Entrepreneur | | 0.883 | 0.813 | 0.786 | 1.045 |
| | | (0.770) | (0.837) | (0.846) | (0.862) |
| Retired | | 0.066 | -0.155 | -0.156 | 0.259 |
| | | (0.602) | (0.652) | (0.659) | (0.688) |
| *House PCA* | | | | | |

| | | | | |
|---|---|---|---|---|
| Second decile | 0.315 | -0.078 | -0.069 | -0.125 |
| | (0.701) | (0.747) | (0.764) | (0.771) |
| Third decile | -1.035 | -1.149 | -1.130 | -1.121 |
| | (0.683) | (0.729) | (0.738) | (0.743) |
| Fourth decile | -0.515 | -1.200* | -1.192* | -1.153 |
| | (0.652) | (0.707) | (0.715) | (0.730) |
| Fifth decile | -0.472 | -0.976 | -0.963 | -0.986 |
| | (0.682) | (0.736) | (0.745) | (0.753) |
| Sixth decile | -0.167 | -0.730 | -0.665 | -0.746 |
| | (0.648) | (0.700) | (0.709) | (0.714) |
| Seventh decile | -0.672 | -1.011 | -1.059 | -0.976 |
| | (0.649) | (0.692) | (0.706) | (0.715) |
| Eighth decile | 0.026 | -0.601 | -0.632 | -0.769 |
| | (0.641) | (0.694) | (0.708) | (0.718) |
| Ninth decile | -0.207 | -1.009 | -0.979 | -1.068 |
| | (0.623) | (0.671) | (0.679) | (0.688) |
| Tenth decile | 0.037 | -0.851 | -0.822 | -1.021 |
| | (0.673) | (0.731) | (0.740) | (0.759) |
| Household size | -0.092 | -0.045 | -0.073 | -0.029 |
| | (0.144) | (0.158) | (0.161) | (0.163) |
| *Municipality size* | | | | |
| 20-40 thousand inhabitants | 0.290 | 0.304 | 0.372 | 0.225 |
| | (0.381) | (0.418) | (0.425) | (0.434) |
| 40-500 thousand inhabitants | 0.003 | -0.332 | -0.317 | -0.389 |
| | (0.318) | (0.349) | (0.354) | (0.360) |
| More than 500 thousand inhabitants | -1.129* | -0.950 | -0.932 | -0.658 |
| | (0.629) | (0.676) | (0.680) | (0.741) |
| *Education attained* | | | | |
| Undergraduate | | 5.457*** | 5.487*** | 5.403*** |
| | | (0.632) | (0.636) | (0.649) |
| Graduated | | 3.603*** | 3.640*** | 3.695*** |
| | | (0.380) | (0.385) | (0.396) |
| Post graduate | | -0.804 | -0.794 | -0.657 |
| | | (0.805) | (0.811) | (0.816) |
| Still in education | | -0.226 | -0.264 | -0.166 |
| | | (0.341) | (0.345) | (0.346) |
| Worked under age 20 | | 1.117** | 1.137** | 1.360** |
| | | (0.556) | (0.560) | (0.578) |
| Migrated | | 0.973 | 1.009 | 0.976 |
| | | (0.665) | (0.672) | (0.672) |
| *Marital status* | | | | |
| Not married | | 0.634 | 0.619 | 0.614 |
| | | (0.549) | (0.557) | (0.558) |
| Separated/divorced | | 2.118 | 2.194 | 2.359 |
| | | (1.774) | (1.804) | (2.251) |
| *Job status* | | | | |
| Employed | | -0.882*** | -0.890*** | -0.850*** |
| | | (0.280) | (0.283) | (0.287) |
| Self employed | | -1.078*** | -1.145*** | -1.067** |

| | | | | | |
|---|---|---|---|---|---|
| | | | (0.417) | (0.423) | (0.425) |
| Unemployment (t0) | | | | -0.126 | |
| | | | | (0.091) | |
| GDP growth rate (t0) | | | | -0.084 | |
| | | | | (0.119) | |
| Unemployment (t1) | | | | | -0.170* |
| | | | | | (0.096) |
| GDP growth rate (t1) | | | | | -0.059 |
| | | | | | (0.086) |
| Male | 0.200 | 0.006 | 0.503* | 0.529* | 0.507* |
| | (0.221) | (0.244) | (0.274) | (0.277) | (0.281) |
| Age | 2.928*** | 3.125*** | 2.806*** | 2.943*** | 2.983*** |
| | (0.624) | (0.851) | (0.946) | (0.958) | (0.970) |
| Age squared | -0.046*** | -0.050*** | -0.045*** | -0.047*** | -0.047*** |
| | (0.011) | (0.014) | (0.016) | (0.016) | (0.016) |
| Constant | -46.057*** | -48.857*** | -43.190*** | -44.235*** | -46.113*** |
| | (9.275) | (12.982) | (14.443) | (14.658) | (14.814) |
| Observations | 1,787 | 1,421 | 1,421 | 1,410 | 1,369 |
| Number of id | 834 | 688 | 688 | 682 | 656 |

*Note:* Dependent variable dummy Out of course 1/0; RE panel logit estimation with robust standard errors in parentheses; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include year, birth region and cohort dummies; Omitted category for Household head occupation "unemployed", for House PCA "first decile", Municipality size "less than 20,000 inhabitants", Education attained "High school", Marital status "Married", Job status "Unemployed".

**Table 3.1. The positive effect of IoP and PB on the probability to have be out of course. Marginal effects**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.052 | -0.002 | -0.018 | -0.003 |
| | (0.064) | (0.055) | (0.056) | (0.056) |
| High Parental Background (PB) | -0.002 | 0.004 | 0.010 | 0.004 |
| | (0.044) | (0.038) | (0.038) | (0.039) |
| High IoP*High PB | 0.109 | 0.177*** | 0.173*** | 0.179*** |
| | (0.075) | (0.065) | (0.065) | (0.065) |
| Observations | 1,421 | 1,421 | 1,410 | 1,369 |
| Student, Work <20, Migrated | No | Yes | Yes | Yes |
| Education attained | No | Yes | Yes | Yes |
| Job and Marital status | No | Yes | Yes | Yes |
| NUTS3 economic variables t-1 | No | No | Yes | No |
| NUTS3 economic variables t | No | No | No | Yes |

*Note:* Dependent variable dummy Out of course 1/0; Marginal effects RE panel logit estimation with robust standard errors in parentheses; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include Adolescence control variables, year, birth region and cohort dummies;

**Table 4. The negative effect of IoP and PB on years of work experience.**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.481 | 0.967* | 0.846** | 0.936*** | 0.844** |
| | (0.425) | (0.514) | (0.349) | (0.354) | (0.357) |
| High Parental Background (PB) | -0.773*** | 0.532 | 0.343 | 0.317 | 0.271 |
| | (0.253) | (0.346) | (0.234) | (0.237) | (0.250) |
| High IoP*High PB | | -0.957 | -0.998** | -0.996** | -0.968** |
| | | (0.631) | (0.429) | (0.430) | (0.439) |
| Household head educated | | -1.712*** | -0.646*** | -0.707*** | -0.599** |
| | | (0.322) | (0.225) | (0.227) | (0.233) |
| *Household head occupation* | | | | | |
| Blue collar | | -0.334 | -0.133 | -0.142 | -0.169 |
| | | (0.543) | (0.367) | (0.368) | (0.384) |
| White collar | | -1.196** | -0.087 | -0.079 | -0.239 |
| | | (0.559) | (0.382) | (0.383) | (0.401) |
| Self-employed | | -0.858 | -0.004 | -0.034 | -0.243 |
| | | (0.601) | (0.407) | (0.409) | (0.431) |
| Entrepreneur | | -0.368 | 0.466 | 0.434 | 0.323 |
| | | (0.767) | (0.512) | (0.515) | (0.527) |
| Retired | | -0.109 | -0.048 | -0.067 | -0.205 |
| | | (0.591) | (0.399) | (0.400) | (0.422) |
| *House PCA* | | | | | |
| Second decile | | -0.501 | -0.138 | -0.214 | -0.032 |
| | | (0.672) | (0.453) | (0.462) | (0.469) |
| Third decile | | -0.332 | -0.008 | 0.006 | 0.154 |
| | | (0.623) | (0.420) | (0.425) | (0.435) |
| Fourth decile | | -0.511 | 0.158 | 0.218 | 0.282 |
| | | (0.617) | (0.414) | (0.421) | (0.432) |
| Fifth decile | | -0.331 | -0.205 | -0.244 | -0.072 |
| | | (0.652) | (0.436) | (0.443) | (0.450) |
| Sixth decile | | -0.735 | 0.011 | 0.044 | 0.268 |
| | | (0.623) | (0.423) | (0.429) | (0.442) |
| Seventh decile | | 0.148 | 0.558 | 0.613 | 0.861* |
| | | (0.623) | (0.420) | (0.425) | (0.442) |
| Eighth decile | | -1.424** | -0.348 | -0.308 | -0.160 |
| | | (0.632) | (0.431) | (0.438) | (0.451) |
| Ninth decile | | -1.542** | -0.173 | -0.149 | 0.046 |
| | | (0.621) | (0.422) | (0.427) | (0.440) |
| Tenth decile | | -1.870*** | -0.557 | -0.480 | -0.198 |
| | | (0.682) | (0.462) | (0.468) | (0.486) |
| Household size | | 0.074 | 0.121 | 0.149 | 0.126 |
| | | (0.153) | (0.103) | (0.104) | (0.106) |
| *Municipality size* | | | | | |
| 20-40 thousand inhabitants | | -0.347 | -0.275 | -0.291 | -0.136 |
| | | (0.381) | (0.256) | (0.257) | (0.268) |
| 40-500 thousand inhabitants | | -0.392 | -0.240 | -0.267 | -0.125 |
| | | (0.335) | (0.225) | (0.225) | (0.235) |
| More than 500 thousand inhabitants | | -1.345* | -0.978** | -0.944* | -1.223** |

| | | | | | |
|---|---|---|---|---|---|
| | | (0.717) | (0.494) | (0.494) | (0.604) |
| *Education attained* | | | | | |
| Secondary school | | | 1.102 | 1.105 | 0.491 |
| | | | (0.811) | (0.813) | (0.889) |
| Professional school | | | 0.609 | 0.627 | 0.155 |
| | | | (0.839) | (0.841) | (0.915) |
| High school | | | 0.642 | 0.660 | 0.140 |
| | | | (0.811) | (0.812) | (0.881) |
| Undergraduate | | | -1.619* | -1.627* | -2.209** |
| | | | (0.873) | (0.874) | (0.942) |
| Graduated | | | -2.466*** | -2.437*** | -3.054*** |
| | | | (0.834) | (0.836) | (0.903) |
| Post graduate | | | -2.659*** | -2.603*** | -3.215*** |
| | | | (0.944) | (0.946) | (1.008) |
| Still in education | | | -0.405 | -0.408 | -0.439 |
| | | | (0.498) | (0.500) | (0.504) |
| Worked under age 20 | | | 4.937*** | 5.032*** | 5.073*** |
| | | | (0.215) | (0.219) | (0.224) |
| Migrated | | | 0.549 | 0.612 | 0.666 |
| | | | (0.511) | (0.511) | (0.529) |
| *Marital status* | | | | | |
| Not married | | | -0.648** | -0.638** | -0.541* |
| | | | (0.305) | (0.306) | (0.314) |
| Separated/ divorced | | | -2.014** | -2.042** | -2.834*** |
| | | | (1.016) | (1.016) | (1.090) |
| *Job status* | | | | | |
| Employed | | | -0.078 | -0.077 | -0.131 |
| | | | (0.209) | (0.212) | (0.215) |
| Self employed | | | -0.686** | -0.731*** | -0.791*** |
| | | | (0.270) | (0.273) | (0.275) |
| Unemployment (t0) | | | | 0.067 | |
| | | | | (0.058) | |
| GDP growth rate (t0) | | | | 0.129* | |
| | | | | (0.077) | |
| Unemployment (t1) | | | | | -0.085 |
| | | | | | (0.067) |
| GDP growth rate (t1) | | | | | -0.035 |
| | | | | | (0.054) |
| Male | 0.929*** | 0.945*** | -0.064 | -0.076 | -0.077 |
| | (0.250) | (0.268) | (0.187) | (0.188) | (0.195) |
| Age | -1.064** | -0.442 | 0.118 | 0.138 | 0.202 |
| | (0.515) | (0.696) | (0.584) | (0.588) | (0.593) |
| Age squared | 0.030*** | 0.020* | 0.010 | 0.010 | 0.009 |
| | (0.009) | (0.011) | (0.010) | (0.010) | (0.010) |
| Constant | 12.879 | 4.901 | -5.711 | -7.024 | -3.264 |
| | (7.935) | (10.928) | (9.057) | (9.144) | (9.430) |
| Observations | 1,553 | 1,291 | 1,291 | 1,276 | 1,208 |
| Number of id | 773 | 674 | 674 | 667 | 631 |

*Note:* Dependent variable Years of work experience; RE panel OLS estimation with robust standard errors in parentheses; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include year, birth region and cohort dummies; Omitted category for Household head occupation "unemployed", for House PCA "first decile", Municipality size "less than 20,000 inhabitants", Education attained "Primary school", Marital status "Married", Job status "Unemployed".

**Table 4.1. The negative effect of IoP and PB on years of work experience. Marginal effects.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.967* | 0.846** | 0.936*** | 0.844** |
| | (0.514) | (0.349) | (0.354) | (0.357) |
| High Parental Background (PB) | 0.532 | 0.343 | 0.317 | 0.271 |
| | (0.346) | (0.234) | (0.237) | (0.250) |
| High IoP*High PB | -0.957 | -0.998** | -0.996** | -0.968** |
| | (0.631) | (0.429) | (0.430) | (0.439) |
| Observations | 1,553 | 1,291 | 1,291 | 1,276 |
| Student, Work <20, Migrated | No | Yes | Yes | Yes |
| Education attained | No | Yes | Yes | Yes |
| Job and Marital status | No | Yes | Yes | Yes |
| NUTS3 economic variables t-1 | No | No | Yes | No |
| NUTS3 economic variables t | No | No | No | Yes |

*Note:* Dependent variable Years of work experience; Marginal effects after RE panel OLS estimation with robust standard errors in parentheses; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include Adolescence control variables, year, birth region and cohort dummies.

**Table 5. The role of parental occupation and parental education**

| | Graduated | Out of course | Work experience | Graduated | Out of course | Work experience |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| High Inequality of Opportunity (IoP) | 0.065* | 0.065 | 0.272 | 0.048 | 0.041 | 0.246 |
| | (0.039) | (0.057) | (0.355) | (0.039) | (0.057) | (0.354) |
| HH-head entrepreneur or white collar | 0.067 | 0.081 | 0.312 | | | |
| | (0.086) | (0.088) | (0.523) | | | |
| High IoP*HH-head entrep. or W.C. | -0.097** | 0.019 | 0.520 | | | |
| | (0.049) | (0.064) | (0.432) | | | |
| Educated HH-head | | | | 0.221*** | 0.001 | -0.807*** |
| | | | | (0.030) | (0.038) | (0.245) |
| High IoP*Educated HH-head | | | | -0.062 | 0.070 | 0.609 |
| | | | | (0.046) | (0.065) | (0.441) |
| Observations | 1,928 | 1,421 | 1,291 | 1,928 | 1,421 | 1,291 |
| Student, Work <20, Migrated | Yes | Yes | Yes | Yes | Yes | Yes |
| Education attained | Yes | Yes | Yes | Yes | Yes | Yes |
| Job and Marital status | Yes | Yes | Yes | Yes | Yes | Yes |

*Note:* Marginal effects after logit panel random effects estimation in columns 1, 2, 4 and 5. Marginal effects after OLS panel random effects estimation in columns 3 and 6; Robust standard errors in parenthesis; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include Adolescence control variables, year, birth region and cohort dummies.

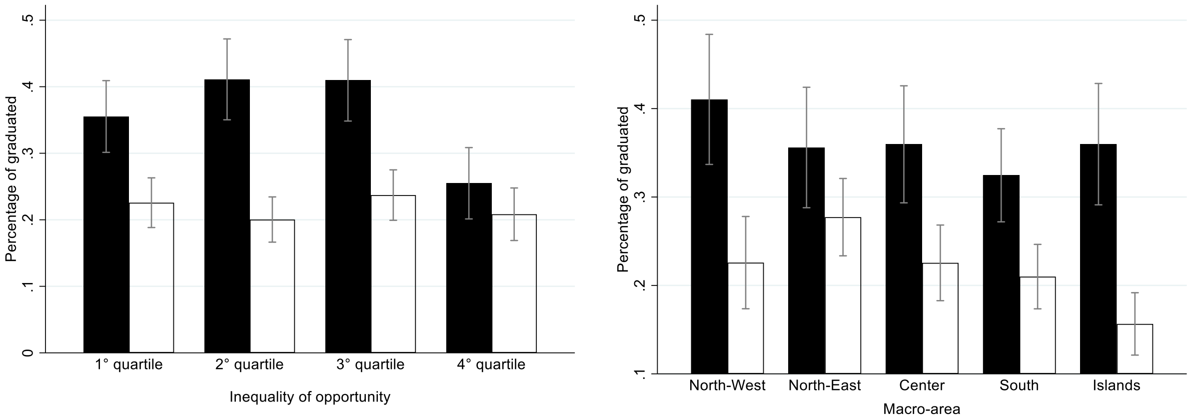
**Table 6. Robustness check. DFBETA.**

| Omitted region | Graduated | | Out of course | | Work experience | |
|---|---|---|---|---|---|---|
| | Observations | DFBETA | Observations | DFBETA | Observations | DFBETA |
| Piemonte | 1,824 | 0.362 | 1,369 | 0.012 | 1,206 | -0.136 |
| Lombardia | 1,803 | 0.187 | 1,321 | 0.012 | 1,194 | -0.050 |
| Trentino Alto Adige | 1,897 | 0.330 | 1,398 | -0.086 | 1,265 | 0.141 |
| Veneto | 1,824 | 0.215 | 1,348 | -0.296 | 1,198 | 0.153 |
| Friuli Venezia Giulia | 1,869 | 0.403 | 1,367 | 0.081 | 1,244 | -0.464 |
| Liguria | 1,901 | 0.695 | 1,396 | 0.013 | 1,272 | 0.016 |
| Emilia-Romagna | 1,722 | 0.033 | 1,261 | 0.056 | 1,124 | -0.321 |
| Toscana | 1,821 | 0.201 | 1,341 | -0.101 | 1,211 | -0.147 |
| Umbria | 1,860 | 0.336 | 1,365 | 0.108 | 1,230 | -0.038 |
| Marche | 1,844 | -0.013 | 1,355 | -0.116 | 1,229 | 0.077 |
| Lazio | 1,811 | -0.731 | 1,334 | 0.025 | 1,207 | 0.513 |
| Abruzzo | 1,867 | 0.204 | 1,363 | -0.148 | 1,256 | 0.140 |
| Molise | 1,910 | -0.166 | 1,311 | -0.799 | 1,279 | 0.166 |
| Campania | 1,786 | -0.765 | 1,318 | 0.773 | 1,211 | 0.331 |
| Puglia | 1,780 | -0.642 | 1,388 | -0.197 | 1,187 | -0.534 |
| Basilicata | 1,885 | 0.178 | 1,388 | -0.177 | 1,266 | 0.208 |
| Calabria | 1,824 | 0.084 | 1,334 | 0.031 | 1,261 | 0.008 |
| Sicilia | 1,687 | 0.038 | 1,268 | 0.493 | 1,197 | -0.172 |
| Sardegna | 1,789 | 0.845 | 1,320 | 0.301 | 1,201 | 0.058 |

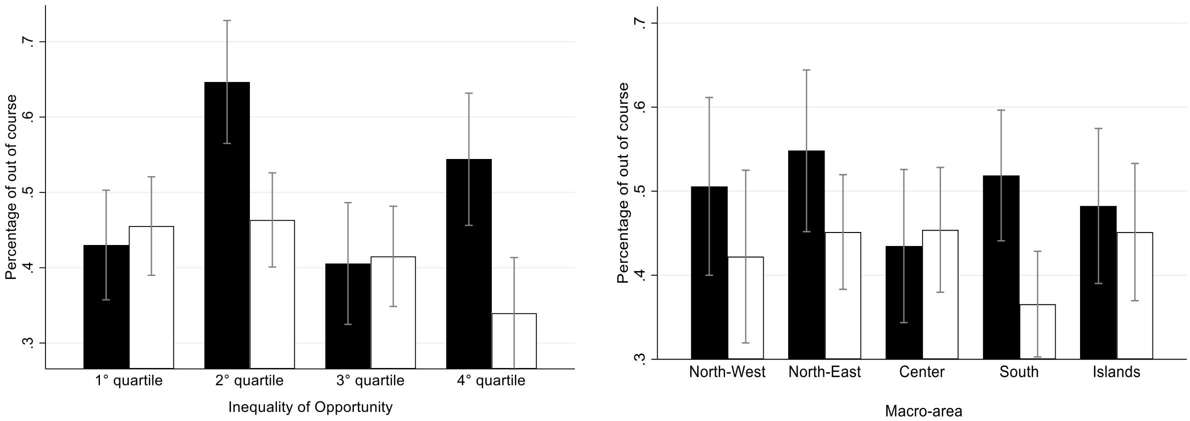
*Note:* The table reports the DFBETA test for the coefficient of the interaction term *High IoP*High PB* of the models in column 3 of Table 2 (*graduated),* Table 3 *(out of course)*, and Table 4 *(work experience)*.

**Figure 6. Share of graduated, out of course, and average work experience, by IoP and macro-area**

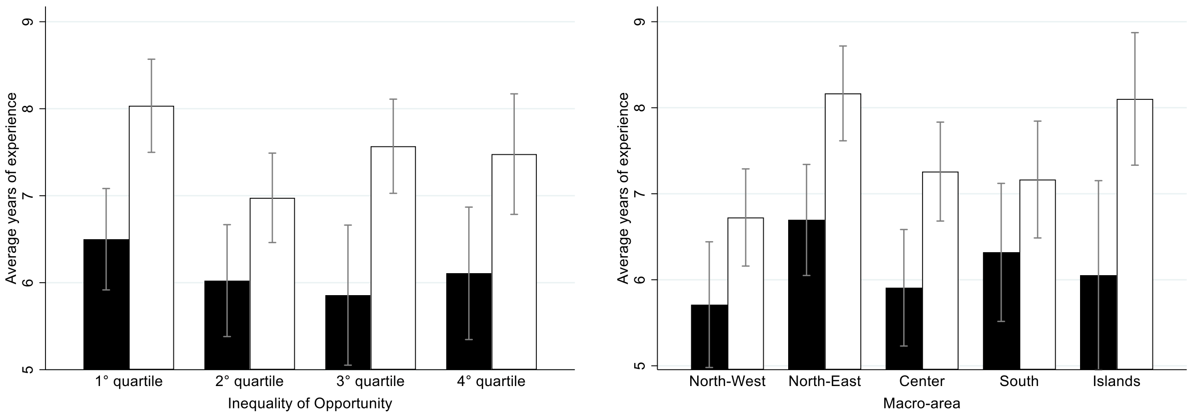
*Panel A*




*Panel B*




*Panel C*




*Note:* Our elaboration based on SHIW data, 2004-2016. Black bars are for high parental background: household income in top 30%, white bars are for low parental background: household income in bottom 70%. I quartile: IoP < 4%; IV quartile: IoP >9.5%. *Panel A:* share of graduated, bachelor or master, in the age range 26-35, by parental background at age 18 and IoP, left, and by parental background at age 18 and macro-area, right. *Panel B:* share of out of course students, in the age range 26-35, by parental background at age 18 and IoP, left, and by parental background at age 18 and macro-area, right. *Panel C:* average years of work experience in the age range 26-35, by by parental background at age 18 and IoP, left, and by parental background at age 18 and macro-area, right.

**Table 7. Robustness check. Bootstrap estimation. Marginal effects**

| | Graduated | Out of course | Work experience |
|---|---|---|---|
| High Inequality of Opportunity (IoP) | 0.064 | -0.002 | 0.849*** |
| | (0.039) | (0.055) | (0.301) |
| High Parental Background (PB) | 0.025 | 0.004 | 0.348** |
| | (0.030) | (0.038) | (0.178) |
| High IoP*High PB | -0.112** | 0.177*** | -1.017*** |
| | (0.051) | (0.065) | (0.374) |
| Observations | 1,928 | 1,421 | 1,291 |
| Student, Work <20, Migrated | Yes | Yes | Yes |
| Education attained | Yes | Yes | Yes |
| Job and Marital status | Yes | Yes | Yes |

*Note:* Marginal effects after bootstrap estimation with 500 repetitions of models in column 3 of Table 2 (*graduated),* Table 3 *(out of course)*, and Table 4 *(work experience)*; C.I. *** p<0.01; ** p<0.05; * p<0.1; All models include Adolescence control variables, year, birth region and cohort dummies.

**References**

Acciari, P., Polo, A., & Violante, G. (2019). 'And Yet, it Moves': Intergenerational Mobility in Italy.

Aina, C. (2013). Parental background and university dropout in Italy. Higher Education, 65(4), 437-456.

Allesina, S. (2011). Measuring nepotism through shared last names: the case of Italian academia. PLoS one, 6(8), e21160.

Aparicio-Fenoll, A. (2016). Returns to education and educational outcomes: The case of the spanish housing boom. Journal of Human Capital, 10(2), 235-265.

Becker, G. 1964. Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. New York: Columbia Univ. Press

Belsley, D. A., Kuh, E., and Welsch, R. E. (1980). *Regression Diagnostics*: Identifying Influential Data and Sources of Collinearity, John Wiley & Sons.

Bingley, P., Christensen, K., & Jensen, V. M. (2008). The Intergeneratonal Transmission of Parental Schooling and Child Development: New Evidence using Danish Twins and their Children. In Annual Conference European Association of Labour Economists.

Björklund, A., & Jäntti, M. (2009). Intergenerational income mobility and the role of family background. Oxford handbook of economic inequality, 491-521.

Björklund, A., & Salvanes, K. G. (2011). Education and family background: Mechanisms and policies. In Handbook of the Economics of Education (Vol. 3, pp. 201-247). Elsevier.

Ernesto Caroleo, F., & Pastore, F. (2012). Talking about the Pigou paradox: Socio-educational background and educational outcomes of AlmaLaurea. International Journal of Manpower, 33(1), 27-50.

Checchi, D. (2006). The economics of education: Human capital, family background and inequality. Cambridge University Press.

Chen, C., Lee, S. Y., & Stevenson, H. W. (1996). Long-term prediction of academic achievement of American, Chinese, and Japanese adolescents. Journal of Educational Psychology, 88(4), 750.

Cohen, G.A. (1989). On the currency of egalitarian justice. Ethics 99, 906–944

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. Journal of Economic Perspectives, 27(3), 79-102.

DeBacker, J. M., & Routon, P. W. (2017). Expectations, education, and opportunity. Journal of Economic Psychology, 59, 29-44.

Duncan, G. J., & Murnane, R. J. (2016). Rising inequality in family incomes and children's educational outcomes. RSF: The Russell Sage Foundation Journal of the Social Sciences, 2(2), 142-158.

Dworkin, R. (1981). What is equality? Part1: equality of welfare. Philos. Public Aff. 10, 185–246, 283–345

Ermisch, J., & Francesconi, M. (2001). Family matters: Impacts of family background on educational attainments. Economica, 68(270), 137-156.

Ferreira, F. H., & Peragine, V. (2016). Individual responsibility and equality of opportunity. In The Oxford Handbook of Well-Being and Public Policy.

Gagliarducci, S., & Manacorda, M. (2016). Politics in the family nepotism and the hiring decisions of Italian firms.

Fleurbaey, M. (1995). Three solutions for the compensation problem. J. Econ. Theory 65, 505–521

Fleurbaey, M. (2008). Fairness, Responsibility, and Welfare. Oxford University Press, London

Foster, J. E., & Shneyerov, A. A. (2000). Path independent inequality measures. Journal of Economic Theory, 91(2), 199-222.

Frey, B. S. and Stutzer, A., (2000). Happiness, economy and institutions. The Economic Journal, 110, 918–938.

Gevrek, D., & Gevrek, Z. E. (2010). Nepotism, incentives and the academic success of college students. Labour Economics, 17(3), 581-591.

Jerrim, J., & Macmillan, L. (2015). Income inequality, intergenerational mobility, and the great gatsby curve: Is education the key?. Social Forces, 94(2), 505-533.

Juárez, F. W. C., & Soloaga, I. (2014). iop: Estimating ex-ante inequality of opportunity. The Stata Journal, 14(4), 830-846.

Kearney, M. S., & Levine, P. B. (2014). Income inequality, social mobility, and the decision to drop out of high school (No. w20195). National Bureau of Economic Research.

Lauer, C. (2003). Family background, cohort and education: A French–German comparison based on a multivariate ordered probit model of educational attainment. Labour Economics, 10(2), 231-251.

McIntosh, J., & Munk, M. D. (2007). Scholastic ability vs family background in educational success: evidence from Danish sample survey data. Journal of Population Economics, 20(1), 101-120.

Otterbach, S. (2010). "Mismatches between actual and preferred work time: Empirical evidence of hours constraints in 21 countries". Journal of Consumer Policy, 33(2), 143-161.

Piatek, R., & Gensowski, M. (2016). Skills, Occupations and Educational Attainment.

Pistolesi, N. (2009). Inequality of opportunity in the land of opportunities, 1968–2001. The Journal of Economic Inequality, 7(4), 411.

Roemer, J.E. (1993). A pragmatic theory of responsibility for the egalitarian planner. Philos. Public Aff. 22, 146–166

Roemer, J.E. (1998). Equality of Opportunity. Harvard University Press, Cambridge

Sansone, C., & Berg, C. A. (1993). Adapting to the environment across the life span: Different process or different inputs?. International Journal of Behavioral Development, 16(2), 215-241.

Scoppa, V. (2009). Intergenerational transfers of public sector jobs: a shred of evidence on nepotism. Public Choice, 141(1-2), 167-188.

Shorrocks, A. F. (1980). The class of additively decomposable inequality measures. Econometrica: Journal of the Econometric Society, 613-625

# PERCEIVED IMMIGRATION AND VOTING BEHAVIOR

*Davide Bellucci*
University of Turin

*Pierluigi Conzo*§
University of Turin & Collegio Carlo Alberto

*Roberto Zotti*
University of Turin

This version: *June 2019*

**ABSTRACT**

A growing number of studies have found significant effects of inflows of migrants on electoral outcomes. However, the role of perceived immigration, which in many European countries is above official migration statistics, is overlooked. This paper investigates the effects of perceived threat of immigration on voting behavior, by looking at whether local elections in Italy were affected by sea arrivals of refugees before the election day. While, upon arrival, refugees cannot freely go to the destination municipality, landing episodes were discussed in the media especially before the elections, thereby influencing voters' perceptions about the arrivals. We develop an index of exposure to arrivals that varies over time and across municipalities depending on the nationality of the incoming refugees. This index captures the impact of perceived immigration on voting behavior, on top of the effects of real immigration as proxied for by the stock of immigrants and the presence of refugee centers. Results show that, in municipalities where refugees are more expected to arrive, participation decreases, whereas protest votes and support for extreme-right, populist and anti-immigration parties increase. Since these effects are driven by areas with fast broadband availability, we argue that anti-immigration campaigns played a key role.

**JEL Codes**: D72; P16; O15; J61

**Keywords**: Immigration; Voting; Political Economy; Populism; Electoral campaigns; Media exposure.

§ Address correspondence to *Pierluigi Conzo*, Dept. of Economics and Statistics "S. Cognetti de Martiis", University of Turin – Campus Luigi Einaudi, Lungo Dora Siena 100A. Email: pierluigi.conzo@unito.it.

## 1. INTRODUCTION

Recent national and European Parliament elections across European countries have shown increasing support for far-right and right-wing populist political parties, calling for a rise of nationalism in Europe (e.g. Guiso et al. 2017 and 2018). This political scenario has been exacerbated by the refugee crisis that occurred in the last few years when thousands of migrants arrived on the Greek and Italian coasts as well as at the borders of Germany, Austria and Hungary. As migration became a key issue in the political debate, support to populist and nationalist parties raised. An interesting, yet overlooked issue is to what extent the rise of anti-immigration and populist right-wing parties results from (mis)perceptions of immigration, likely induced by biased news and anti-immigration campaigns, rather than real exposure to (i.e. contact with) migrants.

In many European countries, the perceived presence of immigrants does not match with the data. This is true especially in Italy, where over-estimation of the number of immigrants living in the country is among the highest in Europe[1]. In addition, while in official statistics the actual number of migrants landed in the ports of Italy, Greece and Spain peaked only in October 2015 and declined soon after to its pre-2015 level (UNHCR data, 2018), inflow of immigrants continues to populate the political debate and to influence the public opinion. The frequency of articles in Italian newspapers containing the words "immigrant(s)" and "crime(s)" raised considerably since 2016, whereas refugee arrivals decreased and crime rates remained constant. Furthermore, Eurobarometer data suggest that immigration and terrorism are still the main concerns among European citizens, whereas economy, finance and unemployment have gradually lost importance since 2011. Not surprisingly, natives in Germany, France, Italy, and the UK on average believe that there are between two and three times as many immigrants as there are in reality (Alesina et al. 2018).

This paper focuses on the role of perceived immigration in political competitions. We depart from previous studies based on real immigration statistics (e.g. Dustmann et al. 2018; Steinmayr 2019; Edo et al. 2019), and test whether and how the sea-arrival of refugees before the local elections shaped Italians' voting behavior. While, upon arrival, refugees could not freely go to the destination municipality, landing episodes were largely discussed in the media before the elections, thereby influencing voters' perceptions about the arrivals. Our focus is on local elections in Italy, which ranks among the first countries in Europe not only for over-estimation of immigrants, but also for the rise of populist parties (42 percentage points from 2008 to 2018). Moreover, Italy, jointly with UK and France, is in the bloc of countries where right-wing and populist groups did best in the EU elections in 2019.

[1] Source: Integration of immigrants in the European Union – Eurobarometer (2018).

Our main hypothesis is that, rather than the presence of migrants itself, the perceived threat of (and anxiety about) an inflow of refugees significantly contributed to the decline in turnout and the increase in protest, extreme right-wing and populist votes that has occurred in Italy from 2010 to 2018. Voting preferences, we argue, were gradually shaped not much by the overall share of (regular) immigrants, but, rather, by negative perceptions associated with the inflow of refugees. Arrival episodes gained importance in the media especially before the elections, and were used by far-right parties to represent immigration as a threat for natives. As a consequence, salience of immigration and misperceptions about the severity of the inflows increased, especially where refugees were more expected to arrive, and independently from the stock of immigrants residing in the city.

To assess the impact of perceived immigration on electoral outcomes, we rely on official data on the arrivals of refugees at Italian ports and exploit variation in the nationality composition of the incoming boats, which is (reasonably) exogenous to the local electoral cycle. Thus, we build an index of exposure that varies by municipality and over time: it weights the number of arriving nationalities by time-distance from the (exogenously determined) election day as well as by the share of co-nationals residing in each municipality. Since, after disembarking, refugees cannot freely and immediately reach the desired destination, our index captures the increased salience (and perceived threat) of immigration due to arrival episodes occurred in the weeks preceding the elections. As a matter of fact, voters located far away from the main ports of arrival could know about the refugee inflow only through the media. News and public discussions about the arrivals could therefore increase perception of immigration to a larger (lower) extent where refugees are more (less) expected to go after landing, i.e. in municipalities with a high (low) share of regular migrants having the same nationality as that of the arriving refugees.

We use data on Italian municipal elections from 2010 to 2018, and consider only municipalities that voted twice in this time window. We perform first-differences estimates to net out municipality fixed effects, and control for time-varying factors that may interact with migration inflows and electoral outcomes, i.e. the presence of centers for refugees and asylum seekers, and demographic and economic characteristics of the municipalities. Conditional on the share of regular migrants residing in the municipality and proximity to refugee centers, both capturing *real* exposure to migration, our reduced-form strategy provides estimated impact of *perceived* migration on changes in electoral outcomes. We consider five outcomes separately: turnout, share of protest votes, and share of votes for anti-immigration, populist and extreme-right parties.

Our results show that the increase in perceived exposure to arrivals significantly predicts the negative trend in turnout that Italian municipalities experienced in the last years. It also explains the recent rise in protest and populist votes, as well as the increased consensus gathered by anti-immigration and extreme-right parties. As expected, these effects are mainly driven by voters in municipalities with wider access to informal media, as proxied for by broadband diffusion; in contrast, voters in municipalities with high newspaper circulation do not react to the arrival episodes before the elections. This finding is consistent with previous studies, which attribute a sizeable part of the rise in populism in Italy to use of internet as main source of political information (Campante et al. 2018; Shaub and Morisi 2019).

The rest of the paper is structured as follows. Section 2 sets the stage for the empirical analysis by discussing misperceptions of migration and the rise of populism, jointly with the institutional and political context. Section 3 discuss the related literature, while Section 4 presents the variables used in the analysis, the data sources and provides descriptive statistics. Section 5 introduces the empirical model. Section 6 shows our baseline results while in Section 7 we show robustness checks and various tests for heterogeneity, which allow to shed lights on the main mechanisms behind our findings. Section 8 concludes.

## 2. BACKGROUND

### *2.1 MISPERCEPTION OF MIGRATION AND POPULISM*

European countries have recently witnessed an increase in the share of votes for far-right and right-wing populist political parties. The Freedom Party in Austria (26%), the Swiss People's Party in Switzerland (29%), the Northern League in Italy (17.4%), Vox in Spain (10.3%), the Danish People's Party in Denmark (21%), Fidesz in Hungary (49%) are few examples of national parties that have increased consistently their percentage of votes in the most recent national elections[2]. The last European elections have seen nationalist and far-right parties across Europe increasing their political power (especially in Italy, France and United Kingdom) as well as their chances to promote radical anti-euro and anti-immigration policies.

As far as Italy is concerned, the leader of Northern League (the deputy Prime Minister, Matteo Salvini) spearheaded the new government's anti-immigration stance, turning away humanitarian rescue ships from Italian ports. His party has had a long Eurosceptic reputation, and a number of its candidates for the European elections want to leave the eurozone. The arrivals of refugees to European countries has exacerbated such political scenario up to the point that Italian government wants to abolish key forms of protection for migrants, suspend the refugee application process of those who are considered socially dangerous or who have been convicted of a crime, and make it easier for the latter to be deported.

[2] https://www.bbc.com/news/world-europe-36130006.

Although countries are still struggling to absorb migrants' sea arrivals, migration to Europe is going down sharply, whereas the perception that it represents a real crisis is not. In the last years, the actual number of arrivals is back to its pre-peak level, which has been reached in late 2015[3]. Indeed, according to the European Border and Coast Guard Agency, an estimated 150,000 people entered the European Union through irregular crossings in 2018; yet this number represents the lowest total since 2013 and it is 92% below the peak recorded during the 2015 crisis[4]. Nevertheless, the politics of migration still presents Europe as a continent under siege from migrants, even though the numbers depicts a very different picture. For instance, the far-right prime minister of Hungary claimed "we have failed to defend ourselves against the migrant invasion"[5], the Czech prime minister said "there are 700,000 illegal migrants – they need to go home" [6], the German interior minister has threatened to turn back refugees at his country's southern border and wants to close borders[7], and Italy's deputy prime minister and interior minister (also leader of the Northern League) tweeted that the ports have been (and remain) closed[8].

This strategy seems to have reached the awaited consequences as Europeans appear more concerned about immigration than about any other social challenge. In facts, the inflow of immigrants as measured in official records does not often match with subjective estimates of the citizens, which tend to respond to the political debate on migration in the months preceding elections. Official statistics show that, in comparison with other European Union (EU) citizens, Italians have the most biased perceptions ---they over-estimate the share of immigrants living in their country by 18 percentage points (Figure 1). This is not only an Italian issue, since EU respondents, on average, over-estimate the proportion of immigrants in their country by about 10 percentage points. Lack of knowledge about migration could be one of the reasons behind these biased beliefs: when asked how much they were informed about immigration and integration issues, 62% of Italians answered either that they were not at all or not informed, two percentage points above the EU-28 average[9]. Indeed, the little is known about a key topic in the political debate, the higher is the scope for political parties to influence voters' behavior.

[3] According to the island of Lampedusa's mayor (one of the southernmost point of Italy and therefore among the main front line of the crisis), "the number of arrivals has dramatically reduced" such that the place is now as "quietest it's been since 2011" (https://www.nytimes.com/interactive/2018/06/27/world/europe/europe-migrant-crisis-change.html).
[4] See also https://www.bbc.com/news/world-europe-46764500
[5] https://www.kormany.hu/en/the-prime-minister/the-prime-minister-s-speeches/prime-minister-viktor-orban-s-speech-at-a-conference-held-in-memory-of-helmut-kohl.
[6] https://www.theguardian.com/world/2018/oct/25/europe-migrants-need-to-go-home-says-czech-prime-minister
[7] https://www.nytimes.com/2018/06/15/world/europe/germany-merkel-migrants-bavaria-seehofer.html
[8] https://twitter.com/matteosalvinimi/status/1107755836259139585
[9] Source: Integration of immigrants in the European Union – Eurobarometer (2018).

[Figure 1 around here]

In this paper, we argue that voting preferences are not so much shaped by the overall share of (regular) immigrants, but, rather, by the expectation of refugees' inflows, as boosted by news announcing arrival episodes (and by the following public debate). These episodes were, in facts, largely discussed in formal and informal media before the elections. Google Trends statistics show that the frequency of searches of a migration-related topic in Italy tend to follow the electoral cycle (Figure 2)[10]. Google searches containing the Italian words "Sbarchi" (boat landings) or "Migranti" (migrants) seem also to mirror the distribution of the actual arrivals, rising substantially in the month preceding or during the elections, and decreasing thereafter. Data on joint occurrences of the words "Immigrati/o" (immigrant/s) and "Reato/i" (crime/s) in Italian newspapers underlines a gradual mismatch between perceptions and reality: the frequency of these words display an increasing trend, especially after 2016; however, refugee arrivals started to decline in 2016, while the number of immigrant's and native's crimes remained constant for the entire period considered (Figure 3).

Misperceptions of immigrants, likely induced by anti-immigration campaigns spread out in the media, might have therefore played a non-negligible role in electoral outcomes. From a descriptive perspective, countries with the largest share of citizens showing biased estimates of migration are also those in which populist parties have obtained the highest share of votes between 2008 and 2018 (Figure 4). Interestingly, Italy ranks among the first EU countries not only for over-estimation of immigrants, but also for the rise of populist parties, i.e. from around 8% in 2008 to almost 50% in 2018. Greece, Spain, France, Hungary, Czech Republic are other cases in which misperception of migrants and support to national parties are both at high levels.

[Figures 2, 3 and 4 around here]

While informative, this descriptive evidence does not allow to trace a causal link between misperceptions of migration and political outcomes. Our paper contributes in this direction by exploiting (plausible) exogenous variation in the distribution of nationalities in the landing episodes preceding the predetermined election day.

### *2.2 INSTITUTIONAL AND POLITICAL CONTEXT*

[10] Google Trends gives a 0–100 index of interest over time of a given word or phrase, compared to the total number of Google searches done during that time.

Since our study relies on data on Italian municipal elections held from 2010 to 2018, we provide in this section a brief description of the institutional background of the country.

The municipal level of government in Italy includes over 8,000 authorities. The average population size is around 7,000 inhabitants, and the number of cities above 100,000 inhabitants is only around 40; just two of them exceed one million residents, with more than half localities having less than 3,000 residents.

Elections for municipal governments (local council and mayor) take place every five years, with direct election of the mayor in a single or dual ballot depending on resident population size. Cities with more than 15,000 inhabitants have a runoff stage among the two most voted candidates if none of them collects more than 50% of the votes in the first stage. Voters can express a vote for a mayor candidate as well as for a councilor candidate. Two thirds of the council seats are assigned to the councilor candidates that are typically grouped in a list supporting the mayor that is elected. Voting is formally mandatory for all citizens aged above 18, yet no sanctions exist for abstainers.

The electoral schedule across the country is staggered ---several elections occurred in the years considered in this paper and, more importantly, not all the municipalities vote in the same year and at the same time[11]. This feature allows us also to take into account how salience of migration varies according to the time distance between the date of the landing episodes and the date of local elections.

At national level, in the last two decades in Italy there were five parliamentary national elections, i.e. in 2001, 2006, 2008, 2013 and 2018. Two of them (2001 and 2006) were won by the center-right coalition, headed by Mr. Silvio Berlusconi, while the third round (2008) was, instead, won by the center-left coalition, headed by Mr. Romano Prodi. In the fourth round (2013), the Centre-Left Democratic Party led by social democrat Pier Luigi Bersani emerged as the Italian voters' first choice. The Centre-Right alliance, led by Mr. Silvio Berlusconi was the second-most preferred party. An important feature of this election term was the electoral success of the populist party "Five Star Movement", which ranked third in the election.

Finally, in 2018 Italy voted for the first time with a new electoral law, passed by Parliament in the autumn of 2017. The Five Star Movement was the most voted party, while the center-right alliance was the most voted coalition. Within this coalition, the Northern League ("Lega Nord") received the largest share of votes. This party started as a regionalist party in the '90s, with a political agenda focused on fiscal federalism and political autonomy of the Italian northern regions. At the

[11] The exact day of the election is chosen each year by decree of the Minister of Internal Affairs among all Sundays in the period 15 April to 15 June and it is the same for all municipalities that are in the election year. Usually municipal elections are held every five years to replace the mayor, the municipal government and the council. The only case in which a municipality votes with a different schedule is in the case the mayors, or at least half of the councilors, resign before the end of the term. Early termination can be also due to a dissolution for suspected mafia presence in the council, merging with other municipalities and other violations of the law.

beginning of the 2000s, the party reached increasing success in the country, taking the form of a proper nationalist party as other national parties in Europe (e.g. National Front in France, Freedom Party in Austria, AfD in Germany, Danish People's Party in Denmark, Progress Party in Norway). More importantly, this party is associated with anti-euro and anti-immigration campaign. Their leaders have repeatedly promised to expel all illegal migrants from Italy under the slogan "*Italians first"*. Along with Northern League, there are also extreme right parties, such as neo-fascist groups like "Casa Pound" and "Forza Nuova", which openly revive the symbols, vocabulary and ideas of Mussolini-era fascism.

### *2.3 IMMIGRATION TRENDS AND POLICIES IN ITALY*

Upon arrival, migrants receive first aid and assistance in first-level centers set up near to the main places of disembarkation. They are free to exit from first reception centers during the daytime, but they have the duty to re-enter during the night-time. The Protection System for Asylum Seekers and Refugees (SPRAR) centers are the second level of the reception that host refugees coming from the first level of reception. Allocations of asylum applicants from first-reception centers to second-level reception centers are managed by the Home Office through call for tenders. Municipalities that open a SPRAR center receive substantial fiscal grants from higher levels of government. Thus, for a municipal government, opening a reception center may be an investment, with benefits for the local economy (e.g. Gamalerio 2018)[12].

Especially in the first-reception centers, refugees' freedom of movement is rather restricted. This means that the migrants arriving at the Italian ports cannot freely circulate over the territory, and eventually reach their co-national fellows in other municipalities –at least not legally, and not immediately after the landing (upon arrival, refugees enter immediately the formal reception process). This legal feature allows us to restrict the analysis of voting behavior to the arrivals occurred in different time windows preceding the election day. For instance, when looking at the effects of the arrivals one month before the election day, refugees could only be *expected* to arrive since it is very unlikely that they can actually reach their co-nationals in the voting municipality soon after disembarking. Since landings occur mainly in the ports located in the southern regions of Sicily, Calabria, Puglia and Campania, it is very likely that voters living far away from these ports form their

[12] SPRAR was created in 2002 in order to establish a network of local institutions that implement reception projects for forced migrants. The primary objective of SPRAR is to provide support for each individual in the reception system, and make interventions that go beyond the simple distribution of food and housing, by also providing complementary services such as legal and social guidance and support in order to promote socioeconomic inclusion and integration. A fundamental element of those services is the temporary nature of reception, which is intended in all cases to ensure the independence and integration of recipients. The participation of local institutions in the network of reception projects is voluntary.

expectations through formal and informal media, and feel more vulnerable to immigration the higher is the share of migrants in their municipality having same nationality as that of the incoming refugees.

Thus, controlling also for the share of resident migrants in the municipality and for the presence of SPRAR centers in the province, the effect we measure would capture expectations of (perceptions about) migration, instead of changes in natives' attitudes stemming from direct interactions with immigrants.

## 3. CLOSELY RELATED LITERATURE

This paper is connected to different strands of literature that focus on the role of migration in shaping voting behavior and electoral outcomes.

A first strand of literature is the political economy of immigration, which aims to explore whether immigration has a positive impact on the support for extreme-right parties and anti-immigration policies. One way to answer these questions empirically is to relate variation in voting outcomes to variation in immigrants' settlement. However, a major challenge in this strategy is that immigrants are not randomly allocated across electoral districts. For instance, they tend to avoid hostile regions, e.g. regions where citizens are likely to vote for far-right candidates, leading to a spurious correlation between immigration and anti-immigration votes. A recent paper by Bracco et al. (2018) studies the effect of far-right parties on the location choice of immigrants in Italy; they find that the election of Northern-League mayors discouraged immigrants from moving into a municipality. On the contrary, Halla et al. (2017) find no evidence that election outcomes in Austria drive immigrant sorting. A widespread strategy to tackle this source of endogeneity rests on instrumenting current immigrant stocks with historical settlement, as pioneered by Altonji and Card (1991)[13]. A common result in this literature is that immigration affects voters' preferences, leading to the rise of anti-immigration parties through a variety of mechanisms, e.g. cultural diversity (Mendez and Cutillaz 2014; Brunner and Kuhn 2018), competition in the labor market and redistributive consequences (Barone et al. 2016; Halla et al. 2017; Edo et al. 2019), concerns over welfare and compositional amenities (Otto and Steinhard 2014; Halla et al. 2017), etc.

Our paper investigates the issue from an alternative perspective, i.e. we assess the role of perceived rather than real immigration. Moreover, while most studies focus on economic migrants, our focus is on refugees – the group that has so dramatically entered the political debate in Europe

[13] Employing a different strategy, Harmon (2018) uses historical housing stock data in order to address the issue of endogenous location choices of immigrants arguing that the share of high-rise buildings in a municipality decades ago provides a valid instrument for the increase in ethnic diversity in more recent times, which is in turn associated with more votes for the extreme right.

and beyond. From the empirical point of view, we exploit municipality-level variation in the nationalities of the refugees landing to Italian coasts before the elections. Since migrants cannot freely decide *where* and *when* to go (neither before nor after leaving), this source of variation is reasonably orthogonal to the local electoral process.

Relying on contact (Allport 1954) or conflict (Key 1949) theories, a slightly different body of the literature has shown that electoral outcomes are affected by proximity to refugee centers (Dustmann et al. 2018; Vertier and Viskanic 2018; Steinmayr 2019; Dinas et al. 2019; Hangartner et al. 2019), which spurs anti-immigration attitudes[14]. Our focus, instead, is on the role of perceived immigration in voting behavior; by controlling for supply of SPRAR in the province, the effect of exposure to arrivals we estimate is net of the confounding effect of proximity to refugees' centers. Similar to Dinas et al. (2019) and Hangartner et al. (2019), we also explore the intensity to exposure to refugees using migrants' boat arrivals to Italian ports. Yet, this paper differs from the aforementioned studies since it explores the role of "potential", rather than "actual" contact with immigrants in voting behavior. In our empirical framework, the refugees' arrivals occurring a few weeks before local elections do not turn into an increase in the number of migrants in the city; thus, there is no scope for real intergroup interactions.

## 4. VARIABLES, DATA SOURCES, AND DESCRIPTIVE STATISTICS

### *4.1 SOURCES OF DATA*

The main dataset results from a combination of different sources of data. The first part of the dataset reports electoral outcomes of all the Italian municipalities that voted twice in the period from 2010 to 2018, with a distance of 5 years between the first and the second election. The dataset gathers information on the day of election, electorate and electoral turnout, blank and null ballot papers, number of candidate mayors and the share of votes all the parties[15]. We merge this information with data on municipality characteristics, i.e. total population, share of migrants and taxable income, which have been downloaded from the Italian National Statistical Institute (ISTAT)'s website.

[14] In line with the predictions of the contact theory (Allport 1954), the presence of individuals characterized by different backgrounds may help to reduce prejudice towards foreigners due to the intercultural interchange between communities. Therefore, in presence of certain conditions such as equal status of the groups, presence of common goals, cooperation between the groups and support of authorities, direct or mass-mediated contact with immigrants may reduce support for anti-immigration parties and help to improve attitudes towards migration. In these situations, the larger the fraction of immigrants already present in an area, the lower would be the threat natives perceive from additional immigrants, which would probably be reflected in less support for a far-right party. However, as suggested by the conflict theory put forward by (Key 1949) immigrants could be perceived, instead, as a threat to the culture of the native population, generating a sense of collective prejudice and disadvantage. Under these circumstances, natives living in high-immigrant areas perceive higher threat from additional immigrants and will be more opposed to refugee allocation, leading to an increase in votes for the center-right coalition and in support to political ideas less favorable to immigrants.

[15] The dataset is available from the Italian Ministry of Interior at the website: https://elezionistorico.interno.gov.it

The second dataset contains detailed information on immigrants' arrivals through boat arrivals at Italian ports. For each landing episode, we gather information on the day and place of arrival, the total number of persons landed, and its composition in terms of nationalities[16].

We also collect information at province level on SPRAR. Specifically, for each year in our dataset, we gather information on presence of SPRAR centers across Italy and on the number of available beds of each center. Although the number of available beds does not faithfully represent the actual presence of immigrants (some of the centers might be under or overcrowded), this variable may nevertheless proxy for hosted refugees' presence. This information is publicly accessible consulting the annual reports and documents published on the SPRAR website[17].

Along with this data, we extract information at province level (i.e. NUTS-3 level) on unemployment rate of the working age population (i.e. individuals aged 15 and over) and on crime rates (per electorate) from ISTAT[18]. We also collect data about the number of newspapers sold at province level, which is publicly provided by ADS Institute (Accertamenti Diffusione Stampa)[19]. To construct our measure of news diffusion, we consider only daily and weekly newspapers with national coverage[20].

The last source of data is the AGCOM website (Autorità per la Garanzia nelle Comunicazioni), which provides data about broadband diffusion at province level. In particular, this database allows us to compute the share of households at province level with an ADSL connection, and to group them depending on their average download speed (< 30 Mbps; <100 Mbps; >100 Mbps).

### *4.2 THE "EXPOSURE TO ARRIVALS" INDEX*

In order to capture the effect of perceived immigration on electoral outcomes, for each municipality we construct an index of exposure to immigrants arrived at Italian ports. We exploit the plausibly exogenous match between nationalities in the boats approaching the Italian ports before the elections and the nationalities residing in the voting municipalities.

First, we compute the shares of immigrants of nationality $j$ in municipality $i$ as the ratio between the number of immigrants of nationality $j$ and the total number of immigrants in the municipality $i$. Then, as shown in equation (1) below, in the time period between the 1st of January

[16] Data have been kindly provided by Statistic Office of the Ministry of Interior - Dipartimento Libertà Civili e Immigrazione.
[17] www.sprar.it/pubblicazioni
[18] We compute the crime rate at province level as the ratio between the total number of crimes reported by the police in a given province, over the annual-regional average of the number of crimes.
[19] http://www.adsnotizie.it/_dati_certificati.asp
[20] Specifically, we extract aggregated information on the diffusion of main Italian newspapers such as il Corriere della Sera, La Repubblica, Il Sole 24 Ore, Il Mattino, La Stampa, Il Tempo, Il Tirreno, Il Messaggero, and Il Fatto Quotidiano. ADS is accessible through its website at following link http://www.adsnotizie.it/index.asp

and the election day, for each municipality $i$ and for each single ship landing $k$, we sum up these shares for nationalities $j$ of immigrants arriving in boat $k$ that are represented also in the municipality $i$. We consider nationality $j$ as represented in municipality $i$ if the municipality has at least one resident migrant of the nationality $j$ at the time of the landing.

Then, for each arrival $k$, we sum up the number of arriving immigrants whose nationality matches with that in the municipality $i$ ($Immigrants_{j,k}$), and multiply it by the sum of shares of immigrants with matching nationalities in that municipality ($ShareImmigrants_{j,k}$). This step is important for our estimation strategy since it allows to exploit within-year, across-municipality variation in exposure to arrivals: municipalities with a large (small) share of official migrants whose nationality matches with those of the incoming migrants are more (less) exposed to the arrivals.

To take into account the time distance between the date of arrival and the date of election, we also weight the index by the inverse of 1 plus the logarithm of the number of days between the day of arrival and the day of election ($WDistance_k$).

The resulting index is a measure of municipal exposure to each single boat landing $k$ occurred in the period preceding the election. The final exposure index is an arithmetic average of the exposure indices calculated for each single arrival episode $k$.

In sum, our exposure index is a measure of intensity of exposure at municipal level that considers both the share of migrants in the municipality and the number of entrant migrants, whenever their nationality matches. It can be interpreted as the average number of incoming immigrants expected to arrive in the municipality, because of boat landings before elections.

$$Exposure\ Index_i = \frac{\sum_{j,k} Immigrants_{j,k} * ShareImmigrants_{j,i} * WDistance_k}{N_k} \tag{1}$$

We compute the index considering different time windows. In the first version we consider all the boat landings occurred in the period between the beginning of the year and the day of election (usually in May). In the second version, we restrict our attention to the 30 days before the election day. Then, we repeat the procedure focusing on arrivals relative to the second and third month before the election day, i.e. we compute the index considering all the landings that occurred between 30 and 60 days, and between 60 and 90 days before the election[21]. As a robustness check, we also calculate the index

[21] The following example clarifies the procedure. Consider 2 municipalities *A* and *B*. Municipality *A* has 5 immigrants of nationalities *x,* 10 *y,* and 5 *z.* Municipality *B* has 10 immigrants of nationalities *x,* 20 *q,* and 20 *w.* Suppose that, before the election day, there are two ships landing on the Italian coasts (*1* and *2*). *Boat landing 1* counts 20 immigrants of nationality *x,* 30 of nationality *y,* and 50 of nationality *q. Boat landing 2* instead is composed by 20 immigrants of nationality *x, 20* of nationality *y,* 20 *q* and 20 *w.* Then, municipality *A* has an index of exposure equal to 33,75 (67,5/2), while municipality *B* of 51 (102/2). A possible concern this index does not directly consider the relative weight of the immigrant population with respect to the total population. Two municipalities with the same number and type of foreign

expanding the time-window so to include all landing episodes occurred 30, 60 or 90 days before the elections. In all the empirical specifications, we use a logarithmic transformation of the index (i.e. $\ln(1 + Exposure\ Index_i)$) to account for the high frequency of values that are close to zero.

### *4.3 ELECTORAL OUTCOMES*

Turnout and votes distribution *per-type* of votes are our main outcome variables. Turnout is calculated as the ratio between number of valid votes and the total electorate. Valid votes are computed as the difference between the number of people who voted, net of blank and null ballot papers. Electorate is the number of individuals entitled to vote.

Distribution of votes allows us to directly observe political preferences of citizens. We group votes into four non-mutually exclusive categories, and compute their relative share of votes. Firstly, we consider protest vote, which groups together null and white votes.

Secondly, we use anti-immigration votes (i.e. the sum of preferences expressed in favor of right and extreme-right parties[22]). To categorize anti-immigrants parties, we group together all those parties characterized by a strong rhetoric against immigrants and ethnic minorities, that publicly refer to migration flows as a concern for the national security, that aim at national borders closure, and that place domestic population in a position of primacy against foreign citizens[23].

Thirdly, we consider populist votes as the sum of votes in favor of populist parties. To distinguish between populist and mainstream parties we mainly rely on the seminal work by Van Kessel (2015), who classifies as populist those parties whose political ideas hinge mainly i) on the distinction between *"*the people", referred to as the unique good part of the society, and *"*the elite*"*, ii) on the supremacy of the former over the latter, and iii) on motives of national sovereignty[24]. Finally, we also take into account Northern League coalition, i.e. the sum of all the votes directly collected by "Lega" and strictly related parties[25]. Different definitions of populism are discussed and used as further robustness checks in Section 7.5.

### *4.4 DESCRIPTIVE STATISTICS*

Our dataset contains municipalities that voted twice in the time period between 2010-2018 at a distance of five years from the first to the second election. We have 2803 municipalities, for a total

---

nationalities could be equally exposed even if one of the two hosts more migrants than the other in relative terms. As a potential remedy, we control for both the size of the electorate and the share of regular migrants residing in the municipality.

[22] Extreme right parties are Casapound, Forza nuova, Movimento Sociale Italiano and Alleanza Nazionale.

[23] The group includes Lega, Forza Nuova, Casa Pound, Movimento Sociale Italiano and Alleanza Nazionale

[24] Populist parties are Forza Italia, Il Popolo delle libertà, Lega and Movimento 5 Stelle.

[25] Lega list contains votes expressed for Lega, Lega Nord and Lega Padana.

of 5606 observations. From 2010 to 2018, Italy has been intensively exposed to immigrants' arrival. During this period there have been 29,242 boat landings, with a total of 725,915 immigrants reaching the Italian coasts. The majority of them arrived between 2014 and 2017 (Figure 2).

As far as the exposure index is concerned, Figure 5 shows its distribution across Italian municipalities in the first election round election (years 2010 – 2013, Panel A), and in the second election round (years 2015 – 2018, Panel B). More specifically, our exposure index averages at 1.4 and varies from a minimum value of 0, due either to the absence of migrants within the municipality or to the lack of matches between nationalities of arrived and resident migrants, to a maximum of 32.15, recorded in Brognaturo (Vibo Valentia) in 2017. Reflecting arrivals on Italian coasts, our index of exposure grows steadily across all macro-area from 2012 to 2017, to sharp decline in 2018 (Figure 6, Panel A). As illustrated in Figure 6, Panel B, on average, northern Italy is the area mainly exposed to the arrivals as measured by our index.

On average, roughly 2 out of 3 citizens voted in the municipal elections (67.6%). As reported in Figure 7, Panel A, average turnout steadily declined since 2010. The decline in voters' turnout couples with an increase in the share of protest votes, which has grown sensibly since 2011, reaching the peak in 2017 elections (Figure 7, Panel B).

On average, the share of votes in favor of anti-immigration parties is 4.4%, with peaks of 100% as in Moriago della Battaglia (Treviso) in 2018, or Rovere' Veronese (Verona) in 2011. The share of populist votes follows a similar pattern, with an average of 5.9% of preferences and a maximum of 73.7% in the aforementioned municipalities. However, as shown in Figure 8, Panel A, votes in favor of extreme-right and populist parties has grown dramatically since 2015 in Italy. The most pronounced increase has been registered in northern and central Italy, while islands are less inclined to vote for extreme-right and populist parties over the period considered (Figure 8, Panel B).

[Figures 5, 6, 7 and 8 around here]

The number of available beds in SPRAR centers averages to around 340 units per municipality, while the share of resident migrants averages at 7.5%. Ageing index, calculated as the ratio between the share of elder individuals (i.e. over 65 years) and the share of pupils and children (i.e. from 0 to 14 years), is a compact index informing about the age structure of the municipality. It ranges from 0.24 to 56. As of criminality, proxied for by the number of reported crimes, provinces in our sample suffered, on average, 3.6 crimes per electorate. The province of Milan is the most problematic, with more than 18 thousand crimes recorded by police in 2012. For what concern unemployment rates, northern regions of Italy are historically those that on average enjoy lower rates. In particular, the province of Cuneo (Piemonte) in 2010 had a very low rate, less than 4%. By contrast, southern regions suffer it most. Several provinces, mostly in Calabria and Sardinia, reached levels of unemployment greater than 30% in 2015. Taxable income follows a very similar pattern, with northern regions being richer than central and southern areas, with Milan registering a taxable income of more than 300 million euro in 2011. Finally, regarding news diffusion, over the time period considered, around 20 newspapers per electorate per day are sold on average at the province level. The province of Rome ranks first in newspaper circulation, registering a total of more than 340 thousand journals sold in 2010. Provinces with lower newspapers circulation are concentrated in Calabria and Sardinia in 2018.

Finally, we use data on average download speed of household in 2017 across Italian provinces to proxy for quality and diffusion of internet connection, thereby capturing access to information through (social) media. More than half of the families surf the Internet with a speed lower than 30 Mbps, while almost 21% browse with an average speed between 30 and 100 Mbps. Those who enjoy fast internet connection represent 10% of the sample (9% between 100 and 500 Mbps, 1% faster than 500). The rest of households (12%) does not have any internet connection available at home.

See Table 1 for the descriptive statistics and Table A1 in Appendix for further details on the construction of variables.

[Table 1 around here]

## 5. THE EMPIRICAL STRATEGY

To investigate the impact of immigration on extreme voting, we estimate the following equation:

$$\Delta Votes_{it} = \beta_1 \cdot \Delta Exposure\ Index_{it} + \beta_2 \cdot \Delta Share\ of\ migrants_{it} + \beta_3 \cdot \Delta Municipality\ Characteristics_{it} + \delta_t + \Delta\epsilon_{it} \quad (2)$$

The dependent variable is the difference in turnout, protest votes or vote shares for anti-immigrant, populist and Northern League parties between two elections at municipal level. For example, $\Delta Votes_{it} = (turnout)_{it} - (turnout)_{i,t-1}$ in case the dependent variable is political participation.

We measure the change in the exposure to migration at municipality level by $\Delta Exposure\ Index_{it} = Exposure\ Index_{it} - Exposure\ Index_{i,t-1}$ where $Exposure\ Index_{it}$ is our treatment variable defined in eq. (1), expressed in natural logarithm.

We measure the change in immigrant share at municipal level as $\Delta Share\ of\ migrants_{it} = Share\ of\ migrants_{it} - Share\ of\ migrants_{i,t-1}$, where $Share\ of\ migrants_{it}$ is the population share of immigrants (excluding those with Italian citizenship) living in municipality $i$ at time $t$; this variable allows us to control for the pre-existing presence of migrants at municipal level.

*Municipality characteristics* is a vector including, as first differences, *Total SPRAR beds,* i.e. the total number of available beds in SPRAR centers at province level as proxy for presence of refugee centers, which allows us to control for the effect that direct contact with refugees and asylum seekers through refugee allocation has on voting behavior; *Electorate,* i.e. the number of individuals entitled to vote at municipal level, which takes into account the changes in the size of the electorate due, for instance, to the historical variation in the dimension of the cohorts entering the electorate for the first time; *Number of mayors,* i.e. the number of mayor candidates at the elections at municipal level, which allows to control for political competition (higher values imply higher competition); *Share of taxable income greater that 120,000 euro,* i.e. the share of citizens with annual personal taxable income greater that 120,000€, which takes into account that political support for immigration may change with individual income. Finally, in order to capture demographic dynamics, we also include an *Ageing index,* i.e. the ratio between the share of elder individuals over 65 years old and the share of children between 0 and 14 years old. All these controls are included for each municipality $i$ at time $t$.

We also include a vector of time fixed effects $\delta_t$ to control for common factors specific to each year such as, for instance, the business cycle. Municipality fixed effects are differenced out in first-difference panel estimations. In all the specification, standard errors are clustered at province level to account for within-province error correlation.

The main parameter of interest is $\beta_1$, which identifies the effect of the change in the exposure to migration across municipalities on changes in the electoral outcome. When also dependent variables are expressed in logarithms, it provides time elasticities, i.e. the percentage point change in the electoral outcome in response to a 1 percentage increase in exposure to arrivals from the previous elections.

Endogenous sorting of immigrants does not represent a serious concern in our framework. It is unlikely that, in each landing episode preceding the election date – which has been exogenously determined –, the composition of the incoming nationalities is affected by the *local* political process. For this type of sorting to be a problem, refugees should be able to schedule the day and choose the destination city in response to the political process in that city. We can exclude this possibility because, at the departure, migrants do not enjoy freedom of choice regarding the day of leaving and the day and place of arrival: such decisions depend mainly on the informal shipping industry managed by local smugglers. Allocations to second-level refugee centers (SPRAR), instead, is managed by

Home Office. In other words, migrants could not exactly know *when* they will travel, *when* they will land, and *whether* and *when* they will eventually reach the municipality they intend to go.

Controlling also for the share of regular immigrants and presence of SPRAR centers, our treatment variable (exposure index) would therefore capture to what extent the *threat* of a refugee crisis – as clamored in pre-electoral campaigns – affected voting behavior.

## 6. RESULTS

### 6.1 *PERCEIVED IMMIGRATION AND POLITICAL PARTICIPATION*

This section investigates the effects of intensity of migration exposure on political participation. The dependent variable is the turnout rate at municipal level. Table 2 reports the estimates for our main coefficient of interest, e.g. exposure index. We start by measuring the index taking into account all the arrivals occurring from the beginning of the year to the election day (Table, 2 Column 1), and subsequently experiment with shorter time spans such as 1, 2 or 3 months (Table 2, Columns 2, 3 and 4), which would further restrict the possibility that refugees legally or illegally reach the municipality.

Results highlight that the increase in exposure to immigration causes a decrease in turnout, suggesting that the recent trends in immigration may have contributed to a surge of disaffection toward political participation. It could be the case, as suggested by Barone et al. (2016), that part of the center and left-wing voters, who are ideologically more in favor of a multiethnic society but are not happy about the immigration trends and regulations, might have decided not to vote instead of directly voting for the center-right coalition[26]. This result is also confirmed by Edo et al. (2019) who find that high immigration increases abstention rates (i.e. lower turnout).

To further explore the nexus between subjective exposure to migration and political participation, we also consider, as dependent variable, the number of blank and invalid ballots. If citizens are not satisfied with any of the existing political parties and their immigration policies, then we should also expect an increase in protest votes. Accordingly, we find that exposure has a positive effect on the share of blank/invalid votes (Table 3), which is consistent with the idea that the prospect of incoming refugees, as presented in the pre-electoral debate throughout the media, has contributed to an increase in dissatisfaction with how ruling parties address the issue (see again Barone et al. 2016 for a similar result).

[26] In a different setting, Dustmann et al. (2018) document, instead, that a higher share of allocated refugees leads to a higher share of individuals voting (e.g. increase turnout) in municipality elections but not in Parliamentary election. Steinmayr (2019) finds that turnout is not significantly affected by hosting refugees in a municipality. Dinas et al. (2019) show that overall turnout increased significantly in Greek islands receiving refugees, suggesting that the refugee crisis also acts as mobilizer of new voters who previously had not participated in elections.

[Tables 2 and 3 around here]

### *6.2 PERCEIVED IMMIGRATION AND SHARE OF VOTES*

This section investigates the effects of the intensity to migration exposure on support for populist and far-right candidates. The parameter of interest now identifies the effect of the change in the exposure to migration across municipalities on the change in votes for anti-immigration parties (Table 4), populist parties (Table 5) and Northern-League candidates (Table 6). As before, we measure the index taking into account all the migrants' arrivals in the months preceding the election day, and then with shorter time spans (one, two, or three months). Results show a positive effect of perceived immigration on votes for center-right coalitions, which have a political platform less favorable to immigrants.

More specifically, Table 4 summarizes the results when the share of votes for anti-immigration parties is considered as dependent variable. Exposure to migration increases support for anti-immigration parties when the index takes into account of all the arrivals from January 1st to the election day. When we restrict the time span of arrivals, we find that exposure to migrants drives the electoral outcome only when we consider the influx of refugees within a month from the date of the elections, consistent with the idea that anti-immigration campaigns affects voting behavior especially when elections are approaching.

Table 5 shows that the increase in the share of votes for populist parties is driven by exposure to arrivals independently from the time-window considered to measure arrivals; however, as expected, we find a higher coefficient especially when only the arrivals in the 4 weeks preceding the elections are considered (Table 5, Column 2).

Finally, Table 6 summarizes results for the share of votes for the Northern League. In this case, the sample is restricted to municipalities in the North macro-area, where the party enjoys higher consensus. Results document that exposure to arrivals increased support for the right-parties when the index includes all the arrivals since the beginning of the year; however, the effect is mainly driven by the exposure to arrivals occurring four weeks before the elections (Table 6, Column 2), suggesting again that what matters is perceived (media-influenced) rather than actual immigration.

[Tables 4, 5 and 6 around here]

## 7. HETEROGENEITY AND ROBUSTNESS CHECKS

### *7.1 HETEROGENEOUS EFFECTS: THE ROLE OF MEDIA EXPOSURE*

The proposed mechanism underlying our results is the increased salience of (and anxiety for) immigration through formal and informal media coverage of arrivals during electoral campaigns. We therefore study the role of media first by looking at local newspapers in disseminating information to voters in order to test whether the effect of exposure varies with availability of news. We split the sample according to per electorate newspapers sales below and above the median value, which has been computed for each region and year separately[27].

Local newspapers either directly report news on migrants' boat arrivals or interview politicians in order to comment on refugees' allocation policies. They often host pre-electoral propaganda of competing parties. By doing so, they lower the cost of information, and increase both the number of informed voters and, perhaps, the quality of the information they have (Drago et al. 2014; Repetto 2018). Therefore, we expect that municipalities where newspapers are more widespread are less sensitive to pre-electoral arrivals of refugees. We find that the negative effect of arrivals on participation and support to anti-immigration and populist parties is mainly driven by municipalities with below-median diffusion of newspapers (Table 7, Column 1, 3, 5 and 7).

[Table 7 around here]

The second test for media exposure hinges on data on expansion of broadband coverage. When we split the sample for values of connection speed below and above the median in the region, we find that the effect of subjective exposure to immigration increases with the speed of the available connection (Table 8).

[Table 8 around here]

Results on newspaper and internet availability, jointly considered, provide support to our main hypothesis: the inflow of refugees affected voters' behavior through access to (often biased) informal media, rather than through personal interactions with immigrants. The effect of exposure to perceived inflows of refugees is in fact higher in municipalities where most citizens tend to substitute traditional (and potentially more informative) media with internet as the main source of political information (Gentzkow 2006; Campante 2017; Shaub and Morisi 2019).

### *7.2 HETEROGENEOUS EFFECTS ACROSS COMMUNITIES: THE ROLE OF CRIME*

[27] We define the median for each region separately because using the national level median would essentially divide the sample in north and south (see Repetto 2018).

A possible channel behind the effect of migration exposure on far-right voting is the perception that immigration can increase the level of criminal activities (Bianchi et al. 2012; Barone et al. 2016). To test this source of heterogeneity, we split the sample in tertiles according to the values of crime per electorate in the region. The higher the crime rate in a given municipality, the higher may be the perception (often influenced by mass media) that immigrants are associated with criminal activities, thereby leading to high support for right-wing parties. However, we could also expect an opposite result if residents of high-crime areas are less sensitive to a marginal increase in delinquency expected from the arrival of migrants.

Results, summarized in Table A2 in Appendix, show that only in low-crime municipalities there is a slightly positive and significant relationship between migration exposure and protest votes (Table A2, Panel B). Instead, in those municipalities, a stronger positive relationship exists between migration exposure and anti-immigration and populist votes (Table A2, Panels C and D). This evidence suggests that increased sensitivity to arrival episodes characterizes municipalities that are less exposed to crime.

### *7.3 CHARACTERISTICS OF THE MUNICIPALITIES: POPULATION & UNEMPLOYMENT*

Evidence in the literature on immigration and political attitudes and electoral outcomes suggests that municipality size matters. Immigration inflows produce large increases in the votes obtained by far-right parties especially in small towns, while leaving large towns mostly unaffected (Barone et al. 2016; Dustmann et al. 2018). We therefore split the sample according to the municipality's population size below and above the $90^{th}$ percentile as in Dustmann et al. (2018).

Results in Table A3 in Appendix show that, consistent with previous studies, the main effect of exposure to arrivals is not significant in the largest cities. There are different explanations to this finding (Barone et al. 2016; Dustmann et al. 2018). First, in larger cities, natives and migrants tend to live far away from each other, and therefore there is less need for the former to compete with the latter for local public services. Second, weaker competition is expected also in the labor market, since more skilled workers usually tend to concentrate in larger cities. Third, larger cities attracted migrants before the smallest ones; therefore, residents of the former are more accustomed to ethnic diversity, and adapted earlier to the positive and negative sides of immigration.

All these explanations suggest that in big cities people tend to develop positive attitudes towards refugees. Therefore, it is not surprising to find that they do not react significantly to the pre-electoral inflow of immigrants and to the anti-immigration rhetoric associated with the arrivals.

Furthermore, economic theory suggests that changes in attitudes of natives towards migrants and the increased support to anti-immigration parties are driven by concerns on labor-market opportunities. Since those providing substitutable skills might lose the most from migration, low-skilled immigration is perceived as problematic: the native-immigrant contest for jobs might be tougher for unskilled native workers. Therefore, we would expect that support for right-wing parties is higher in municipalities characterized by high unemployment, and hence by a stronger (expected) labor market competition. To further this issue, we use data on unemployment at province level splitting the sample in tertiles according to the values of unemployment in the region (for a similar analysis see Halla et al. 2019).

Results in Table A4 in Appendix show that, consistent with previous studies, the main effect of exposure to arrivals has the strongest impact on far-right voting in communities with high unemployment (Table A4, Panel C and D). This is consistent with the idea that immigration hurts natives supplying production factors closely substitutable by those of the immigrants. Therefore, far-right parties might be more appealing for voters who can lose the most from immigration. As a consequence, the relative economic insecurity associated with the possibility of hosting refugees would push voters in high unemployment areas towards far-right, populist parties in response to immigration episodes (Halla et al. 2019).

### *7.4 COMPETITION FOR PUBLIC SERVICES*

Immigration also has an impact on public finance and policies (Halla et al. 2017). Indeed, the expected financial burden associated with low-skilled immigrants, who are those more likely to be net recipients of welfare (Otto and Steinhardt 2014), would also increase electoral support for anti-immigration parties. Increased immigration has negative effects on natives' attitudes towards redistribution, driven by voters supporting center- and the right-wing parties (Dahlberg et al. 2012). If more immigrants are expected to arrive in their city, natives might expect stronger competition for public services, such as compositional amenities stemming from neighborhoods, schools, and workplaces, thereby increasing anti-immigration sentiments (Edo et al. 2019). The prospective increase in immigration rates could be associated with a huge rise in the share of immigrant relative to native children. This could further increase future competition between immigrants and natives for public services for children. For instance, areas with a high share of the population in early schooling may be more sensitive to arrivals of migrants if natives believe that immigrants will get priority in admission to schools.

To assess the role of competition for public services, we split the sample by the share of children aged 0-15 (see for a similar analysis Barone et al. 2016). The intuition is that the higher the share of native children, the higher may be the perception that immigrants, for instance, can "steal" admission to school from the natives' set of rights. More specifically, we divide municipalities below and above the median share of 0-15 children in the region. Results, reported in Table A5 in Appendix, provide scarce support for this channel: migration exposure increases vote for the far-right parties both below and above the median presence of children.

### *7.5 AN ALTERNATIVE DEFINITION OF POPULISM*

One limit to the use of Van Kessel's strategy to group populist parties is that it focuses exclusively on parties with political representation in the national parliament[28]. Therefore, strictly relying on Van Kessel's classification would imply to consider as non-populist a set of minor parties that instead fit well the criteria.

Another widely used benchmark to identify populist parties is the Chapel Hill Expert Survey (CHES)[29]. The 2017 survey scores 132 political parties in 11 European countries, over a long list of dimensions, through questionnaires conducted with experts about European political parties. The survey uses experts' opinion to estimate the ideological and political positions of each representative party. Aassve et al. (2018), for example, consider as populist those parties with an average score higher than 6, over a maximum value of 10, on the question "the people, not politicians, should make the most important decisions". However, also CHES only focuses on political parties that are representative at national level.

In order to overcome this limit, as in Aassve et al. (2018), we look at parties' political program and include in the list of populist parties a number of other minor parties that: i) concurred in municipal elections, ii) according to our judgement, satisfy Van Kessels' conditions, and iii) score higher than 6 on the aforementioned CHES question. The parties we include are: Casa Pound, Il Popolo della Famiglia (both right wing parties), and Potere al Popolo (left wing). Although often present in media, considered together these parties collected less 3% of preferences in last Italian elections (held in March 2018).

Importantly, our main results using these alternative definitions of populism do not change substantially (Tables A6 and A7 in Appendix).

### *7.6 MAGNITUDE*

When the dependent variables are expressed in logarithms, $\beta_1$ in eq. 2 measures the percentage point change in the electoral outcome in response to a 1% change in the index of exposure to migration.

---

[28] Van Kessel lists as populist parties Lega Nord, Movimento 5 Stelle, Fratelli d'Italia and Popolo delle Libertà.
[29] The unique difference between Van Kessel and Chapel Hill Expert Survey (CHES), is that the latter consider as populist only Lega Nord, Movimento 5 Stelle and Fratelli d'Italia.

Results in Table A8 in Appendix show that an increase in exposure by 1% from previous elections decreases turnout by about 1.6% points, while it increases protest votes by 0.5% and votes for anti-immigration, populist and League parties by 0.8%, 2% and 1.2%, respectively.

### *7.7 DIFFERENT TIME-WINDOWS*

As an additional robustness check, we re-estimate our baseline models with an alternative version of the exposure index. More specifically, we extend the time-period from the election day to the arrivals so to include all the arrivals occurred 60 or 90 days before the elections. This version of the index differs from the previous one because these new time windows include also the arrivals occurred later in time (and close to the election day).

Results, reported in Tables A9a-b in Appendix, suggest that estimated effect of exposure does not seem to vary substantially across the different time-windows considered. This evidence underlines that our exposure index measures the effects of the anti-immigration campaign, rather than the effects of the real inflow of refugees that might have occurred (legally or illegally) after the arrivals. For real inflow to matter, we should expect a significant increase in the coefficient of the exposure index when expanding the time-window to 60 or 90 days before the elections, i.e. considering a larger time-span so to include regular or irregular refugees who might have reached the municipality after landing. However, we do not find empirical support for this hypothesis since the effect of exposure does not vary substantially when including arrivals occurred 60 o 90 days before the elections.

## 8. CONCLUSIONS

This paper aims to understand the effects of perceived immigration on voting behavior in Italy. To this purpose, we rely on a reduced-form identification strategy that exploits two main sources of exogenous variation. First, we rely on the predetermined calendar of mayoral elections occurring every five years, and according to a staggered electoral schedule, across the about 2,700 Italian municipalities. Second, we build an index of exposure that exploits the (plausibly) exogenous variation in the nationality of immigrants approaching the Italian ports from 2010 to 2018. In each year, exposure to arrivals varies at the intensive margin across municipalities, with more (less) exposed cities having larger (lower) share of regular immigrants with the same nationality of those approaching the Italian coasts before the elections.

Since we also control for the share of regular immigrants, our reduced-form estimates capture the additional role that the arrival episodes, widely announced and discussed in the media before the elections, played on voting behavior. We claim that it is not the actual share of immigrants that favor disaffection towards political participation and the rise of populist or far-right parties; it is, rather, the perception of migration, influenced by anti-immigration campaign populating formal and informal media, that played a key role in voting behavior.

The main results show that perceived exposure to arrivals decreases turnout, whereas it increases protest votes and support for extreme-right, populist and anti-immigration parties. Tests for heterogeneity of the effect provide further insights into the mechanisms underlying our results.

First, we find that the impact of perceived immigration is driven by voters who are less likely to read newspapers and more exposed to a fast internet connection. Since supporters of mainstream parties tend to rely more on the traditional media as main sources of political information (Shaub and Morisi 2019), these results suggest that the effect of refugees' arrivals can be due to crowding-out of internet over traditional (and potentially more informative) media as main source of political information (e.g. Gentzkow 2006; Campante 2017). Overall, this evidence provides support to our hypothesized pathway from exposure to arrivals to electoral outcomes: it is the increased salience of (and anxiety for) immigration during electoral campaigns, rather than the personal contact with immigrants, that spurred the changes in voting behavior observed in the last years.

Second, large cities, where citizens tend to have more positive attitudes towards immigration, are less sensitive to the prospect of an inflow of refugees. Third, exposure to arrivals explains the rise of anti-immigration parties mainly in low-delinquency municipalities, where citizens are perhaps more sensitive to the increase in crime envisaged by far-right politicians. Fourth, we find a stronger effect of perceived immigration in high-unemployment areas, where the prospect of an increase in labor-market competition associated with the future inflow of refugees offered larger support to far-right and nationalist parties.

These results, jointly considered, suggest that, as immigration became central in electoral disputes, misperceptions about the issue, jointly with perception of insecurity due to the socio-economic costs of hosting refugees, raised. Representation of immigration as a permanent crisis in the media, even though this was not always the case, spurred or reinforced such negative perceptions, and raised voters' disappointment about mainstream parties. By losing trust in the ruling right- or left-wing parties, citizens reduced political participation and increased protest or populist votes (Barone et al. 2016; Guiso et al. 2017 and 2018; Algan et al. 2018). However, strong anti-immigration campaigns were successful for far-right parties, which, by emphasizing the severity of the arrivals and proposing severe restrictions to solve the "refugee crisis", obtained larger support in the cities where refugees were more expected to arrive.

## REFERENCES


Algan, Y., Beasley, E., Cohen, D., and Foucault, M. (2018). The rise of populism and the collapse of the left-right paradigm: lessons from the 2017 French presidential election (August 2018). CEPR Discussion Paper n. DP13103 (available at https://ssrn.com/abstract=3235586).

Alesina, A., Miano, A., and Stantcheva, S. (2018). Immigration and redistribution. National Bureau of Economic Research WP n. 24733 (available athttps://www.nber.org/papers/w24733.pdf).

Allport, G. (1954). The Nature of Prejudice. Addison-Wesley.

Altonji, J.G. and Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In: Immigration, Trade and the Labor Market. University of Chicago Press, pp. 201–234.

Aassve, A., Gianmarco, D. and Le Moglie, M. (2018). Never forget the first time: the persistent effects of corruption and the rise of populism in Italy (available at https://ssrn.com/abstract=3280498).

Barone, G., D'Ignazio, A., de Blasio, G., and Naticchioni, P. (2016). Mr. Rossi, Mr. Hu and politics. The role of immigration in shaping natives' voting behavior. *Journal of Public Economics*, 136, 1–13.

Bianchi, M., Buonanno, P., and Pinotti, P. (2012). Do immigrants cause crime? *Journal of the European Economic Association,* 10 (6), 1318–1347.

Bracco, E., De Paola, M., Green, C. P., and Scoppa, V. (2018). The effect of far right parties on the location choice of immigrants: Evidence from Lega Nord Mayors. *Journal of Public Economics*, 166, 12–26.

Brunner, B., and Kuhn, A. (2018). Immigration, cultural distance and natives' attitudes towards immigrants: evidence from Swiss voting results. *Kyklos*, 71 (1), 28–58 .

Campante, F., Durante, R., and Sobbrio, F. (2018). Politics 2.0: The multifaceted effect of broadband internet on political participation. *Journal of the European Economic Association*, *16*(4), 1094-1136.

Dahlberg, M., Edmark, K., and Lundqvist, H. (2012). Ethnic diversity and preferences for redistribution. *Journal of Political Economy*, 120, 41–76.

Dinas, E., Matakos, K., Xefteris, D., and Hangartner, D. (2019). Waking up the golden dawn: does exposure to the refugee crisis increase support for extreme-right parties? *Political Analysis*, vol. 27:244–254.

Drago, F., Nannicini, T., and Sobbrio, F. (2014). Meet the press: how voters and politicians respond to newspaper entry and exit. *American Economic Journal: Applied Economics*, 6 (3): 159-88.

Dustmann, C., Vasiljeva, K., and Damm, A. P. ( 2018). Refugee Migration and Electoral Outcomes, *The Review of Economic Studies*, 1, 57.

Edo, A., Giesing, Y., Öztunc, J., and Poutvaara, P. (2019). Immigration and electoral support for the far-left and the far-right. *European Economic Review*, 115, 99–143.

Gamalerio, M. (2018). Not welcome anymore: the effect of electoral incentives on the reception of refugees. CESifo Working Papers, n. 7212 (https://www.ifo.de/DocDL/cesifo1_wp7212.pdf).

Gentzkow, M. (2006). Television and Voter Turnout. *The Quarterly Journal of Economics*, 121 (3), 931–972.

Guiso, L., Herrera, H., Morelli, M., and Sonno, T. (2018). Global crises and populism: the role of Eurozone institutions. *Economic Policy* (https://doi.org/10.1093/epolic/eiy018).

Guiso, L., Herrera, H., Morelli, M., & Sonno, T. (2017). Populism: Demand and Supply. CEPR Discussion Paper N. DP11871 (available at https://ssrn.com/abstract=2924731 (available at https://ssrn.com/abstract=2924731).

Halla, M., Wagner, A.F., and Zweimüller, J. (2017). Immigration and voting for the far right. *Journal of the European Economic Association*, 15, 1341–1385 .

Hangartner, D., Dinas, E., Marbach, M., Matakos, K., and Xefteris, D. (2019). Does exposure to the refugee crisis make natives more hostile? *American Political Science Review*, 113, 2, 442–455.

Harmon, N.A. (2018). Immigration, Ethnic Diversity, and Political Outcomes: Evidence from Denmark. *Scand. J. of Economics*, 120 (4), 1043–1074.

Key, V. O. (1949). Southern Politics in State and Nation (Knoxville: University of Tennessee).

Mendez, I., and Cutillas, I. (2014). Has immigration affected Spanish presidential elections results? *Journal of Population Economics*, 27 (1), 135–171.

Otto, A.H., and Steinhardt, M.F. (2014). Immigration and election outcomes: evidence from city districts in Hamburg. *Regional Science and Urban Economics*, 45, 67–79 .

Repetto, R. (2018). Political budget cycles with informed voters: evidence from Italy. *The Economic Journal,* 128, 3320–3353.

Schaub, M., and D. Morisi (2019). Voter mobilization in the echo chamber: Broadband internet and the rise of populism in Europe. Carlo Alberto Notebooks, N. 584 (available at https://www.carloalberto.org/wp-content/uploads/2019/03/no.584.pdf).

Steinmayr, A. (2019). Contact matters: exposure to refugees and voting for the far-right. Working Paper (available at https://sites.google.com/site/andreassteinmayr/research).

Van Kessel, S. (2015). Populist parties in Europe: Agents of discontent?. Springer.

Vertier, P. and Viskanic, M. (2018). Dismantling the “Jungle”: migrant relocation and extreme voting in France. CESifo Working Papers, n. 6927 (https://www.ifo.de/DocDL/cesifo1_wp6927.pdf).

# TABLES

Table 1 – Descriptive statistics

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Turnout | 5605 | .643 | .115 | .139 | .961 |
| Turnout (log) | 5606 | -0.46 | 0.20 | -1.98 | -0.04 |
| Share of anti-immigrants votes | 5606 | .044 | .12 | 0 | 1 |
| Share of anti-immigrants votes (log) | 5606 | .037 | .099 | 0 | .737 |
| Share of populist votes | 5606 | .058 | .132 | 0 | 1 |
| Share of populist votes (log) | 5606 | .050 | .108 | 0 | .737 |
| Share of populist votes (including minor parties) | 5606 | .059 | .132 | 0 | 1 |
| Share of populist votes (including minor parties) (log) | 5606 | .051 | .109 | 0 | 0.737 |
| Share of Lega coalition votes | 5606 | .042 | .12 | 0 | 1 |
| Share of Lega coalition votes (log) | 5606 | .036 | .098 | 0 | .737 |
| Share of protest votes | 5605 | .051 | .044 | 0 | .811 |
| Share of protest votes (log) | 5605 | .049 | .039 | 0 | .594 |
| Electorate | 5606 | 7941.768 | 32380.95 | 79 | 1010000 |
| Number of mayors | 5592 | 4.274 | 4.855 | 1 | 41 |
| Exposure index | 5606 | 1.403 | 2.725 | 0 | 32.152 |
| Exposure index 30 days before | 5606 | 4.671 | 8.645 | 0 | 97.367 |
| Exposure index 30-60 days before | 5606 | 2.482 | 6.324 | 0 | 82.605 |
| Exposure index 60-90 days before | 5606 | 2.54 | 5.808 | 0 | 66.279 |
| Exposure index 0-60 days before | 5606 | 3.511 | 6.738 | 0 | 76.323 |
| Exposure index 0-90 days before | 5606 | 3.322 | 6.433 | 0 | 73.411 |
| Exposure index (log) | 5606 | .562 | .689 | 0 | 3.501 |
| Exposure index 30 days before (log) | 5606 | 1.015 | 1.099 | 0 | 4.589 |
| Exposure index 30-60 days before (log) | 5606 | .665 | .879 | 0 | 4.426 |
| Exposure index 60-90 days before (log) | 5606 | .674 | .917 | 0 | 4.209 |
| Exposure index 0-60 days before (log) | 5606 | .897 | .988 | 0 | 4.348 |
| Exposure index 0-90 days before (log) | 5606 | .876 | .966 | 0 | 4.310 |
| Share of household with annual income > 120k | 5427 | .03 | .044 | 0 | .464 |
| Total SPRAR beds | 5606 | 338.813 | 684.754 | 0 | 5165 |
| Total SPRAR beds (log) | 5606 | 4.5 | 1.992 | 0 | 8.55 |
| Ageing index | 5426 | 2.833 | 3.086 | .235 | 56 |
| Share of migrants | 5420 | .075 | .078 | .001 | .752 |
| Share of migrants (log) | 5420 | .07 | .067 | .001 | .561 |
| No. of reported crimes (per electorate) | 5606 | 3.684 | 6.207 | 0.011 | 87.032 |
| Crimes rate I tertile (per electorate) | 5606 | .341 | .474 | 0 | 1 |
| Crimes rate II tertile (per electorate) | 5606 | .331 | .470 | 0 | 1 |
| Crimes rate III tertile (per electorate) | 5606 | .326 | .479 | 0 | 1 |
| News diffusion (per electorate) | 5604 | 20.005 | 66.607 | 0.020 | 1849.03 |
| News diffusion above median value (per electorate) | 5604 | .494 | .500 | 0 | 1 |
| Share of household with 2<ADS≤30 Mbps | 5426 | .538 | .378 | 0 | 1 |
| Share of household with 30<ADS≤100 Mbps | 5426 | .208 | .278 | 0 | 1 |
| Share of household with 100<ADS≤500 Mbps | 5426 | .087 | .159 | 0 | .854 |
| Unemployment rate (aged 15 and over) | 5606 | 11.862 | 5.849 | 3.341 | 31.456 |
| Unemployment rate I tertile | 5606 | .449 | .497 | 0 | 1 |
| Unemployment rate II tertile | 5606 | .342 | .475 | 0 | 1 |
| Unemployment rate III tertile | 5606 | .208 | .406 | 0 | 1 |
| Year 2010 | 5606 | .093 | .29 | 0 | 1 |
| Year 2011 | 5606 | .195 | .396 | 0 | 1 |
| Year 2012 | 5606 | .127 | .333 | 0 | 1 |
| Year 2013 | 5606 | .085 | .28 | 0 | 1 |
| Year 2015 | 5606 | .093 | .29 | 0 | 1 |
| Year 2016 | 5606 | .195 | .396 | 0 | 1 |
| Year 2017 | 5606 | .127 | .333 | 0 | 1 |
| Year 2018 | 5606 | .085 | .28 | 0 | 1 |
| North Italy | 5592 | .406 | .491 | 0 | 1 |
| Center Italy | 5592 | .124 | .33 | 0 | 1 |
| Southern Italy and Islands | 5592 | .469 | .499 | 0 | 1 |

Table 2 – Exposure to arrivals and turnout

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Turnout* | | | |
| Exposure index (log) | -0.009*** | | | |
| | (0.003) | | | |
| Exposure index 30 days before (log) | | -0.005** | | |
| | | (0.002) | | |
| Exposure index 30-60 days before (log) | | | -0.007*** | |
| | | | (0.002) | |
| Exposure index 60-90 days before (log) | | | | -0.006*** |
| | | | | (0.002) |
| Total SPRAR beds | 0.000* | 0.000** | 0.000* | 0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | 0.005 | -0.004 | 0.005 | -0.007 |
| | (0.034) | (0.035) | (0.033) | (0.032) |
| Electorate | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | 0.007*** | 0.007*** | 0.007*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Taxable income share > 120,000 | -0.084 | -0.087 | -0.084 | -0.084 |
| | (0.073) | (0.073) | (0.073) | (0.072) |
| Ageing index | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | 0.588*** | 0.587*** | 0.589*** | 0.589*** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| Observations | 5,396 | 5,396 | 5,396 | 5,396 |
| R-squared | 0.415 | 0.414 | 0.415 | 0.415 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table 3 – Exposure to arrivals and protest votes

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Share of protest votes* | | | |
| Exposure index (log) | 0.005** | | | |
| | (0.002) | | | |
| Exposure index 30 days before (log) | | 0.003 | | |
| | | (0.002) | | |
| Exposure index 30-60 days before (log) | | | 0.004*** | |
| | | | (0.002) | |
| Exposure index 60-90 days before (log) | | | | 0.003** |
| | | | | (0.001) |
| Total SPRAR beds | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | 0.016 | 0.023 | 0.015 | 0.024 |
| | (0.025) | (0.026) | (0.025) | (0.024) |
| Electorate | -0.000** | -0.000** | -0.000** | -0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Taxable income share > 120,000 | 0.004** | 0.004** | 0.003** | 0.004** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Ageing index | 0.025 | 0.026 | 0.024 | 0.025 |
| | (0.031) | (0.031) | (0.030) | (0.031) |
| Constant | 0.074*** | 0.075*** | 0.073*** | 0.073*** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Observations | 5,396 | 5,396 | 5,396 | 5,396 |
| R-squared | 0.041 | 0.039 | 0.041 | 0.040 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table 4– Exposure to arrivals and share of anti-immigration votes

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Share of votes for anti-immigration parties* | | | |
| Exposure index (log) | 0.009*** | | | |
| | (0.003) | | | |
| Exposure index 30 days before (log) | | 0.009*** | | |
| | | (0.002) | | |
| Exposure index 30-60 days before (log) | | | 0.002 | |
| | | | (0.002) | |
| Exposure index 60-90 days before (log) | | | | 0.001 |
| | | | | (0.003) |
| Total SPRAR beds | 0.000** | 0.000** | 0.000** | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | 0.025 | 0.015 | 0.050 | 0.055* |
| | (0.029) | (0.030) | (0.031) | (0.032) |
| Electorate | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | -0.002** | -0.002** | -0.002** | -0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Taxable income share > 120,000 | -0.080 | -0.079 | -0.076 | -0.076 |
| | (0.124) | (0.123) | (0.124) | (0.124) |
| Ageing index | -0.005*** | -0.005*** | -0.005*** | -0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 0.047** | 0.044** | 0.050** | 0.051** |
| | (0.022) | (0.022) | (0.023) | (0.023) |
| Observations | 5,397 | 5,397 | 5,397 | 5,397 |
| R-squared | 0.042 | 0.045 | 0.040 | 0.040 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table 5 – Exposure to arrivals and share of populist votes

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Share of votes for populist parties* | | | |
| Exposure index (log) | 0.024*** | | | |
| | (0.005) | | | |
| Exposure index 30 days before (log) | | 0.016*** | | |
| | | (0.003) | | |
| Exposure index 30-60 days before (log) | | | 0.014*** | |
| | | | (0.003) | |
| Exposure index 60-90 days before (log) | | | | 0.011*** |
| | | | | (0.003) |
| Total SPRAR beds | -0.000 | -0.000* | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | 0.024 | 0.031 | 0.047 | 0.073 |
| | (0.041) | (0.040) | (0.044) | (0.046) |
| Electorate | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | -0.002 | -0.002 | -0.002 | -0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Taxable income share > 120,000 | -0.147 | -0.140 | -0.144 | -0.142 |
| | (0.137) | (0.137) | (0.138) | (0.137) |
| Ageing index | -0.006*** | -0.006*** | -0.007*** | -0.006*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 0.082* | 0.082 | 0.085* | 0.084* |
| | (0.049) | (0.050) | (0.049) | (0.048) |
| Observations | 5,397 | 5,397 | 5,397 | 5,397 |
| R-squared | 0.055 | 0.055 | 0.050 | 0.048 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6 – Exposure to arrivals and share of votes for Northern League party

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Share of votes for Northern League* | | | |
| Exposure index (log) | 0.015* | | | |
| | (0.008) | | | |
| Exposure index 30 days before (log) | | 0.015** | | |
| | | (0.006) | | |
| Exposure index 30-60 days before (log) | | | 0.003 | |
| | | | (0.005) | |
| Exposure index 60-90 days before (log) | | | | 0.003 |
| | | | | (0.006) |
| Total SPRAR beds | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | -0.049 | -0.063 | -0.013 | -0.010 |
| | (0.052) | (0.053) | (0.055) | (0.055) |
| Electorate | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Taxable income share > 120,000 | -0.168 | -0.164 | -0.165 | -0.164 |
| | (0.181) | (0.179) | (0.182) | (0.182) |
| Ageing index | -0.005** | -0.005** | -0.005** | -0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 0.119*** | 0.110*** | 0.129*** | 0.129*** |
| | (0.026) | (0.025) | (0.027) | (0.028) |
| Observations | 2,264 | 2,264 | 2,264 | 2,264 |
| R-squared | 0.080 | 0.084 | 0.078 | 0.078 |
| Number of municipalities | 1,137 | 1,137 | 1,137 | 1,137 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table 7 – Exposure to arrivals and turnout: the role of newspaper diffusion

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variables: | Turnout | | Protest votes | | Share of vote for anti-immigration parties | | Share of vote for populist parties | | Share of vote for Northern League | |
| | ≤median | >median | ≤median | >median | ≤median | >median | ≤median | >median | ≤median | >median |
| Exposure index 30 days before (log) | -0.005** | -0.005 | 0.003** | 0.002 | 0.008*** | 0.005 | 0.020*** | 0.007 | 0.008 | 0.012 |
| | (0.002) | (0.004) | (0.001) | (0.003) | (0.002) | (0.004) | (0.004) | (0.005) | (0.006) | (0.010) |
| Total SPRAR beds | 0.000*** | 0.000 | -0.000*** | 0.000 | -0.000 | 0.000*** | -0.000** | -0.000 | -0.000 | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | -0.064 | 0.054 | 0.058** | -0.012 | 0.064 | -0.024 | 0.075 | -0.022 | 0.017 | -0.089 |
| | (0.038) | (0.062) | (0.029) | (0.048) | (0.048) | (0.038) | (0.065) | (0.047) | (0.094) | (0.057) |
| Electorate | 0.000 | -0.000*** | -0.000*** | 0.000* | 0.000 | 0.000*** | -0.000 | 0.000*** | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | 0.004*** | 0.021*** | -0.001* | -0.012*** | -0.002** | -0.004 | -0.002 | -0.002 | -0.006*** | -0.010 |
| | (0.001) | (0.005) | (0.001) | (0.003) | (0.001) | (0.002) | (0.002) | (0.003) | (0.001) | (0.006) |
| Taxable income share > 120,000 | -0.054 | -0.087 | 0.058 | 0.008 | 0.121 | -0.260 | -0.032 | -0.273 | 0.159 | -0.366 |
| | (0.086) | (0.085) | (0.049) | (0.040) | (0.100) | (0.192) | (0.141) | (0.189) | (0.149) | (0.243) |
| Ageing index | 0.001 | -0.000 | 0.002* | 0.004** | -0.012*** | -0.002 | -0.016*** | -0.002 | -0.016*** | -0.002 |
| | (0.002) | (0.001) | (0.001) | (0.002) | (0.003) | (0.002) | (0.004) | (0.002) | (0.004) | (0.002) |
| Constant | 0.588*** | 0.711*** | 0.064*** | 0.024 | 0.079*** | -0.071** | 0.167*** | -0.162** | 0.198*** | -0.109 |
| | (0.016) | (0.032) | (0.011) | (0.030) | (0.024) | (0.033) | (0.055) | (0.064) | (0.028) | (0.131) |
| Observations | 2,738 | 2,658 | 2,738 | 2,658 | 2,738 | 2,659 | 2,738 | 2,659 | 1,145 | 1,119 |
| R-squared | 0.540 | 0.378 | 0.069 | 0.068 | 0.081 | 0.031 | 0.119 | 0.026 | 0.133 | 0.065 |
| Number of municipalities | 1,415 | 1,377 | 1,415 | 1,377 | 1,415 | 1,377 | 1,415 | 1,377 | 586 | 575 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

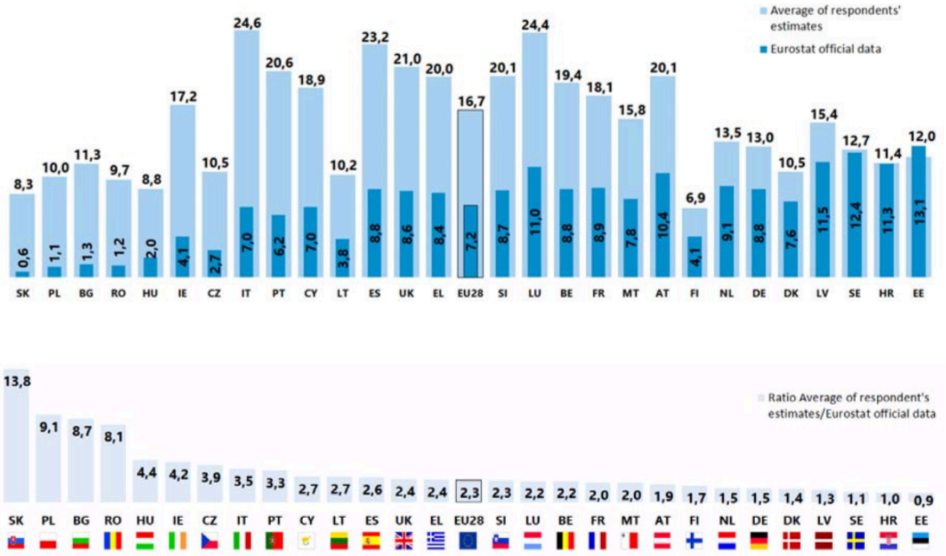
Table 8 – Exposure to arrivals and electoral outcomes: the role of internet diffusion

| | | (1) | (2) |
|---|---|---|---|
| Electoral outcome: | % hh with adsl speed (in 2018): | ≤ regional median | > regional median |
| Turnout | | | |
| | *2-30 mbps* | -0.009** | -0.001 |
| | | (0.003) | (0.003) |
| | *30-100 mbps* | -0.004 | -0.006* |
| | | (0.003) | (0.003) |
| | *100-500 mbps* | -0.003 | -0.008*** |
| | | (0.003) | (0.003) |
| Share of protest votes | | | |
| | *2-30 mbps* | 0.006* | -0.000 |
| | | (0.003) | (0.002) |
| | *30-100 mbps* | 0.001 | 0.004 |
| | | (0.002) | (0.003) |
| | *100-500 mbps* | 0.001 | 0.006* |
| | | (0.002) | (0.003) |
| Share of anti-immigration votes | | | |
| | *2-30 mbps* | 0.012*** | 0.003 |
| | | (0.004) | (0.003) |
| | *30-100 mbps* | 0.003 | 0.015*** |
| | | (0.003) | (0.005) |
| | *100-500 mbps* | 0.003 | 0.011** |
| | | (0.003) | (0.004) |
| Share of populist votes | | | |
| | *2-30 mbps* | 0.025*** | 0.003 |
| | | (0.005) | (0.003) |
| | *30-100 mbps* | 0.005* | 0.025*** |
| | | (0.003) | (0.006) |
| | *100-500 mbps* | 0.005* | 0.019*** |
| | | (0.003) | (0.006) |
| Share of Northern League | | | |
| | *2-30 mbps* | 0.030*** | 0.003 |
| | | (0.010) | (0.007) |
| | *30-100 mbps* | 0.004 | 0.040** |
| | | (0.006) | (0.015) |
| | *100-500 mbps* | 0.006 | 0.024* |
| | | (0.006) | (0.014) |

Regression coefficients and std. errors from estimates of the electoral outcome on exposure to arrivals. Robust standard errors in parentheses clustered at province level. *** p<0.01, ** p<0.05, * p<0.1

# FIGURES

Figure 1 – Actual versus perceived: the proportion of immigrants in each EU country

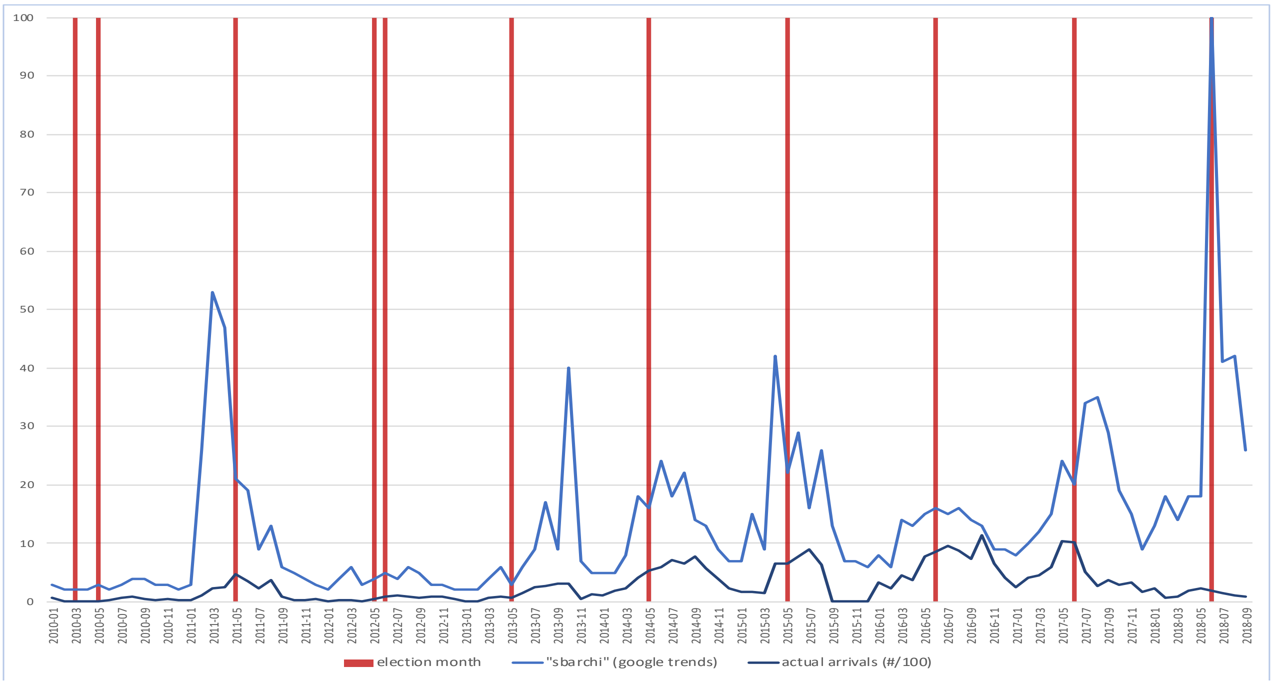



*Base size: 19,957 (respondents who gave an estimate of the proportion of immigrants in the total population in their country)*

*Source*: Integration of immigrants in the European Union – Eurobarometer (2018)

Figure 2 - Google Search of the words “Sbarchi” (boat landing), Panel A, and “Immigrati” (immigrants), Panel B, compared with actual arrivals.

*Panel A*




*Panel B*

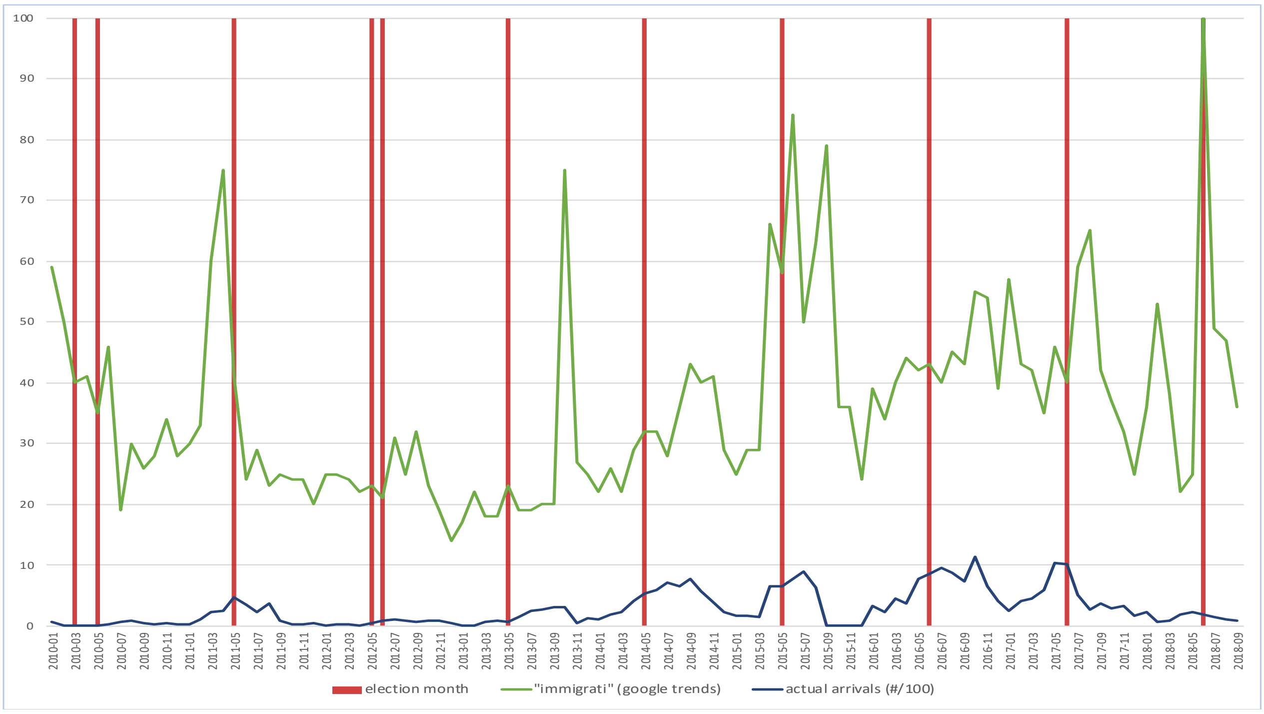
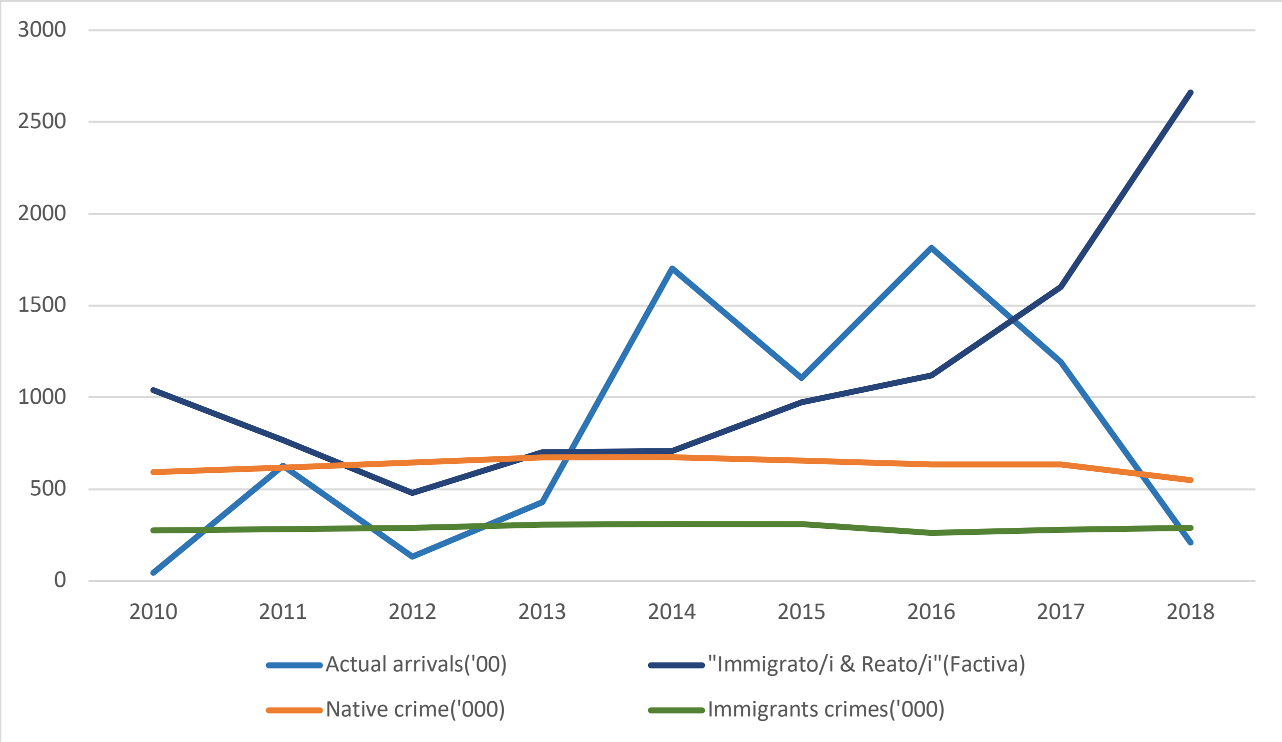
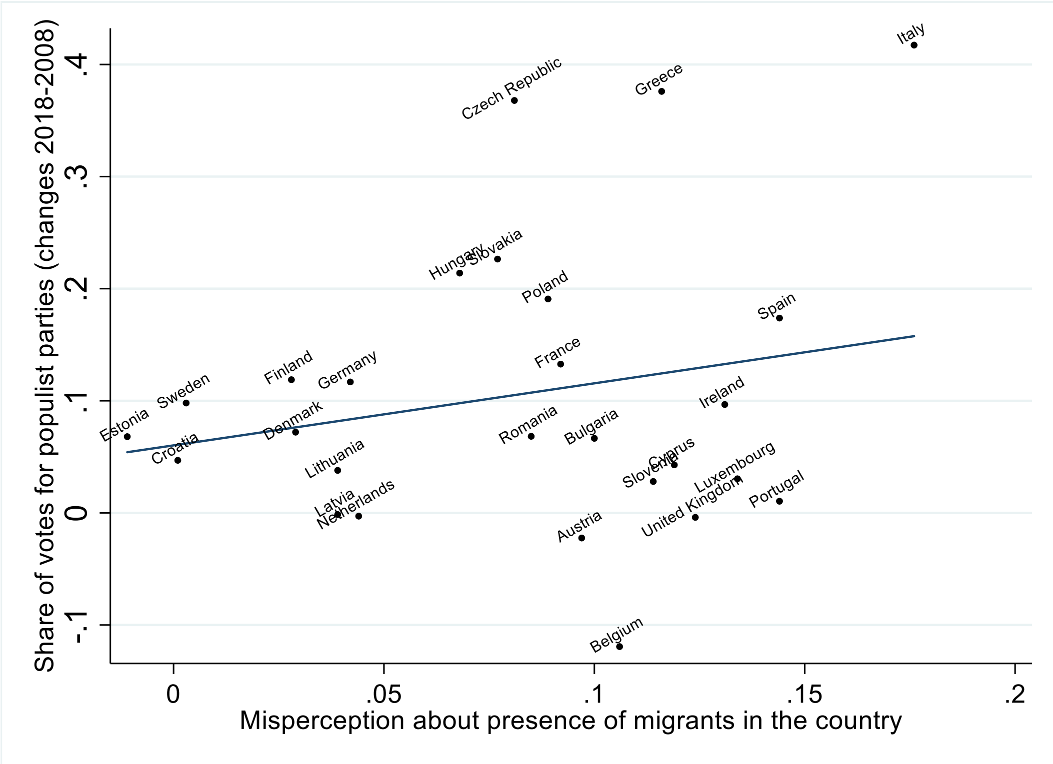


Figure 3 – Occurrences of the words "Immigrato/i" (immigrant/s) and "Reato/i" (crime/s) in newspaper articles, compared with refugee arrivals and crimes committed by natives or immigrants




*Notes*: The variable "Immigrato/i &/or Reato/i" counts the number of times the words "immigrato" (immigrants) and "reato" (crime), or their respective plurals jointly appear within a phrase written in the main Italian newspaper and news websites, across the years 2010 – 2018. They are constructed by means of a FACTIVA search. "Actual arrival" and "Native crimes" report the number of immigrants arrived on Italian shores and the number of crimes reported by the police, respectively, across the years 2010 – 2018, in thousands.

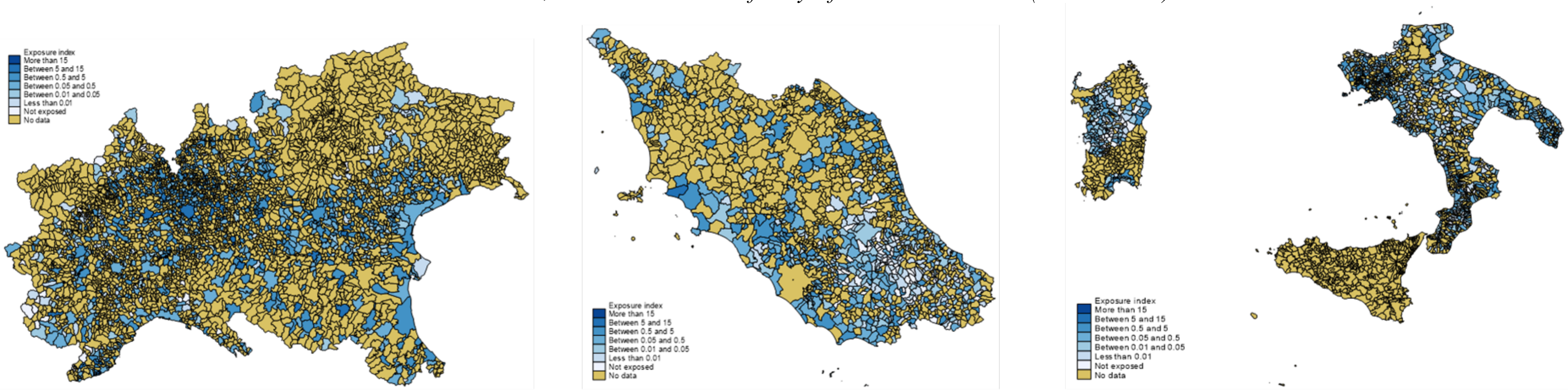
Figure 4 – Growth of populist parties share and misperception of immigration, 2008-2018



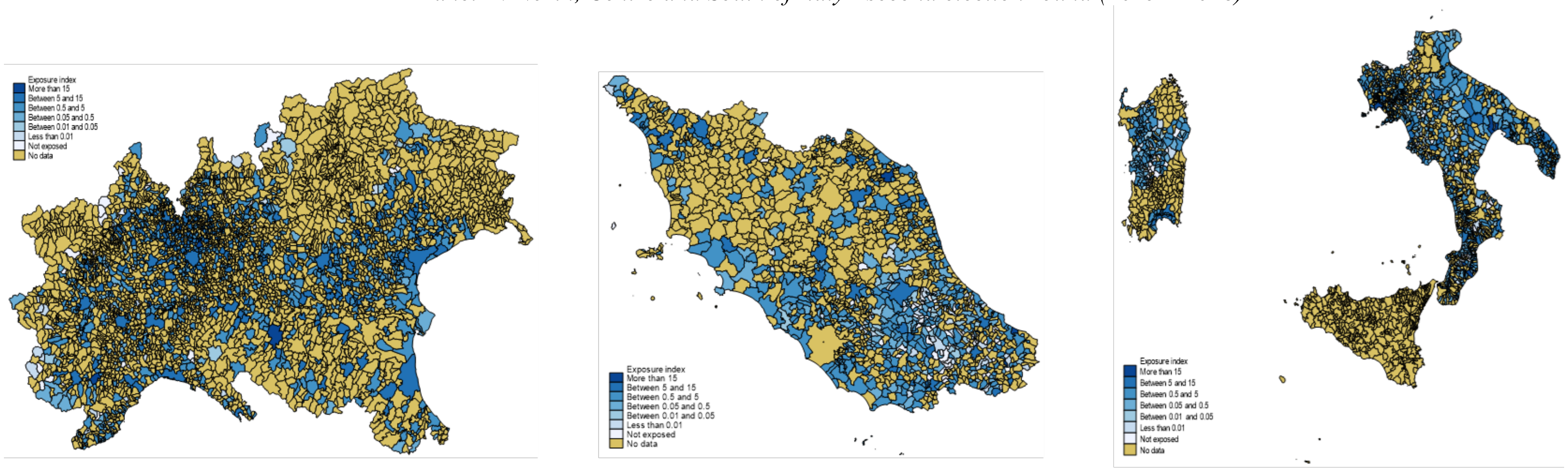

*Sources*: https://www.euronews.com/2018/03/15/explained-the-rise-and-rise-of-populism-in-europe; Integration of immigrants in the European Union – Eurobarometer (2018)

Figure 5 - Distribution of the exposure index across Italian municipalities in the first and the second election round

*Panel A: North, Centre and South of Italy - first election round (2010 – 2013)*



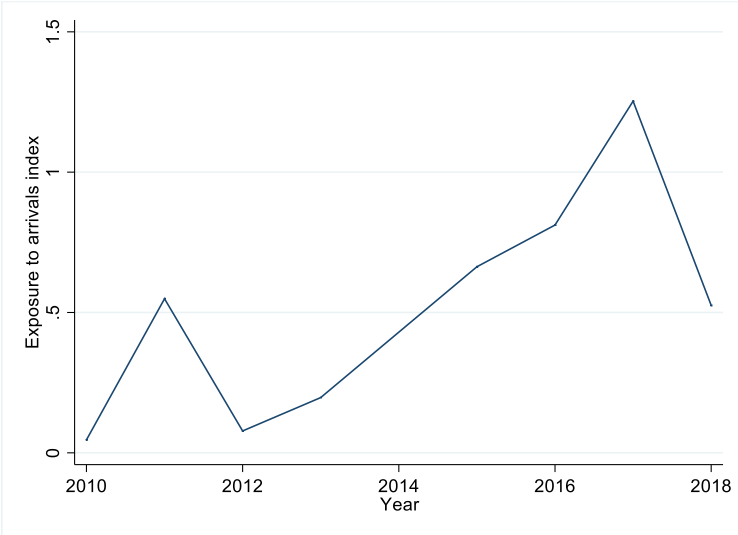

*Panel B: North, Centre and South of Italy - second election round (2015 – 2018)*




*Source:* Our elaboration, based on population composition per nationality at municipal level and ship landing data

Figure 6 – Evolution of exposure to arrivals

*Panel A*




*Panel B*

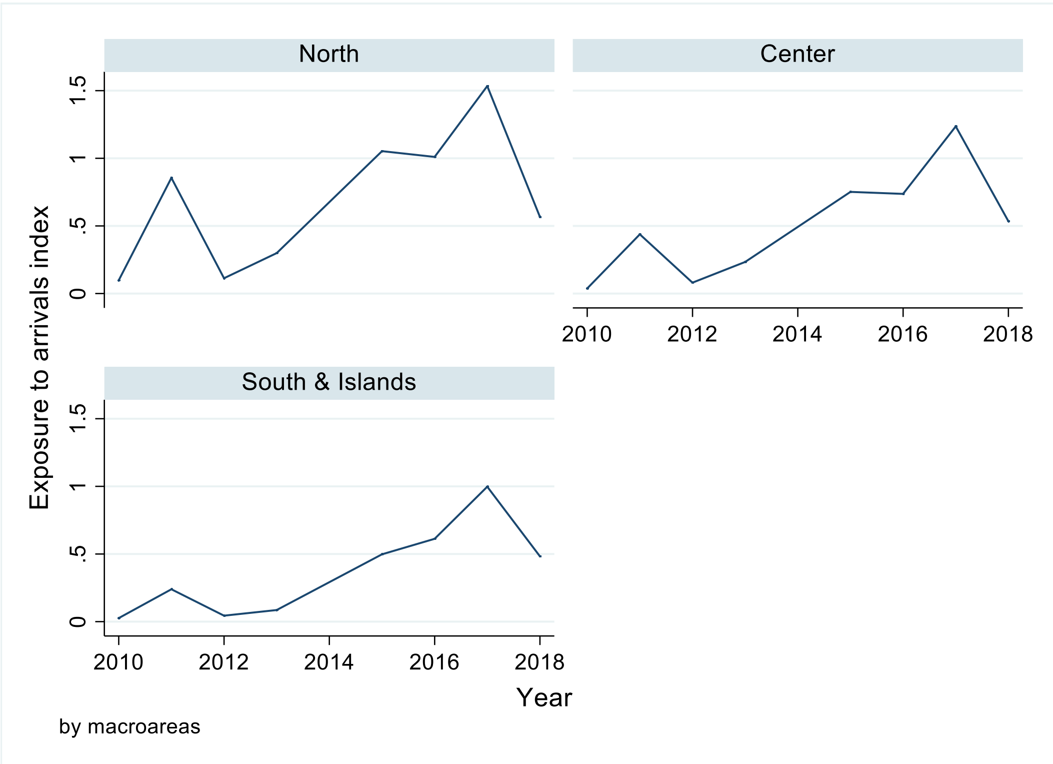


Figure 7 – Turnout and protest votes

*Panel A* *Panel B*

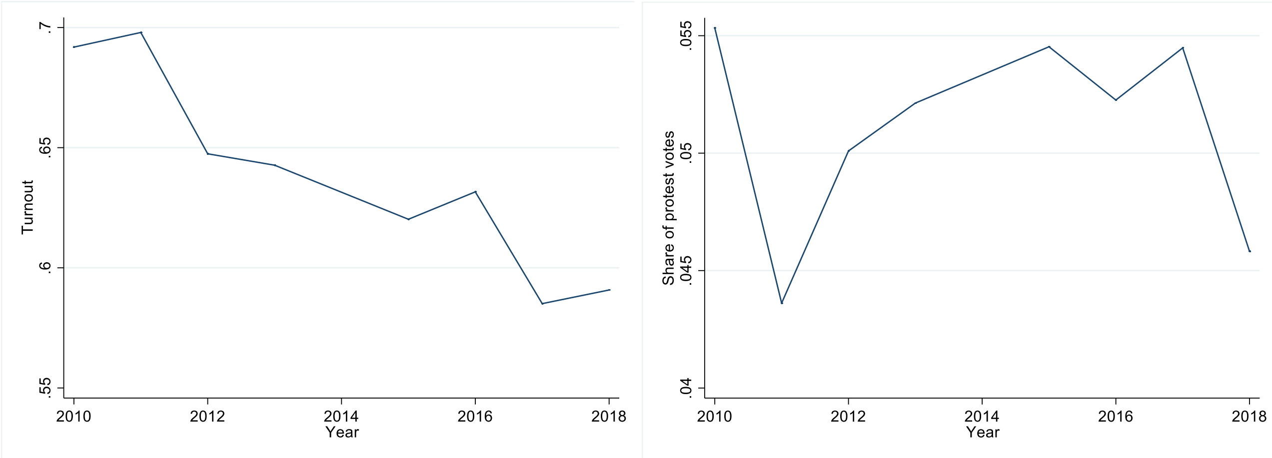
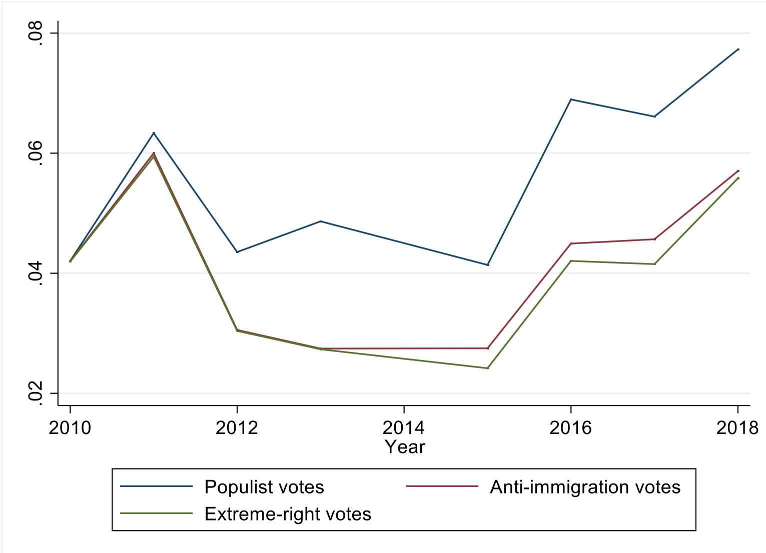
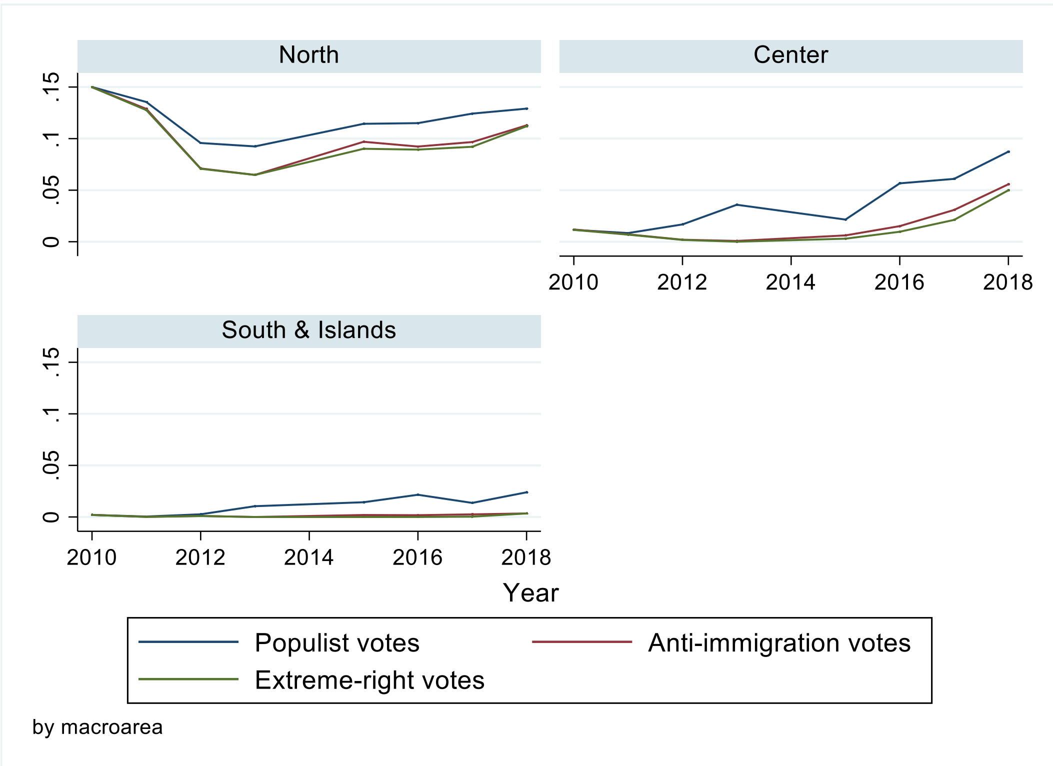


Figure 8 – Populist, extreme-right and anti-immigration votes

*Panel A*




*Panel B*



# APPENDIX

Table A1 – Variable legend

| Variable | Description |
|---|---|
| Turnout | Reports the share of individuals entitled to vote at municipal level who went voting at the election, net of the null and void ballot papers |
| Share of anti-immigrants votes | Share of votes expressed in favor of Casa Pound, Forza Nuova, Movimento Sociale Italiano and Alleanza Nazionale |
| Share of anti-immigrants votes (log) | Logarithmic transformation of Share of anti-immigrants votes |
| Share of populist votes | Share of votes expressed in favor of Forza Italia, Il Popolo delle libertà, Lega and Movimento 5 Stelle |
| Share of populist votes (log) | Logarithmic transformation of Share of populist votes |
| Share of populist votes (including minor parties) | Share of votes expressed in favor of Forza Italia, Il Popolo delle libertà, Lega, Movimento 5Stelle, Casa Pound, Il Popolo della Famiglia and Potere al Popolo. |
| Share of populist votes (log) (including minor parties) | Logarithmic transformation of Share of populist votes (including minor parties) |
| Share of Lega coalition votes | Share of votes expressed in favor of Lega, Lega Nord and Lega Padana |
| Share of Lega coalition votes (log) | Logarithmic transformation of Share of Lega list |
| Share of protest votes | Share of white, null and void ballot papers |
| Share of protest votes (log) | Logarithmic transformation of Share of protest vote |
| Electorate | Number of individuals entitled to vote at municipal level |
| Number of mayors | Number of mayor candidates at the election |
| Exposure index | Index of exposure to immigrants' arrivals. Captures the perception of new entrant immigrants at municipal level |
| Exposure index 30 days before | Index of exposure to immigrants' arrivals calculated in the 30 days preceding the election |
| Exposure index 30-60 days before | Index of exposure to immigrants' arrivals calculated between 30 and 60 days preceding the election |
| Exposure index 60-90 days before | Index of exposure to immigrants' arrivals calculated between 60 and 90 days preceding the election |
| Exposure index 0-60 days before | Index of exposure to immigrants' arrivals calculated between the election day and 60 days preceding the election |
| Exposure index 0-90 days before | Index of exposure to immigrants' arrivals calculated between the election day and 90 days preceding the election |
| Exposure index (log) | Logarithmic transformation of the index of exposure to immigrants' arrivals |
| Exposure index 30 days before (log) | Logarithmic transformation of the index of exposure to immigrants' arrivals calculated in the 30 days preceding the election |
| Exposure index 30-60 days before (log) | Logarithmic transformation of the index of exposure to immigrants' arrivals calculated between 30 and 60 days preceding the election |
| Exposure index 60-90 days before (log) | Logarithmic transformation of the index of exposure to immigrants' arrivals calculated between 60 and 90 days preceding the election |
| Exposure index 0-60 days before (log) | Logarithmic transformation of the index of exposure to immigrants' arrivals calculated between the election day and 60 days preceding the election |
| Exposure index 0-90 days before (log) | Logarithmic transformation of the index of exposure to immigrants' arrivals calculated between the election day and 90 days preceding the election |
| Share of household with annual income > 120k | Share of citizens with annual personal income greater than 120 thousand at municipal level |
| Total SPRAR beds | Total number of available beds in SPRAR centers at province level |
| Total SPRAR beds (log) | Logarithmic transformation of the total number of available beds in SPRAR centers at province level |
| Ageing index | Index of age structure at municipal level, calculated as the ratio between the share of elder individuals (i.e. over 65 years) and the share of pupils and children (i..e from 0 to 14 years) |
| Share of migrants | Share of non-native population with respect to the total resident population, at municipal level |
| Share of migrants (log) | Logarithmic transformation of Share of migrants |
| No. of reported crimes per electorate | Number of crimes reported to the police at province level (NUTS3), divided by electorate (at municipal level). |
| Crimes per electorate I tertile | Dummy variable taking value 1 if the province number of crimes per electorate is in the first tertile of the regional annual distribution, 0 otherwise. |

| | |
|---|---|
| Crimes per electorate II tertile | Dummy variable taking value 1 if the province number of crimes per electorate is in the second tertile of the regional annual distribution, 0 otherwise. |
| Crimes per electorate III tertile | Dummy variable taking value 1 if province number of crimes per electorate is in the third tertile of the regional annual distribution, 0 otherwise. |
| News diffusion per electorate | Annual average of the total number of newspapers daily sold at province level, divided by electorate (at municipal level). |
| News diffusion per electorate, above median value | Dummy variable taking value 1 if the province has a number news diffusion per electorate greater than the median value, calculated by year at regional level (NUTS2), 0 otherwise. |
| Umployment rate | Annual unemployment rate of the working age population (i.e. individuals aged 15 and over) computed at province level (NUTS3) |
| Umployment I tertile | Dummy variable taking value 1 if the province unemployment rate is in the first tertile of the regional annual distribution, 0 otherwise |
| Umployment II tertile | Dummy variable taking value 1 if the province unemployment rate is in the second tertile of the regional annual distribution, 0 otherwise |
| Umployment III tertile | Dummy variable taking value 1 if the province unemployment rate is in the third tertile of the regional annual distribution, 0 otherwise |
| Share of household with 2<ADS<=30 Mbps | Share of household with average download speed (ADS) between 2 and 30 Mbps at province level (NUTS3) |
| Share of household with 30<ADS<=100 Mbps | Share of household with average download speed between 30 and 100 Mbps at province level (NUTS3) |
| Share of household with 100<ADS<=500 Mbps | Share of household with average download speed between 100 and 500 Mbps at province level (NUTS3) |

Table A2 – Exposure to arrivals and turnout: the role of crime

| | (1) | (2) | (3) |
|---|---|---|---|
| | Crimes per voter (region/year) | | |
| | 1st tertile | 2nd tertile | 3rd tertile |
| | | Panel A: Turnout | |
| Exposure index 30 days before (log) | -0.004 | -0.005 | -0.001 |
| | (0.003) | (0.004) | (0.005) |
| Observations | 1,837 | 1,785 | 1,774 |
| R-squared | 0.672 | 0.461 | 0.362 |
| Number of municipalities | 961 | 969 | 923 |
| | | Panel B: Protest votes | |
| Exposure index 30 days before (log) | 0.003* | 0.002 | -0.001 |
| | (0.002) | (0.004) | (0.004) |
| Observations | 1,837 | 1,785 | 1,774 |
| R-squared | 0.171 | 0.063 | 0.121 |
| Number of municipalities | 961 | 969 | 923 |
| | | Panel C: Anti-immigration votes | |
| Exposure index 30 days before (log) | 0.008*** | 0.003 | 0.003 |
| | (0.003) | (0.004) | (0.005) |
| Observations | 1,837 | 1,785 | 1,775 |
| R-squared | 0.138 | 0.037 | 0.047 |
| Number of municipalities | 961 | 969 | 923 |
| | | Panel D: Populist votes | |
| Exposure index 30 days before (log) | 0.021*** | 0.003 | 0.003 |
| | (0.005) | (0.005) | (0.005) |
| Observations | 1,837 | 1,785 | 1,775 |
| R-squared | 0.240 | 0.046 | 0.033 |
| Number of municipalities | 961 | 969 | 923 |
| | | Panel E: Northern-league votes | |
| Exposure index 30 days before (log) | 0.008 | 0.005 | 0.004 |
| | (0.009) | (0.010) | (0.010) |
| Observations | 767 | 751 | 746 |
| R-squared | 0.202 | 0.077 | 0.082 |
| Number of municipalities | 403 | 409 | 388 |

Table A3 – Exposure to arrivals and votes for extreme-right parties: the role of municipalities' characteristics – population size

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variables: | Turnout | | Protest votes | | Share of vote for anti-immigration parties | | Share of vote for populist parties | | Share of vote for Northern League | |
| | ≤90th pc | >90th pc | ≤90th pc | >90th pc | ≤90th pc | >90th pc | ≤90th pc | >90th pc | ≤90th pc | >90th pc |
| Exposure index 30 days before (log) | -0.005** | 0.004 | -0.001 | 0.002 | 0.008*** | -0.002 | 0.013*** | -0.001 | 0.015** | -0.027 |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) | (0.005) | (0.003) | (0.011) | (0.007) | (0.023) |
| Total SPRAR beds | 0.000 | 0.000 | -0.000** | 0.000 | 0.000*** | 0.000* | -0.000 | -0.000 | 0.000** | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | 0.003 | -0.084 | 0.044 | 0.020 | -0.006 | 0.155*** | 0.019 | 0.032 | -0.078 | -0.010 |
| | (0.038) | (0.056) | (0.036) | (0.029) | (0.034) | (0.050) | (0.045) | (0.117) | (0.062) | (0.131) |
| Number of mayors | 0.011*** | 0.001 | 0.001 | -0.005*** | -0.002 | -0.002* | 0.001 | -0.005*** | -0.007** | -0.007*** |
| | (0.002) | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.003) | (0.002) |
| Taxable income share > 120,000 | -0.081 | -0.974*** | 0.606*** | 0.020 | -0.090 | 1.563** | -0.141 | 2.089*** | -0.170 | 1.098 |
| | (0.071) | (0.332) | (0.210) | (0.031) | (0.124) | (0.613) | (0.135) | (0.719) | (0.178) | (1.143) |
| Constant | 0.582*** | 0.623*** | 0.028 | 0.063*** | 0.045*** | 0.011 | 0.047*** | 0.169*** | 0.102*** | 0.187** |
| | (0.008) | (0.027) | (0.017) | (0.005) | (0.007) | (0.037) | (0.009) | (0.061) | (0.019) | (0.084) |
| Observations | 4,917 | 479 | 479 | 4,917 | 4,918 | 479 | 4,918 | 479 | 2,058 | 206 |
| R-squared | 0.397 | 0.831 | 0.615 | 0.032 | 0.036 | 0.381 | 0.029 | 0.625 | 0.075 | 0.484 |
| Number of municipalities | 2,470 | 244 | 244 | 2,470 | 2,470 | 244 | 2,470 | 244 | 1,036 | 105 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table A4 – Exposure to arrivals and votes for extreme-right parties: the role of the labor market

| | (1) | (2) | (3) |
|---|---|---|---|
| | Unemployment (region/year) | | |
| | *1st tertile* | *2nd tertile* | *3rd tertile* |
| | | *Panel A: Turnout* | |
| Exposure index 30 days before (log) | -0.005 | 0.001 | -0.000 |
| | (0.004) | (0.006) | (0.004) |
| Observations | 2,407 | 1,848 | 1,141 |
| R-squared | 0.393 | 0.393 | 0.422 |
| Number of municipalities | 1,551 | 1,446 | 897 |
| | | *Panel B: Protest votes* | |
| Exposure index 30 days before (log) | 0.002 | 0.001 | 0.000 |
| | (0.002) | (0.005) | (0.002) |
| Observations | 2,407 | 1,848 | 1,141 |
| R-squared | 0.028 | 0.051 | 0.068 |
| Number of municipalities | 1,551 | 1,446 | 897 |
| | | *Panel C: Anti-immigration votes* | |
| Exposure index 30 days before (log) | 0.007* | 0.007*** | 0.021** |
| | (0.004) | (0.002) | (0.009) |
| Observations | 2,408 | 1,848 | 1,141 |
| R-squared | 0.054 | 0.099 | 0.144 |
| Number of municipalities | 1,551 | 1,446 | 897 |
| | | *Panel D: Populist votes* | |
| Exposure index 30 days before (log) | 0.010** | 0.019*** | 0.036*** |
| | (0.004) | (0.005) | (0.010) |
| Observations | 2,408 | 1,848 | 1,141 |
| R-squared | 0.078 | 0.199 | 0.180 |
| Number of municipalities | 1,551 | 1,446 | 897 |
| | | *Panel E: Northern-league votes* | |
| Exposure index 30 days before (log) | 0.014 | 0.014** | 0.011 |
| | (0.014) | (0.007) | (0.010) |
| Observations | 882 | 831 | 551 |
| R-squared | 0.075 | 0.160 | 0.413 |
| Number of municipalities | 585 | 674 | 452 |

Table A5 – Exposure to arrivals and votes for extreme-right parties: the role of competition for public services

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variables: | Turnout | | Protest votes | | Share of vote for anti-immigration parties | | Share of vote for populist parties | | Share of vote for Northern League | |
| | ≤median | >median | ≤median | >median | ≤median | >median | ≤median | >median | ≤median | >median |
| Exposure index 30 days before (log) | -0.003 | -0.005* | 0.002 | 0.001 | 0.009** | 0.009*** | 0.019*** | 0.015*** | 0.016* | 0.013* |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.004) | (0.003) | (0.005) | (0.004) | (0.009) | (0.007) |
| Total SPRAR beds | 0.000* | 0.000* | -0.000** | -0.000 | -0.000 | 0.000*** | -0.000* | -0.000 | -0.000* | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | 0.042 | -0.029 | 0.038 | 0.010 | 0.023 | -0.004 | 0.023 | 0.060 | -0.072 | -0.087 |
| | (0.057) | (0.043) | (0.036) | (0.036) | (0.028) | (0.063) | (0.047) | (0.088) | (0.061) | (0.173) |
| Electorate | 0.000** | 0.000 | -0.000 | -0.000** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | 0.010*** | 0.005*** | -0.001 | -0.006*** | -0.000 | -0.003** | -0.003 | -0.001 | -0.002 | -0.011*** |
| | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.003) | (0.002) | (0.002) | (0.003) |
| Taxable income share > 120,000 | -0.136 | -0.179* | 0.022 | 0.062 | -0.109 | 0.045 | -0.131 | -0.075 | -0.186 | -0.099 |
| | (0.086) | (0.093) | (0.053) | (0.044) | (0.137) | (0.282) | (0.142) | (0.303) | (0.201) | (0.416) |
| Constant | 0.505*** | 0.608*** | 0.063*** | 0.134*** | -0.006 | 0.014 | 0.019 | 0.022 | 0.054 | -0.080 |
| | (0.030) | (0.026) | (0.012) | (0.033) | (0.027) | (0.046) | (0.072) | (0.088) | (0.050) | (0.136) |
| Observations | 2,716 | 2,680 | 2,680 | 2,716 | 2,716 | 2,681 | 2,716 | 2,681 | 1,138 | 1,126 |
| R-squared | 0.394 | 0.455 | 0.032 | 0.050 | 0.035 | 0.053 | 0.046 | 0.070 | 0.077 | 0.106 |
| Number of municipalities | 1,538 | 1,516 | 1,516 | 1,538 | 1,538 | 1,517 | 1,538 | 1,517 | 643 | 635 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table A6 – Exposure to arrivals and share of populist votes – Alternative definition

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Share of votes for populist parties* | | | |
| Exposure index (log) | 0.016*** | | | |
| | (0.003) | | | |
| Exposure index 30 days before (log) | | 0.011*** | | |
| | | (0.003) | | |
| Exposure index 30-60 days before (log) | | | 0.009*** | |
| | | | (0.002) | |
| Exposure index 60-90 days before (log) | | | | 0.007** |
| | | | | (0.003) |
| Total SPRAR beds | -0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | -0.018 | -0.015 | -0.002 | 0.013 |
| | (0.035) | (0.034) | (0.037) | (0.039) |
| Electorate | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Taxable income share > 120,000 | -0.160 | -0.156 | -0.158 | -0.157 |
| | (0.123) | (0.123) | (0.123) | (0.123) |
| Ageing index | -0.005*** | -0.005*** | -0.005*** | -0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 0.086** | 0.085** | 0.088** | 0.087** |
| | (0.036) | (0.037) | (0.036) | (0.036) |
| Observations | 5,397 | 5,397 | 5,397 | 5,397 |
| R-squared | 0.034 | 0.034 | 0.031 | 0.030 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table A7 – Exposure to arrivals and share of populist votes – Alternative definition

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: *Share of votes for populist parties* | | | |
| Exposure index (log) | 0.016*** | | | |
| | (0.003) | | | |
| Exposure index 30 days before (log) | | 0.011*** | | |
| | | (0.003) | | |
| Exposure index 30-60 days before (log) | | | 0.009*** | |
| | | | (0.002) | |
| Exposure index 60-90 days before (log) | | | | 0.008** |
| | | | | (0.003) |
| Total SPRAR beds | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Share of migrants | -0.011 | -0.008 | 0.006 | 0.020 |
| | (0.035) | (0.034) | (0.038) | (0.039) |
| Electorate | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Taxable income share > 120,000 | -0.157 | -0.153 | -0.155 | -0.154 |
| | (0.122) | (0.122) | (0.123) | (0.123) |
| Ageing index | -0.005** | -0.004** | -0.005** | -0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 0.083** | 0.083** | 0.086** | 0.084** |
| | (0.037) | (0.037) | (0.037) | (0.037) |
| Observations | 5,397 | 5,397 | 5,397 | 5,397 |
| R-squared | 0.037 | 0.037 | 0.034 | 0.033 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table A8 – Exposure to arrivals and electoral outcomes – Elasticities

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables.: | Turnout (log) | | Protest votes (log) | | Share of vote for anti-immigration parties (log) | | Share of vote for populist parties (log) | | Share of vote for Northern League (log) | |
| Exposure index (log) | -0.016*** | | 0.005** | | 0.008*** | | 0.020*** | | 0.012* | |
| | (0.006) | | (0.002) | | (0.002) | | (0.004) | | (0.007) | |
| Exposure index 30 days before (log) | | -0.010** | | 0.002 | | 0.007*** | | 0.013*** | | 0.013** |
| | | (0.004) | | (0.001) | | (0.002) | | (0.003) | | (0.005) |
| Total SPRAR beds (log) | 0.008*** | 0.008*** | -0.001 | -0.001 | 0.003** | 0.003** | 0.002 | 0.002 | 0.003 | 0.003 |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) | (0.003) |
| Share of migrants (log) | 0.062 | 0.047 | 0.012 | 0.020 | 0.034 | 0.022 | 0.033 | 0.043 | -0.041 | -0.062 |
| | (0.093) | (0.097) | (0.029) | (0.031) | (0.030) | (0.030) | (0.046) | (0.045) | (0.054) | (0.055) |
| Electorate | 0.000 | 0.000 | -0.000** | -0.000** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of mayors | 0.012*** | 0.013*** | -0.003*** | -0.003*** | -0.001* | -0.002* | -0.001 | -0.001 | -0.005*** | -0.005*** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Taxable income share > 120,000 | -0.170 | -0.175 | 0.020 | 0.021 | -0.052 | -0.051 | -0.111 | -0.106 | -0.123 | -0.120 |
| | (0.133) | (0.134) | (0.029) | (0.029) | (0.104) | (0.104) | (0.113) | (0.112) | (0.151) | (0.149) |
| Ageing index | -0.001 | -0.001 | 0.003** | 0.003** | -0.004*** | -0.004*** | -0.005*** | -0.005*** | -0.004** | -0.004** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | -0.590*** | -0.592*** | 0.073*** | 0.074*** | 0.024 | 0.023 | 0.050 | 0.051 | 0.088*** | 0.080*** |
| | (0.033) | (0.033) | (0.011) | (0.011) | (0.021) | (0.021) | (0.043) | (0.044) | (0.027) | (0.026) |
| Observations | 5,396 | 5,396 | 5,396 | 5,396 | 5,397 | 5,397 | 5,397 | 5,397 | 2,264 | 2,264 |
| R-squared | 0.365 | 0.364 | 0.043 | 0.042 | 0.049 | 0.051 | 0.056 | 0.056 | 0.087 | 0.091 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 1,137 | 1,137 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table A9a – Exposure to arrivals and votes for extreme-right parties – Alternative time-windows

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variables: | | Turnout | | | Protest votes | |
| Exposure index 30 days before (log) | -0.005** | | | 0.003 | | |
| | (0.002) | | | (0.002) | | |
| Exposure index 0-60 days before (log) | | -0.006** | | | 0.004** | |
| | | (0.002) | | | (0.002) | |
| Exposure index 0-90 days before (log) | | | -0.006*** | | | 0.004** |
| | | | (0.002) | | | (0.002) |
| Observations | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 | 5,396 |
| R-squared | 0.414 | 0.415 | 0.415 | 0.039 | 0.040 | 0.041 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table A9b – Exposure to arrivals and votes for extreme-right parties – Alternative time-windows

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dependent variables: | | Anti-immigration votes | | | Populist votes | | | Northern-league votes | |
| Exposure index 30 days before (log) | 0.009*** | | | 0.016*** | | | 0.015** | | |
| | (0.002) | | | (0.003) | | | (0.006) | | |
| Exposure index 0-60 days before (log) | | 0.007*** | | | 0.017*** | | | 0.012* | |
| | | (0.002) | | | (0.003) | | | (0.006) | |
| Exposure index 0-90 days before (log) | | | 0.006*** | | | 0.017*** | | | 0.011* |
| | | | (0.002) | | | (0.003) | | | (0.006) |
| Observations | 5,397 | 5,397 | 5,397 | 5,397 | 5,397 | 5,397 | 2,264 | 2,264 | 2,264 |
| R-squared | 0.045 | 0.043 | 0.042 | 0.055 | 0.054 | 0.053 | 0.084 | 0.081 | 0.080 |
| Number of municipalities | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 2,706 | 1,137 | 1,137 | 1,137 |

Robust standard errors in parentheses clustered at province level. All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1