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Forced Displacement and Social Capital: Long-run Impact of the Indian Partition*

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Abstract

We investigate whether the historical shock of the Indian Partition, one of the largest forced displacements in the twentieth century, affected social capital in affected parts of India in the long-run. India was partitioned in 1947 into India and Pakistan (East and West Pakistan). At this time, many Hindus and Sikhs migrated from Pakistan to India while Muslims migrated from India to Pakistan. The Partition shock is measured as the proportion of "displaced" migrants in Indian districts in 1951 from census data. Using data from the World Health Organisation Survey on the Aged and Elderly conducted in six Indian states, we find 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 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. Our study contributes to the understanding of large forced displacement events and their shadow on institutions-here social capital-over the long run.

Keywords: Partition, Social Capital

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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). We study the effect of an important historical political shock, the Partition of India in 1947, on contemporary social capital, as measured in 2007. 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).[1] 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.[2] Thus, it is imperative to analyse how such a life-changing historical event had ramifications in the Indian society in particular and South Asian societies in general, especially in the long run.

[1] 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.

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

Moreover, understanding large scale population displacements and their implication on migrant recipient societies finds immediate relevance in the world today with almost 26 million cross border and 41.3 million internally displaced people in 2018 (UN High Commission for Refugees. [3]) While 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 on social capital in the contemporary India, but to also provide an important lens to distil more recent displacement events.

The Partition of India was not a monolithic event-experiences varied in different parts of India (and Pakistan). In particular, some areas of contemporary India (in particular, the northern state of Punjab) saw two-sided movement of population with West Pakistan (contemporary Pakistan). However, other areas of independent India experienced a largely one sided movement into India over time (for example, the eastern state of Bengal). This paper focuses largely on areas that saw one sided movements- which is more typical of forced migration.[4] The partition was a large shock to society-while it 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 who were enumerated as Partition migrants. Such migrants, recorded officially as "displaced persons", were tallied separately from other non-Partition migrants in a district.

To measure contemporary social capital, we use individual data from the World Health Organization (WHO) survey on the Aged and Elderly for 2007-08 conducted across six Indian states. Our measure aggregates responses to questions on community participation, social cohesion and trust into an index. These questions capture common social capital variables

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

[4]We look at the states of Assam, Rajasthan, Karnataka, Maharashtra, Uttar Pradesh and West Bengal-the choice of states is determined by the survey used in this paper.

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 Pakistan and Bangladesh, indicators for poor soil and rural districts, and the area of the district (based on their boundaries in 2007). Third, we control for 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 Muslims and an indicator for former Princely

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

[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.

States. 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. This is a relatively large effect-equivalent to 2 years less education for surveyed individuals in our sample. [7]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).

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

[7]The years of education is an important positive predictor of social capital in our analysis with a mean of 4 and standard deviation of 5.

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.

In deciphering the possible mechanisms from more Partition migration to lower social capital, 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. While we find a decline of social capital with age, we find no uniform evidence of a sharper decline in social capital for older adults in districts with more Partition migration. Our results show a higher negative impact among those who are in the age group 45-55 (who were 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 age heaping, a 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 the final section, we directly include control variables that could mediate the results on

Partition migration. This strategy provides suggestive evidence for a specific channel. We find contemporary differences in education, income, religion, migration and public goods provision do not attenuate the coefficient on Partition migration. In the same vein, differences in urbanisation, literacy and gender ratios between 1961 and 2001 are also not the mediators. Our results suggest that the level of violence in partition districts-a mixture of community conflict (which could be caste or religious) as well violent crime mediate the effect of partition. Hindu-Muslim riots just after the Partition, i.e., in between the years of 1950-1955, show attenuation of the main variable of interest, and work as a mediator variable in explaining the baseline result of diminishing social capital-though this effect is small and explains only 7 % of the estimated impact of partition migrants. The result is not entirely unexpected- riots along the religious line (Hindu-Muslim) were quite prevalent in the aftermath of Partition (Varshney and Wilkinson, 2006; Chatterji 2007) but what is significant is that such riots in the past have a long lasting effect on longer run social capital. 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.

We delve deeper into explaining the potential mechanism by looking at two particular pathways. The first one involves using micro data from the India Human Development Survey (2005) and sheds light on whether households living in partition districts experience 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., religious, caste and sub-caste skirmishes. While religious conflict dominates the historical narrative of the partition, our results is consistent with the narrative that posists this strife may also be caste driven - recent partition literature highlights partition being not only along religious and geographical lines, but also manifested across caste dimensions (Kumar 2006). In-fact, newer histories of the Bengal partition (Sen, 2018; Bandopadhyay and Chaudhury 2017) point out that the question of migration, rehabilitation and post- partition politics was 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).

The second pathway 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 Record Bureau of India, which is averaged over the period 1987-2007.[8] In this instance also, our coefficient of interest (partition migrants) attenuates-formal causal mediation ascribes around 18 % of the effect to such violence. The two channels do point out that districts that saw a large inflow of migrants post partition have ended up with violent, conflict ridden societies and this may have hampered the social capital of these places significantly.

Our paper contributes to three literatures. First, it relates to the literature 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, 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 run effects even among co-religionists when they

[8] The data is censored at 1987.

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 lead by Bharadwaj and co-authors. For example, 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) find 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 Pakistan and finds long term effects of Partition 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) find 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.

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. All results and discussions are presented in Section 5. Finally, Section 6 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 kilometers. 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).[9] About 12 million people became refugees and more than a million people lost their lives due to the ensuing riots.[10]

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

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

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

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 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).[11] 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

[11]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.

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 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 World Health Organisation (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).[12] The SAGE

[12]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

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.[13] 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 Cohesion 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 stepping 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

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/healthinfo/sage/en/

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

index (SC_{ihds}), following Anderson (2008).[14]

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.[15] Our measure is motivated by our 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 our sample are shown in Figure 1.

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%.[16] Disaggregating by state, West Bengal, 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

[14] 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.

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

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

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.[17]

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. 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 through the districts (kms) and average height of the district (kms).[18] 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.[19]

We also employ control variables constructed from historical Indian censuses.[20] We collected data on 1951 total and urban population, male and female population, Scheduled Caste (SC), Scheduled Tribes (ST), Muslim population, and the number of literates. From the 1931 census, we collected information on district population, number of Brahmans, Muslims, and

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

[18] These data are from http://www.diva-gis.org/.

[19] The other soil types are clay and loam.

[20] Most of the historical censuses are available at https://dspace.gipe.ac.in

the total number of migrants from out of 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).[21] For information on the decades between 1961 and 1991 we used district level census data organised in the University of Maryland Indian District Database.[22]

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.

4 Empirical Strategy

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:

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

In this model, SC_{ihds} is the index of social capital for individual i, in household h residing

[21] We do not use data from 1941 India census as the data collected during these wars years has been reported to be incorrect.

[22] This is available at http://vanneman.umd.edu/districts/index.html.

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.[23] 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.[24] 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 members and an indicator that controls for whether the individual belongs to an "old" strata household.[25] 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 urbanisation share, 1951 literacy rate, 1951 Muslim share, 1951 gender ratio defined as total male population over total female population, and the 1951 shares of Scheduled

[23]The main results remain qualitatively similar with the untransformed variable as well.

[24]Region is defined as any village or city within the state of residence.

[25]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.

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 1931 share of Muslims. We 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). To control for pre-1947 differences in migration across districts, we include the 1931 share of migrants in a district that were born outside the British Indian province or Princely State to which the district belonged.[26]

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 Pakistan, distance of the village/city of residence of the household to Bangladesh, 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.[27]

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

[26] 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).

[27] 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.

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 Pakistan 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 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 - as mentioned in the introduction, 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. The R^2 in specification (3) suggests our controls explain 86% 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 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.

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 idea 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

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

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.

The application of the Lewbel's method require three conditions to be met. First, the residuals from the regression mentioned above should indeed be heteroskedastic: this can be checked with a Breusch-Pagan test. Second, assuming that the number of the constructed instruments are larger than the number of endogenous variables, the instruments should pass a standard over identification test. Third, the constructed instruments should be correlated with the endogenous variable, which can be evaluated using the F-statistic. In our case, we choose, as is convention, exogenous variables within the full set available, such that the last two conditions are met.[28]

[28] 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.

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 your 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 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 spurious spatial correlations in the data. Using 25 studies on persistence, he 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 his 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$^{\text{th}}$ percentile and below the 10$^{\text{th}}$ 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.[29] 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

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

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 discussed in Section 4, we regress our potentially endogenous variable $Prop1951Displaced_{ds}$ on all the exogenous variables. A Breusch-Pagan test rejects the null hypothesis of constant variance at 1%.[30] Next, if we consider the dummy variable that the district has infertile soil and the mean annual rainfall as the relevant exogenous variables, and construct the instruments using the residual and these exogenous variables, then it satisfies the over-identification test (with a p value of 0.20) and has a Kleibergen-Paap rk Wald F statistic of 137.8. Thus it satisfies the identification conditions mentioned in section 4. The results using these instruments yields a coefficient for $Prop1951Displaced_{ds}$ as -0.11 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. Such selection into districts is likely to lead to underestimation of negative effects.

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 Partition. 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. [31]

[30] $\chi^2(1) = 665.24$

[31] Further disaggregation of our index into an index of social cohesion and index of trust yields that both

5.2 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 dimensions. Table 7 first looks at age.[32]

Individuals in our sample are 50 years 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, we find no differential linear effect by age and Partition displaced migration in specification (1). In specification (2), we use an indicator for individuals above the median age (52) in the sample. Again, we find 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), we interact Partition displaced migration 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 where as the former group represents those who were born around and just after partition. Our 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).[33] 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 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.

[32] 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.

[33] 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.

are only around 1,000 individuals aged 70 and above, and 285 individuals 80 and above in the sample. We are thus drawing interpretations based on fewer 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 we find strong results with the largest coefficient for those between ages 45-55 points out to the fact that our results are not driven by age groups which suffer from such biases.

We explore heterogeneity along other dimensions in Table 8. Specification (1) looks at gender. Male respondents score higher on the index of social capital, but we find 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 effects for them. We do find some heterogeneity for permanent residents in specification (3). Permanent residence is an indicator for whether individuals have lived their entire lives 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) we find no differential effects 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. So next we look at specific district characteristics.

5.3 Mechanisms

Now we test for underlying mechanisms by looking at current district conditions, specific factors mentioned in the Partition literature, issues of conflict, in particular Hindi-Muslim riots and incidents of crime. We directly add these factors as independent variables in the main regression and see if they attenuate the coefficient on Partition displaced migration. Formal mediation analysis requires one mediator variable. For the sake of presentation, we consider such analysis only in the case where the mediator is significantly correlated with partition migration and where inclusion of the mediator reduces the point estimate of the main variable of interest, the historical Parition displaced people in the district.

5.3.1 Current Conditions

While our results document a correlation between historical Partition displaced migration and contemporary social capital, the main analysis does not include controls for current differences across districts. Such variables are likely endogenous and bad controls in the language 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 explore this conjecture, specification (2) in Table 9 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 [34] 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 on 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 A7 reports the partial correla-

[34] 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.

tion between 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.[35] Appendix Table A7 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 9 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.

5.3.2 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.

[35] We construct a public goods index using principle component analysis of availability of public goods and use the first factor. The public goods we consider 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

To test whether these variables are mediating the results, we include these variables as additional controls in Table 10. 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. 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 A8 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.

5.3.3 Violence: Conflict and Crime

The influx of displaced migrants in 1951 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 differential exposure to riots across Partition displaced districts is the underlying mechanism, we control for the number of riots between 1950 and 1955 in column (2) and the number of riots between 1950 and 1995 in column (3) in Table 11. These data are from Varshney and Wilkinson (2006).[36]. In an alternative specification- column (4), we control

[36]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

for the riots per capita, averaged over the period 1997-2007, as reported by the National Crime Research Bureau (NCRB).[37] The results in Table 11 show that the riots between 1950-1955, i.e., historical riots just after the Partition, have statistically significant, though relative small in magnitude, role in explaining the baseline findings with the coefficient attenuating from 0.043 to 0.040. A formal mediation analysis (Appendix Table A10) reveals that 7.2 percent of the total effect is mediated by the riots just after Partition (1950-1955).

To augment this suggestive mechanism, we present additional evidence from micro data using the India Human Development Survey (IHDS) conducted in 2005.[38] 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 much conflict would you say there is among the communities/jatis that live here".[39]Based on the response to the question, we create a variable $Community conflict$ 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.[40].

The estimation results are presented in Table 12. 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

[37]Note that the district level data on riots and crime are available only from the period 1987 onwards. We deflate by the district population in 2001.

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

[39]Jatis refer to sub-caste groups like brahmins, rajputs, bhumihars, vaisyas etc.

[40]The IHDS does not cover all districts of India

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).

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 reported for 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 our mediator variable in column (2) of Table 13). The results reveal that the coefficient of interest attenuates with the inclusion of the crime variable). Moreover, formal mediation analysis in Table A10 shows that almost 17% of the effect comes through violent crime, with a 95 % confidence interval of 10-48 %. Thus partition districts also tend to be crime prone and mediate a non-trivial part of the impact of partition inflows on social capital.[41]

It is important to point out here while conflict and crime are essentially different potential mechanisms, there could be possible overlap due to the sensitivity of such issues. Civil strifes, especially along ethnic lines are often sensitive and may not be reported as such or could be

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

misspecified as violent crime.[42]. What we find is that these partition districts have evolved to be more violent and presence of such violence could be a potential source of low social capital.

6 Conclusion

This paper investigates the long run effect of the Indian Partition on contemporary social capital. The Partition was one of the largest forced migration events of the 20th century. 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 unearth some plausible mechanisms driving the main result: the riots in the aftermath of Partition, i.e., between 1950-1955, higher community conflicts as well violent crimes paint a strife driven picture of such districts and seem to 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-so no work on such a theme can have external validity. However, such episodes tell us what may happen-it is important therefore to guard against possible negative falls-outs. The lesson 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- can 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.

[42]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.

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7 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 Pakistan border	8,860	989.18	514.43	11.28	2076.70
Distance to Bangladesh border	8,860	836.22	578.46	0.40	1673.44
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
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	.083	0.86	1.75
1931 Controls					
Prop. Brahman,	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%
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
1931 Controls					
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 Ln, Prop. 1951 Partition Displaced Persons

	(1)	(2)	(3)
Distance to Pakistan border (District Av)	0.001	-0.003*	-0.002
	(0.002)	(0.002)	(0.002)
Distance to Bangladesh border (District Av)	-0.002	0.002	0.000
	(0.003)	(0.003)	(0.003)
Latitude	0.086	0.036	-0.051
	(0.870)	(0.760)	(0.657)
Square of Latitude	0.009	0.003	0.008
	(0.018)	(0.015)	(0.014)
Longitude	-2.019	1.238	0.529
	(2.792)	(2.477)	(2.245)
Square of Longitude	0.009	-0.006	-0.004
	(0.016)	(0.014)	(0.012)
Indicator, Sandy/Non fertile soil	-1.687	-0.030	-0.164
	(1.220)	(1.099)	(1.006)
Average River Length	-0.043	-0.031	-0.038
	(0.037)	(0.031)	(0.031)
Coastal District	0.303	0.968	-0.127
	(0.834)	(0.726)	(0.719)
Elevation	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
Area Square Mt	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Annual Rainfall	-0.001	-0.004	-0.000
	(0.003)	(0.003)	(0.003)
Prop. Brahman 1931		8.796**	1.602
		(4.274)	(5.482)
Prop. Muslim 1931		5.858***	5.980**
		(1.331)	(2.347)
Prop. Out of State, Migrants, 1931		8.957***	4.762
		(2.245)	(3.048)
Dummy: Princely State		-1.862***	-1.256***
		(0.436)	(0.442)

	(1)	(2)	(3)
Log of District Pop 1951			0.646*
			(0.328)
Prop. Urban 1951			2.105
			(1.607)
Prop Literate 1951			8.367**
			(3.785)
Prop. Muslim 1951			-2.629
			(2.918)
Gender Ratio 1951			0.907
			(2.229)
Share ST, 1951			2.032
			(1.671)
Share SC, 1951			3.516
			(2.139)
State FE	Yes	Yes	Yes
Observations	121	121	121
R^2	0.758	0.824	0.868

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

Table 4: Outcome - Index of Social Capital

	(1)	(2)	(3)	(4)	(5)
Ln, 1951 Prop Partition Displaced Persons	-0.054***	-0.043***	-0.047***	-0.043***	-0.043***
	(0.013)	(0.010)	(0.012)	(0.013)	(0.013)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.024	0.075	0.079	0.184	0.185
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 5: Index of Social Capital, Spatial Robustness Checks

	(1)	(2)	(3)	(4)
Ln, 1951 Prop Partition Displaced Persons	-0.048***	-0.040***	-0.029**	-0.047***
	(0.017)	(0.014)	(0.014)	(0.012)
Observations	7,422	7,764	7,972	7,853
R^2	0.172	0.170	0.155	0.135
Robustness Check	No Karnataka	No Maharashtra	Below 90^{th} percentile of Index	Above 10^{th} 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
Ln, 1951 Prop Partition Displaced Persons	-0.043***	-0.110***
	(0.013)	(0.043)
Observations	8,860	8,860
R^2	0.185	0.181
Hansen J Statistic (Over id)		1.657
p-value:		0.198
Kleibergen-Paap Wald F statistic		137.79

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

Table 7: Heterogeneous Effects by Age, Index of Social Capital

	(1)	(2)	(3)	(4)
Ln, 1951 Prop Partition Displaced Persons	-0.0595***	-0.0479***	-0.0412***	-0.0407***
	(0.0187)	(0.0132)	(0.0141)	(0.0141)
Age	-0.0034			
	(0.0021)			
Ln, 1951 Prop Displaced*Age	0.0003			
	(0.0003)			
Age - Above Median (52)		-0.0448		
		(0.0598)		
Ln, 1951 Prop Displaced*Age - Above Median		0.0093		
		(0.0096)		
Age Above 45			0.0325	
			(0.0678)	
Ln, 1951 Prop Displaced*Age - Above 45			-0.0025	
			(0.0097)	
Age 45-55				-0.0994
				(0.0694)
Ln, 1951 Prop Displaced*Age - 45-55				-0.0247***
				(0.0092)
Age Above 55				-0.0225
				(0.0772)
Ln, 1951 Prop Displaced*Age - Above 55				0.0054
				(0.0109)
Standard Controls	Yes	Yes	Yes	Yes
Observations	8,860	8,860	8,860	8,860
R^2	0.185	0.184	0.183	0.185

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

Table 8: Heterogeneous Effects, Index of Social Capital

	(1)	(2)	(3)	(4)	(5)
Ln, 1951 Prop Partition Displaced Persons	-0.03**	-0.04***	0.00	-0.03	-0.04***
	(0.015)	(0.013)	(0.024)	(0.020)	(0.013)
Ln, 1951 Prop Displaced*Male	-0.03				
	(0.020)				
Ln, 1951 Prop Displaced*SC		-0.01			
		(0.013)			
Ln, 1951 Prop Displaced*ST		0.01			
		(0.018)			
Ln, 1951 Prop Displaced*Muslim		0.02			
		(0.016)			
Ln, 1951 Prop Displaced*Permanent Resident			-0.05**		
			(0.021)		
Ln, 1951 Prop Displaced*Rural				-0.01	
				(0.015)	
Border District					-0.58**
					(0.237)
Ln, 1951 Prop Displaced*Border District					-0.12*
					(0.069)
Standard Controls	Yes	Yes	Yes	Yes	Yes
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.186	0.185	0.185	0.185	0.185

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

Table 9: Mechanisms, Current Conditions and Public Goods

	(1)	(2)	(3)
Ln, 1951 Prop Partition Displaced	-0.0430*** (0.0128)	-0.0427** (0.0136)	-0.0463*** (0.0158)
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

Table 10: Literacy, Urbanisation and Gender Ratios

	(1)	(2)	(3)	(4)
Ln, 1951 Prop Partition Displaced	-0.0421*** (0.0127)	-0.0448*** (0.0146)	-0.0559** (0.0226)	-0.0500*** (0.0166)
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	0.201	0.204	0.202	0.206

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

Table 11: Violence: Riots

	(1)	(2)	(3)	(4)
Ln, 1951 Prop Partition Displaced	-0.043*** (0.013)	-0.040*** (0.012)	-0.042*** (0.012)	-0.043*** (0.013)
Robustness Check	Baseline	Riots 1950-1955	Riots 1950-1995	Riots (NCRB) 1997-2007
Observations	8,860	8,860	8,860	8860
R^2	0.185	0.185	0.187	0.185

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

Table 12: Community conflict

	Community/Jati Conflict	
	All	
Ln, 1951 Prop Partition Displaced Persons	0.013* (0.007)	0.013* (0.007)
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	0.068	0.07

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.

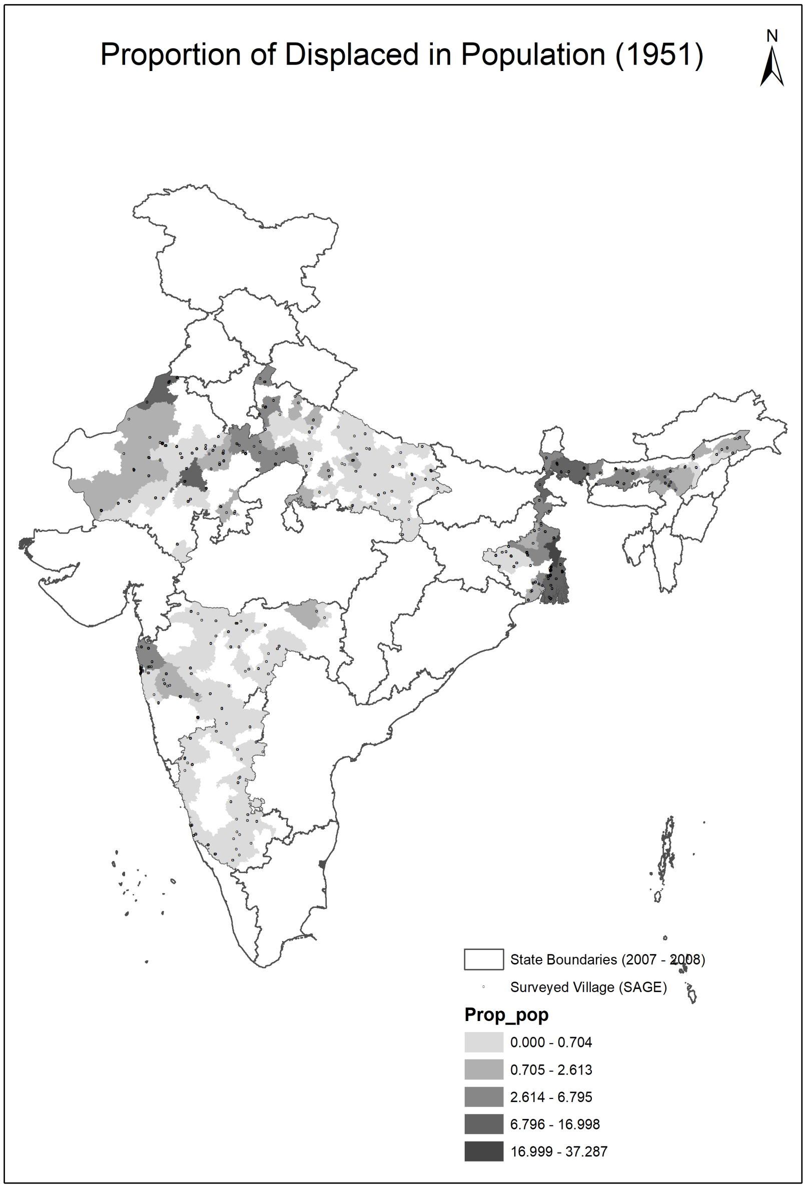
Table 13: Violence: Violent Crime

	(1)	(2)
Ln, 1951 Prop Partition Displaced	-0.043***	-0.036***
	(0.013)	(0.014)
Robustness Check	Baseline	Violent Crime (NCRB)
Observations	8,860	8,860
R^2	0.185	0.185

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

8 Figures

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



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

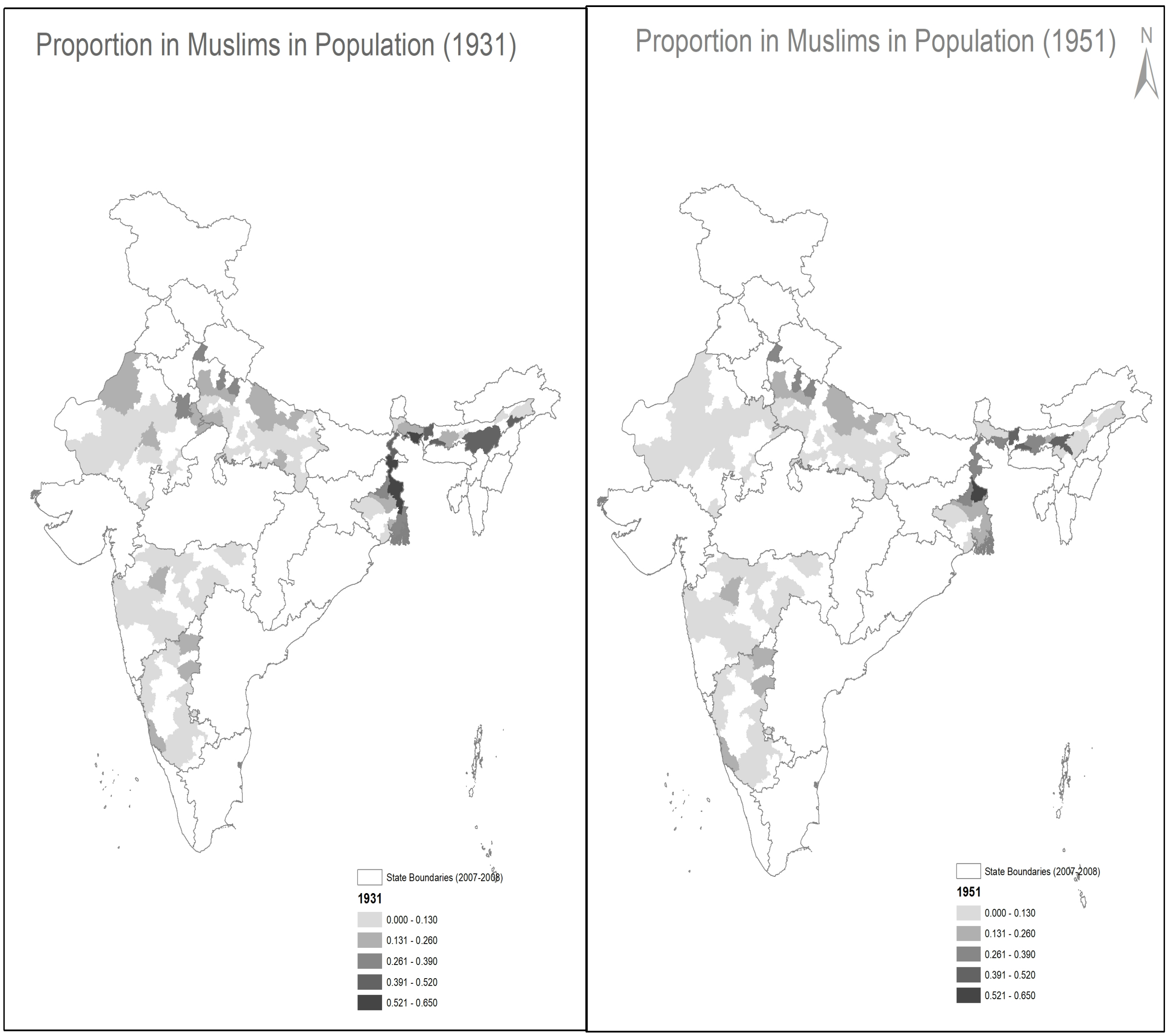
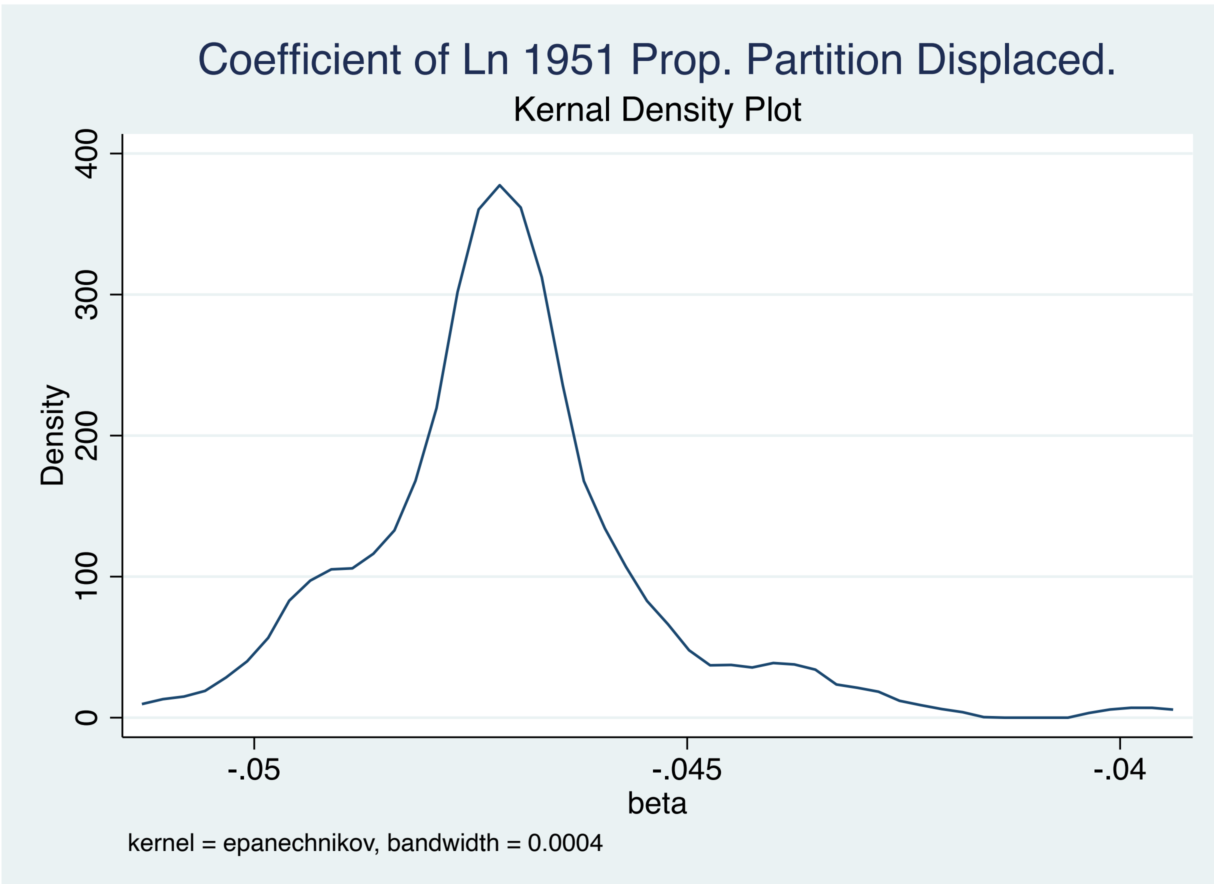


Figure 4: Dropping One District



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)
Ln, 1951 Prop Partition Displaced Persons	-0.054***	-0.043***	-0.047***	-0.043***	-0.043***
	(0.013)	(0.010)	(0.012)	(0.013)	(0.013)
Distance to Pakistan border		-0.002	-0.002	-0.002	-0.002
(in 10 km units)		(0.002)	(0.002)	(0.002)	(0.002)
Distance to Bangladesh border		-0.001	-0.001	-0.000	0.000
(in 10 km units)		(0.003)	(0.004)	(0.004)	(0.004)
Latitude		-0.174**	-0.274***	-0.240***	-0.239***
		(0.073)	(0.086)	(0.089)	(0.089)
Square of Latitude		0.005***	0.007***	0.006***	0.006***
		(0.002)	(0.002)	(0.002)	(0.002)
Longitude		0.132	0.344	0.516	0.526
		(0.253)	(0.341)	(0.382)	(0.382)
Square of Longitude		-0.001	-0.002	-0.003	-0.003
		(0.001)	(0.002)	(0.002)	(0.002)
Indicator, Sandy/Non fertile		-0.383***	-0.332**	-0.348**	-0.351**
soil		(0.137)	(0.134)	(0.134)	(0.134)
Average River Length		0.008*	0.006	0.006	0.006
		(0.004)	(0.006)	(0.006)	(0.006)
Coastal District		0.105	0.060	0.086	0.085
		(0.089)	(0.088)	(0.076)	(0.077))
Elevation		-0.003**	-0.005***	-0.005***	-0.005***
(in 10 mt units)		(0.001)	(0.002)	(0.002)	(0.002)
Area Square Mt		0.001	0.002	0.005	0.005
		(0.006)	(0.006)	(0.006)	(0.006)
Rural Dummy		-0.005	-0.005	0.046	0.048
		(0.047)	(0.049)	(0.042)	(0.042)
Annual Rainfall		-0.002***	-0.002***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)

	(1)	(2)	(3)	(4)	(5)
Prop. Brahman, 1931			0.932	1.175	1.187
			(0.749)	(0.759)	(0.756)
Prop. Muslim, 1931			-0.413	-0.576	-0.575
			(0.356)	(0.363)	(0.364)
Prop. Out of State, Migrants,1931			-0.007	-0.169	-0.170
			(0.583)	(0.580)	(0.577)
Dummy: Princely State			-0.039	-0.001	-0.001
			(0.071)	(0.065)	(0.065)
Ln, Pop 1951			0.000	-0.037	-0.040
			(0.052)	(0.056)	(0.057)
Prop. Urban, 1951			0.286	0.503**	0.490**
			(0.231)	(0.233)	(0.231)
Lit Rate, 1951			-0.356	-0.408	-0.383
			(0.542)	(0.551)	(0.550)
Prop. Muslim, 1951			0.160	0.447	0.459
			(0.460)	(0.474)	(0.477)
Gender Ratio 1951			0.223	-0.071	-0.051
			(0.520)	(0.522)	(0.519)
Prop ST, 1951			0.538*	0.286	0.275
			(0.311)	(0.325)	(0.328)
Prop SC, 1951			-0.708	-0.651	-0.651
			(0.563)	(0.576)	(0.578)
Age				-0.004***	-0.005***
				(0.001)	(0.002)
Male				0.560***	0.556***
				(0.056)	(0.059)
SC				-0.036	-0.037
				(0.030)	(0.030)
ST				0.070	0.067
				(0.069)	(0.070)
Permanent Resident				-0.002	-0.007
				(0.062)	(0.062)
Years of Education				0.023***	0.022***
				(0.003)	(0.003)
Married				0.087***	0.089***
				(0.030)	(0.032)
Never Married				-0.066	-0.060
				(0.063)	(0.068)
Hindu				0.033	0.041
				(0.045)	(0.045)
Religion-Other				0.106	0.117*
				(0.067)	(0.067)

	(1)	(2)	(3)	(4)	(5)
Household Size					0.001
					(0.006)
# Children below 10					0.000
					(0.012)
Avg. Educ Household					0.002
					(0.005)
Avg. Age Household					-0.002
					(0.001)
Old Household Strata					0.078*
					(0.042)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.024	0.075	0.079	0.184	0.185
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 A3: Dropping One State

	(1)	(2)	(3)	(4)	(5)
Ln, 1951 Prop Partition Displaced	-0.042***	-0.05***	-0.036***	-0.040**	-0.040***
	(0.013)	(0.016)	(0.012)	(0.016)	(0.013)
Observations	7,878	7,461	6,666	7,109	8,825
R^2	0.201	0.197	0.196	0.172	0.184
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)
Ln, 1951 Prop	-0.043***	-0.043***	-0.043***	-0.043***	-0.043***
Partition Displaced Persons	(0.012)	(0.009)	(0.009)	(0.007)	(0.008)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.185	0.185	0.185	0.185	0.185
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)
Ln, 1951 Prop Partition Displaced Persons	-0.055***	-0.035**	-0.041***	-0.036***	-0.036***
	(0.015)	(0.013)	(0.015)	(0.014)	(0.014)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.024	0.087	0.092	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)
Ln, 1951 Prop Partition Displaced Persons	-0.017	-0.026*	-0.023	-0.024	-0.023
	(0.012)	(0.014)	(0.019)	(0.020)	(0.020)
Observations	8,860	8,860	8,860	8,860	8,860
R^2	0.002	0.051	0.055	0.074	0.075
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: Current Conditions and Partition Migration

	(1)	(2)	(3)	(4)
	Muslim Share, 2001	District Pop, 2001	% SC, 2001	% ST, 2001
Ln, 1951 Prop Partition Displaced	-0.003 (0.003)	0.020 (0.031)	1.246 (1.879)	0.702 (1.021)
	Ln Lights, 2001	Share Urban, 2001	% Illiteracy, 2001	Share Migrants, 2001
Ln, 1951 Prop Partition Displaced	0.078** (0.032)	0.023*** (0.008)	-0.847 (0.632)	0.009 (0.006)
	Public Goods, Educ	Public Goods, Med	Public Goods, Water	Public Goods, Power
Ln, 1951 Prop Partition Displaced	84.7 (77.1)	26.5 (38.4)	172.2 (115.1)	75.2 (59.6)
	Public Goods, Bus	Public Goods, Rail	Public Goods, Road	
Ln, 1951 Prop Partition Displaced	28.2 (26.3)	1.98 (3.8)	46.95 (33.9)	

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 A8: 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
Ln, 1951 Prop Partition Displaced	0.022*	0.026**	0.032**	0.038***	0.026***
	(0.013)	(0.011)	(0.013)	(0.013)	(0.010)
	Share Literate, 1961	Share Literate, 1971	Share Literate, 1981	Share Literate, 1991	Share Literate, 2001
Ln, 1951 Prop Partition Displaced	0.007*	0.010**	0.012***	0.010**	0.010
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
	Gender Ratio, 1961	Gender Ratio, 1971	Gender Ratio, 1981	Gender Ratio, 1991	Gender Ratio, 2001
Ln, 1951 Prop Partition Displaced	0.006***	0.006**	0.012***	0.013***	0.012***
	(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 A9: Violence: Riots and Crime

	(1)	(2)	(3)	(4)
	Riots 1950-1955	Riots 1950-1995	Riots (NCRB) 1997-2007, per 10,000	Violent Crime (NCRB) per 10,000
Ln, 1951 Prop Partition Displaced	0.065**	0.223**	0.018	0.07***
	(0.031)	(0.085)	(0.061)	(0.023)

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 A10: Mediation Analysis

Mediator	% of Total Effect Mediated	[95 % Confidence Interval]
Riots 1950-1955	7.2	[4.5,16.3]
Violent Crimes per 10,000	17.6	[10.7,48.04]

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