Global Economic Integration and Nativist Politics in India

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Abstract

Nativist political movements are globally ascendant. In advanced democracies, rising anti-immigrant politics is in part a backlash against economic globalization. In emerging economies, where nativists primarily target internal migrants, there is little investigation of whether trade liberalization fuels anti-migrant sentiment, perhaps because trade benefits workers in these contexts. I argue that global economic integration causes nativist backlash in emerging economies even though it does not dislocate workers. I highlight an alternative mechanism: geographic labor mobility. Workers strategically migrate to access geographically uneven global economic opportunity. This liberalization-induced mobility interacts with native-migrant cleavages to generate nativist backlash. I explore these dynamics in the Indian textile sector, which experienced a positive shock following global trade liberalization in 2005. Using a difference-in-differences analysis, I find that exposed localities experienced increased internal migration and nativism, manifesting in anti-migrant rioting and nativist party support. Liberalization can fuel nativism even when its economic impacts are positive.

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Nativist movements are ascendant across a range of global contexts. Politicians in advanced democracies who promise to restrict ***international*** migration and limit migrant rights have enjoyed recent electoral success (Noury and Roland 2020). Nativism is similarly pervasive in emerging economies. Though anti-immigrant sentiment is typically directed at ***internal*** migrants, the political dynamics are in many ways analogous (Bhavnani and Lacina 2018). Politicians increasingly accommodate nativist demands, excluding internal migrants from local employment and social services and engaging in violent repression (Thachil 2020; Gaikwad and Nellis 2021).[1] What explains the global success of nativist political movements?

In the United States and Europe, the politicization of nativist attitudes is in part a backlash against globalization. Trade liberalization drives anti-immigrant movements when it causes economic dislocation and fears of status threat (Colantone and Stanig 2019; Rhodes-Purdy et al. 2021). Increasing exposure to import competition contributed to the election of Donald Trump (Jensen et al. 2017), Brexit (Colantone and Stanig 2018), and the rise of radical right anti-immigrant parties (Colantone and Stanig 2019). Does globalization cause rising nativism in emerging economies? Workers in these contexts are also increasingly integrated into global markets, yet there is little investigation of liberalization's consequences for nativist movements outside the Global North.

Existing perspectives suggest that liberalization should ***not*** cause nativist backlash in emerging economies. Political economy models predict that deepening integration brings new employment and higher wages to the majority of workers in these contexts – the opposite of what occurs in advanced economies (Milner and Kubota 2005; Hanson 2012; Gaikwad and Suryanarayan 2021). Because mobilizing dislocated voters or credibly stoking fears of status threat is not possible, it might appear that globalization has little to do with the success of anti-immigrant politics in such environments.

I argue that global economic integration ***does*** fuel nativist movements in emerging economies,

[1] Appendix Figure A.1 shows a growing trend of lower-income countries adopting restrictive internal migration policies.

though not via economic dislocation. I instead foreground a novel causal mechanism: ***geographic labor mobility***. When liberalization brings new opportunity, many people are poorly positioned to take advantage. Because emerging economies are weakly ***internally*** integrated, export-oriented production clusters in the handful of localities with requisite infrastructure and access to global markets (Fujita and Hu 2001). As a result, most people are initially excluded from new global opportunities. These unequal concentrations of new employment increase the returns to geographic mobility, stimulating internal migration toward centers of export-oriented production (Hering and Paillacar 2016; Facchini et al. 2019; Ghose 2021).

Liberalization-induced labor mobility interacts with existing native-migrant cleavages, generating nativist reaction on the part of locals against migrants. In emerging economies, where within-country ethnolinguistic diversity is often high, internal migration is as politically controversial as international migration in the US and Europe. Natives charge that migrants take job opportunities and overburden public services, and political parties take up their cause (Bhavnani and Lacina 2015; Gaikwad and Nellis 2017, 2021).[2] This manifests in anti-migrant violence and support for nativist parties. In short, I argue that in contexts where globalization stimulates new internal population flows, it can activate nativist sentiment and cause anti-immigrant backlash.

I investigate these dynamics in India, an emerging economy that is increasingly integrated into world markets. I focus on textile and apparel production, an industry in which India is a global leader, experiencing massive growth over the past several decades. This growth is in large part due to trade liberalization (Mukherjee and Mukherjee 2012). The Indian textile sector's labor force is largely composed of lower-skilled interstate migrants, many of whom move from rural states (Kumar et al. 2020).

I harness the expiration of the Multi-Fiber Arrangement (MFA), an international agreement that governed trade in textiles, in 2005 as an external shock to Indian textile pro-

[2]Whether migrants actually have these effects is a separate question; the economic consensus casts serious doubt on this proposition (Hainmueller and Hopkins 2014).

duction. The expiration of the MFA meant that overnight, 40 percent of Indian textile production was freed from quotas (Harrigan and Barrows 2009), leading to massive new investment and integration into world markets (see Figure 1) (Alam et al. 2019). Using a difference-in-difference research design, I show that this shock increased rioting in exposed localities, a form of public violence closely related to nativist concerns in India (Bhavnani and Lacina 2015). I also show that liberalization increased internal migration toward centers of textile production, and liberalization-exposed areas with greater inward migration saw the largest increases in rioting. Politically, I find that this shock increased support for nativist parties. These results are robust to alternative explanations and suggest a substantively important relationship between global economic integration and nativism in India.

Existing research highlights that liberalization drives anti-immigrant backlash when it results in economic dislocation. This article suggests that global economic integration can contribute to nativist movements via its ostensibly *positive* economic impacts. When liberalization incentivizes human mobility, it can provide new fuel to anti-immigrant movements in contexts where internal migration is contentious. While my findings are limited to India, my framework is more generally applicable to emerging economies, where animus toward internal migrants is widespread (Bhavnani and Lacina 2018; Thachil 2020).

My findings suggest that globalization can threaten domestic political stability, limiting the gains to integration for some workers. Liberalization should benefit lower-skilled workers and provide employment opportunities to groups who face discrimination in domestic labor markets (Milner and Kubota 2005; Peters and Osgood 2017; Li et al. 2020; Gaikwad and Suryanarayan 2021). Yet if accessing these opportunities requires physically moving, members of these groups are likely to face political exclusion by virtue of being migrants. Reaping the gains of openness requires addressing social cleavages that globalization activates, particularly by intervening to empower internal migrants (Gaikwad and Nellis 2021).

Global Economic Integration and Nativism

Political economy scholars increasingly blame economic globalization for the rise of nativist movements in the US and Europe. Trade liberalization creates economic adversity for some workers in advanced economies. Specific factors models predict that liberalization increases real returns to relatively abundant factors of production and decreases returns to relatively scarce factors (Stolper and Samuelson 1941). In labor-scarce economies, trade lowers the real returns to workers and leads to economic dislocation. More sophisticated models also illustrate that liberalization has adverse consequences for workers in advanced economies, particularly in labor-intensive industries (Autor et al. 2016).

Scholars leverage heterogeneity in exposure to liberalization to identify whether it fuels nativist backlash.[3] An emerging consensus suggests that liberalization contributes to the success of anti-immigrant parties and politicians who promise to reduce *international* migration. Import competition from emerging economies is linked to stronger support for Brexit (Colantone and Stanig 2018), the rise of nativist radical right parties in Europe (Colantone and Stanig 2019), and the election of Donald Trump in 2016 (Jensen et al. 2017).[4] In each case, liberalization resulted in electoral success for anti-immigrant politicians. The dislocation that results from trade generates status threat, pushing voters to support parties who claim they will address economic distress and preserve social hierarchies (Baccini and Weymouth 2021; Ballard-Rosa et al. 2021). Restricting immigration – and curtailing the rights of foreigners – is a primary objective of these political entrepreneurs, as immigrants serve as a scapegoat for economic woes (Colantone and Stanig 2019).

There is little exploration of this relationship in emerging economies, where nativism similarly flourishes. New research documents growth in anti-immigrant politics in India, Pak-

[3]See Noury and Roland (2020) for an overview of globalization and nativism in Europe.

[4]See Scheve and Serlin (2021), who find a trade shock in Great Britain increased support for left-wing parties. They also find that this shock elevated xenophobic concerns.

istan, South Africa, Malaysia, and Brazil (Gaikwad and Nellis 2017; Bhavnani and Lacina 2018; Thachil 2020). The focus of nativist political entrepreneurs in these contexts is typically on *internal* rather than *international* migrants, but the dynamics are largely analogous. Because ethnic, religious, and cultural differences are typically more pronounced in developing countries, internal migration is equally politically contentious. Nativist political parties capitalize by valorizing subnational groups and vilifying out-groups. They fight for nativist affirmative action policies, exclude migrants from social services, promote migrant discrimination, and organize anti-migrant violence (Bhavnani and Lacina 2015). Migrants, who often face exclusion, have little power to counter nativist voters (Gaikwad and Nellis 2021).

What explains the rising tide of nativist politics outside advanced democracies? Despite growing interest in nativism in emerging economies, we do not know whether global economic integration plays a role. The episodes of liberalization that dislocated workers in advanced economies involved the increasing integration of countries like China, India, Brazil, and Mexico into world markets (UNCTAD 2019). Can globalization be blamed for the success of anti-immigrant movements beyond the US and Europe?

Trade models give little reason to expect that globalization should fuel nativism in these contexts. While workers in labor-scarce economies *suffer* from liberalization, workers in labor-abundant economies should *benefit.* Liberalization increases the real returns to workers in emerging economies, increasing employment and wages, especially in the formal sector (McCaig and Pavcnik 2018).[5] Widespread economic dislocation in the US and Europe often corresponds to large *increases* in labor demand in emerging economies as labor-intensive production geographically shifts (Hanson 2012). At first glance, there is little reason to suspect that global economic integration should contribute to nativist backlash when its economic impacts are *beneficial* for the majority of workers.

[5] Gaikwad and Suryanarayan (2021) also identify that trade benefits workers in emerging economies, linking liberalization's benefits for marginalized ethnic groups to greater support for openness in India.

Liberalization, Internal Migration, and Nativism

I argue that global economic integration *does* cause nativist backlash in emerging economies, even though it does not result in economic dislocation for many workers. Instead, I highlight an alternative causal mechanism: *geographic labor mobility*. My argument focuses on how workers in emerging economies strategically migrate in response to liberalization, and how those migration decisions interact with social cleavages to cause nativist political backlash.

Models of trade predict that liberalization should benefit workers in labor-abundant economies, increasing employment and wages. Yet on-the-ground realities create frictions that are not acknowledged in simple economic models. Structural conditions in emerging economies prevent many people from reaping the gains of globalization. A lack of *internal* economic integration means that many workers are geographically distant from global production, effectively excluding them from these opportunities. Infrastructure that is prerequisite to competing in global markets, such as roads, railroads, ports, and electricity, is severely under-provided in emerging economies (Schwab 2017). Because only a handful of localities possess the conditions necessary for export-oriented production, global employment opportunities cluster in a small number of locations (Fujita and Hu 2001).

As a result, while liberalization increases labor demand in emerging economies, it does so unequally across space. Localities with sufficient infrastructure provision, a concentration of industry affected by liberalization, and connections to world markets will see large increases in labor demand; other areas may see weaker, or no, gains. How do workers respond? As new production clusters subnationally, I argue that it incentivizes geographic labor mobility: workers *migrate* toward areas of export-oriented production to take advantage of increased labor demand that liberalization brings. Geographic mobility is a strategic response to the arrival of new employment opportunity. In particular, relatively lower-skilled workers who represent an emerging economy's comparative advantage migrate in response to integration. The result is trade-induced geographic labor mobility toward export-oriented localities.

This proposition is substantiated by economics research. In China, market-oriented reforms generated migration toward localities with export-oriented production (Liang 1999). China's entry into agreements like the World Trade Organization (WTO) and Permanent Normal Trade Relations (PNTR) with the US stimulated internal labor mobility toward centers of global production (Cheng and Potlogea 2018; Facchini et al. 2019). Global economic integration also led the Chinese government to relax ***hukou***, China's restrictive internal migration regulations (Tian 2019).

Beyond China, an exogenous positive shock to the Indian information technology (IT) sector due to the Year 2000 Problem (Y2K) resulted in significant internal migration to take advantage of increased labor demand (Ghose 2021). Meanwhile, the entry of labor-intensive production in Brazil generated internal migration toward places in which global production agglomerated (Hering and Paillacar 2016). Across a range of emerging economies, liberalization leads to greater internal migration to take advantage of the geographically unequal opportunities that liberalization creates. Notably, research on trade shocks in the US and Europe, where internal economic integration is much deeper, finds that relatively little geographic mobility occurs as a result of import competition.[6]

I argue that liberalization-induced internal migration interacts with native-migrant cleavages to activate nativist sentiment. The increase in migration that results from global economic integration increases contact between ethnically and linguistically different groups, heightening feelings of social threat among natives (Enos 2014; Hangartner et al. 2019). The presence of larger migrant populations feeds nativist fears of burdened social services and public goods. This heightened feeling of threat and competition provides an opening for political entrepreneurs, who construct nativist appeals for local citizens and organize anti-immigrant backlash. Even though liberalization may not increase labor market competition between natives and migrants in emerging economies, as it broadly brings economic benefits,

[6]See p. 1,829 in Autor et al. (2014) for a discussion of how geographic labor mobility is of little importance in Americans' adjustment to import competition.

it can fuel anti-immigrant political behavior by inducing greater native-migrant interaction.

In short, liberalization stimulates migrant flows in emerging economies, contributing to nativist backlash in places where export-oriented production concentrates. While migration may broadly activate nativist sentiment, this might especially be the case if liberalization incentivizes marginalized groups to migrate, who due to discrimination are on average lower-skilled. Several accounts suggest that these populations stand to benefit most from globalization (Milner and Kubota 2005; Peters and Osgood 2017; Gaikwad and Suryanarayan 2021), and might be most incentivized to migrate. Because conflict already exists between dominant and marginalized groups, liberalization could be particularly relevant for understanding nativist movements outside advanced economies.

My argument arrives at a counterintuitive point in the political economy of liberalization literature. Existing research finds that economic dislocation resulting from global economic integration causes nativist backlash in the US and Europe (Colantone and Stanig 2019). My argument suggests that liberalization can also cause anti-immigrant behavior in emerging economies when its economic impacts are ostensibly *positive*. When liberalization generates new internal migration toward centers of labor demand, it can provoke anti-immigrant backlash by natives in exposed areas.

My framework posits a mechanism, internal labor mobility, not acknowledged by existing research. While few people migrate following liberalization in the US and Europe, this is not the case in emerging economies. Due to subnational inequalities in internal integration, global opportunities are more geographically concentrated, increasing the returns to internal migration (Cheng and Potlogea 2018; Erten and Leight 2019). Workers in the US and Europe compensate for dislocation via social safety nets (Autor et al. 2016), allowing them to remain immobile despite incentives to migrate. Minimal welfare provision in emerging economies means that the costs of remaining *im*mobile despite new opportunity are higher. Identifying how liberalization causes nativist backlash in emerging economies requires grappling with different initial conditions and causal mechanisms beyond static income effects.

Background: India, Textiles, and Nativism

I apply my argument to India, the fifth-largest economy and largest electoral democracy. Since the early 1990s, India has liberalized its economy, reducing tariffs and restrictions on foreign capital (Topalova and Khandelwal 2011; Li et al. 2020). This makes India an informative case – an emerging economy with weak internal integration that has become increasingly connected with the global economy.

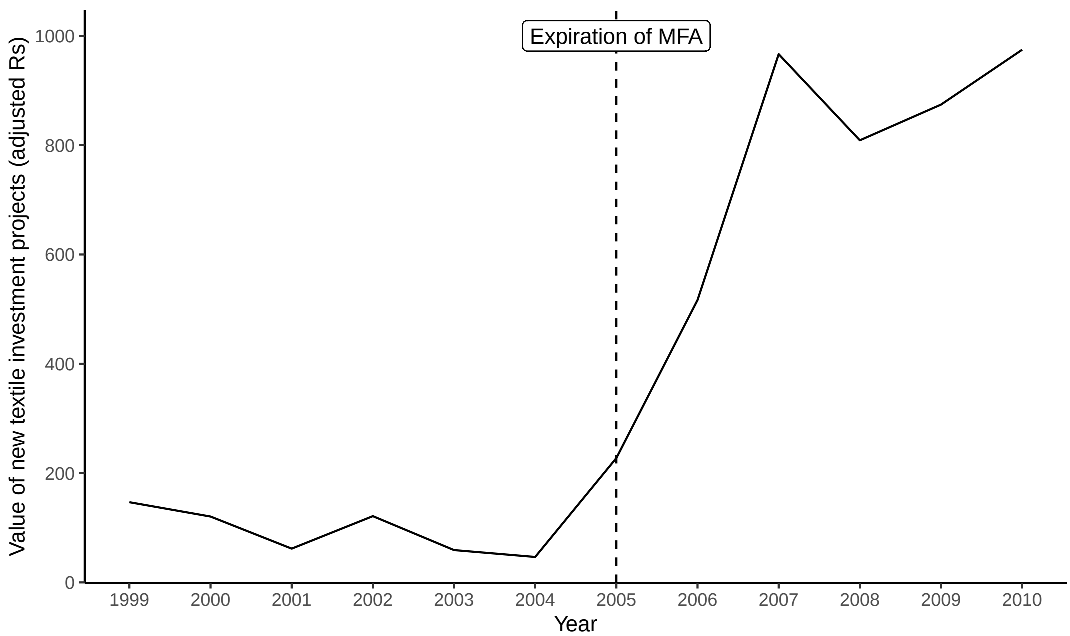
Indian Textile Sector and the MFA

I focus on the Indian textile and apparel sector. India has a large and globally competitive textile sector: it is the world's second largest producer of textiles and garments (after China). Textile production is the oldest and largest manufacturing activity, employing 45 million workers; only agriculture employs more. Textiles and apparel account for about 2.5 percent of India's GDP and 15 percent of its export earnings (IBEF 2020). The textile industry is central in the history of globalization: building a textile and apparel sector is often a first step toward global economic integration (Rosen 2002).

Besides being a large part of the economy, the textile and apparel sector has grown significantly due to trade liberalization. From 1974 to 1995, global trade in textiles and apparel was governed by the Multi-Fiber Arrangement (MFA). The MFA constructed a system of quotas limiting the amount that developing countries could export to developed countries. In 1995, the Agreement on Textiles and Clothing (ATC) was created to phase out the protectionist MFA gradually. Over a period of ten years, all quotas would be eliminated, at which point textiles and apparel would be brought under WTO rules.

However, the ATC's gradual roll-out did not go according to plan. A large proportion of quotas remained until the end of the ten-year period, on January 1, 2005. This overnight elimination of a large number of quotas created an abrupt shock to international textile trade. For instance, approximately 40 percent of India's textile exports were relieved from quotas instantly (Harrigan and Barrows 2009). While observers recognized that the end of the

Figure 1: New Capital Investment In Textiles in India, 1999-2010



Value (in inflation-adjusted rupees) of new textile investment in India, 1999-2010. (Source: CapEx, Center for Monitoring the Indian Economy).

MFA would reshape world markets, predictions as to which countries would "win" or "lose" were uncertain. Most experts agreed that China would see increased global market share, while firms in advanced economies would lose (Brambilla et al. 2010). However, precise estimates as to the effects on other countries, such as India, Bangladesh, and Vietnam, differed significantly (Alam et al. 2019).

Soon after the MFA's full expiration at the end of 2004, its beneficial effects for India became clear. Figure 1 illustrates the positive shock to capital investment that the Indian textile sector experienced following liberalization. The figure shows the inflation-adjusted value of new domestically owned textile investment projects in rupees between 1999 and 2010.[7] 2005-2010 represents a sea change in terms of industry growth.

This investment growth proved globally significant: India gained about 2.2 percentage points of global market share in apparel between 2004 and 2014, and its export growth

[7]I discuss these data in much greater detail in the section that follows.

rate doubled post-liberalization. Only a handful of other countries, primarily China and Bangladesh, benefited more than India (Harrigan and Barrows 2009; Alam et al. 2019). I use the expiration of the MFA as a shock to the Indian textile sector and explore its consequences for nativist politics.

Migrants in the Indian Textile Sector

The Indian textile sector employs a large number of internal migrants. Some reports suggest that a substantial majority of Indian textile workers are interstate migrants (Kumar et al. 2020). Textile production attracts workers engaged in agriculture and informal employment. In Northern India, producers primarily employ migrants from rural and less developed states like Bihar and Uttar Pradesh (ILO 2017). In Southern Indian clusters, producers often use contractors to recruit out-of-state migrants (Mezzadri and Srivastava 2015).

Migrant workers in the textile and apparel industry often come from marginalized communities, either belonging to religious minorities or Scheduled Castes. They often live in dense urban slum areas and share housing with migrants from the same origin village (Kumar et al. 2020).[8] Migrant textile workers are primarily employed on short-term contracts, and though wages are higher than in agricultural and informal production, they typically remain below the technical Indian minimum wage for manufacturing. While men have been the primary beneficiaries of increased textile employment, women are increasingly engaged in production, especially in southern clusters like Tiruppur and Bangalore (ILO 2017). Migrant workers are often blamed by natives for depressing wages and undercutting unionization efforts, though there is little solid supporting evidence (Mezzadri and Srivastava 2015).

Nativism in India

Nativist politics have a long history in India. "Sons-of-the-soil" movements are a well-studied phenomenon; members of these movements charge that migrants unfairly take local economic

[8] For more historical and ethnographic accounts of textile-related migration in India, see Dandekar (1986) and De Haan (1997).

opportunities without adequately contributing to the maintenance of public goods (Weiner 1978). The Shiv Sena, a nativist political party based in Maharashtra, has historically made its name on anti-migrant rhetoric and the promotion of affirmative action for natives (Verma 2011).[9] Nativism is not limited to certain areas of India, but rather is a pervasive dynamic, and is often wrapped up in other religious, ethnic, and caste-based divides (Abbas 2016). As a recent example, the state of Haryana passed a bill in March 2021 that reserves 75 percent of positions in ***private*** employment for natives for the next ten years (Mint 2021). State repression of migrants by the police is commonplace (Thachil 2020) and migrants face political exclusion in their destination communities (Gaikwad and Nellis 2021).

The success of nativist movements, driven by increases in internal migration, is often accompanied by outbreaks of violence in the form of rioting. Native-migrant conflict is often at the root of communal riots (Bhavnani and Lacina 2015, 2018). In 2018, for instance, natives in Gujarat targeted migrant workers in a week of rioting, pushing tens of thousands of migrants to flee (BBC 2018). More recently, the mobility restrictions enacted by the Indian government during the COVID-19 pandemic have fomented violence against migrants, who were unable to return home and did not receive adequate public services (Mehta 2020).

Although identifying the root cause of any particular riot is difficult if not impossible, the historical record demonstrates frequent entanglement of migrant workers, textile production, and the outbreak of public violence. In his seminal study of riots in India, Wilkinson (2004, p. 15) notes that Muslim migrant workers in Mumbai's textile and garment industry found themselves in the middle of riots in 1993, with many of them fleeing to their home states of Uttar Pradesh and Bihar to escape targeting. Wilkinson also notes that in Bhiwandi and Meerut, increasing economic competition in the textile and garment industry between natives and newcomers has been said to contribute to large-scale riots; these divides often align with other cleavages, particularly religious ones (Wilkinson 2004, p. 27-28).

[9]Recently, the Shiv Sena has arguably shifted toward a broader Hindu nationalist message and a stronger focus on governance during the COVID-19 pandemic (Koppikar 2020).

An archival search of *The Times of India* reveals many instances in which the textile sector and migrant workers are mentioned in the context of riots.[10] A 2002 *Times* report from Ahmedabad suggested that recent rioting was the result of Dalit and Muslim migrant textile workers who lived close together in poorer neighborhoods (Mehta 2002). *The Times* often highlights the outbreak of riots in textile-producing cities, including Solapur (Staff 2002), Bhiwandi (Staff 2006a), Malegaon (Staff 2006b), and Kolhapur (Staff 2009). When riots have occurred, articles frequently report that migrant textile workers flee to their homes, indicating that migrants are worried about being the target of violence (e.g. Staff 1984, 1994). The busing in of migrant workers to break strikes is sometimes cited as a contributing factor to the outbreak of riots (Staff 1927; Date 1993). These reports illustrate the frequent interaction of textile production, mobile labor, and rioting in India.

My expectation is straightforward: the expiration of the MFA in 2005 created a sudden, positive shock to export-oriented textile production in India. This shock generated new investment, increasing employment opportunities unequally across space and attracting new migrants to centers of production. The rise in migration toward these centers activated existing nativist sentiment and catalyzed an anti-migrant backlash from locals, resulting in the outbreak of nativist rioting.

Empirical Analysis

I use a difference-in-differences research design to estimate the effect of exposure to the MFA's expiration on rioting between 1999 and 2010. To do so, I employ data on rioting crimes, textile employment, new textile investment, and internal migration. The empirical analyses presented here use Indian administrative districts as the unit of observation. Districts are somewhat equivalent to American counties in that they nest within states, but are typically much larger in population. There are approximately 580 districts in India. All analyses use district boundaries set at the 2001 Indian Census; all districts created after 2001 were

[10] I conducted this search using ProQuest's *Times of India* database.

reassigned to their previous 2001 district status.[11] I include all mainland districts in the analysis with the exception of those in the state of Rajasthan, due to reporting irregularities of rioting crimes in that state.[12]

Dependent Variable: Riots

My primary dependent variable to measure nativist sentiment is the count of reported rioting crimes in a district-year.[13] Rioting is defined in India as the use of violence by groups of five people or more toward a commonly shared goal (NCRB 2001). Rioting data is reported by district police forces and is available from the National Crime Records Bureau (NCRB).[14] I collect district-level data on murder from the NCRB for use in subsequent placebo tests.

Bhavnani and Lacina (2015) discuss the advantages and disadvantages of using aggregate reported rioting crimes in analyses of nativism. One issue is that the variable reflects total rioting, not only riots with nativist origins. However, in India, riots cannot be reliably distinguished between their causes. There is intense elite competition to define the initial cause of rioting, with religious divides often dominating (Brass 1997). This masks the importance

[11] I also employ data that falls slightly before the 2001 Census. District boundaries in this short time frame were quite stable and largely align with 2001 Census classifications.

[12] Rioting crimes in Rajasthani districts follow a highly irregular and statistically implausible trend when compared to districts in other states. Each Rajasthani district experiences massive, monotonic declines in rioting crimes during this period. Jaipur, for instance, experienced an implausible 30-fold decline in rioting crimes during the period. Other Rajasthani districts experienced 15-fold declines or more. This trend was not present in any other state, and there is no clear explanation available other than statistical irregularity. As a result, I exclude Rajasthani districts from the analysis of rioting crimes. However, the main results hold when excluding only Jaipur, the worst offender, from the analysis. Results are available upon request.

[13] Appendix Figure A.2 shows a density plot of rioting crimes for all district-years.

[14] An alternative source of rioting data in India is Varshney and Wilkinson (2006), who identify riots using newspaper reports. This data ends before the MFA expiration.

of nativism as a driver of violence, which is prevalent in India but significantly underreported. For instance, riots deemed as religious or ethnic in nature may spring from the fact that migrants belong to different religious or ethnic groups, as Bhavnani and Lacina (2015) illustrate. While these reasons justify employing total rioting as a meaningful measure of nativism, I estimate the effect of exposure to the MFA on murder to test if liberalization specifically affects rioting alone and not broader violent crime. I also estimate models that identify the effect of differential increases in immigration on rioting across exposed districts.

Independent Variable: Exposure to Post-MFA Shock

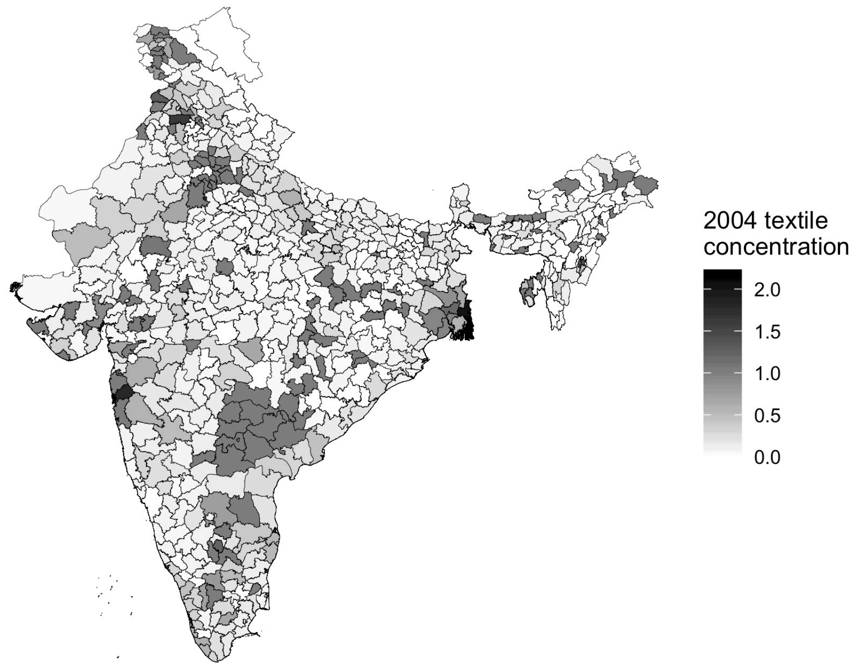
To measure exposure to post-MFA liberalization, I use pre-treatment data on textile employment agglomerations. Using the 2004 round of the Indian National Sample Survey (NSS), a nationally representative economic survey, I construct a time-invariant, continuous treatment indicator based on the relative size of pre-treatment textile employment. I calculate $TextileEmp_{i2004}$, the total national share of textile-related employment in district i in 2004.[15] This variable ranges from zero (i.e. district i had no textile-related employment in 2004) to two percent (i.e. district i had two percent of national textile-related employment in 2004). This variable is designed to capture the relative size of local textile agglomeration, which predicts future industry expansion, and to avoid reverse causality concerns regarding the use of post-treatment data on textile investment or production. The upper map in Figure 2 illustrates the geographic distribution of $TextileEmp_{i2004}$.

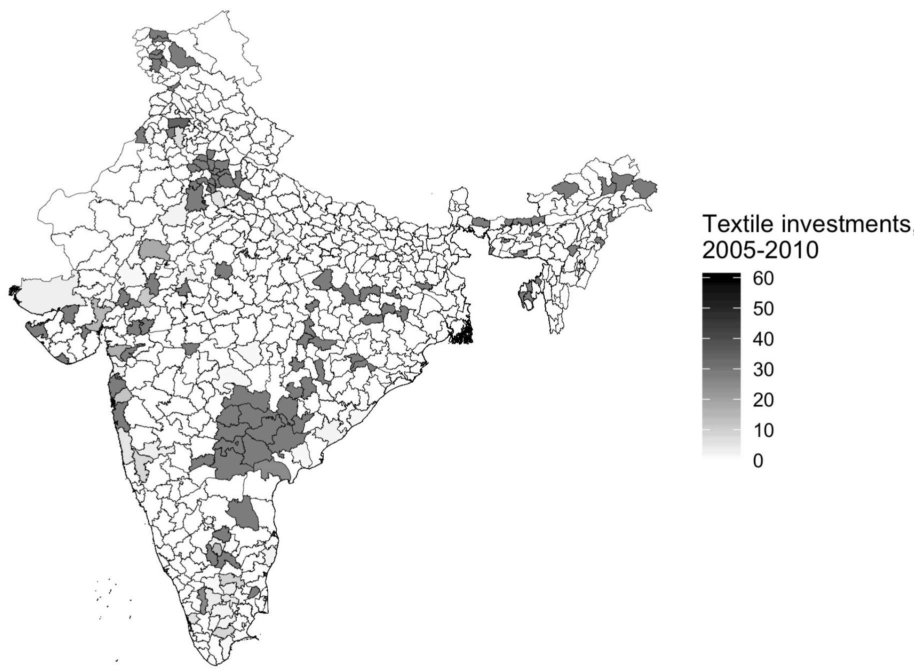
To validate that pre-treatment exposure is associated with the post-liberalization shock, I use project-level data on textile investment from the Center for Monitoring the Indian Economy's (CMIE) CapEx database, which tracks capacity-enhancing investment projects.[16]

[15] Textile employment is defined by the 1998 Indian National Industrial Classification System (NICS). Workers in ***Division 17: Manufacture of textiles*** and ***Division 18: Manufacture of wearing apparel*** are counted as textile workers.

[16] CMIE obtains this information through press reports, government filings, and correspondence with firms. It aims to cover the universe of projects worth more than US$250,000.

Figure 2: 2004 Textile Concentrations and Post-2005 Textile Investment





Upper map: share of total national textile employment, 2004 (Source: National Sample Survey). Lower map: count of new textile investment projects, 2005-2010 (Source: Center for Monitoring the Indian Economy).

CapEx projects can represent either new investments or substantial expansions of existing facilities. During this period, 60 percent of textile-related projects are new investments while 40 percent are renovations or expansions.[17] I take from this data all new domestically owned textile and apparel-related investments between 1999 and 2010 and assign them to districts.[18] In subsequent analyses, I use counts of new projects in a district-year, as well as inflation-adjusted value of district-year investment, which is provided for nearly all projects.

The lower map in Figure 2 illustrates the spread of textile investment between 2005 and 2010, the years following liberalization. The maps illustrate that pre-treatment textile employment concentration is strongly associated with post-liberalization investment; these two variables are correlated at about 0.6. I later systematically test this relationship.

Internal Migration

I measure internal migration using the 2011 Indian Census, which provides district-level migration data over time. The Census identifies migrants as people who are in a different location than their last enumeration and asks migrants when they moved. Allowable answers are: less than one year ago, one to four years, five to nine years, ten to 19 years, or more than 20 years. The Census identifies from which state the migrant moved; this is useful as out-of-state migrants are more related to nativist concerns. I create a district-level panel of migration with two equally sized time periods: the number of migrants who arrived to district i between 2001 and 2005 (pre-liberalization) and the number of migrants who arrived between 2006 and 2010 (post-liberalization). I separately collect data on in-state and out-of-state migration and calculate immigration rates based on district population.

One primary concern regarding the use of of Census migration data is that it does not

[17] I code projects in the following industries as textile-related: cloth, cotton and blended yarn, diversified cotton textiles, readymade garments, and textile processing.

[18] During this time period, a large majority of Indian textile production is domestically owned. In more recent years (i.e. since 2015), there is significant growth in foreign ownership in the textile sector (IBEF 2020), but this falls after my sample period.

capture temporary or circular mobility patterns. Circular migrants are an important part of the textile labor force. Given the lack of adequate data on circular migration, Census data offer a second-best picture of internal mobility.

Control Variables

I draw on the 2001 Indian Census to construct pre-treatment control variables. These variables capture salient district demographic and socioeconomic characteristics that might simultaneously influence textile production and local rioting propensity. These variables are: district population, employment rate, literacy rate, and proportion of the population that belongs to a Scheduled Caste. Appendix Table A.1 shows summary statistics for all variables.

Models

I first estimate my primary difference-in-differences model of rioting crimes:

$$\begin{aligned} Riots_{it} \; = \; & \alpha_0 + \alpha_1 TextileEmp_{i2004} * Post_t + \alpha_2 Pop_{i2001} * \kappa_t + \alpha_3 Emp_{i2001} * \kappa_t + \\ & \alpha_4 Lit_{i2001} * \kappa_t + \alpha_5 SC_{i2001} * \kappa_t + \theta_i + \kappa_t \end{aligned} \tag{1}$$

where $Riots_{it}$ represents the count of rioting crimes committed in district i at time t, $TextileEmp_{i2004}$ represents district i's share of total national textile employment in 2004, $Post_t$ is an indicator that takes the value of 1 for years 2005-2010 and 0 otherwise, Pop_{i2001} is the logged population of district i in 2001, Lit_{i2001} is the percentage of the population of district i that is literate in 2001, Emp_{i2001} is the percentage of the population of district i that is employed in 2001, and SC_{i2001} is the percentage of the population of district i that belongs to a Scheduled Caste in 2001. Each of these time-invariant variables are interacted with year indicators. θ_i and κ_t represent a complete set of district and year fixed effects, respectively. I estimate this model using Pseudo-Poisson maximum likelihood (PPML) with robust standard errors clustered by district. I estimate an alternative model of logged rioting crimes using ordinary least squares (OLS). The coefficient of interest is α_1, on $TextileEmp_{i2004} * Post_t$; the expectation is that greater exposure to liberalization increases the number of rioting crimes.

To validate the main measure, I estimate a difference-in-differences model of textile investment:

$$\begin{aligned} Investment_{it} = {} & \beta_0 + \beta_1 TextileEmp_{i2004} * Post_t + \beta_2 Pop_{i2001} * \kappa_t + \beta_3 Emp_{i2001} * \kappa_t + \\ & \beta_4 Lit_{i2001} * \kappa_t + \beta_5 SC_{i2001} * \kappa_t + \theta_i + \kappa_t + \epsilon_{it} \end{aligned} \tag{2}$$

where $Investment_{it}$ represents either the logged inflation-adjusted value (in rupees) or logged count of textile investment projects in district i at time t and ϵ_{it} is the error term. All other notation is the same as Equation 1. These models are estimated using OLS with robust standard errors clustered by district. The coefficient of interest is β_1; the expectation is that greater exposure to liberalization increases the value and number of textile investments.

Finally, I estimate a difference-in-differences model of internal migration:

$$\begin{aligned} ImmigrationRate_{it} = {} & \gamma_0 + \gamma_1 TextileEmp_{i2004} * Post_t + \gamma_2 Pop_{i2001} * \kappa_t + \gamma_3 Emp_{i2001} * \kappa_t + \\ & \gamma_4 Lit_{i2001} * \kappa_t + \gamma_5 SC_{i2001} * \kappa_t + \theta_i + \kappa_t + \epsilon_{it} \end{aligned} \tag{3}$$

where $ImmigrationRate_{it}$ represents either the number of in-state or out-of-state migrants to district i in period t divided by 2001 district population. All other notation is the same as in Equation 1. I estimate these models using OLS with robust standard errors clustered by district. The coefficient of interest is γ_1; the expectation is that greater exposure to liberalization increases the out-of-state immigration rate.

Results

Table 1 presents the baseline results. Model (1) is bivariate, Model (2) controls for district population, and Models (3) and (4) include additional controls. The outcome in Models (1), (2), and (3) is the count of rioting crimes; these models are estimated with PPML. The outcome in Model (4) is logged rioting crimes; this model is estimated with OLS. In all models, pre-treatment textile exposure has a positive and statistically significant effect on

Table 1: Liberalization and Rioting Crimes

	Dependent variable:			
	Riots	Riots	Riots	log(riots)
	(1)	(2)	(3)	(4)
$TextileEmp_{i2004} * Post_t$	0.233***	0.259***	0.250***	0.214**
	(0.052)	(0.062)	(0.066)	(0.097)
Control for district pop.	X	X	X	X
Other district controls	X	X	X	X
District FEs	X	X	X	X
Year FEs	X	X	X	X
Number of districts	537	537	537	537
Observations	6,440	6,440	6,440	6,040

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. Models (1), (2), and (3) estimated with pseudo-Poisson maximum likelihood. Model (4) estimated with OLS. $Post_t = 1$ for years 2005-10. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

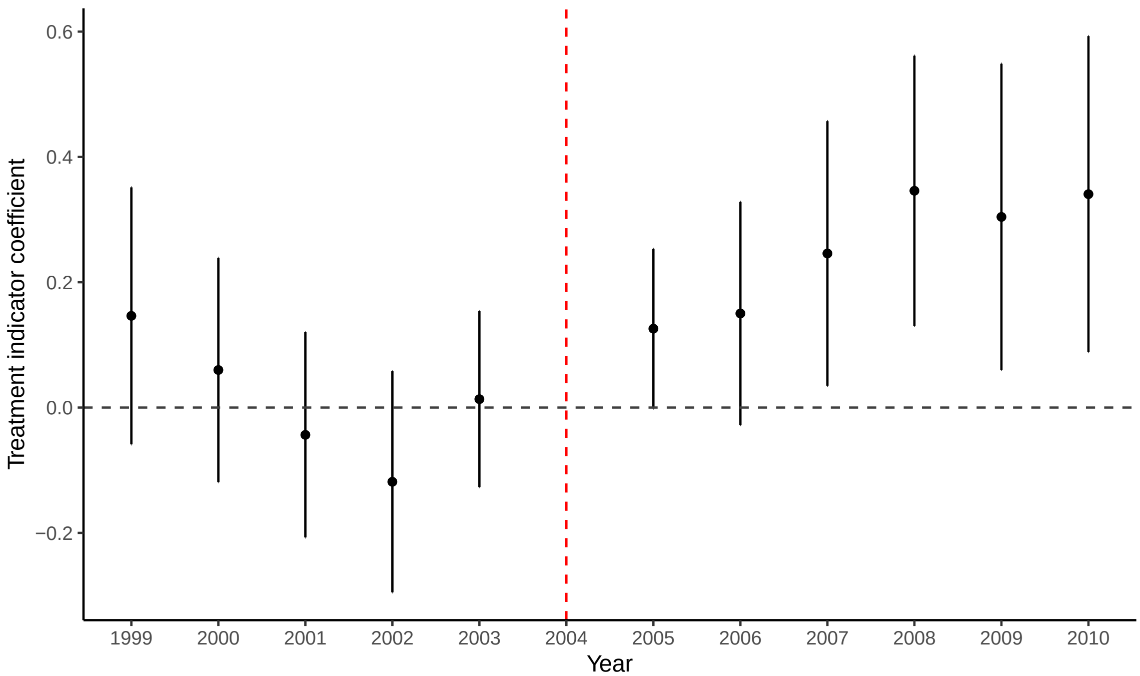
rioting crimes following liberalization. To give a sense of magnitude, I compare the predicted number of rioting crimes for two districts with significant textile industries: Mumbai and Pune. Mumbai has about two percent of national textile employment in 2004, while Pune has about 0.5 percent. For a district like Mumbai, the post-2005 shock results in about 78 additional rioting crimes each year. For a city like Pune, the effect is significantly smaller, at about 17 rioting crimes.[19] These results suggest that there is a substantively important, causal relationship between liberalization and rioting.

I extend the main results in several ways to probe the robustness of the baseline findings.

Event study I estimate an event study model to check for the existence of differential pre-trends and to illustrate the dynamic effect of liberalization on rioting crimes. Figure 3 shows the yearly treatment indicator coefficients across the sample period with 95 percent

[19]Predictions from Model (3), Table 1.

Figure 3: Event Study Estimation



Yearly coefficient of treatment indicator from event study model with 95% confidence intervals. 2004 omitted as reference period. Estimates in Model (1) of Appendix Table A.2.

confidence intervals; I omit 2004 as the reference period.[20] The increase in rioting crimes in exposed areas corresponds to the timing of liberalization. In pre-treatment years, the treatment indicator has no statistically significant effect on rioting crimes. While the year-by-year treatment indicator is significant at $p < .1$ in 2005 and 2006, the estimated effect more strongly emerges in 2007, at which point new post-MFA textile investments are fully realized. These results provide additional confidence that the estimate reflects a true relationship between exposure to liberalization and rioting and is not due to differential trends.[21]

I also ensure that the results are robust to the potential for heterogeneous treatment

[20]Estimates are available in Model (1), Appendix Table A.2.

[21]I depict average rioting crimes per 1,000 people over time for districts with above- and below-average textile concentration in Appendix Figure A.3; the figure shows little evidence of differential trends in this unconditional comparison. This figure does not account for covariates or continuous variation along $TextileEmp_{i2004}$.

effects by using the estimator proposed in de Chaisemartin and D'Haultfœuille (2020).[22] These results are available in Appendix Table A.3. My results remain robust.

Excluding low riot incidence areas One potential concern is that low-population districts, because they have little industry and experience little rioting, are not valid comparisons. Controlling for population mitigates this concern, and district fixed effects exclude areas that experience no rioting during the period. As an additional check, I re-estimate the models in Table 1 but exclude districts in the bottom 10 percent of rioting crimes during the period. These results are in Appendix Table A.4. The coefficient on $TextileEmp_{i2004} * Post_t$ is virtually identical when excluding districts with low riot incidence.

Placebo model of murder Given measurement concerns about using total rioting crimes regardless of cause, I estimate a placebo model of district-level murder in line with Bhavnani and Lacina (2015). Appendix Table A.5 shows estimations of Equation 1 with murder as the outcome. Exposure to liberalization predicts no increase in murder, suggesting liberalization specifically increases riots and not broader violent crime.

Excluding international migrant destinations My argument focuses on *internal* migration as a mechanism linking liberalization to rioting. This may overlook the fact that some parts of India experience *international* migration, particularly from Bangladesh. A resulting concern is that the relationship is due to international, not internal, migration. I re-estimate the main models but exclude Mumbai and Kolkata, the two primary destinations for international migrants. The estimated effect remains virtually identical.[23]

Potential increased import competition One alternative explanation is that liberalization increased imports of raw/intermediate goods. From this perspective, violence may be the result of import competition and dislocation rather than internal migration. District trade statistics are not available, so it is not possible to control for imports.

[22]Because I do not leverage differential treatment timing across units for identification, other recent advances in the difference-in-differences literature are not applicable.

[23]Results available upon request.

This might be a concern if exporting firms import a significant amount of their inputs. To explore this possibility, I use firm-level data from the World Bank Enterprise Survey, which asks a representative sample of Indian manufacturers whether they produce for export and the percentage of their inputs that are sourced domestically versus internationally. Surveys are available in 2002, 2006, and 2014; Indian garment and textile manufacturers are well-represented. On average, domestically owned Indian garment and textile exporters in 2002 reported sourcing 92 percent of their inputs domestically. This percentage is high and constant over time. In 2006, immediately following the MFA expiration, it stood at around 95 percent, and in 2014 it remained high at 92 percent.[24] This limits concerns about import competition as a confounding factor.

Textile Investment Increases Post-Liberalization

I next validate that districts with larger pre-treatment textile concentrations experienced more textile industry growth after liberalization. I estimate difference-in-differences models of textile investment, as well as placebo investment models for other industries.

Appendix Table A.6 presents the results. The dependent variable in Models (1) and (2) is logged value of total new textile investment in inflation-adjusted rupees, while in Models (3) and (4) the dependent variable is the logged count of new textile projects. All models are estimated with OLS. Larger pre-treatment textile concentration is associated with larger amounts of new textile investment following liberalization. These results suggest that the treatment indicator does meaningfully relate to post-MFA shock exposure.

In Model (2) of Appendix Table A.2, I estimate an event study model of logged new project counts to look at over-time effect heterogeneity and the potential for differential pre-trends. The treatment indicator predicts large increases in textile investment following liberalization. The coefficient on the year-by-year treatment indicator is not significant at

[24] In comparative perspective, Indian textile producers source the largest majority of their inputs domestically (Alam et al. 2019).

$p < .05$ in any years prior to MFA expiration.

One concern is that $TextileEmp_{i2004} * Post_t$ may be correlated with investment in unrelated, co-located manufacturing sectors, meaning the observed relationship could be due to separate economic trends. I estimate placebo investment models in which the dependent variable is the logged count of new investments (either foreign or domestic) in seven other prominent Indian manufacturing sectors, also collected from CapEx.[25] These results are available in Appendix Table A.7. Across these industries, $TextileEmp_{i2004} * Post_t$ predicts investment in only one, pharmaceuticals; the estimated effect is less than half of that on textile investment. Pharmaceutical production is much less labor-intensive than textiles, making it unlikely that this explains the identified relationship. This suggests that the exposure measure captures the post-liberalization textile shock and not other economic trends.

Internal Migration Increases Post-Liberalization

Do districts that are more exposed to liberalization experience more internal migration, in line with my argument? Table 2 displays the estimation of Equation 3, a difference-in-differences model of migration. These models are estimated with OLS. The dependent variable in Model (1) is the within-state immigration rate, while in Model (2) it is the out-of-state immigration rate. Exposure to liberalization increases inflows of out-of-state migrants, but not within-state migrants. This is consistent with accounts of the Indian textile sector labor force, which is primarily composed of interstate migrants (ILO 2017; Kumar et al. 2020). This is also consistent with accounts of nativism: out-of-state migrants are most politically contentious because of greater perceived ethnolinguistic and cultural difference (Gaikwad and Nellis 2017).

How much additional out-of-state immigration is due to this shock? A one-standard deviation increase in exposure to liberalization results in a 0.2 percentage point increase of

[25] I analyze: agricultural/industrial machinery, automobiles (incl. components), metals, chemicals, pharmaceuticals, food products, and furniture/leather/rubber. Sectors selected based on McKinsey report on Indian manufacturing (Dhawan and Sengupta 2020).

Table 2: Liberalization and Internal Migration

	Dependent variable: $ImmigrationRate_{it}$ (%)			
	Within-state Total	Out-of-state Total	Out-of-state Males	Out-of-state Females
	(1)	(2)	(3)	(4)
$TextileEmp_{i2004} * Post_t$	0.236	0.820^{***}	0.587^{***}	0.233^{**}
	(0.190)	(0.306)	(0.216)	(0.097)
Observations	1,160	1,160	1,160	1,160
Number of districts	580	580	580	580
Controls	X	X	X	X
District FEs	X	X	X	X
Period FEs	X	X	X	X

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. Robust standard errors clustered by district in parentheses. Models estimated with OLS. $Post_t = 1$ for period 2006-2010. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate interacted with period indicator (Source: 2001 Indian Census).

the out-of-state immigration rate. This estimate represents a substantively important level of new immigration: across the range of pre-treatment textile concentration, the immigration rate increases by nearly two percentage points. In Columns (3) and (4), I disaggregate immigration rates by sex and find that the estimated effect is primarily driven by male migration. This is also significant, as nativist concerns are historically driven by male migration, which is usually for employment purposes, while female migration in India is associated with marriage and is less controversial (Weiner 1978).[26]

It is possible that liberalization drives ***international***, not just internal, migration. A complication is that because many international migrants in India do not have documentation and wish to avoid detection, they may report being from India. These migrants are often from neighboring Bangladesh. One way to ensure robustness is to exclude migrants who report being from West Bengal, the neighboring state to Bangladesh. Results remain robust

[26]However, recall that females are increasingly involved in textile production, especially in southern states.

when excluding West Bengal migrants.[27]

Riots Increase More in Higher-Immigration Districts

An additional observable implication is that rioting should increase most in exposed areas that experience greater amounts of out-of-state immigration. It should be in these localities where nativist grievances are strongest, given greater exposure to migrants. I explore this possibility by adding a triple interaction between $TextileEmp_{i2004}$, $Post_t$, and $ImmigrationRate_{it}$ (out-of-state) to Equation 1.

Table 3 presents these results.[28] The results suggest that rioting differentially increased in exposed districts that experienced higher out-of-state immigration rates following liberalization. The triple interaction is positive and statistically significant at $p < .1$; the estimated coefficient remains relatively stable with the inclusion of district-level controls. These models suggest that nativist grievances are strongest in exposed districts with greater immigration.

Global Economic Integration and Nativist Party Support

My argument suggests that local voters will increase their support for nativist parties in liberalization-exposed areas as a means to address nativist grievances. To explore this possibility, I analyze legislative assembly elections in the state of Maharashtra. I focus on Maharashtra because it has a history of nativist politics and has easily identifiable, explicitly nativist parties. Maharashtra is a state of more than 110 million people and contains Mumbai, India's largest metropolitan area. The textile sector is prominent in the Maharashtran economy, home to about 10 percent of all Indian textile-related employment.

Many native Marathis support nativist parties. The strongest, the Shiv Sena (SS), engages in anti-migrant rhetoric, passes pro-native affirmative action policies, and denies migrants local rights and public services (Gaikwad and Nellis 2017). The SS has long been

[27] The estimated effect on out-of-state immigration is slightly attenuated, but still positive and statistically significant. Results available upon request.

[28] All constituent terms are included in the models but suppressed from the table.

Table 3: Liberalization, Immigration, and Rioting Crimes

	Dependent variable:			
	Riots	Riots	Riots	log(riots)
	(1)	(2)	(3)	(4)
$TextileEmp_{i2004} * Post_t *$ $ImmigrationRate_{it}$	0.058* (0.031)	0.055* (0.030)	0.051* (0.031)	0.072* (0.039)
$TextileEmp_{i2004} * Post_t$	0.202** (0.092)	0.217** (0.092)	0.219** (0.099)	0.135 (0.126)
Control for district pop.	X	X	X	X
Other district controls	X	X	X	X
District FEs	X	X	X	X
Year FEs	X	X	X	X
Number of districts	535	535	535	535
Observations	6,416	6,416	6,416	6,021

$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Models (1), (2), and (3) estimated with pseudo-Poisson maximum likelihood. Model (4) estimated with OLS. $Post_t = 1$ for years 2005-10. $ImmigrationRate_{it}$ refers to out-of-state immigration rate. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

blamed for fomenting nativist rioting (Engineer 1984). Besides the SS, there are at times other nativist parties operating simultaneously. Nativist parties are not only viable but highly successful: the SS is the current leader of the coalition government in Maharashtra.

I analyze the performance of nativist parties in Maharashtran legislative assembly elections in 2004, 2009, and 2014.[29] The unit of analysis is a state legislative constituency, each of which nests within a district. I construct $NativistShare_{cit}$, the share of votes received by nativist parties in constituency c nested in district i at time t, by summing the vote shares of the two most prominent nativist parties during this period: the SS and the Maharashtra

[29]Results are substantively similar when only analyzing 2004 and 2009.

Navnirman Sena (MNS), a more extreme splinter party of the SS. Data come from the India National and State Election Dataset (Bhavnani 2014).

I estimate the following difference-in-differences model:

$$
\begin{aligned}
NativistShare_{cit} \quad = \quad & \delta_0 + \delta_1 TextileEmp_{i2004} * Post_t + \delta_2 Pop_{i2001} * \kappa_t + \delta_3 Emp_{i2001} * \kappa_t + \\
& \delta_4 Lit_{i2001} * \kappa_t + \delta_5 SC_{i2001} * \kappa_t + \theta_i + \kappa_t + \epsilon_{it}
\end{aligned}
\tag{4}
$$

where $NativistShare_{cit}$ represents SS/MNS vote share in constituency c nested in district i at time t and $TextileEmp_{i2004}$ represents the treatment indicator in district i in which constituency c is nested. All notation is the same as Equation 1. The coefficient of interest is δ_1. I estimate this model using OLS and cluster standard errors by district.

Apendix Table A.8 displays the results. The models suggest that in areas most exposed to liberalization, nativist political parties saw significantly increased support at the ballot box. A one standard deviation increase in local textile concentration is associated with a roughly 4 percentage point increase in vote share for nativist parties, on average; this effect is both statistically significant and electorally meaningful.[30]

Conclusion

Globalization is linked to nativist movements in advanced democracies, as liberalization-induced economic dislocation creates adversity and fears of status threat. While global economic integration is broadly beneficial to workers in emerging economies, I argue that it can still contribute to nativism. Liberalization induces internal labor mobility toward centers of export-oriented production. Liberalization-induced mobility activates anti-migrant sentiment, fueling nativist movements against internal migrants. Via different causal mechanisms, liberalization can have similar effects regardless of whether its economic impacts are positive or negative.

[30] In Appendix Table A.9, I estimate separate models for each party. The success of the MNS, which is relatively more ideologically extremist, drives the overall results.

I test my argument in India, zooming in on the shock to textile production following the expiration of the MFA. My results indicate this shock generated nativist backlash, as rioting increased in more exposed districts. These same districts received the lion's share of new textile investment and received significantly larger migrant flows post-liberalization. Exposed districts that received relatively more migrants saw even stronger anti-immigrant backlash. This liberalization-induced nativism spilled into electoral politics, where nativist parties benefited. My argument and findings present a new explanation for the success of nativist politics outside advanced democracies.

This article suggests that rising nativism can limit the benefits of global economic integration in emerging economies. Liberalization can boost the prospects of lower-skilled workers, especially those who face labor market discrimination (Milner and Kubota 2005; Peters and Osgood 2017; Gaikwad and Suryanarayan 2021). Yet if workers must engage in migration to access those opportunities, they may face new forms of marginalization as a result of their migrant status (Gaikwad and Nellis 2021). Politically empowering migrants who seek global employment opportunities is necessary to limit discrimination and exclusion.

More broadly, this article suggests that identifying how workers strategically react to global economic integration, especially in the face of unfavorable structural conditions, can help us better understand the relationship between globalization and politics in emerging economies. Geographic mobility is just one way in which workers respond to the incentives globalization brings. Exploring the impacts of other potential responses to integration, such as human capital acquisition or inter-industry mobility, is an area ripe for future research.

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A Appendix

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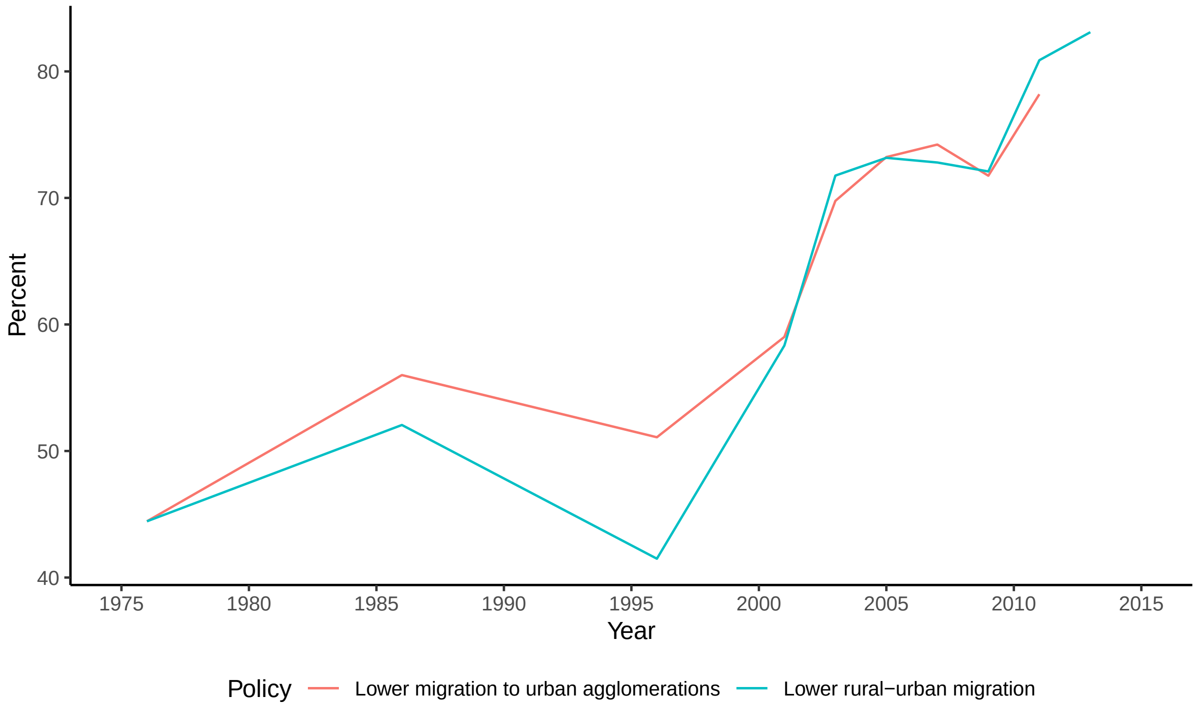
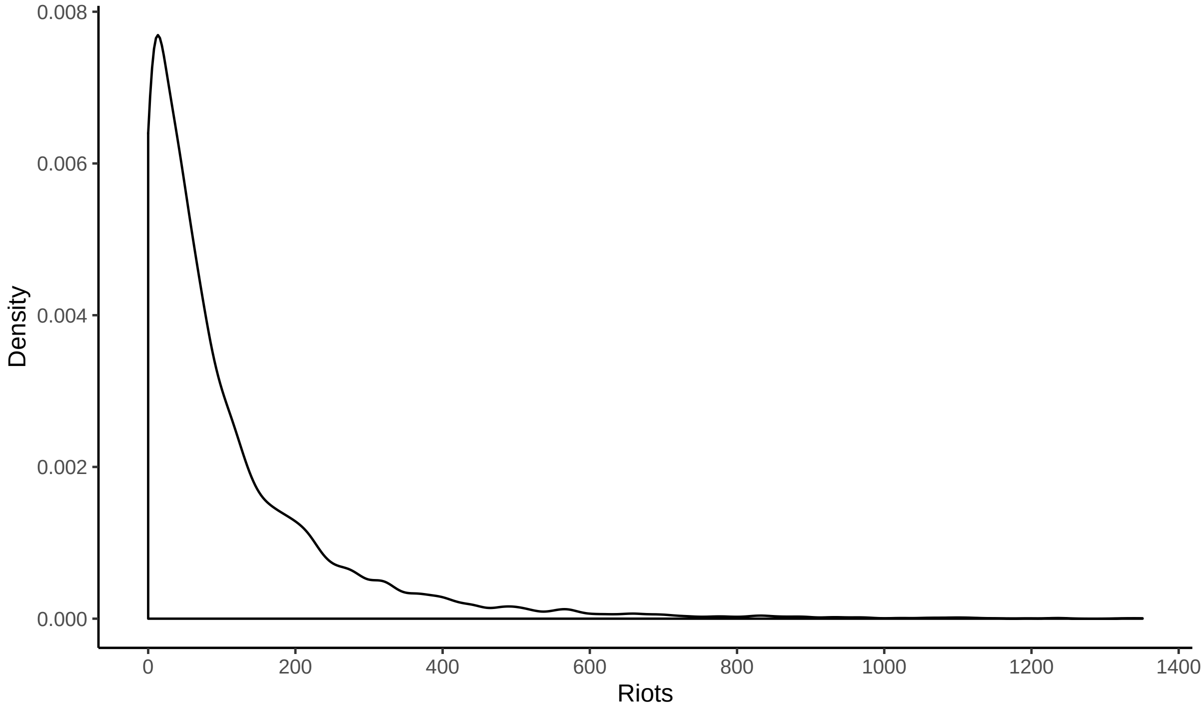
Appendix Figure A.1: Internal Migration Policy in Lower-Income Countries



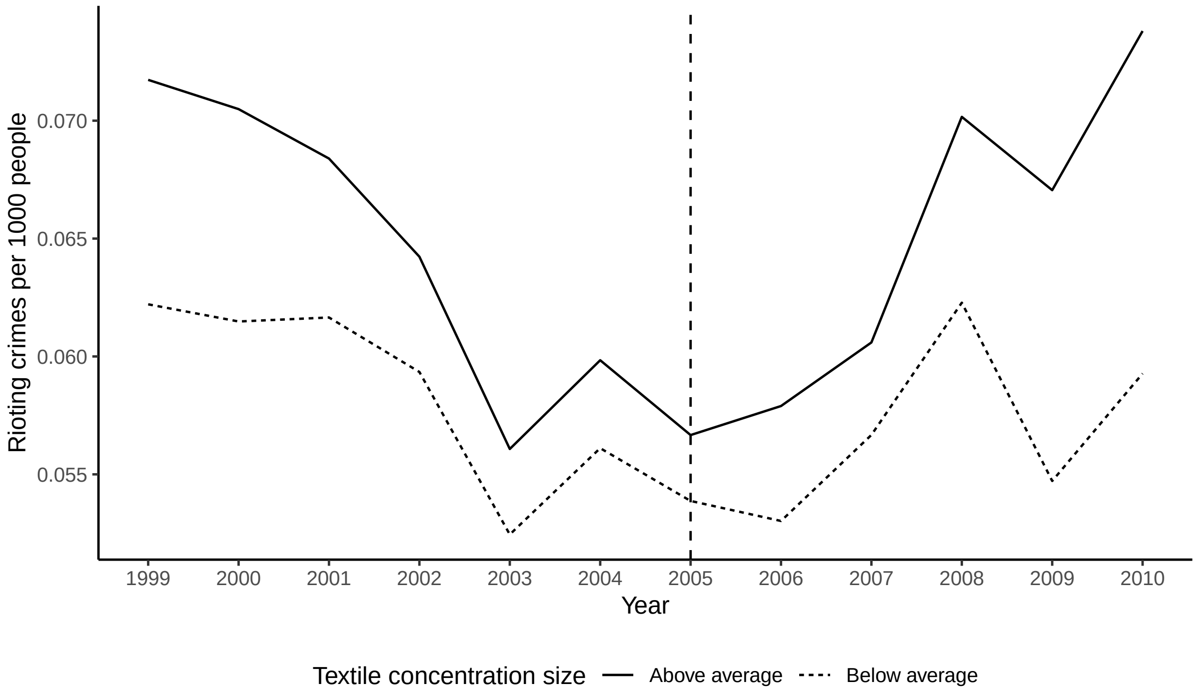
Percentage of low- and middle-income countries that state they intend to lower migration to urban agglomerations and to lower rural-urban migration, 1976-2015 (source: United Nations World Population Prospects).

Appendix Figure A.2: Density Plot of Rioting Crimes



Density plot of rioting crimes for all district-years (source: National Crime Records Bureau).

Appendix Figure A.3: Riot Incidence Over Time by Textile Concentration Size



Average rioting crimes per 1,000 people in districts with above-average and below-average textile concentrations, 1999-2010 (source: National Crime Records Bureau).

Appendix Table A.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
$Riots_{it}$	109.845	143.811	0	1,351
$Murders_{it}$	58.910	51.296	0	542
$TextileEmp_{i2004}$	0.167	0.251	0	2.178
$TextileValue_{it}$	0.756	10.419	0	542.699
$TextileProjects_{it}$	0.084	0.607	0	18
Pop_{i2001}	1,777,250.328	1,388,602.757	33,224	11,978,450
Emp_{i2001}	0.406	0.071	0.241	0.635
Lit_{i2001}	0.540	0.122	0.242	0.854
SC_{i2001}	0.148	0.087	0	0.501
$ImmigrationRate_{it}$ (within-state)	1.839	1.382	0	12.549
$ImmigrationRate_{it}$ (beyond-state)	1.162	2.724	0.014	59.664
$NativistShare_{ct}$	21.955	19.716	0	86.836

Appendix Table A.2: Event Study Estimates

	Dependent variable:	
	Riots	log(projects)
	(1)	(2)
$TextileEmp_{i2004} * 1999$	0.146	0.063
	(0.105)	(0.041)
$TextileEmp_{i2004} * 2000$	0.060	0.055
	(0.091)	(0.052)
$TextileEmp_{i2004} * 2001$	−0.044	−0.098*
	(0.084)	(0.058)
$TextileEmp_{i2004} * 2002$	−0.118	0.068
	(0.090)	(0.054)
$TextileEmp_{i2004} * 2003$	0.013	0.047
	(0.072)	(0.062)
$TextileEmp_{i2004} * 2005$	0.126*	0.031
	(0.065)	(0.072)
$TextileEmp_{i2004} * 2006$	0.150*	0.108
	(0.091)	(0.094)
$TextileEmp_{i2004} * 2007$	0.246**	0.177**
	(0.108)	(0.086)
$TextileEmp_{i2004} * 2008$	0.346***	0.149**
	(0.110)	(0.063)
$TextileEmp_{i2004} * 2009$	0.304**	0.159*
	(0.125)	(0.096)
$TextileEmp_{i2004} * 2010$	0.341***	0.264***
	(0.129)	(0.084)
Controls	X	X
District FEs	X	X
Year FEs	X	X
Number of districts	537	546
Years	1999-2010	1999-2010
Observations	6,440	6,545

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Model (1) estimated with pseudo-Poisson maximum likelihood. Model (2) estimated with OLS. 2004 omitted as reference period. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

Appendix Table A.3: Robustness to Heterogeneous Treatment Effects

	Dependent variable:
	log(riots)
	(1)
$TextileEmp_{i2004} * Post_t$	0.90**
	(0.438)
Observations	491
District FEs	X
Year FEs	X
District controls	X

Notes: *p<0.1; **p<0.05; ***p<0.01. Model estimated using procedure in de Chaisemartin and D'Haultfoeuille (2020) and implemented with ***did_multiplegt*** command in Stata. $Post_t = 1$ for years 2005-10. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

Appendix Table A.4: MFA Expiration and Rioting Crimes – Excluding Low Riot Incidence Districts

	Dependent variable:			
	Riots	Riots	Riots	log(riots)
	(1)	(2)	(3)	(4)
$TextileEmp_{i2004} * Post_t$	0.234***	0.259***	0.250***	0.232**
	(0.052)	(0.062)	(0.066)	(0.010)
Control for district pop.	X	X	X	X
Other district controls	X	X	X	X
District FEs	X	X	X	X
Year FEs	X	X	X	X
Number of districts	537	537	537	546
Years	1999-2010	1999-2010	1999-2010	1999-2010
Observations	5,876	5,876	5,876	5,838

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Model (4) estimated with OLS. $Post_t = 1$ for years 2005-10. Robust standard errors clustered by district in parentheses. Sample excludes districts in the bottom 10 percent of total rioting crimes during sample period. Models (1), (2), and (3) estimated with pseudo-Poisson maximum likelihood. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

Appendix Table A.5: MFA Expiration and Murders

	Dependent variable:			
	Murders	Murders	Murders	log(murders)
	(1)	(2)	(3)	(4)
$TextileEmp_{i2004} * Post_t$	0.048	0.048	−0.019	−0.028
	(0.037)	(0.045)	(0.045)	(0.058)
Control for district pop.	X	X	X	X
Other district controls	X	X	X	X
District FEs	X	X	X	X
Year FEs	X	X	X	X
Number of districts	546	546	546	546
Years	1999-2010	1999-2010	1999-2010	1999-2010
Observations	6,545	6,545	6,545	6,518

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. Models (1), (2), and (3) estimated with pseudo-Poisson maximum likelihood. Model (4) estimated with OLS. $Post_t = 1$ for years 2005-10. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

Appendix Table A.6: MFA Expiration and New Capital Investment in Textiles

	Dependent variable:			
	log(value)	log(value)	log(projects)	log(projects)
	(1)	(2)	(3)	(4)
$TextileEmp_{i2004} * Post_t$	0.441^{***}	0.346^{**}	0.167^{***}	0.125^{**}
	(0.127)	(0.141)	(0.052)	(0.054)
Controls	X	X	X	X
District FEs	X	X	X	X
Year FEs	X	X	X	X
Number of districts	546	546	546	546
Observations	6,516	6,516	6,545	6,545

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. Models estimated with OLS. $Post_t = 1$ for years 2005-10. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

Appendix Table A.7: Placebo Tests of Investment in Other Industries

	Dependent variable: log(projects)						
	Machinery	Automobiles	Metals	Chemicals	Pharmaceuticals	Food	Furniture/ Leather/Rubber
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$TextileEmp_{i2004} * Post_t$	0.006	0.011	0.012	0.006	0.057**	0.012	0.0002
	(0.016)	(0.021)	(0.014)	(0.016)	(0.025)	(0.017)	(0.011)
Controls	X	X	X	X	X	X	X
District FEs	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X
Number of districts	546	546	546	546	546	546	546
Observations	6,545	6,545	6,545	6,545	6,545	6,545	6,545

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. Models estimated with OLS. $Post_t = 1$ for years 2005-10. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with year indicators (Source: 2001 Indian Census).

Appendix Table A.8: Support for Nativist Parties

	Dependent variable: SS/MNS vote share		
	(1)	(2)	(3)
$TextileEmp_{i2004} * Post_t$	6.269***	5.090**	5.860**
	(1.075)	(1.981)	(2.752)
Control for district pop.	X	X	X
Other district controls	X	X	X
District FEs	X	X	X
Year FEs	X	X	X
Number of districts	34	34	34
Observations	861	861	861

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. All models estimated with OLS. $Post_t = 1$ for elections in 2009 and 2014. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with election dummies (Source: 2001 Indian Census).

Appendix Table A.9: Support for Nativist Parties – Splitting SS and MNS Vote Shares

	Dependent variable:	
	(1) SS vote share	(2) MNS vote share
$TextileEmp_{i2004} * Post_t$	1.493	4.367**
	(2.160)	(1.739)
District controls	X	X
District FEs	X	X
Year FEs	X	X
Number of districts	34	34
Observations	861	861

$^{*}p$ <0.1; $^{**}p$ <0.05; $^{***}p$ <0.01. All models estimated with OLS. $Post_t = 1$ for elections in 2009 and 2014. Robust standard errors clustered by district in parentheses. Controls: 2001 population, employment rate, literacy rate, and Scheduled Caste rate all interacted with election dummies (Source: 2001 Indian Census).