THREE ESSAYS ON MIGRATION AND ORGANIZED CRIME

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This doctoral thesis consists of three independent essays on the economics of international migration and organized crime. Chapter 1 explores the relationship between immigration and voting for the far-right party in Finland. I find that one percentage point increase in the share of foreign citizens in a municipality decreases Finns Party's vote share by 3.4 percentage points. The far-right votes lost to immigration are captured by the two pro-immigration parties. Turning to potential mechanisms, the negative effect is only present in municipalities with high initial exposure to immigrants. Moreover, I provide some evidence for welfare-state channel as a plausible mechanism behind the main result. Chapter 2 studies the public health effects of a recent immigrant regularization program in the United States – the 2012 Deferred Action for Childhood Arrivals (DACA). I find that DACA increased insurance coverage among eligible immigrants. Despite the increase in insurance coverage, there is no evidence of significant increases in health care use, although there is some evidence that DACA increased demand for mental health services. After 2012, DACA-eligible individuals were also more likely to report a usual place of care and less likely to delay care because of financial restrictions. Finally, I find some evidence that DACA improved self-reported health and mental health among eligible individuals. Chapter 3 analyzes the origins and consequences of the Russian Mafia (*vory-v-zakone*). Using a unique web scraped data, I first show that Russian Mafia originated in the *Gulag* - Soviet system of forced labor camps which operated in the USSR primarily during the 1920s-1950s Stalin era. Second, I document that the distance to the nearest camp is a strong negative predictor of mafia presence in Russia's communities in the early-to-mid 1990s. Finally, I show that the communities with mafia presence in the 1990s experienced a dramatic rise in crime driven by turf wars which erupted among rival clans around 1993 and lingered on until the late 1990s. This is suggested by a sharp increase in attacks against the members of Russia's economic elite in places with mafia presence.

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PREFACE

I am very grateful to my committee chair, Osea Giuntella, for his continuous support and unconditional mentorship throughout my doctorate studies, especially during the times when I doubted my own abilities to finish the program. I'm also very thankful to Arie Beresteanu, Daniel Berkowitz, Daniele Coen-Pirani, Paolo Pinotti, Werner Troesken, and Federico Varese for being great advisors throughout my Ph.D. journey. I want to thank Volker Grzimek, James Blackburn-Lynch, Jing-Pang Lee, Andrew Baskin, and Jeff Pool for their mentorship during my college years. I would not have been able to pull it through the first year of graduate school had I not had such an intensive prior training in economics and mathematics. Finally, I want to thank Mary Kay and Mike Johnsons, Tibor Krska, Romana Sumska, Vladimir Balko, Gabriela Kubova, Slavo Kuba, Katarina Majdisova, Gustav Majdis, and, of course, my beloved parents Jana and Jindro, as well as my siblings Jana and Henrich. They have supported me throughout my studies in many different ways.

1 INTRODUCTION

International migration and organized crime are both topics of significant (and often heated) public, political, and academic debate. Between 2010 and 2017, the number of migrants worldwide has grown by almost 50% (Kobler and Lattes, 2017), while the total organized crime profits from various illicit activities – including migrant smuggling – have been recently estimated at some $6.2 trillion (10% of global GDP) (Novakoff, 2015). This doctoral thesis analyzes migration and organized crime as two separate topics, although it is without a doubt that the two issues are connected in many different ways.

The thesis consists of three independent essays, two of them analyzing recent policy-relevant issues in migration, while the third one delves into the 20th century history of the Russian (Soviet) organized crime, prison system, and their lasting effects on society.

More specifically, Chapter 1 focuses on the recent rise of the far-right parties in Europe, exploring migration as potentially a key factor determining their electoral support. I conduct a case study of Finland's *Finns Party* after the 2004 EU enlargement, where the effect of immigration on far-right votes is analyzed on a micro (municipality) level. Chapter 2 is a policy evaluation of the 2012 temporary immigrant authorization program in the United States – the Deferred Action for Childhood Arrivals (DACA). The focus is on the impact of policy on immigrant health insurance coverage, access to and demand for health care, and a broad set of physical and mental health outcomes. Finally, in Chapter 3, I explore the origins of the Russian Mafia during the 1920s-1950s Stalin-era *Gulag* archipelago, and its consequences on Russian Communities in the mid-1990s. The latter focuses on the impact of Russian Mafia on local crime and violence, as those were endemic throughout the post-Soviet Russia.

2 DOES IMMIGRATION DECREASE FAR-RIGHT POPULARITY? EVIDENCE FROM FINNISH MUNICIPALITIES

2.1 INTRODUCTION

The popularity of far-right (sometimes also referred to as populist radical right)[1] parties across Europe has been rising rapidly in recent years. In December 2015, the *National Front* won the first round of the regional election in France. In December 2016, the *Freedom Party of Austria's* candidate lost presidential election only after a repeated runoff. In May 2017, National Front's leader Marine Le Pen captured a respectable 34 percent in the French presidential election runoff. And last year, the *Northern League* placed third in the Italian general election, forming a populist coalition government with the *Five Star Movement*. Thus, it is clear that the far-right no longer belongs to the fringes of the European political spectrum. Moreover, latest political developments in Europe such as the upcoming *Brexit* suggest that the surge of the far-right could have significant negative economic and political consequences for EU as a whole.

The rise of the far-right appears to be driven (in large part) by immigration. Virtually all far-right parties have strong anti-immigration platforms, a feature stemming from their ideology of ethno-nationalism (or nativism). According to Betz (2008), nativism is defined as a strong belief that different societies and cultures adopt entirely different values, which are neither inferior, nor superior, but essentially incompatible with each other. This ideology makes far-right parties both nationalistic and xenophobic, and in recent years also Islamophobic (Mudde, 2007). Since the early 1990s, Europe has experienced significant migration flows. First, the East to West migration from post-communist countries which began with the fall of the Soviet Union, and accelerated after the EU enlargements in 2000s. And in recent years, a large inflow of asylum seekers from Asia and Africa fueled by a number of armed conflicts. Both of these immigration shocks likely sparked

[1]The term far-right (or far right) is used in Betz (2008), Davies (2008), Ellinas (2010), Goodwin (2008), and Roxburgh (2002). The label populist radical right is preferred by Arter (2010) and Mudde (2007). Still, others use the terms right-wing populist (Norocel, 2016; Swank and Betz, 2002) or even extreme right (Carter, 2005; Ignazi, 2003). These different labels generally refer to the same party family.

nativist sentiments across the continent contributing to an unprecedented wave of electoral success among far-right parties.

This paper studies the effect of immigration on voting for the far-right on a local (municipality) level. The local effect of immigration, which can be very different from the national effect (e.g. national media, politicians), is theoretically ambiguous[2] and thus requires empirical examination. This study focuses on Finland, a country which had a single far-right party (*the Finns Party*) for nearly 25 years (1995-2017), but was long considered immune to the surge of the far-right seen in other European countries (Figure 1; Ellinas 2010; Goodwin 2008; Ignazi 2003). The period of study is 2006-2015. These years are characterized by both the historically largest inflow of foreign citizens into Finland (Figure 2; Koivukangas 2003), and a remarkable rise in Finns Party's popularity (Figure 1). Indeed, taken together, Figures 1 and 2 suggest a positive correlation between immigration and far-right voting on the national level. The analysis employs a novel panel dataset which spans 7 election years and 297 municipalities (all of mainland Finland). All types of national elections (i.e. parliamentary, presidential, and European parliamentary) are considered.

The sudden and unprecedented increase in immigration into Finland that followed the 2004 EU enlargement also provides an excellent setup for identification. The 2003 distributions of immigrants by continent of citizenship can be used to construct a "shift-share" instrument (Altonji and Card, 1991; Orrenius and Zavodny, 2015a) to identify the effect of immigration on far-right voting. One thing that makes this instrument particularly convincing in this case is the change in immigrant composition that followed the 2004 enlargement. While the 1990s and early 2000s were characterized primarily by an influx of Ingrian Finns from the former Soviet Union and asylum seekers from countries such as Somalia and former Yugoslavia (Koivukangas, 2003), the 2004 and the subsequent EU enlargements brought in mostly economic migrants from Central and Eastern Europe. This minimizes the concern that IV results could be driven by a persistence of trends in anti-immigrant or pro-immigrant attitudes across municipalities.

Using the shift-share instrument, I find an economically meaningful and statistically significant negative effect of municipal in-migration of foreigners on Finns Party's vote share. The IV coef-

[2]Group conflict theory (Sherif et al., 1961) and ethnic competition theory (Olzak, 1992) suggest a positive effect, while the intergroup contact theory (Allport, 1954) predicts the opposite. Economic theories of labor market competition and welfare-state are less clear-cut; the predictions depend on the precise characteristics of immigrants and natives (Scheve and Slaughter, 2001; Facchini and Mayda, 2012; Dustmann and Preston, 2007).

ficient from the preferred specification suggests that one percentage point increase in the share of foreign citizens in municipality (68% of the mean) decreases Finns Party's vote share by about 3.35 percentage points (28% of the mean). A placebo test using pre-period (1996-2003) data confirms the IV estimate is not driven by persistent trends at the municipality level. To further validate the IV design, I re-estimate the main specification using a shift-share instrument constructed with 1991 immigrant distributions.[3] The resulting coefficient remains negative, statistically significant at 5%, and slightly larger in magnitude than the original estimate. Additional robustness checks such as a first-difference estimation, exclusion of potential outliers, and estimation with larger geographical units confirm the main result.

Considering the effect of immigration on voting for other parties, I find that the strongly pro-immigration *Green League* and *Swedish People's Party* gain votes. Indeed, their positive coefficients roughly add up to the negative estimate for the Finns Party. These positive effects are also relatively large; one percentage point increase in the foreign share increases Green League's vote share by 23% and Swedish People's Party's vote share by 57% with respect to the sample mean. Immigration also increases voter turnout (3% with respect to mean) while the share of protest votes remains unaffected.

Heterogeneity analysis reveals that the negative effect of immigration on Finns Party's vote share is only present in municipalities with above-median initial immigrant share. In addition, municipalities with below-median initial far-right vote share experience a larger reduction in Finns Party's support due to immigration. However, I find no effect heterogeneity with respect to initial population size, density, level of education, or economic conditions. Finally, using the same shift-share instrument, I find a mild positive effect of immigration on municipality per capita personal income tax revenue, while there appears to be no effect on municipal per capita spending on social services, health care, and education. This evidence is consistent with welfare-state channel as a plausible mechanism behind the main result (Facchini and Mayda, 2012, 2009; Dustmann and Preston, 2007).

My analysis contributes to the growing economics literature on the effects of immigration on

[3]Before any major immigrant inflow into Finland occurred.

voting for the far-right and other anti-immigrant parties in Europe.[4] [5] Most studies find a positive effect (Halla et al., 2017; Barone et al., 2016; Becker and Fetzer, 2016; Edo et al., 2018; Gerdes and Wadensjö, 2008; Harmon, 2012; Mendez and Cutillas, 2014; Otto and Steinhardt, 2014; Brunner and Kuhn, 2014). Halla et al. (2017) use a shift-share instrument to study the effect of immigrant inflow on voting for the Freedom Party of Austria (FPÖ). Their positive effect is driven by voters' fear of adverse labor market effects of immigration as well as a negative effect of immigrant inflow on local compositional amenities. In an Italian setting, Barone et al. (2016) find that foreign municipal inmigration increases vote share of the anti-immigrant center-right coalition (which includes the far-right Northern League). Proposed mechanisms in this study include cultural diversity, competition in the labor market and for public services, and political competition.

In contrast with the previous studies, Dustmann et al. (2016) use a quasi-random allocation of refugees into municipalities to study the impact of immigration on voting in Denmark. Documenting a large effect heterogeneity, the authors find that in all but the most urban municipalities, refugee inflow increases vote share of both anti-immigrant and center-right parties, while the vote share of center-left parties declines. However, in the most urban municipalities, refugee allocation actually decreases support for anti-immigrant parties.

Thus far, the (overall) negative effect of immigration on far-right voting has been documented only in Steinmayr (2018) who suggests that hosting refugees in Austrian municipalities dampened the overall positive trend in support for the Freedom Party (FPÖ). However, he also finds that the exposure to a large number of refugees passing through on their way to Germany actually increased FPÖ's vote share. These findings are largely consistent with Allport (1954)'s *intergroup contact theory*, suggesting that a meaningful contact between natives and immigrants can effectively ameliorate natives' anti-immigrant attitudes.

This paper makes several contributions to the existing literature. First, it is the first study to find a negative effect of the inflow of economic migrants on far-right vote share. By contrast,

[4] A number of correlational studies in political science have also considered the relationship between immigration and voting for European far-right parties. Results are mixed: positive association is found in Golder (2003), Swank and Betz (2002), and Anderson (1996); while Dülmer and Klein (2005), Messina (2007), and Kitschelt and McGann (1995) estimate a negative relationship.

[5] There is also a closely related economics literature on the determinants of natives' attitudes towards immigrants and their preferences over immigration policy. Two economic channels have been identified: the *labor market hypothesis* (Scheve and Slaughter, 2001; Mayda, 2006), and the *welfare-state channel* (Facchini and Mayda, 2012, 2009; Dustmann and Preston, 2007). In addition, a number of studies have considered non-economic channels such as xenophobia, crime, and cultural/national identity (O'Rourke and Sinnott, 2006; Nunziata, 2015; Mayda, 2006).

both Steinmayr (2018) and Dustmann et al. (2016) consider the exposure to refugees through refugee allocation schemes. In addition, Steinmayr (2018) evaluates the impact of a specific and relatively short-term event - the *European refugee crisis* - and considers only the extensive margin of immigration. This paper, on the other hand, focuses on the intensive margin and the study period spans 10 years and involves three types of national elections. Regarding Dustmann et al. (2016), the negative effect is present only in a subanalysis of the 5% largest and most urban Danish municipalities (the subsample consists of only 26 observations). By contrast, I find no effect heterogeneity with respect to initial population size - the negative effect is present in municipalities both above and below the median initial population size.

Second, this study is one of the first to provide evidence of the welfare-state channel as a possible mechanism through which immigration affects far-right voting. This is particularly appealing given that Finland is a country with generous welfare system (managed primarily by municipalities), and thus native concerns about immigrant "benefit tourism" are especially relevant in this context. Previous papers have focused mostly on labor market and compositional amenities (Halla et al., 2017; Barone et al., 2016; Becker and Fetzer, 2016), cultural diversity (Barone et al., 2016), the intergroup contact theory (Steinmayr, 2018), and other non-economic aspects (Otto and Steinhardt, 2014). Otto and Steinhardt (2014) do consider welfare channel as well, but they provide only indirect evidence.

Third, this paper examines a broad set of electoral outcomes and indicators of voter behavior such as voting for other parties, voter turnout, and protest vote. A few previous studies have considered the impact of immigration on voter turnout. Barone et al. (2016) find a negative effect while Steinmayr (2018) finds no effect. Dustmann et al. (2016) find a positive effect but only in municipal elections, whereas I find an increase in turnout in context of the national elections. As far as the protest vote is concerned, the only other paper that considers it is Barone et al. (2016). While they find an increase in the share of invalid ballots in response to immigrant inflow, I find no effect on the protest vote.

Fourth, I explore a unique setting which is distinct from previous studies. Before the 2004 EU enlargement, Finland was a country with minimal immigrant inflow and very low popularity of the far-right party. However, the study period (2006-2015) is characterized by a significant increase in both the immigrant share and the Finns Party vote share on the national level. The negative local

effect of foreign migration on Finns Party's vote share that I find therefore stands in stark contrast with the strong positive correlation observed on the national level.

The paper is organized as follows: Section 2 discusses the background. In Section 3, I describe the data and identification strategy. Results are presented in Section 4. Section 5 discusses the potential mechanisms. Section 6 concludes.

2.2 BACKGROUND

2.2.1 THE FINNS PARTY

The Finns Party (previously known as the True Finns; Finnish: *Perussuomalaiset*, PS) was the single far-right party in Finland since its establishment in 1995 until it split into two in mid-2017. In 1997, its first chairman, Raimo Vistbacka, was replaced by Timo Soini who led the party until 2017. Following a series of unsuccessful elections, the party made a break-through into the mainstream Finnish politics during the 2009 European election when it gained 9.79% of total votes. In 2015 parliamentary election, the Finns Party finished as a runner-up and for the first time formed a coalition government with the Centre Party and the National Coalition Party. Soini became the Minister of Foreign Affairs and the Deputy Prime Minister of Finland. In June 2017, following the election of new a chairman, Jussi Halla-aho, the party split into two: the Blue Reform remained in the coalition government while the Finns Party went into opposition.[6] My study period (2006-2015) ends two years before the split occurred. The following description applies to the period of Finns Party's uniform existence.

According to Norocel (2016), some Finnish scholars argue that the party is not necessary a clear-cut case of far-right due to its strong left-leaning political agenda on economic matters. However, as Westinen (2014) points out, there is little doubt that the Finns Party is a nationalist-populist movement which combines ethno-nationalism and anti-elitism, typical features of far-right parties in Europe (Mudde, 2007).[7] This view is shared by Arter (2010) who claims that the notion of true Finnishness (*suomalaisuus*) is the pre-eminent concept of Finns Party's ideology. Finally, Yla-

[6] The Finns Party (official website): `https://www.perussuomalaiset.fi/`

[7] According to Mudde (2007), European far-right parties share three common ideological features: ethno-nationalism, populism, and authoritarianism. Populism considers society to be ultimately separated into two groups, "the pure people" and "the corrupt elite", and argues that politics above all should be expression of the will of the people. Authoritarianism is defined as a disposition to glorify, to be subservient to and remain uncritical toward authoritative figures of the ingroup (hence the reason why far-right parties are typically led by authoritative leaders such as Le Pen, Wilders, Soini, etc.).

Anttila and Yla-Anttila (2015) underline the points mentioned above suggesting that the Finns Party's ideology combines a populist defense of a common man against corrupt elites, a defense of welfare state against market-led policies, and a nationalist defense of the sovereignty and unity of the Finnish people against immigration and federalist tendencies of the European Union. These points clearly suggest that the Finns Party can be considered a member of the European far-right family.

The party has a strong anti-immigration platform, as described in the following statement from its 2015 parliamentary election campaign pamphlet:

> *Immigration will change, irreversibly, the host country's population profile, disrupt social cohesion, overburden public services and economic resources, lead to the formation of ghettoes, promote religious radicalism and its consequences, and foster ethnic conflicts. [...] It can still be possible to avoid the immigration disasters of Sweden, France and the United Kingdom but it will require a determined policy and clear legislation (Source: The Finns Party's Immigration Policy, 2015).*

Moreover, according to the Chapel Hill Expert Survey (CHES) data, which describes policy and ideological positions of national political parties in the EU, the Finns Party has been the sole anti-immigrant party in Finland since 2006. As Table 22 suggests, throughout the study period, the party was consistently in favor of a tough immigration policy while strongly opposing multiculturalism (advocating for immigrant assimilation instead). In addition, immigration policy was a very salient topic in Finns Party's manifestos (Table 22, column 4). Table 22 also reveals that none of the other main parties were anti-immigrant throughout the study period.

2.2.2 OTHER POLITICAL PARTIES IN FINLAND

There are seven main political parties in Finland (other than the Finns Party): *Social Democratic Party (SDP)*, *Centre Party (Kesk)*, *National Coalition Party (Kok)*, *Green League (Vihr)*, *Swedish People's Party (SFP/RKP)*, *Christian Democrats (KD)*, and *Left Alliance (vas.)*. The first three (SDP, Kesk, Kok), each founded over a century ago, have traditionally been the strongest parties

regularly placing on top of the electoral lists.[8] SDP is a moderate center-left social democratic party, while Kesk is centrist and Kok center-right, both of them having a liberal-conservative ideology (source: European Election Database). Although none of the seven parties were anti-immigrant during the study period, two of them - Green League and Swedish People's Party - did have strong pro-immigration platforms. Indeed, as Table 22 shows, between 2006 and 2014, Vihr and SFP/RKP had low scores on both *Immig. policy position* and *Multiculturalism*, indicating an opposition to tough immigration policy as well as a preference for multiculturalism. Moreover, as with the Finns Party, Vihr and SFP/RKP both considered immigration policy to be a very important topic in political discourse (Table 22, column 4).

2.2.3 NATIONAL ELECTIONS IN FINLAND

Parliamentary elections

Parliament of the Republic of Finland (*Eduskunta*) is unicameral, composed of 200 members directly elected by people for a 4-year term. Seats in the parliament are distributed among 13 electoral districts (or constituencies) in proportion to their populations 6 months prior to election. This means that each constituency effectively holds its own parliamentary election. Candidates may be nominated by political parties or constituency associations (founded by at least 100 enfranchised persons from the same constituency). MPs are then chosen based on the number of votes they receive as well as the number of votes received by their party (or constituency association). Elections take place on the third Sunday in April, and voting can take place either in advance or on election day.[9] Eligible to vote are all Finnish citizens aged 18 or above regardless of their domicile (Ministry of Justice 2010).

Presidential elections

The President of the Republic of Finland is elected in a direct vote for a 6-year term. Each presidential candidate must be a native-born Finnish citizen, and no individual can stay in the office for more than 2 consecutive terms. Candidates are nominated by parties that have currently at least 1 seat in the parliament, or by constituency associations established by at least 20,000 people

[8] In recent years, before the 2017 split, the Finns Party briefly joined this "elite" club.

[9] An exception is the 2007 parliamentary election which was held on March 18 due to the 100th anniversary of the first Finnish parliamentary election (March 15-16, 1907).

entitled to vote. The election proceeds in one or two rounds, the second round being essentially a runoff between the two most successful candidates from the first round. The second round takes place only if no candidate gains more than 50% of all votes in round 1. Each presidential election is held on the fourth Sunday of January (round 1), with the second round taking place two weeks later. Voting eligibility is the same as in parliamentary elections; advance voting is also allowed (Ministry of Justice 2010).

European elections

As a member of the European Union, Finland can elect Members of the European Parliament (MEPs) who serve 5-year terms. The number of Finnish MEPs is determined by the ratio of Finnish population to the population of the whole EU (Finland has had 13 MEPs since 2009, 14 between 1999 and 2009, and 16 from 1996 to 1999). Candidates for the European Parliament are nominated by political parties or constituency associations (established by at least 2000 people), and voting proceeds as in the parliamentary elections. In contrast with parliamentary elections though, each candidate for an MEP enters the European election for the entire country. The election day is generally the second Sunday in June (Ministry of Justice 2010).[10]

2.2.4 IMMIGRATION INTO FINLAND

Historically, Finland has been characterized by emigration (Sarvimäki, 2011). From the end of the World War II until the early 1970s, the country attracted very few migrants. Although immigration increased in the 1970s, throughout the 1970s and 1980s some 85 percent of immigrants were return migrants coming mostly from Sweden. A small number of refugees from Vietnam and Chile also arrived during this period (Triandafyllidou and Gropas, 2008). It was not until the 1990s that Finland experienced a major inflow of foreign citizens (Koivukangas, 2003). As Figure 2 suggests, the first significant wave of foreigners began arriving in 1991 and was caused by the dissolution of the Soviet Union and the civil wars in the (former) Yugoslavia and Somalia. Ingrian Finns from Russia and Estonia and asylum seekers from Yugoslavia and Somalia made up the largest

[10] Although there are exceptions: the 1996 election was held on October 20, while the 2014 election took place on May 25.

foreign immigrant groups in Finland throughout the 1990s (Koivukangas, 2003). Due (in part) to a restrictive refugee policy,[11] the fraction of population with foreign citizenship remained below 2% until 2003, one of the lowest in the EU during this period (Figure 3; Koivukangas 2003).

As Figure 2 depicts, migration flow of foreign nationals into Finland increased dramatically in the late 2000s. In May 2004, the European Union accepted ten new member states (EU8 plus Malta and Cyprus).[12] This historic enlargement was followed by the accession of Bulgaria and Romania (January 2007), and later Croatia (July 2013). Due to fears of mass migration of workers induced by the large economic disparities between East and West, EU member states agreed upon the so called *transitional restrictions*. These restrictions allowed each old member to postpone the opening of its labor market to the new members for a period of up to seven years. Finland opened its labor market to Malta and Cyprus immediately in 2004, but chose to wait until May 2006 for all EU8 countries. For Bulgaria, Romania, and Croatia, the work-related immigration restrictions were lifted immediately upon their EU accession in January 2007 and July 2013, respectively (Pytliková, 2014). Thus, while the 2004 enlargement already induced some inflow of foreigners (such as students) from Central and Eastern Europe, the two main immigration-inducing shocks were the 2006 and 2007 labor market openings. The period 2006 onwards is indeed the time of the largest immigrant inflow in Finnish history, and therefore it is the focus on this study (see Figure 2; Koivukangas 2003). As Figure 4 confirms, the vast majority of incoming foreigners during this time were European citizens, primarily economic migrants from the new EU member states in Central and Eastern Europe.

In the last couple of years, Finland has also witnessed a sizable inflow of asylum seekers from Northern Africa and Middle East. However, since the last national election in Finland took place in mid-2015, my study period ends at the onset of the recent European refugee crisis, before any significant number of asylum seekers arrived in Finland.

[11] The annual refugee quota was 500 throughout the 1990s. In 2001, the quota was raised by the Finnish Parliament to 750. In recent years, due to an ongoing civil war in Syria, Finland has admitted more than a thousand quota refugees per year (Source: Finnish Immigration Service).

[12] EU8 refers to the following countries: Czech rep., Poland, Hungary, Slovenia, Slovakia, Estonia, Latvia, and Lithuania.

2.3 DATA AND EMPIRICAL STRATEGY

2.3.1 DATA

The empirical analysis uses a municipality-by-election year panel dataset with 7 election years (2006-2015) and 297 municipalities. The following elections are used in the study: 2007, 2011, 2015 parliamentary elections; 2006, 2012 presidential elections (first round only); 2009, 2014 European elections. The Finns Party's candidate in both presidential elections was its leader, Timo Soini, who was eliminated in the first round in both cases. Municipal elections are not used in the analysis since any foreigner with a permanent residency in a given municipality is eligible to vote in that municipality's local election.[13] A similar concern arises with European elections since non-Finnish EU citizens with a municipality of residence in Finland are eligible to vote for Finnish MEPs (Ministry of Justice 2010). Figure 5 plots the distribution of the share of votes cast by non-Finnish EU citizens across all municipalities in the 2014 European election. The histogram shows that almost 35% of municipalities had no foreigners casting a vote.[14] Moreover, almost all municipalities are located below the 0.5% mark meaning the proportion of foreign votes cast in most cases was negligible. Histogram generated for the 2009 European election (available upon request) shows distribution that is even more skewed to the right. Nevertheless, as an additional robustness check I exclude the 2009 and 2014 European elections from the analysis.

Spatially, the analysis extends to all of mainland Finland; excluded are only the Åland Islands (16 municipalities). Åland is a Swedish-speaking autonomous region that belongs to Finland and is located between continental Finland and Sweden. Its population makes up roughly 0.5% of the country's total population (sources: Statistics Finland, Statistics and Research Åland). Although the region has its own parliament, the people of Åland also elect one member of the Finnish Parliament in every national parliamentary election. However, the Islands have their own political parties and so voting for the Finns Party is not an option. Moreover, since the region is not only linguistically but also culturally Swedish, it would not be appropriate to include these municipalities in the same analysis with the rest of the country.[15]

In past 12 years, the number of municipalities in Finland has been steadily shrinking to 313 (as

[13] Data on the number of foreign votes cast in local elections (overall and for individual parties) is not available.
[14] 102 out of 297 municipalities (34.3%) had exactly 0 foreign votes in 2014 European election.
[15] The Office of Åland website: `http://www.aland.ax/en/facts-about-aland/`.

of January 1, 2016). Municipality changes were mostly merges of two (or more) municipalities together. Information on all changes was provided by The Association of Finnish Local and Regional Authorities as well as Statistics Finland. The panel dataset is constructed using the 2016 municipality format. The dependent variable in the analysis is the Finns Party's share of valid votes. The independent variable of interest is the share of foreign citizens in a municipality. The analysis also includes the following municipality-specific time-varying controls that likely affect voting for the Finns Party: log of total population, population density (per km^2), share of females in adult population, share of population (25-64) with tertiary education, share of aged 65+ in adult population, ratio of skilled to unskilled labor (in population aged 20-64), total crime rate (per 100,000), unemployment rate and media household disposable income (per consumption unit). More details about the covariates are reported in Section A of the Appendix. All data comes from Statistics Finland's public-use StatFin database.

A potential pitfall with using election vote share is *naturalization*, a process through which most foreigners without family ties to Finnish citizens obtain Finnish citizenship. Since naturalized Finns are de facto foreigners, a significant number of votes from these individuals will contaminate the dependent variable. However, as Gozdecka (2013) points out, Finnish citizenship has been a rather exclusive good aimed at foreign nationals who have put substantial effort into finding employment in Finland, learning Finnish language, and integrating themselves into Finnish society. This is indeed reflected in the total number of Finnish citizenships granted (as a share of country's population), which in its peak in 2012 was only 0.17% and has been declining ever since.[16] Thus, although the problem with naturalization cannot be completely ruled out, anecdotal evidence suggests that the number of naturalized Finns is not high enough to alter the results.

2.3.2 BASELINE FIXED EFFECTS SPECIFICATION

The baseline empirical specification is the fixed effects model of the form:

$$\text{Far-right}_{i,t} = \alpha + \beta\ \text{Foreign}_{i,t} + X'_{i,t}\gamma + \lambda_t + \mu_i + \epsilon_{i,t} \tag{1}$$

[16] Statistics Finland: StatFin database (All vital statistics by area 1987-2015, Citizenships granted according to country of previous citizenship 1990-2015). This number includes citizenships granted via all means, including naturalization. Thus, if only naturalizations were counted, the number would be even lower.

where $Far\text{-}right_{i,t}$ is the Finns Party's share of valid votes in municipality i and election year t. All elections used in the estimation take place in the first half of the year. The independent variable of interest, $Foreign_{i,t} = \left(\frac{\#of\ Foreign\ Citizens_{i,t}}{Population_{i,2003}}\right)$, is the share of foreign citizens (as % of population in 2003) in municipality i and election year t. The foreign share is measured on the first day of the calendar year. As commonly done in immigration literature, I standardize the number of foreigners by the population in the base year of the IV (discussed later). Population at t is not used since it is likely endogenous to immigration. $X_{i,t}$ represents the set of municipality-specific time-varying controls mentioned earlier. Since covariate values at time t are potential mechanisms through which immigration affects far-right vote share, I include them as one calendar year lags instead. The main specification also includes a full set of municipality fixed effects (μ_i) to capture municipality-specific time-invariant determinants of Finns Party's vote share, and election year fixed effects (λ_t) to control for year-specific shocks that equally affect all municipalities (e.g. 2009 Eurozone sovereign debt crisis). Finally, the preferred specification also includes region-by-election year fixed effects to control for local business cycles and other year-specific shocks that affect equally all municipalities within the same administrative region. Table 2 provides the descriptive statistics for all variables.

OLS estimation of equation (1) will likely suffer from endogeneity issues arising from sorting among both natives and immigrants. An inflow of immigrants into a municipality may trigger an outflow of natives who face direct labor market competition (Borjas, 2006). Also, as immigrants move in, natives who are anti-immigrant for non-economic reasons may decide to leave. A disproportionate number of natives who leave might therefore consist of far-right voters, in which case the OLS estimate will be biased downwards. On the other hand, pro-immigrant natives who derive positive utility from living in a diverse community could decide to move in together with the immigrants. Such inflow of natives who arguably do not support the Finns Party would bias the OLS estimate downwards as well.

Immigrants may decide to avoid anti-immigrant far-right strongholds, or leave municipalities that become hostile towards them. This reverse causality would bias OLS downwards. As Borjas et al. (1996) suggest, immigrants may also cluster in areas with better socioeconomic conditions which are less supportive of the far-right, resulting in a downward bias as well. On the other hand, as Halla et al. (2017) point out, if a community is hit by a negative economic shock which depresses

housing prices, it may actually attract immigrants. If this shock also shifts voters' preferences to the far right, the resulting bias will be positive.

2.3.3 IDENTIFICATION

To identify the causal effect of interest, I employ instrumental variable approach using a "shift-share" IV (Altonji and Card, 1991). This instrument is based on an observation that immigrants tend to cluster in ethnic enclaves set up decades ago. My analysis uses a version of the instrument proposed by Orrenius and Zavodny (2015a). More specifically, I first determine the distribution of foreigners by continent of citizenship across mainland Finnish municipalities in 2003 (base year). Then, for each of the election years in 2006-2015, the total national[17] counts of foreign citizens are distributed according to the 2003 distributions. The instrument has the form:

$$\widehat{\text{Foreign}}_{i,t} = \frac{\sum_{j=1}^{6} \text{Foreign}_t^j * \text{Share in i}_{2003}^j}{\text{Population}_{i,2003}} \tag{2}$$

where $\widehat{Foreign}_{i,t}$ is the predicted share of foreign citizens in municipality i in election year t, $Foreign_t^j$ is the number of foreign citizens from continent j in mainland Finland in election year t, and *Share in* i_{1991}^j is the share of foreigners with continent of citizenship j in municipality i in 2003. As the summation indicates, immigrants are divided into 6 groups based on their citizenship (each groups roughly corresponds to a continent): EU27 Europe,[18] non-EU Europe, Africa, Asia, America (North, Central, and South America combined), and Oceania.

For the instrument to be valid, the predicted share of foreigners can affect Finns Party vote share only through its direct effect on the actual share of foreigners. 2003 is chosen as the base year because it precedes the 2004 EU enlargement and the subsequent inflow of Central and Eastern European migrants. Moreover, it marks a change in the composition of immigrants coming into Finland (from asylum seekers to economic migrants). Thus, conditional on covariates and fixed effects, the 2003 distributions are unlikely to be correlated with unobservable predictors of anti-immigrant attitudes and Finns Party popularity after 2006. As an additional robustness check, the IV analysis was re-estimated using 1991 as the base year (15 years before my study period). Since

[17] The term "national" refers to mainland Finland.

[18] This definition includes all 27 current members of the European Union (excluding Finland).

immigration of foreigners into Finland was minimal before 1991, the results from this alternative IV estimation serve as further evidence validating the exclusion restriction of the original instrument.

The IV estimates could still be invalid if there is a persistence of municipality-specific trends in pro-immigrant and/or anti-immigrant attitudes. The inclusion of the region-by-election year fixed effects mitigates this concern. In addition, I conduct a placebo test with pre-period election data (1996-2003) to directly test for such persistence. Finally, if natives "vote with their feet" and if this native sorting after 2006 is correlated with the baseline immigrant distributions, IV estimate will be biased. I therefore re-estimate equation (1) using the same IV approach, but larger geographical units (administrative subregions and regions). A significant change in the IV coefficient will indicate a presence of such bias. In addition, I conduct a direct test of native sorting using an approach proposed in Peri and Sparber (2011).

2.4 RESULTS

2.4.1 MAIN RESULTS

Table 3 presents main results. First three columns include OLS estimates of eq. 1 while the last three contain IV coefficients. The coefficient of interest is negative and remains significant at 5% in all specifications. The OLS estimates are fairly small in magnitude (5-11% with respect to the sample mean). The IV coefficients are roughly 2-5 times larger than OLS depending on the specification. First-stage results (Table A.1) confirm the instrument is strong; the Kleibergen-Paap rk Wald F-statistic (22.77) exceeds the Stock-Yogo 10% maximum IV size critical value even in the full specification. The IV coefficient from the preferred specification (last column) suggests that one percentage point increase in the share of foreigners in a municipality (68% of the mean) decreases Finns Party's electoral support by about 3.35 percentage points (28% of the mean). Put differently, one standard deviation increase in the foreign share decreases Finns Party's vote share by 0.58 standard deviations. The large magnitude implies an economically important effect.

The difference between the OLS and IV estimates is likely caused by attenuation bias arising from measurement error in the main independent variable. As Angrist and Pischke (2008) explain, if the measurement error is random, the OLS coefficient will be biased towards zero. An instrumental variable approach can correct for this bias. In context of immigration, Aydemir and Borjas (2011)

suggest that the attenuation bias arising from even a small measurement error can be significant if the model includes a large number of fixed effects. That is indeed the case here. Results in Section 4.4 lend further credibility to the idea of attenuation bias. Using the same IV to estimate the effect of immigration on other electoral outcomes (e.g. voter turnout, other parties' vote share), I find that in every specification, the OLS estimate is attenuated towards zero, regardless of the coefficient sign (see Section 4.4 for more details).

2.4.2 ROBUSTNESS CHECKS AND PLACEBO TEST

I conduct a series of robustness checks to test the sensitivity of the IV estimates. Results are reported in Appendix B. Using 1991 (instead of 2003) as the base year for the instrument slightly increases the magnitude of the IV estimates, although the standard errors increase as well due to a weaker first stage (Table A.2). In addition, the IV estimates are robust to the exclusion of European elections (Table A.3), the exclusion of 9 largest municipalities as potential outliers (Table A.4), and the estimation of a first-difference specification instead of the fixed-effects model (Table A.5). Finally, I re-estimated the model separately for each election type (parliamentary, presidential, European). The coefficient on immigrant share is negative, statistically significant, and with comparable magnitudes across the three specifications suggesting that the negative effect is not limited to a specific type of national election (Table A.6).

A natural concern with a shift-share instrument is that persistent trends at the municipality level may be correlated both with the IV and the outcome of interest. To partially address this endogeneity concern I conduct a placebo test using pre-period election data. In particular, I estimate the following cross-sectional specification using OLS:

$$\Delta\text{Far-right}_{i,1996-2003} = \alpha + \beta\ \Delta\widehat{\text{Foreign}}_{i,2006-2015} + \phi_r + \epsilon_i \tag{3}$$

where $\Delta \textit{Far-right}_{i,1996-2003}$ is the level change (or % change) in Finns Party's vote share in municipality i between 1996 and 2003, and $\Delta\widehat{\textit{Foreign}}_{i,2006-2015}$ is the level change (or % change) in the IV (using 2003 as baseline) in municipality i between 2006 and 2015. The regression also controls for region fixed effects (ϕ_r). Results of the placebo test are presented in Table 4. Reassuringly, a lack

of any statistically significant correlation supports the validity of the IV's exclusion restriction.

2.4.3 DIRECT TEST OF NATIVE SORTING

As noted earlier, another threat to identification comes from immigrant-induced native mobility. Different specifications have been suggested to test for it.[19] Peri and Sparber (2011) evaluate each of these specifications using simulated data and find that some of them have built-in biases. They suggest estimating the following model which is based on Card (2007):

$$\left(\frac{\mathrm{N}_{i,t}-\mathrm{N}_{i,t-1}}{\mathrm{Pop}_{i,t-1}}\right)=\alpha+\beta\left(\frac{\mathrm{F}_{i,t}-\mathrm{F}_{i,t-1}}{\mathrm{Pop}_{i,t-1}}\right)+\phi_i+\lambda_t+\epsilon_{i,t} \tag{4}$$

where $N_{i,t}$ is the number of Finnish citizens in municipality i and election year t, and $N_{i,t-1}$ is the number of Finnish citizens in i in $t-1$ (i.e. one calendar year before t). Similarly, $F_{i,t}$ and $F_{i,t-1}$ refer to the number of foreign citizens in i at t and $t-1$, respectively. $Pop_{i,t-1}$ is the total population in municipality i in $t-1$. The specification also controls for municipality fixed effects (ϕ_i) and election year fixed effects (λ_t). The coefficient of interest is β and its interpretation is as follows: $\beta > 0$ means there is an attraction between natives and immigrants, while $\beta < 0$ suggests a native outflow in response to the inflow of immigrants. Sá (2014) further points out that OLS estimation of eq. (4) will likely lead to an upward bias in the estimate of β, since unobserved factors that attract immigrants into municipality could also attract natives. Therefore, I estimate (4) using the same shift-share instrument as before (with minor adjustments).[20] Eq. (4) is estimated using both municipality-level and subregional-level data, where 67 subregions approximate local labor markets. Results (OLS and IV) are presented in Table 5. All four coefficients are insignificant suggesting that immigration did not induce native mobility.

Another way to confirm that native sorting does not bias the main IV estimates is to re-estimate eq. (1) using larger geographical units (subregions and regions). Mainland Finland consists of 18 administrative regions. The required underlying assumption states that if natives are mobile, they

[19] Among others Borjas (2006), Card (2001), Card (2007), and Cortes (2008).

[20] The instrument distributes national net flows of immigrants by continent between $t-1$ and t, based on the 2003 distributions. The predicted net flow of immigrants in i between $t-1$ and t is then standardized by population in $t-1$.

will sort within regions but not across regions (due to family ties and other costs of moving). Estimation results are shown in Table A.7. All three estimates are negative and statistically significant. The regional-level coefficient is smaller in magnitude than its municipality-level counterpart, but the coefficients are not statistically different from one another. The subregional-level coefficient, if anything, is larger in magnitude than the municipality-level estimate. This mitigates the concern that native sorting and spillover effects confound my analysis.

2.4.4 IMMIGRATION AND OTHER ELECTION OUTCOMES

An important aspect of any election study is understanding which parties benefit from one party's loss of votes. In context of my analysis, this means finding out which parties gained the votes Finns Party lost due to immigration. Thus, I re-estimated eq. (1) using vote share of every main party as the dependent variable.[21] Table 6 presents the results. As expected, the two parties that gained votes were the pro-immigration Green League and Swedish People's Party. Their positive coefficients indeed add up to the size of the Finns Party's negative coefficient. Moreover, the relative gains of these two parties were large, especially for the Swedish People's Party (57% with respect to the sample mean).

Finally, to obtain a complete picture of the native voting behavior, it is important to consider the impact of immigration on voter turnout (share of eligible voters who cast ballot in election) and protest vote (fraction of total ballots that are invalid). As Table 7 shows, foreign municipal in-migration increased voter turnout although the effect was small (3%). Protest vote was not affected. This suggests immigration induced natives' participation in the election process, potentially activating anti-far-right voters who would otherwise not vote. It is also worth noting that the OLS counterparts to all coefficients in Tables 6 and 7 are smaller in magnitude (see Tables A.8 and A.9), suggesting the presence of attenuation bias due to measurement error in the share of foreign citizens.

2.5 HETEROGENEITY ANALYSIS AND POTENTIAL MECHANISMS

In order to shed some light on the potential mechanisms through which immigration reduces Finns Party's support, I test for the heterogeneity in the effect with respect to various initial conditions.

[21] Left Alliance is not considered as it did not participate in all elections during the study period.

In particular, first, the sample is split based on the values of initial conditions (i.e. population, population density, immigrant share, Finns Party's vote share, share of tertiary educated, skill ratio, median household income, unemployment rate)[22] into those above and those below the median. Then, separately for each initial condition, the share of foreign citizens is interacted with the above-median/below-median dummies. All regressions are estimated using the same IV as before. Results are reported in Table 8. The strong negative effect is present across municipalities regardless of their initial size, density, level of education, skill ratio, median income, and unemployment rate. The coefficient is remarkably stable across different specifications both in terms of its magnitude and statistical significance. However, columns (3) and (4) do show some heterogeneity in the effect, since in both cases, the hypothesis that the two coefficients are equal can be rejected. Column (4) suggests that municipalities with higher pre-existing support for the far-right experienced a smaller reduction in anti-immigrant attitudes than the municipalities where Finns Party was less popular to begin with. However, the effect of immigration on high-nationalist municipalities is still negative and sizable, suggesting that inflow of immigrants even into the far-right "strongholds" can ameliorate natives' attitudes towards foreigners.

The most interesting result of Table 8 is presented in column (3). The negative effect of immigration on Finns Party's vote share is found only in municipalities with high pre-existing immigrant share. In other words, places where natives are already living side-by-side with immigrants are the ones that experience a reduction in anti-immigrant attitudes as a result of further immigrant inflow.

Another potential mechanism that could explain my main finding is the welfare-state channel. There are two possible policy scenarios through which immigration affects welfare system of the host country. On one hand, migration can lead to changes in tax rates while per capita benefits are kept constant (*tax adjustment model*). On the other hand, tax rates might remain unchanged while per capita benefits adjust (*benefit adjustment model*). Under both scenarios, if immigrants are, on average, net contributors to the system (i.e. their tax contributions exceed the amount of social assistance they receive), both high-skilled and low-skilled natives will likely benefit from the presence of foreign workers due to a positive welfare spillover (Facchini and Mayda, 2012, 2009). Therefore, an influx of such immigrants can ameliorate natives' attitudes towards them, and thus

[22] Measured at the beginning of 2004. Finns Party's vote share is taken from 2003 parliamentary election since 2004 European election took place after the EU enlargement.

make natives less supportive of the anti-immigrant Finns Party.

In the absence of any individual-level data on immigrant tax contributions and social assistance program take-up, I turn to municipality-level data instead. Using data from 2006-2010 (including non-election years), I consider the effect of immigration on municipal tax revenue and spending.[23] The analysis uses the same IV as the main estimation. I find a small positive effect of municipal in-migration of foreign citizens on per capita personal income tax revenue (2.5%), although the coefficient is statistically significant only at 10% (Table 9, column 2). On the other hand, there is clearly no effect of immigration on per capita property tax revenue or corporate tax revenue (Table 9, columns 3 and 4).

The provision of social welfare in Finland is delegated to individual municipalities (source: Ministry of Social Affairs and Health). As Hytti and Paananen (2003) explain, immigrants with a resident permit valid for at least a year have the same rights to social security (i.e. unemployment benefits, family benefits linked to childbirth and child-rearing, and income support) as the native population. As Table 9, column (5) suggests, immigration had virtually no effect on municipal per capita spending on social and health care services. In addition, there is no effect of immigration on per capita spending on education and cultural activities. These findings suggest that an inflow of foreigners into a municipality did not overburden the provision of social welfare and other public services. Together with the positive effect on municipal income tax revenue, this suggests that welfare-state channel appears to a plausible mechanisms explaining the main finding.

2.6 CONCLUSION

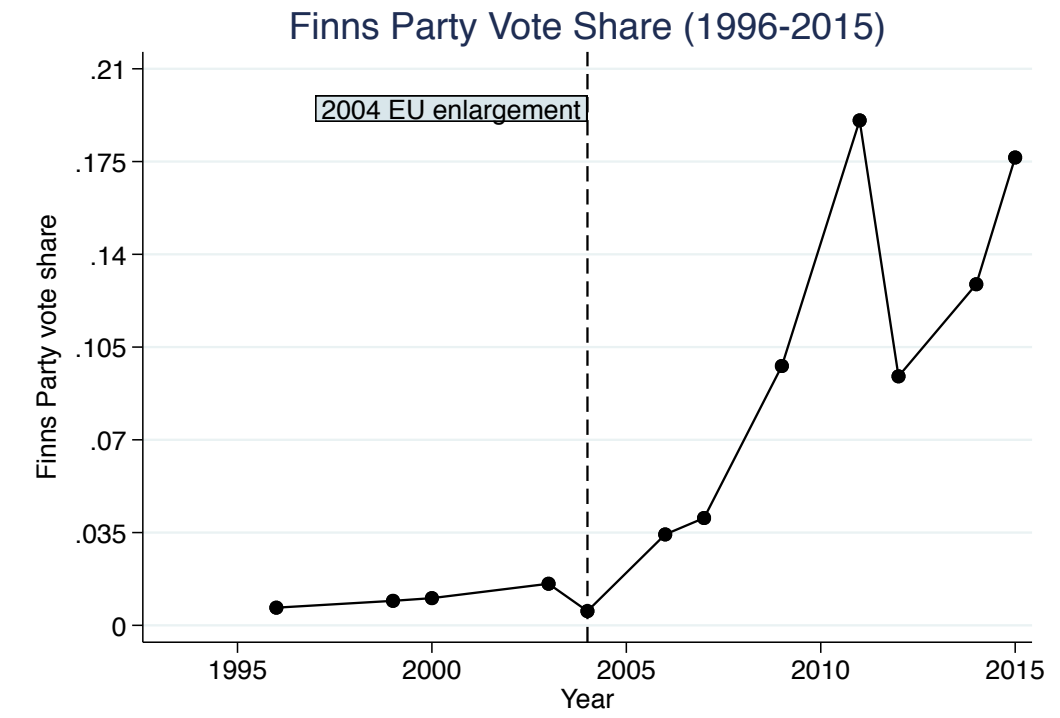
This paper uses a novel panel dataset to study the effect of immigration on voting for the far-right Finns Party in Finland. Using instrumental variable approach based on previous settlement patterns of immigrants, I show that municipal in-migration of foreign citizens has a statistically significant and sizable negative effect on Finns Party's electoral support. In particular, one percentage point increase in the share of foreign citizens in municipality decreases Finns Party's vote share by 3.5 percentage points (28% of the mean). This result runs contrary to most findings in the previous literature. Placebo test using data from a pre-period suggests that the negative

[23] Data comes from Statistics Finland's database titled *Economic data reported by municipalities and joint municipal boards*. Only limited data is available after 2010.

effect is not driven by persistent trends at the municipality level. The votes Finns Party loses due to immigration are captured by the two pro-immigration parties - the Green League and the Swedish People's Party. In addition, immigration increases voter turnout while protest vote remains unaffected. The main result is robust to heterogeneity with respect to a number of initial socio-economic conditions such as median population, level of education, and unemployment rate. However, there is some effect heterogeneity with respect to initial far-right support and immigrant share. Places that started with above-median far-right vote share experienced a smaller reduction in Finns Party's support due to immigration, although the estimated effect in these municipalities is still negative and statistically significant. In addition, immigration reduced far-right popularity only in municipalities with above-median initial immigrant share suggesting that the level of initial immigrant exposure matters. Finally, I provide some evidence for welfare-state channel as a potential mechanism through which immigration affects voting for the far-right. In particular, I find that foreign migration increases per capita municipal personal income tax revenue, while per capita spending on social services, health care, and education remain unaffected.

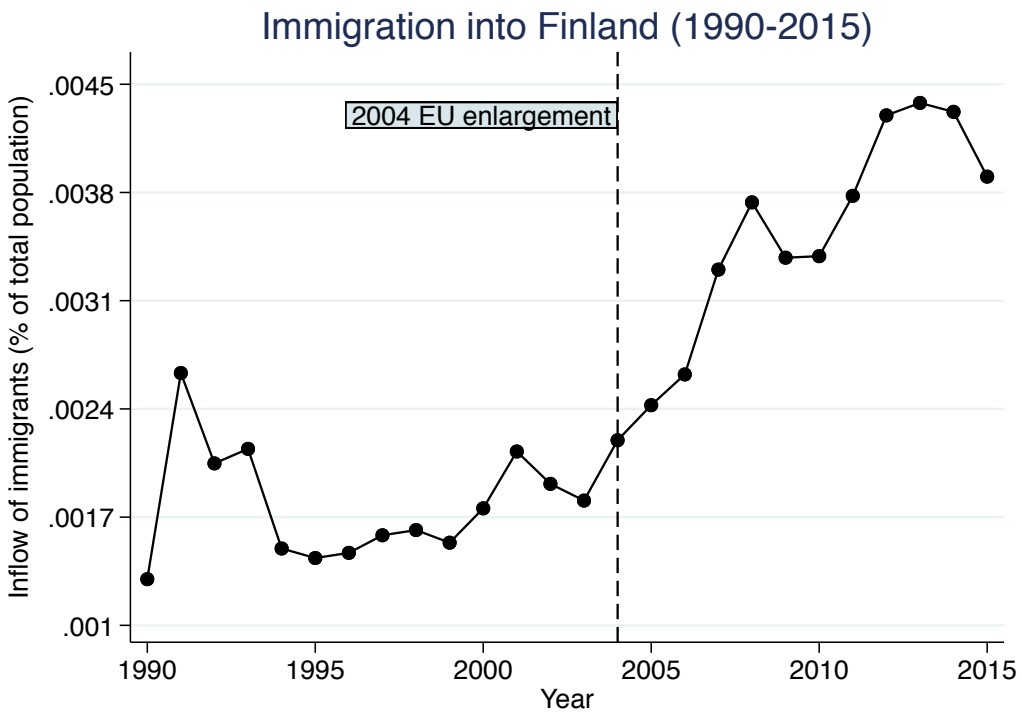
Given the serious nature of the threat far-right parties pose to the European integration process, Europe's security (with respect to the ongoing Russian aggression), and potentially even the future of liberal democracy, the role of far-right parties in Western societies remains one of the most important topics of the public debate in Europe today. This paper contributes to the debate by presenting a unique case study showing that under some conditions, local immigrant inflow can actually reduce far-right popularity. To better understand the complexity of the relationship between immigration and far-right voting, future research needs to carefully address the interplay between micro-level and macro-level exposure to immigrants, and how these two, independently and together, affect far-right popularity.

Figure 1: Finns Party's Vote Share (All of Finland), 1996-2015



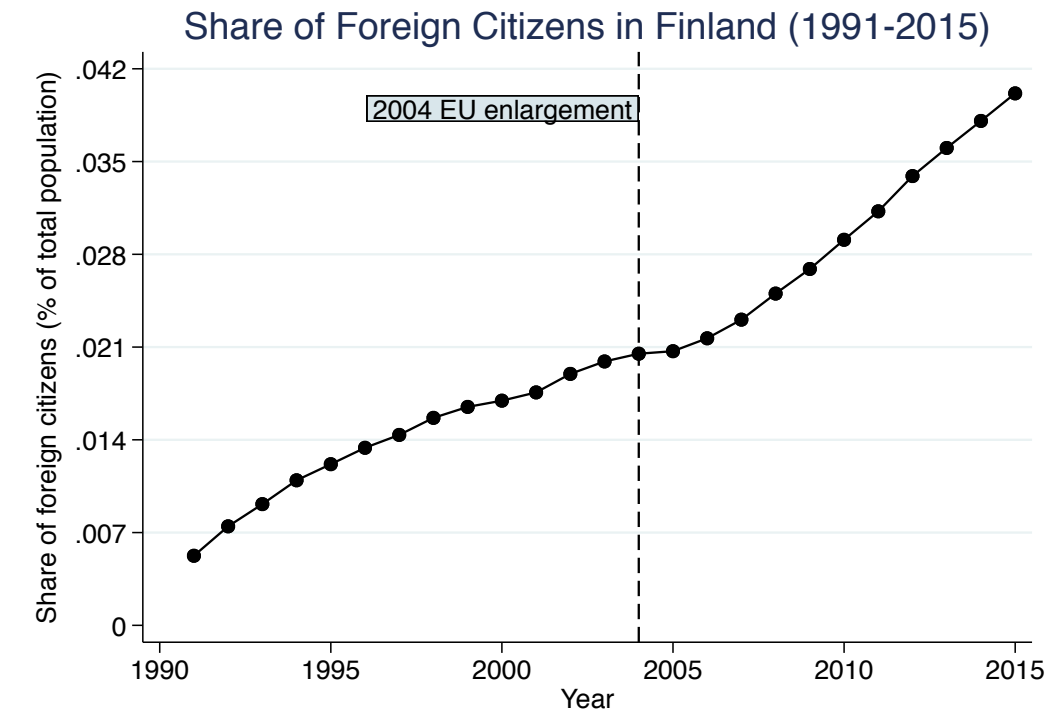
Notes - Data comes from Statistics Finland's StatFin database.

Figure 2: Yearly Inflow of Immigrants with Foreign Citizenship: 1990-2015



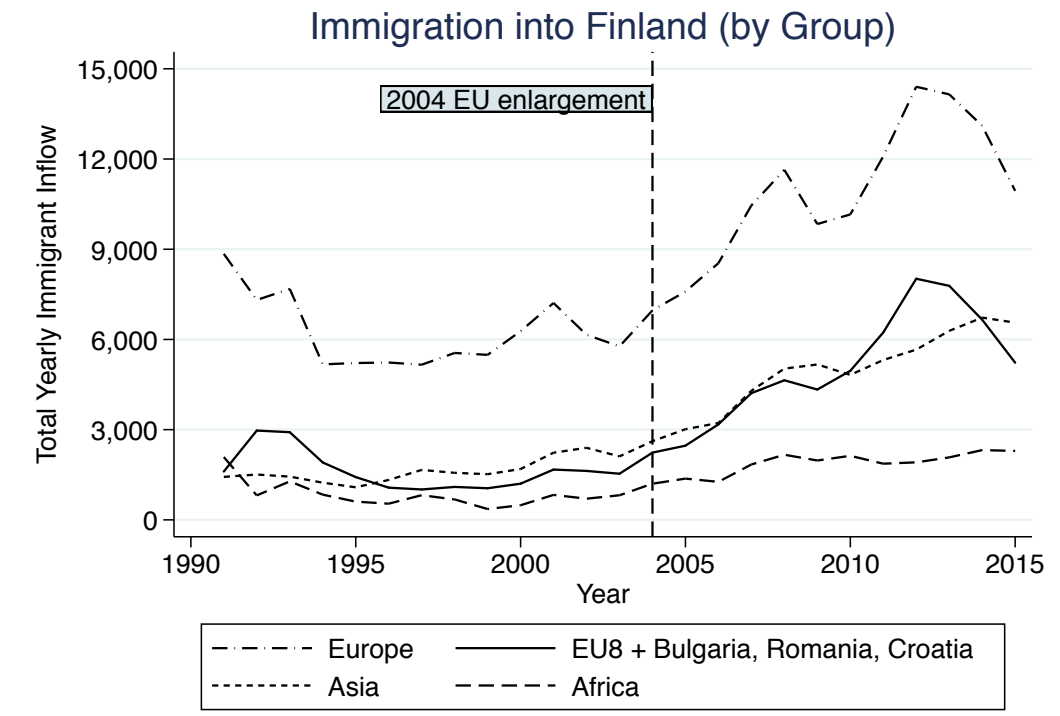
Notes - Data comes from Statistics Finland's StatFin database.

Figure 3: Share of Foreign Citizens (% of Total Population) at the Beginning of the Year, 1991-2015



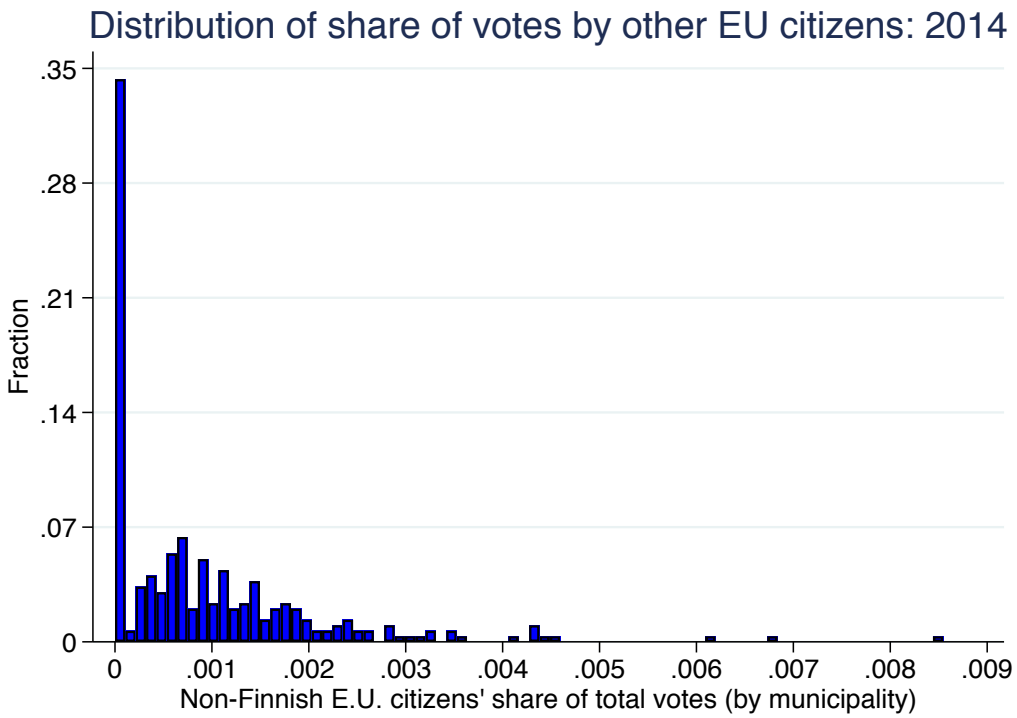
Notes - Data comes from Statistics Finland's StatFin database.

Figure 4: Yearly Inflow of Immigrants by Citizenship, 1991-2015



Notes - Data comes from Statistics Finland's StatFin database.

Figure 5: Distribution of Non-Finnish EU Citizens' Vote Share (2014 EU Election)



Notes - Data comes from Statistics Finland's StatFin database.

Table 1: Immigration Position & Salience - Main Political Parties in Finland (2006-2014)

Party	Election Year	Immig. policy position	Immig. policy salience	Multiculturalism
Finns Party	2006	8.11	8.22	7.89
	2010	9.1	8.9	9.1
	2014	9	-	9.38
Vihr	2006	1.56	5.89	2.67
	2010	2	7.1	2.1
	2014	1.38	-	1.25
SFP/RKP	2006	2	5.78	2.89
	2010	2.2	6.7	2.4
	2014	2.75	-	2.13
Kok	2006	5	4.33	5.56
	2010	5.8	4.5	5.5
	2014	5.13	-	5.25
Kesk	2006	5.67	3.89	5.67
	2010	5.8	4.6	6.5
	2014	5.63	-	6.25
SDP	2006	4.78	3.78	5.11
	2010	5.3	4.3	5.6
	2014	4.13	-	4
KD	2006	5.11	4.67	6
	2010	6	5.56	6.89
	2014	6.14	-	7.29
vas.	2006	3.11	4.56	4
	2010	3.7	4.9	4.3
	2014	2.88	-	2.25

Notes - *Immig. policy position* - position on immigration policy (0 - 10; 0 - "strongly opposes tough policy"; 10 - "strongly favors tough policy"). *Immig. policy salience* - importance/salience of immigration policy (0 - 10; 0 - "not important at all"; 10 - "extremely important"). *Multiculturalism* - position on integration of immigrants and asylum seekers (0 - 10; 0 - "strongly favors multiculturalism"; 10 - "strongly favors assimilation"). *Vihr* - Green League; *SFP/RKP* - Swedish People's Party; *Kok* - National Coalition Party; *Kesk* - Centre Party; *SDP* - Social Democratic Party; *KD* - Christian Democrats. Data comes from the 1999-2014 Chapel Hill Expert Survey (CHES) trend file.

Table 2: Descriptive Statistics

	Mean	Standard deviation	Min	Max
Finns Party's vote share	0.120	0.076	0.001	0.534
Share of foreign citizens (% of population in 1991)	0.014	0.014	0.000	0.142
Population	17,895.13	44,697.37	763	612,664
Population density (per km^2)	56.93	222.74	0.17	3,051.04
Share of females in adult population	0.499	0.014	0.438	0.543
Share of population (25-64) with tertiary education	0.272	0.075	0.118	0.694
Share of aged 65+ in adult population	0.264	0.056	0.113	0.460
Ratio of skilled to unskilled labor	3.44	1.10	1.35	8.93
Total crime rate (per 100,000)	5,633.45	3,130.57	1,071.26	63,930.13
Unemployment rate	0.119	0.043	0.028	0.288
Median household disposable income (EUR)	20,572.79	2,538.48	14,765	36,799

Notes - Number of observations: 2,079. Data comes from Statistics Finland's StatFin database.

Table 3: Main Results

	(OLS) Finns Party	(OLS) Finns Party	(OLS) Finns Party	(IV) Finns Party	(IV) Finns Party	(IV) Finns Party
Share of foreign citizens	-0.659*	-1.284***	-0.656*	-1.464***	-4.103***	-3.351***
(% of population in 2003)	(0.300)	(0.341)	(0.303)	(0.373)	(0.809)	(0.936)
Municipality/Election Year FE	YES	YES	YES	YES	YES	YES
Time-varying controls (lag)		YES	YES		YES	YES
Region FE x Election Year FE			YES			YES
Observations	2079	2079	2079	2079	2079	2079
Adjusted R-squared	0.832	0.836	0.880	-	-	-
Mean of dep. variable	12%	12%	12%	12%	12%	12%
Std. dev. of dep. variable	7.56%	7.56%	7.56%	7.56%	7.56%	7.56%
Kleibergen-Paap rk Wald F-stat.	-	-	-	62.32	34.53	22.77

Notes - Standard errors in parentheses, clustered at municipality level. Based on slope estimate in the last column, 1 std. dev. increase in share of foreign citizens decreases FP vote share by 4.36 p.p. (58% of its std. deviation). Time-varying controls: log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Table 4: Placebo Test (OLS)

	Δ Finns Party (1996-2003)	% Δ Finns Party (1996-2003)
Δ IV (2006-2015)	0.220	
	(0.179)	
% Δ IV (2006-2015)		0.131
		(0.479)
Region FE	YES	YES
Observations	297	294
Adjusted R-squared	0.194	0.264

Notes - Δ *Finns Party (1996-2003)* - level change in Finns Party's share of valid votes between 1996 and 2003. *%* Δ *Finns Party (1996-2003)* - percentage change in Finns Party's share of valid votes between 1996 and 2003. Δ *IV (2006-2015)* - level change in the predicted share of foreign citizens between 2006 and 2015. *%* Δ *IV (2006-2015)* - percentage change in the predicted share of foreign citizens between 2006 and 2015. Robust standard errors in parentheses. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Table 5: Direct Test of Native Mobility

	OLS Native Net Flow (municipality)	IV Native Net Flow (municipality)	OLS Native Net Flow (subregion)	IV Native Net Flow (subregion)
Immigrant Net Flow (municipality)	0.118	0.709		
	(0.155)	(1.104)		
Immigrant Net Flow (subregion)			0.102	-1.894
			(0.207)	(1.423)
Observations	2079	2079	469	469
Kleibergen-Paap rk Wald F-stat.	-	18.53	-	14.91
Anderson-Rubin chi-sq. test p-val.	-	0.521	-	0.117

Notes - *Native Net Flow* - yearly net flow of Finnish citizens (% of population at $t-1$). *Immigrant Net Flow* - yearly net flow of foreign citizens (% of population at $t-1$). Standard errors in parentheses, clustered at respective levels (municipality, subregion). First two columns control for municipality fixed effects and election year fixed effects, while the last two columns control for subregion fixed effects and election year fixed effects. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Table 6: Immigration and Election Outcomes (All Main Parties)

	(IV) Finns Party	(IV) Vihr	(IV) SFP/RKP	(IV) Kok	(IV) Kesk	(IV) SDP	(IV) KD
Share of foreign citizens	-3.351***	1.159***	2.303*	-0.900†	0.645	-1.013	-0.317
(% of population in 2003)	(0.936)	(0.295)	(1.130)	(0.527)	(0.475)	(0.833)	(0.251)
Observations	2079	2079	2079	2079	2079	2079	2079
Mean (dep. var.)	12%	5%	4.07%	17.4%	33.4%	17.5%	3.95%
Std. dev. (dep. var.)	7.56%	4.36%	13.6%	10%	16.8%	12.6%	3.38%
Kleibergen-Paap rk Wald F-stat.	22.77	22.77	22.77	22.77	22.77	22.77	22.77

Notes - *Finns Party* - Finns Party's share of valid votes; *Vihr* - Green League's share of valid votes; *SFP/RKP* - Swedish People's Party's share of valid votes; *Kok* - National Coalition Party's share of valid votes; *Kesk* - Centre Party's share of valid votes; *SDP* - Social Democratic Party's share of valid votes; *KD* - Christian Democrats' share of valid votes. Standard errors in parentheses, clustered at municipality level. All regressions control for municipality fixed effects, election year fixed effects, region-by-election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Table 7: Immigration and Voter Turnout, Protest Vote

	(IV) Voter turnout	(IV) Protest vote
Share of foreign citizens	1.711**	0.021
(% of population in 2003)	(0.530)	(0.025)
Observations	2079	2079
Mean (dep. var.)	59.7%	0.51%
Std. dev. (dep. var.)	15.4%	0.24%
Kleibergen-Paap rk Wald F-stat.	22.77	22.77

Notes - *Voter turnout* - share of eligible voters who cast ballot in election. *Protest vote* - share of invalid ballots. Standard errors in parentheses, clustered at municipality level. Both regressions control for municipality fixed effects, election year fixed effects, region-by-election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Table 8: Heterogeneity Analysis

	(1) Finns Party (Population)	(2) Finns Party (Popul. Dens.)	(3) Finns Party (Immig. Share)	(4) Finns Party (Vote Share)	(5) Finns Party (Education)	(6) Finns Party (Skill Ratio)	(7) Finns Party (Income)	(8) Finns Party (Unemploy.)
ForeignSh x Above Med	-4.131***	-3.985***	-3.289***	-3.468***	-4.052***	-4.271***	-4.113***	-4.176***
	(0.814)	(0.847)	(0.740)	(0.650)	(0.965)	(0.871)	(0.847)	(0.978)
ForeignSh x Below Med	-4.747***	-4.803***	-0.774	-4.901***	-3.902*	-4.933***	-4.174*	-4.097***
	(1.193)	(0.810)	(1.348)	(0.888)	(1.921)	(1.343)	(1.705)	(0.808)
p-value (F-test coef. are equal)	0.44	0.26	0.01	0.01	0.90	0.41	0.96	0.89
Observations	2079	2079	2079	2079	2079	2079	2079	2079
Mean (dep. var.)	12%	12%	12%	12%	12%	12%	12%	12%
Std. dev. (dep. var.)	7.56%	7.56%	7.56%	7.56%	7.56%	7.56%	7.56%	7.56%
First-Stage F-stat.	11.58	18.58	17.52	16.16	12.25	8.191	20.12	21.29

Notes - *Finns Party* - Finns Party's share of valid votes. *ForeignSh x Above Med* - interaction between share of foreign citizens and above-median dummy. *ForeignSh x Below Med* - interaction between share of foreign citizens and below-median dummy. Above/below-median dummies determined by following initial conditions (columns 1-8): population (2004), population density (2004), share of foreign citizens (2004), Finns Party's share of valid votes (2003), share of tertiary educated (2004), ratio of skilled to unskilled labor (2004), median household income (2004), unemployment rate (2004). Standard errors in parentheses, clustered at municipality level. All regressions control for municipality fixed effects, election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Table 9: Immigration and Municipality Tax Revenue & Spending (2006-2010)

	(IV) Total tax revenue	(IV) Income tax revenue	(IV) Property tax revenue	(IV) Corporate tax revenue	(IV) Social & health care spending	(IV) Edu & culture spending
Share of foreign citizens	39.08	56.04†	-2.43	-13.91	-11.70	-45.78
(% of population in 2003)	(43.74)	(33.74)	(13.20)	(20.06)	(142.7)	(43.42)
Observations	1485	1485	1485	1485	1485	1485
Mean of dep. variable	2697.7	2323.9	163.4	210.4	3235.5	1268.5
Std. dev. of dep. variable	527.4	467.5	123.9	134.4	711.6	260.2
Kleibergen-Paap rk Wald F-stat.	21.81	21.81	21.81	21.81	21.81	21.81

Notes - *Total tax revenue* - total municipality tax revenue (EUR per capita); *Income tax revenue* - municipality personal income tax revenue (EUR per capita); *Property tax revenue* - municipality property tax revenue (EUR per capita); *Corporate tax revenue* - municipality corporate income tax revenue (EUR per capita); *Social & health care spending* - municipality spending on social and health care services (EUR per capita); *Edu & culture spending* - municipality spending on education and cultural activities (EUR per capita). Standard errors in parentheses, clustered at municipality level. All regressions control for municipality fixed effects, election year fixed effects, region-by-election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, unemployment rate, median household income. Data comes from Statistics Finland's database titled *Economic data reported by municipalities and joint municipal boards*. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

3 THE EFFECTS OF DACA ON HEALTH INSURANCE, ACCESS TO CARE, AND HEALTH OUTCOMES

3.1 INTRODUCTION

Immigration continues to be a contentious topic in the political arena and the discussion of immigration reforms ignites the public debate in many advanced economies. In 2015, there were 11 million unauthorized immigrants in the U.S., representing 3.4% of the country's population and more than 5% of its labor force (Krogstad et al., 2015). Despite a recent slowdown in the influx of undocumented immigrants into the U.S. (source : PEW Research Center on Migration), regulating their status without further increasing illegal immigration remains a crucial challenge for the government. Legalization programs have been historically used as a policy tool to foster immigrants' integration and well-being. The debate on the costs and effectiveness has become even more relevant with the announced changes in the U.S. immigration policy that are currently under discussion.

Illegal immigrants constantly face the threat of deportation and the lack of work permits, access to credit, and access to government welfare programs (e.g. Medicaid, unemployment insurance, Social Security). These challenges can have detrimental effects on their human capital and productivity. Previous research shows that illegal immigrants have substantially lower hourly wage rates (for both genders), family income, and higher male labor force participation rates than their legal immigrant or native-born counterparts (Capps, 2007; Rivera-Batiz, 1999; Borjas, 2017). Studies also suggest that legalization of these immigrants can increase their probability of being employed, participate in the labor force (Kossoudji and Cobb-Clark, 2002; Devillanova et al., 2014; Amuedo-Dorantes and Antman, 2017; Pope, 2016), can lead to a significant growth in their wages (Rivera-Batiz, 1999) and contribute to private sector GDP (Edwards and Ortega, 2017). At the same time there is evidence that programs requiring employers to check workers' eligibility to work legally in the US reduce average hourly earnings among likely unauthorized Mexican immigrants (Orrenius and Zavodny, 2015b).

Most of the political discussion on immigrant legalization programs focuses on the potential costs

associated with regularizing undocumented immigrants. Yet little is known about how legalization affects public programs take-up. There are two notable exceptions. In a recent study, Cascio and Lewis (2016) explore the effects of the 1986 Immigration Reform and Control Act (IRCA) on Earned Income Tax Credit (EITC), and find that areas with higher applicant shares experienced relatively large increases in EITC transfers after IRCA. Borjas and Slusky (2017) use counterfactual analysis to estimate the additional public costs of legalizing the undocumented population by estimating models of disability as a function of medical conditions. However, to the best of our knowledge, there has been no analysis of the effects of immigrant legalization on health insurance coverage and health care use, and only a few recent studies have considered the effects on health outcomes (Venkataramani et al., 2017; Hainmueller et al., 2017). Our paper intends to fill this gap in the literature.

We focus on the effect of a large-scale immigration policy change - 2012 Deferred Action for Childhood Arrivals (DACA). DACA is an executive memorandum issued by President Obama on June 15, 2012, which provides certain unauthorized immigrants who came to the U.S. as minors with temporary reprieve from deportation and work authorization (DACA status can be renewed every two years). Although DACA does not provide a path to citizenship or a *de jure* legal status, one can think of it as a (temporary) *de facto* immigrant legalization.

To estimate the effects of DACA, we employ a difference-in-differences strategy exploiting the discontinuities in the DACA eligibility criteria. We confirm that DACA-eligible immigrants are more likely to participate in the labor force and some evidence of an increase in income (Pope, 2016). Using American Community Survey data, we document that DACA eligibility increased health insurance coverage. We show that DACA increased insurance coverage throughout the country by enhancing individual ability to purchase private plans. In California and New York (among the three states with the highest DACA-eligible population), where Medicaid eligibility was granted to DACA recipients, the increase in insurance coverage was mostly driven by an increase in public insurance coverage. Despite the increase in insurance coverage, using data from the National Health Interview Survey and the California Health Interview Survey, we find little evidence of significant effects on health care use, although after 2012, DACA-eligible individuals reported more mental health care visits. On the other hand, we provide evidence that DACA increased the likelihood of reporting a usual place of care and reduced the likelihood of deferring care due to financial

reasons. There is also some evidence of improvements in mental health outcomes and self-reported health. These effects are largely driven by subjects with income below the federal poverty level. Our findings are largely consistent with the evidence from the Rand Health Insurance Experiment and the Oregon Health Insurance Experiment (Aron-Dine et al., 2013; Finkelstein et al., 2012; Kamberg and Newhouse, 1985) showing that health insurance coverage had no or little effect on physical health, but possibly improved perceived health and mental health among the population at higher risk. The lack of significant impact on health care use is likely explained by the demographic characteristics of the DACA-eligible population.

Our paper is closely related to a handful of recent studies analyzing the economic effects of DACA. Pope (2016) documented the positive effects of DACA on the labor market opportunities of undocumented immigrants. There is also evidence that DACA reduced the likelihood of life in poverty (Amuedo-Dorantes and Antman, 2016), while Ortega et al. (2018) estimate that DACA increased GDP by almost 0.02%. The evidence on the effects of DACA on human capital is less conclusive. Amuedo-Dorantes and Antman (2017) and Hsin and Ortega (2017) show that DACA may have incentivized work over educational investment. However, using administrative data from California, Kuka et al. (2018) find evidence that DACA increased high school graduation rates and college attendance. Finally, a few recent studies examined the effects of DACA on health. Venkataramani et al. (2017) using data from the National Health Interview Survey provide evidence that economic opportunities and protection from deportation can have large positive effects on the mental health of undocumented immigrants, confirming associations found by Patler and Pirtle (2017). Using Medicaid claims data from Oregon, Hainmueller et al. (2017) find that children of DACA-eligible mothers had 50% fewer diagnoses of adjustment and anxiety disorder than children with non-eligible mothers. However, to the best of our knowledge, this is the first paper to provide a systematic analysis of the effects of DACA on insurance coverage, access to care, health care use, and health outcomes. Furthermore, our findings highlight that the effects of DACA on stress and mental health outcomes are concentrated at the bottom of the income distribution. Our findings mirror recent evidence on the health and mental health effects of local immigration enforcement (Wang and Kaushal, 2018).

The paper is organized as follows: Section 2 discusses the background. In Section 3, we illustrate the data and identification strategy. We present the results in Section 4. Section 5 concludes.

3.2 BACKGROUND, IDENTIFICATION STRATEGY, AND DATA

3.2.1 DEFERRED ACTION FOR CHILDHOOD ARRIVALS (DACA)

On June 15, 2012, President Obama issued an executive memorandum announcing the Deferred Action for Childhood Arrivals. It is the largest immigration reform since the approval of the Immigration Reform and Control Act (IRCA, 1986). The program targets up to 1.7 million unauthorized immigrants (Passel and Lopez, 2012) providing eligible applicants with a two-year renewable reprieve from deportation, work authorization, and a temporary Social Security number. DACA does not provide any form of legal immigrant status or a path to citizenship. The United States Department of Homeland Security's Citizenship and Immigration Services started accepting applications for the program on August 15, 2012.

To be eligible, applicants have to meet the following seven criteria: (1) no lawful status as of June 15, 2012; (2) under the age of 31 as of June 15, 2012; (3) entered U.S. before reaching 16th birthday; (4) continuously residing in the States since June 15, 2007; (5) physically present in the U.S. on June 15, 2012, and at the time of applying for DACA; (6) currently in school, with high school diploma (or GED), or honorably discharged veteran of the Coast Guard or Armed Forces of the United States; (7) not convicted of felony, significant misdemeanor, or three or more other misdemeanors. In addition, applicants have to be 15 years or older, and they are required to pay a processing fee of 495 dollars. DACA applicants have to provide evidence that they were living in the United States at the prescribed times, proof of education, and confirmation of their identities.[24] They also have to pass a background check, fingerprinting, and other checks that consider their identifying biological features. Applicants do not need legal representation. Officials can revoke DACA protection if individuals pose a threat to public safety or national security. About 1,500 people have had their deferral canceled due to a crime or gang-related activity or an admission to such activity. This is less than 0.2% of the total number of people accepted into the program (source: Immigration and Customs Enforcement).

As of September 2017, approximately 800,000 individuals were ever granted DACA. Out of these, 689,800 individuals were actively enrolled in the program in September 2017, while 40,000

[24] Documents showing individual arrived in the U.S. before 16th birthday include: passport with admission stamp, Form I-94, school records from U.S. schools attended. USCIS provides a complete list of accepted documents for each of the eligibility criteria: `https://www.uscis.gov/archive/consideration-deferred-action-childhood-arrivals-daca`

had adjusted to lawful permanent resident status and roughly 70,000 either had not renewed the status or had had their renewal request denied. There have been 606,264 renewal cases overall with only 4,703 of the requests denied. Most of current DACA recipients come from Latin America. Mexico is the major source country (548,000), followed by El Salvador (26,000) and Guatemala (17,700). 75% of DACA recipients live in 20 U.S. metropolitan areas. Los Angeles-Long Beach-Anaheim had the largest concentration of DACA enrollees (89,900 DACA recipients) followed by New York (47,200) and Dallas (36,700). A third of DACA recipients live in California (29%), while 16% of the enrolled in DACA are in Texas. Approximately 66% of the approved applicants are 25 or younger, 53% of them women, and 85% of them are single (USCIS and PEW Research Center).

The program was rescinded by President Trump's administration in September 2017, although this repeal of DACA has since been blocked by three preliminary injunctions issued by federal district court judges in California, New York, and D.C. As a result, since January 2018, Department of Homeland Security has been accepting only requests for renewal of the existing status, but not new applications. However, according to the most recent court ruling (August 2018), the administration has to fully restore the program (source: U.S. Customs and Immigration Service).

The main benefits of DACA for unauthorized immigrants are the deferral of deportation and the working permit. DACA recipients receive a Social Security Number which enables them to open a bank account and build credit history. Furthermore, most states (the only exceptions being Arizona and Nebraska) allow DACA recipients to obtain a driver's license. DACA does not provide access to federal welfare programs or federal student aid. However, DACA recipients are immediately eligible for Earned Income Tax Credit (upon meeting all other criteria) since Social Security Administration does not distinguish between DACA and non-DACA Social Security Numbers.

As with other unauthorized immigrants, no provisions of the 2010 Patient Protection and Affordable Care Act apply to DACA recipients. That means, DACA grantees cannot purchase health insurance through Marketplaces (not even at unsubsidized rates). In addition, DACA recipients are not eligible for federally-funded Medicaid program, and they are not eligible for the CHIPRA sec. 214 state option that covers lawfully residing children and/or pregnant women. However, all low-income undocumented immigrants do quality for federally-funded emergency Medicaid which covers basic live-saving procedures. As such, all unauthorized immigrants (including DACA recipients) are exempt from the individual responsibility requirement to have health insurance (Tiffany,

2016).

However, DACA grantees can obtain employer-sponsored insurance or buy health insurance directly from the carrier. Furthermore, a few states grant access to their state-funded Medicaid programs. In New York, DACAmented individuals became eligible for Medicaid immediately because of a 2001 State Court of Appeals ruling. In California, the expansion of Medi-Cal coverage to DACA recipients did not take place until January 2014 (Brindis et al., 2014). While other states also expanded Medicaid to grant access to DACA-eligible population (Minnesota, Massachusetts, D.C., Illinois, Oregon, Washington state), the expansion was limited or started after the end of our study period.[25]

California and New York are respectively the first and the third state with the largest DACA-eligible population.[26] In these two states, low-income DACA recipients are eligible for full scope state-funded Medicaid since they fall under the state definition of Permanently Residing in the U.S. under Color of Law (PRUCOL). For these reasons, we present separate analysis for California and New York.

3.2.2 IDENTIFICATION STRATEGY

To identify the effect of DACA, we follow the difference-in-differences approach proposed by Pope (2016) and Amuedo-Dorantes and Antman (2016), which exploits the discontinuities in the eligibility criteria of the DACA program and compares DACA-eligible with DACA-ineligible individuals, before and after the implementation of the reform. DACA-eligible individuals are defined as those who: (1) were under the age of 31 as of June 15, 2012; (2) have lived in the U.S. since June 15, 2007; (3) entered U.S. before reaching 16th birthday; (4) have at least a high school degree (or equivalent); (5) were born outside the U.S. and its territories; and (6) are not U.S. citizens.[27] [28]

[25] Minnesota extended eligibility for its state-funded MinnesotaCare program to DACA recipients in January 2017 (outside of our study period). In D.C., all low-income undocumented immigrants (regardless of DACA status) are eligible for the locally-funded Health Care Alliance program. In Washington state, only disabled DACA recipients are eligible for the state-funded Medical Care Services. And finally, California, New York, Illinois, Massachusetts, Oregon, and Washington state use state-only funds to provide health insurance coverage to all undocumented children.

[26] Migration Policy Institute's *Deferred Action for Childhood Arrivals (DACA) Data Tools*: `https://www.migrationpolicy.org/programs/data-hub/deferred-action-childhood-arrivals-daca-profiles`.

[27] Similarly, to define the DACA-eligible population in year 2012 and before, we restricted to those who were: (1) under the age 31 as of June 15 of the previous calendar year; (2) have lived in the U.S. for at least six years; (3) entered U.S. before reaching 16th birthday; (4) have at least a high school degree (or equivalent); (5) were born outside the U.S. and its territories; and (6) are not U.S. citizens.

[28] It is worth noting that as we only use a subset of the requirements listed in Section 2.1, we are comparing potentially eligible individuals. Furthermore, there may be measurement error bias due to the fact that some legal

In the ACS, our main estimation sample comprises all non-citizens ages 18-35 with at least a high school degree (or equivalent).[29] As noted by Pope (2016), since nearly 40% of the non-citizen sample in the ACS data are authorized immigrants (Baker and Rytina, 2014), the intent-to-treat effect of DACA will be approximately 1.6 times larger than the estimates from our DID estimation. Furthermore, it is worth remarking that not all DACA-eligible individuals applied and received DACA status. As of January 2018, 682,750 individuals obtained DACA status. The Migration Policy Institute estimates that there were 1,326,000 DACA-eligible individuals in 2017.[30] Based on these estimates the program participation rate is 52%, suggesting that the treatment on the treated effects could potentially be as much as 2 times larger than the intent-to-treat effects.

In the NHIS and CHIS, to ensure we have enough identification power, we extend the sample to all non-citizens and citizens aged 18-50 with at least a high school degree (or equivalent). While we use a larger control group to increase the sample size with these survey data, as a robustness check, we test the sensitivity of results to different sample choices. The main empirical specification has the following form:

$$\mathrm{Y}_{it} = \alpha + \beta_1 \mathrm{Post}_{it} + \beta_2 \mathrm{Elig}_{it} + \tau \mathrm{Post}_{it} * \mathrm{Elig}_{it} + \beta_3 X_{it} + \beta_4 Z_{it} + \Lambda_t + \Theta_c + \Theta_c t + \epsilon_{it} \qquad (5)$$

where Y_{it} refers to the outcome of interest of individual i in year t (e.g. health status, health insurance coverage, etc.); $Post_{it}$ is a binary variable equal to one if the survey took place in a year after DACA implementation (2013 or later); and $Elig_{it}$ is a dummy equal to one if individual i is DACA-eligible when the survey is administered. The coefficient of interest (τ) measures the intention-to-treat effect of DACA. The regression also controls for individual i's demographic characteristics[31] (X_{it}), year fixed effects (Λ_t), area (county, state, or region) fixed effects (Θ_c), and state or region-specific time trends ($\Theta_c t$).[32] Finally, the vector Z_{it} non-parametrically controls for eligibility criteria by including fixed effects for individual i's age, education, and age of

immigrants may be classified as part of our treatment group.

[29] This is the same sample used by Pope (2016).

[30] `https://www.migrationpolicy.org/programs/data-hub/deferred-action-childhood-arrivals-daca-profiles`.

[31] Sex, race, ethnicity, and marital status.

[32] Results are not sensitive to the inclusion of state-specific time trends (results without state-specific trends available upon request).

arrival into the U.S. Equation (1) is estimated using ordinary least squares. Standard errors are heteroskedasticity-robust (NHIS sample; CHIS sample; ACS: California + New York sample), or clustered at the state-year level (ACS: total U.S. sample; ACS: U.S. without CA and NY sample).[33]

3.2.3 DATA

We use data from three different sources: the American Community Survey (ACS), the National Health Interview Survey (NHIS), and the California Health Interview Survey (CHIS).

ACS

To analyze labor market outcomes and insurance coverage we use data from the American Community Survey (2005-2016), the largest household survey that the U.S. Census Bureau administers (Ruggles et al., 2017). We start with 2005 since it's the first year with a full one-percent sample of the U.S. population. 2016 is the last year for which the survey data is available. Designed as a replacement for the long form of the decennial census, ACS contains a detailed set of standard socio-demographic characteristics and labor market outcomes (e.g. employment, labor force participation, annual income). Furthermore, since 2008, the survey provides information on health insurance coverage and the type of coverage. The ACS also contains information on US citizenship status, number of years spent in the US, quarter of birth, and educational attainment, which can be used to determine respondents' DACA eligibility status. However, the survey does not include information about individual criminal convictions, or whether the respondent has been honorably discharged from the military. As far as the sampling procedure is concerned, unauthorized immigrants are no more or less likely to be selected into the sample than authorized immigrants or natives. This follows from the fact that U.S. Census Bureau uses a near universe of housing addresses from its Master Address File as the sample frame from which it draws systematic sample of addresses each month. The ACS is then mailed to the selected addresses. Non-respondents are contacted one month later for a computer-assisted telephone interview. After that, one third of non-respondents who still remain are contacted in person to complete the ACS one month after the telephone survey attempt (Pope, 2016). Between 2005 and 2016, The Master Address File covered

[33] Alternatively, we adjusted for clustering at the state level (see Table B.1 in the Appendix).

98.3-99.1% of all housing units and 76.2-99.8% of all group quarters in the U.S., encompassing 91.9-95.1% of the total U.S. population. The survey response rate in this period was 89.9-98.0% for the housing units and 95.1-98.0% for the group quarters.[34]

NHIS

NHIS is the largest health survey in the United States and the nation's primary source of general health information (Blewett et al., 2016). It is designed by CDC's National Center for Health Statistics and administered by the U.S. Census Bureau. The survey is conducted continuously since 1957 via in-person interviews, and each annual national sample consists of roughly 90,000 individuals. The annual response rate is approximately 70% of the eligible households in the sample.[35] We focus on the period 2000-2016. Unfortunately, the public version of NHIS data that we use does not contain precise information on the number of years since migration, which determines two of our three eligibility cutoffs. Instead, foreign-born respondents are grouped into the following categories: (1) less than 1 year; (2) 1 year to less than 5 years; (3) 5 years to less than 10 years; (4) 10 years to less than 15 years; (5) 15 years or more. Therefore, we classify as DACA-eligible only those individuals for whom we know for sure that they meet the age of entry and length of residence criteria. This measurement error will likely result in attenuation bias as many DACA-eligible respondents will be labeled as ineligible.

CHIS

The California Health Interview Survey (CHIS) is the nation's largest state health survey (UCLA Center for Health Policy Research, 2016). The survey is conducted by the UCLA Center for Health Policy Research in collaboration with the California Department of Public Health, and the Department of Health Care Services. It is a random-dial telephone survey conducted on a continuous basis and covers a wide range of health topics. Both landline and cellular phone numbers are sampled and the interview is computer-assisted. The survey provides a detailed picture of

[34] https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/
[35] https://www.cdc.gov/nchs/nhis/about_nhis.htm

the health and health care needs of California's large and diverse population. The first survey was conducted in 2000-01 on 55,000 households. Biennial surveys were conducted until 2011 on approximately 45,000 households. Starting in 2011, CHIS transitioned from a biennial survey model to a continuous survey model, interviewing roughly 20,000 Californians (adults, teenagers, and children) each year. Yearly samples are representative of California's population. Our analysis employs confidential data from 2003-2015, which includes precise information on the number of years foreign-born individuals lived in the U.S., exact date of CHIS interview, respondent's month and year of birth, and other variables which enable us to minimize the measurement error in the definition of the DACA-eligible population.[36] Since CHIS is a telephone-based survey, the response rates are lower than for the ACS or NHIS. However, as noted in the survey documentation, "CHIS response rates are similar to, and sometimes higher than other comparable surveys that interview by telephone."

3.3 RESULTS

3.3.1 DACA AND HEALTH INSURANCE COVERAGE

Difference-in-differences estimates of the effect of DACA on health insurance coverage are reported in Table 10. Panel A reveals that throughout the country, DACA-eligible immigrants were more likely to acquire insurance coverage after 2012. This finding is confirmed in Figures 6-10, which plot the interactions between DACA eligibility indicator and year-specific indicators. In states that extended full-scope Medicaid coverage to low-income DACA recipients (California and New York), insurance coverage increased due to a sharp increase in public coverage (Figures 11-15). Reassuringly, the difference in pre-trends in the outcome variables of treatment and control groups are statistically non-significant. This increase begins in 2014 - the year when DACA recipients in California became eligible for the state-funded Medi-Cal.[37] As Panel B, column 1 reports, DACA-eligible immigrants were 4 percentage points more likely to report insurance coverage in California and New York, a 6% increase with respect to the insurance rate in the sample. Although this surge in coverage is largely driven by the Medicaid (Panel B, column 2), there is also evidence of a 1 percentage point increase in private coverage (column 3), and in particular employer-based

[36] Data from 2000-01 survey are not included in the analysis because many variables from this wave cannot be trended with subsequent waves of the survey.

[37] As noted earlier, DACA recipients in New York became eligible for the state-funded Medicaid immediately.

insurance (column 4).

In the rest of the U.S., there was no increase in public coverage as immigrants were not eligible for Medicaid or other public programs, but private insurance coverage did go up (Figures 16-20). The increase in insurance coverage is substantially smaller than in New York and California, and it is driven by the 7% increase (with respect to the mean) in individually purchased insurance (see Panel C, columns 1 and 5). However, we cannot reject that the effect of DACA on any private coverage is the same in California and New York as in the rest of the states, suggesting that crowding out effects of access to public coverage are negligible. Results on health insurance are robust to eliminating (a number of) legal immigrants from the main sample using the residual method (see Table B.2).[38] Moreover, findings are robust to including individuals with less than a high school diploma but still in school, as these were also eligible for DACA (results available upon request).

3.3.2 DACA, ACCESS TO CARE, AND HEALTH CARE USE

Using NHIS data, we examined the impact of DACA on access to care and health care utilization. DACA-eligible individuals after 2012 were less likely to delay care because of financial constraints (-20%). We also find that DACA led to a 5 percentage point decrease in the cost-related inability to seek specialized care when needed (Figure 21 and Table 11). In California, DACA increased the likelihood of reporting having a usual place of care by 11% and a personal doctor by 13% (Figure 22, Table 12). Despite the observed increase in insurance coverage and access to care, there is little evidence of any increase in health care use (e.g. total doctor visits, emergency room visits; see Figures 23-24, and Tables 13-14).[39] However, in California after 2012, DACA-eligible individuals

[38] Following the approach proposed by Borjas (2017) and based on previous work by Passel and Cohn (2014), we exclude from the sample immigrants who are likely to have a legal status, thus reducing the attenuation bias of our estimates. It is worth noting that in our case, we can only use a subset of the exclusion conditions used by Borjas (2017), as some of the criteria used to identify legal immigrants from the sample (e.g. local/state government employment, occupational licensing) may lead to the exclusion of DACAmented individuals. In practice, we only exclude any foreign-born non-citizen who satisfies one (or more) of the following conditions:

(a) arrived in the U.S. before 1980;

(b) was born in Cuba;

(c) is federal government employee;

(d) receives any Social Security benefits or Supplementary Security Income (SSI).

[39] In addition to the variables presented in Table 13, in NHIS, we tested the effect of DACA on a number of other measures of health care utilization. We found no effect of the policy in all instances. The following variables were considered: *Number of nights in hospital (past 12 mo.); Number of times in hospital overnight (past 12 mo.); Number of ER visits (past 12 mo.); Time since last doctor visit; Individual saw/talked to a general doctor (past 12 mo.); Individual saw/talked to a foot doctor (past 12 mo.), Individual ever received dental care; Time since last dental care*

were more likely to receive mental care services (Figure 24, Table 14 - columns 4 and 5).[40] We find no evidence of significant differences even when restricting to individuals below the federal poverty level (Tables B.3-B.4).

3.3.3 EFFECTS ON HEALTH STATUS AND MENTAL HEALTH

There is some evidence that DACA had mild positive effects on self-reported health status and mental health (Figure 25 and Table 15). While the direction of the effect is consistent across the outcomes considered (columns 1-9), results are precisely estimated only when examining self-reported health status (columns 1 and 2). Despite the large standard errors, our estimates suggest that DACA eligibility reduced the likelihood of reporting depression symptoms, moderate or serious psychological distress, and hypertension. Interestingly, when we restrict the analysis to individuals with income below the federal poverty level (Table 16), we find evidence of significant improvements in mental health and well-being (columns 4-9). For this group, DACA reduced by 36% the likelihood of reporting depression, by 50% the likelihood of feeling hopeless, and by 34% the likelihood of feeling that "everything had been an effort". In addition, the measure of non-specific psychological distress (Kessler 6 Scale) declined by about 23%, the likelihood of reporting moderate or serious psychological distress by 29%, and the probability of being diagnosed with hypertension also by 29% with respect to the sample mean. Results are even larger when restricting the analysis to Hispanics with income below the poverty level (see Table B.5).

Examining CHIS data (Figure 26 and Table 17), we find mild evidence of improvements in self-reported health status in the overall sample, but consistent with results from NHIS, there is evidence of significant reductions in anxiety, distress, and hypertension among those below the poverty level (Table 18). In this group, DACA eligibility reduced the likelihood of feeling restless and experiencing psychological distress by approximately 54%, and the likelihood of reporting hypertension by 33%.

visit; Individual had a surgery (past 12 mo.).

[40] The sample size in Tables 13 and 14 changes due to the fact that not all variables are available in all years and for all the respondents. However, in both tables, restricting the analysis to a consistent sample yields similar results.

3.3.4 POTENTIAL MECHANISMS

The increase in private insurance coverage and the mild positive effects on mental health may be in part explained by the positive effects on labor market outcomes documented in previous studies (Pope, 2016; Amuedo-Dorantes and Antman, 2016). Using data from the American Community Survey, we replicated the findings of Pope (2016), extending the analysis by including 2015 and 2016. We confirm that DACA substantially increased the likelihood of recipients currently working or having worked at some point in the past year. In addition, DACA led to a higher immigrant labor force participation and a lower probability of being unemployed (Figure B.1). Finally, consistent with Pope (2016), DACA had a positive effect on the number of hours worked and income of eligible individuals, but no significant effect on self-employment (Figures B.1 and B.2).

We have also considered the effects of DACA on non-pecuniary working conditions. As Figure B.2 depicts, there is no evidence of any changes in the work schedules or task-intensity of immigrant jobs (Peri and Sparber, 2009; Giuntella et al., 2017), suggesting that DACAmented individuals are not moving to "better" jobs in terms of these particular non-pecuniary characteristics. Results are similar when restricting the analysis to California alone (Figures B.3 and B.4).

Temporary work authorization also reduced immigrants' exposure to chronic stressors, such as the constant fear of being deported, the inability to get a driver's license, regular job, or open a bank account. Observational studies suggest that undocumented immigrants who belong to the 1.5 generation report higher levels of anxiety, depression, and fear, which affect their transition from adolescence to adulthood, during which about 75% of lifetime psychiatric disorders can emerge (Stacciarini et al., 2015; Gonzales et al., 2014; Delva et al., 2013). Taken together, our findings suggest that the reduced exposure to chronic stressors, increased income, higher labor force participation, improved access to care, and the financial security associated with insurance coverage can explain the positive effects on health and depression symptoms, which are stronger among those at the bottom of the income distribution.

3.3.5 ROBUSTNESS CHECKS

In the Appendix, we report a full set of robustness checks. Table B.2 shows the sensitivity of our analysis to restricting the sample to individuals who are more likely to be undocumented.

Unfortunately, we can only conduct this test using ACS data, as we have limited information and limited sample sizes when using NHIS and CHIS data. Reassuringly, the results lean in the same direction and, if anything, point estimates are slightly larger than the ones presented in Table 10, consistent with a reduction in attenuation bias due to measurement error in the definition of the eligible population. Results are also robust to adjusting for clustering at the state-level (see Table B.1).

As mentioned above, in the baseline analysis we treated 2012 as a control year. However, omitting the adoption year (2012) yields substantially identical results (see Tables B.6-B.9). As age-cutoffs may be vulnerable to non-parallel trends (Slusky, 2017), we confirm the main results using a shorter time window around the policy change (2011-2012 vs 2013-2014). Furthermore, the results are robust to dropping individulas who were 30-31 in 2012 (see Tables B.10-B.13).

Tables B.14-B.19 replicate Tables 11-15 and Table 17, restricting the sample to non-citizens aged 18-35, and with a high school degree or equivalent. For most of the outcomes the results lean in the same direction and point estimates are not substantially different, although due to the small sample sizes, standard errors increase substantially and many of the coefficients are not precisely estimated.

3.4 CONCLUSION

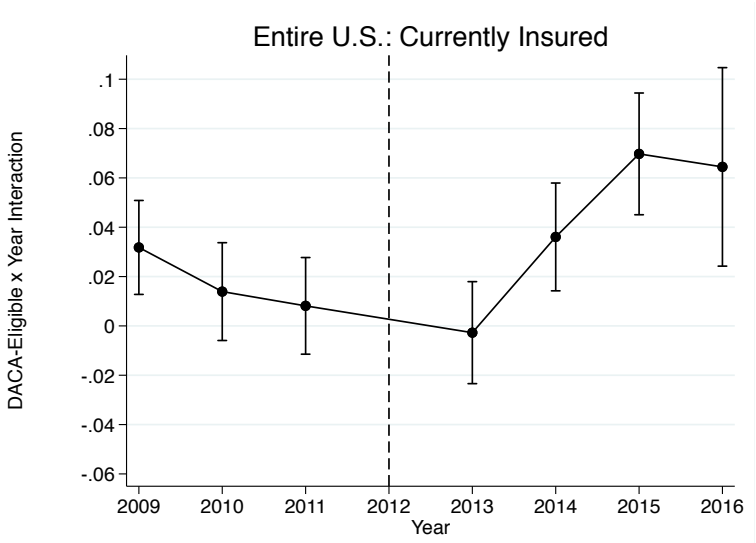
The Deferred Action for Childhood Arrivals (DACA) is currently a subject of intense political debate. Previous studies showed evidence of positive effects of this reform on labor market participation and income of those at the bottom of the income distribution, but documented some negative effects on academic outcomes. Furthermore, there is evidence that DACA had positive effects on adult mental health and child health outcomes.

We examine the effects of DACA on health insurance coverage and provide evidence that DACA eligibility increased insurance coverage. This increase was driven by an increase in public coverage in states that extended Medicaid access to low-income DACA-eligible immigrants. However, even in states that did not expand Medicaid to include DACA-eligible immigrants, there was an increase in individually purchased health insurance. Despite the increase in insurance coverage, there is little evidence of significant increases in health care use, although DACA-eligible individuals were more likely to report a usual place of care and less likely to delay health care due to financial

constraints. Finally, we find some evidence that DACA led to improvement in self-reported health, mental health, stress, and hypertension. These positive effects are concentrated among individuals with income below the federal poverty level. Our findings are broadly consistent with previous experimental evidence on the health effects of health insurance coverage (Aron-Dine et al., 2013; Finkelstein et al., 2012).

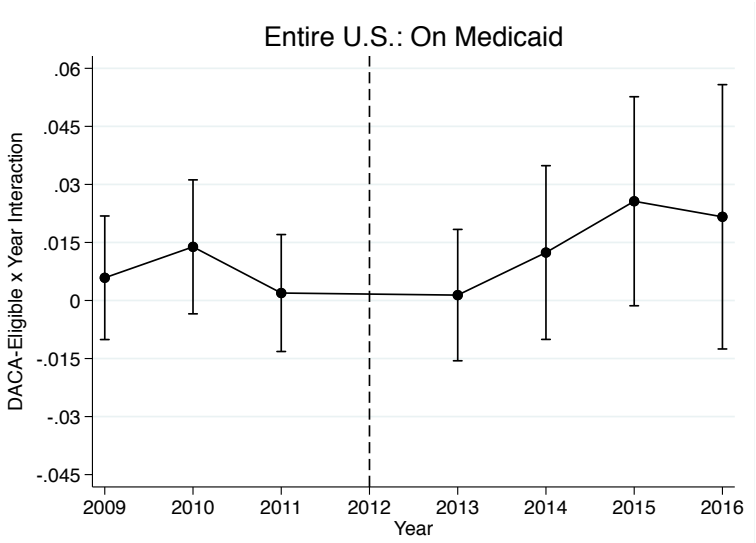
Overall, our results suggest that DACA promoted financial security through its effects on income and insurance coverage, and improved perceived health and mental health of DACA-eligible immigrants – particularly those with an income below the federal poverty level – without significantly changing their demand for care. These effects should not be neglected when examining the impact of DACA. In contrast, restricting DACA might have detrimental effects on the access to care and mental health of DACA-eligible individuals, and particularly on the nearly 1 million people who benefited from the program thus far. The lack of alternative policy solutions will pose difficult challenges to health care providers and public health officials across the country.

Figure 6: DACA and Insurance Coverage in U.S.



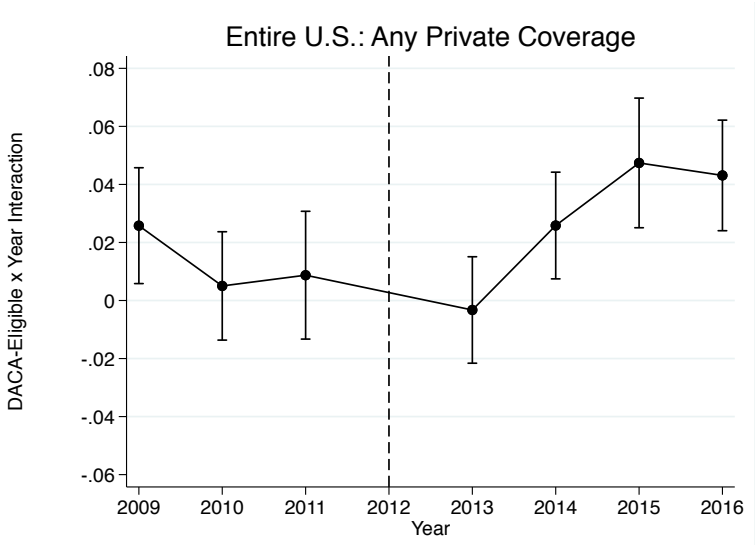
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Any Coverage* - is binary var. equal 1 if individual is currently with health insurance coverage. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 7: DACA and Medicaid Coverage in U.S.



Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Medicaid* - is binary var. equal 1 if individual is currently on Medicaid. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 8: DACA and Any Private Coverage in U.S.



Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Any Private* - is binary var. equal 1 if individual is currently with private health insurance (i.e. via employer/union or purchased directly from insurer). Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Table 10: The Effects of DACA on Health Insurance Coverage

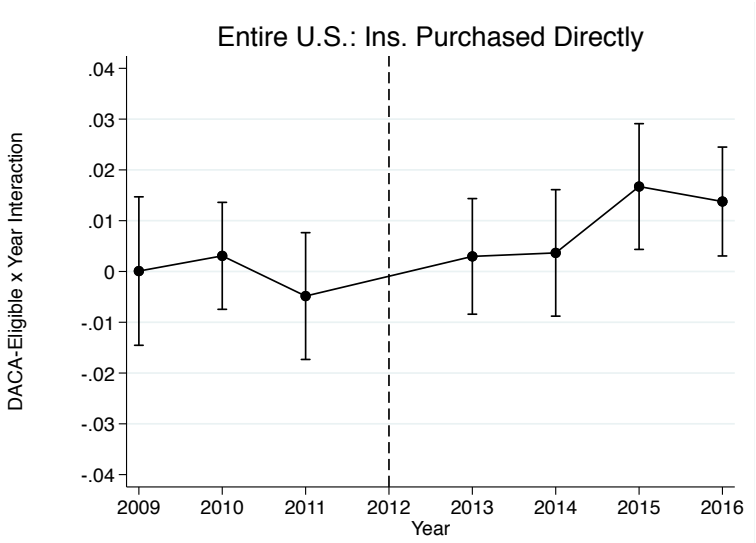
	(1) Any Coverage	(2) Medicaid	(3) Any Private	(4) Employer-Sponsored	(5) Indiv. Purchased
Panel A: Entire U.S.					
DACA-Eligible * Post 2012	0.0224***	0.0084	0.0137**	0.0061	0.0081**
	(0.008)	(0.007)	(0.006)	(0.006)	(0.004)
Observations	395,902	395,902	395,902	395,902	395,902
R-squared	0.221	0.079	0.250	0.188	0.095
Mean of Dep. Var.	0.642	0.089	0.558	0.435	0.137
Std. Dev. of Dep. Var.	0.480	0.284	0.497	0.496	0.344
Panel B: California & New York					
DACA-Eligible * Post 2012	0.0409***	0.0256***	0.0134*	0.0114	0.0025
	(0.007)	(0.006)	(0.007)	(0.007)	(0.004)
Observations	127,886	127,886	127,886	127,886	127,886
R-squared	0.193	0.111	0.261	0.207	0.124
Mean of Dep. Var.	0.662	0.147	0.521	0.409	0.127
Std. Dev. of Dep. Var.	0.473	0.354	0.500	0.492	0.333
Panel C: Entire U.S. (except California and New York)					
DACA-Eligible * Post 2012	0.0145*	-0.0019	0.0171**	0.0074	0.0107**
	(0.008)	(0.004)	(0.007)	(0.007)	(0.004)
Observations	268,016	268,016	268,016	268,016	268,016
R-squared	0.249	0.059	0.267	0.198	0.101
Mean of Dep. Var.	0.632	0.061	0.575	0.447	0.142
Std. Dev. of Dep. Var.	0.482	0.240	0.494	0.497	0.349

Notes - *Any Coverage* - binary var. equal 1 if individual currently with health insurance coverage; *Medicaid* - binary var. equal 1 if individual currently on Medicaid; *Any Private* - binary var. equal 1 if individual currently with private health insurance (i.e. via employer/union or purchased directly from insurer); *Employer-Sponsored* - binary var. equal 1 if individual currently with health insurance via employer or union; *Indiv. Purchased* - binary var. equal 1 if individual currently with health insurance purchased directly from insurer. Standard errors in parentheses, heteroskedasticity-robust (Panel B), and clustered at state-year level (Panels A and C). Estimates in all columns are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), year fixed effects, and state-specific time trends. In addition, all columns in Panels A and C control for state fixed effects, while all columns in Panel B control for PUMA fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Figure 9: DACA and Employer-Sponsored Coverage in U.S.

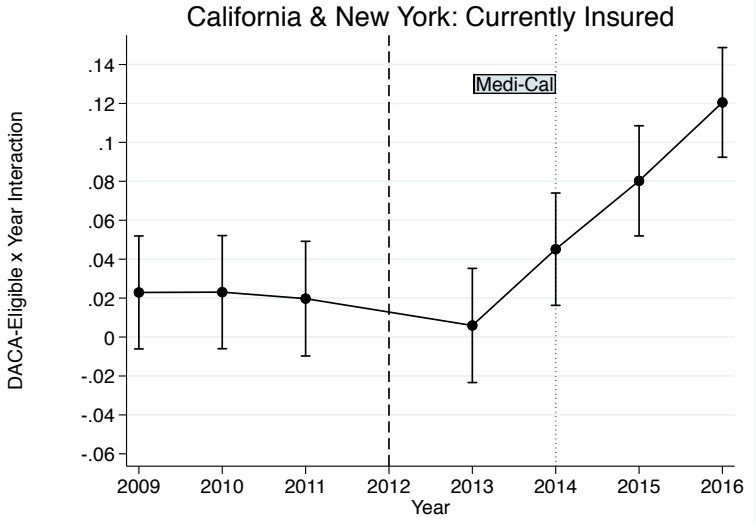
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Employer-Sponsored* - is binary var. equal 1 if individual is currently with health insurance via employer or union. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 10: DACA and Individually Purchased Coverage in U.S.



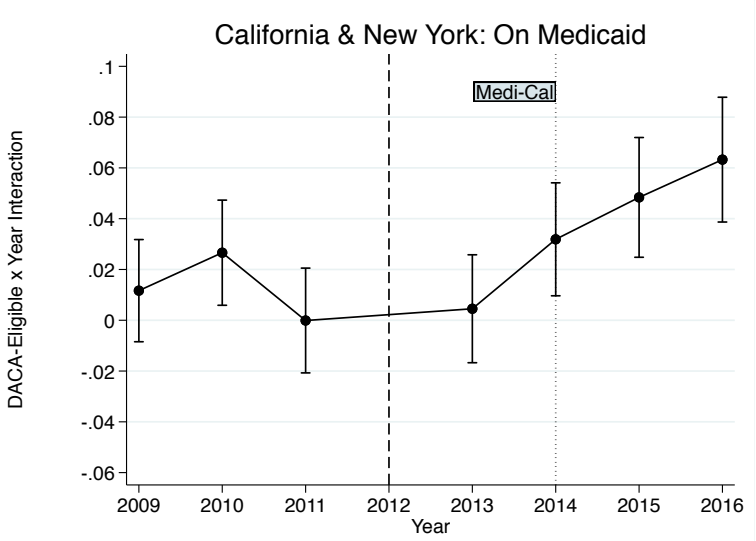
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Indiv. Purchased* - is binary var. equal 1 if individual is currently with health insurance purchased directly from insurer. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 11: DACA and Insurance Coverage in California and New York



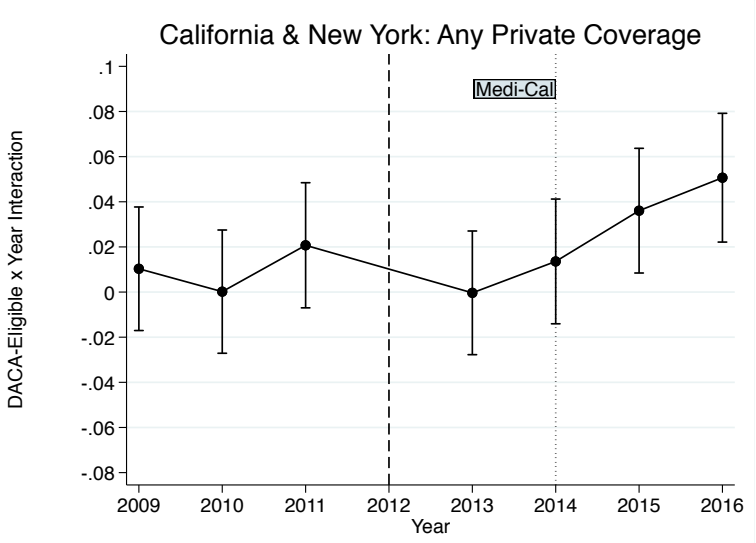
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Any Coverage* - is binary var. equal 1 if individual is currently with health insurance coverage. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, year fixed effects, and state-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 12: DACA and Medicaid Coverage in California and New York



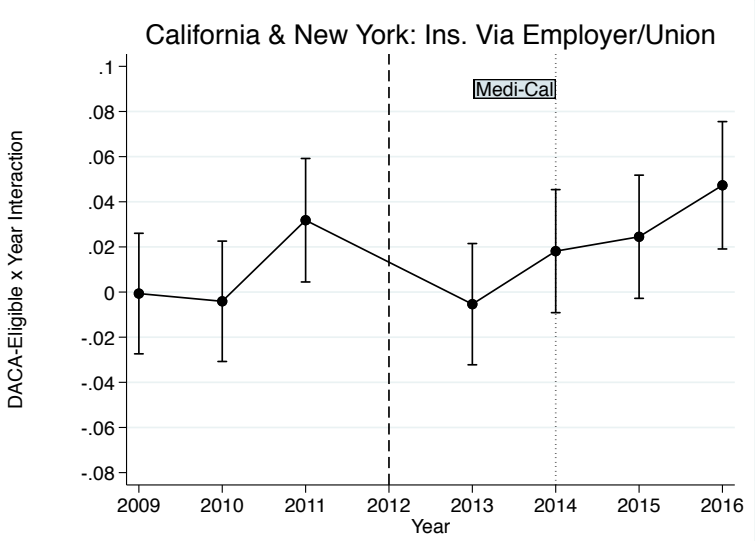
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Medicaid* - is binary var. equal 1 if individual is currently on Medicaid. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, year fixed effects, and state-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 13: DACA and Any Private Coverage in California and New York



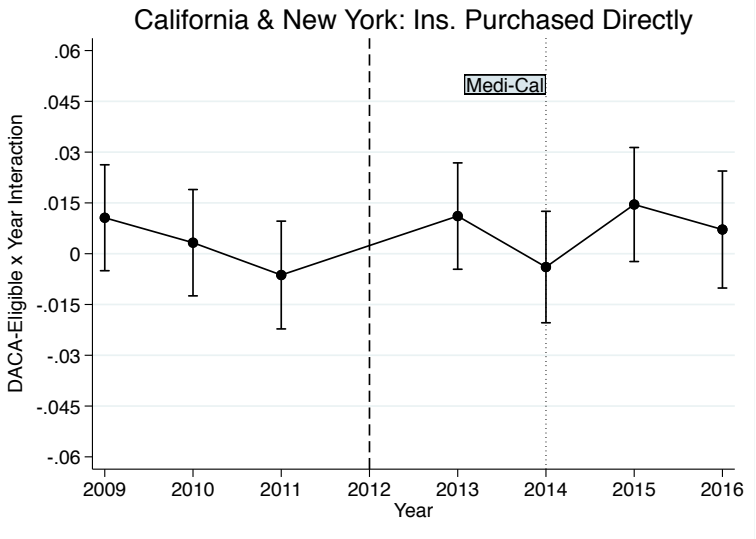
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Any Private* - is binary var. equal 1 if individual is currently with private health insurance (i.e. via employer/union or purchased directly from insurer). Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, year fixed effects, and state-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 14: DACA and Employer-Sponsored Coverage in California and New York



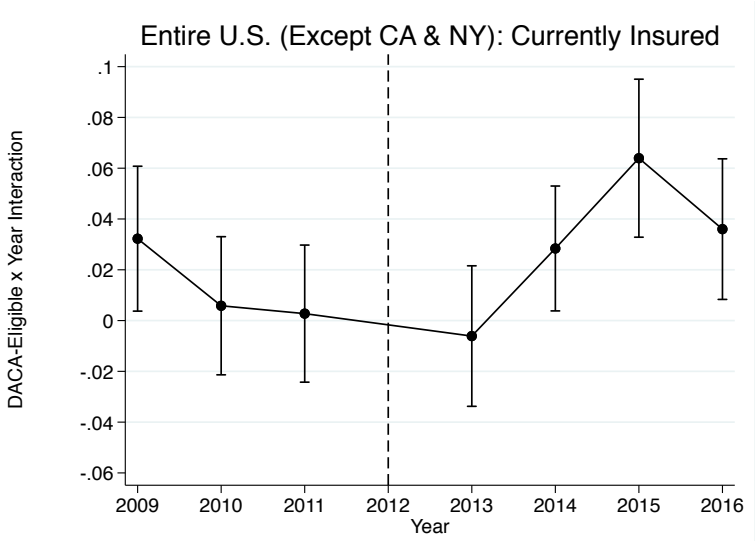
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Employer-Sponsored* - is binary var. equal 1 if individual is currently with health insurance via employer or union. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, year fixed effects, and state-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 15: DACA and Individually Purchased Coverage in California and New York



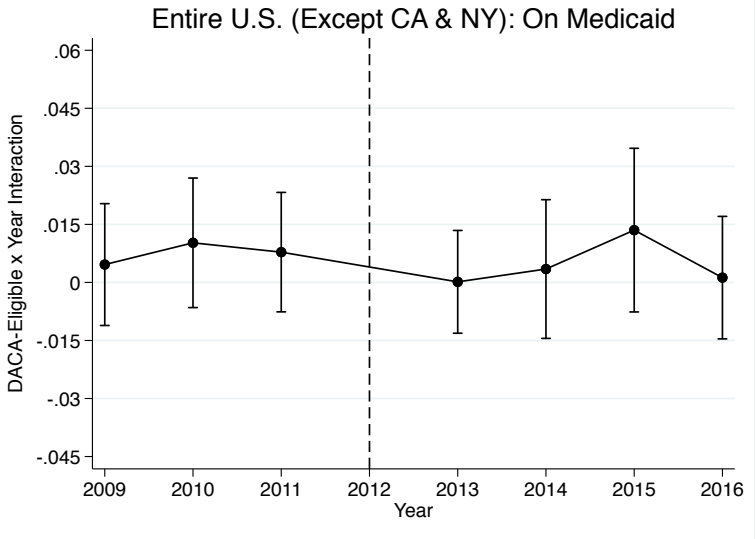
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Indiv. Purchased* - is binary var. equal 1 if individual is currently with health insurance purchased directly from insurer. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, year fixed effects, and state-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 16: DACA and Insurance Coverage in U.S. (outside CA, NY)



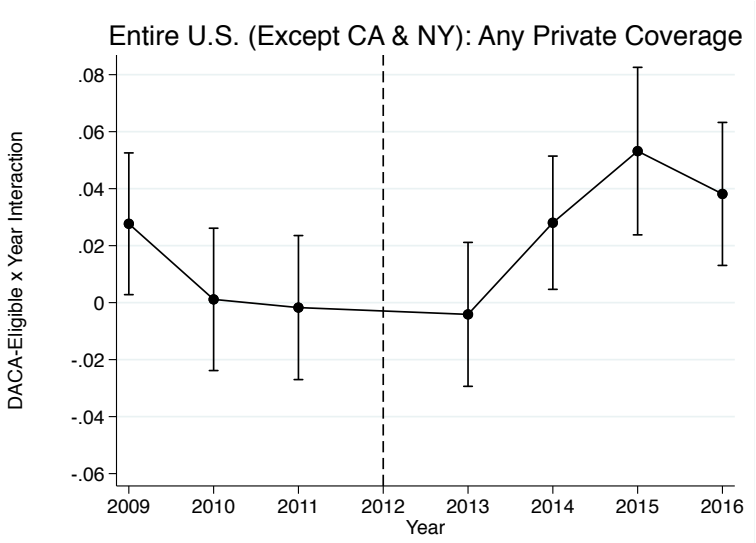
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Any Coverage* - is binary var. equal 1 if individual is currently with health insurance coverage. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 17: DACA and Medicaid Coverage in U.S. (outside CA, NY)



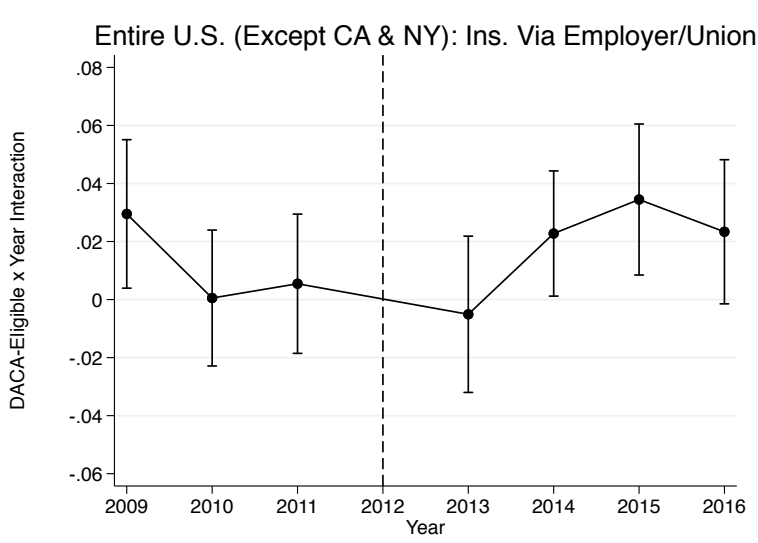
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Medicaid* - is binary var. equal 1 if individual is currently on Medicaid. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 18: DACA and Any Private Coverage in U.S. (outside CA, NY)



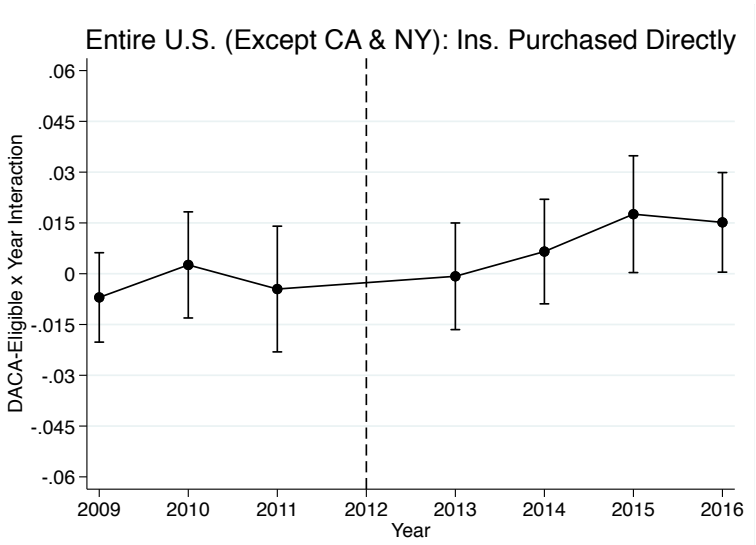
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Any Private* - is binary var. equal 1 if individual is currently with private health insurance (i.e. via employer/union or purchased directly from insurer). Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 19: DACA and Employer-Sponsored Coverage in U.S. (outside CA, NY)



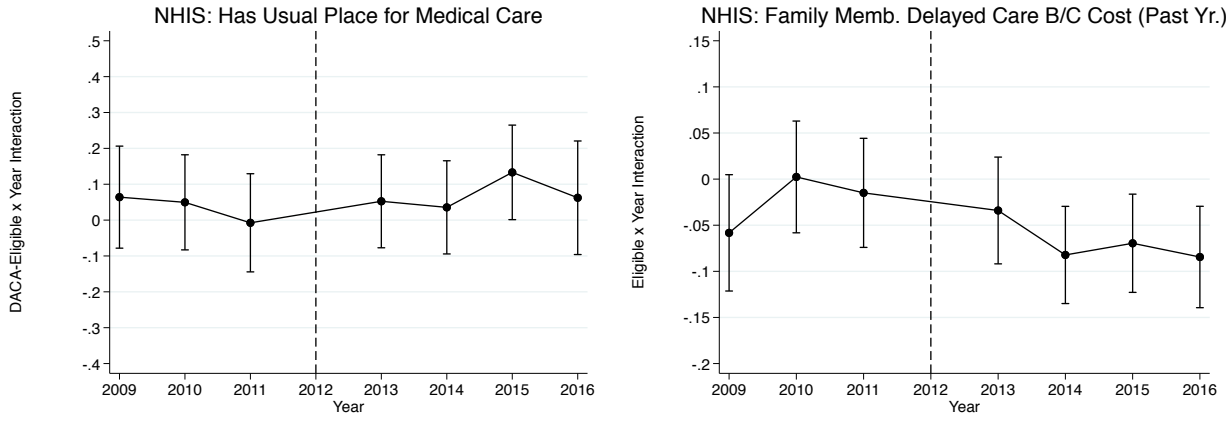
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Employer-Sponsored* - is binary var. equal 1 if individual is currently with health insurance via employer or union. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 20: DACA and Individually Purchased Coverage in U.S. (outside CA, NY)



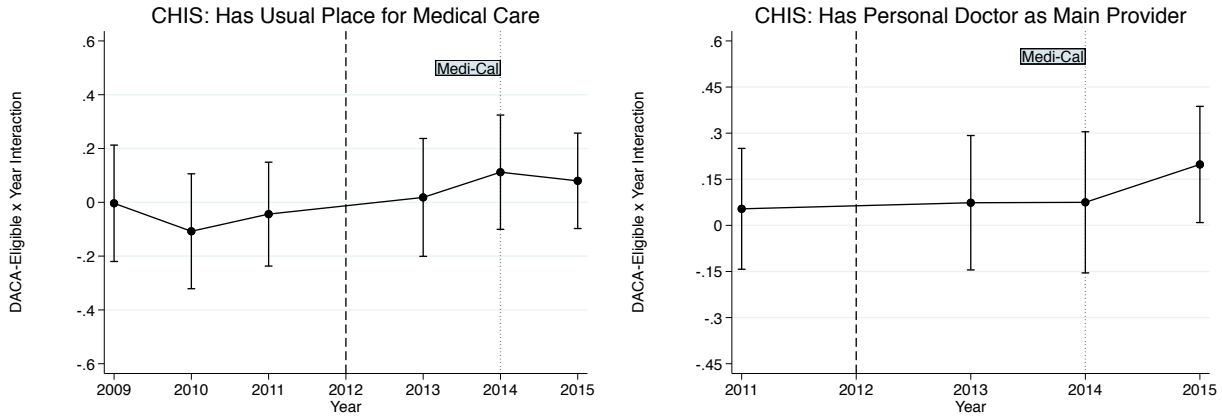
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. The dependent variable - *Indiv. Purchased* - is binary var. equal 1 if individual is currently with health insurance purchased directly from insurer. Estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure 21: DACA and Health Care Access, Affordability (Entire U.S.: NHIS)



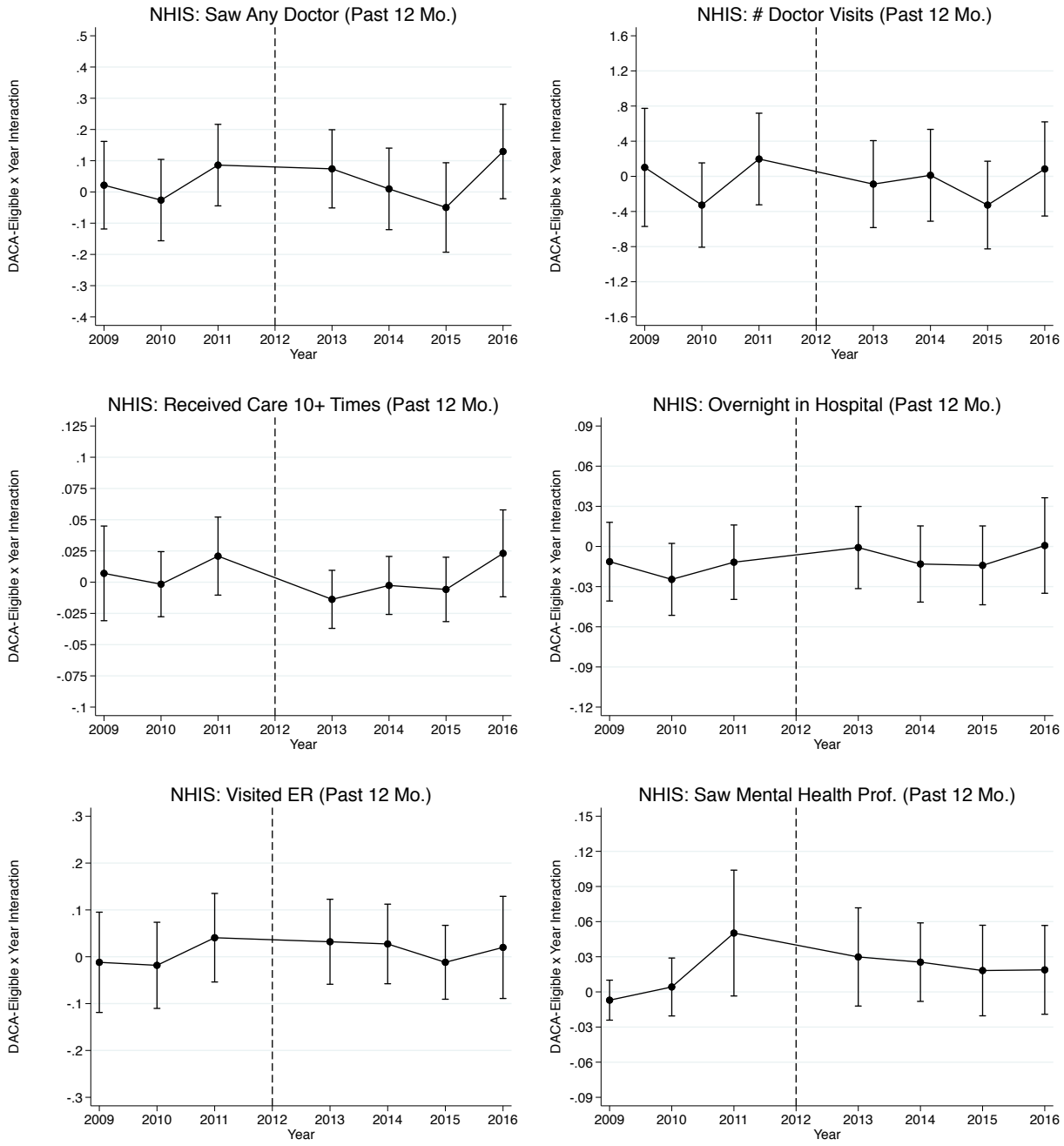
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right): *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Any Care Delay* - binary var. equal 1 if any member of respondent's family delayed seeking medical care due to cost (in past 12 months). All estimates are derived from a sample of non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), region fixed effects, year fixed effects, and region-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 22: DACA and Health Care Access (California: CHIS)



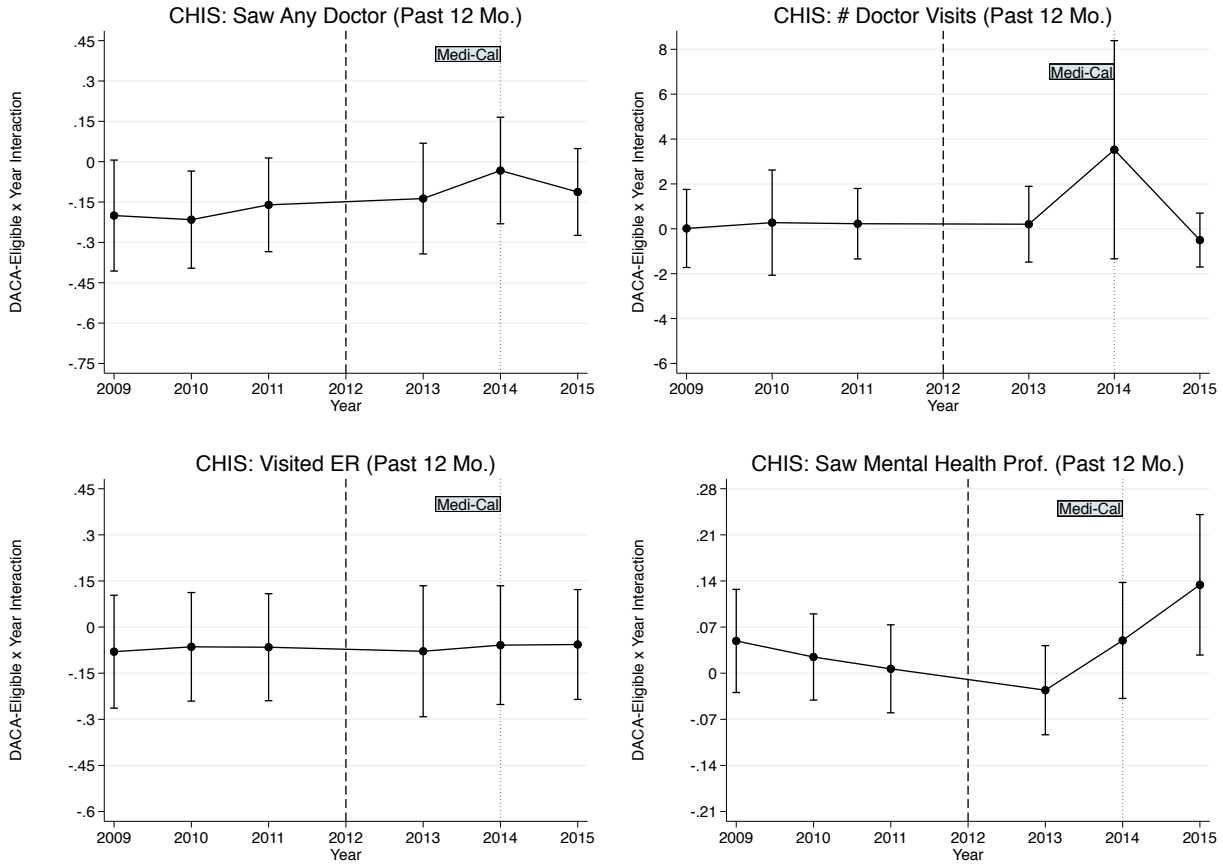
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right): *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Personal MD* - binary var. equal 1 if individual has personal doctor as main medical provider. All estimates are derived from a sample of non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. Standard errors are heteroskedasticity-robust.

Figure 23: DACA and Health Care Use (Entire U.S.: NHIS)



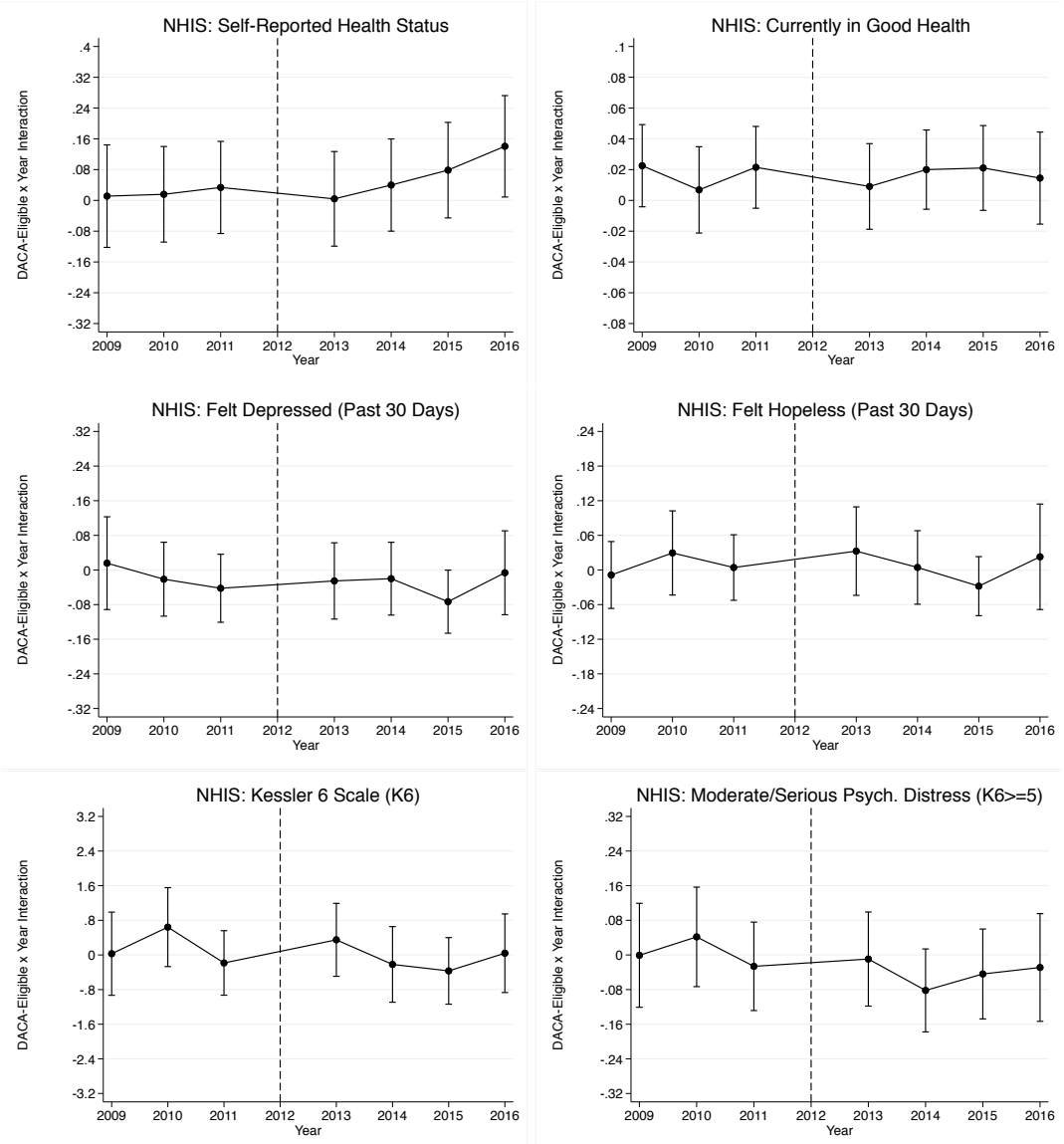
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *Care 10+* - binary var. equal 1 if individual received medical care 10+ times in past 12 months; *Hosp. Night* - binary var. equal 1 if individual was in a hospital overnight in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to mental health professional (psychiatrist, psychologist, etc.) in past 12 months. All estimates are derived from a sample of non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), region fixed effects, year fixed effects, and region-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 24: DACA and Health Care Use (California: CHIS)



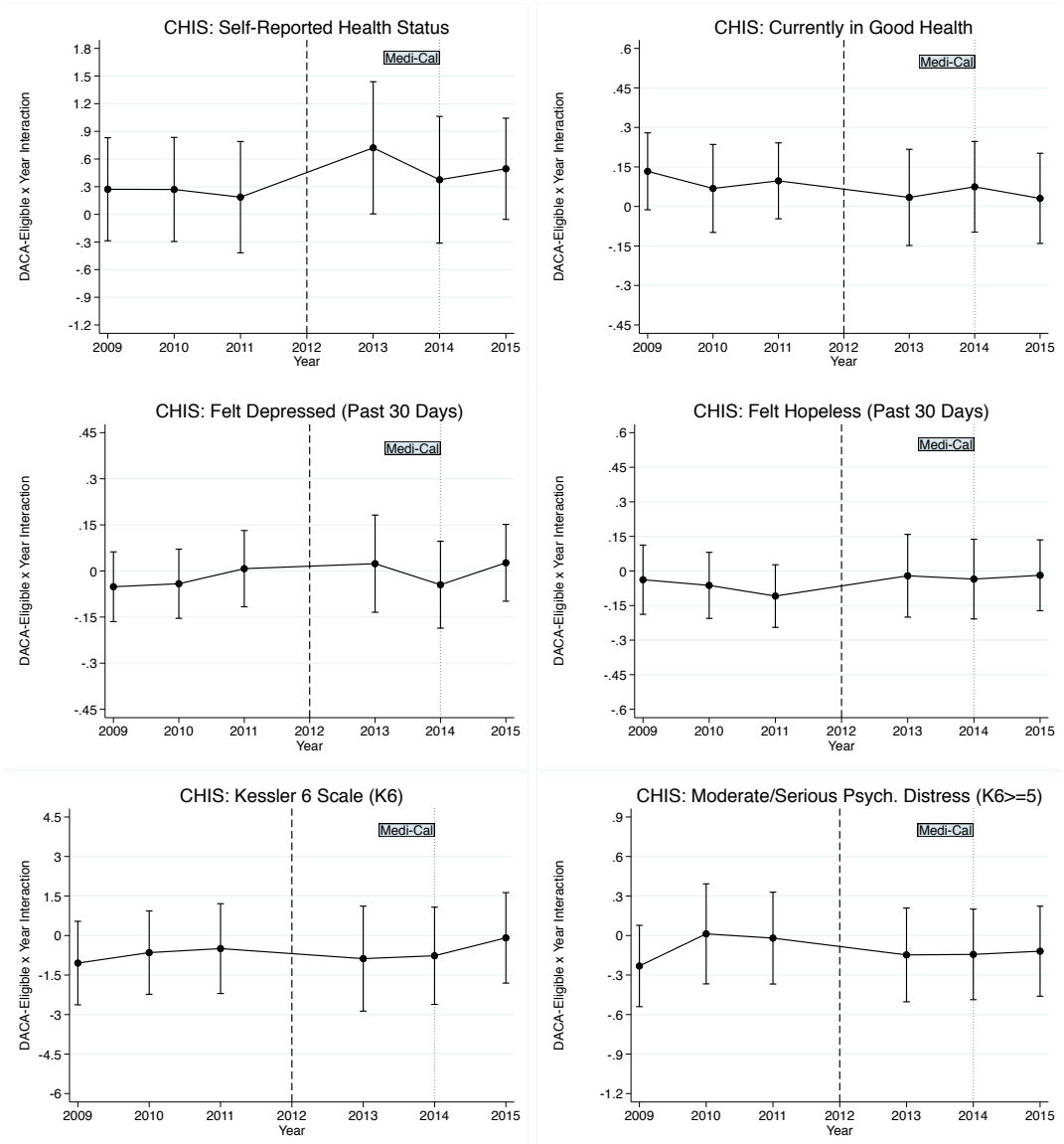
Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Eligi_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to a medical professional (psychiatrist, psychologist, etc.) for mental or alcohol/drug problems in past 12 months. All estimates are derived from a sample of non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. Standard errors are heteroskedasticity-robust.

Figure 25: DACA and Health (Entire U.S.: NHIS)



Notes - The figure plots the coefficients obtained from estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$). All estimates are derived from a sample of non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), region fixed effects, year fixed effects, and region-specific time trends. Standard errors are heteroskedasticity-robust.

Figure 26: DACA and Health (California: CHIS)



Notes - The figure plots the coefficients obtained estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$). All estimates are derived from a sample of non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are drawn the 2003-2015 waves of CHIS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. Standard errors are heteroskedasticity-robust.

Table 11: DACA and Health Care Access, Affordability (Entire U.S.: NHIS)

	(1) Usual	(2) Any Care Delay	(3) Special. Not Afford.
DACA-Eligible * Post 2012	0.0146	-0.0325***	-0.0511**
	(0.031)	(0.011)	(0.024)
Observations	247,900	583,051	92,841
R-squared	0.072	0.025	0.017
Mean of Dep. Var.	0.812	0.157	0.052
Std. Dev. of Dep. Var.	0.390	0.364	0.221

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Any Care Delay* - binary var. equal 1 if any member of respondent's family delayed seeking medical care due to cost (in past 12 months); *Special. Not Afford.* - binary var. equal 1 if individual needed but couldn't afford specialist (in past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 12: DACA and Health Care Access (California: CHIS)

	(1) Usual	(2) Personal MD
DACA-Eligible * Post 2012	0.0918**	0.0913
	(0.046)	(0.066)
Observations	106,247	31,396
R-squared	0.079	0.108
Mean of Dep. Var.	0.848	0.683
Std. Dev. of Dep. Var.	0.359	0.465

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Personal MD* - binary var. equal 1 if individual has personal doctor as main medical provider. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 13: DACA and Health Care Use (Entire U.S.: NHIS)

	(1) Doctor	(2) # Visits	(3) Care 10+	(4) Hosp. Night	(5) ER	(6) Saw Special	(7) Saw Eye	(8) Saw Mental
DACA-Eligible * Post 2012	0.0112	0.0411	0.0001	0.0012	0.0089	-0.0119	0.0013	0.0083
	(0.031)	(0.109)	(0.006)	(0.007)	(0.022)	(0.014)	(0.027)	(0.010)
Observations	246,178	246,178	582,213	582,929	247,041	247,025	247,090	247,101
R-squared	0.072	0.073	0.019	0.018	0.024	0.027	0.042	0.020
Mean of Dep. Var.	0.776	2.243	0.082	0.065	0.195	0.192	0.315	0.086
Std. Dev. of Dep. Var.	0.417	2.161	0.274	0.247	0.396	0.394	0.464	0.281

Notes - *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *Care 10+* - binary var. equal 1 if individual received medical care 10+ times in past 12 months; *Hosp. Night* - binary var. equal 1 if individual was in a hospital overnight in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Special* - binary var. equal 1 if individual saw/talked to medical specialist in past 12 months; *Saw Eye* - binary var. equal 1 if individual saw/talked to eye doctor in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to mental health professional (psychiatrist, psychologist, etc.) in past 12 months. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 14: DACA and Health Care Use (California: CHIS)

	(1) Doctor	(2) # Visits	(3) ER	(4) Saw Mental	(5) # Mental Visits
DACA-Eligible * Post 2012	0.0094	0.9150	-0.0084	0.0387*	0.8404*
	(0.047)	(0.918)	(0.040)	(0.023)	(0.487)
Observations	106,247	106,247	85,776	66,315	66,315
R-squared	0.055	0.028	0.020	0.041	0.018
Mean of Dep. Var.	0.807	4.075	0.184	0.159	1.808
Std. Dev. of Dep. Var.	0.395	9.201	0.387	0.366	8.541

Notes - *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to a medical professional (psychiatrist, psychologist, etc.) for mental or alcohol/drug problems in past 12 months; *# Mental Visits* - # of visits to professional for problems with mental health or drugs/alcohol (during past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 15: DACA and General Health Status, Mental Health (Entire U.S.: NHIS)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Effort	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.1188***	-0.0036***	0.0071	-0.0254	-0.0076	-0.0311	-0.2014	-0.0389	-0.0103
	(0.028)	(0.001)	(0.005)	(0.018)	(0.017)	(0.021)	(0.208)	(0.024)	(0.017)
Observations	583,085	583,085	583,085	246,199	246,172	246,032	245,701	245,701	249,479
R-squared	0.079	0.011	0.033	0.025	0.016	0.018	0.033	0.025	0.064
Mean of Dep. Var.	4.009	0.011	0.937	0.106	0.063	0.148	2.484	0.194	0.142
Std. Dev. of Dep. Var.	0.950	0.105	0.243	0.307	0.243	0.356	3.726	0.395	0.349

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Effort* - binary var. equal 1 if individual reported feeling "everything was an effort" some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 16: DACA and General Health Status, Mental Health - Individuals in Poverty (Entire U.S.)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Effort	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.1778***	-0.0011	0.0094	-0.0688**	-0.0639**	-0.0845**	-0.8849**	-0.0905**	-0.0445**
	(0.065)	(0.005)	(0.014)	(0.029)	(0.026)	(0.039)	(0.353)	(0.042)	(0.020)
Observations	57,449	57,449	57,449	32,371	32,361	32,338	32,277	32,277	32,827
R-squared	0.151	0.043	0.104	0.051	0.044	0.041	0.064	0.046	0.118
Mean of Dep. Var.	3.661	0.034	0.850	0.190	0.129	0.248	3.867	0.316	0.155
Std. Dev. of Dep. Var.	1.105	0.182	0.357	0.393	0.335	0.432	4.857	0.465	0.362

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Effort* - binary var. equal 1 if individual reported feeling "everything was an effort" some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). This sample is further restricted to contain only individuals with family's before-tax income (from preceding calendar year) below U.S. Census Bureau's official poverty threshold. Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 17: DACA and General Health Status, Mental Health (California: CHIS)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Restless	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.3920**	0.0098	-0.0166	0.0190	0.0139	-0.0357	0.1003	-0.1035	0.0342
	(0.167)	(0.015)	(0.037)	(0.031)	(0.036)	(0.041)	(0.396)	(0.073)	(0.033)
Observations	106,247	106,247	106,247	85,731	85,731	85,731	85,776	85,731	106,247
R-squared	0.079	0.016	0.044	0.020	0.019	0.024	0.041	0.034	0.058
Mean of Dep. Var.	3.703	0.023	0.880	0.076	0.096	0.274	3.637	0.298	0.154
Std. Dev. of Dep. Var.	1.016	0.151	0.326	0.265	0.295	0.446	3.686	0.457	0.361

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Restless* - binary var. equal 1 if individual reported feeling restless or anxious some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 18: DACA and General Health Status, Mental Health - Individuals in Poverty (CA: CHIS)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Restless	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.3255	0.0454	0.1016	-0.0325	-0.0791	-0.1777*	-1.6753	-0.2354*	-0.0600**
	(0.316)	(0.071)	(0.106)	(0.053)	(0.091)	(0.098)	(1.131)	(0.123)	(0.024)
Observations	12,060	12,060	12,060	10,176	10,176	10,176	10,188	10,176	12,060
R-squared	0.096	0.068	0.073	0.048	0.050	0.049	0.067	0.052	0.114
Mean of Dep. Var.	3.192	0.063	0.735	0.160	0.182	0.327	5.021	0.435	0.182
Std. Dev. of Dep. Var.	1.101	0.243	0.441	0.367	0.386	0.469	4.682	0.496	0.386

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Restless* - binary var. equal 1 if individual reported feeling restless or anxious some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). This sample is further restricted to contain only individuals with family's before-tax income (from preceding calendar year) below U.S. Census Bureau's official poverty threshold. Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

4 GULAGS, CRIME, AND VIOLENCE: ORIGINS AND CONSEQUENCES OF THE RUSSIAN MAFIA

4.1 INTRODUCTION

Transnational organized crime has been a worldwide phenomenon, with estimated profits generated by various illicit markets totalling some $6.2 trillion (10% of global GDP) in 2011 (Novakoff, 2015). During the chaotic 1990s post-communist transition, Russian Federation experienced an unprecedented proliferation of organized crime groups (OCGs). According to Klebnikov (2000), by 1994, the number of OCGs operating in Russia was estimated to be around 5,700, totaling some 3 million members. These groups managed to penetrate almost every aspect of Russia's legal economy, with 40 percent of private businesses, 60 percent of state-owned enterprises, and 85 percent of banks having proven or suspected ties to organized crime. The boom in Russian organized crime during the 1990s brought about significant costs to the society. To mention just the most prominent example, during the 1992-93 "Great Chechen Bank Fraud", a network of corrupt officials and (mostly) Chechen organized crime groups managed to embezzle at least $500 million from Russia's Central Bank (a third of the credit line the IMF granted to Russia that year) (Klebnikov, 2000).

This paper focuses on a specific organized crime group operating in Russia during the 1990s – the criminal fraternity *vory-v-zakone* (Eng. "thieves-with-a-code-of-honor"). Tracing its roots back to the Stalinist GULAG archipelago, vory became the primary non-state actor supplying private protection to legal businesses at the time of weak institutions that accompanied Russia's chaotic transition to capitalism during the 1990s. In addition, they were known as *co-ordinators* in Russia's illicit markets, orchestrating illegal activities and governing the underworld in their territories. Sharing a number of similarities[41] with mafia-type organizations in other countries, such as the Sicilian *Cosa Nostra* or the Italian-American Mafia, vory-v-zakone – unlike other OCGs operating in Russia at the time – can thus be considered the Russian Mafia (Varese, 2001, 1996).

This paper studies the origins of the Russian Mafia, its persistence under the repressive Soviet

[41] E.g. initiation ritual, strict code of conduct, control over the market for private protection,

state apparatus, and finally its impact on Russia's communities in mid-1990s. To that end, I web scraped a unique data source which contains detailed biographical information of more than 5,000 members of the vory-v-zakone criminal fraternity. This database, dubbed the *PCNA Dataset*, spans more than a century of the mafia existence, from the very first initiation in 1916, until the last recorded death in 2017. Information available includes, among other things, members' year and place of birth, initiation, and death, as well as their place of residence and prison history.

Using the PCNA Dataset, I first show that the Russian Mafia originated in the Soviet GULAG – a system of nearly 500 forced labor camp complexes spread across the entire USSR, which operated between 1920s-1950s and housed, on average, roughly four million prisoners at any given time. This finding builds upon previous studies which argue that vory-v-zakone originated in GULAG sometime in late 1920s/early 1930s (Varese, 2001, 1998; Serio, 2008). I contribute to this literature by providing first systematic empirical evidence in support of this claim. More specifically, using information about vory deaths and places of residence, I show that in 1921-1960, half of them lived in a 19km radius of the nearest gulag, while half of all vory deaths during this period occurred within just 3km of the nearest camp.

Second, I document that vory remained near camps in the period 1961-1991, despite the fact that majority of the camps were shut down by 1960. In particular, half of the initiation rituals during this period took place only 12km away from the nearest gulag, while half of all deaths were recorded within 15km of the nearest camp. Among those alive between 1961-1991, 50% lived within just 32km of the nearest gulag. These findings can be attributed primarily to the heavy restrictions on criminals' mobility imposed by Soviet authorities as well as the internal code of conduct according to which those released from the camps had to remain living nearby (Varese, 2001, 1998).

Third, using the PCNA Dataset, I build direct measures of both the extensive and the intensive margin of mafia presence across Russia's subregions in mid-1990s. The former is captured by a binary variable equal to 1 if a vor resides in a subregion between 1994-95 (1994-97, respectively), while the latter is measured by the number of vory per 100,000 population during the same time period. Using these measures, I show that distance to the nearest gulag is a strong negative predictor of mafia presence (both extensive and intensive margins) in Russia's subregions in the mid-1990s. More specifically, based on the estimates from the preferred specification, a subregion

located within 27km of the nearest camp (15th percentile) is 14 percentage points (0.5 standard deviations) more likely to host mafia in 1994-97 than a subregion located further away.

Finally, using an instrumental variable approach which exploits the proximity of mafia to the gulags, I consider the effect of mafia presence on local crime and violence in Russia in mid-1990s. In particular, I show that places with mafia presence experienced a rapid rise in crime driven by turf wars which erupted among rival clans in the early 1990s. In particular, hosting mafia in 1994-97 led to an increase in 1998 crime rate by 36 crimes per 10,000 (0.16 std. deviations). Moreover, the probability that a subregion witnessed an attack against a member of Russia's economic elite in 1996-98 rose by 36 percentage points due to mafia presence. Considering the heterogeneity in these attacks, I find that the rise in violence in mid-1990s was indiscriminate – mafia presence led to a higher likelihood of an attack regardless of whether the victim was a politician, a law enforcement official, a businessmen, or a fellow criminal.

4.2 DATA

4.2.1 PRIME CRIME NEWS AGENCY: INTRODUCING THE DATASET

This project combines several data sources. First and foremost, I have assembled a novel, arguably the most comprehensive dataset on the Russian Mafia to date. This dataset contains detailed biographical information of 5,043 current and former members of the *vory-v-zakone* criminal fraternity operating in the countries of the (former) Soviet Union at some point between 1916-2017. The data has been web scraped from the *Prime Crime News Agency (PCNA)*[42], a mass media website operating in Russia since 2006. PCNA is the culmination of more than 20 years of data collection and compilation by the website's founder, a Moscow-based businessman known only by his first name – Alexander. Figure 27 shows an excerpt from the website's profile of the vor Vyacheslav Kirillovich Ivankov (nicknamed *"Yaponchik"*; Eng. "The Jap"), one of the most prominent vory in the post-Soviet period. His profile is divided into two main parts - a detailed biography on the left-hand side and a summary table with a profile picture on the right-hand-side (Figure 27). In addition, the profile contains an extensive collection of photos of Mr. Ivankov as well as a comment section where fans, wannabes, and even criminals can anonymously post their comments or request

[42] `www.primecrime.ru`

corrections (not shown in Figure 27).

PCNA has been described by the media as "perhaps the world's most exhaustive information resource about the *vory-v-zakone* available to the public" (Schreck, 2009), and is regularly cited in news stories on Russian organized crime (Schwirtz, 2008). PCNA has also been cited as an important primary source of information about the vory fraternity in the academic literature (Varese, 2018; Galeotti, 2018; Belokurova, 2014; Slade, 2017, 2013). Further credibility of this data source is suggested by the fact that the vory themselves (as well as other Russian criminals) follow the website closely in order to get updates about the organization (e.g. who has been initiated, killed, arrested, etc.). For example, in January 2013, Italian police intercepted a phone conversation between two prominent vory discussing the recent assassination of the boss Ded Khasan in front of a Moscow restaurant (Tribunale Bari, 2012). Another vor was recorded boasting about his online PCNA profile during a phone conversation intercepted in December 2012 (Tribunale Bari, 2012). Even "official" documents pertaining to the organization have been leaked to the website in the past. As Varese (2018) mentions, in December 2012, after an initiation ceremony that took place in Dubai, a document containing the names of all 16 newly-admitted members appeared on the PCNA. It is thus not surprising then that the Italian police believes that the Russian Mafia uses the PCNA as a means of communication (Varese, Lonsky, and Podvysotskiy, 2019).

In Varese, Lonsky, and Podvysotskiy (2019), we further verify the validity the PCNA dataset by comparing it to two external data sources, both of which contain a significantly smaller number of vory compared to the PCNA dataset. Slade (2013) analyzes personal information of 279 vory residing in Georgia after 1991. This data was obtained from the Special Operations Department of the Georgian Anti-Organized Crime Unit (AOCU). Although we do not have access to Slade (2013)'s data, using the PCNA dataset, we were able to derive a distribution of vory across the 12 Georgian regions which is consistent with the distribution presented in Slade (2013)[43].

In addition, in Varese, Lonsky, and Podvysotskiy (2019), we digitized a 1994 document produced by the Russia's Ministry of the Interior (MVD), which contains full names, nicknames, and birth years of 266 vory present in Russia after 1991 (see Podlesskikh and Tereshonok (1994), Varese (2001)). Using full name and nickname as matching variables, we were able to merge all 266 mafia bosses into our PCNA dataset. We then compared the birth years of these individuals across the

[43] Figure 5.2 (page 99). The figure shows the distribution of vory by region of birth within Georgia.

two dataset and found a 95.11% match. These findings further suggest the reliability and accuracy of the PCNA dataset.

4.2.2 PCNA DATASET: DESCRIPTIVE STATISTICS

The PCNA is an individual-level dataset with each observation representing a Russian Mafia boss - a full member of the *vory-v-zakone* criminal fraternity. The data contains 5,043 individuals, a substantially larger number than any previous estimate of the size of the organization (Varese, 2001; Slade, 2011; Serio, 2008).[44] This minimizes my concern that the PCNA dataset misses some non-trivial share of *vory-v-zakone* members.

Table 19 presents select descriptive statistics and the information about missing values for all main variables in the PCNA dataset. There is significant variation in the share of non-missing values across variables, ranging from 6.78% for *Place of status revocation* to 91.59% for *Nationality/ethnicity*. However, the key variable for the empirical analysis - *Place of residence* - is missing only for a relatively low fraction of criminals (less than 26%). Moreover, for some of the variables, such as *Year of death* or *Year of status revocation*, it is mostly impossible to distinguish between values that are truly missing and the cases in which the individual is still alive or has not had his status revoked.

PCNA dataset spans the entire known period of existence of the vory fraternity, from the early days of the Soviet Union until the present-day Putin Russia (Varese, 2001). The first recorded initiation took place in 1916 while the most recent death is from December 2017. Figure 33 shows the trends in recorded initiations, deaths, and status revocations over time. It is important to keep in mind, however, that *Year of initiation* is available only for about a quarter of the sample (Table 19), which means that the initiations - particularly in the early period of the vory existence (1920s-1950s) - are grossly underestimated. Nevertheless, taken together, the three graphs in Figure 33 clearly show the major historic milestones in the organization, as described in the previous literature (Varese, 2018, 2001, 1998; Slade, 2013; Cheloukhine, 2008). In particular, the rise in deaths[45] and status revocations in the 1950s is consistent with the occurrence of the *such'ia voina* (Eng. bitches'

[44] Slade (2011), for example, estimates the number of vory in the post-Soviet space to be around 1,000-1,200. By contrast, my conservative estimate suggests that there have been at least 1,678 vory operating in the countries of the former Soviet Union since 1991.

[45] Mostly violent deaths, as shown in Figure C.1.

war), an internal conflict between two opposing factions which almost destroyed the organization (Varese, 2001, 1998; Cheloukhine, 2008). Second, Figure 33 shows the proliferation of the Russian Mafia after the dissolution of USSR in 1991, brought about by the chaotic transition to capitalism which increased both demand and supply of protection (Varese, 1996, 1994). Moreover, as Figure 33 suggests, this was accompanied by a sharp rise in violence, as rival clans competed for new territories and criminal opportunities. And finally, after a brief hiatus in the 2000s, early 2010s saw another rise in initiations which could be attributed to the conflict between the *Tbilisi clan* ledear Aslan ("Grandpa Khasan") Usoyan and the *Kutaisi clan* leader Tariel ("The Tarot") Oniani (Varese, 2018; Schwirtz, 2008). However, in contrast with previous conflicts, after the assassination of Mr. Usoyan in December 2012, this conflict appears to have been resolved without further bloodshed (i.e. status revocations increased but violent deaths did not; see Figures 33 and C.1).

Figure 33 also offers a unique piece of evidence not mentioned in the literature before. There is a sudden spike in deaths in late 1930s coinciding with the Great Terror - a brutal campaign of Stalin's political repression carried out in 1937-38 (Applebaum, 2003). Indeed, my dataset suggests that in 1937 alone, 90 vory lost their lives, 86 of which were confirmed executions in front of a firing squad. It is rather surprising that the vory were caught up in the politically-motivated Great Terror, given the "apolitical" stance of the criminal fraternity, as suggested by their code of behavior (Varese, 2001).

Last but not least, in Table 20, I present a breakdown of the PCNA dataset by recorded nationality/ethnicity of its members. Interestingly, Russians make up only about 30% of the sample. Indeed, almost half of the mafia bosses belong to one of Caucasian ethnic groups (mainly Georgians, Armenians, and Azerbaijani). Other Soviet ethnic minorities such as Jews or Yazidis are also over-represented relative to their shares in the general population. However, such a disproportionately high representation of minority groups within the mafia is not a unique feature of the *vory-v-zakone*. As Hill (2003) points out, the same is true for the Japanese *Yakuza* whose clans, such as the *Yamaguchi-gumi* family, have disproportionately high shares of ethnic Koreans and those with *burakumin* origin.

4.2.3 OTHER DATA SOURCES

Data on location of Gulag camps operating in USSR between 1921-1960 was compiled by Tatiana Mikhailova,[46] based on the information gathered by *The Memorial* (Moscow-based NGO). The dataset includes precise locations of 460 camps as well as information about the estimated prison population and the type of industrial activity in each camp.

My analysis also uses the *Russian elite economic violence dataset (REEV Dataset)* - a compilation of roughly 6,000 attacks against business, judicial, and political elites in Russia between 1990 and 2010. The database, which was compiled by Galina Belokurova,[47] contains exact date and location of each attack as well as information about the victim(s) and sometimes perpetrator(s) (see Belokurova (2018)). This paper is the first to exploit the precise geographical locations of the attacks.

Finally, my analysis uses subregional-level[48] data from 1990s Russia. In particular, I take advantage of the data on the 1995 Russia's legislative election as well as various 1990s' socioeconomic indicators (e.g. population density, crime rate, unemployment rate, average wage, etc.), provided by Enikolopov et al. (2011). In addition, 1990s' road and railroad densities were calculated using spatial data from the DIVA-GIS database, while the exact locations of 1,030 prisons operating across the Russian Federation in the 1990s were obtained from the Russian daily newspaper *Kommersant*.[49] The spatial data from PCNA as well as all prison locations were geocoded using Google Maps Geocoding API which enables high-precision geocoding of unparsed physical address written in Cyrillic script.

4.3 ORIGINS OF THE RUSSIAN MAFIA: 1919-1960

It has been argued in criminology literature that the proto-mafia group *vory-v-zakone* originated in the Soviet GULAG in the late 1920s or early 1930s (Varese, 2001, 1998; Slade, 2013; Serio, 2008; Serio and Razinkin, 1995). Using the PCNA dataset, I provide the most systematic empirical evidence to date in support of this claim.

[46] Data can be obtained on her personal website: `https://sites.google.com/a/nes.ru/tatiana-mikhailova/home`

[47] Dataset can be accessed here: `https://www.openicpsr.org/openicpsr/project/101540/version/V1/viewe`

[48] Equivalent to the Nomenclature of Territorial Units for Statistics (NUTS) 3 classification.

[49] `https://www.kommersant.ru/`. The prison database can be accessed on: `http://www.index.org.ru/turma/st/vsetur.htm?fbclid=IwAR353q1naW6w55M3C-dknSvI-iIN9KXv8Rpa9HzzULkIOv3AGFSV6nOqwFQ`

4.3.1 GULAG (1919-1960)

GULAG[50] was a system of force labor camps that existed throughout the USSR between 1920s-1950s. Although a few of the camps had been remnants of the Czarist Russia, the vast majority of them were constructed after the 1917 October Revolution in order to house political opponents and other "enemies of the state", as well as ordinary criminals (Applebaum, 2003; Ivanova, 2000; Varese, 2001). From 1929 onwards, USSR experienced a rapid expansion in the camps mainly due to Stalin's politically-motivated cleansing culminating with the Great Terror of 1937-38. Although the camps continued to expand after the World War II, following Stalin's death in March 1953, the Soviet political leadership decided to gradually dismantle them. The final order to shut down the camps came from the Ministry of the Interior (MVD) in 1960, although some of them were transformed and remained operational throughout the 1980s (Applebaum, 2003; Varese, 2001).

According to Applebaum (2003), there were at least 476 distinct camp complexes spread across the Soviet Union between 1921-1960.[51] These consisted of thousands of individual camps. Using information that was gathered and digitized by the Moscow-based NGO - *Memorial Society*[52] - Tatiana Mikhailova geocoded 460 of these camp complexes.[53] Figure 23 shows the distribution of gulags across the Soviet Union. Although the highest concentration of camps was in the European part of USSR, they were clearly spread out across all twelve Soviet time zones. In Table 21, I provide basic characteristics of the Gulag system (based on Mikhailova's data). The total prisoner population averaged across the 1921-1960 period was more than 4 million, although half of the complexes had fewer than 5,000 prisoners. Overall, it is estimated that some 18 million people passed through the Gulag system between 1929 and 1953 (Applebaum, 2003).

As a source of forced labor, gulags were important in the pre-World War II industrialization of USSR (Applebaum, 2003). Table 21 shows the main types of economic activity taking place in the camps. By far, the majority of them were focused on building infrastructure (61%). Other important activities included engineering (38%), forrest and woodwork (34%), and housing construction (24%). Naturally, a single camp was often involved in multiple economic activities.

Gulag prison population consisted of political prisoners ("politicals") as well as ordinary crimi-

[50] The acronym stands for *Glavnoe Upravlenie Lagerei* or Main Camp Administration. The term Gulag (or gulag), however, became a symbol of Soviet political repression in general (Applebaum, 2003).

[51] Same number is also given by Ivanova (2000).

[52] `https://www.memo.ru/en-us/`

[53] `https://sites.google.com/a/nes.ru/tatiana-mikhailova/home`

nals. Before World War II, the vast majority of inmates were criminals (roughly 82-88% in 1937-38), although the share of politicals rose to about 30% after the war. However, it is important to point out that many of the criminal prisoners had been sentenced for "crimes" which would hardly constitute crimes in other societies[54] (Applebaum, 2003). Thus, the share of actual criminals was substantially lower.

4.3.2 VORY-V-ZAKONE IN THE CAMPS

Gulag system played an exceptional role in the development of the vory-v-zakone criminal fraternity. Although the vory likely evolved from criminal groups operating in the pre-Revolutionary Russia, gulags enabled their rapid expansion across the Soviet Union (Varese, 2001, 1998; Serio, 2008). The rules of the organization were also unified within the camp walls. Vory become known for their highly selective membership, obscure initiation ritual (which involved a candidate choosing his own nickname), and strict code of behavior. This involved, for example, no cooperation with camp authorities, systematic refusal to work, contempt towards accumulation of assets, and strong opposition to unnecessary violence (including murder) (Varese, 2001, 1998).

By early 1930s, vory-v-zakone established a firm foothold within the camp structure. According to official government estimates at the time, the fraction of vory within the ranks of professional criminals in the camps did not exceed 6-7 percent (Varese, 2001). This "elitist" criminal society enjoyed prominent status in gulags with many privileges over ordinary prisoners. Vory had a common fund - *obshchak* - which supported all members. They also had their own courts called *skhodki* (meetings). At such a meeting, vory discussed any breaches of the code of conduct by fellow members and determined proper punishment (often severe), which was then swiftly carried out. Any decisions made at the meeting were communicated across the camps, and, if necessary, the punishment was effectively meted out by members in a different camp (Varese, 2001).

The expansion of the criminal fraternity continued until the end of World War II when an internal conflict broke out between two rivals factions. This so called *Bitches' War* (approx. 1948-1954), was a conflict between traditional vory – those who obeyed the strict code of behavior – and the *suki* ("bitches") – those who had served in the Red Army during World War II and/or decided

[54] For example, a man received a five-year camp sentence for being repeatedly late for work; a woman was sent to camps for stealing a pencil at work for her son to use at school (Applebaum, 2003).

to cooperate with camp authorities. Depicted in Figures 33 and C.1, this full-scale mob war almost wiped out the organization by the end of 1950s (Varese, 2001, 1998; Serio, 2008).

In this section, I provide new empirical evidence showing that the early period of the vory-v-zakone criminal fraternity was indeed closely tied to the Gulag camp system. Using the PCNA dataset, I calculated the distance to the nearest camp for all recorded: (1) initiation rituals, (2) places of residence, and (3) deaths during the official period of GULAG existence (1921-1960). Resulting distributions are depicted in Figure 33. Histograms for both places of residence and deaths show a clear pattern of proximity to the camps. In particular, during this period, 284 out of 568 vory lived within 18.8 km of the nearest gulag, while 101 out of 202 vory died within just 3.2 km of the nearest camp. Unfortunately, the histogram for initiations is not very informative due to a limited underlying sample size (only 35 observations). These findings are consistent with previous literature. According to Varese (2001), movement across the USSR was heavily restricted for former criminals and gulag convicts. Any vor released from a camp was required to register his residency in a nearby community. Moreover, according to the rules of the fraternity, he was expected to join other free vory in a local commune known as *kodla*. Members of such communes were expected to support each other as well as those still locked up in the camps (Varese, 2001, 1998). Thus, during the early period of vory-v-zakone existence, it was unlikely that any vor could be found residing far away from the camps.

4.4 VORY-V-ZAKONE IN POST-GULAG USSR (1961-1991)

The Bitches' War (1948-1954) led to an almost complete destruction of vory-v-zakone. As Serio (2008) notes, law enforcement organs in the Soviet Union were convinced that the criminal fraternity had practically disappeared by the end of the 1950s. However, as Figure 33 clearly shows, initiations continued (albeit in modest numbers) even after the Bitches' War and throughout the 1960s. The early 1970s saw a resurgence of vory, as the number of initiations increased and the organization regrouped (Fig. 33). An upward trend in initiations continued throughout the 1980s, eventually leading to an explosion in the membership in the early 1990s. Interestingly, 1980s also saw an increase in the number of expulsions from the organization (Fig. 33), while violent deaths remained low (Fig. C.1). As Varese, Lonsky, and Podvysotskiy (2019) argue, this ability to regulate membership by non-violently revoking status made the organization more resilient to internal and

external pressures.

As mentioned in the previous section, GULAG was officially closed down in 1960. However, some of the camps were re-designed and turned into regular prisons which operated until the 1980s (Applebaum, 2003; Varese, 2001).[55] The prison population during the post-GULAG period was made up mostly of criminals. According to Amnesty International's estimates from mid-1970s, only about 1% of all prisoners had political sentences (Applebaum, 2003). Despite large-scale amnesties in the 1950s, which reduced the camp population by some 80% between 1953-1960 (Dobson, 2009), many vory remained imprisoned through the 1960s and 1970s. Figure 31 shows the pattern of vory prison releases, as recorded in the PCNA dataset. First large-scale release saw 21 vory leave prison in 1976-77.[56] Releases then continued throughout the 1980s, peaking just before the dissolution of USSR in 1991 (Fig. 31). Even upon their release, vory were still not allowed to move away from the prisons due to restrictions on mobility imposed by authorities and the internal rules of the fraternity (Varese, 2001). Moreover, as Kozlov (2002) suggests, many politicals were unwilling to leave familiar places where they had spent much of their lives serving lengthy prison sentences.

Using PCNA data, I show that during the post-GULAG period of 1961-1991, vory-v-zakone remained in close geographic proximity to the Gulags. Using the initial distribution of 460 camp complexes, I once again calculated the distance to the nearest camp for each initiation and each death between 1961-1991, and for the places of residence of all vory alive in this period. Figure 32 presents the results. Remarkably, the median initiation took place only 11.9 km away from the camps, while the median death was recorded just 15.3 km away form the nearest camp. Furthermore, 50% of vory lived within 32 km of the nearest camp walls during this period. This confirms that by 1991, vory-v-zakone organization was still geographically clustered around the locations of the original 460 Gulag camps.

4.5 RUSSIAN MAFIA IN POST-SOVIET RUSSIA

In this section, I show that as vory-v-zakone evolved into a mafia-type organization operating in post-Soviet Russia, the territories under their control remained in the vicinity of the original GULAG locations. This paper is the first to argue that gulags played a key role in determining

[55] Such as *Perm-36* which has since been turned into a museum.
[56] With 10 of them released on June 26, 1976, according to PCNA data.

the presence of Russian Mafia across Russia in the early-to-mid 1990s. I contribute to the recent economics literature exploring the origins of organized crime in general, and mafia-type groups in particular. These studies have focused mainly on the case of Sicilian Mafia (Buonanno et al., 2015; Dimico et al., 2017; Acemoglu et al., 2018). However, a recent paper also explores the roots of Mexican cartels (Murphy and Rossi, 2017).

4.5.1 TRANSITION TO CAPITALISM & WEAK INSTITUTIONS

Although Soviet citizens were entitled to items of personal property, state owned all means of production. This began to change when Mikhail Gorbachev introduced economic reforms in 1986, which led to a dramatic increase in the number of property owners. In July 1991, a large-scale privatization began in USSR and continued in Russia after the dissolution of USSR in December 1991 (Shleifer and Vishny, 1994). By 1993, there were 82,000 privatized enterprises and 49,770 private peasant farms operating in Russia – almost one third of the entire value of Russia's productive capital (Varese, 1994). This increase in property ownership was, however, not matched by clearly defined and enforced property rights, business regulation, tax regulations, and copyright laws. In addition, a sharp increase in crime – especially violent crime[57] – during this period meant that the state was not able to protect the lives and property of its own citizens. Weak legal institutions thus created a demand for protection from non-state actors, which vory-v-zakone readily supplied (Varese, 2001, 1994).

Vory operated in both legal and illegal markets. Their main trade was the provision of protection. Vory not only sold protection, they seeked to monopolize the market for protection. In the overworld, vory provided a so-called "roof" (*krysha*) to legal businesses which mainly consisted of protection from "unprofessional" racketeers (and other street criminals). However, in many cases, vory also helped enforce contracts and resolve disputes with other businesses (Varese, 1996; Sokolov, 2004). In essence, vory-v-zakone thus served as a substitute for weak state institutions, more specifically, the backlogged courts and ineffective law enforcement agencies.

In the underworld, vory led their own criminal groups while also serving as *co-ordinators* orchestrating activities of other criminal elements, namely the *pseudo-businessmen*, *gangsters*, *"embezzlers of state property"*, and *corrupt officials* (Varese, 1996). As Varese (1996) further explains:

[57] Between 1989 and 1992, the number of murders in Russia rose by 70% (Varese, 1994).

1. *Co-ordinators ensure[d] protection to pseudo-businessmen from gangsters and provide[d] a 'shield' of corrupt officials to them.*
2. *They help[ed] gangsters to divide spheres of influence among themselves, find new targets for criminal activities, and ensure[d] protection from the authorities through their contacts with corrupt officials who operate[d] in institutions of law enforcement.*
3. *They ensure[d] those that steal state properties (embezzlers of state property) with opportunities to dispose of their loot, protection from gangsters and again provide[d] them with a 'shield' against corrupt officials.*
4. *They suppl[ied] corrupt officials with new clients to be 'sheltered' and provide[d] them with opportunities to arrest criminals who [had] disobeyed criminal rules. Corrupt public officials thus maintain[ed] the impression of fighting crime actively.*

Thus, one can think of vory-v-zakone as an organization whose goal was not only to operate in the underworld, but also to "govern" it. As a criminal fraternity with a strict code of conduct and an obscure initiation ritual, which provided protection and extra-legal governance in its territories, vory – unlike other criminal groups operating in Russia at the time – can justifiably be called the Russian Mafia (Varese, 2001).

4.5.2 MEASURING RUSSIAN MAFIA PRESENCE IN MID-1990S RUSSIA

The wealth of personal information assembled in the PCNA dataset enables the construction of a direct, first-of-its-kind measure of Russian Mafia presence in Russia' subregions during the period of early post-Soviet transition. This novel approach differs from previous studies of mafia-type organizations, which use various proxies for mafia presence such as mafia-related crimes or city council dissolutions due to mafia infiltration.[58]

The approach proposed in this paper employs two steps. First, using information on each member's year of birth, initiation, status revocation & death (if any), I determine which vory were "made" members of the organization between 1994-95 (1994-97, respectively). Second, I distribute these mafiosi into Russia's 2,445 subregions according to their place of residence (i.e. exact street

[58] See for example Peri (2004), Barone and Narciso (2015), or Daniele and Dipoppa (2017).

address). Those living outside of Russia are omitted. Information about the place of residence is available for 74% (3,746 out of 5,043) of individuals in the PCNA dataset. While a single address is available for 70% of these individuals (2,609 out of 3,746), the remaining 1,137 vory have multiple addresses on record. In such cases, moving date(s) are used to determine their most likely address during the period of interest.[59]

Such approach enables the construction of variables measuring both the extensive and the intensive margin of mafia presence in Russia' subregions. Extensive margin is captured by a binary variable equal to 1 if a vor resides in a subregion in 1994-95 (1994-97, resp.), and 0 otherwise. It is important to note that vory-v-zakone is a fraternity of equals (even though distinction can be made between junior and senior vory), and each member is expected to lead his own criminal group (Varese, 2001). Thus, observing a vor in a subregion means there is a local criminal group around him. Such groups, consisting of many non-member associates, can be large. For instance, the *Solntsevskaya Bratva*, one of the largest clans operating in Moscow during the 1990s, had an estimated 9,000 members in total. However, only 12 of them were made vory, each leading his own crew. These 12 vory formed the leadership of *Solntsevskaya Bratva* – the supreme council – which met regularly to discuss group's organizational matters (Varese, 2001).

The intensive margin of mafia presence is captured by the total number of vory per 100,000 population living in a subregion during 1994-95 (1994-97, resp.). This variable approximates the strength of the Russian Mafia in a given subregion. Figure 33 shows the geographic distribution of Russian Mafia across Russia's subregions. In 1994-95, 236 subregions (9.7%) had Mafia presence. These included the ten most populous cities in Russia.[60] By 1997, vory spread to 14 additional subregions. Among these were two large cities – Irkutsk and Cheboksary.

4.5.3 1990S RUSSIAN MAFIA AND GULAGS: EMPIRICAL SPECIFICATION

Remarkably, as Figures 29 and 33 suggest, most subregions where Russian Mafia operated in the mid-1990s had been in a close proximity to the GULAG camps during the 1920s-1950s, despite the fact that the majority of camps were shut down by 1960. To test how the distance to the nearest camp predicts Mafia presence in post-Soviet Russia, I estimate the following cross-sectional model

[59] If moving date(s) are missing, the first address on record is used (since addresses are ranked chronologically).

[60] Moscow, Saint Petersburg, Novosibirsk, Yekaterinburg, Nizhny Novgorod. Kazan, Chelyabinsk, Omsk, Samara, and Rostov-on-Don.

using ordinary least squares:

$$\text{Mafia}_i = \alpha + \beta_1 \text{Gulag}_i + \gamma X_i + \eta_s + \epsilon_i \tag{6}$$

where $Mafia_i$ is the measure of extensive/intensive margin of mafia presence in subregion i in the mid-1990s (as defined in section 5.2). $Gulag_i$ is a binary variable derived from the distance of subregion i's centroid to its nearest camp. To derive this variable, I first determine the overall distribution of the distance to the nearest labor camp (across all 2,445 Russia's subregions). Then, I use the 10th (17.6km), 15th (26.9km), and 20th (37.4km) percentiles from this distribution as alternative cutoff points to define $Gulag_i$. For example, a subregion is assigned the value 1 if it lies within 17.6km of the nearest camp, and 0 otherwise. As discussed in previous sections, most vory remained close to the camps once released due to the restrictions on mobility imposed by both the authorities as well as the internal rules governing the criminal fraternity. $Gulag_i$ is therefore defined as a binary variable to capture this non-linear relationship. Moreover, I test different higher order polynomials as alternative explanatory variables. Finally, eq. 6 also controls for region fixed effects (η_s) and subregion-specific characteristics (X_i).[61] Standard errors (ϵ_i) are heteroskedasticity robust.

4.5.4 1990S RUSSIAN MAFIA AND GULAGS: RESULTS

Table 23 presents the results of estimating eq. 6 with foucs on the extensive margin of mafia presence. As expected, the distance to the nearest camp is a strong negative predictor of mafia locations in mid-1990s. In particular, across all specifications, the coefficient estimates are positive and significant at 1%, suggesting that the likelihood of a subregion hosting mafia increases in the immediate vicinity of the camps. According to the coefficient from the preferred specification (column 4), subregions located within 27km of the nearest camp have 14 p.p. higher probability of hosting mafia in 1994-97 than those located further away. The effect is large in magnitude

[61] *1990s road & railroad densities (in km per km^2)* – proxies for local economic development; *Distance to region's administrative center* – proxy for strength of local institutions; and *Distance to nearest prison in 1990s.*

– chances of having mafia in these subregions increase by 0.5 standard deviations on average. The non-linearity of the relationship between mafia presence and distance to the nearest gulag is confirmed by estimating eq. 6 with second and third degree distance polynomials instead of the binary variables (see Table C.1).

The analysis of the intensive margin of mafia presence (i.e. number of vory per 100,000 inhabitants) paints a similar picture. Results are shown in Table C.2. The "strength" of the Russian Mafia increases, on average, by 0.16 vory per 100,000 (0.2 standard deviations) when a subregion is located within 27km of the nearest gulag (Table C.2, col. 4).

4.6 CONSEQUENCES OF THE RUSSIAN MAFIA IN 1990S RUSSIA

The effect of organized crime groups on local communities is an important policy-relevant question. Previous studies have documented detrimental effects on local economies (Pinotti, 2015; Peri, 2004; Daniele and Marani, 2011), allocation of public resources (Daniele and Dipoppa, 2018; Barone and Narciso, 2015), as well as local political outcomes (Feo and Luca, 2017; Daniele and Geys, 2015; Acemoglu, Feo, and Luca, 2018) and political violence (Alesina, Piccolo, and Pinotti, 2019; Daniele and Dipoppa, 2017). This study is the first to estimate the effect of mafia presence on local crime. In addition, I contribute to the studies of political violence by considering the impact of mafia on both political and non-political violence in 1990s Russia.

The effect of mafia presence on crime is *ex ante* ambiguous. As Varese (2014) explains, on one hand, mafia may shield other criminals from authorities, thus promoting ordinary crimes. It may even allow some types of crime to go unpunished in order to keep the demand for its protection services high. Moreover, if an open conflict between rival clans breaks out, this can lead to a surge in violent crime in affected communities. Such conflict will also likely divert law enforcement resources away from battling street crime (especially property crime), thus emboldening petty criminals to scale up their activities.

On the other hand, in the absence of any conflict between the clans, mafia might want to keep petty crimes low in order not to attract police attention (Varese, 2014). After all, mafia-type organizations strive to govern the underworld, and it is unlikely that any illicit activity could take place in its territory without its prior approval. Mafia may also choose to provide some kind od public safety in its neighborhoods. Indeed, as Gambetta (1993) describes: "The [Sicilian M]afia at

times polices its territory as if it were responsible for public safety. Young thugs are recruited just to keep them off the street." Finally, even a violent mafia feud can lead to a decrease in the overall crime in the long run, if state and/or regional authorities response to such conflict by allocating a disproportionate amount of law enforcement resources to the affected localities. Thus, the effect of mafia on local crime remains an empirical question.

4.6.1 EMPIRICAL SPECIFICATION

To determine the effect of Russian Mafia on local crime and violence, I estimate the following cross-sectional specification:

$$\text{Outcome}_i = \alpha + \beta_1 \text{Mafia}_i + \gamma X_i + \eta_s + \mu_i \tag{7}$$

where $Outcome_i$ is the crime rate (per 10,000 inhabitants) in subregion i in 1998, and $Mafia_i$ is the measure of extensive/intensive margin of mafia presence in 1994-97 (defined in section 5.2). Alternatively, the dependent variable used is a binary measure equal to 1 if subregion i experienced an attack against a member of Russia's *economic elite* between 1996-98. In such specification, $Mafia_i$ is measured in 1994-95. The term "economic elite", as broadly defined by Belokurova (2018), encompasses politicians, judges, law enforcement & army officers, businessmen & managers, journalists, and even prominent criminals. In further analysis, a breakdown of attacks into four categories explores potential heterogeneity across different types of victims: (1) businessmen and managers; (2) criminals; (3) law enforcement, army, and judges; (4) politicians and public figures. These categories are not necessarily mutually exclusive. For example, a number of individuals in the REEV dataset are classified as both businessmen and criminals.

Eq. 7 further controls for region fixed effects (η_n) and a broad set of subregion-specific characteristics (X_i), which are divided into three groups: (1) economic controls;[62] (2) population controls; [63] and (3) institutional controls.[64] Finally, μ_i is the idiosyncratic heteroskedasticity-robust error

[62] *1998 unemployment rate, 1996 log of average wage, 1990s road & railroad densities (in km/km^2).*
[63] *1996 population density, 1998 share of retired people.*
[64] *Distance to region's administrative center, Distance to nearest prison in 1990s.*

term. The location choices of mafia members, conditional on observables, are likely endogenous to both the outcome of interest and some unobserved factors. Thus, OLS estimate of β_1 will likely be biased.

4.6.2 IDENTIFICATION

To identify a plausibly causal effect of mafia presence on local crime and violence, I employ instrumental variable approach that exploits the proximity of 1990s Russian Mafia to the 1921-1960 GULAG archipelago, as detailed in Table 23. The instrument of choice is defined as:

$$\text{Gulag IV}_i = \begin{cases} 1, & \text{if distance of subregion i to nearest gulag} < 26.9\text{km} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where 26.9km is the 15th percentile from the population distribution of the distance to the nearest camp across Russia's subregions. However, I test different distance thresholds as well as higher order distance polynomials as alternative instruments. As shown in Table 23, distance to the nearest camp is a strong negative predictor of mafia presence in mid-1990s Russia. For the instrument to be exogenous, the initial placement of the camps has to be orthogonal to any socioeconomic factors of that time, which could have persisted, affecting the spatial distribution of crime and violence in 1990s Russia. To argue that this is indeed the case, I use data from Acemoglu et al. (2011) to show that gulag and non-gulag regions are not systematically different in a number of socioeconomics indicators in the early period of GULAG history. In addition, during the German invasion of USSR in 1941, Soviet leadership implemented a "scorched earth" tactics, moving industrial production that was in the path of the advancing German Army behind Ural Mountain, and destroying the capital that could not be moved. Given that the majority of gulags were built in the European part of USSR (see Figure 29), this developmnet during the war makes it even less likely that any economic conditions that determined the gulag initial placement could have persisted into the 1990s.

Second concern with the exclusion restriction is the potential direct effect of gulags on 1990s crime and violence in the communities nearby. However, most of the camps were shut down by 1960.

To account for a possible direct effect of those camps that remained open and were transformed into regular prisons, I control directly for the distance to the nearest correctional institution in Russia in the 1990s. This measure is derived using exact addresses of 1,033 jails, prisons, corrective colonies, medical correctional facilities, and educational colonies operating in Russia throughout the 1990s.[65]

4.6.3 RESULTS

Tables 24, 25, and 26 present the results. First, I consider the effect of mafia presence on local crime rates. As Table 24 suggests, both the extensive and the intensive margin of mafia presence positively affect the overall crime rate in a subregion. According to the result from the preferred specification (Table 24, col. 5), the presence of a vor in a subregion increases crime rate by about 150 crimes per 10,000 pop. (0.7 standard deviations of the dependent variable).

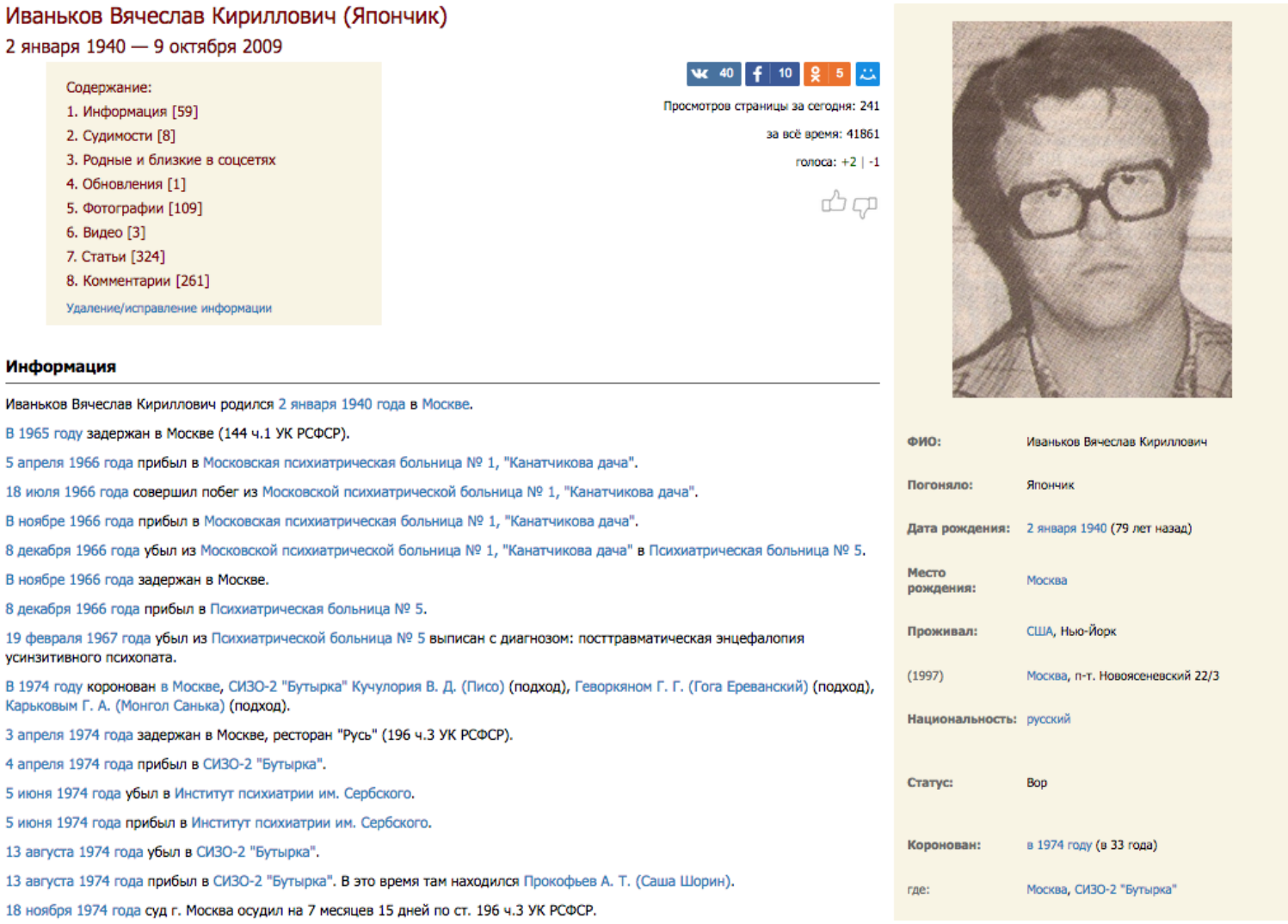
To better understand which type of crime drives this result, I turn to the Russian Economic Elite Violence dataset. As Table 25 indicates, the presence of the mafia in mid-1990s led to a spike in the attacks against local economic elites in the surrounding communities. These attacks appear to have been indiscriminate – targeting fellow criminals, businessmen, police officers, and politicians alike (Table 26). Klebnikov (2000) helps to shed more light on the situation in the Russian criminal underworld in the early-to-mid-1990s. In April 1993, a war broke out between the Chechens and the vory (with many vory siding with the Chechens), which quickly spread throughout Russia. Virtually all organized crime groups in Russia at the time sided with one faction or the other. Importantly, the attacks against prominent local elites became a primary weapon of this war – which officially lasted until the end of 1994, but likely lingered on throughout the 1990s. Criminals from one faction murdered those on the other side of the front, businessmen used contract killers to eliminate their competition, while many police officers and judges died trying to stem this violence (Klebnikov, 2000).

[65] Full list of correctional institutions was provided by Russian daily newspaper *Kommersant*, and can be accessed here: `http://www.index.org.ru/turma/st/vsetur.htm?fbclid=IwAR0nEekNNZjHrSqqB81Zrm25xvCfrUnCpmERTvL3T5B3rryR5lrO4xN3BC8`.

4.7 CONCLUSION

This dissertation chapter studies the origins and consequences of the Russian Mafia, known as vory-v-zakone. I assembled a unique data set that contains detailed biographies of more than 5,000 members of the vory criminal fraternity. Using this dataset, I then show that the Russian Mafia originated in the Soviet Gulag system, and remained near gulags even some 30+ years after the camps were officially shut down in 1960. Moreover, using an instrumental variable approach that exploits the spatial distribution of gulags in the USSR, I show that communities with mafia presence in the mid-1990s experienced a significant increase in crime driven by violence among rival organized crime groups. This paper provides a unique perspective on the study of organized crime through its use of a one-of-a-kind dataset that spans more than 100 years of history of the Russian Mafia. The results of this study could help policymakers and law enforcement officials design better policies that address the resurgence of organized crime in countries that undergo a sudden transition from communism to capitalism, which is often accompanied by inadequate institutional reforms.

Figure 27: Excerpt From the Profile of Mafia Leader Vyacheslav Kirillovich Ivankov ("The Jap")



Иваньков Вячеслав Кириллович (Япончик)

2 января 1940 — 9 октября 2009

Содержание:

1. Информация [59]
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Удаление/исправление информации

40 10 5

Просмотров страницы за сегодня: 241

за всё время: 41861

голоса: +2 | -1

Информация

Иваньков Вячеслав Кириллович родился 2 января 1940 года в Москве.

В 1965 году задержан в Москве (144 ч.1 УК РСФСР).

5 апреля 1966 года прибыл в Московская психиатрическая больница № 1, "Канатчикова дача".

18 июля 1966 года совершил побег из Московской психиатрической больница № 1, "Канатчикова дача".

В ноябре 1966 года прибыл в Московская психиатрическая больница № 1, "Канатчикова дача".

8 декабря 1966 года убыл из Московской психиатрической больница № 1, "Канатчикова дача" в Психиатрическая больница № 5.

В ноябре 1966 года задержан в Москве.

8 декабря 1966 года прибыл в Психиатрическая больница № 5.

19 февраля 1967 года убыл из Психиатрической больница № 5 выписан с диагнозом: посттравматическая энцефалопия усинзитивного психопата.

В 1974 году коронован в Москве, СИЗО-2 "Бутырка" Кучулория В. Д. (Писо) (подход), Геворкяном Г. Г. (Гога Ереванский) (подход), Карьковым Г. А. (Монгол Санька) (подход).

3 апреля 1974 года задержан в Москве, ресторан "Русь" (196 ч.3 УК РСФСР).

4 апреля 1974 года прибыл в СИЗО-2 "Бутырка".

5 июня 1974 года убыл в Институт психиатрии им. Сербского.

5 июня 1974 года прибыл в Институт психиатрии им. Сербского.

13 августа 1974 года убыл в СИЗО-2 "Бутырка".

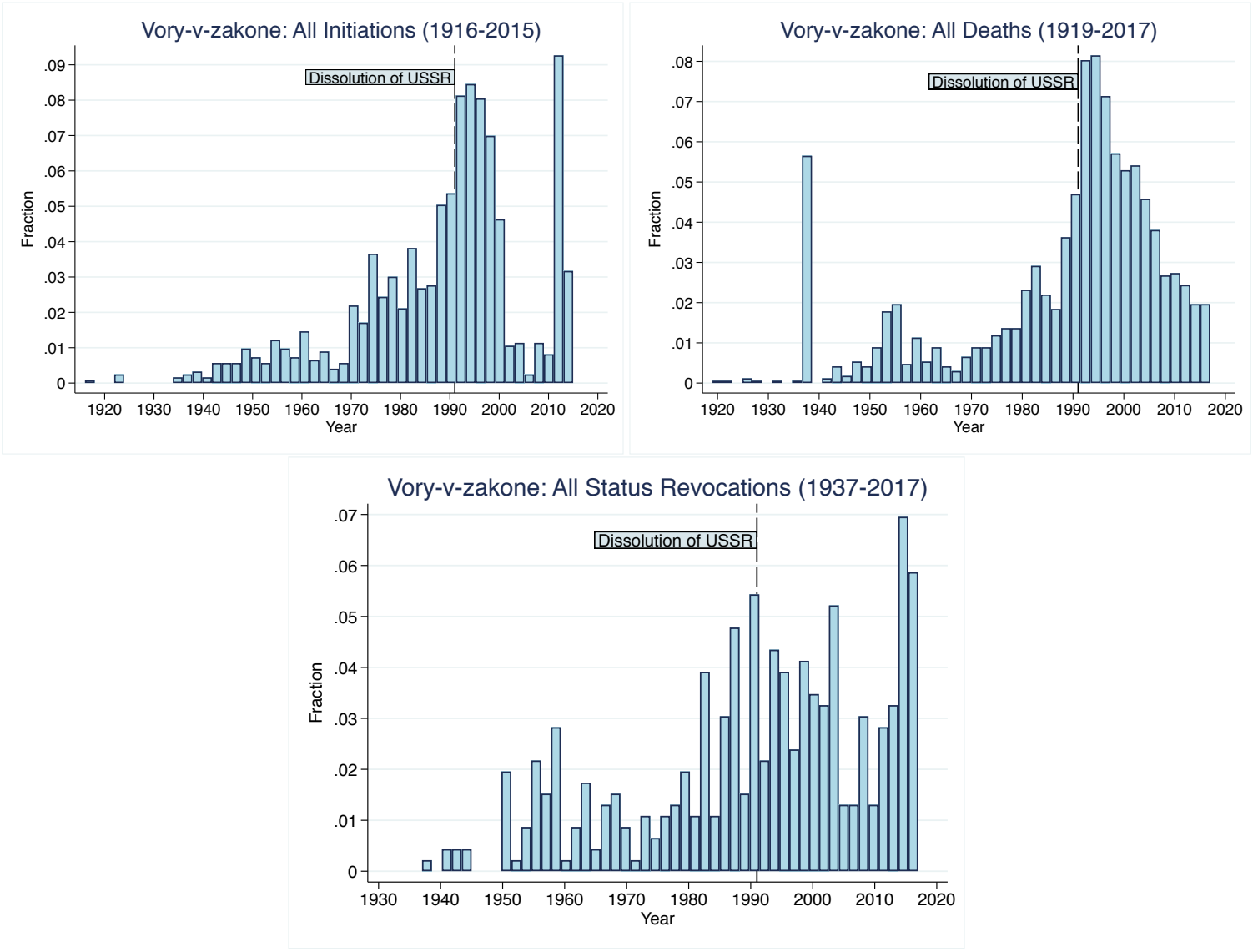
13 августа 1974 года прибыл в СИЗО-2 "Бутырка". В это время там находился Прокофьев А. Т. (Саша Шорин).

18 ноября 1974 года суд г. Москва осудил на 7 месяцев 15 дней по ст. 196 ч.3 УК РСФСР.

ФИО:	Иваньков Вячеслав Кириллович
Погоняло:	Япончик
Дата рождения:	2 января 1940 (79 лет назад)
Место рождения:	Москва
Проживал:	США, Нью-Йорк
(1997)	Москва, п-т. Новоясеневский 22/3
Национальность:	русский
Статус:	Вор
Коронован:	в 1974 году (в 33 года)
где:	Москва, СИЗО-2 "Бутырка"

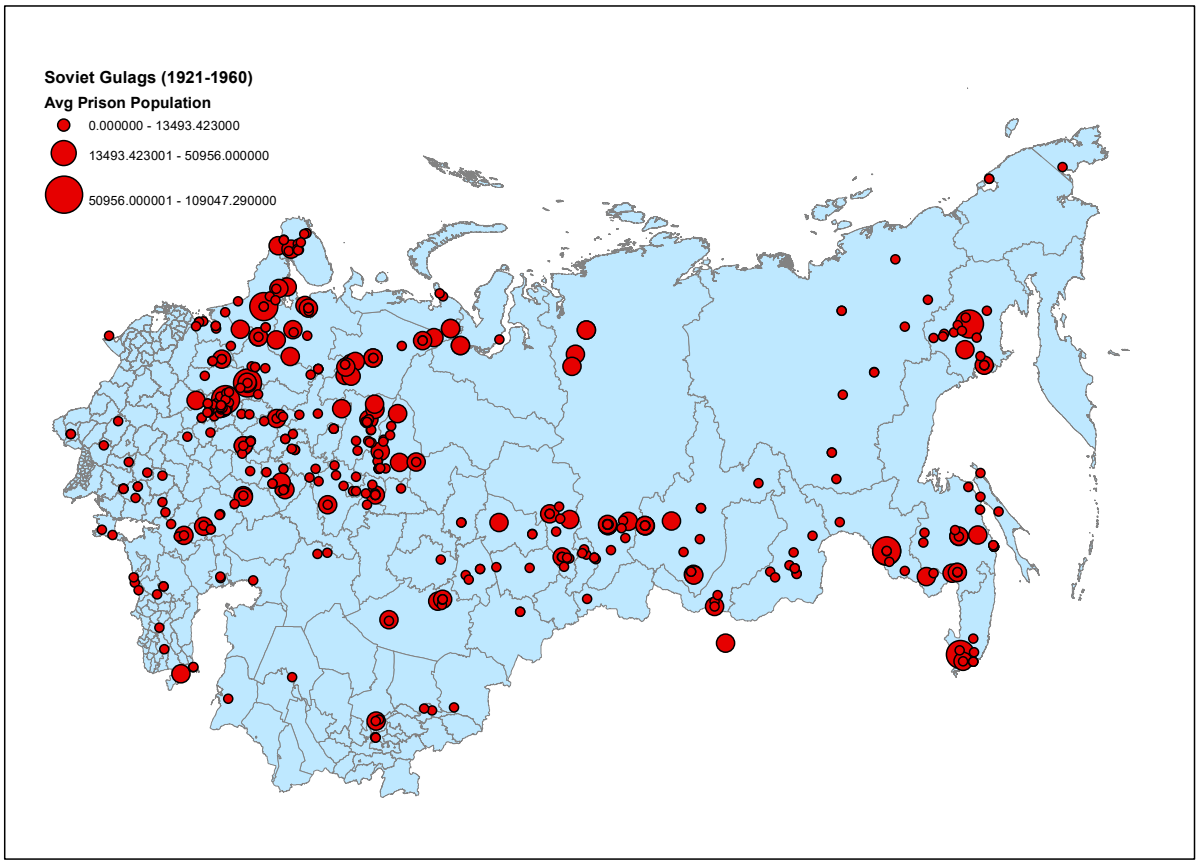
Notes - Source: *Prime Crime News Agency*. The figure shows only an excerpt from Mr. Ivankov's profile. The full profile can be accessed here: `http://www.primecrime.ru/characters/574/`.

Figure 28: Mafia Initiations, Deaths, and Status Revocations over Time



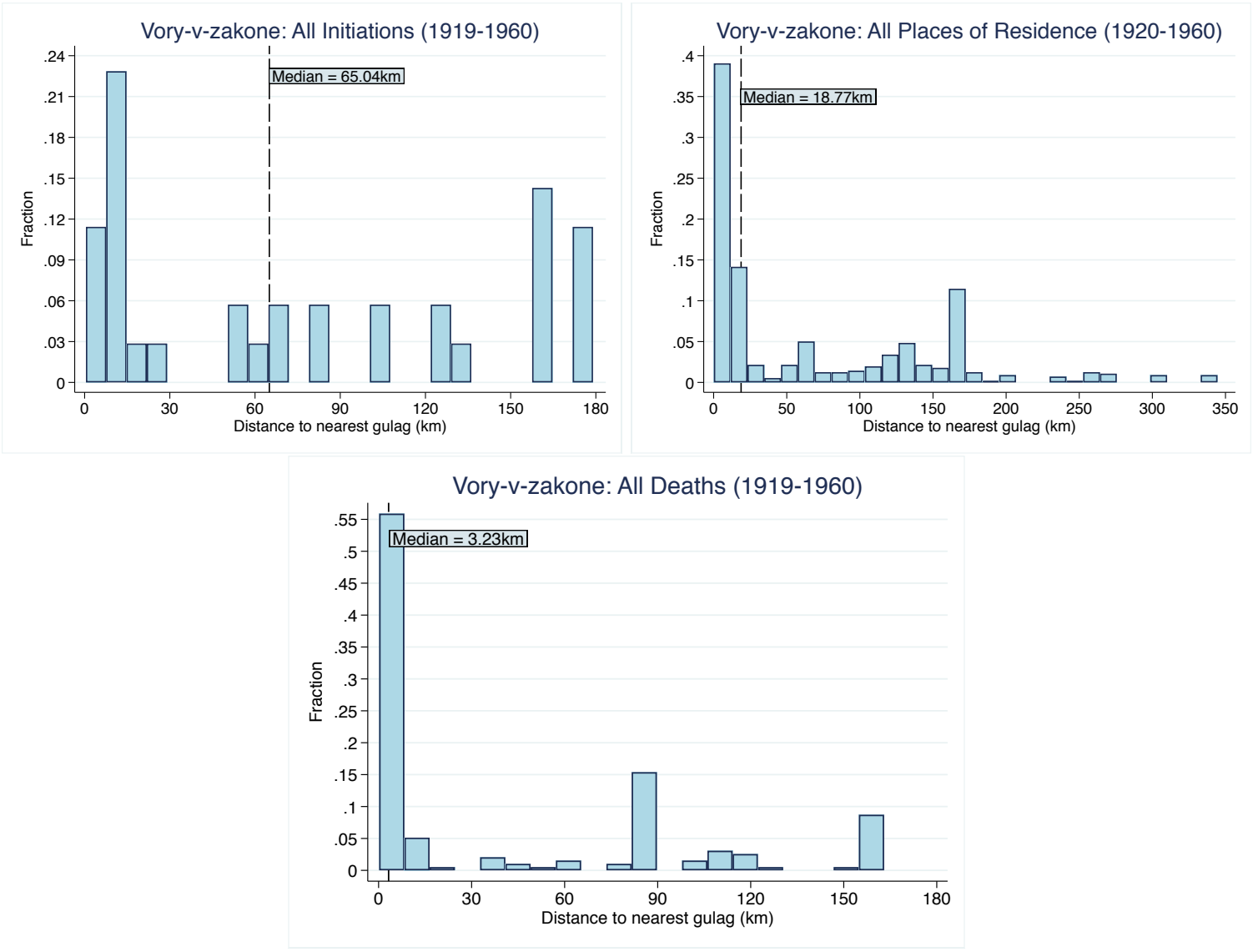
Notes - Data comes from *Prime Crime News Agency*. Underlying sample sizes are as follows: 1,230 unique initiations (top-left hist.); 1,681 deaths (top-right hist.); 460 unique status revocations (bottom hist.). USSR was dissolved on December 26, 1991. 100% of sample is depicted in each histogram. The number of bins is set to 50.

Figure 29: 460 Labor Camps of the Soviet Gulag (1921-1960)



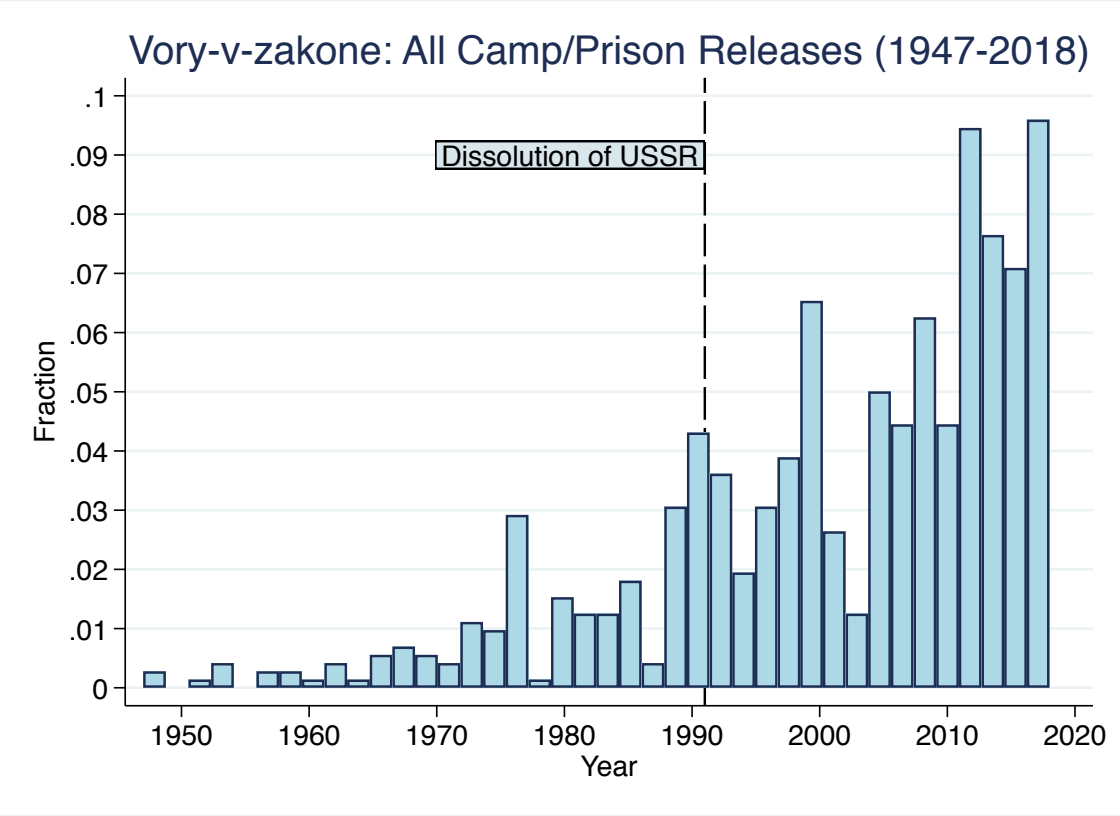
Notes - Geocoded locations of all 460 camps were provided by Tatiana Mikhailova based on the information from the Moscow-based NGO - *Memorial Society*. Only camps with available geographical location (latitude & longitude) are used in the analysis. 34 of the camps have missing info on average prison population, and thus are labeled as 0. The map uses *Asia North Albers Equal Area Conic* projected coordinate system, and shows NUTS 2 (region-level) classification of the Soviet Union (as of 1989).

Figure 30: Mafia Deaths, Initiations, and Places of Residence During GULAG Period: 1919-1960



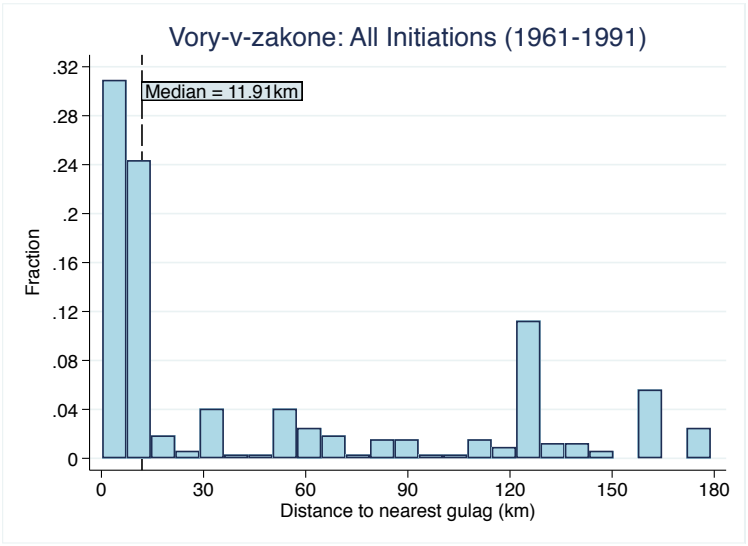
Notes - Data comes from *Prime Crime News Agency*. Underlying sample sizes are as follows: 35 unique initiations (top-left) – 100% of sample is depicted in hist.; 568 unique places of residence (top-right) – 98.2% of sample is depicted in hist.; 202 deaths (bottom-center) – 96.5% of sample is depicted in hist. Number of bins was set to: 25 (top-left); 30 (top-right); 20 (bottom-center).

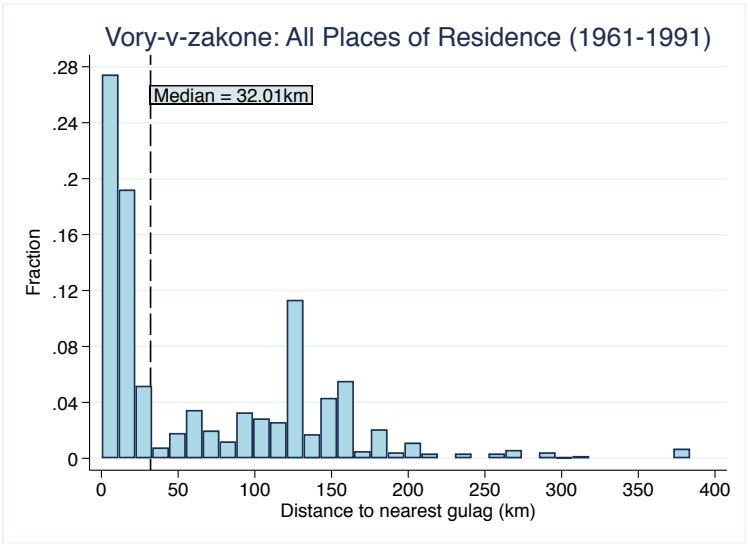
Figure 31: All Recorded Camp/Prison Releases: 1947-2018

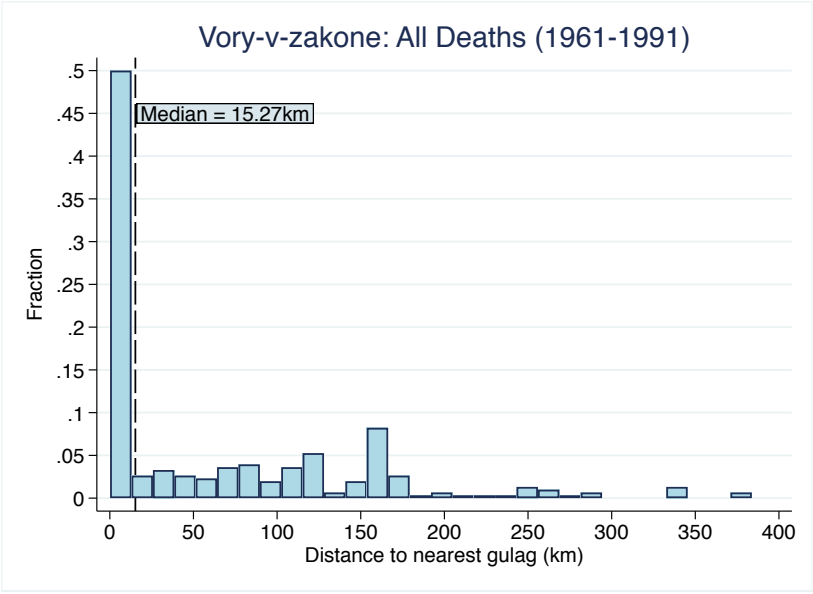


Notes - Data comes from *Prime Crime News Agency*. The histogram was generated using 719 unique prison releases. USSR was dissolved on December 26, 1991. 100% of sample is depicted in the histogram. The number of bins is set to 40.

Figure 32: Mafia Deaths, Initiations, and Places of Residence in Post-GULAG Period: 1961-1991

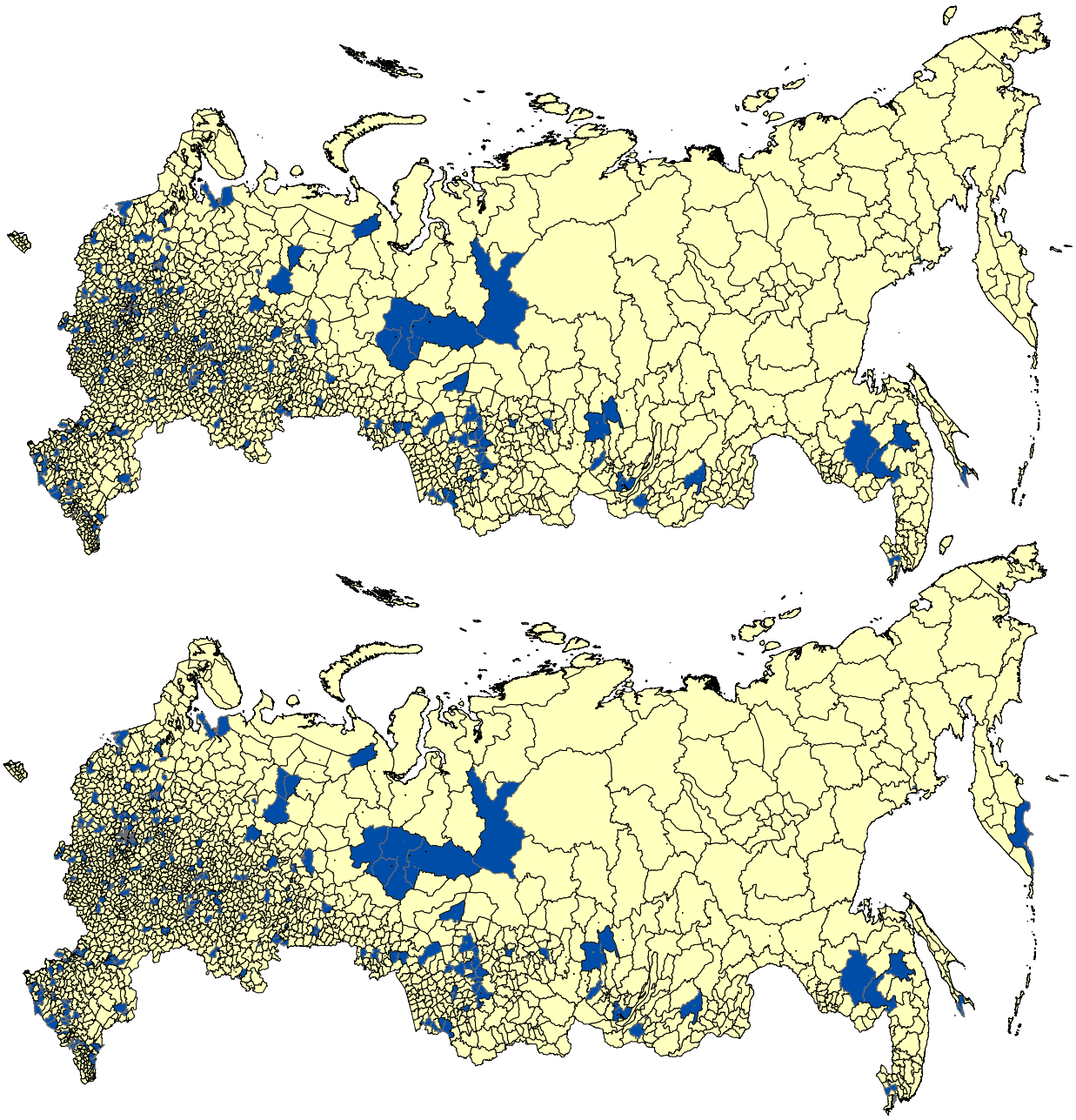






Notes - Data comes from *Prime Crime News Agency*. Underlying sample sizes are as follows: 323 unique initiations (top-left) – 99.1% of sample is depicted in hist.; 1,185 unique places of residence (top-right) – 97.5% of sample is depicted in hist.; 308 deaths (bottom-center) – 98.7% of sample is depicted in hist. Number of bins was set to: 25 (top-left); 35 (top-right); 30 (bottom-center).

Figure 33: Russian Mafia Presence in Russia's Subregions (1994-95 vs. 1994-97)



Notes - Data comes from *Prime Crime News Agency*. Vory-v-zakone presence across Russia's subregions. Blue areas indicate those subregions with at least 1 vor present in: (1) 1994-95 (above); (2) 1994-97 (below).

Table 19: PCNA Dataset: Main Variables & Select Descriptive Statistics

Variable	Non-Missing Values (#)	Non-Missing Values (%)	Mean	Standard Deviation
Full name	3,466	68.73	–	–
Nickname	4,478	88.80	–	–
Nationality/ethnicity	4,619	91.59	–	–
Year of birth	2,820	55.92	1949.62	22.06
Place of birth	3,775	74.86	–	–
Year of initiation	1,230	24.39	1988.58	17.35
Place of initiation	1,001	19.85	–	–
Age at initiation	1,190	23.60	27.21	7.27
Place of residence	3,746	74.28	–	–
Year of status revocation	460	9.12	1990.90	19.16
Place of status revocation	342	6.78	–	–
Year of death	1,682	33.35	1988.23	20.53
Place of death	1,409	27.94	–	–
Age at death	1,398	27.72	45.54	15.20
Exact cause of death	897	17.79	–	–

Notes - Source: Prime Crime News Agency. The total number of observations is 5,043. Each observation represents an individual (vor).

Table 20: PCNA Dataset: Vory by Nationality/Ethnicity

Nationality/Ethnicity	**#**	**% of Total**
Russian	1,485	29.45
Georgian	1,249	24.77
Armenian	884	17.53
Azerbaijani	175	3.47
Other Caucasian nationality/ethnicity	134	2.66
Jew	172	3.41
Yazidi	129	2.56
Ukrainian	112	2.22
Other (non-Caucasian) nationality/ethnicity	279	5.53
No information provided	424	8.41
Total	5,043	100

Notes - Source: Prime Crime News Agency. Each observation represents an individual (vor). *Other Caucasian nationality/ethnicity* - Abkhazian, Adyghean, Avar, Balkar, Bosha, Chechen, Circassian, Dargin, Ingush, Kabardian, Karachay, Kumyk, Lak, Lezgin, Ossetian, Talysh. *Other (non-Caucasian) natinality/ethnicity* - Assyrian, Bashkir, Belarusian, Bulgarian, Buryat, Chuvash, Gagauz, German, Greek, Gypsy, Iranian, Kazakh, Komi-Zyryan, Korean, Kyrgyz, Lithuanian, Moldovan, Mordvin, Pole, Serb, Spaniard, Tajik, Tatar, Turk, Turkmen, Udmurt, Uyghur, Uzbek.

Table 21: Soviet Gulags (1921-1960): Basic Characteristics

Total # of Labor Camps	460
Total Prisoner Population	4,180,304
Median Prison Population	5,000
Std. Dev. of Prison Population	13,622.77
% Infrastructure Construction	60.65%
% Engineering/Industrial Engineering	37.85%
% Forrest and Woodwork	33.91%
% Housing Construction	23.91%
% Agriculture	21.74%
% Construction of Mining Plants	19.35%
% Mining of Coal/Uranus/Ore/Gold/Apatite/Tin/Rock	15.73%
% Services	15.00%
% Fuel and Energy Complex	6.74%
% Metallurgy	4.57%
% Military Industrial Complex	4.57%
% Research & Development	4.13%
% of Transit Points	1.09%

Notes - Data comes from Tatiana Mikhailova. Only camps with available geographical location (latitude & longitude) are used in the analysis. *Total Prisoner Population* - total number of prisoners averaged over the entire period (1921-1960). The shares are computed based on the number of camps with available information for the given industrial activity.

Table 22: Average Characteristics of Mafia vs Non-Mafia Subregions of Russia

	Mafia Subegions			*Non-Mafia Subregions*			*Difference-in-means test*	
OUTCOME	**Obs.**	**Mean**	**SD**	**Obs.**	**Mean**	**SD**	**t**	**Prob(|T| > |t|)**
Population (1996)	203	170,895	274,160	1,802	41,911	53,126	-17.32	0.000
Population Density (1996)	203	1,820.8	11,104.1	1,802	4,340.3	25,847.8	1.37	0.170
Share of Retired Population (1998)	201	25.40	10.36	1,774	25.35	10.78	-0.07	0.948
Log of Avg. Wage (1996)	196	2.66	2.89	1,771	2.53	2.82	-0.62	0.537
1990s Road Density (km per km^2)	250	0.59	1.83	2,195	1.46	13.73	0.99	0.320
1990s Railrod Density (km per km^2)	250	0.65	5.72	2,195	0.94	7.09	0.61	0.541
Dist. to region's administrative center (km)	250	93.24	123.28	2,195	169.43	208.44	5.67	0.000
Dist. to nearest prison in 1990s (km)	250	29.39	49.47	2,195	75.06	132.07	5.42	0.000
# Doctors per 10,000 pop. (1998)	201	33.42	29.40	1,774	22.05	13.07	-9.84	0.000
# Nurses per 10,000 pop. (1998)	201	93.22	74.77	1,774	86.91	36.81	-2.01	0.045
Crime Rate (1998)	201	190.22	312.73	1,774	161.58	205.47	-1.76	0.079

Notes - Data comes from Prime Crime News Agency.

Table 23: Gulag & Mafia Presence in 1990s (OLS)

	(1) Mafia presence (1994-95)	(2) Mafia presence (1994-97)	(3) Mafia presence (1994-95)	(4) Mafia presence (1994-97)	(5) Mafia presence (1994-95)	(6) Mafia presence (1994-97)
Gulag distance < 10th percentile (10p = 17.6km)	0.145*** (0.029)	0.148*** (0.030)				
Gulag distance < 15th percentile (15p = 26.9km)			0.131*** (0.024)	0.137*** (0.024)		
Gulag distance < 20th percentile (20p = 37.4km)					0.107*** (0.020)	0.110*** (0.020)
Region FE	YES	YES	YES	YES	YES	YES
Road & Railroad Densities (km/km^2)	YES	YES	YES	YES	YES	YES
Distance to region's admin. center (km)	YES	YES	YES	YES	YES	YES
Distance to nearest prison in 1990s (km)	YES	YES	YES	YES	YES	YES
Observations	2,445	2,445	2,445	2,445	2,445	2,445
F-statistic	47.29	47.23	52.68	55.69	42.40	43.48
R-squared	0.120	0.126	0.122	0.129	0.118	0.125
Mean of dep. variable	0.097	0.102	0.097	0.102	0.097	0.102
Std. dev. of dep. variable	0.295	0.303	0.295	0.303	0.295	0.303

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Mafia presence (1994-95)* - binary var. equal 1 if at least one vor present in subregion between 1994-95. *Mafia presence (1994-97)* - binary var. equal 1 if at least one vor present in subregion between 1994-97. *Gulag distance < 10th percentile* - binary var. equal 1 if subregion is located within 17.6km of the nearest gulag camp. *Gulag distance < 15th percentile* - binary var. equal 1 if subregion is located within 26.9km of the nearest gulag camp. *Gulag distance < 20th percentile* - binary var. equal 1 if subregion is located within 37.4km of the nearest gulag camp. Estimation sample consists of all 2,445 subregions within the Russian Federation (as of 1992). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 24: Mafia Presence & Local Crime in 1990s Russia

	(OLS) Crime rate (1998)	(OLS) Crime rate (1998)	(OLS) Crime rate (1998)	(IV) Crime rate (1998)	(IV) Crime rate (1998)	(IV) Crime rate (1998)
Presence of mafia (1994-97)	35.78***	33.79***		151.60**	149.60**	
	(10.25)	(10.36)		(67.46)	(75.25)	
Mafia per 100,000 pop. (1994-97)			10.40***			117.8*
			(3.921)			(65.70)
Region FE	YES	YES	YES	YES	YES	YES
Population & Economic controls		YES	YES		YES	YES
Road & Railroad Densities (km/km^2)		YES	YES		YES	YES
Institutional controls		YES	YES		YES	YES
Observations	1,975	1,938	1,938	1,975	1,938	1,938
Adjusted R-squared	0.807	0.811	0.810	–	–	–
Mean of dep. variable	164.5	166.5	166.5	164.5	166.5	166.5
Std. dev. of dep. variable	218.9	220.2	220.2	218.9	220.2	220.2
Angrist-Pischke F-stat	–	–	–	32.62	28.53	9.430

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Crime rate (1998)* - # of crimes per 10,000 inhabitants in 1998. *Presence of mafia (1994-97)* - binary var. equal 1 if a vor present in subregion in 1994-97. *Mafia per 100,000 pop. (1994-97)* - # of vory per 100,000 inhabitants present in subregion in 1994-97. The instrument used in the IV estimation is a binary var. equal 1 if subregion was within 26.9km km (i.e. 15th percentile) of the nearest gulag. Population controls: population density (1996), share of retired people (1998). Economic controls: unemployment rate (1998), log of average wage (1996). Institutional controls: distance to region's administrative center, distance to the nearest prison (operating in the 1990s). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 25: Mafia Presence & Economic Elite Attacks in 1990s Russia

	(OLS) Any Attack (1996-98)	(OLS) Any Attack (1996-98)	(OLS) Any Attack (1996-98)	(IV) Any Attack (1996-98)	(IV) Any Attack (1996-98)	(IV) Any Attack (1996-98)
Presence of mafia (1994-95)	0.366***	0.350***		0.747***	0.916***	
	(0.033)	(0.037)		(0.115)	(0.148)	
Mafia per 100,000 pop. (1994-95)			0.062***			0.701***
			(0.014)			(0.209)
Region FE	YES	YES	YES	YES	YES	YES
Road & Railroad Densities (km/km^2)		YES	YES		YES	YES
Institutional controls		YES	YES		YES	YES
Population & Economic controls		YES	YES		YES	YES
Observations	2,445	1,938	1,938	2,445	1,938	1,938
Adjusted R-squared	0.230	0.218	0.107	–	–	–
Mean of dep. variable	0.079	0.077	0.077	0.079	0.077	0.077
Std. dev. of dep. variable	0.270	0.267	0.267	0.270	0.267	0.267
Angrist-Pischke F-stat	–	–	–	62.06	44.79	11.69

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Any Attack (1996-98)* - binary equal 1 if any attack against a member of the Russia's economic elite (see Belokurova (2018)) occurred in 1996-98. *Presence of mafia (1994-95)* - binary var. equal 1 if a vor present in subregion in 1994-95. *Mafia per 100,000 pop. (1994-95)* - # of vory per 100,000 inhabitants present in subregion in 1994-95. The instrument used in the IV estimation is a binary var. equal 1 if subregion was within 26.9km km (i.e. 15th percentile) of the nearest gulag. Economic controls: unemployment rate (1998), log of average wage (1996). Institutional controls: distance to region's administrative center, distance to the nearest prison (operating in the 1990s). Population controls: population density (1996), share of retired people (1998). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 26: Mafia Presence & Elite Attacks by Type in 1990s Russia

	(IV) Any Attack (1994-98)	(IV) Any Business Attack (1994-98)	(IV) Any Criminal Attack (1994-98)	(IV) Any Police Attack (1994-98)	(IV) Any Political Attack (1994-98)
Presence of mafia (1994-95)	0.886***	0.712***	0.735***	0.379***	0.191***
	(0.150)	(0.130)	(0.116)	(0.083)	(0.068)
Region FE	YES	YES	YES	YES	YES
Road & Railroad Densities (km/km^2)	YES	YES	YES	YES	YES
Institutional controls	YES	YES	YES	YES	YES
Population & Economic controls	YES	YES	YES	YES	YES
Observations	1,938	1,938	1,938	1,938	1,938
Mean of dep. variable	0.093	0.074	0.042	0.021	0.018
Std. dev. of dep. variable	0.291	0.262	0.200	0.144	0.133
Angrist-Pischke F-stat	44.79	44.79	44.79	44.79	44.79

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Any Attack (1994-98)* - binary equal 1 if any attack against a member of the Russia's economic elite occurred in 1994-98. *Any Business Attack (1994-98)* - binary equal 1 if any attack against a businessman or manager occurred in 1994-98. *Any Criminal Attack (1994-98)* - binary equal 1 if any attack against a criminal occurred in 1994-98. *Any Police Attack (1994-98)* - binary equal 1 if any attack against a member of law enforcement, army, or against a judge occurred in 1994-98. *Any Political (1994-98)* - binary equal 1 if any attack against a politican or public figure occurred in 1994-98. *Presence of mafia (1994-95)* - binary var. equal 1 if a vor present in subregion in 1994-95. The instrument used in the IV estimation is a binary var. equal 1 if subregion was within 26.9km km (i.e. 15th percentile) of the nearest gulag. Economic controls: unemployment rate (1998), log of average wage (1996). Institutional controls: distance to region's administrative center, distance to the nearest prison (operating in the 1990s). Population controls: population density (1996), share of retired people (1998). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

5 CONCLUSION

The goal of this interdisciplinary doctoral thesis is to provide new knowledge and policy insights into hotly-debated issues in international migration and organized crime. Building upon extensive prior literature in economics, political science, public health, psychology, and criminology, this thesis draws three main conclusions. First, under certain circumstances, local foreign in-migration can lead to a decrease in the electoral support for the far-right parties in Europe. Second, immigrant legalization programs can have positive effects on immigrant health insurance coverage, access to health care, and their mental health. Third, presence of mafia-type organizations in countries with rapid institutional transition (particularly from communism to capitalism) tends to increase (rather than contain) local crime and violence. My hope is that these findings will provide valuable information to policymakers as well as law enforcement officials across the globe, and further stimulate much-needed research into these topics.

APPENDIX A

- ***Log of total population*** - to capture demographic dynamics (Barone et al., 2016).
- ***Population density*** (inhabitants per km^2; proxy for urbanization) - far-right parties tend to gather larger support among people from rural municipalities.
- ***Share of women in the adult population*** - women tend to be less supportive of the Finns Party (Niemi, 2012).
- ***Share of old people in the adult population*** (65 and above) - far-right parties generally score high points among old people (appeal to tradition, conservatism, etc.).
- ***Total crime rate*** (crimes per 100,000 inhabitants) - far-right parties often campaign on issues related to law and order. Higher crime rate might therefore lead to higher Finns Party's popularity.
- ***Unemployment rate*** - poor economic performance of a municipality reflected in high unemployment rate is expected to be a strong predictor of far-right support.
- ***Share of population (25-64) with tertiary education*** - people with university education are less likely to accept nationalist-populist agenda, and therefore are less likely to vote for the far-right parties.
- ***Skill ratio*** (skilled/unskilled workers) - proxied by the number of people (aged 20 or above) with education levels 2 and 3 divided by the number of people with education level 1 (Mayda, 2006). Level 1 corresponds to ISCED[66] categories 0, 1, 2 (i.e. basic education), level 2 to ISCED categories 3, 4 (i.e. completed upper secondary education), and level 3 to ISCED categories 5-8 (i.e. tertiary education). Literature suggests that low-skilled workers are more likely to vote for far-right parties than high-skilled ones.
- ***Median disposable income of household unit per consumption unit*** (in EUR) - controls for differences in standards of living across municipalities. Municipalities with higher

[66] UNESCO's International Standard Classification of Education.

income level should be less prone to vote for the Finns Party. There are two drawbacks with this variable: first, it is not adjusted for the variation in price levels across municipalities. Second, according to Statistics Finland, due to revisions in income concepts, 1995-2009 and 2010-2014 data are not fully comparable. Nevertheless, since municipality-level GDP data is not available, median disposable income together with the unemployment rate are the best economic measures on the municipality level that I have available.

Robustness checks and further results

Main IV analysis: first-stage estimates

Table A.1: IV: First Stage Estimates

	(1) Share of foreign citizens	(2) Share of foreign citizens	(3) Share of foreign citizens
Predicted share of foreign citizens	0.943***	0.653***	0.555***
(% of population in 2003)	(0.120)	(0.111)	(0.116)
Municipality/Election Year FE	YES	YES	YES
Time-varying controls (lag)		YES	YES
Region FE x Election Year FE			YES
Observations	2079	2079	2079
Kleibergen-Paap rk Wald F-stat.	62.32	34.53	22.77
Stock-Yogo weak ID test (10% max. IV size c.v.)	16.38	16.38	16.38

Notes - Share of foreign citizens - share of foreign citizens (% of population in 2003). Standard errors in parentheses, clustered at municipality level. Time-varying controls: log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

IV estimation using 1991 as base year

Table A.2: IV Results Using 1991 Distributions (Second Stage)

	(1) Finns Party	(2) Finns Party	(3) Finns Party
Share of foreign citizens	-2.379***	-5.707***	-5.026*
(% of population in 1991)	(0.544)	(1.445)	(2.093)
Municipality/Election Year FE	YES	YES	YES
Time-varying controls (lag)		YES	YES
Region FE x Election Year FE			YES
Observations	2079	2079	2079
Mean of dep. variable	12%	12%	12%
Std. dev. of dep. variable	7.56%	7.56%	7.56%
Kleibergen-Paap rk Wald F-stat.	32.65	14.81	6.51
Anderson-Rubin chi-sq. test p-val.			0.00000

Notes - *Finns Party* - Finns Party's share of valid votes. Standard errors in parentheses, clustered at municipality level. Time-varying controls: log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Exclusion of all European elections

Table A.3: 2009 and 2014 European Elections Omitted (IV Results)

	(1) Finns Party	(2) Finns Party	(3) Finns Party
Share of foreign citizens	-1.802***	-4.365***	-3.954***
(% of population in 2003)	(0.424)	(0.879)	(1.126)
Municipality/Election Year FE	YES	YES	YES
Time-varying controls (lag)		YES	YES
Region FE x Election Year FE			YES
Observations	1485	1485	1485
Mean of dep. variable	11.9%	11.9%	11.9%
Std. dev. of dep. variable	8.53%	8.53%	8.53%
Kleibergen-Paap rk Wald F-stat.	62.50	33.60	22.06

Notes - *Finns Party* - Finns Party's share of valid votes. Standard errors in parentheses, clustered at municipality level. Time-varying controls: log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Checking for outliers: exclusion of 9 largest Finnish municipalities

To check if outliers are not driving the main results, I exclude 9 largest municipalities from the analysis. These municipalities are the only ones with population of 100,000 or more during the 2006-2015 period. The following municipalities are omitted: Helsinki, Espoo, Tampere, Vantaa, Turku, Oulu, Jyväskylä, Lahti, and Kuopio. With the exception of Oulu (which is in central Finland), all of them are located in the southern part of the country. Results are presented in Table A.4. Overall, the analysis suggests that outliers do not drive the main IV estimates.

Table A.4: 9 Largest Municipalities Omitted (IV Results)

	(1) Finns Party	(2) Finns Party	(3) Finns Party
Share of foreign citizens	-1.889***	-5.001***	-4.975*
(% of population in 2003)	(0.564)	(1.136)	(2.180)
Municipality/Election Year FE	YES	YES	YES
Time-varying controls (lag)		YES	YES
Region FE x Election Year FE			YES
Observations	2016	2016	2016
Mean of dep. variable	12.1%	12.1%	12.1%
Std. dev. of dep. variable	7.6%	7.6%	7.6%
Kleibergen-Paap rk Wald F-stat.	46.34	23.78	10.74
Anderson-Rubin chi-sq. test p-val.			0.0026

Notes - *Finns Party* - Finns Party's share of valid votes. Standard errors in parentheses, clustered at municipality level. Time-varying controls: log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Alternative specification using net flow of immigrants

I estimate an alternative, first-difference version of equation (1) which uses net immigrant flow as the main independent variable. The specification is based on the main estimating equation in Sá (2014) and has the following form:

$$\Delta\text{Far-right}_{i,t} = \beta \left(\frac{\Delta \text{ Foreign-born}_{i,t}}{\text{Population}_{i,2003}} \right) + X'_{i,t-1}\gamma + \lambda_t + \sigma_i + \epsilon_{i,t} \tag{9}$$

where $\Delta \textit{Far-right}_{i,t}$ is the level change in Finns Party's vote share in municipality i between elections at $t-1$ and t.[67] $\Delta \textit{Foreign-born}_{i,t}$ is the change in the number of foreign citizens in municipality i between $t-1$ and t. To be consistent with equation (1), I standardize the change in the number of immigrants by population in the base year (2003). Covariates are included in lagged levels ($X_{i,t-1}$) since the level changes between $t-1$ and t are endogenous to immigration. Estimating a first-difference model means that the municipality-specific fixed effects are differenced out. Thus, σ_i captures municipality-specific trends in Finns Party's vote share. Finally, λ_t captures national trends in factors that affect far-right vote share, such as the trend in Finland's GDP per capita. To deal with endogeneity in β (the coefficient of interest), I construct the following instrument which uses the same distributions of immigrants by background continent in 2003 as the instrument in my main analysis:

$$\frac{\sum_{j=1}^{6} \delta_{i,j,2003} * \Delta\text{Foreign-born}_{j,t}}{\text{Population}_{i,2003}} \tag{10}$$

where $\delta_{i,j,2003}$ is the share of immigrants with background continent j living in municipality i in 2003. $\Delta \textit{Foreign-born}_{j,t}$ is the change in the overall number of foreign citizens from continent j in mainland Finland between $t-1$ and t. Estimation results are presented in Table A.5. In column (2), I replicate the analysis with population at $t-1$ (instead of the population in 2003) in the denominator. Although the interpretation of β in the first-difference case differs from that in my

[67] For those election years that are more than one calendar year apart, $t-1$ refers to the preceding election year and not the preceding calendar year.

main specification, the results in Table A.5 are clearly consistent with my main IV estimates.

Table A.5: Alternative First-Difference Specification (IV Results)

	(1) Δ Finns Party	(2) Δ Finns Party
Net Immigrant Flow (% of population in 2003)	-4.566* (2.059)	
Net Immigrant Flow (% of population in t-1)		-5.269* (2.279)
Observations	1782	1782
Mean of dep. variable	2.55%	2.55%
Std. dev. of dep. variable	7.52%	7.52%
Kleibergen-Paap rk Wald F-stat.	53.52	45.88

Notes - Δ *Finns Party* - level change in Finns Party's share of valid votes between elections at $t-1$ at t. *Net Immigrant Flow* - change in number of foreign citizens between election year $t-1$ and t. Standard errors in parentheses, clustered at municipaity level. All regressions control for municipality-specific time trends (municipality dummies), national trends (election year dummies), and the following set of municipality-specific time-varying controls (measured at $t-1$): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Immigration and Finns Party vote share: separate analyses by election type

Table A.6: Parliamentary, Presidential, and European Elections IV Estimates

	(IV) Finns Party (parliamentary)	(IV) Finns Party (presidential)	(IV) Finns Party (European)
Share of foreign citizens	-3.941**	-2.963**	-2.236**
(% of population in 2003)	(1.204)	(0.740)	(0.845)
Observations	891	594	594
Mean of dep. variable	14.9%	7.33%	12.3%
Std. dev. of dep. variable	9.31%	4.21%	4.23%
Kleibergen-Paap rk Wald F-stat.	20.40	21.70	18.92

Notes - *Finns Party* - Finns Party's share of valid votes. First column uses data from parliamentary elections in 2007, 2011, 2015; second column uses data from presidential elections in 2006, 2012; third column uses data from European parliamentary elections in 2009, 2014. Standard errors in parentheses, clustered at municipality level. All regressions control for municipality fixed effects, election year fixed effects, region-by-election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

IV sensitivity to native sorting

Table A.7: Municipality, Subregional, and Regional IV Estimates

	(IV) Finns Party (municipality)	(IV) Finns Party (subregion)	(IV) Finns Party (region)
Share of foreign citizens (% of population in 2003)	-1.820***		
	(0.285)		
Share of foreign citizens (% of population in 2003)		-2.619***	
		(0.542)	
Share of foreign citizens (% of population in 2003)			-1.428**
			(0.351)
Observations	2079	469	126
Mean of dep. variable	12%	11.7%	11.7%
Standard deviation of dep. variable	7.56%.	6.95%	6.49%
Kleibergen-Paap rk Wald F-stat.	97.71	40.08	60.61

Notes - *Finns Party* - Finns Party's share of valid votes. Standard errors in parentheses, clustered at respective levels (municipality, subregion, region). All regressions control for election year fixed effects, and the following municipality/subregion/region-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Immigration and election outcomes (all main parties): OLS

Table A.8: Immigration and Election Outcomes (All Main Parties): OLS

	(OLS) Finns Party	(OLS) Vihr	(OLS) SFP/RKP	(OLS) Kok	(OLS) Kesk	(OLS) SDP	(OLS) KD
Share of foreign citizens	-0.656*	0.147	0.746*	-0.208	0.235	-0.162	-0.074
(% of population in 2003)	(0.303)	(0.094)	(0.333)	(0.160)	(0.224)	(0.224)	(0.110)
Observations	2079	2079	2079	2079	2079	2079	2079
Adjusted R-squared	0.880	0.881	0.637	0.881	0.598	0.939	0.513
Mean (dep. var.)	12%	5%	4.07%	17.4%	33.4%	17.5%	3.95%
Std. dev. (dep. var.)	7.56%	4.36%	13.6%	10%	16.8%	12.6%	3.38%

Notes - *Finns Party* - Finns Party's share of valid votes; *Vihr* - Green League's share of valid votes; *SFP/RKP* - Swedish People's Party's share of valid votes; *Kok* - National Coalition Party's share of valid votes; *Kesk* - Centre Party's share of valid votes; *SDP* - Social Democratic Party's share of valid votes; *KD* - Christian Democrats' share of valid votes. Standard errors in parentheses, clustered at municipality level. All regressions control for municipality fixed effects, election year fixed effects, region-by-election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

Immigration and voter turnout, protest vote: OLS

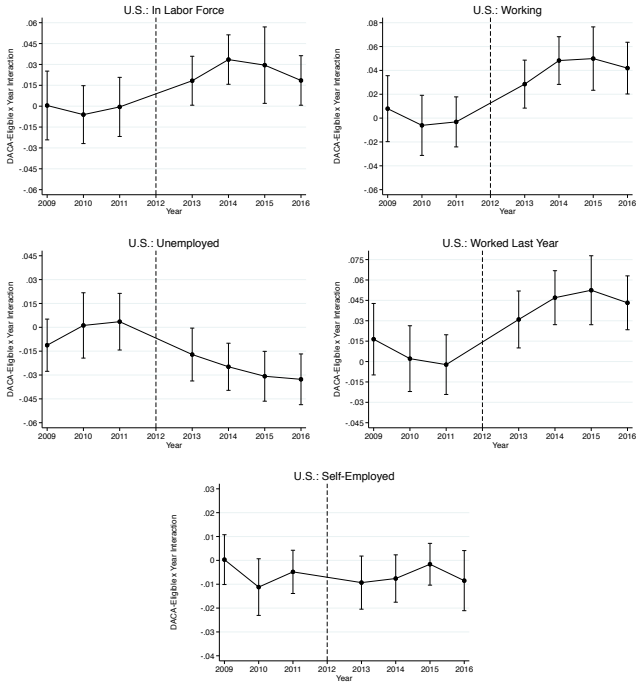
Table A.9: Immigration and Voter Turnout, Protest Vote: OLS

	(IV) Voter turnout	(IV) Protest vote
Share of foreign citizens (% of population in 2003)	0.369* (0.154)	0.005 (0.012)
Observations	2079	2079
Adjusted R-squared	0.985	0.453
Mean (dep. var.)	59.7%	0.51%
Std. dev. (dep. var.)	15.4%	0.24%

Notes - *Voter turnout* - share of eligible voters who cast ballot in election. *Protest vote* - share of invalid ballots. Standard errors in parentheses, clustered at municipality level. Both regressions control for municipality fixed effects, election year fixed effects, region-by-election year fixed effects, and the following municipality-specific time-varying controls (in lagged form): log of population, population density, share of females, share of tertiary educated, share of aged 65+, ratio of skilled to unskilled labor, total crime rate, unemployment rate, median household income. Data comes from Statistics Finland's StatFin database. *** Significant at the 0.1% level. ** Significant at the 1% level. * Significant at the 5% level. † Significant at the 10% level.

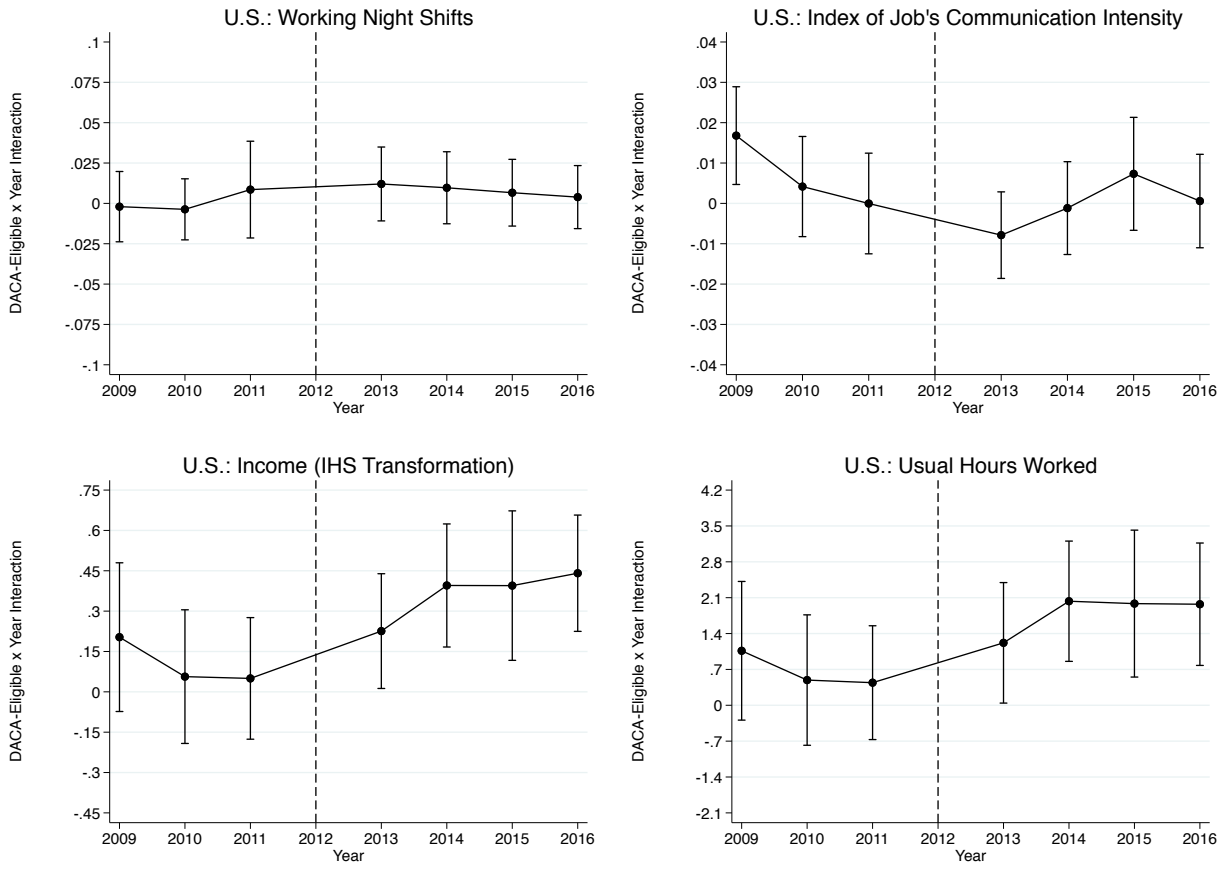
APPENDIX B

Figure B.1: DACA and Labor Market Outcomes (U.S.)



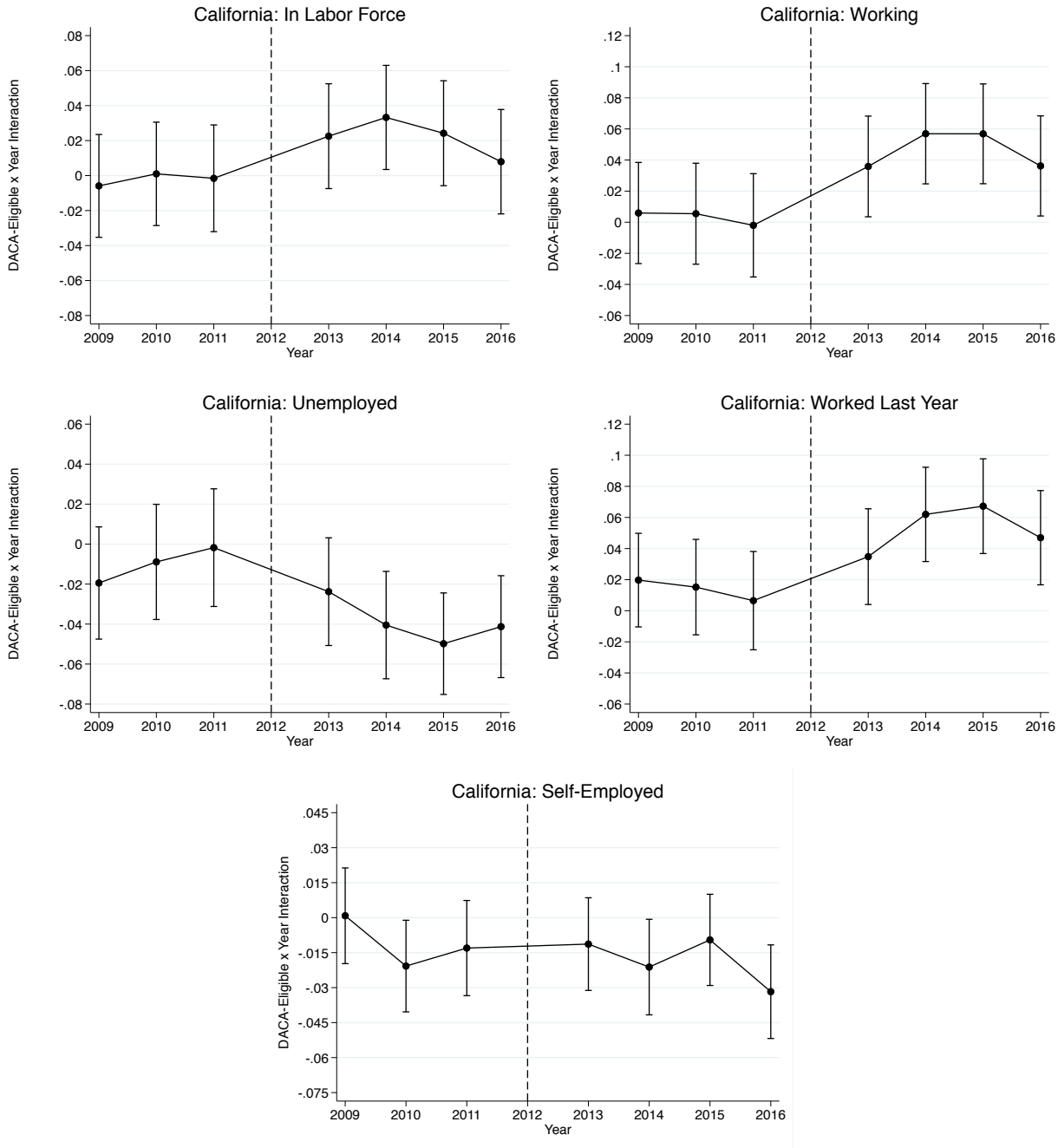
Notes - The figure plots the coefficients obtained estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *In Labor Force* - binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Worked Last Year* - binary var. equal 1 if individual had worked at all for profit, pay, or as an unpaid family worker during previous 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. All estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2016 waves of ACS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure B.2: DACA and Labor Market Outcomes/Working Conditions (U.S.)



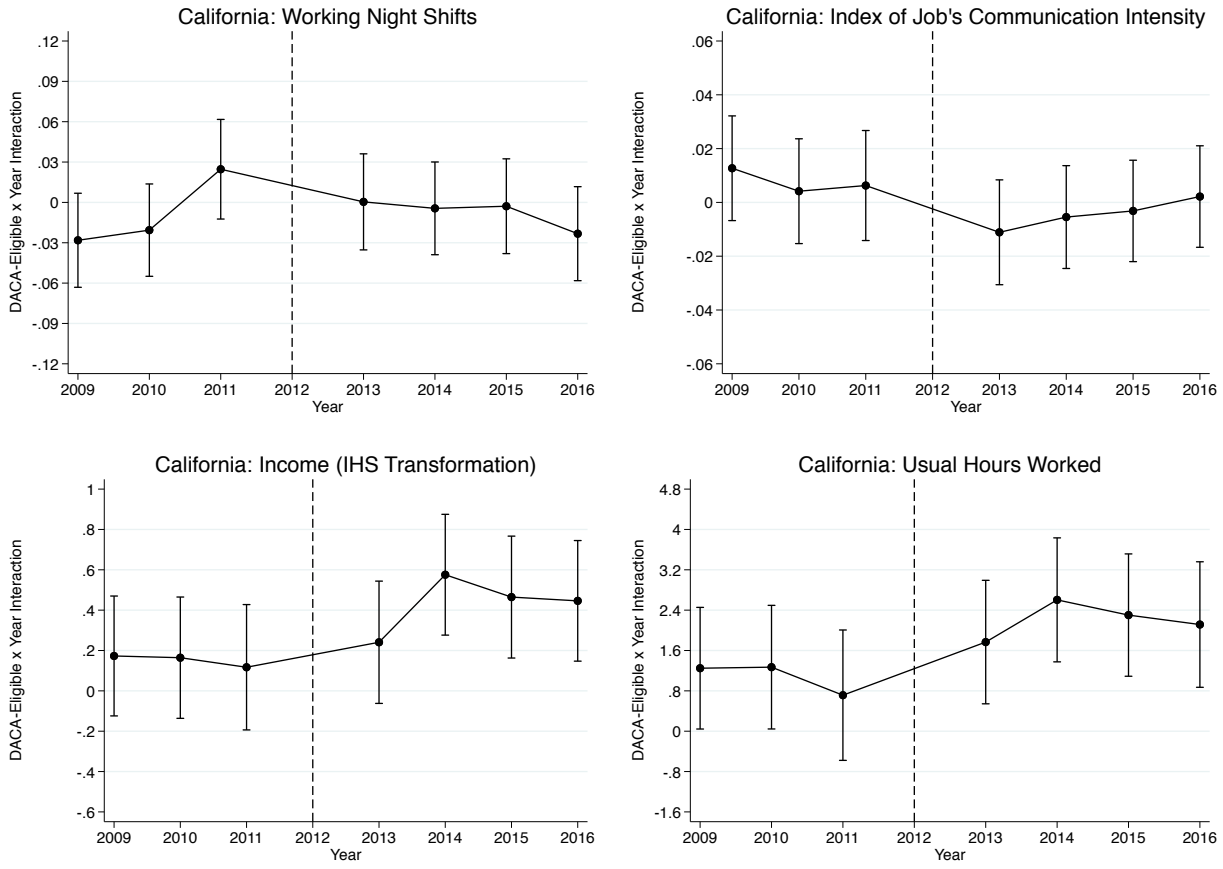
Notes - The figure plots the coefficients obtained estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graphs. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *Working Night Shifts* - binary var. equal 1 if individual is currently working night shifts (i.e. individual departs for work between 6pm and 6am); *Index of Job's Communication Intensity* - index of communication skill intensity of occupation (0-100; see Peri and Sparber (2009) for more details); *Income (IHS Transformation)* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income (or losses) from all sources for the previous 12 months; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months. All estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2016 waves of ACS. Regressions control for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at state-year level.

Figure B.3: DACA and Labor Market Outcomes (California)



Notes - The figure plots the coefficients obtained estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *In Labor Force* - binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Worked Last Year* - binary var. equal 1 if individual had worked at all for profit, pay, or as an unpaid family worker during previous 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. All estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, and year fixed. Standard errors are heteroskedasticity-robust.

Figure B.4: DACA and Labor Market Outcomes/Working Conditions (California)



Notes - The figure plots the coefficients obtained estimating Eq.(5) with the variable $Elig_{it}$ interacted with a binary variable for each year (2012 is the omitted interaction). 95% confidence limits of the interaction estimates are included in the graph. Following dependent variables were used in the regressions (left-to-right, starting with the uppermost row): *Working Night Shifts* - binary var. equal 1 if individual is currently working night shifts (i.e. individual departs for work between 6pm and 6am); *Index of Job's Communication Intensity* - index of communication skill intensity of occupation (0-100; see Peri and Sparber (2009) for more details); *Income (IHS Transformation)* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income (or losses) from all sources for the previous 12 months; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months. All estimates are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2016 waves of ACS. Regression controls for DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), PUMA fixed effects, and year fixed. Standard errors are heteroskedasticity-robust.

Table B.1: The Effects of DACA on Health Insurance Coverage (State-Level Clustering)

	(1) Any Coverage	(2) Medicaid	(3) Any Private	(4) Employer-Sponsored	(5) Indiv. Purchased
Panel A: Entire U.S.					
DACA-Eligible * Post 2012	0.0224***	0.0084	0.0137**	0.0061	0.0081**
	(0.006)	(0.008)	(0.006)	(0.005)	(0.003)
Observations	395,902	395,902	395,902	395,902	395,902
R-squared	0.221	0.079	0.250	0.188	0.095
Mean of Dep. Var.	0.642	0.089	0.558	0.435	0.137
Std. Dev. of Dep. Var.	0.480	0.284	0.497	0.496	0.344
Panel B: Entire U.S. (except California and New York)					
DACA-Eligible * Post 2012	0.0145**	-0.0019	0.0171**	0.0074	0.0107**
	(0.007)	(0.004)	(0.006)	(0.006)	(0.004)
Observations	268,016	268,016	268,016	268,016	268,016
R-squared	0.249	0.059	0.267	0.198	0.101
Mean of Dep. Var.	0.632	0.061	0.575	0.447	0.142
Std. Dev. of Dep. Var.	0.482	0.240	0.494	0.497	0.349

Notes - *Any Coverage* - binary var. equal 1 if individual currently with health insurance coverage; *Medicaid* - binary var. equal 1 if individual currently on Medicaid; *Any Private* - binary var. equal 1 if individual currently with private health insurance (i.e. via employer/union or purchased directly from insurer); *Employer-Sponsored* - binary var. equal 1 if individual currently with health insurance via employer or union; *Indiv. Purchased* - binary var. equal 1 if individual currently with health insurance purchased directly from insurer. Standard errors in parentheses, clustered at state level. Estimates in all columns are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), year fixed effects, state fixed effects, and state-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.2: The Effects of DACA on Health Insurance Coverage (Residual Method)

	(1) Any Coverage	(2) Medicaid	(3) Any Private	(4) Employer-Sponsored	(5) Indiv. Purchased
Panel A: Entire U.S.					
DACA-Eligible * Post 2012	0.0261***	0.0112*	0.0147**	0.0057	0.0080**
	(0.008)	(0.006)	(0.006)	(0.006)	(0.004)
Observations	382,069	382,069	382,069	382,069	382,069
R-squared	0.226	0.083	0.252	0.189	0.096
Mean of Dep. Var.	0.640	0.085	0.559	0.437	0.138
Std. Dev. of Dep. Var.	0.480	0.279	0.496	0.496	0.345
Panel B: California & New York					
DACA-Eligible * Post 2012	0.0422***	0.0264***	0.0134*	0.0103	0.0018
	(0.007)	(0.006)	(0.007)	(0.007)	(0.004)
Observations	125,317	125,317	125,317	125,317	125,317
R-squared	0.196	0.112	0.262	0.209	0.124
Mean of Dep. Var.	0.659	0.144	0.521	0.409	0.127
Std. Dev. of Dep. Var.	0.474	0.351	0.500	0.492	0.333
Panel C: Entire U.S. (except California and New York)					
DACA-Eligible * Post 2012	0.0195**	0.0019	0.0185***	0.0073	0.0109**
	(0.008)	(0.004)	(0.007)	(0.007)	(0.004)
Observations	256,752	256,752	256,752	256,752	256,752
R-squared	0.257	0.063	0.270	0.199	0.103
Mean of Dep. Var.	0.631	0.056	0.578	0.451	0.143
Std. Dev. of Dep. Var.	0.482	0.231	0.494	0.498	0.350

Notes - *Any Coverage* - binary var. equal 1 if individual currently with health insurance coverage; *Medicaid* - binary var. equal 1 if individual currently on Medicaid; *Any Private* - binary var. equal 1 if individual currently with private health insurance (i.e. via employer/union or purchased directly from insurer); *Employer-Sponsored* - binary var. equal 1 if individual currently with health insurance via employer or union; *Indiv. Purchased* - binary var. equal 1 if individual currently with health insurance purchased directly from insurer. Standard errors in parentheses, heteroskedasticity-robust (Panel B), and clustered at state-year level (Panels A and C). Estimates in all columns are derived from a sample of (likely) unauthorized immigrants ages 18-35 with at least a high school diploma (or equivalent). Data comes from the 2008-2016 waves of ACS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), year fixed effects, and state-specific time trends. In addition, all columns in Panels A and C control for state fixed effects, while all columns in Panel B control for PUMA fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.3: DACA and Health Care Access/Use - Individuals in Poverty (Entire U.S.: NHIS)

	(1) Usual	(2) Doctor	(3) # Visits	(4) Care 10+	(5) Hosp. Night	(6) ER	(7) Saw Special	(8) Saw Eye	(9) Saw Mental
DACA-Eligible * Post 2012	0.0868	-0.0795	-0.0390	0.0293	0.0097	-0.0427	-0.0009	-0.0219	-0.0080
	(0.058)	(0.064)	(0.221)	(0.018)	(0.019)	(0.040)	(0.022)	(0.051)	(0.019)
Observations	32,610	32,381	32,381	57,405	57,448	32,472	32,488	32,510	32,508
R-squared	0.066	0.073	0.080	0.044	0.024	0.044	0.034	0.049	0.050
Mean of Dep. Var.	0.739	0.735	2.326	0.113	0.096	0.293	0.172	0.258	0.130
Std. Dev. of Dep. Var.	0.439	0.441	2.347	0.316	0.295	0.455	0.377	0.438	0.336

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *Care 10+* - binary var. equal 1 if individual received medical care 10+ times in past 12 months; *Hosp. Night* - binary var. equal 1 if individual was in a hospital overnight in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Special* - binary var. equal 1 if individual saw/talked to medical specialist in past 12 months; *Saw Eye* - binary var. equal 1 if individual saw/talked to eye doctor in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to a mental health professional (psychiatrist, psychologist, etc.) in past 12 months. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). This sample is further restricted to contain only individuals with family's before-tax income (from preceding calendar year) below U.S. Census Bureau's official poverty threshold. Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.4: DACA and Health Care Access/Use - Individuals in Poverty (California: CHIS)

	(1) Usual	(2) Doctor	(3) # Visits	(4) ER	(5) Saw Mental	(6) # Mental Visits
DACA-Eligible * Post 2012	0.0318	-0.1637	2.0765	-0.0827	0.0375	0.2156
	(0.131)	(0.119)	(3.207)	(0.123)	(0.082)	(1.205)
Observations	12,060	12,060	12,060	10,188	8,548	8,548
R-squared	0.086	0.083	0.045	0.066	0.089	0.037
Mean of Dep. Var.	0.743	0.746	4.772	0.255	0.194	2.537
Std. Dev. of Dep. Var.	0.437	0.435	12.74	0.436	0.396	12.08

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to a medical professional (psychiatrist, psychologist, etc.) for mental or alcohol/drug problems in past 12 months; *# Mental Visits* - # of visits to professional for problems with mental health or drugs/alcohol (during past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). This sample is further restricted to contain only individuals with family's before-tax income (from preceding calendar year) below U.S. Census Bureau's official poverty threshold. Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.5: DACA and General Health Status, Mental Health - Hispanics in Poverty (U.S.)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Effort	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.2280***	0.0049	0.0035	-0.0632*	-0.0949***	-0.1366***	-1.4069***	-0.1490***	-0.0710***
	(0.078)	(0.007)	(0.019)	(0.035)	(0.034)	(0.045)	(0.432)	(0.050)	(0.026)
Observations	15,018	15,018	15,018	6,827	6,823	6,820	6,806	6,806	6,891
R-squared	0.067	0.031	0.052	0.057	0.043	0.051	0.068	0.051	0.084
Mean of Dep. Var.	3.670	0.025	0.872	0.179	0.124	0.197	3.349	0.271	0.121
Std. Dev. of Dep. Var.	1.064	0.157	0.334	0.384	0.330	0.398	4.700	0.445	0.326

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Effort* - binary var. equal 1 if individual reported feeling "everything was an effort" some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). This sample is further restricted to contain only Hispanic/Latino individuals with family's before-tax income (from preceding calendar year) below U.S. Census Bureau's official poverty threshold. Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.6: The Effects of DACA on Health Insurance Coverage (Omitting 2012)

	(1) Any Coverage	(2) Medicaid	(3) Any Private	(4) Employer-Sponsored	(5) Indiv. Purchased
Panel A: Entire U.S.					
DACA-Eligible * Post 2012	0.0165**	0.0065	0.0093	0.0020	0.0077**
	(0.008)	(0.007)	(0.006)	(0.006)	(0.004)
Observations	352,047	352,047	352,047	352,047	352,047
R-squared	0.220	0.081	0.247	0.186	0.093
Mean of Dep. Var.	0.647	0.090	0.562	0.438	0.139
Std. Dev. of Dep. Var.	0.478	0.285	0.496	0.496	0.346
Panel B: California & New York					
DACA-Eligible * Post 2012	0.0292***	0.0198***	0.0071	0.0070	-0.0004
	(0.008)	(0.006)	(0.008)	(0.007)	(0.004)
Observations	113,520	113,520	113,520	113,520	113,520
R-squared	0.193	0.114	0.259	0.207	0.123
Mean of Dep. Var.	0.669	0.149	0.527	0.413	0.128
Std. Dev. of Dep. Var.	0.471	0.356	0.499	0.492	0.334
Panel C: Entire U.S. (except California and New York)					
DACA-Eligible * Post 2012	0.0097	-0.0038	0.0136*	0.0039	0.0111**
	(0.008)	(0.005)	(0.007)	(0.007)	(0.005)
Observations	238,527	238,527	238,527	238,527	238,527
R-squared	0.248	0.060	0.265	0.196	0.100
Mean of Dep. Var.	0.636	0.061	0.579	0.450	0.144
Std. Dev. of Dep. Var.	0.481	0.240	0.494	0.497	0.351

Notes - *Any Coverage* - binary var. equal 1 if individual currently with health insurance coverage; *Medicaid* - binary var. equal 1 if individual currently on Medicaid; *Any Private* - binary var. equal 1 if individual currently with private health insurance (i.e. via employer/union or purchased directly from insurer); *Employer-Sponsored* - binary var. equal 1 if individual currently with health insurance via employer or union; *Indiv. Purchased* - binary var. equal 1 if individual currently with health insurance purchased directly from insurer. Standard errors in parentheses, heteroskedasticity-robust (Panel B), and clustered at state-year level (Panels A and C). Estimates in all columns are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2011 & 2013-2016 waves of ACS. 2012 is omitted as it is the year DACA was implemented. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), year fixed effects, and state-specific time trends. In addition, all columns in Panels A and C control for state fixed effects, while all columns in Panel B control for PUMA fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.7: DACA and Health Care Access, Affordability - Omitting 2012 (Entire U.S.: NHIS)

	(1) Usual	(2) Any Care Delay	(3) Special. Not Afford.
DACA-Eligible * Post 2012	0.0083	-0.0280**	-0.0305
	(0.031)	(0.011)	(0.029)
Observations	232,067	544,039	77,045
R-squared	0.072	0.025	0.016
Mean of Dep. Var.	0.815	0.155	0.050
Std. Dev. of Dep. Var.	0.389	0.362	0.218

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Any Care Delay* - binary var. equal 1 if any member of respondent's family delayed seeking medical care due to cost (in past 12 months); *Special. Not Afford.* - binary var. equal 1 if individual needed but couldn't afford specialist (in past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2011 & 2013-2016 waves of NHIS. 2012 is omitted as it is the year DACA was implemented. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.8: DACA and Health Care Use - Omitting 2012 (Entire U.S.: NHIS)

	(1) Doctor	(2) # Visits	(3) Care 10+	(4) Hosp. Night	(5) ER	(6) Saw Special	(7) Saw Eye	(8) Saw Mental
DACA-Eligible * Post 2012	0.0073	0.0531	-0.0001	0.0021	0.0081	-0.0100	0.0019	0.0065
	(0.031)	(0.110)	(0.007)	(0.007)	(0.022)	(0.014)	(0.027)	(0.010)
Observations	230,469	230,469	543,238	543,911	231,289	231,271	231,332	231,341
R-squared	0.072	0.072	0.019	0.018	0.023	0.027	0.042	0.020
Mean of Dep. Var.	0.778	2.248	0.082	0.065	0.195	0.193	0.315	0.086
Std. Dev. of Dep. Var.	0.416	2.161	0.275	0.247	0.396	0.395	0.464	0.280

Notes - *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *Care 10+* - binary var. equal 1 if individual received medical care 10+ times in past 12 months; *Hosp. Night* - binary var. equal 1 if individual was in a hospital overnight in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Special* - binary var. equal 1 if individual saw/talked to medical specialist in past 12 months; *Saw Eye* - binary var. equal 1 if individual saw/talked to eye doctor in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to mental health professional (psychiatrist, psychologist, etc.) in past 12 months. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2011 & 2013-2016 waves of NHIS. 2012 is omitted as it is the year DACA was implemented. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.9: DACA and General Health Status, Mental Health - Omitting 2012 (Entire U.S.: NHIS)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Effort	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.1250***	-0.0036***	0.0059	-0.0252	-0.0096	-0.0388*	-0.2205	-0.0388	-0.0121
	(0.028)	(0.001)	(0.005)	(0.018)	(0.017)	(0.021)	(0.212)	(0.025)	(0.017)
Observations	544,085	544,085	544,085	230,250	230,222	230,090	229,775	229,775	233,492
R-squared	0.079	0.011	0.033	0.025	0.017	0.018	0.033	0.025	0.063
Mean of Dep. Var.	4.011	0.011	0.938	0.106	0.063	0.149	2.496	0.195	0.141
Std. Dev. of Dep. Var.	0.949	0.105	0.242	0.308	0.243	0.356	3.733	0.396	0.348

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Effort* - binary var. equal 1 if individual reported feeling "everything was an effort" some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* >= 5); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2011 & 2013-2016 waves of NHIS. 2012 is omitted as it is the year DACA was implemented. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.10: The Effects of DACA on Health Insurance Coverage (Omitting Individuals Aged 30-31 in 2012)

	(1) Any Coverage	(2) Medicaid	(3) Any Private	(4) Employer-Sponsored	(5) Indiv. Purchased
Panel A: Entire U.S.					
DACA-Eligible * Post 2012	0.0233***	0.0091	0.0140**	0.0060	0.0083**
	(0.008)	(0.007)	(0.006)	(0.006)	(0.004)
Observations	344,148	344,148	344,148	344,148	344,148
R-squared	0.217	0.080	0.245	0.177	0.103
Mean of Dep. Var.	0.635	0.091	0.550	0.420	0.145
Std. Dev. of Dep. Var.	0.481	0.287	0.497	0.494	0.352
Panel B: California & New York					
DACA-Eligible * Post 2012	0.0419***	0.0273***	0.0125*	0.0110	0.0023
	(0.008)	(0.006)	(0.007)	(0.007)	(0.004)
Observations	111,238	111,238	111,238	111,238	111,238
R-squared	0.191	0.113	0.257	0.199	0.136
Mean of Dep. Var.	0.655	0.150	0.512	0.393	0.133
Std. Dev. of Dep. Var.	0.475	0.357	0.500	0.488	0.340
Panel C: Entire U.S. (except California and New York)					
DACA-Eligible * Post 2012	0.0154*	-0.0016	0.0177**	0.0067	0.0114**
	(0.008)	(0.004)	(0.008)	(0.007)	(0.005)
Observations	232,910	232,910	232,910	232,910	232,910
R-squared	0.245	0.059	0.263	0.187	0.109
Mean of Dep. Var.	0.626	0.062	0.568	0.432	0.150
Std. Dev. of Dep. Var.	0.484	0.241	0.495	0.495	0.357

Notes - *Any Coverage* - binary var. equal 1 if individual currently with health insurance coverage; *Medicaid* - binary var. equal 1 if individual currently on Medicaid; *Any Private* - binary var. equal 1 if individual currently with private health insurance (i.e. via employer/union or purchased directly from insurer); *Employer-Sponsored* - binary var. equal 1 if individual currently with health insurance via employer or union; *Indiv. Purchased* - binary var. equal 1 if individual currently with health insurance purchased directly from insurer. Standard errors in parentheses, heteroskedasticity-robust (Panel B), and clustered at state-year level (Panels A and C). Estimates in all columns are derived from a sample of non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2008-2016 waves of ACS. Individuals aged 30-31 in 2012 are omitted from 2013-2016 waves. Individuals aged 31-32 (at the time of interview) are omitted from 2008-2012 waves. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), year fixed effects, and state-specific time trends. In addition, all columns in Panels A and C control for state fixed effects, while all columns in Panel B control for PUMA fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.11: DACA and HC Access, Affordability - Omitting Aged 30-31 in 2012 (Entire U.S.)

	(1) Usual	(2) Any Care Delay	(3) Special. Not Afford.
DACA-Eligible * Post 2012	0.0218	-0.0284**	-0.0378
	(0.032)	(0.011)	(0.023)
Observations	231,623	547,821	86,579
R-squared	0.073	0.025	0.017
Mean of Dep. Var.	0.813	0.157	0.051
Std. Dev. of Dep. Var.	0.390	0.364	0.221

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Any Care Delay* - binary var. equal 1 if any member of respondent's family delayed seeking medical care due to cost (in past 12 months); *Special. Not Afford.* - binary var. equal 1 if individual needed but couldn't afford specialist (in past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. Individuals aged 30-31 in 2012 are omitted from 2013-2016 waves. Individuals aged 31-32 (at the time of interview) are omitted from 2000-2012 waves. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.12: DACA and Health Care Use - Omitting Individuals Aged 30-31 in 2012 (Entire U.S.)

	(1) Doctor	(2) # Visits	(3) Care 10+	(4) Hosp. Night	(5) ER	(6) Saw Special	(7) Saw Eye	(8) Saw Mental
DACA-Eligible * Post 2012	0.0148	0.0427	0.0006	0.0017	0.0055	-0.0115	0.0012	0.0102
	(0.032)	(0.112)	(0.007)	(0.007)	(0.022)	(0.015)	(0.027)	(0.010)
Observations	229,994	229,994	547,022	547,706	230,814	230,793	230,859	230,870
R-squared	0.072	0.071	0.019	0.017	0.024	0.028	0.043	0.019
Mean of Dep. Var.	0.777	2.243	0.082	0.064	0.195	0.193	0.317	0.086
Std. Dev. of Dep. Var.	0.416	2.159	0.274	0.245	0.396	0.395	0.465	0.281

Notes - *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *Care 10+* - binary var. equal 1 if individual received medical care 10+ times in past 12 months; *Hosp. Night* - binary var. equal 1 if individual was in a hospital overnight in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Special* - binary var. equal 1 if individual saw/talked to medical specialist in past 12 months; *Saw Eye* - binary var. equal 1 if individual saw/talked to eye doctor in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to mental health professional (psychiatrist, psychologist, etc.) in past 12 months. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. Individuals aged 30-31 in 2012 are omitted from 2013-2016 waves. Individuals aged 31-32 (at the time of interview) are omitted from 2000-2012 waves. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.13: DACA and Health Status, Mental Health - Omitting Aged 30-31 in 2012 (Entire U.S.)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Effort	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.1190***	-0.0036***	0.0057	-0.0269	-0.0091	-0.0364*	-0.2235	-0.0406	-0.0045
	(0.028)	(0.001)	(0.005)	(0.019)	(0.017)	(0.021)	(0.215)	(0.025)	(0.018)
Observations	547,852	547,852	547,852	230,017	229,990	229,864	229,553	229,553	233,107
R-squared	0.080	0.011	0.034	0.025	0.016	0.018	0.032	0.024	0.066
Mean of Dep. Var.	4.005	0.011	0.936	0.106	0.063	0.148	2.488	0.194	0.144
Std. Dev. of Dep. Var.	0.952	0.106	0.244	0.308	0.243	0.356	3.736	0.396	0.351

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Effort* - binary var. equal 1 if individual reported feeling "everything was an effort" some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens and citizens ages 18-50 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. Individuals aged 30-31 in 2012 are omitted from 2013-2016 waves. Individuals aged 31-32 (at the time of interview) are omitted from 2000-2012 waves. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.14: DACA and HC Access, Affordability (NHIS: All Non-Citizens, 18-35, with HS Degree)

	(1) Usual	(2) Any Care Delay	(3) Special. Not Afford.
DACA-Eligible * Post 2012	0.0343	-0.0173	-0.0430*
	(0.034)	(0.012)	(0.026)
Observations	13,074	31,650	4,998
R-squared	0.093	0.029	0.030
Mean of Dep. Var.	0.618	0.145	0.048
Std. Dev. of Dep. Var.	0.486	0.352	0.214

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Any Care Delay* - binary var. equal 1 if any member of respondent's family delayed seeking medical care due to cost (in past 12 months). *Special. Not Afford.* - binary var. equal 1 if individual needed but couldn't afford specialist (in past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment, # years in U.S.), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.15: DACA and Health Care Access (CHIS: All Non-Citizens, 18-35, with HS Degree)

	(1) Usual	(2) Personal MD
DACA-Eligible * Post 2012	0.0586	0.0141
	(0.053)	(0.074)
Observations	6,010	1,691
R-squared	0.111	0.234
Mean of Dep. Var.	0.695	0.380
Std. Dev. of Dep. Var.	0.460	0.485

Notes - *Usual* - binary var. equal 1 if individual has usual place to go to when sick or needing health advice; *Personal MD* - binary var. equal 1 if individual has personal doctor as main medical provider. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment, age at entering U.S.), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.16: DACA and Health Care Use (NHIS: All Non-Citizens, 18-35, with HS Degree)

	(1) Doctor	(2) # Visits	(3) Care 10+	(4) Hosp. Night	(5) ER	(6) Saw Special	(7) Saw Eye	(8) Saw Mental
DACA-Eligible * Post 2012	0.0248	0.0777	-0.0043	0.0073	-0.0051	-0.0167	0.0075	0.0191*
	(0.034)	(0.117)	(0.007)	(0.008)	(0.024)	(0.017)	(0.028)	(0.010)
Observations	12,990	12,990	31,633	31,659	13,022	13,023	13,029	13,029
R-squared	0.113	0.121	0.019	0.044	0.018	0.029	0.052	0.015
Mean of Dep. Var.	0.610	1.505	0.042	0.061	0.136	0.098	0.176	0.028
Std. Dev. of Dep. Var.	0.488	1.846	0.201	0.240	0.343	0.298	0.381	0.163

Notes - *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *Care 10+* - binary var. equal 1 if individual received medical care 10+ times in past 12 months; *Hosp. Night* - binary var. equal 1 if individual was in a hospital overnight in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Special* - binary var. equal 1 if individual saw/talked to medical specialist in past 12 months; *Saw Eye* - binary var. equal 1 if individual saw/talked to eye doctor in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to a mental health professional (psychiatrist, psychologist, etc.) in past 12 months. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment, # years in U.S.), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.17: DACA and Health Care Use (CHIS: All Non-Citizens, 18-35, with HS Degree)

	(1) Doctor	(2) # Visits	(3) ER	(4) Saw Mental	(5) # Mental Visits
DACA-Eligible * Post 2012	-0.0239	0.8294	-0.0337	0.0379	0.9387*
	(0.054)	(0.865)	(0.046)	(0.029)	(0.511)
Observations	6,010	6,010	4,661	3,583	3,583
R-squared	0.101	0.091	0.069	0.060	0.051
Mean of Dep. Var.	0.694	2.830	0.144	0.072	0.504
Std. Dev. of Dep. Var.	0.461	5.053	0.351	0.259	3.189

Notes - *Doctor* - binary var. equal 1 if individual saw/talked to any doctor in past 12 months; *# Visits* - total number of doctor's office visits in past 12 months; *ER* - binary var. equal 1 if individual visited emergency room in past 12 months; *Saw Mental* - binary var. equal 1 if individual saw/talked to a medical professional (psychiatrist, psychologist, etc.) for mental or alcohol/drug problems in past 12 months; *# Mental Visits* - # of visits to professional for problems with mental health or drugs/alcohol (during past 12 months). Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment, age at entering U.S.), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.18: DACA and General/Mental Health (NHIS: All Non-Citizens, 18-35, with HS Degree)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Effort	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.0826***	-0.0001	0.0024	-0.0183	0.0031	-0.0261	-0.1321	-0.0330	0.0004
	(0.031)	(0.001)	(0.006)	(0.020)	(0.018)	(0.022)	(0.226)	(0.026)	(0.019)
Observations	31,662	31,662	31,662	12,999	12,988	12,982	12,962	12,962	13,157
R-squared	0.039	0.003	0.012	0.016	0.013	0.017	0.026	0.022	0.015
Mean of Dep. Var.	4.119	0.003	0.968	0.102	0.053	0.105	1.900	0.150	0.047
Std. Dev. of Dep. Var.	0.878	0.056	0.175	0.302	0.223	0.306	3.137	0.358	0.213

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Effort* - binary var. equal 1 if individual reported feeling "everything was an effort" some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2000-2016 waves of NHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment, # years in U.S.), year fixed effects, region fixed effects, and region-specific time trends. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

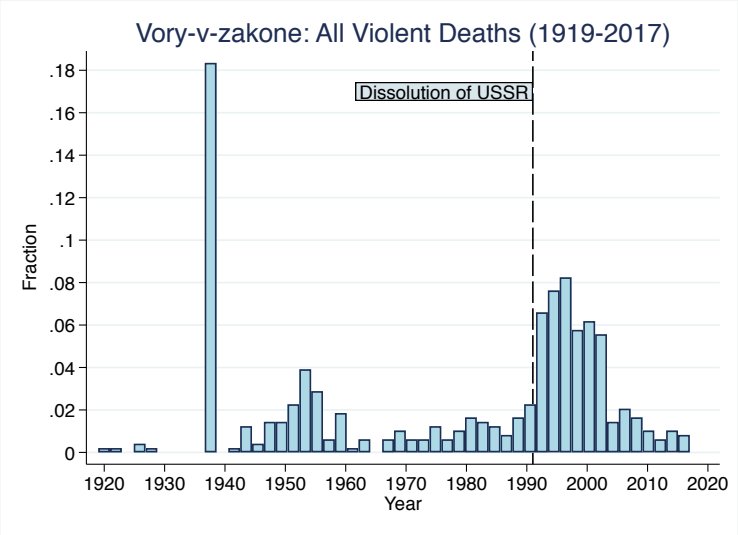
Table B.19: DACA and General/Mental Health (CHIS: All Non-Citizens, 18-35, with HS Degree)

	(1) Health	(2) Poor Health	(3) Good Health	(4) Depressed	(5) Hopeless	(6) Restless	(7) K6 Scale	(8) Distress	(9) Hyperten.
DACA-Eligible * Post 2012	0.3117*	0.0155	-0.0438	0.0301	0.0377	0.0001	0.3795	-0.1005	0.0492
	(0.173)	(0.014)	(0.042)	(0.035)	(0.039)	(0.047)	(0.413)	(0.076)	(0.034)
Observations	6,010	6,010	6,010	4,661	4,661	4,661	4,661	4,661	6,010
R-squared	0.142	0.053	0.082	0.052	0.049	0.061	0.086	0.079	0.051
Mean of Dep. Var.	3.554	0.013	0.857	0.098	0.122	0.213	3.686	0.318	0.068
Std. Dev. of Dep. Var.	1.001	0.112	0.350	0.297	0.327	0.409	3.460	0.466	0.252

Notes - *Health* - self-reported general health status (categorical variable: 1 - poor, 2 - fair, 3 - good, 4 - very good, 5 - excellent); *Poor Health* - binary var. equal 1 if individual self-reported his/her general health status as poor (category 1); *Good Health* - binary var. equal 1 if individual self-reported his/her general health status as excellent, very good, or good (categories 5, 4, 3); *Depressed* - binary var. equal 1 if individual reported feeling sad or depressed such that "nothing could cheer them up" some/most/all of the time in past 30 days; *Hopeless* - binary var. equal 1 if individual reported feeling hopeless some/most/all of the time in past 30 days; *Restless* - binary var. equal 1 if individual reported feeling restless or anxious some/most/all of the time in past 30 days; *K6 Scale* - continuous measure of nonspecific psychological distress during the past 30 days using Kessler 6-Item (K6) Psychological Distress Scale (0-24; higher values represent higher levels of distress); *Distress* - binary var. equal 1 if individual experienced moderate or serious psychological distress in past 30 days (i.e. *K6 Scale* $>= 5$); *Hyperten.* - binary var. equal 1 if individual was ever told had hypertension/high blood pressure. Robust standard errors in parentheses. Estimates in all columns are derived from a sample of all non-citizens ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2003-2015 waves of CHIS. All regressions control for Post-DACA implementation dummy, DACA eligibility dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, education attainment, age at entering U.S.), county fixed effects, and year fixed effects. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

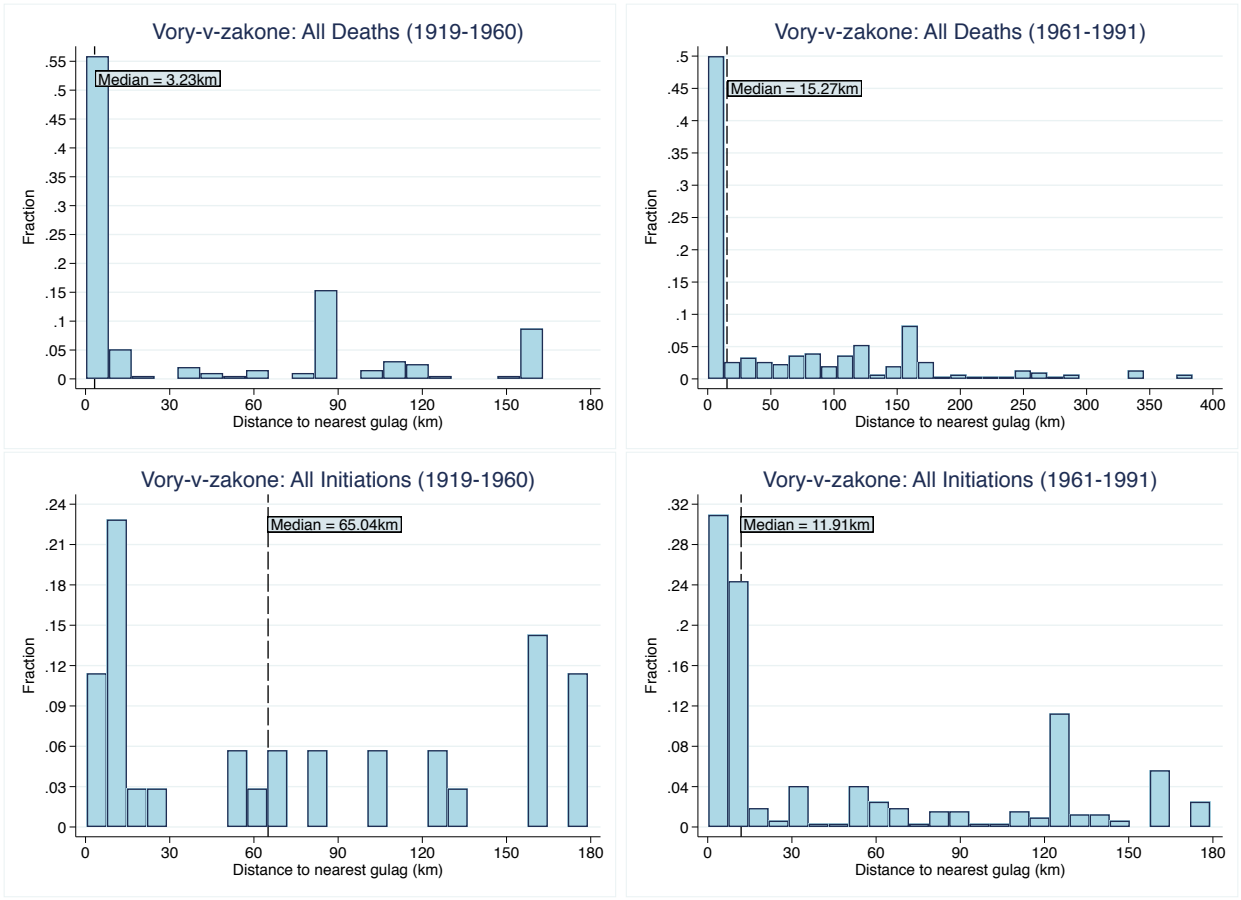
APPENDIX C

Figure C.1: Mafia Initiations, Deaths, and Status Revocations over Time (Histograms)



Notes - Data comes from *Prime Crime News Agency*. Underlying sample consists of 485 unique violent deaths. USSR was dissolved on December 26, 1991. In the histogram, I set the number of bins to 50.

Figure C.2: Mafia Deaths and Initiations in USSR: 1919-1960 vs. 1961-1991 (Histograms)



Notes - Data comes from *Prime Crime News Agency*. Underlying sample sizes are as follows: upper-left figure (202 individuals); upper-right figure (308 individuals); lower-left figure (35 individuals); lower-right figure (323 individuals).

Table C.1: Gulag & Mafia Presence in 1990s (OLS): Linear Term & Higher Order Polynomials

	(1) Mafia presence (1994-95)	(2) Mafia presence (1994-97)	(3) Mafia presence (1994-95)	(4) Mafia presence (1994-97)	(5) Mafia presence (1994-95)	(6) Mafia presence (1994-97)
Gulag distance (in 100s of km)	-0.0077	-0.0035	-0.0592***	-0.0594***	-0.1080***	-0.1100***
	(0.0080)	(0.0084)	(0.0134)	(0.0136)	(0.0228)	(0.0232)
Gulag distance^2			0.0088***	0.0095***	0.0266***	0.0280***
			(0.0016)	(0.0017)	(0.0058)	(0.0060)
Gulag distance^3					-0.0013***	-0.0013***
					(0.0004)	(0.0004)
Region FE	YES	YES	YES	YES	YES	YES
Road & Railroad Densities (km/km^2)	YES	YES	YES	YES	YES	YES
Distance to region's admin. center (km)	YES	YES	YES	YES	YES	YES
Distance to nearest prison in 1990s (km)	YES	YES	YES	YES	YES	YES
Observations	2,445	2,445	2,445	2,445	2,445	2,445
F-statistic	0.695	0.134	12.72	14.02	11.27	12.20
R-squared	0.103	0.109	0.112	0.119	0.115	0.122
Mean of dep. variable	0.097	0.102	0.097	0.102	0.097	0.102
Std. dev. of dep. variable	0.295	0.303	0.295	0.303	0.295	0.303

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Mafia presence (1994-95)* - binary var. equal 1 if at least one vor present in subregion between 1994-95. *Mafia presence (1994-97)* - binary var. equal 1 if at least one vor present in subregion between 1994-97. *Gulag distance (in 100s of km)* - distance to the nearest GULAG camp complex (in 100s of km). *Gulag distance*^{2} - squared term of the distance polynomial. *Gulag distance*^{3} - cubed term of the distance polynomial. Estimation sample consists of all 2,445 subregions within the Russian Federation (as of 1992). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table C.2: Gulag & Mafia Presence in 1990s (OLS): Intensive Margin

	(1) Vory per 100,000 (1994-95)	(2) Vory per 100,000 (1994-97)	(3) Vory per 100,000 (1994-95)	(4) Vory per 100,000 (1994-97)	(5) Vory per 100,000 (1994-95)	(6) Vory per 100,000 (1994-97)
Gulag distance < 10th percentile (10p = 17.6km)	0.192** (0.078)	0.188** (0.078)				
Gulag distance < 15th percentile (15p = 26.9km)			0.152*** (0.059)	0.158*** (0.059)		
Gulag distance < 20th percentile (20p = 37.4km)					0.128** (0.053)	0.126** (0.053)
Region FE	YES	YES	YES	YES	YES	YES
Road & Railroad Densities (km/km^2)	YES	YES	YES	YES	YES	YES
Distance to region's admin. center (km)	YES	YES	YES	YES	YES	YES
Distance to nearest prison in 1990s (km)	YES	YES	YES	YES	YES	YES
Observations	2,005	2,005	2,005	2,005	2,005	2,005
F-statistic	9.127	8.405	8.027	8.318	6.910	6.506
R-squared	0.048	0.052	0.047	0.052	0.047	0.051
Mean of dep. variable	0.182	0.191	0.182	0.191	0.182	0.191
Std. dev. of dep. variable	0.736	0.751	0.736	0.751	0.736	0.751

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Vory per 100,000 (1994-95)* - # of vory present in subregion between 1994-95, per 100,000 inhabitants. *Vory per 100,000 (1994-97)* - # of vory present in subregion between 1994-97, per 100,000 inhabitants. *Gulag distance < 10th percentile* - binary var. equal 1 if subregion is located within 17.6km of the nearest gulag camp. *Gulag distance < 15th percentile* - binary var. equal 1 if subregion is located within 26.9km of the nearest gulag camp. *Gulag distance < 20th percentile* - binary var. equal 1 if subregion is located within 37.4km of the nearest gulag camp. Estimation sample consists of all 2,445 subregions within the Russian Federation (as of 1992). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table C.3: Mafia Presence & Attacks by Type in 1990s Russia: Intensive Margin

	(IV) Any Attack (1994-98)	(IV) Any Business Attack (1994-98)	(IV) Any Criminal Attack (1994-98)	(IV) Any Police Attack (1994-98)	(IV) Any Political Attack (1994-98)
Mafia per 100,000 pop. (1994-95)	0.678***	0.545***	0.563***	0.290***	0.146**
	(0.202)	(0.170)	(0.166)	(0.098)	(0.064)
Region FE	YES	YES	YES	YES	YES
Road & Railroad Densities (km/km^2)	YES	YES	YES	YES	YES
Institutional controls	YES	YES	YES	YES	YES
Population & Economic controls	YES	YES	YES	YES	YES
Observations	1,938	1,938	1,938	1,938	1,938
Mean of dep. variable	0.093	0.074	0.042	0.021	0.018
Std. dev. of dep. variable	0.291	0.262	0.200	0.144	0.133
Angrist-Pischke F-stat	11.69	11.69	11.69	11.69	11.69

Notes - Heteroskedasticity-robust standard errors in parentheses. Estimation sample consists of Russia's subregions (equivalent to NUTS 3 classification). *Any Attack (1994-98)* - binary equal 1 if any attack against a member of the Russia's economic elite occurred in 1994-98. *Any Business Attack (1994-98)* - binary equal 1 if any attack against a businessman or manager occurred in 1994-98. *Any Criminal Attack (1994-98)* - binary equal 1 if any attack against a criminal occurred in 1994-98. *Any Police Attack (1994-98)* - binary equal 1 if any attack against a member of law enforcement, army, or against a judge occurred in 1994-98. *Any Political (1994-98)* - binary equal 1 if any attack against a politican or public figure occurred in 1994-98. *Mafia per 100,000 pop. (1994-95)* - # of vory per 100,000 inhabitants present in subregion in 1994-95. The instrument used in the IV estimation is a binary var. equal 1 if subregion was within 26.9km km (i.e. 15th percentile) of the nearest gulag. Economic controls: unemployment rate (1998), log of average wage (1996). Institutional controls: distance to region's administrative center, distance to the nearest prison (operating in the 1990s). Population controls: population density (1996), share of retired people (1998). *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

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