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Forced Displacement and Social Capital in the Long Run: Lessons from the Indian Partition

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Abstract

This paper investigates the impact of migrant inflows due to forced displacement events on the social capital in the recipient societies. We exploit the setting of Partition of India into India and Pakistan (East and West Pakistan) in 1947. Using data from districts in post 1947 India belonging to six states that saw a higher inflow of migrants, relative to outflow, we analyse how the 'shock' inflow of migrants affected social capital in the districts sixty years later. The shock is measured as the proportion of "displaced" migrants in Indian districts in 1951 from census data. Employing information from the World Health Organisation Study on global AGEing and adult health conducted in 2007, the results indicate that social capital is lower in districts that received more Partition migrants. The effect remains strongly robust to spatial robustness checks, contemporary differences in demographics and income, public goods provisions, literacy, urbanisation and the gender ratio. We find that these effects are mediated through riots, community conflicts and violent crime that start from Partition sixty years ago and continue through to more recent times. We also find that political participation, a proxy for social capital, falls over time in districts which see a relatively larger flow of displaced migrants. Our study contributes to the understanding of the long run implications of large forced displacement events.

JEL classification

O15, N3, J61, Z13

Keywords

partition, social capital, forced displacement

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1 Introduction

There is a growing recognition in economics that institutions like culture, informal norms and beliefs, matter. In the last decade or so, a large body of work shows that culture affects outcomes such as economic growth, public goods provision, labor force participation, and corruption among many others (Alesina and Giuliano, 2015). Much of these studies focus on culture, often measured using survey responses to questions on trust, social cohesion, cooperation or the extent of collectivist beliefs, as an explanatory variable against an economic outcome. However, more recent scholarly pursuits analyze the dynamics of culture itself in different contexts (Becker et al., 2016). Why do some societies like the Japanese exhibit high levels of trust (Fukuyama 1995)? Why do more diverse societies in Africa exhibit lower levels of social capital as manifested in the slave trade (Nunn and Wantchekon, 2011)? How do historical episodes like Spanish Civil War affect social capital today (Tur-Prats and Caicedo, 2020)?

Our paper relates to such recent questions on culture that we define as "(those) customary beliefs and values that ethnic, religious and social groups transmit fairly unchanged from generation to generation" à la Guiso, Sapienza, and Zingales (2006). In this paper, we study the impact of the inflow of displaced migrants as a consequence of a large shock event on the long run social capital of the recepient society. The large shock is the Partition of India in 1947 that split undivided India into India and Pakistan. We focus on the impact on post partition India, in particular areas of the country which received a large inflow of migrants, without comparable levels of outmigration. The motivation in doing so is primarily driven by data at hand - the survey conducted in 2007 that we use to construct the social capital indicator was not undertaken in Punjab- the state that saw a population exchange and garners the focus of attention for scholars working on Partition. In addition, one sided migrations, from shocks and wars, are becoming ubiquitious in the current world; hence, understanding large scale population displacements and their implication on migrant recipient societies remains very important in the world today with almost 26 million cross border and 41.3 million internally displaced people in 2018 (UN High Commission for Refugees.[1]). While

[1]https://www.unhcr.org/news/press/2019/6/5d03b22b4/worldwide-displacement-tops-70-million-un-refugee-chief-urges-greater-solidarity.html

generalizations across time and contexts should be done with care, investigations of such path-breaking, and often-time, painful historical episodes, could disentangle important forces at play, which in turn, shape societal values and trust in the long run. Our study is one such attempt to not only chronicle the effect of Partition driven net inflows on social capital in the contemporary India, but to also provide an important lens to distil more recent displacement events.

The Indian Partition, one of the world's largest forced population transfer in the modern era, involved the migration of almost 18 million people over four years across three different nascent state entities, viz., India, Pakistan and Bangladesh (Bharadwaj et al., 2008).[2] Almost 12 million people became refugees and between half-a-million to one million people lost their lives due to the riots and religious violence engulfed during the Partition.[3].

The Partition of India was a large shock to the society. While the country bifurcation was expected in the years leading upto the independence of India and Pakistan, where boundaries would be drawn was not clear. Hence, many found themselves on the "wrong" side of the boundary and were forced to move-some immediately, others over time as their conditions deteriorated. We measure the Partition shock using the share of the district population in the 1951 census of post independent India, who were enumerated as Partition migrants. Such migrants, recorded officially as "displaced persons", were tallied separately from other non-Partition migrants in a district. We investigate the impact of this displacement on the social capital after sixty years. Our study focuses on the Indian states of Assam, Rajasthan, Karnataka, Maharashtra, Uttar Pradesh and West Bengal-the choice of states is determined by the World Health Organization (WHO) sponsored Study on global AGEing and adult health (SAGE). Since the partition was not a monolithic event-experiences varied in different parts of India (and Pakistan)-we do not claim to provide the "full" impact of partition, especially since Punjab, an important recipient of the displaced is not a part of the data sample. However some of the big, adjacent to border, states in the study, received a substantial number of displaced migrants and hence provide us with a unique

[2]In 1947 colonial India was partitioned into India and Pakistan, which included West Pakistan (present day Pakistan) and East Pakistan (present day Bangladesh.) In 1971, Bangladesh became an independent country after fighting a war of independence with Pakistan.

[3]However, the number of people lost their lives or missing is fiercely debated, see Bharadwaj et al. (2008), pg. 42 onward.

platform in analyzing how the Indian society is affected in the long run by net inflow of displaced people.[4]

To measure contemporary social capital, we use individual data from the WHO SAGE survey for 2007-08 conducted across six Indian states. Our metric aggregates responses to questions on community participation, social cohesion and trust into an index. These questions capture common social capital variables used in the literature (Glaeser et al., 2002). We then match an individual's district to the share of 1951 Partition displaced migrants in that district.[5] This allows us to investigate if the large inflow of Partition migrants affects contemporary social capital.

Partition migrants did not randomly settle across Indian districts, especially in the western border state of Punjab where immigrants were directed to particular settlements in Punjab and Rajasthan (Kudaisya, 1995; Bharadwaj and Mirza, 2019). Bharadwaj et al. (2008) find that migrants settled in districts close to the borders of India and Pakistan, districts that saw greater outflows to Pakistan, namely districts with large Muslim populations, and districts with large cities such as Calcutta, closer to the eastern side of the Indian border. Yet, there is variation in the share of Partition migrants even after controlling for these factors. For example, Nadia, a border district in West Bengal had 37% partition migrants compared to 3% in Murshidabad, another border district of West Bengal.

To identify a credible estimate of Partition migration on social capital, we thus control for a rich set of factors that may be correlated with the settlement decisions of Partition migrants, and contemporary social capital attitudes. First, we exploit variation across districts within states because of the many unobserved differences across Indian states. Second, we control for a host of geographical attributes like the latitude and longitude of a district centroid plus their squared terms, the average elevation of a district, average annual rainfall between 1900 and 1950, distance from the surveyed household to nearest border and it's square, indicators for poor soil and rural districts, and the area of the district (based on their boundaries in 2007). Third, we control for

[4]It can be argued that the displacement in Punjab, while being an important part of the partition experience, is atypical of the usual displacement episodes in the world since it saw a two sided movement of population transfer with West Pakistan (contemporary Pakistan).

[5]Since districts in 1951 are bigger than in 2007-08, we map household locations to districts in 1951.

1951 district characteristics such as population, urbanisation, literacy, share of Muslims, share of marginal groups like scheduled castes and scheduled tribes, and the gender ratio.[6] Fourth, we control for historical (pre-partition) differences with the 1931 share of Brahmans (the elite Hindu caste), 1931 Share of literates, 1931 share of Muslims, an indicator for former Princely States and the 1931 share of migrants that came from other states (reflecting its attractiveness as a destination for migration). Finally, we control for individual characteristics such as age, gender, education, religion, marital status, permanent residency status and household characteristics of the individual.

Conditional on such rich and varied controls, we find negative and significant effects of 1951 Partition migration on the contemporary index of social capital. A standard deviation increase in the log 1951 Partition migration reduces contemporary social cohesion by 0.12 standard deviations. The coefficient remains robust to incrementally adding more controls, estimating Conley standard errors accounting for spatial correlation, excluding extreme values of the social capital index as suggested by Kelly (2020), and dropping one state (or alternately one district) at a time. The effect remains similar but with greater magnitude in comparison to the baseline finding when employing the instrumental variable strategy proposed by Lewbel (2012).

To explore if the fall in social capital started in years closer to the partition of India, we look at a political participation in state elections, as a proxy for social capital.[7] Due to data limitations, as well as changing format of elections in India between 1950 and 1960, we look at the association between partition migration and state assembly level voter turn our ratios (which are aggregated at 1951 district boundaries) over the period 1962-2000. Using district fixed effects, we find that higher the proportion of displaced migrants in 1951, the more the fall in the average district voter turn out ratio over time. Using 1962-1969 as the reference period, we find negative effects in the decades 1970-1980 and 1991-2000. This confirms that the fall in social capital is not something

[6]Ideally, one would want to account for differences between districts just before partition. However, it is well documented that the data in the 1941 census of India was of poor quality due to the Second World War (Bharadwaj et al. 2008). Hence, inspite of the fact that some of these variables in 1951 are consequences of the partition of India, we include them to take into account any differences between districts that may confound our results. Results are similar even if we do not control for these variables.

[7]This follows work by Putnam (1993), Svendsen and Svendsen (2009) who use voter turn out ratio as a measure of social capital.

peculiar to the year of the survey, and has a relatively longer history.

The decline in contemporary social capital could be reconciled with findings from the extant literature. Putnam (2000) posits that there is overall decline in trust in general in the USA after the Second World War. Tur-Prats and Caicedo (2020) find that the Spanish Civil War of 1933-1936 had a detrimental, long-run impact on contemporary generalized trust. In the same vein, Alesina and Tabellini (2020) document that large amounts of immigrants arrival in a short period of time could have negative connotations on social and political cohesion. Looking at it from a different perspective, Fouka (2020) shows that even forced assimilation policies in the recipient countries like the USA (Americanization policies like compulsory english language training in schools etc) could not enhance trust between the host community (Americans) and Germans after the first World War.

Note that for India, there were no deliberate social policies to assimilate the displaced persons into the recipient districts except that the rehabilitation and resettlement were tried by offering lands and associated livelihoods in a haphazard manner. For instance, in the western states of Punjab and Rajasthan resettlement was done easily due to availability of agricultural land, whereas in the eastern states of West Bengal and Assam, there were dearth of lands for rehabilitation as these states did not experience complete population transfer unlike in western states (Bharadwaj et al. 2008; Kudaisya, 1995). The West Bengal Government tried some half-hearted resettlements by offering poor quality agricultural land in infertile districts in the states of Odisha and Madhya Pradesh (Kudaisya 1995) but these policies were not helpful.

The Partition of India was a fractious event, the effects of which are likely to correlate with incidents of communal violence. However for this to be a plausible channel, districts that saw higher proportion of displaced migrants in the population should show higher conflict and violence post partition. To investigate if this is indeed the case, we use heterogeneity analysis that explores if the evolution of violence over time is correlated with share of Partition migrants in 1951. The outcome variable we look at is the annual number of riots (mostly hindu-muslim) over the period 1900 to 1995. For the period 1950-1995, we use data from Varshney and Wilkinson (2006).[8] The

[8]Varshney, Ashutosh, and Wilkinson, Steven. Varshney-Wilkinson Dataset on Hindu-Muslim Violence in In-

riots data for 1900-1949 is sourced from Wilkinson (2005).[9] Since partition migration began in 1946 (and is reported from that year in the census of India) we use 1945 as the reference year. The findings reveal that as compared to 1945, districts that had a higher proportion of Partition migrants show higher number of riots not only post independence but continue showing higher violence all the way till 1994.[10] In contrast, focusing on the period 1902-1944, there is no significant difference in riots as compared to 1945, thus pointing out to no pre-existing trends in districts. These results control for state level trends and trends that vary by baseline characteristics. We also find similar results when we conduct a synthetic difference in difference analysis following Abramitzky et al. (2021) and Ciccia (2024). This finding is not entirely unexpected - riots along the religious line (especially, Hindu-Muslim) were quite prevalent in the aftermath of Partition (Varshney and Wilkinson, 2006; Chatterji 2007) but what is significant is that such riots continue almost 20 years after the incident. In a separate analysis, we show that when controlling for riots in between 1946-1995, our coefficient of interest attenuates by 20 % showing that such riots are a plausible mechanism driving our result. This finding, akin to Tur-Prats and Caicedo (2020), points out to processes set in motion 50 years ago that have cast a long shadow on contemporary social capital.

Next, we delve further into the issue of conflict. While religious conflict dominates the historical narrative of the partition, recent trends in literature highlight partition being not only along religious and geographical lines, but also manifested across caste dimensions (Kumar 2006). Infact, newer histories of the Bengal partition (Sen, 2018; Bandopadhyay and Chaudhury 2017) point out that the question of migration, rehabilitation and post-partition politics were very heavily fractured along caste dimensions. Hence community conflict was not just between Hindus and Muslims – but also between upper and lower caste Hindu communities (Chatterji 2007). We explore this mechanism in two ways. The first one involves using micro data from the India Human Development Survey (2005) and sheds light on whether households living in partition districts ex-

dia, 1950-1995, Version 2. Inter-university Consortium for Political and Social Research [distributor], 2006-02-17. https://doi.org/10.3886/ICPSR04342.v1.

[9]The authors wish to thank an anonymous referee for pointing us to the source of data on riots all the way to 1900.

[10]We are constrained to use 1995 as the last year due to lack of such compiled data beyond 1995.

perienced higher community conflicts, which in turn, could be responsible for lower social cohesion. We find evidence that households living in partition affected districts do witness increased level of community, i.e., caste and sub-caste skirmishes in 2005. To show that similar concerns were not there in the districts which saw higher proportion of displaced migrants before 1947, we use a data set compiled by researchers working on caste conflict in pre-independence India.[11] Using accounts written by historians focussing on pre-independence incidents of caste conflict, they identify districts where such incidents were reported. Again, our analysis reveals that the proportion of displaced migrants do not correlate with the occurrence of such caste based incidents; moreover the coefficient of Proportion of displaced migrants hardly budges when we control for this variable in our regressions.

A third exercise that we do exploits the finding in the existing literature which documents that inflow of migrants is often perceived with worsening situations of crime in the host communities (Fitzgerald, Curtis and Corliss 2012; Nunziata 2015). To investigate this dimension, i.e., if partition districts have experienced more incidents of crime over the years, we use data on violent crimes from the National Crime Records Bureau of India, which is averaged over the period 1987-2007.[12] In this instance also, the coefficient of interest (partition migrants) attenuates, i.e., the formal causal mediation ascribes around 22 % of the effect to such violence. Taken together, the above three mechanisms point out that districts with large inflow of migrants post partition have ended up with violent conflict, both along religious as well as caste dimensions, which in turn, eroded the social capital of these places significantly.

Investigating further, we test for heterogeneous effects by age, gender and religion. The extant studies report that social capital increases and then decreases with age (Glaeser et al., 2002). In our case, older adults are more likely to have lived through the trauma of Partition, even if they are not migrants themselves. This would reinforce the negative effects of increasing age. The results show a decline of social capital with age, but there is no uniform evidence of a sharper decline in social capital for older adults in districts with more Partition migration. Our estimates show

[11] We wish to thank Saheli Bose for sharing this data. This is a part of an unpublished manuscript by Bose, S. and Stratmann T. (2021) titled *Culture, caste and drinking water*.

[12] The district level data is censored at 1987.

a higher negative impact among those who are in the age group 45-55 (i.e., children during the partition of India, or born just after), but no incrementally higher marginal effects for those older than 55 (as compared to the reference group of those aged 20-44). This may be related to general mis-measurement of age in India or due to survival bias among those who are very old. Or, it may well be that the effects of Partition migration persist inter-generationally as posited by Tabellini (2008) -"where values evolve gradually over time and during the transition they reflect historical features of the external environment". In our context, we could argue that Indian Partition and the subsequent upheaval was a huge negative shock within the external environment of recipient and displaced communities, which eroded the generalized social cohesion and trust. This is then the historic feature that is reflected in the social capital of the districts that inherited a large proportion of displaced migrants. By way of other results, males score higher on the social capital index as do those who are married or those with higher years of education. But, there is no heterogeneity of Partition migration along these dimensions. In an attempt to explore what characteristics of Partition migrants affected the evolution of social capital, we explore heterogeneities by where the migrants came from and their occupation. We find that the decline in social capital did not depend on where the displaced came from. However, our results show that if more migrants were employed in a myriad of relatively less lucrative non-agriculture professions in contrast to being employed in *commerce* (an economically more prosperous profession), this led to larger fall in the long run social capital. Other non-agriculture professions was also the broad occupation category, where 50.4 % of residents and 25 % of displaced migrants worked, opening to possibilities of competition.

Finally, we investigate if the effects estimated could be attributed to differences in current levels of education, income, religion, migration and public goods provision. We test this by controlling for contemporary differences in education, income, religion, migration and public goods provision but find that our coefficient on Partition migration remains unchanged. In the same vein, differences in urbanisation, literacy and gender ratios between 1961 and 2001 do not affect the estimate of the coefficient on Partition migration- hence our estimated effects are not confounded by these variables. Further, we find that migration recorded just after the wars with Pakistan (1965 and 1971) do not yield the results we see; our results remain unaffected by inclusion of

migrants from these countries in 1971 and 1981.

Our paper contributes to three strands of literatures. First, it relates to the studies on long-run consequences of forced migration (Becker, 2020; Becker and Ferrara, 2019; Maystadt et al, 2019). Unlike economic migrants, forced migrations occur in response to wars or natural disasters where migrants often loose physical assets and fear for their safety while traveling to new locations. Many papers look at the effects of such migrants, refugees, on economic outcomes such as wages and employment of the migrants and resident populations but there is no broad consensus on a general effect-contexts matter. A smaller number of studies find such migrants affect political outcomes in their new locations (Dippel and Heblich, 2021). In many of these studies, migrants have different ethnic, religious and linguistic backgrounds compared to natives. For example, Muslims from Syria and other countries have been migrating to predominantly western Christian countries in the last decade. Unlike these episodes, Indian Partition migrants were largely Hindus for example migrating for East Pakistan to India. They also shared a common language in many cases. Yet, we observe negative effects on social capital, which suggests such episodes can generate long term impacts even among co-religionists when they are from another place.

Second, our paper relates to a large literature on the persistence of historical episodes on contemporary outcomes (Nunn 2009). Seminal work by Acemoglu et al. (2001) argues that settler mortality shaped colonial institutions, which in turn affected contemporary institutions and hence economic development. Nunn (2008) finds that exposure to Africa's slave trade explains contemporary differences in development across African countries. In the case of India, Banerjee and Iyer (2005), Iyer (2010), and Chaudhary and Garg (2015) look at the long term effects of colonial institutions. We study whether the Indian Partition, a large shock of forced migration, has shaped local social capital attitudes.

Third and finally, our paper contributes to the small and growing economics literature on the Indian Partition pioneered by Bharadwaj and co-authors. Bharadwaj et al. (2008) were among the first to document important patterns on inflows and outflows of migrants at the district-level. Following on, Bharadwaj et al. (2015) find Partition migration had large effects on literacy, occupation and gender ratios because of compositional differences in migrants leaving from India/Pakistan

and those arriving in India/Pakistan. Bharadwaj and Mirza (2019) show that districts that received more Partition migrants had higher yields and are more likely to adopt high yielding variety of seeds after the Green Revolution. Mirza (2018) studies the Partition shock in Pakistan and finds long term effects on literacy due to increased urbanisation and a move away from agriculture. Bharadwaj and Fenske (2012) look at the jute industry after Partition where jute mills in Calcutta on the Indian side were separated from jute growers in East Pakistan on the other side of the boundary. Districts that received more migrants then took up more jute cultivation, jute yields increased with no decline in the price of jute. Jha and Wilkinson (2012) show that districts with a higher proportion of former combat soldiers experienced more Partition-related violence. Similar to Mirza (2018) and Bharadwaj and Mirza (2019), we look at the long term effects of Partition but our lens is different-that of social capital. We acknowledge though that due to the truncated nature of our sample-especially in the absence of Punjab from our sample-we do not claim that this is the overall effect of the Partition, unlike the aforementioned papers.

The rest of the paper is organised as follows. The next section briefly overviews the history of the Partition as relevant to our study. Section 3 describes the data. Section 4 lays out the empirical framework. Our main results as well as results on plausible mechanisms are presented in Section 5. Section 6 describes the heterogeniety results and Section 7 lays out the extensive robustness results. Finally, Section 8 concludes the paper.

2 Partition of India

Colonial India was partitioned into two countries in 1947, namely India and Pakistan. The two parts of Pakistan, East and West Pakistan, were separated by almost 2,000 kilo-meters. Religion was the main driving force behind Partition. Given the intermingling of Hindus, Muslims and Sikhs across colonial districts, the boundary was based on the population shares of religious groups in contiguous "areas", where the definition of "areas" was somewhat ambiguous and arbitrary (Tan and Kudaisya, 2000). Sir Cyril Radcliffe, a British lawyer, was tasked with demarcating the borders of the new nations. Apart from having never visited India before 1947, he had less than a month to complete his report. He in turn, used out-of-date maps and population shares from

the 1941 Census, to divide the two largest colonial provinces, Punjab on the West and Bengal on the East. The general public was informed about the precise boundary the day after Indian independence on 15th August, 1947. Suddenly, many people found themselves on the 'wrong' side of the border, and had to migrate to the other side. This lead to one of the largest forced migrations in the modern era involving around 17.5 million migrants.(Bharadwaj et al., 2008).[13] About 12 million people became refugees and more than a million people lost their lives due to the ensuing riots.[14]

2.1 Settlement of Migrants

The Eastern and Western borders had very different migration patterns. Along the Western border, the quick outflows of Muslims from Indian Punjab to Pakistan were matched by inflows of Hindus and Sikhs from Pakistan to India (Bharadwaj, et al., 2008). This lead to vacant agricultural land and property on both sides of the border where refugees settled. The Indian government in Punjab supported these transfers with an effective land redistribution program that began in 1947. Although there was disparity in the quantity and quality of land vacated by the refugees in Pakistan compared to the land in India, the government found a way to compensate the refugees based on their Pakistani holdings (Tan and Kudaisya, 2000). And, much of the refugee resettlement was complete by the early 1950s.

In contrast, there was a large inflow of Hindus from East Pakistan to India compared to smaller outflows of Muslims to East Pakistan. Moreover, these Hindu migrants from East Pakistan came in waves. Following the Noakhali riots in 1946, some Hindus began moving east even before independence. These migrations continued till 1951. Between 1947 and 1951, the migrants were largely educated, middle-class and high caste Hindus (like Bengali brahmins) with contacts and established networks in West Bengal (Kudaisya, 1995; Chatterji, 2007). Another large group of refugees arrived in 1960-61 following targeted killings of Hindus in Pabna, Rajshahi and Dhaka districts of East Pakistan (Sinha, 1998). Unlike the earlier wave, these refugees were mainly

[13] https://www.bbc.com/news/world-asia-40643413

[14] The precise number of people that lost their lives or went missing is fiercely debated. See Bharadwaj et al. (2008), pg. 42 onward.

agriculturists (Kudaisya, 1995) and mostly lower sub-caste of Hindus like "namashudras" and "matuas" (Bandopadhyay and Chaudhury 2017) . Yet, they settled in the same districts as the earlier 1951 Partition migrants (Chatterji 2007). Although the government made efforts to rehabilitate some of these refugees in other parts of the country because of land pressure, most schemes failed with refugees returning to the districts where they first settled (Tan and Kudaisya, 2000; Chatterji, 2007).[15] Many migrants also went to other Eastern border states with the 1951 Census reporting close to 115,000 displaced migrants in Assam (Sarma, 2015). It is interesting to note that a large chunk of the refugees were of lower sub-castes engaged in mainly agricultural activities and did not have much educational qualifications.

On the western side, the migrants also settled in bordering districts of Indian Punjab and Rajasthan. Sharma and Vanjani (1990) mention that over 55,000 refugees, mostly peasants, were rehabilitated in the Alwar district of Rajasthan. Many of these refugees were given land in Rajasthan to engage in agricultural activities. Rajasthan also saw migrants arriving and then returning back to Pakistan. Unlike Punjab and West Bengal, these migrations were relatively peaceful (Maini, 2013). Copeland (1998) mentions that only two Rajasthani districts of Alwar and Bharatpur experienced Hindu-Muslim riots during Partition. Moreover, Rajasthan remained relatively peaceful even after Partition.

Bharadwaj, et al. (2008) confirm many of the qualitative accounts of where migrants settled using detailed district-level data. They find that migrants moved to border districts, those with large cities and large Muslim populations. That said, the distance effect was not uniform especially within states. In addition, Bharadwaj et al. (2008) point to the "population replacement" effect to account for in-migration of refugees to places where other migrants moved out. Again, this replacement effect was strong on the Western border, but not so on the Eastern border (Tan and Kudaisya, 2000; Jha and Wilkinson, 2012).

The difference between characteristics of in-migrants and out-migrants also lead to changes

[15]Due to the large influx of migrants, and smaller outflows of people from India to East Pakistan, there was pressure on land, and especially agricultural land in the border states of Eastern India, namely West Bengal, Assam and Tripura (Tan and Kudaisya, 2000). Kudaisya (1995, page 89) mentions that by 1958, the West Bengal government had acquired 61,000 acres of agricultural land for redistribution which was grossly inadequate given the number of refugees from Bangladesh.

in receiving districts of India. Bharadwaj, et al. (2015) study the short-term effect of Partition on literacy, occupation and gender ratios in 1951. They find that the population exchange increased literacy, increased job losses in agriculture, and moved the gender ratio in favour of women. To assess the role of these factors in affecting long run attitudes on social cohesion and trust, we study their evolution over decades after partition as potential mediators in the analysis.

3 Data

In the empirical analysis we merge individual data collected by the WHO as a part of the survey, Study on global AGEing and adult health (SAGE), for 2007-08 with district-level data from various Indian censuses (1931, 1951-2001).[16] The SAGE survey collects data on adults 50 years and older, plus a smaller sample of adults aged 18 to 49. It covers many health related characteristics with questions on bio-markers, mental health, social connections, and participation. SAGE samples 11,230 individuals across six Indian states.[17] Due to missing data on some variables, our final sample consists of 8,860 individuals across 121 districts. These districts cover 258 villages and 64 towns across those six states. We map the 121 districts of 2007 vintage to their 1951 borders, which translates into 103 districts of 1951 vintage. These are shown in Figure 1. The SAGE data is used to construct the main outcome variable, an index of social capital as we describe next.

3.1 Measuring Social Capital and Trust

Our index of social capital aggregates responses to questions on social cohesion, trust and participation as answered by individuals in SAGE. Figure 2 shows the list of questions asking respondents about their involvement in the community and their trust in various groups of people. The questions on community involvement ask about attending public meetings, meeting community leaders, attending club meetings, working with people in the neighbourhood, having friends over, going to visit people, socialising with co-workers, attending religious services as well as step-

[16]The data collection for SAGE was implemented by the International Institute for Population Sciences (IIPS), Mumbai in collaboration with the WHO. While this is a longitudinal study, we use round 2, referred to as Wave 1, since the first round conducted in 2003 did not ask the relevant questions of interest to this paper. For more on SAGE see https://www.who.int/data/data-collection-tools/study-on-global-ageing-and-adult-health

[17]They are Assam, West Bengal, Rajasthan, Uttar Pradesh, Karnataka and Maharashtra.

ping out of the house to attend events. To each of these questions, the possible responses are "Never", "Once or Twice per Year", "Once or Twice per Month", "Once or Twice per week" and "Daily". We construct a dichotomous variable based on each question, that takes the value 1, if the frequency of such participation is "Once or Twice per Month" or more, 0 otherwise. For the trust questions, individuals are asked about their trust in people in their neighbourhood, about people with whom they work with and trust in strangers. The possible responses to these questions are "To a very great extent", "To a great extent", "Neither great nor small extent", "To a small extent" and "To a very small extent". We construct a binary variable for each question, which takes the value 1 when the trust is to a great extent or more, 0 otherwise. Given these dichotomous variables, we combine them into a variance-weighted index (SC_{ihds}), following Anderson (2008).[18]

3.2 Measuring 1951 Partition Displaced Migration

In 1951, the Census of India recorded the stock of people in a district who were "displaced". The census defined a "Displaced Person" as "any person who has entered India having left or being compelled to leave his home in Western Pakistan on or after the 1st March, 1947, or his home in Eastern Pakistan on or after the 15th October, 1946, on account of civil disturbances or on account of the setting up of the two Dominions of India and Pakistan." This was recorded for each district as part of the Social and Cultural Tables. We define $Prop1951Displaced_{ds}$ as the proportion of the 1951 district population that has been displaced from East and West Pakistan and settled in district d in state s. Thus our measure looks at the *inflow* of displaced migrants as a proportion of the total population of the district.[19] The measure is motivated by the research question namely whether the long term impact of outsiders in a particular district affects contemporary social capital outcomes. Since these data are recorded for 1951 districts (103 of them), our unit of variation is at the 1951 district-level. The areas covered by the data sample are shown in Figure 1.

[18]The index is a weighted average value of the individual variables with weights recovered from the inverse covariance matrix, following the procedure of Anderson (2008). This procedure ensures that highly correlated outcomes receive less weight while outcomes that are uncorrelated and thus represent new information receive more weight. We use STATA routine *make_index_gr.do* to construct this index.

[19]This is in contrast to measuring what proportion of the district population moved out of the district.

The average proportion of 1951 displaced migrants in our sample is 2.26% (Table 1). However it varies substantially ranging from 0.00179% for the bottom 5% of individuals and 16% for the top 1% of individuals. The maximum value is 37%.[20] Disaggregating by state, West Bengal (the state bordering erstwhile East Pakistan and now Bangladesh), unsurprisingly, has the highest proportion of displaced people at 9.41% followed by Rajasthan at roughly 3%, Assam at close to 2.4%, and finally Maharashtra and Uttar Pradesh at around 1%. However, comparing districts across states may be spurious given the many differences between them. In our empirical analysis, we exploit variation across districts within states to estimate the effect of Partition displacement. We have sufficient variation within states as shown in Appendix Table A1 where every state exhibits variation in $Prop1951Displaced_{ds}$; for example, even within West Bengal districts, the proportion varies from 0.70% to 37%. Since $Prop1951Displaced_{ds}$ is a skewed variable, we use a log transformation in the analysis.[21]

3.3 Individual, Geographic and Historical Controls

SAGE also reports individual and household demographic attributes such as age, gender, years of education, marital status, religion, ethnic group (Scheduled Caste, Schedule Tribe), and whether the individual has always lived in the same region (defined in the next section) as where he/she was surveyed. Moreover, the household roster gives information on all household members allowing us to construct measures of household size, number of household members below age 10, the average education of household members and the average age of household members. Such individual and household characteristics may be correlated with social capital.

In addition, SAGE provides the latitude and longitude of each village, which we use to calculate the shortest distance from the household to the borders of Bangladesh and Pakistan, respectively. Using these we calculate the minimum distance to any of the borders. Moreover, the latitude and longitude of the centroid of the district (circa 2007) where the individual is surveyed is measured using Arc GIS. We also extracted information on average length of rivers that pass

[20] The proportions are similar if we consider the 1951 districts as units of analysis. See Table 2.

[21] The skewness falls from 3.15 for the untransformed variable to -0.79 when we consider the log transformation.

through the districts (kms) and average height of the district (kms).[22] The total district area (in square kms) are calculated using Arc GIS. We obtained data on district level rainfall for the period 1900-2007 from the Indian Meteorological Department. The information on district soil composition is compiled from the 1991 Soils of India report; we use the proportion of the soil that is sandy.[23]

We also employ control variables constructed from historical Indian censuses.[24] We collected data on 1951 total and urban population, male and female population, Scheduled Caste (SC), Scheduled Tribes (ST), Muslim population, whether there was city with more than 50000 population in 1951 within the district and the number of literates. From the 1931 census, we collected information on district population, proportion of Brahmans, Literates, Muslims, and the proportion of migrants which were from outside the province or state. Finally, we created an indicator for districts in our sample that were historically a part of Princely India, i.e., under the direct control of hereditary rulers in the colonial period as opposed to under direct British rule (i.e., British India) as there is evidence of heterogenity across princely and British ruled districts (Iyer, 2010).[25] For information on the decades between 1961 and 1991 we used district level census data organised in the University of Maryland Indian District Database.[26]

From the 2001 census, we collated data on total population, disaggregated by religion, urbanisation, education, village and city share, and the share of the village or city population that is SC and ST. The district level data on crime rates for 2007 are collected from the National Crime Research Bureau, Government of India. We merged the district information for different years using the Indian Administrative Atlas 1872-2001. We also used the Bharadwaj et al. (2008) mapping to match 1931 district boundaries to 2001 district boundaries. Tables 1 and 2 report the summary statistics for the individual data and district data respectively.

[22] These data are from http://www.diva-gis.org/.
[23] The other soil types are clay and loam.
[24] Most of the historical censuses are available at https://dspace.gipe.ac.in
[25] We do not use data from 1941 India census as the data collected during these wars years has been reported to be incorrect.
[26] This is available at http://vanneman.umd.edu/districts/index.html.

4 Empirical Framework

We employ a cross-sectional ordinary least squares (OLS) specification as the baseline to estimate the relationship between individual social capital and Partition displaced migration at the district-level. Later, the Lewbel's method is used to tease out the potential causal relationship between social capital and displaced migration.

4.1 OLS specification

We first estimate an OLS model of the following form:

$$SC_{ihds} = \beta ln(Prop1951Displaced_{ds}) + \gamma' x_i + \zeta' v_h + \gamma' z_d + \eta_s + \epsilon_{id} \quad (1)$$

In this model, SC_{ihds} is the index of social capital for individual i, in household h residing in district d and state s. As described in Section 3 the index has mean 0 and standard deviation of 1. $Prop1951Displaced_{ds}$ measures the 1951 share of displaced migrants on account of the Partition of India in district d. Since this variable is skewed, we transform the share into logs.[27] The standard errors are clustered at the 1951 district-level to allow correlation in errors across individuals in the same district.

We control for individual characteristics that may be correlated with location and social capital attitudes in vector x_i. In particular, we control for an individual's age, gender (dummy that the individual is male), years of education, marital status (indicators for married or never married), and religion. We measure religion with indicators for Hindu and others. Muslims are the omitted group. We include separate indicators if an individual belongs to a Scheduled Caste or Scheduled Tribe. These capture historically marginalised castes and tribal groups. We also include an indicator for whether the individual is a permanent resident of the region in which they were surveyed.[28] The vector v_h' controls for household characteristics such as size, number of children below age 10, average education of other household members, average age of other household

[27] The main results remain qualitatively similar with the untransformed variable as well.
[28] Region is defined as any village or city within the state of residence.

members and an indicator that controls for whether the individual belongs to an "old" strata household.[29] Such household characteristics may also be correlated with location and individual attitudes towards social capital.

Since we are exploiting variation across districts in the 1951 proportion of Partition displaced migrants, we control for 1951 district characteristics and past historical differences that may be correlated with where displaced migrants settled and subsequent attitudes towards social cohesion. These are captured in the vector z_d. They include the 1951 log of district population, the 1951 district urbanisation share, 1951 district literacy rate, 1951 district Muslim share, 1951 district gender ratio defined as total male population over total female population, and the 1951 district shares of Scheduled Castes and Scheduled Tribes. Many of these controls have been highlighted in the literature (Bharadwaj, et al., 2015; Bharadwaj and Mirza, 2019). For example, Bharadwaj, et al. (2015) find that cross-border migration due to the Partition affected 1951 literacy and gender ratios. Controlling for such factors is important to isolate the long-run impact of displaced migration on social capital, separate from 1951 literacy and demographics.

We also control for historical differences across districts by including the 1931 share of Brahmans, the elite caste of Hindus, and the literacy rate-these are strongly correlated with the level of human capital in a district. Since the share of muslims in a district pre independence plays a pivotal role in partition movement, we account for it by including the 1931 share of muslims. Some districts have a history of migration of "outsiders" into their boundaries -these have independent effects on the evolution of social capital and may confound our results. Hence we partial out its impact by controlling for 1931 share of migrants in a district that were born outside the British Indian province or Princely State to which the district belonged.[30] We also include an indicator if the district was part of a former Princely State. Princely States saw lower in and out migration during Partition (Census of India, 1951).

[29]The SAGE used two strata for sampling: one that surveyed households where the surveyed member would be in the age group 18-49, and another where the member would be 50 years or above. The aim of this was to give larger representation to older members in the population. We control for this dummy to take into account any possibility that our results may be affected by this stratification procedure. Our results go through even if we do not account for this variable.

[30]We look at migrants born outside a Province or Princely State because break-up of historical districts artificially increases the share of migrants born outside a district (Skeldon, 1986).

Finally, we control for geographic differences across districts that may be correlated with the 1951 share of Partition displaced migrants and current attitudes towards social capital. In particular, we control for the latitude and longitude of the district centroid plus their squares, average elevation of the district, average river length in a district, indicator for coastal districts, average annual rainfall in the district between 1900 and 2007, distance of the village/city of residence of the household to the nearest border and it's square[31], an indicator for rural districts, an indicator for sandy soil, which is a proxy for infertile conditions, and the area of the district in square kilo-meters.[32]

Our OLS specifications assume that the share of Partition displaced migration is plausibly exogenous after controlling for these rich historical and geographic differences across districts. We recognise that the proportion is not randomly assigned, yet we explain over 80% of the variation in Partition displacement using our geographic and historical controls as shown in Table 3 on the correlates of 1951 Partition displaced migration at the district-level. We include state fixed effects in all the specifications. Specification (1) includes the geographic controls, specification (2) includes the geographic and 1931 controls, and specification (3) includes geographic, 1931 and 1951 controls.

Our results show that the latitude and longitude variables are insignificant in columns (1)-(3), but this is due to the collinearity between the linear and quadratic terms. In column (2), we find that distance to border has a significant negative effect on the proportion to partition in-migrants. Districts with a larger proportion of Muslims in 1931 are positively correlated with Partition migrants. This is unsurprising as these districts likely saw a relatively larger outflow of Muslims from India to Pakistan with migrants coming the other way from Pakistan to India. We find no significant effect on the 1951 Muslim share because of strong multi-collinearity between 1951 and 1931 Muslim shares. An important observation about our sampled districts is that in spite of the 1931 proportion of Muslims predicting the Partition migration inflow, the proportion

[31]The partition literature finds non linear impacts of distance to border.

[32]We control for latitude and longitude using the district centroid, while using village geo-location to calculate the exact distance to Pakistan and Bangladesh as separate control variables. We cannot directly control for household latitude and longitude because is it highly correlated with the distances calculated using the same information.

of Muslims over the 1931-1951 period does not change as dramatically as other parts of India, namely Punjab. This can also be seen in Figure 3. In contrast to the Indian side of Punjab, which saw a swap of population with Pakistan, our sampled areas did not see as much outflow of Muslims immediately after Partition. We see this as a strength of our sample - we may be able to learn about he impacts of a large population movement into a recipient country - a type of migration flow that is more typical of modern times.

Moving on to other results, we find that more literate and demographically larger districts had more Partition migrants, while former Princely States experienced less Partition migration. It is also the case that districts that had more migrants from out of state in 1931 attracted displaced migrants post partition. So did districts that had cities in 1951. The R^2 in specification (3) suggests our controls explain 89% of the variation in Partition displaced migration. Our identifying assumption is that the variation in Partition displaced migration is exogenous, conditional on the above extensive and rich set of geographic and historical controls. It captures exposure to Partition driven "outsiders". Qualitative accounts of the Partition (Kudaisya 1995, Tan and Kudaisya 2000, Chatterji 2007) suggest that favourable networks may be likely to be in the error term because Partition migrants settled in districts where they had family or friends. However, this implies that any negative effect of exposure to outsiders on social capital is likely to be an underestimate.[33]

4.2 Lewbel Method

To address potential endogeneity concerns, we also use an alternative instrumental variable strategy following Lewbel (2012). The Lewbel (2012) method is typically applied for linear regression models that contain an endogenous regressor where no plausible external instruments are available. The identification is based on the intuition that if the endogenous variable is regressed on a subset of exogenous variables (which are part of the main regression), and the residuals from this regression are heteroskedastic, then these residuals can be used to construct instruments.

The following is the simplistic representation of Lewbel's method. Let

[33]This is an assumption-it is possible that areas where friends live are, for some other reasons, areas of low social capital.

$$Z_j = (X_j - \bar{X})'(\lambda_j) \tag{2}$$

In the above, Z_j is the generated instrument. X_j and $\bar{X}$ are exogenous variables and their mean-centered form, respectively. Finally, (λ_j) is the vector of residuals from the first stage of the regression of the endogenous regressor on all or subset of exogenous variables.

We follow the framework laid out in Baum and Lewbel (2019) to provide some validation of the assumptions under which such an IV estimator is valid. The first assumption that the framework makes is that the endogenous variable (Proportion partition displaced) contains an error component that also determines the social capital, but which is unobserved-this is plausible as the displaced may have been ended up in places from where people left for west and east pakistan-in-fact the possibility that these places may well have been more fractious historically is the main concern regarding endogeneity in our empirical analysis. The second assumption needed is that the square of the this common unobserved component is not correlated to Z_j, the set of generated instruments.[34]. This can be tested using a Pagan-Hall statistic. The test needs us to estimate the regression of interest (our main regression) using the generated instruments in a 2 SLS procedure. The residuals from such a regression should not be correlated with the variables in Z_j (these variables need to be uncentered) for the procedure to be applicable. This procedure assumes that the generated instruments are valid. When Z_j has more than one element, an over-identification test can be run to substantiate the exogeneity of the instruments.

Note that the instruments do no need to have the usual underlying intuition that motivates an IV estimation in settings where a "real" exogenous instrument is available. The set of IVs are such that they meet these test of the the two assumptions laid out, in addition to a third one that follows below. The three variables chosen are average river length, the dummy that the district is a coastal district and the mean rainfall which are then interacted with the square of the residuals to generate instruments. The third assumption, alluded to above, and which the choice of instruments must satisfy is that the square of the residuals of a regression of the the

[34]In other words the common unobserved component is homoscedastic.

endogenous variable on X must be correlated to Z- in other words the errors (estimated by the predicted residuals) must be heteroscedastic. This is checked by a Bruesch Pagan test. [35] It must be pointed out that though this is based on the structural and functional forms assumed and while the conducted test increase the confidence in the procedure, one should always interpret the results with caution.

5 Social Capital and Partition Displaced Migrants

5.1 Main Results

Table 4 shows the main results of Partition displaced migration on the index of social capital. We add more controls moving from specification (1) to specification (5). Specification (1) is the simple bi-variate relationship between Partition displacement and the social capital index without any controls. We add state fixed effects and geographic controls in specification (2). Specification (3) adds the 1951 and 1931 controls. Specification (4) adds the individual characteristics, and specification (5) includes the full set of controls. Individual and household characteristics account for 10% of the variation in the social capital index leaving a significant role for district characteristics. This is line with other findings such as Algan and Cahuc (2014), which suggest attitudes towards social capital are shaped by both individual factors (such as gender, age, and religion) and features of individuals living environment such as current conditions and past historical shocks.

Across the specifications, we find negative and significant effects of Partition displaced migration on contemporary social capital. A standard deviation increase in the log of 1951 Partition displacement reduces contemporary trust by 0.043, that is, 0.12 standard deviations (SD) of the social capital index. This effect size is not small: by way of comparison, it is equivalent to the effect of 2 more years of education (the mean value of years of education is 4)- a variable that is a robust predictor of social capital in our analysis (more on education results below). The

[35] Use of such instruments are standard in contexts where "real" instruments are hard to find. For example, Emran and Hou (2013) employ Lewbel's method to evaluate the impact of access to domestic and international markets on consumption in rural China. Similarly, Huang et al. (2009) use the Lewbel's method to estimate the effect of inequality on growth and vice-versa. Note that the Lewbel method has some drawbacks. It makes assumptions on the form of heteroskedasticity of the underlying unobserved component, which are difficult to check.

coefficients are stable when we include more controls with the final coefficient in specification (5) being smaller than the one in specification (1) with no controls.

Among other results (Appendix Table A2), individuals at higher latitudes (more North) exhibit lower social capital, albeit with non-linearities. Individuals in districts at higher elevation, higher average rainfall and with sandy soil also exhibit lower social capital. Individuals in districts with a larger 1951 share of Urban population score higher on the index. With regard to individual characteristics, younger individuals, married individuals, males and those with more years of education exhibit higher social capital. Some of these results are in line with the literature (for e.g., Glaeser et al., 2002, Algan and Cahuc 2014).

Our main results document a correlation between a historical variable, share of Partition displaced migration and contemporary attitudes on social capital. In a recent critique, Kelly (2020) suggests such "persistence" results maybe due to spurious spatial correlations in the data. Using 25 studies on persistence, Kelly (2020) shows the results are insignificant after accounting for basic spatial trends. To ensure our results are not driven by spatial trends, we test our main results using Kelly's (2020) recommendations. First, he suggests the analysis should include regional fixed effects. Second, he suggests including the square of latitude and longitude to account for "directional gradients" (p. 4). Third, he suggests excluding extreme values of the dependent variable. We incorporate his first (include state fixed effects) and second (include squares of latitude and longitude) suggestions in all our specifications.

We address Kelly's (2020) third suggestion in specifications (1) and (2) of Table 5. In specification (1) we exclude individuals from Karnataka, a state where individuals score higher on the index of social capital, while specification (2) excludes individuals from Maharashtra, a state where individuals score lower on the index of social capital. Excluding individuals from these states does not change much the size or significance of the Partition coefficient. In specifications (3) and (4) we go further by dropping individuals with social capital indices above the 90^{th} percentile and below the 10^{th} percentile of the index distribution. While we observe a change in the size of the coefficient, the significance remains the same as our main results in Table 4.

In Appendix Table A3, we drop individuals from each state to ensure no single state is

driving our results.[36] Again, we observe changes in coefficient sizes, but no major changes in size or significance. We drop individuals from the outlier district of Nadia in specification (5) because it has the highest share of Partition displaced migrants in our sample. The results are similar to before. In Figure 4, we plot the beta coefficients on Partition displaced migrants dropping one district at a time. As seen the coefficients cluster around the same effect size of 0.04 to 0.05. We also estimate spatially adjusted Conley standard errors for different cutoff distances in Table A4. Our results are robust to these spatial checks suggesting they are not driven by extreme values or spatial trends in the data.

Further, following the method suggested by Lewbel (2012) and the framework of Baum and Lewbel (2019) discussed in Section 4, we test first our various assumption. The case for the first assumption has already been laid out. As Table 6. shows, the Pagan-Hall test rejects heteroscedascity (with a p value of 0.42) and the Hansen over-identification test statistic is insignificant and supports the asssumption of exogeneity of instruments. These validate assumption 2. Assumption 3 is validated by running a Breush-Pagan test-in our context the statistic takes the value 501.69 and the null hypothesis of homoscedasticity is rejected with a p value close to 0. In addition our generated instruments are strong: a Kleibergen-Paap rk Wald F statistic of 188.7.

The results using these generated instruments yields a coefficient for $Prop1951Displaced_{ds}$ as -0.10 as seen in Table 6. This suggests that the bias, if any, underestimates the effect. This is consistent with our reading of partition literature-some of which (e.g. Kudaisya, 1995) contends that displaced migrants went to places with friends and family. [37]

The main findings seem to be in line with a broad literature from developed countries perspective. Alesina and Tabellini (2020) find that large amounts of immigrants arrival in a short period of time could have negative connotations on social and political cohesion. Abramitzky and Boustan (2017) review the recent literature on immigration to the US and find heterogeneities in immigrants assimilation into the native US population on various dimensions. Note that the immigrant flow to US was largely voluntary and was not forced unlike in the case of Indian Par-

[36] We don't show the results again here dropping Karnataka and Maharashtra that are shown in Table 5.

[37] We do not claim though that this is indeed a true fact.There may also be other explanations that explain the larger coefficient). Our results suggest that the OLS estimation may be underestimating the negative effects.

tition. It is important to point out that for the Indian Partition case, there were no deliberate social policies (unlike in the US) to assimilate the displaced persons into the native districts except the rehabilitation and resettlement that was tried by offering land and associated livelihoods in a piece-meal fashion in the district of Punjab (Kudaisya 1995), a state that is not part of our sample. [38]

5.2 Temporal Evidence from Political Participation

The results discussed thus far find that partition migration measured at 1951, is associated with a lowering of the index of social capital, measured in 2007. Though such a long gap is beneficial for examining the long shadow of history, the opaqueness in describing how social cohesion evolved over time in such high displaced migration districts is not ideal. In this section, therefore we provide evidence from one of the only measures of social capital that has temporal data in India- political participation. The use of voter turnout ratio as a measure of social capital is common in the literature on social capital (Putnam, 1993; Svendsen and Svendsen, 2009). We use data on voter turn out ratio (as defined by the number of registered voters who cast their votes) in assembly constituencies for the period 1962 to 1999 to examine if this measure of political participation is associated with partition migration.[39] For our analysis, we add all the votes cast across all assembly constituencies in a district (of vintage 1951) and divide it by the total number of registered voters in the relevant constituencies. We estimate this association with district fixed effects, trends by a Dummy that indicates if the district is a border district, trends by geographic

[38] Further disaggregation of our index into an index of social cohesion and index of trust yields that both are negatively affected by partition migration (Appendix Table A5 and Appendix Table A6). However, while the results for the latter are imprecise with only one specification- with fewer controls- yielding statistically significant result, the coefficient with larger number of controls remains similar pointing out to a power issue. Further, disaggregation by each question (Appendix Table A7) shows that individuals living in partition migration districts interact less socially with people from outside their neighbourhood, have lower trust in their neighbours and go out less to social meetings.

[39] We are grateful to Sabyasachi Das and Rohit Joseph for sharing the assembly constituency level data available at https://tcpd.ashoka.edu.in mapped to 1951 district boundaries. We do not have access to such a mapping for the elections held between 1951-1962. However, inspection of the raw data for this period reveals some anomalies- for example, in some constituencies, the total valid votes casted exceeds the total number of electors. As a case in point, among many such cases, Ajmer (South West) has 22,111 registered voters but 25,618 voters who voted. The TCPD–IED website states that the elections in 1951-1962 and the elections held thereafter are "separate entities due to irreconcilable differences in the underlying structure. For instance, before 1962, it was possible for one constituency to have multiple winners (2-3)". Hence we start our analysis from 1962.

features- proportion of district soil that is sandy and the average elevation of the topography in the district as well as well as a time trend by the share of district population that is Muslim in 1931.

Our empirical analysis finds that higher the proportion of displaced migrants in 1951, the more the average district voter turn out ratio falls over time.(Table 7). Thus, by this measure, social capital is falling over the years in districts where the proportion of displaced migrants was high. In the fourth column of Table 7, we also present results where we interact $Prop1951Displaced_{ds}$ with a dummy for each decade 1971-1980, 1981-1990 and 1991-2000 (with 1962-1969 as the reference period). We find that the coefficients for all three decades are negative and statistically significant. This also points out to the decline in social trust over decades.[40] But more significantly, it shows that the fall in social capital is not something restricted to years around our survey period only.[41]

5.3 Plausible Mechanisms: Violence, Conflict and Crime

The influx of displaced migrants during partition of India coincided with episodes of civil strifes and social unrest (Varshney and Wilkinson, 2006; Chatterji 2004). Chatterji (2007) also refers to horrendous experiences in the partition districts, especially closer to the border areas. Some of these were communal in nature. In particular, Hindu and Muslim riots were prevalent in the 1950s and after. To test if exposure to riots post partition correlates with the share of migrant population in 1951, we conduct a district panel data analysis which we explain more below. The outcome variable is the annual number of riots (mostly hindu-muslim) over the period 1900 to 1995. The choice of 1995 as the end point is dictated by availability of primary post independence source of data. For the period 1950-1995, we use data from Varshney and Wilkinson (2006).[42] The data for 1900-1949 is sourced from Wilkinson (2005).[43] We use 1945 as our reference year-since

[40]It is not possible to show these results of periods of shorter length since states hold elections asynchronously in India; hence there aren't enough elections for the 6 states in our sample within a short period of time.

[41]We acknowledge that we are not able to show how the decade 1962-1970 behaves with respect to 1951-1960 for afore-mentioned reasons.

[42]Varshney, Ashutosh, and Wilkinson, Steven. Varshney-Wilkinson Dataset on Hindu-Muslim Violence in India, 1950-1995, Version 2. Inter-university Consortium for Political and Social Research [distributor], 2006-02-17. https://doi.org/10.3886/ICPSR04342.v1.

[43]The authors wish to thank an anonymous referee for pointing out this data base to us. A previous version of this paper used the India Riots database for the period 1939-1947. Even while we don't use this dataset due to more limited coverage, we wish to acknowledge Rahul Mehrotra at the Graduate Institute (Geneva) who gave us

partition migration had already started by then. The census of India records partition migrants from 1946 to 1951, which motivates the choice of 1945 as reference year.

The time-district panel data allows us to estimate a district fixed effects regression where, in a baseline specification we interact the dummy variables for each of the years, 1900 to 1995, with share of Partition displaced migration (1951)-a dummy for each year is also included in the specification. This specification allows us to check if over the years, average annualised riots are higher where the Partition migration was higher. We use as a reference group the period 1945. We also allow in our specification state level trends, a trend interacted with the Dummy that the district is at the border, a trend interacted with some time invariant district level geographical characteristics- the proportion of district soil that is sandy and the average height of the topography within a district. The relevant result of this regression- the coefficient of the interaction terms- are presented in Figure 5.[44] Results show that as compared to 1945, districts that had a higher proportion of Partition migrants show higher average number of riots well into the 90s. Violence is sporadic but is positively correlated with the proportion of Partition migration in 1951. The marginal effects are significant at 10 percent significance level for many years: not surprisingly for the years 1946 to 1951 but even afterwards in subsequent decades, and as late as 1994. In contrast, when we look at the period 1900-1944, we do not see that there are more riots in such districts as compared to 1945; on the contrary, for some early years, we see a significant negative effect. Only in three years, such districts show somewhat large positive point estimate-1926, 1927 and 1939, but the coefficient is insignificant at the 10 percent significance. This suggests no pre-existing trends in districts which had a higher value of Partition displaced migrants in 1951. To reconfirm our results, we also conduct synthetic Difference in Difference estimation procedure on the lines of Abramitzky et al. (2021) extended to event studies by Ciccia (2024). A small change is however necessitated as the synthetic DID event study analysis needs the treatment variable to be a binary variable. We define binary variable that takes the value 1 if the log of 1951 proportion displaced is above 0.84 (this is the 75 percentile cut off; this corresponds to a proportion of displaced migrants

access to the India Riots dataset.

[44]The regression results that underpin this figure as well as results without trends, as well as those with only state level trends are reported in Appendix Table A8.

of about 2.3 percent) and 0 otherwise. We control for trends similar to the estimation exercise described above. Results show a significant (at 5 percent) ATT of 0.0839 (the mean number of riots pre 1946 is 0.058) which is denoted by the dashed line in (Figure 6). Analogous to before, the dynamic effects for many years post 1946, going all the way to 1994, are positive and significant.

The results suggested by these two exercises is not entirely unexpected- riots along the religious line (especially, Hindu-Muslim) were quite prevalent in the aftermath of Partition (Varshney and Wilkinson, 2006; Chatterji 2007) but what is significant is that such riots continue almost 50 years after the incident, more in places that saw larger inflow. This finding, akin to Tur-Prats and Caicedo (2020), points out to processes set in motion 50 years ago that have cast a long shadow on contemporary social capital.

Do such incidents of conflict, especially in the years following the Partition of India, drive our results. To explore this we estimate our main specification controlling for the total number of riots in the period 1946 to 1995 as well as the number of years for which a district reports any riot- any attenuation of our main variable indicates that riots are a plausible channel through with Partion migration affects the index of social trust. Results from this exercise, reported in column (2) in Table 8 suggest that this is indeed the case. The coefficient of Partion displaced migration reduces from -0.043 to -0.034 which is a 20% effect through these riots. In contrast, in line with the earlier results that there are no pre-trends in riots before 1946, controlling for total number of riots and the number of years with riots for the period 1939-45 does not change attenuate our coefficient by much (column(4)).[45]

To supplement this suggestive mechanism, we present additional evidence from micro data using the India Human Development Survey (IHDS) conducted in 2005.[46] Since IHDS is not representative at the district level, it is difficult to conduct a formal mediation analysis by controlling for a district level indicator of conflict. Instead suggestive evidence is provided by showing that the households living in partition districts report higher community conflict. We exploit the relevant IHDS survey question which asks households the following -"In this village/neighborhood, how

[45]We do not do formal intermediation because that allows only one mediator but we have two.

[46]The 2005 IHDS is a representative survey of India and does not suffer from issues of attrition that subsequent follow up surveys do.

much conflict would you say there is among the communities/jatis that live here".[47] Based on the response to the question, we create a variable *Communityconflict* that takes the value 1 if there is a lot of conflict and 0, otherwise. The household data is matched with the corresponding district level $Prop1951Displaced_{ds}$. In addition, the dataset is mapped to the geographical and historical characteristics which were used in the main regressions. The final data covers 9591 households (6379 in rural areas) residing in 79 districts of 1951 vintage.[48].

The estimation results are presented in Table 9. In column (1) the dependent variable is regressed on the log of $Prop1951Displaced_{ds}$, geographical and historical covariates, dummy variables that indicate whether the location of the household is a non-metro city, a developed village or a less developed village (those living in a metro city are the reference group) and state dummies. In column (2) we add household covariates: household income and dummy variables for ethnic group identity of the household (Dalit-SC, Adivasis-ST, Other Backward Castes and Non-Hindu with Upper Castes being the reference group). We find a significant positive association (at 10 %) between log of $Prop1951Displaced_{ds}$ and the reported occurrence of high community/Jati conflict. The results resonate with the recent partition literature which sheds light on partition being not only along religious and geographical lines, but also has subtleties involving caste identities (Kumar 2006). For example, newer histories of the Bengal partition point out that the question of migration, rehabilitation and post- partition politics was very heavily fractured along caste dimensions (Bandopadhyay and Chaudhury 2017; Bandopadhyay 2009). The tussle for representation and resources was (and is) not simply between Hindus and Muslims– though this was obviously present (as our results on riots show) but also between upper and lower caste Hindu communities (Chatterji 2007; Bandopadhyay and Chaudhury 2017).

Our argument is that both religious and caste conflicts are important plausible mechanisms for our effect. In the case of religious conflict we are able to show that there are no pre-trends and controlling for such conflicts leads to some attenuation. In the case of caste conflict, the evidence is novel, though more suggestive. Lack of pre-trends are harder to show for caste conflicts but

[47] Jatis refer to sub-caste groups like brahmins, rajputs, bhumihars, vaisyas etc.
[48] The IHDS does not cover all districts of India

we provide some suggestive evidence that the displaced migrants did not move into areas with caste conflict. To do so, we exploit a data set compiled by researchers working on caste conflict in pre-independence India. Using accounts written by historians who focus on pre-independence incidents of caste conflict, Bose and Stratmann (2021) identify districts where such incidents were reported [49]. Again we find that the proportion of displaced migrants do not correlate with the occurrence of such caste based incidents (Column (2) in Appendix Table A10). Further, the coefficient of Proportion of displaced migrants hardly budges when we control for this variable in our regressions (Column (4) in Table 8). These data are based on scholarship on these topics-while there is no doubt that these are suggestive results, they provide re-assurance that the results are not driven by pre-independence occurance of riots and caste conflict.

Similar results have been seen in the migration literature. Inflow of migrants is often perceived with worsening situations of crime in the host communities (Fitzgerald, Curtis and Corliss 2012; Nunziata 2015). To investigate this dimension, i.e., if partition districts have experienced more incidents of crime, we use crime data from the NCRB. The crime data is averaged over the period 1987-2007. The overall crime data are based on police records and often suffers from mis-measurement. However, violent crime, measured by cases of murders, culpable homicides and attempted murders, are found to be more credible(Banerjee et al. 2012). Thus, we employ these violent crime indicator per 10,000 people as the mediator variable in column (3) of Table 8. The results reveal that the coefficient of interest attenuates with the inclusion of the crime variable.[50] Moreover, formal mediation analysis in Table A11 shows that almost 22.3% of the effect comes through violent crime, with a 95 % confidence interval of 11.1-49.6 %. Thus partition districts also tend to be crime prone and mediate a non-trivial part of the impact of partition inflows on social capital.[51]

It is important to note that while conflict and crime are essentially different potential mechanisms, there could be possible overlap due to the sensitivity of such issues. Civil strife, especially

[49] Appendix Table A9 lists sources to construct this dataset

[50] Violent crime is itself highly correlated with Proportion of displaced migrants as can be seen in Appendix Table A10.

[51] This finding lends credence to the conjecture of Blakeslee and Fishman (2018) which posits that crime dynamics in India has historical moorings.

along ethnic lines are often sensitive and may not be reported as such or could be misspecified as violent crime.[52]. Our findings indicate that these partition districts have evolved to be more violent and presence of such violence could be a potential source of low social capital.

It can be argued that Partition of India was a violent event that led to huge displacement and deaths but one which happened over a short duration. While analysis of how such displacement changed social dynamics over time is hard to show given the paucity of data, how such discontent remained in society is best illustrated by the case of Bengal. The refugees from East Bengal often brought with them distinct dialects, culinary preferences, and cultural practices that differentiated them from the long-settled West Bengali population, contributing to a sense of otherness between the groups.(Chatterji 2007) Over time, these identities were socially codified in the local lexicon: the native community came to be known as *Ghotis*, while the migrants and their descendants were called *Bangals*, a distinction rooted in ancestral origin and maintained through social customs and intra-community preferences. This division was visible not just in everyday discourse but also in popular culture and sport, most notably in the football rivalry between the clubs *Mohun Bagan* (traditionally supported by Ghotis), *East Bengal* (associated with Bangals) and *Mohammadan Sportings* (associated with the native Muslims), where matches became symbolic arenas for expressing and reproducing group identities and rivalries. Each state has it's own story- Refugees from East Pakistan created their own group clashing with locals in Assam; the prosperous Sindhi Community from across the border was looked at suspiciously in Rajasthan (Copeland 2008). The persistence of such identity markers may therefore have kept alive the memories of the painful event- leading to localized tensions and fuelling inter-group strife.

6 Heterogeneous Effects

Our main results suggest individuals living in districts that experienced more Partition displaced migration exhibit lower levels of social capital today. To understand the underlying mechanisms, we begin by testing for heterogeneous effects of Partition displaced migration along several

[52]Varshney-Wilkinson dataset report riots based on media reports, and though this does not depend on official police recordings, it may still potentially miss out on local skirmishes.

dimensions. Table 10 first looks at age.[53]

Individuals in the data sample are 50 years aged on average. Many did not live through the Partition or its immediate aftermath. Yet, attitudes towards outsiders, interacting with your community, and many such social capital traits are often passed from parents to children, i.e., vertical transmission of culture. If vertical transmission is driving the correlation, we may not necessarily expect differential negative effects by age. Indeed, there is no differential linear effect by age and Partition displaced migration in specification (1). In specification (2), an indicator is used for individuals above the median age (52) in the sample. Again, there is no evidence of differential effects.

Next, we look at the impact on people who were born before partition or born just after partition in the last two specifications. In specification (3), Partition displaced migration is interacted with individuals age 45 and above. In specification (4) we break up those above 45 into a group 45-55 and those who are above 55. The attrition rate due to death, survival bias and imperfect recall is likely to be higher among the latter group whereas the former group represents those who were born around and just after partition. The results in column (4) suggest that the impact of partition is largest for the age group 45-55 (the reference group being those who are less than 45).[54] However, the non significance for those above ages of 55 is harder to interpret for two reasons. First, the sample is thin around old people - there are only around 1,000 individuals aged 70 and above, and 285 individuals aged 80 and above in the sample. Hence, interpretations are drawn based on smaller smaple of people. Second and more importantly, people that survive to age 70 are a selected sample in India where life expectancy is 66 (as of 2008, same year as sampled individuals) and varies widely across space. Selective mortality is likely correlated with district characteristics, which makes us cautious in drawing firm conclusions. That said, the fact that there are strong results with the largest coefficient for those between ages 45-55 points out to the fact that the findings are not driven by age groups which suffer from such biases.

[53]Many Indians, especially older people, are unaware of their exact age because age heaping at numbers ending in 0 and 5 was common in the past and continues even today. We try to account for this using age bands in the heterogeneity analysis.

[54]Note that they may have experienced the Partition shock in general in the sense that they were not directly exposed to forced migration due to the Partition event.

Then, we explore heterogeneity along other dimensions in Table 11. Specification (1) looks at gender. Male respondents score higher on the index of social capital, but there is no differential effects of Partition displaced migration for males compared to females. We test differential effects for Scheduled Castes, Scheduled Tribes and Muslims in specifications (2) and find no differential treatments for them. There are some heterogeneities for permanent residents in specification (3). Permanent residence is an indicator for whether individuals have lived their entire life in the same region in which they were surveyed. However, one should not make too much of this result-almost 97 % of individuals report themselves to be permanent residents of the region. In specification (4) there is no differential effect for rural areas. Specification (5) finds larger impacts for border districts, though non-border districts also show significant impacts of partition inflows on social capital. None of these individual characteristics offer deep insights into the mechanism underlying the negative correlation from 1951 Partition displaced migrants to lower social capital in 2008. We can rule out that the effects are only driven by individuals that experienced Partition and survived to 2008. Yet, the other individual heterogeneity analysis suggests few differential effects by gender, religion or caste.

Next, we try to understand whether the characteristics of the migrants affected differentially the long term social capital of the districts. We explore heterogeneity based on two important characteristics of the displaced migrants-whether they came from West or East Pakistan and their occupation.[55] In column (1) of Table 12, we report the results of an interaction of Log 1951 Proportion displaced with Proportion of such migrants who were from West Pakistan. The interaction is insignificant-the marginal effect of the composition of migrants is the same at all levels of displacement. The marginal impact of 1951 displaced migrants is more significant when the proportion of migrants from West Pakistan is more than 50 % (This can be seen in Figure 7). This implies that results are not entirely driven by the migration in the east, even in the absence of the state of Punjab in the sample.

Next, we focus on the reported occupation of the displaced migrants. The state and province

[55]We also explore other dimensions like the sex of the migrants but that yields no differential impact.

level census tables of 1951 displaced migrants classify livelihoods as those who work in agriculture[56], those who list commerce as their occupation and with the remaining engaged in *production other than cultivation*, transport and *other miscellaneous services*. We add the last three categories together and term them as *Non-Commerce non Agriculture Services*. We calculate the proportion of displaced migrants who are in each of the three occupation types and interact two of them with the proportion of displaced migrants, with the proportion of displaced migrants in commerce being the reference group.

In column (2) we find that the impact of displaced migrants is worse when a larger proportion of such migrants were engaged in the non-commerce non agriculture activities instead of being in commerce. The interaction with the proportion of displaced in agriculture is also significant negative. This implies that it is different mix of non-agriculture migrants and agriculture migrants that drives the effect. The literature on Indian economic history treats the fraction of the population in commerce as an indicator of those involved in skilled production and trading activities.[57] Further, as Figure 8 shows, Commerce was the occupation where there were relatively large proportion of displaced migrants (38.7 %) but relatively small proportion of original residents (5.3 %). This asymmetry was true for agriculture as well with 70.32 % of original residents in this profession but with only 10.9 % of the displaced migrants in this occupation. In contrast the overlap between residents and migrants was largest in other non-agriculture occupations with almost 50.4 % and 25 % respectively in those occupations. Hence, it is likely that there was more conflict in these non agriculture occupations. However, due to paucity of data, we are unable to examine the implications this had on the wages in the years just after partition of India. Hence this explanation is merely suggestive of such contest within common occupations.

Last, there were displacements of two kinds in any district due to partition. In the analysis the focus was on those who came into Indian districts. However, there was also outflow from these districts. It could be argued that the impact of the 1951 Partition displaced is different depending

[56]This is further sub-classified into those who cultivate their own land, on others land, rentiers and those who are employed as agricultural labor.

[57]See for example Chaudhary and Garg (2015) who treat the fraction of population in commerce as a proxy for a district being more economically developed.

on where the outflow of migrants was different. We use projections of outflow of migrants from a district calculated by Bhardwaj et al (2015).[58]. Results in Column (3) of Table 12 however show that the negative impact that we find is not differential depending on the proportion of population that out-migrated due to partition.

7 Robustness

The literature on Partion migration points out that areas with high proportion of partition displaced migrants saw increased urbanisation, literacy and gender ratios. We test if these drive the results. Further, we investigate if differences in current district conditions, in terms of other variables, could explain the findings.

7.0.1 Literacy, Urbanisation, and Gender Ratio

Next we consider the role of variables that have been identified as correlated with Partition migration in the literature. Using detailed census data between 1931 and 1951, Bharadwaj, et al. (2015) quantify the effects of Partition migration on literacy, occupation and gender ratios in Eastern and Western India in 1951. Since inflows of Hindus to Eastern India were larger than outflows of Muslims to East Pakistan (Bangladesh), Bharadwaj et al. (2015) focus on the effect of inflows finding that a 10% increase in inflows decreased the population share engaged in agriculture with smaller effects on literacy and gender ratios in Eastern India. In contrast, inflows of Hindus and Sikhs into Western India increased literacy, reduced agricultural employment and reduced the share of males. These findings on agricultural employment suggest urbanisation may have increased in districts that experienced more inflows of Partition migrants.

To test whether these variables are mediating the results, we include these variables as additional controls in Table 13. Since the baseline specification includes the 1951 literacy rate, urbanisation share and gender ratio, we include literacy in each decade between 1961 and 2001 in specification (2), the urbanisation share in each decade in specification (3), and the gender ratio in each decade in specification (4). We show the baseline results in specification (1) for comparison.

[58]We thank Prashant Bharadwaj for sharing this data with us.

Here we exclude the districts of Assam because the census was not conducted in that state in 1981-hence the relevant data are missing for that year for these districts.

A quick look at the estimated coefficients reveal that none of the above variables seem to mediate the results on contemporary social capital. If anything, including literacy, urbanisation and gender ratio only increases the coefficient on 1951 Partition displaced migration. This is perhaps because higher literacy and urbanisation are positively correlated with social capital and Partition displaced migration in this context. This is also in line with the general social capital literatures' finding (Algan and Cahuc 2014). Appendix Table A12 confirms the positive coefficient at the district level between these variables and Partition migration, which suggests that these factors, if anything, are contributing to higher social capital in Partition displaced districts.

7.0.2 Current Conditions

The results so far document a correlation between historical Partition displaced migration and contemporary social capital. However, the main analysis does not include controls for current differences across districts. Such variables are likely endogenous and bad controls in the spirit of Angrist and Pischke (2008). Yet, one may worry that differences in current conditions are driving these correlations as opposed to Partition displaced migration. To investigate this conjecture, specification (2) in Table 14 directly controls for current characteristics such as the 2001 share of Muslims, 2001 urbanisation share, 2001 literacy rate, log of 2001 district population, 2001 share of Scheduled Castes in population, 2001 share of Scheduled Tribes in population, 2001 share of migrants in population [59] and log light density.

If contemporary differences in religion, urbanisation, development and migration are driving the results, we would expect the coefficient on Partition migration to attenuate and perhaps become insignificant after including these variables. But that is not the case. If anything, the coefficient of Partition migration remains closer to the baseline estimate (0.0427 compared to 0.0430 in the baseline). Districts with a larger share of Partition migration were more urbanised in 1951 and continue to remain so up to 2001. Appendix Table A13 reports the partial correlation between

[59] We use the definition of migrants based on place of birth as reported in the census. We define a migrant as one who is not born in the place of enumeration.

these variables and Partition displaced migration at the district-level. Apart from nightlights (a measure of development and urbanization), the share of Partition migration is uncorrelated with current conditions at the district level. Moreover, the positive relationship between Partition migration and nightlights suggests if anything development as a mechanism works in the opposite direction, i.e., would increase social capital.

In specification (3), we control for current public goods that may be correlated with current attitudes towards social capital, and Partition migration.[60] Appendix Table A13 reports no significant relationship between these variables and district Partition migration. Thus, it is unsurprising we find no significant change in the coefficient on Partition migration when we control for public goods in the individual regressions. Hence, although we cannot control for the many ways districts differ from each other, Table 14 suggests that we can rule out contemporary differences in religion, urbanisation, economic development, migration, public goods as the underlying mechanism from Partition migration to contemporary social capital attitudes.

7.0.3 Other Factors

It must be pointed out that since we look at a long run study over a substantial time period, there could be possible apprehensions about other changes that are unrelated to partition that drive our results. In subsection 7.0.1, we establish that our results do not pick up the great changes in urbanization and literacy that ensued in post- independent India. These aside, some other major changes that happened in India over this period were Green Revolution (1960-1980s, in particular), suspension of civil liberties during the Emergency period (1975-77) and external wars with Pakistan (in 1965 and 1971). In a recent study, Bharadwaj and Mirza (2019) find a positive impact of partition refugees on agricultural yields attributed to the Green Revolution. Apart from the fact that this does not suggest that there should be a deterioration of social capital on this count, it is important to note that Punjab was a major participant in the Green Revolution and a recipient of partition migration; however, Punjab is not included in the SAGE data sample we

[60] We construct a public goods index using principle component analysis of availability of public goods and use the first factor. The public goods considered are Primary schools, Electricity, All Weather Roads, Railway Station, Piped water, Public Library, Covered Drainage, Commercial Bank, Bus Service, Maternity and Child Welfare Centre, Primary Health Centre.

use. Further, Green revolution led to economic development of regions, yet in Table 14, we show that the results are not impacted after accounting for economic development. The suspension of political and civil rights during the Emergency period was a pan India disruption and there is no documented evidence that suspension of civil liberties was concentrated in any district within a state. But the wars in 1965 and 1971 pose a greater challenge to our claims, since they led to an inflow of displaced migrants from West and East Pakistan (now Bangladesh) into Rajasthan (1965 war), West Bengal and Assam (1971 war). Given that Rajasthan, West Bengal and Assam are part of our sample states, we cannot rule out apriori, that these inflows have no effect on social capital. Thus, to test whether results are affected by these inflows, we run our main specification controlling for the number of migrants from both Pakistan and Bangladesh living in each district in 1971, and in a separate specification for the total number of migrants from Asia (excluding USSR) in 1981.[61] The subsequent results, presented in the Appendix Table A14 show that the coefficient of log of $Prop1951Displaced_{ds}$ (the main variable of interest) does not change even after including these specific flows. Hence, inflows due to the wars are unlikely to contaminate our findings.

8 Conclusion

This paper investigates the long run effects of the migrant inflow on contemporary social capital of recipient societies. The Partition was one of the largest forced migration events of the 20th century, which led to large movement of people. In the empirical analysis, after controlling for many differences in geographical and historical characteristics across districts within states and over time, we establish that individuals score lower on social capital indices in districts with a larger share of Partition displaced migrants. The findings remain robust to various spatial trends and using a Lewbel (2012) instrument to account for endogeneity. We analyze some plausible mechanisms driving the main result: the Hindu-Muslim riots post independence of India, higher community conflicts as well violent crimes paint a strife driven picture of such districts and seem to

[61] Migrants from Pakistan and Bangladesh constitute 88 % of the Asian migrants. It is however important to note that no Census was conducted in Assam due civil unrest in 1981; hence the specification that controls for 1981 migration flows uses data from the remaining 5 states.

be part of the explanation. It is in contrast to some other recent literature that finds positive, albeit unintended, impacts of partition through higher literacy and great urbanization. This divergence is important to appreciate-given that social capital is sticky and shapes long run institutions, it is possible (indeed plausible, given evidence in other contexts of the long run correlation between social capital and growth) that some of the initial advantages due to in-migration of the forcefully displaced may well be lost going forward.

It is hard to generalize from any large scale event of forced displacement, and research in this domain would be constrained in establishing external validity. However, such episodes tell us what may happen. It is, therefore, important to guard against possible negative fall-outs. The key takeaway from this paper is that forced displacements of people, even one who were part of the same nation only 100 years ago, often shared the same religion and language, could lead to a loss of social cohesion in migrant recipient societies. This calls for more structured assimilation through meaningful and well thought out resettlement plans.

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9 Tables

Table 1: Summary Statistics, Individual Data

	Obs	Mean	SD	Min	Max
Social Capital Index	8,860	0.000	1.000	-1.42	4.32
Prop Partition Displaced Persons	8,860	2.26%	4.3%	0.000179%	37.2%
Ln, 1951 Prop Partition Displaced Persons	8,860	-5.66	2.83	-13.85	-0.98
Household Size	8,860	6.46	3.58	1	40
# Children below 10	8,860	1.42	1.63	0	18
Avg. Educ Household	8,860	5.19	3.35	0	17
Avg. Age Household	8,860	31.60	11.58	9	93
Old Household Strata	8,860	0.58	0.49	0	1
Rural Dummy	8,860	0.79	0.40	0	1
Age	8,860	49.95	16.49	18	106
Male	8,860	0.41	0.49	0	1
SC	8,860	19%	39%	0	1
ST	8,860	8%	26%	0	1
Hindu	8,860	84%	37%	0	1
Religion-Other	8,860	3%	17%	0	1
Permanent Resident	8,860	97%	16%	0	1
Years of Education	8,860	4.25	5.00	0	17
Married	8,860	79%	41%	0	1
Never Married	8,860	5%	23%	0	1
Distance to border	8,860	482.61	371.02	0.40	1362.82
Latitude	8,860	23.25	4.75	12.21	29.946
Square of Latitude	8,860	563.04	201.06	149.08	896.76
Longitude	8,860	81.18	6.35	71.47	95.6
Square of Longitude	8,860	6630.4	1055.14	5108.39	9144.52
Indicator, Sandy Soil	8,860	0.098	0.158	0	1

Avg. River Length	8,860	13.23	4.07	6.79	30.34
Coastal	8,860	.090	0.29	0	1
Elevation	8,860	256.75	229.66	3.97	906.71
Annual Rainfall	8,860	105.31	70.44	18.57	342.14
Area Sq Mt	8,860	6954.86	4805.74	203.21	28438.24
Dummy: Rural	8,860	0.79	.40	0	1
Prop of District with Sandy Soil *1951 Controls*					
Ln, Pop 1951	8,860	14.07	0.54	12.01	15.34
Lit Rate, 1951	8,860	15.24%	6.04%	.4.62%	29.47%
Prop. Urban, 1951	8,860	16.43%	11.73%	1.31%	100%
Prop. Muslim 1951	8,860	14.28%	11.43%	0.17%	55.24%
Prop. ST 1951	8,860	3.52%	7.16%	0%	65.96%
Prop. SC 1951	8,860	14.18%	6.89%	0.46%	40.15%
Gender Ratio 1951	8,860	1.086	0.083	0.86	1.75
Dummy: City in District, 1951	8,860	0.14	0.34	0	1
1931 Controls					
Prop. Literate, 1931	8,860	6.89%	03.57%	2.17%	39.46%
Prop. Brahman, 1931	8,860	5.51%	3.46%	0.66%	15.75%
Prop. Muslim, 1931	8,860	16.50%	13.35%	1.88%	63.96%
Prop. Out-State Mig, 1931	8,860	6.49%	8.83%	0.08%	34.43%
Princely State	8,860	.27	.44	0	1

Table 2: Summary Statistics, District Data

	Obs	Mean	SD	Min	Max
Prop. 1951 Partition Displaced Persons	103	2.26%	5.02%	0.000179%%	37.29%
Latitute	103	23.7	4.6	12.2	29.9
Longitude	103	80.3	5.6	71.5	94.1
Indicator, Sandy Soil	103	10.8%	19.9%	0.0%	100.0%
Avg. River Length	103	13.0	3.9	6.8	30.3
Coastal	103	4%	19%	0%	100%
Elevation	103	256.7	223.7	6.4	906.7
Annual Rainfall	103	96.3	64.5	18.6	335.0
Area Sq Mt	103	6693.4	5004.9	203.2	28438.2
Dummy: Rural	103	95%	22%	0%	100%
Prop of District with Sandy Soil					
1951 Controls					
Ln, Pop 1951	103	13.9	0.5	12.0	15.3
Lit Rate, 1951	103	15%	6%	5%	29%
Prop. Urban, 1951	103	16%	14%	1%	100%
Prop. Muslim 1951	103	12%	10%	0%	55%
Prop. ST 1951	103	4%	10%	0%	66%
Prop. SC 1951	103	15%	7%	0%	40%
Gender Ratio 1951	103	1.1	0.1	0.9	1.8
Dummy: City in District, 1951	8,860	0.13	0.33	0	1
1931 Controls					
Prop. Literate, 1931	8,860	6.41%	4.41%	2.17%	39.46%
Prop. Brahman, 1931	103	6%	4%	1%	16%
Prop. Muslim, 1931	103	15%	13%	2%	64%
Prop. Out-State Mig, 1931	103	5%	8%	0%	34%
Princely State	103	26%	44%	0%	100%

Table 3: Correlates of Log, 1951 Prop Displaced

	Geography	1931 Controls	1951 Controls	Outflow
Distance to Nearest Border (District Avg.)	-0.495	-0.328	-0.585*	-0.586*
	(0.336)	(0.336)	(0.350)	(0.346)
Square:Distance to Nearest Border(District Avg.)	0.035	0.031	0.049	0.049
	(0.032)	(0.030)	(0.035)	(0.035)
Latitude	0.765	0.575	0.782	0.873
	(0.905)	(0.728)	(0.785)	(0.794)
Square of Latitude	-0.004	-0.002	-0.009	-0.011
	(0.018)	(0.015)	(0.015)	(0.016)
Longitude	-0.923	-0.349	0.076	-0.089
	(1.134)	(1.184)	(1.348)	(1.355)
Square of Longitude	0.004	0.001	-0.002	-0.001
	(0.007)	(0.007)	(0.008)	(0.008)
Prop: district with sandy soil	-2.489*	-1.403	-1.248	-1.296
	(1.280)	(1.183)	(1.143)	(1.143)
Average River Length	-0.069*	-0.068**	-0.067**	-0.064**
	(0.038)	(0.032)	(0.029)	(0.029)
Coastal District	0.703	0.897	0.493	0.456
	(0.977)	(0.910)	(0.786)	(0.782)
Elevation	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Log District Area Square Km, 2001	-0.309	0.129	0.182	0.191
	(0.258)	(0.283)	(0.281)	(0.282)
Annual Rainfall	-0.001	-0.003	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Dummy:Big City in 1951 District	1.834***	1.633***	1.144**	1.067**
	(0.537)	(0.511)	(0.524)	(0.515)
Prop: Outflow as % of 1951 Pop.				0.022
				(0.023)
Prop. Lit, 1931		4.275	-13.416	-12.614
		(4.732)	(8.423)	(8.599)
Prop. Brahman, 1931		5.988	6.122	5.517
		(4.104)	(5.011)	(4.765)
Prop. Muslim, 1931		4.867***	6.210***	5.863***
		(1.284)	(2.085)	(2.094)
Out of State Migration, 1931		6.407**	6.350**	5.577*
		(2.586)	(3.189)	(3.014)
Dummy: Princely State		-1.544***	-1.625***	-1.600***
		(0.382)	(0.438)	(0.448)

	Geography	1931 Controls	1951 Controls	Outflow
Log of District Pop, 1951			0.780*	0.708*
			(0.414)	(0.401)
Prop. Urban, 1951			2.670	2.681
			(1.853)	(1.845)
Prop. Muslims, 1951			-3.569	-3.292
			(2.605)	(2.651)
Prop Literate, 1951			6.280**	6.429***
			(2.399)	(2.413)
Gender Ratio, 1951			3.413	3.451
			(2.069)	(2.105)
Prop. STs, 1951			2.389	2.173
			(1.597)	(1.505)
Prop. SCs, 1951			3.596*	3.239
			(2.088)	(2.028)
State FE	Yes	Yes	Yes	Yes
Observations	121	121	121	121
R-squared	0.810	0.861	0.893	0.894

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Outcome - Index of Social Capital

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.054***	-0.054***	-0.050***	-0.043***	-0.043***
	(0.013)	(0.011)	(0.010)	(0.012)	(0.012)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.024	0.076	0.079	0.081	0.187
State FE	No	Yes	Yes	Yes	Yes
Geography	No	Yes	Yes	Yes	Yes
1931 Controls	No	No	Yes	Yes	Yes
1951 Controls	No	No	No	Yes	Yes
Individual Controls	No	No	No	No	Yes
Household Controls	No	No	No	No	Yes

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Index of Social Capital, Spatial Robustness Checks

	(1)	(2)	(3)	(4)
Log, 1951 Prop Displaced	-0.034*	-0.038***	-0.029***	-0.046***
	(0.019)	(0.013)	(0.011)	(0.012)
Observations	7,422	7,764	7,972	7,853
R^2	0.175	0.173	0.157	0.136
Robustness Check	No Karnataka	No Maha-rashtra	Below 90th percentile of Index	Above 10th percentile of Index

Note: Robust standard errors clustered at the district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Lewbel Instrument, Robustness Check

	(1) Baseline	(2) Lewbel
Log, 1951 Prop Displaced	-0.043***	-0.10***
	(0.012)	(0.037)
Observations	8,860	8,860
R^2	0.185	0.183
Pagan-Hall Test		2.843
p-value		0.42
Hansen J Statistic (Over id)		0.792
p-value:		0.673
Kleibergen-Paap Wald F statistic		188.703

Note: Robust standard errors clustered at the district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Political Participation: Assembly Turnout ratios averaged over Districts (1962-1999)

VARIABLES	Average District Voter Turnout Ratio			
Log, 1951 Prop Displaced X Year	-0.03***	-0.05***	-0.06***	
	(0.01)	(0.02)	(0.02)	
Log, 1951 Prop Displaced X Dummy(1971-1980)				-0.86***
				0.22
Log, 1951 Prop Displaced X Dummy(1981-1990)				-1.00***
				0.35
Log, 1951 Prop Displaced X Dummy(1991-2000)				-1.73***
				0.47
District FE	Yes	Yes	Yes	Yes
State Trends	No	Yes	Yes	Yes
Baseline Trends	No	No	Yes	Yes
Observations	1,017	1,017	1,017	1017
R-squared	0.528	0.668	0.673	0.67

Note: Turnout ratios are calculated as votes cast in Assembly elections divided by total number of registered voters in the relevant election. District level Turnout ratios are calculated by adding up the number of voters and votes across all Assembly Constituencies in district of 1951 vintage. Baseline characteristics used for trends are Dummy: Border District, Average Height, Proportion Sandy, and Proportion of Muslim Population 1931. Robust standard errors clustered at the district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Violence: Riots, Conflict and Crime

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop	-0.043***	-0.036***	-0.044***	-0.042***	-0.040***
Displaced	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Mechanism	Baseline	Riots 1950-1995	Violent Crime (NCRB) 1987-2007	Riots 1900-1945	Caste Conflict pre 1947
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.187	0.189	0.187	0.189	0.187

Note: Robust standard errors clustered at the district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Community conflict

	Community/Jati Conflict	
	All	
Log, 1951 Prop	0.011*	0.011*
Displaced	(0.006)	(0.006)
Geographic Covariates	Yes	Yes
Historic Covariates 1951/1931	Yes	Yes
Dummy : Urban Centre	Yes	Yes
Household Covariates	No	Yes
State FE	Yes	Yes
Observations	9591	9591
R-squared	0.070	0.073

Note: Robust standard errors clustered at 1951 District Level *** p0.01, ** p0.05, * p0.1. Data: IHDS 2004-05; Household covariates include Household Income, and caste dummies.

Table 10: Heterogeneous Effects by Age, Index of Social Capital

	(1)	(2)	(3)	(4)
Log, 1951 Prop Displaced	-0.060***	-0.048***	-0.042***	-0.041***
	(0.018)	(0.012)	(0.013)	(0.013)
Age	-0.003			
	(0.002)			
Log, 1951 Prop Displaced*Age	0.000			
	(0.000)			
Age - Above Median (52)		-0.051		
		(0.059)		
Log, 1951 Prop Displaced*Age - Above Median		0.009		
		(0.010)		
Age Above 45			0.031	
			(0.067)	
Log, 1951 Prop Displaced*Age - Above 45			-0.002	
			(0.010)	
Age 45-55				-0.097
				(0.069)
Log, 1951 Prop Displaced*Age - 45-55				-0.024**
				(0.009)
Age Above 55				-0.028
				(0.076)
Log, 1951 Prop Displaced*Age - Above 55				0.005
				(0.011)
Standard Controls	Yes	Yes	Yes	Yes
Observations	8,860	8,860	8,860	8,860
R^2	0.187	0.186	0.185	0.187

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Heterogeneous Effects, Index of Social Capital

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.03**	-0.05***	0.00	-0.03*	-0.04***
	(0.015)	(0.012)	(0.025)	(0.018)	(0.012)
Log, 1951 Prop Displaced *SC		-0.01			
		(0.012)			
Log, 1951 Prop Displaced *ST		0.01			
		(0.017)			
Log, 1951 Prop Displaced *Muslim		0.02			
		(0.016)			
Log, 1951 Prop Displaced *Male	-0.03				
	(0.020)				
Log, 1951 Prop Displaced *Permanent Resident			-0.05**		
			(0.021)		
Log, 1951 Prop Displaced *Rural				-0.01	
				(0.015)	
Log, 1951 Prop Displaced *Border District					-0.18***
					(0.054)
Standard Controls	Yes	Yes	Yes	Yes	Yes
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.188	0.187	0.187	0.187	0.187

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Heterogeneous Effects by Displaced Migrant Characteristics

	(1)	(2)	(3)
Log, 1951 Prop Displaced	-0.02	0.02	-0.05***
	(0.023)	(0.03)	(0.012)
Interaction: Log, 1951 Prop Displaced			
* Prop Displaced from W. Pakistan	-0.0003		
	(0.0003)		
* Prop Displaced in Non commerce		-0.0009***	
non Agri. activities		(0.0003)	
* Prop Displaced in Agri		-0.0000006	
		(0.0006)	
* Prop: Outflow as % of 1951 Pop.			0.0005
			(0.003)
Standard Controls	Yes	Yes	Yes
Observations	8,860	8,589	8,860
R^2	0.187	0.177	0.187

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Literacy, Urbanisation and Gender Ratios

	(1)	(2)	(3)	(4)
Log, 1951 Prop Displaced	-0.039***	-0.038**	-0.043*	-0.059***
	(0.011)	(0.017)	(0.022)	(0.018)
Robustness Check	Baseline w/o Assam	Literacy 1961/71/81 /91/2001	Urbanisation 1961/71/81 /91/2001	Gender Ratio 1961/71/81 /91/2001
Standard Controls	Yes	Yes	Yes	Yes
Observations	7,878	7,878	7,878	7,878
R^2	0.203	0.205	0.204	0.207

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14: Mechanisms, Current Conditions and Public Goods

	(1)	(2)	(3)
Log, 1951 Prop Displaced	-0.043***	-0.041***	-0.058***
	(0.012)	(0.013)	(0.012)
Robustness Check	Baseline	Current Controls	Public Goods
Observations	8,860	8,860	8,820
R^2	0.185	0.186	0.187

Note: Robust standard errors clustered at the district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

10 Figures

Figure 1: Sampled Villages and the Proportion of District Population Displaced (1951)

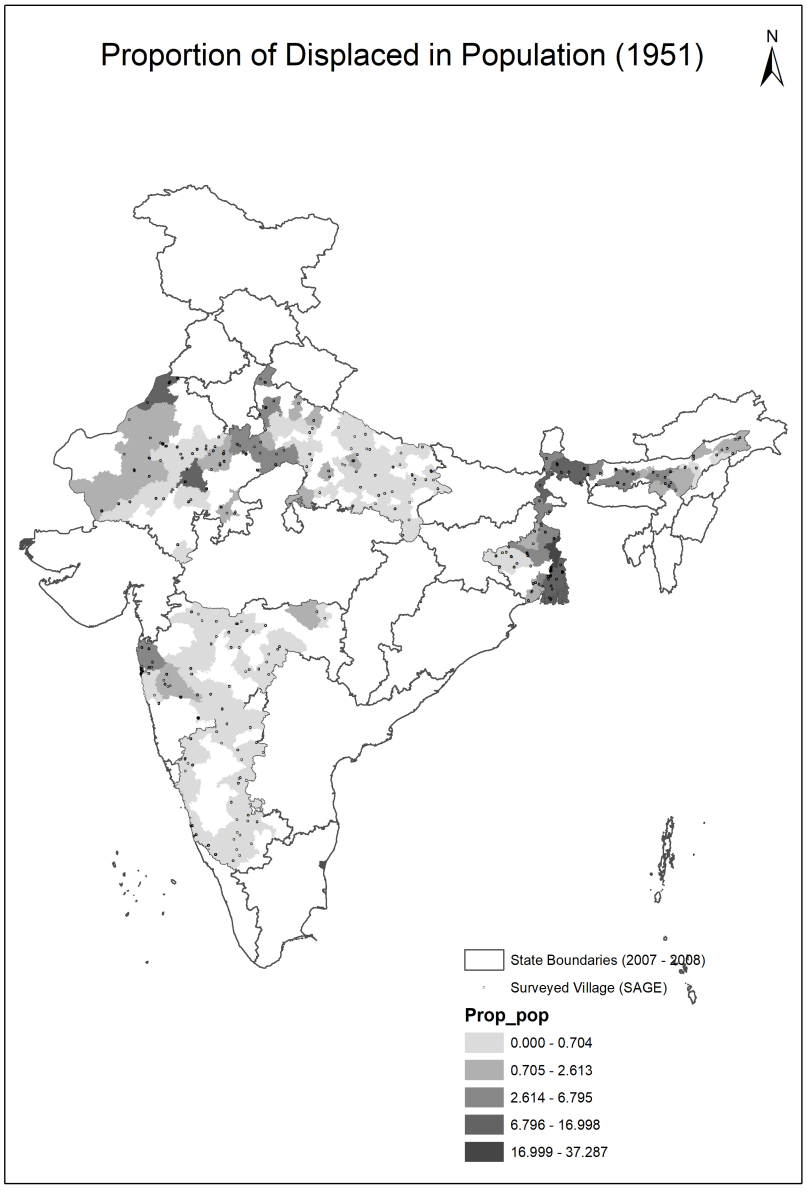


Figure 2: SAGE Questions

Section 6000: Social Cohesion

Time Begin □□:□□

We would like to shift away from questions about your direct health. This section of the survey asks your opinions about other areas and issues in your life. The following questions are to get your opinions about community, social and political aspects in your life.

We'd like to know about some of your involvement in your community. For all of these, I want you just give me your best guess.

	How often in the last 12 months have you ...	Never	Once or twice per year	Once or twice per month	Once or twice per week	Daily
Q6001	... attended any public meeting in which there was discussion of local or school affairs?	1	2	3	4	5
Q6002	... met personally with someone you consider to be a community leader?	1	2	3	4	5
Q6003	...attended any group, club, society, union or organizational meeting?	1	2	3	4	5
Q6004	... worked with other people in your neighborhood to fix or improve something?	1	2	3	4	5
Q6005	... had friends over to your home?	1	2	3	4	5
Q6006	... been in the home of someone who lives in a different neighbourhood than you do or had them in your home?	1	2	3	4	5
Q6007	... socialized with coworkers outside of work?	1	2	3	4	5
Q6008	... attended religious services (not including weddings and funerals)?	1	2	3	4	5
Q6009	... gotten out of the house/your dwelling to attend social meetings, activities, programs or events or to visit friends or relatives?	1	2	3	4	5

(a) Social Cohesion Questions

Next, we'd like to know how much you trust different groups of people.

		To a very great extent	To a great extent	Neither great nor small extent	To a small extent	To a very small extent
Q6014	First, think about people in your neighbourhood. Generally speaking, would you say that you can trust them...?	1	2	3	4	5
Q6015	Now, think about people whom you work with. Generally speaking, would you say that you can trust them ...?	1	2	3	4	5
Q6016	And how about strangers? Generally speaking, would you say that you can trust them ...?	1	2	3	4	5

(b) Trust Questions

Figure 3: Proportion of Muslims, District-level 1931 and 1951

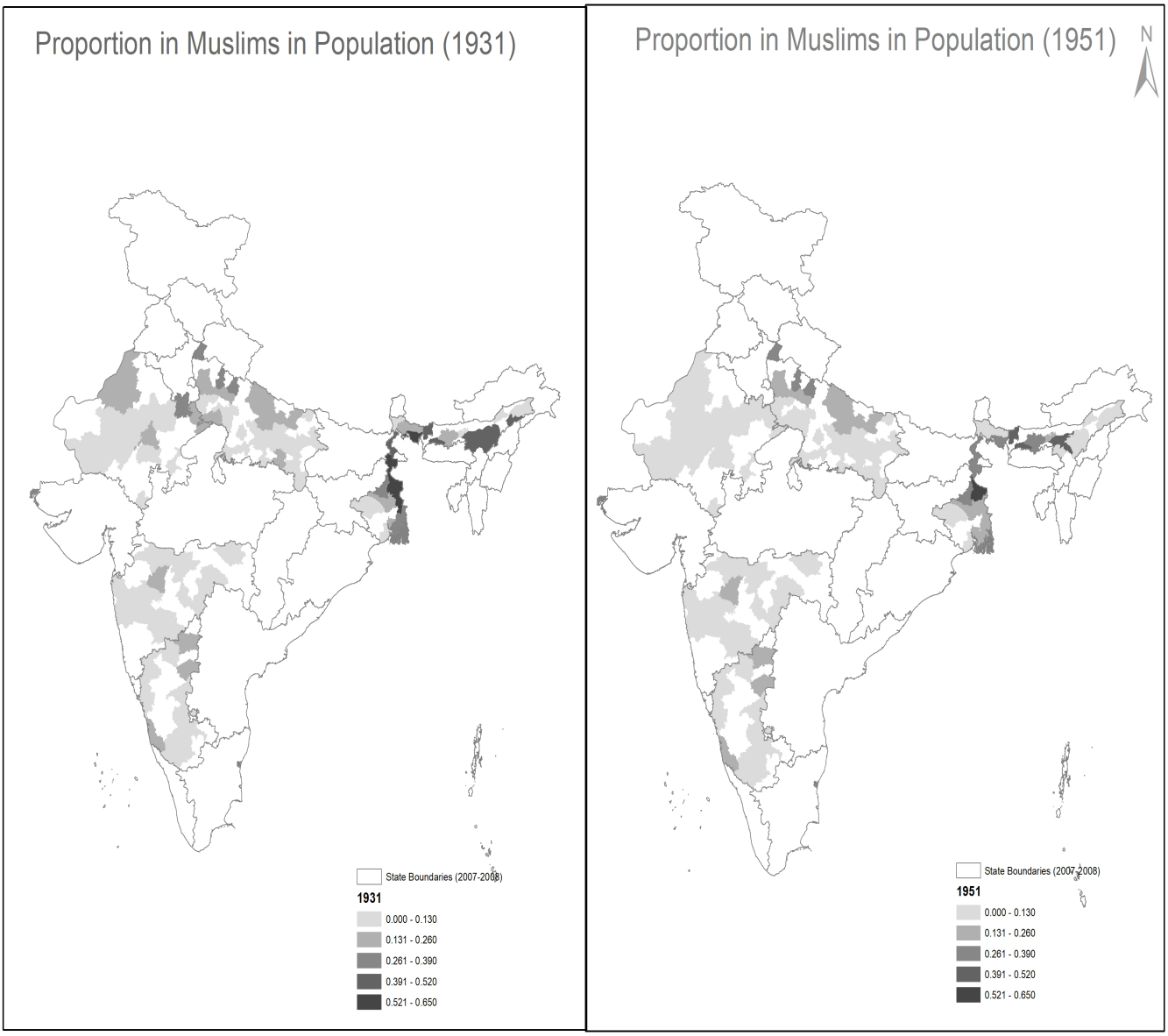


Figure 4: Dropping One District

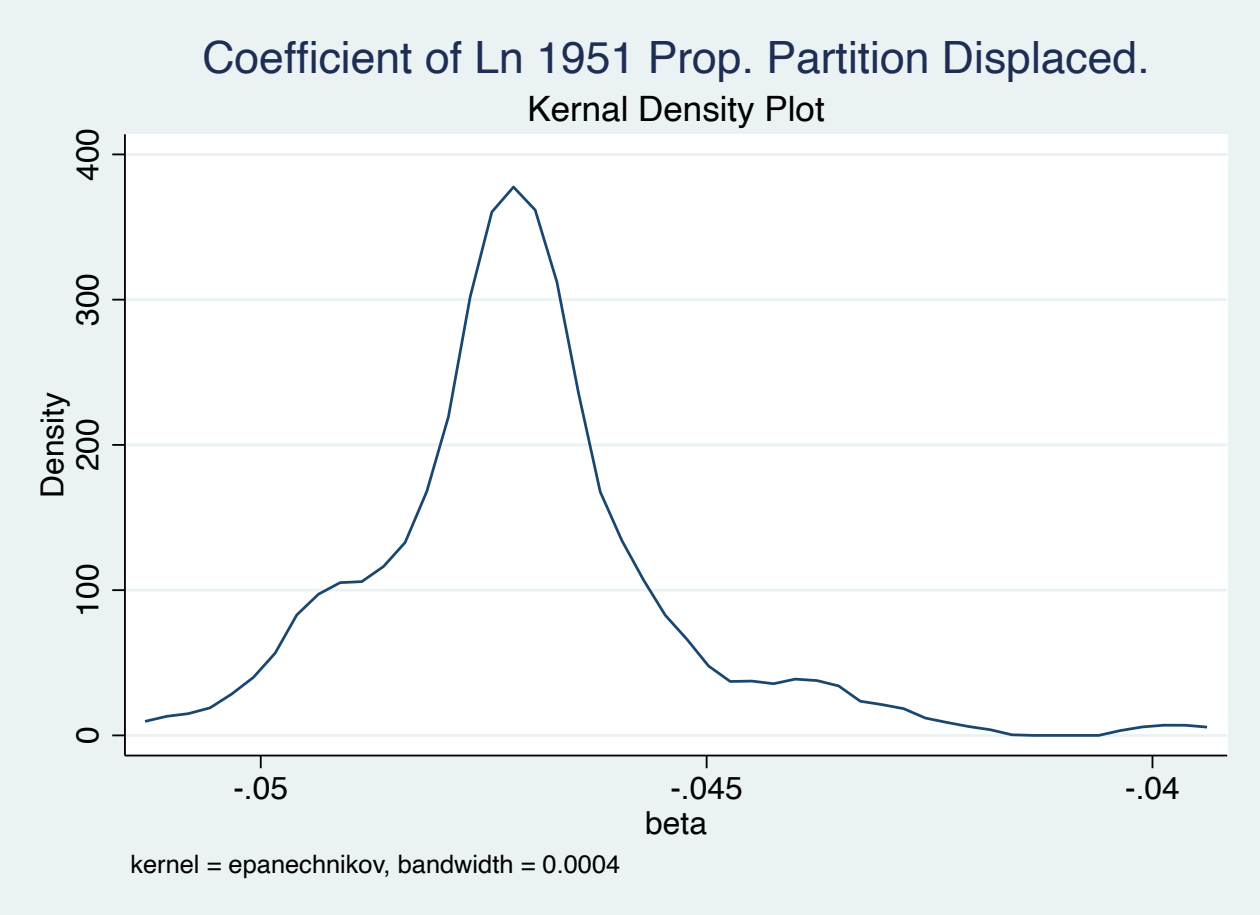


Figure 5: Marginal Effects: Year X Proportion Displace Migration: 1902-1995

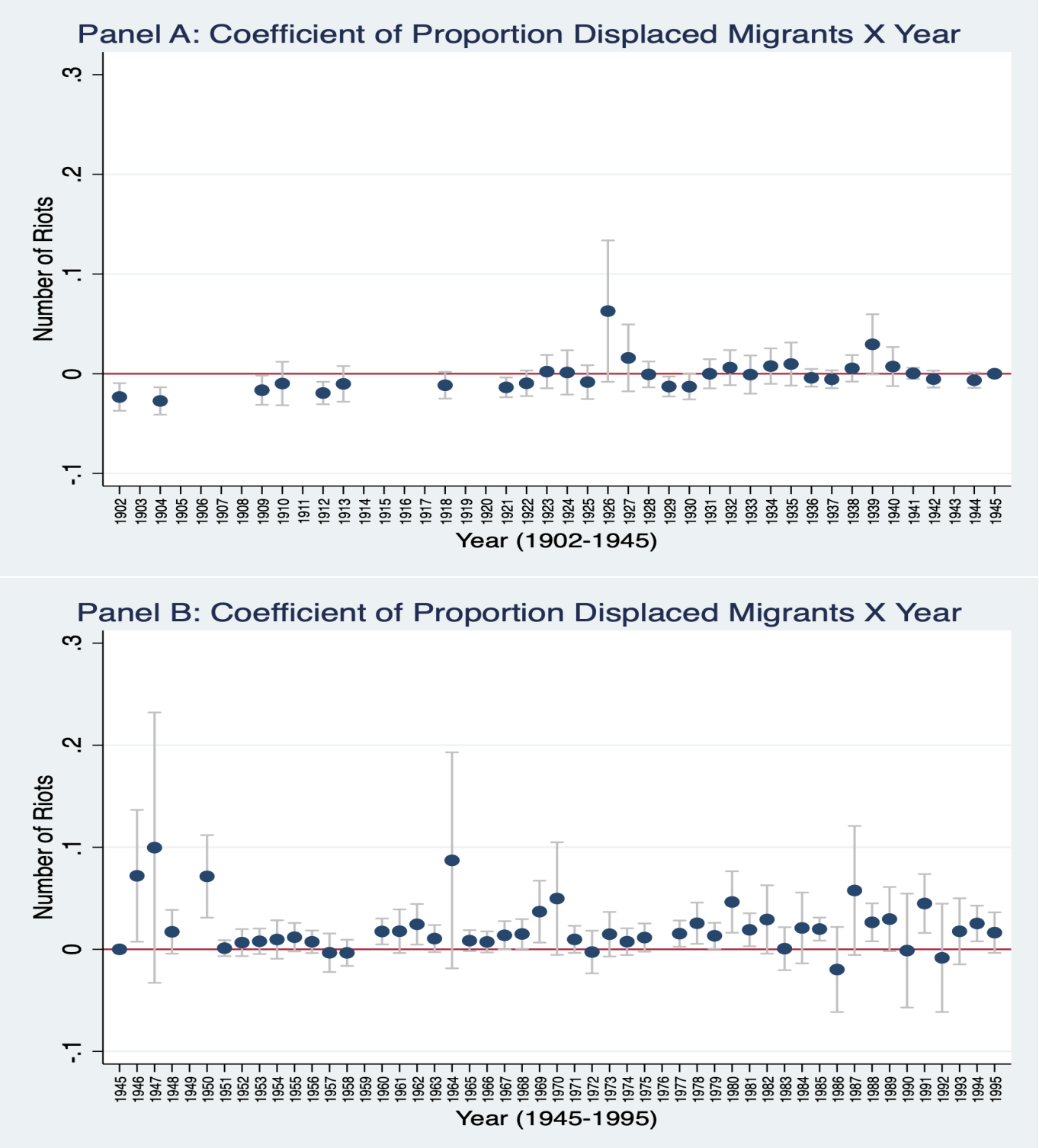
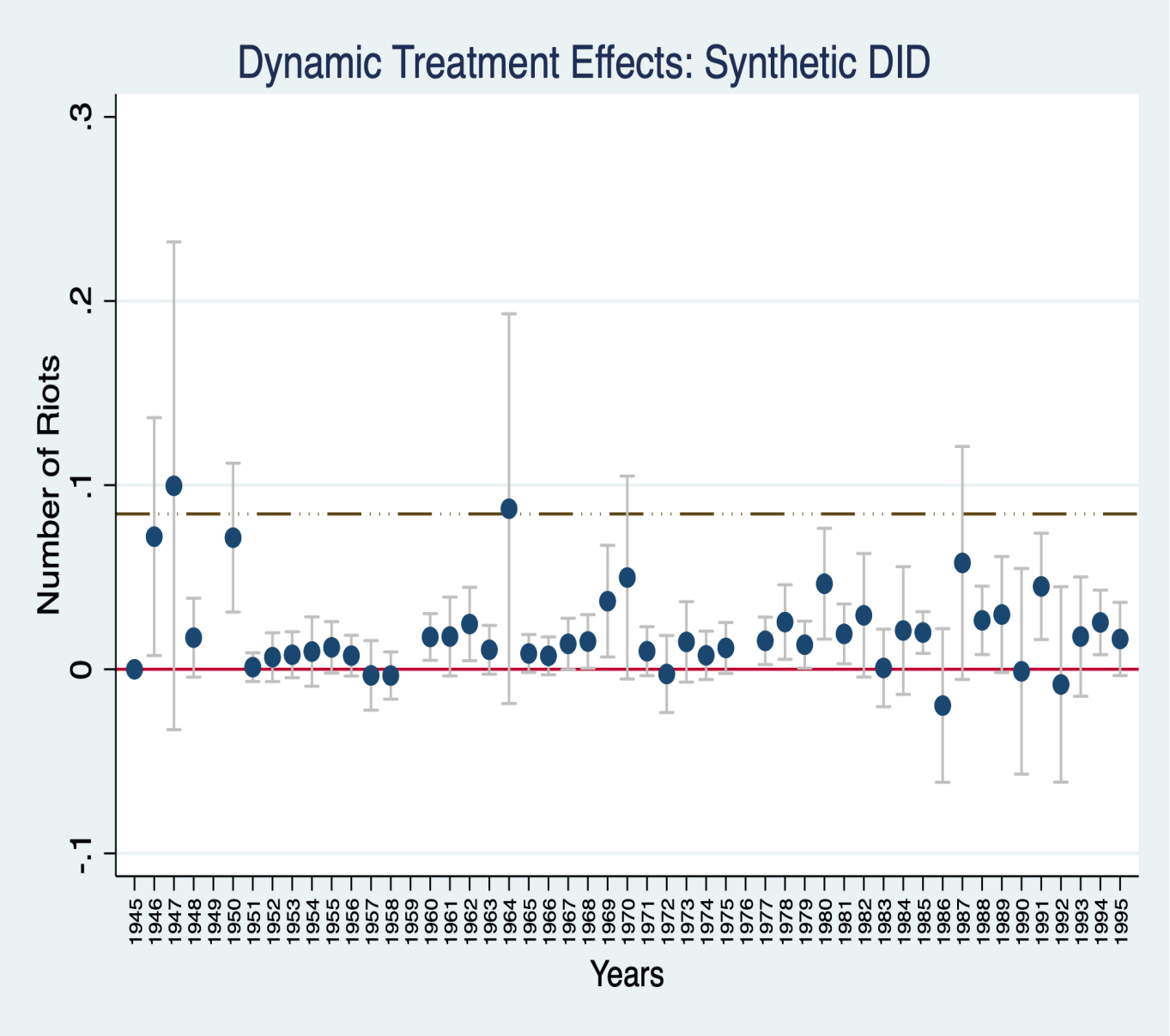


Figure 6: Dynamic Effects: Synthetic DID Event Study: 1945-1995



Note: The reported coefficients are the interaction of each year with a dummy based on the median value (0.83) of Ln Prop Displaced, 1951

Figure 7: Marginal Effect of Log, 1951 Prop. Displaced, by composition of Displaced

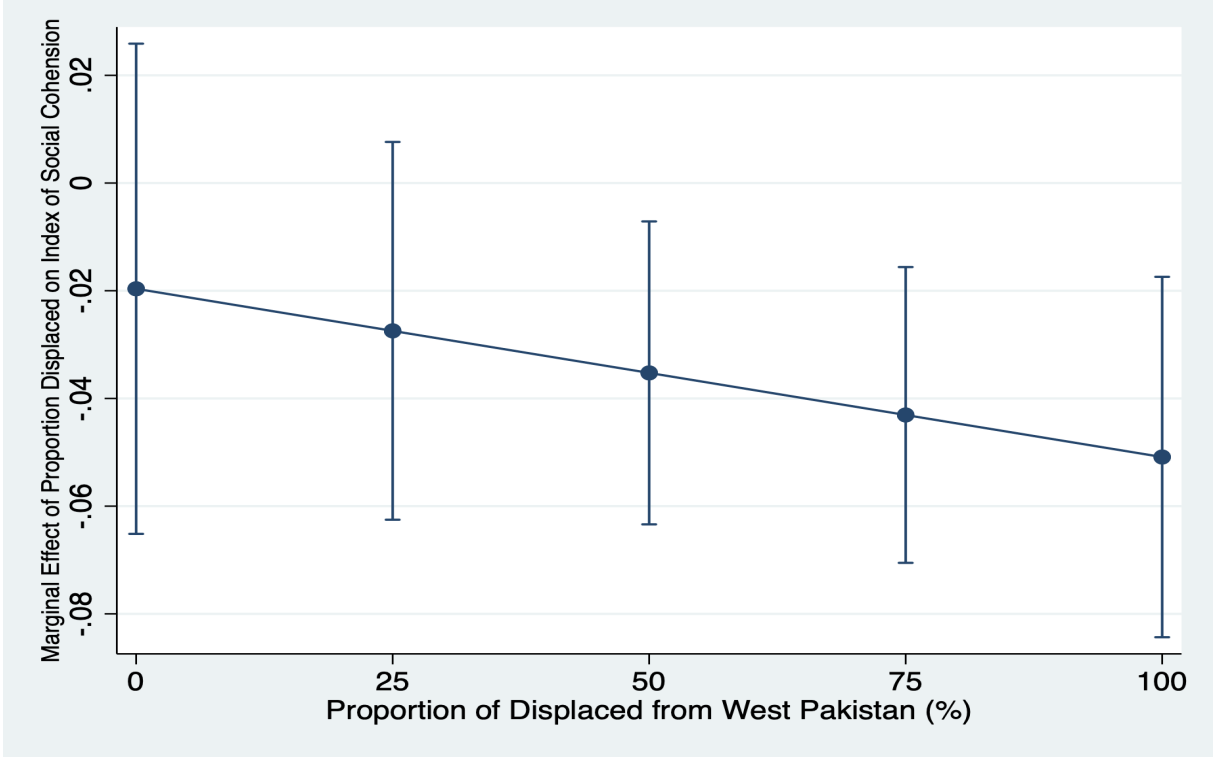
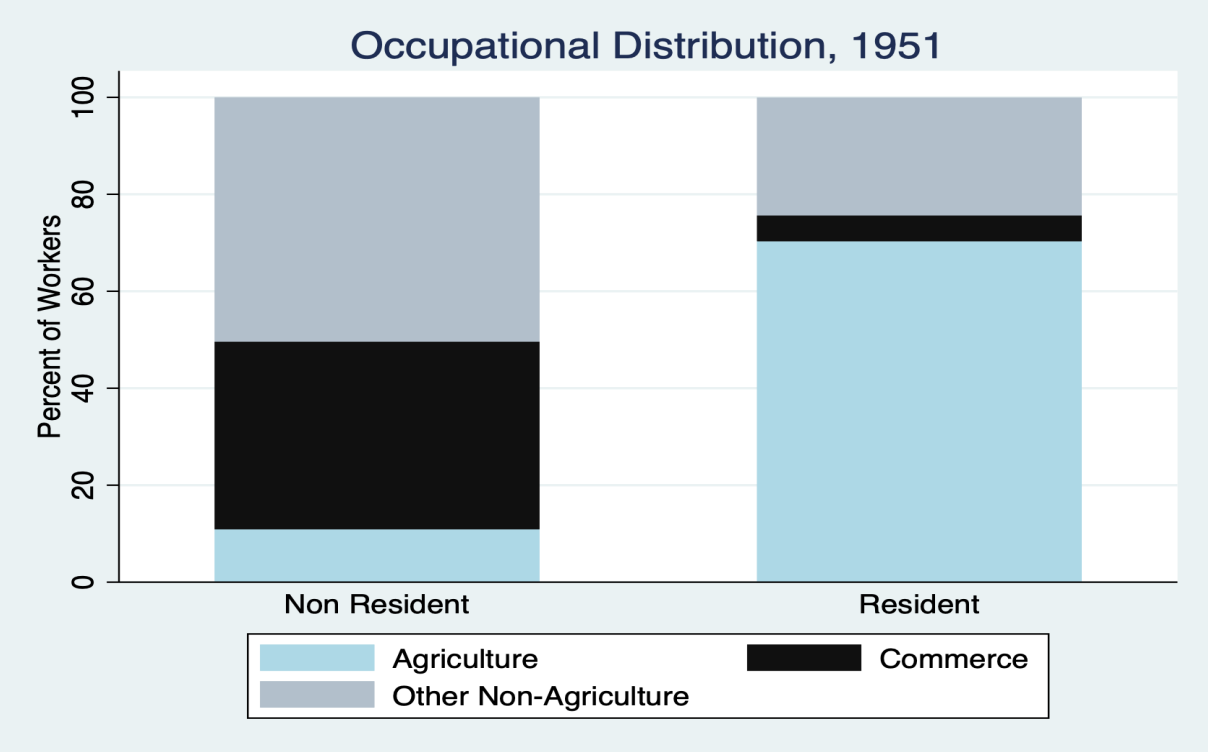


Figure 8: Occupation Structure of Displace Migrants and Residents, 1951



A Appendix Tables

Table A1: Prop. 1951 Partition Displaced Persons

	Mean	SD	Min	Max
Assam	2.35%	1.46%	0.62%	4.35%
Karnataka	0.02%	0.05%	0.00%	0.17%
Maharashtra	0.77%	1.66%	0.01%	6.79%
Rajasthan	3.11%	4.49%	0.03%	15.78%
Uttar Pradesh	0.67%	1.09%	0.02%	4.85%
West Bengal	9.41%	9.87%	0.70%	37.29%

Table A2: Outcome - Index of Social Capital

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.054***	-0.054***	-0.050***	-0.043***	-0.043***
	(0.013)	(0.011)	(0.010)	(0.012)	(0.012)
Distance to Nearest Border		0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Square:Distance to Nearest Border		-0.000	-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Latitude		-0.255**	-0.165	-0.147	-0.110
		(0.117)	(0.135)	(0.144)	(0.141)
Square of Latitude		0.007***	0.005**	0.005*	0.004
		(0.002)	(0.003)	(0.003)	(0.003)
Longitude		0.304*	0.330*	0.273	0.321
		(0.171)	(0.191)	(0.219)	(0.215)
Square of Longitude		-0.002*	-0.002*	-0.002	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)
Prop: district with sandy soil		-0.295*	-0.283**	-0.197	-0.248*
		(0.156)	(0.135)	(0.134)	(0.137)
Average River Length		0.010**	0.009**	0.008	0.008
		(0.004)	(0.004)	(0.005)	(0.005)
Coastal District		0.096	0.006	-0.024	0.021
		(0.108)	(0.068)	(0.081)	(0.076)
Elevation		-0.000**	-0.000**	-0.000**	-0.000**
		(0.000)	(0.000)	(0.000)	(0.000)
Log District Area Square Km, 2001		-0.073	-0.056	-0.066	-0.043
		(0.046)	(0.045)	(0.047)	(0.047)
Dummy: Rural		-0.001	-0.003	-0.002	0.045
		(0.046)	(0.044)	(0.048)	(0.041)
Annual Rainfall		-0.002***	-0.001***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)

	(1)	(2)	(3)	(4)	(5)
Dummy:Big City in 1951 District		0.065	0.007	0.032	0.057
		(0.057)	(0.051)	(0.056)	(0.059)
Prop. Lit, 1931			2.274**	3.170***	2.916**
			(0.894)	(1.124)	(1.128)
Prop. Brahman, 1931			-0.020	0.333	0.623
			(0.650)	(0.712)	(0.702)
Prop. Muslim, 1931			-0.359*	-0.528	-0.640
			(0.197)	(0.378)	(0.392)
Out of State Migration, 1931			-0.692	-0.434	-0.466
			(0.556)	(0.633)	(0.630)
Dummy: Princely State			-0.006	-0.008	0.024
			(0.062)	(0.080)	(0.077)
Log of District Pop, 1951				0.038	0.009
				(0.060)	(0.065)
Prop. Urban, 1951				0.026	0.277
				(0.211)	(0.216)
Prop. Muslims, 1951				0.379	0.590
				(0.445)	(0.475)
Prop Literate, 1951				-1.117**	-1.199**
				(0.489)	(0.471)
Gender Ratio, 1951				-0.155	-0.429
				(0.536)	(0.541)
Prop. STs, 1951				0.629**	0.354
				(0.298)	(0.325)
Prop. SCs, 1951				-0.420	-0.379
				(0.565)	(0.580)

	(1)	(2)	(3)	(4)	(5)
Age (years)					-0.005***
					(0.002)
Dummy: male					0.554***
					(0.059)
Dummy: SC					-0.032
					(0.030)
Dummy: ST					0.083
					(0.067)
Dummy: Permanent Resident					0.002
					(0.060)
Years of Education					0.022***
					(0.003)
Dummy:Married					0.088***
					(0.032)
Dummy:Never Married					-0.063
					(0.067)
Dummy:Hindu					0.034
					(0.043)
Dummy: Non Muslim					0.127*
					(0.065)
Household Size					0.002
					(0.006)
Children below 10					-0.002
					(0.012)
Avg. Edu HH					0.001
					(0.005)
Avg. Age HH					-0.002
					(0.001)
Old HH Strata					0.076*
					(0.043)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.024	0.076	0.079	0.081	0.187
State FE	No	Yes	Yes	Yes	Yes
Geography	No	Yes	Yes	Yes	Yes
1931 Controls	No	No	Yes	Yes	Yes
1951 Controls	No	No	No	Yes	Yes
Individual and Household Controls	No	No	No	No	Yes

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Dropping One State and Nadia District

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.039***	-0.048***	-0.035**	-0.050***	-0.041***
	(0.011)	(0.017)	(0.014)	(0.015)	(0.012)
Observations	7,878	7,461	6,666	7,109	8,825
R^2	0.203	0.199	0.198	0.173	0.185
Robustness Check	No Assam	No Rajasthan	No UP	No West Bengal	No District Nadia

Note: Robust standard errors clustered at the district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p< 0.13

Table A4: Index of Social Capital, Conley Standard Errors

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.043***	-0.043***	-0.043***	-0.043***	-0.043***
	(0.010)	(0.003)	(0.007)	(0.007)	(0.005)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.081	0.187	0.187	0.187	0.187
Cutoff Distance	100	200	300	400	500

Note: *** p<0.01, ** p<0.05, * p<0.1

Table A5: Outcome - Index of Social Cohesion

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.055***	-0.046***	-0.037**	-0.037**	-0.037***
	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.024	0.087	0.093	0.203	0.204
State FE	No	Yes	Yes	Yes	Yes
Geography	No	Yes	Yes	Yes	Yes
1951-1931 Controls	No	No	Yes	Yes	Yes
Individual Controls	No	No	No	Yes	Yes
Household Controls	No	No	No	No	Yes

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Outcome - Index of Trust

	(1)	(2)	(3)	(4)	(5)
Log, 1951 Prop Displaced	-0.017	-0.029*	-0.022	-0.023	-0.022
	(0.012)	(0.015)	(0.021)	(0.021)	(0.021)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.002	0.049	0.053	0.072	0.073
State FE	No	Yes	Yes	Yes	Yes
Geography	No	Yes	Yes	Yes	Yes
1951-1931 Controls	No	No	Yes	Yes	Yes
Individual Controls	No	No	No	Yes	Yes
Household Controls	No	No	No	No	Yes

Note: Robust standard errors clustered at the 1951 district-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Disaggregated-Social Cohesion and Trust

	(1)	(2)	(3)	(4)	(5)
	Attend Any Public Meeting about Local or School Affairs	Met Community Leader	Attended any group, club, society, union or organizational meeting	Worked with Neighbors to fix or improve something	Had Friends over to your home
Log, 1951 Prop Displaced	0.005*	-0.006*	0.003	0.004	-0.019***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.007)
	Socialized with someone in a different Neigborhood	Socialised with coworkers outside of work	Attended Religious services	Gotten out of house to attend social meetings, events, programs or events or to visit friends or relatives	Trust people in Neighborhood
Log, 1951 Prop Displaced	-0.024***	-0.012	-0.017***	-0.023***	-0.022*
	(0.009)	(0.008)	(0.006)	(0.006)	(0.012)
	Trust Coworkers	Trust Strangers			
Log, 1951 Prop Displaced	0.002	-0.003			
	(0.010)	(0.007)			

Note: All the regressions have the controls used in the main regressions. Robust standard errors, clustered (at the 1951 district level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Riots- District Panel Analysis

	Number of Riots		
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Log, 1951 Prop Displaced X			
Dummy: 1902	-0.00222	-0.0226***	-0.0234***
	(0.00438)	(0.00839)	(0.00835)
Dummy: 1904	-0.00716	-0.0266***	-0.0274***
	(0.00527)	(0.00836)	(0.00827)
Dummy: 1909	0.00117	-0.0159*	-0.0166*
	(0.00658)	(0.00888)	(0.00883)
Dummy: 1910	0.00735	-0.00926	-0.00990
	(0.0121)	(0.0132)	(0.0131)
Dummy: 1912	-0.00316	-0.0188***	-0.0194***
	(0.00418)	(0.00684)	(0.00679)
Dummy: 1913	0.00554	-0.00964	-0.0102
	(0.00836)	(0.0107)	(0.0108)
Dummy: 1918	0.00171	-0.0111	-0.0116
	(0.00701)	(0.00811)	(0.00805)
Dummy: 1921	-0.00189	-0.0133**	-0.0137**
	(0.00453)	(0.00601)	(0.00597)
Dummy: 1922	0.00171	-0.00921	-0.00963
	(0.00701)	(0.00778)	(0.00773)
Dummy: 1923	0.0129	0.00251	0.00211
	(0.00879)	(0.01000)	(0.0101)
Dummy: 1924	0.0116	0.00163	0.00125
	(0.0131)	(0.0134)	(0.0134)
Dummy: 1925	0.00145	-0.00804	-0.00841
	(0.00987)	(0.0102)	(0.0102)
Dummy: 1926	0.0722*	0.0631	0.0628
	(0.0426)	(0.0427)	(0.0427)
Dummy: 1927	0.0247	0.0162	0.0158
	(0.0198)	(0.0202)	(0.0202)
Dummy: 1928	0.00765	-0.000419	-0.000728
	(0.00860)	(0.00785)	(0.00781)
Dummy: 1929	-0.00498	-0.0126**	-0.0129**
	(0.00556)	(0.00606)	(0.00602)
Dummy: 1930	-0.00559	-0.0127	-0.0130*
	(0.00716)	(0.00773)	(0.00770)
Dummy: 1931	0.00682	0.000176	-7.80e-05
	(0.00810)	(0.00880)	(0.00881)
Dummy: 1932	0.0125	0.00632	0.00608
	(0.0101)	(0.0105)	(0.0106)

Number of Riots			
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Dummy: 1933	0.00506	-0.000639	-0.000857
	(0.0114)	(0.0116)	(0.0115)
Dummy: 1934	0.0131	0.00784	0.00764
	(0.0104)	(0.0107)	(0.0107)
Dummy: 1935	0.0146	0.00987	0.00969
	(0.0129)	(0.0130)	(0.0130)
Dummy: 1936	0.000332	-0.00394	-0.00410
	(0.00509)	(0.00535)	(0.00535)
Dummy: 1937	-0.00166	-0.00545	-0.00560
	(0.00586)	(0.00542)	(0.00538)
Dummy: 1938	0.00885	0.00553	0.00541
	(0.00786)	(0.00802)	(0.00801)
Dummy: 1939	0.0325*	0.0296	0.0295
	(0.0181)	(0.0182)	(0.0182)
Dummy: 1940	0.00965	0.00728	0.00719
	(0.0120)	(0.0118)	(0.0118)
Dummy: 1941	0.00238	0.000482	0.000409
	(0.00317)	(0.00335)	(0.00336)
Dummy: 1942	-0.00389	-0.00532	-0.00537
	(0.00510)	(0.00514)	(0.00513)
Dummy: 1944	-0.00602	-0.00649	-0.00651
	(0.00461)	(0.00461)	(0.00460)
Dummy: 1946	0.0715*	0.0720*	0.0720*
	(0.0388)	(0.0389)	(0.0389)
Dummy: 1947	0.0987	0.0996	0.0996
	(0.0797)	(0.0798)	(0.0798)
Dummy: 1948	0.0157	0.0171	0.0172
	(0.0129)	(0.0129)	(0.0129)
Dummy: 1950	0.0690***	0.0714***	0.0715***
	(0.0244)	(0.0244)	(0.0244)
Dummy: 1951	-0.00181	0.00103	0.00114
	(0.00456)	(0.00468)	(0.00469)
Dummy: 1952	0.00312	0.00644	0.00657
	(0.00780)	(0.00797)	(0.00798)
Dummy: 1953	0.00396	0.00775	0.00790
	(0.00727)	(0.00750)	(0.00752)
Dummy: 1954	0.00521	0.00948	0.00964
	(0.0109)	(0.0113)	(0.0113)
Dummy: 1955	0.00698	0.0117	0.0119
	(0.00818)	(0.00840)	(0.00841)

	Number of Riots		
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Dummy: 1956	0.00198	0.00720	0.00740
	(0.00632)	(0.00666)	(0.00667)
Dummy: 1957	-0.00924	-0.00355	-0.00333
	(0.0109)	(0.0114)	(0.0114)
Dummy: 1958	-0.00982	-0.00365	-0.00341
	(0.00718)	(0.00773)	(0.00774)
Dummy: 1960	0.0101	0.0173**	0.0175**
	(0.00758)	(0.00768)	(0.00765)
Dummy: 1961	0.00991	0.0175	0.0178
	(0.0115)	(0.0129)	(0.0129)
Dummy: 1962	0.0162	0.0243**	0.0246**
	(0.0117)	(0.0120)	(0.0120)
Dummy: 1963	0.00171	0.0103	0.0106
	(0.00701)	(0.00793)	(0.00799)
Dummy: 1964	0.0778	0.0869	0.0872
	(0.0636)	(0.0637)	(0.0638)
Dummy: 1965	-0.00130	0.00819	0.00856
	(0.00492)	(0.00619)	(0.00621)
Dummy: 1966	-0.00304	0.00692	0.00731
	(0.00465)	(0.00614)	(0.00620)
Dummy: 1967	0.00294	0.0134	0.0138
	(0.00703)	(0.00831)	(0.00837)
Dummy: 1968	0.00375	0.0147*	0.0151*
	(0.00708)	(0.00872)	(0.00878)
Dummy: 1969	0.0252	0.0365**	0.0370**
	(0.0174)	(0.0182)	(0.0183)
Dummy: 1970	0.0375	0.0494	0.0498
	(0.0320)	(0.0329)	(0.0332)
Dummy: 1971	-0.00302	0.00932	0.00979
	(0.00589)	(0.00794)	(0.00803)
Dummy: 1972	-0.0159	-0.00308	-0.00259
	(0.0115)	(0.0125)	(0.0126)
Dummy: 1973	0.00107	0.0144	0.0149
	(0.0110)	(0.0130)	(0.0132)
Dummy: 1974	-0.00674	0.00703	0.00755
	(0.00583)	(0.00784)	(0.00792)

Number of Riots			
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Dummy: 1975	-0.00320	0.0110	0.0116
	(0.00593)	(0.00827)	(0.00834)
Dummy: 1977	-0.000331	0.0149*	0.0154**
	(0.00491)	(0.00775)	(0.00778)
Dummy: 1978	0.00938	0.0250**	0.0256**
	(0.00891)	(0.0121)	(0.0122)
Dummy: 1979	-0.00342	0.0127*	0.0133*
	(0.00433)	(0.00757)	(0.00770)
Dummy: 1980	0.0292*	0.0458**	0.0464**
	(0.0157)	(0.0180)	(0.0181)
Dummy: 1981	0.00146	0.0185*	0.0192*
	(0.00712)	(0.00972)	(0.00979)
Dummy: 1982	0.0111	0.0286	0.0293
	(0.0168)	(0.0201)	(0.0202)
Dummy: 1983	-0.0180	2.05e-05	0.000710
	(0.0114)	(0.0127)	(0.0127)
Dummy: 1984	0.00180	0.0203	0.0210
	(0.0183)	(0.0206)	(0.0209)
Dummy: 1985	0.000222	0.0192***	0.0199***
	(0.00131)	(0.00676)	(0.00682)
Dummy: 1986	-0.0399*	-0.0205	-0.0197
	(0.0240)	(0.0251)	(0.0251)
Dummy: 1987	0.0370	0.0570	0.0577
	(0.0333)	(0.0380)	(0.0381)
Dummy: 1988	0.00536	0.0258**	0.0265**
	(0.00776)	(0.0110)	(0.0112)
Dummy: 1989	0.00805	0.0289	0.0297
	(0.0163)	(0.0189)	(0.0190)
Dummy: 1990	-0.0233	-0.00194	-0.00113
	(0.0309)	(0.0335)	(0.0336)
Dummy: 1991	0.0223*	0.0442**	0.0450**
	(0.0134)	(0.0174)	(0.0174)
Dummy: 1992	-0.0314	-0.00910	-0.00825
	(0.0298)	(0.0320)	(0.0320)
Dummy: 1993	-0.00591	0.0169	0.0177
	(0.0173)	(0.0194)	(0.0195)

Number of Riots			
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Dummy: 1994	0.00128	0.0245**	0.0254**
	(0.00728)	(0.0105)	(0.0106)
Dummy: 1995	-0.00819	0.0155	0.0164
	(0.00888)	(0.0119)	(0.0120)
Constant	0.00971	-8.469***	-10.23***
	(0.0161)	(1.955)	(2.653)

Note: Each regression is run with District Fixed Effects. Dummy 1945 is taken as the reference. Column (2) has state trends. Column (3) controls for trends by Dummy:Border District, trends by Proportion of District that is sandy, and trends by the average Height of the district. The years that are missing have no reported riot incidents in the sampled districts and are removed from the data set. Robust standard errors, clustered (at the 1951 district level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Number of Riots			
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Dummy: 1961	0.0138	0.0244*	0.0237*
	(0.0107)	(0.0135)	(0.0135)
Dummy: 1962	0.0201*	0.0313**	0.0306**
	(0.0108)	(0.0124)	(0.0124)
Dummy: 1963	0.00564	0.0175**	0.0167*
	(0.00567)	(0.00861)	(0.00851)
Dummy: 1964	0.0818	0.0943	0.0935
	(0.0635)	(0.0645)	(0.0644)
Dummy: 1965	0.00264	0.0158**	0.0149**
	(0.00277)	(0.00695)	(0.00722)
Dummy: 1966	0.000894	0.0147**	0.0138*
	(0.00223)	(0.00726)	(0.00757)
Dummy: 1967	0.00688	0.0214**	0.0204**
	(0.00566)	(0.00965)	(0.00961)
Dummy: 1968	0.00769	0.0228**	0.0218**
	(0.00574)	(0.0107)	(0.0109)
Dummy: 1969	0.0291*	0.0449**	0.0439**
	(0.0169)	(0.0195)	(0.0196)
Dummy: 1970	0.0414	0.0579*	0.0568*
	(0.0318)	(0.0335)	(0.0339)
Dummy: 1971	0.000915	0.0180*	0.0169*
	(0.00422)	(0.00971)	(0.0101)
Dummy: 1972	-0.0120	0.00581	0.00466
	(0.0107)	(0.0137)	(0.0140)
Dummy: 1973	0.00500	0.0234	0.0222
	(0.0103)	(0.0149)	(0.0151)
Dummy: 1974	-0.00280	0.0163	0.0150
	(0.00416)	(0.0106)	(0.0110)
Dummy: 1975	0.000733	0.0205*	0.0192*
	(0.00426)	(0.0109)	(0.0113)
Dummy: 1976	0.002*	0.0204*	0.0191*
	(3.38e-10)	(0.0103)	(0.0108)
Dummy: 1977	0.00360	0.0247**	0.0233**
	(0.00278)	(0.0110)	(0.0115)
Dummy: 1978	0.0133*	0.0350**	0.0336**
	(0.00790)	(0.0156)	(0.0160)
Dummy: 1979	0.000521	0.0229**	0.0214*
	(0.00153)	(0.0112)	(0.0117)
Dummy: 1980	0.0331**	0.0562***	0.0547***
	(0.0150)	(0.0201)	(0.0208)
Dummy: 1981	0.00540	0.0291**	0.0276**
	(0.00574)	(0.0133)	(0.0137)
Observations	8,034	8,034	8,034
R-squared	0.130	0.134	0.135

Robust standard errors in parentheses

	Number of Riots		
	(1)	(2)	(3)
VARIABLES	District FE	+ State Trends	+ Baseline Trends
Dummy: 1982	0.0150	0.0394*	0.0378
	(0.0162)	(0.0234)	(0.0235)
Dummy: 1983	-0.0141	0.0109	0.00930
	(0.0107)	(0.0172)	(0.0180)
Dummy: 1984	0.00574	0.0314	0.0297
	(0.0177)	(0.0225)	(0.0228)
Dummy: 1985	0.00416	0.0305**	0.0288**
	(0.00415)	(0.0134)	(0.0139)
Dummy: 1986	-0.0360	-0.00899	-0.0107
	(0.0236)	(0.0302)	(0.0305)
Dummy: 1987	0.0410	0.0686	0.0668
	(0.0330)	(0.0426)	(0.0420)
Dummy: 1988	0.00929	0.0376**	0.0358**
	(0.00652)	(0.0161)	(0.0169)
Dummy: 1989	0.0120	0.0409*	0.0391*
	(0.0156)	(0.0235)	(0.0235)
Dummy: 1990	-0.0194	0.0102	0.00832
	(0.0308)	(0.0383)	(0.0382)
Dummy: 1991	0.0263*	0.0565**	0.0546**
	(0.0138)	(0.0234)	(0.0234)
Dummy: 1992	-0.0275	0.00346	0.00145
	(0.0295)	(0.0345)	(0.0344)
Dummy: 1993	-0.00197	0.0296	0.0276
	(0.0167)	(0.0220)	(0.0221)
Dummy: 1994	0.00522	0.0375**	0.0354**
	(0.00604)	(0.0169)	(0.0176)
Dummy: 1995	-0.00425	0.0287	0.0265
	(0.00788)	(0.0185)	(0.0194)
Share of Muslims 1931 X Year			0.00305
			(0.00399)
Dummy Border District X Year			-0.00115
			(0.000997)
Constant	-0	-1.351	-2.912
	(0.0126)	(2.855)	(3.510)
Observations	5,562	5,562	5,562
R-squared	0.131	0.134	0.134

Note: Each regression is run with District Fixed Effects. Dummy 1945 is taken as the reference. Column (2) has state trends. Column (3) controls for trends by Muslim Share 1931 and trends by Whether the district is a border district Robust standard errors, clustered (at the 1951 district level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9: Pre-Colonial Caste Conflict

State	District	Source
Utta Pradesh	Mathura, Agra, Lucknow, Kanpur Dehat, Kanpur Nagar, Varanasi, Allahabad, Meerut, Moradabad, Bulandshahr, Badaun, Bijnor, Bareily, Pilibhit, Aligarh,	Gooptu, N. (1993). Caste and Labour: Untouchable social movements in urban Uttar Pradesh in the early twentieth century. Dalit Movements and the Meanings of Labour in India, 277-289.
	Saharanpur, Etah, Etawah, Mainpuri, Unnao, Kheri, Sultanpur, Pratapgarh, Jaunpur, Basti, Gorakhpur	Singh, O. P. (2009, January). Evolution of Dalit Identity: History of Adi Hindu movement in United Provinces (1900-1950): In Proceedings of the Indian History Congress (Vol 70; pp 574-585). Indian History Congress
West Bengal	Jalpaiguri, Uttar Dinajpur, Dakshin Dinajpur, Malda, Nadia, South 24 Parganas, North 24 Parganas, Calcutta	Bandyopadhyay, S.(2004). Caste, culture and hegemony: Social dominance in colonial Bengal. Sage. Bandyopadhyay, S.(2011). Caste, protest and identity in colonial India, The Namasudras of Bengal 1872-1947, Oxford University Press
Maharashtra	Nagpur, Nanded, Nashik, Thane, Mumbai, Pune, Ahmednagar, Solapur, Satara, Ratnagiri	Omvedt, G. (1994). Dalits and the democratic revolution: Dr Ambedkar and the Dalit movement in colonial India. SAGE Publications India.
Karnataka	Bellary, Kolar	Omvedt, G. (1994). Dalits and the democratic revolution: Dr Ambedkar and the Dalit movement in colonial India. SAGE Publications India.

Note: This is a replication of the source list provided by Bose , S. and Stratmann T. (2021), *Culture, caste and drinking water*, Mimeo

Table A10: Violence: Crime and Pre-1947 Caste Conflict

	(1)	(2)
	Violent Crime (NCRB) per 10,000	Caste Conflict Pre-1947
Log, 1951 Prop Displaced	0.076***	0.048
	(0.025)	(0.038)

Note: Regressions are run at the district level. All the regressions have the historic and geographic controls. Robust standard errors, clustered (at the 1951 district level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A11: Mediation Analysis

Mediator	% of Total Effect Mediated	[95 % Confidence Interval]
Violent Crimes per 10,000	22.3	[11.1,49.6]

Note: Mediation Analysis is based on 1000 simulations. Hicks, Raymond and Dustin Tingley (2011) mediation: Stata package for causal mediation analysis.

Table A12: District-level Literacy, Urban, Gender Ratios and Partition Migration

	(1)	(2)	(3)	(4)	(5)
	Share Urban, 1961	Share Urban, 1971	Share Urban, 1981	Share Urban, 1991	Share Urban, 2001
Log, 1951 Prop Displaced	0.017	0.020**	0.027**	0.034***	0.027**
	(0.010)	(0.009)	(0.012)	(0.012)	(0.012)
	Share Literate, 1961	Share Literate, 1971	Share Literate, 1981	Share Literate, 1991	Share Literate, 2001
Log, 1951 Prop Displaced	0.008***	0.012***	0.015***	0.013***	0.011
	(0.003)	(0.004)	(0.004)	(0.004)	(0.008)
	Gender Ratio, 1961	Gender Ratio, 1971	Gender Ratio, 1981	Gender Ratio, 1991	Gender Ratio, 2001
Log, 1951 Prop Displaced	0.007***	0.007***	0.012***	0.011***	0.010***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)

Note: Regressions are run at the district level for those districts where data is not missing in 1981. All the regressions have the historic and geographic controls. Robust standard errors, clustered (at the 1951 district level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A13: Current Conditions and Partition Migration

	(1)	(2)	(3)	(4)
	Muslim Share, 2001	District Pop, 2001	% SC, 2001	% ST, 2001
Log, 1951 Prop Displaced	-0.0004	0.001	0.162	0.999
	(0.004)	(0.031)	(1.953)	(1.242)
	Ln Lights, 2001	Share Urban, 2001	% Illiteracy, 2001	Share Migrants, 2001
Log, 1951 Prop Displaced	0.049	0.019*	-1.117	0.010*
	(0.034)	(0.010)	(0.747)	(0.005)
	Public Goods, Educ	Public Goods, Med	Public Goods, Water	Public Goods, Power
Log, 1951 Prop Displaced	69.919	5.42	156.75	71.52
	(77.4)	(36.6)	(123.9)	(58.2)
	Public Goods, Bus	Public Goods, Rail	Public Goods, Road	
Log, 1951 Prop Displaced	9.949	1.389	39.864	
	(27.4)	(4.4)	(34.3)	

Note: All regressions regarding availability of public goods are run at the village/town/city level. All the regressions have the historic and geographic controls. Robust clustered (at the 1951 district level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A14: Migrants: 1971 and 1981

VARIABLES	(1) Migrants from Pak/Bang 1971	(2) Baseline Results (Excl Assam)	(3) Migrants from Asia 1981
Log, 1951 Prop Displaced	-0.042***	-0.039***	-0.039***
	(0.013)	(0.012)	(0.011)
State FE	Yes	Yes	Yes
Observations	8,860	7,878	7,878
R-squared	0.187	0.203	0.203

Note: All regressions All the regressions have the individual, household level, historic and geographic controls. Robust clustered (at the 1951 district level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1