

Bartering Bureaucrats: Foreign Direct Investment and Rent Seeking

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Abstract

What motivates politicians to attract foreign direct investment (FDI)? Existing explanations, focused on industrialized democracies, emphasize credit claiming for economic prosperity. In many developing democracies, however, economic voting is weak. We argue that these politicians view FDI as a valuable source of rents for personal enrichment and campaign finance. We analyze a novel metric of politicians' revealed motives to attract FDI: how they allocate bureaucratic talent. We leverage India's 2005 FDI liberalization to estimate FDI's effects on transfers of Indian Administrative Service officers. We show that transfers increase in FDI-exposed districts, driven by movement of career-constrained officers, who have stronger incentives to facilitate politicians' rent seeking. We document heterogeneity consistent with rent seeking motives. Constrained bureaucrats are disproportionately appointed to powerful positions. Legislators representing FDI-exposed districts experience personal asset growth, but only when their party controls transfers. Our findings highlight how global economic integration can strengthen rent seeking motives.

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1 Introduction

Competition to attract foreign direct investment (FDI) is fierce. In developing democracies, politicians offer multinational corporations (MNCs) costly subsidies and policy concessions to attract FDI (Strange 1996; Simmons 2014; Moehlecke 2020).¹ Current research proposes that politicians seek FDI in order to claim credit from voters for job creation (Jensen and Malesky 2018; Owen 2019; Wang et al. 2022). Yet economic voting, the proposition that voters evaluate incumbents based on economic conditions, is often weak in developing countries (Anderson 2007; Lewis-Beck and Stegmaier 2019). In the absence of economic voting, what motivates politicians in developing democracies to attract FDI?

We argue that politicians in developing democracies look to FDI as a source of rents. We define rents broadly to encompass MNCs’ (in)direct (il)legal payments to politicians (Krueger 1974). In addition to personal enrichment, these politicians have distinct electoral motives to rent seek. In the absence of transparent campaign finance, politicians often rely on rent seeking to fund campaigns, including electoral strategies grounded in distributive politics (Hicken 2011; Golden and Min 2013; Stokes et al. 2013). Politicians in large countries have greater scope to rent seek because MNCs tolerate rent seeking to gain access to lucrative markets (Kobrin 1987; Vernon 1971).

We introduce a novel measure of politicians’ revealed motives to attract FDI: how they manage bureaucrats posted in FDI-exposed areas. Politicians rely on bureaucrats to collect taxes, enforce regulations, and deliver public services, among other tasks vital to democracy and development (Pepinsky et al. 2017). Basic aspects of governance relevant to MNCs – awarding permits, enforcing regulations, public service provision – typically fall under bureaucrats’ purview (Rauch and Evans 2000; Hallward-Driemeier and Pritchett 2015). Com-

¹Although the efficacy of these policies is debated, they can help resolve information asymmetries that are acute in developing countries (Harding and Javorcik 2011). Politicians may also overestimate their efficacy (Poulsen and Aisbett 2013).

petent bureaucrats shielded from political pressure help maximize productivity spillovers from MNCs to local firms (Evans 1995; Haggard 2018).

Even in merit-based bureaucracies, politicians often have discretion to transfer bureaucrats across posts. When bureaucrats have preferences over posts, politicians can use transfers to motivate bureaucrats. We argue that how politicians exercise this discretion in FDI-exposed areas reveals their motives to attract FDI. Political oversight ostensibly makes bureaucracies more efficient because politicians are accountable to voters. When accountability is weak, as is true of many developing democracies, politicians may use oversight to pressure bureaucrats into facilitating their rent seeking (Wade 1985; Brierley 2020).

Our empirical setting is India, where we identify FDI’s effects on bureaucratic transfers by leveraging India’s sudden 2005 FDI liberalization. Liberalization dismantled entry barriers in 110 industries, producing a near tripling in MNCs’ new capital expenditures (see Figure 1). Our analysis exploits the concentration of post-liberalization FDI growth in six Indian states, an artefact of FDI’s tendency to geographically agglomerate. We harness this temporal and cross-state variation in FDI inflows in a difference-in-differences (DID) design and event study estimation. Additionally, we estimate a two-stage instrumental variable model that uses district exposure to FDI liberalization – measured with original industry-level FDI regulation data – to instrument for district-year FDI.

Using these designs, we analyze FDI’s effect on transfers within the Indian Administrative Service (IAS). Described as India’s “steel frame” (Potter 1996), IAS officers are responsible for critical aspects of local, state, and federal governance. State politicians have discretion to transfer officers across posts within their state. Recruitment and promotion procedures, though largely merit-based, produce variation in officers’ career motivations (Bertrand et al. 2020). Career-constrained officers, who have weaker prospects for merit-based advancement, are more likely to facilitate politicians’ rent seeking in exchange for desired posts.

We find that IAS transfers increased in FDI-exposed districts following liberalization, driven by transfers of constrained officers. We document heterogeneity consistent with politi-

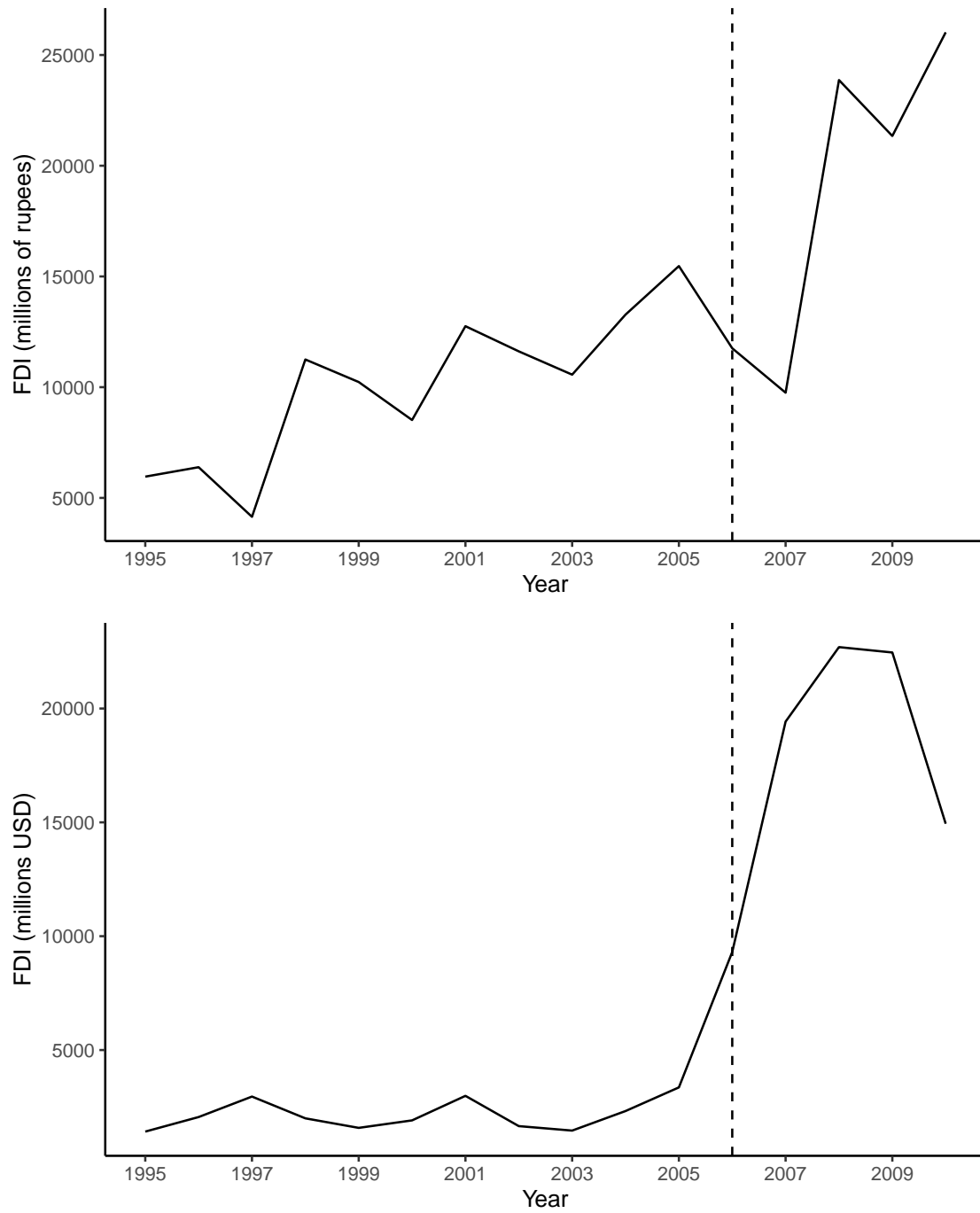


Figure 1: FDI in India Over Time. Top panel: inflation-adjusted value of new completed FDI projects in India (source: CapEx). Bottom panel: inflation-adjusted value of intended FDI in India (source: Reserve Bank of India).

cians’ rent seeking motives. Transfers are concentrated in more corrupt districts, districts with FDI from more corrupt source countries, and FDI intended to produce for the Indian market. FDI-exposed districts become more likely to have a constrained officer appointed as the district magistrate, an exceptionally powerful post. This finding suggests that transfers are not intended to curb officers’ personal rent seeking. We rule out alternative mechanisms related to officers’ competence and local contextual knowledge and address possible bias in our DID estimation (de Chaisemartin and D’Haultfœuille 2020).

Next, we evaluate FDI’s consequences for politicians’ personal assets, an insightful proxy for rent seeking (Fisman et al. 2014). State legislators from FDI-exposed districts experienced significant asset growth. Growth obtains only if their party belongs to the state’s ruling coalition and the district in which their constituency is located has a higher proportion of constrained IAS officers. Politicians’ liquid assets grow, which are more likely to reflect rents. These patterns are inconsistent with FDI’s economic effects driving asset growth.

Our study offers multiple contributions to political economy scholarship. First, we establish a distinct channel through which FDI fuels politicians’ rent seeking. Prior research attributes corruption to MNCs’ pursuit of monopoly profits created by FDI entry barriers (Malesky et al. 2015; Zhu 2017). Whereas this work emphasizes the perspective of MNCs, we shift focus to politicians’ motives to seek rents from MNCs. We extend this research by proposing that liberalizing FDI increases some forms of rent seeking.² Entry barriers may create monopoly profits but, as we argue, often deter MNCs by creating contractual hazards that weaken control over key technologies (Pandya 2014). Countries with large domestic markets become especially attractive FDI destinations following liberalization. Rent seeking by local politicians in these countries, though perhaps not trivial, does not endanger MNCs’ core technologies. FDI entry barriers are increasingly rare, so our findings speak to the experience of a wider range of developing countries.

²Rent seeking with and without entry barriers may be qualitatively different in form, scale, and host country actors.

Second, our theoretical framework suggests that politicians in developing democracies can have distinct electoral motives to attract FDI. Prior FDI research assumes both economic voting and electoral accountability, which are both weak in many developing democracies (Jensen and Malesky 2018; Owen 2019; Jensen et al. 2020). Our argument most closely resembles Wade (1985), who proposes that Indian politicians transfer bureaucrats to collect rents for electoral purposes. When politicians’ electoral fortunes rest on delivering particularistic benefits to key constituencies, rents extracted from MNCs may be more valuable than FDI’s economic development benefits. Although data constraints preclude direct tests of FDI’s effects on distributive politics,³ our framework raises new questions about FDI’s political consequences in developing democracies. Prior research on FDI’s political consequences in this context focuses on autocracies (Malesky 2008; Tomashevskiy 2017).

Third, we highlight political control of bureaucracies as a distinct channel through which democracy shapes political risk. Whereas existing research emphasizes institutional characteristics of democracy,⁴ our findings unpack how state capacity shapes developing countries’ ability to harness the benefits of global economic integration.⁵ Even when institutions inhibit policy change, politicians retain some autonomy over policy implementation through control of bureaucrats. Whereas prior political risk research examines cross-national variation in time-invariant characteristics of bureaucracy (Rauch and Evans 2000), our findings indicate that even in merit-based bureaucracies, politicians may use their limited oversight to extract

³Such politics are difficult to observe across space and time as would be necessary for our research question. Empirical studies of clientelism in India utilize surveys or field experiments and/or have limited geographic scope (e.g., Bussell 2012; Auerbach and Thachil 2018, 2020; Rains and Wibbels 2023).

⁴See Pandya (2016) for a review of this literature.

⁵Lamenting the lack of scholarship on this topic, Haggard (2018) writes “this lacuna is deafening. We know a lot more about how to design an exchange rate regime than we do about making bureaucracies in poor countries work” (p. 69).

rents from MNCs.

2 Conceptual Framework

FDI can be a powerful catalyst for economic development. MNCs, among the world’s most productive firms, establish foreign subsidiaries to undertake their most skill- and technology-intensive production tasks (Helpman et al. 2004). These tasks utilize proprietary technologies and other firm-specific assets over which firms wish to maintain control while exploiting global scale economies.⁶ FDI fuels development when MNCs employ local labor and their technologies help make domestic firms more productive (Bloom and Van Reenen 2007; Alfaro 2017). Relative to otherwise equivalent domestic firms, MNCs pay significantly higher wages (Javorcik 2015) and offer better working conditions (Mosley 2010).

Current research proposes that in democracies, FDI’s economic benefits drive politicians’ electoral motives to attract FDI. When voters associate FDI with economic prosperity, they credit incumbent politicians for attracting investment.⁷ Owen (2019) finds that in Brazilian localities that received new FDI, the incumbent mayor’s party was more likely to retain office. Consistent with electoral motives, Jensen and Malesky (2018) show that US mayors are more likely to offer investment incentives when political institutions facilitate credit claiming. This argument builds on the logic of economic voting: voters evaluate politicians based on past or anticipated economic performance (Anderson 2007; Lewis-Beck and Stegmaier 2019).

Developing democracies, however, exhibit relatively weak economic voting (Tucker 2002;

⁶These motives distinguish FDI from lower-skilled production transacted through arms-length contracting.

⁷Mass attitudes towards FDI can reflect expected economic consequences (Pandya 2014; Owen 2013) and nationalist opposition to foreign ownership (Feng et al. 2021). Politicians receptive to FDI may still have electoral motives to oppose specific projects in sensitive industries.

Kayser 2014). Common institutional features, including weak party-candidate linkages, obfuscate responsibility for economic performance (Jensenius and Suryanarayan 2022). Voters vary widely in awareness of economic conditions and exposure to relevant elite cues (Duch and Stevenson 2008; Alt et al. 2016) and rely more on non-economic considerations like candidate ethnicity (Chandra 2005). Elections can center around forms of distributive politics such as vote buying and clientelism (Hicken 2011; Golden and Min 2013; Stokes et al. 2013). These strategies are common in developing democracies because the marginal benefit of distributive payments to voters are higher at lower income levels (Calvo and Murillo 2004) and poor, risk-averse voters prefer the benefit of direct, immediate payments (Bobonis et al. 2022). Economic liberalization fuels economic insecurity, which can make voters more receptive to payments (Levitsky 2007).

Distributive politics not only undermine electoral accountability that, in other democracies, motivates politicians to maximize FDI’s economic benefits. They also create incentives for politicians to seek rents in order to sustain these electoral strategies (Hicken 2011; Bussell 2012; Gingerich 2013). Though politicians may rent seek for purely personal enrichment, the distinction between personal and politically motivated rent seeking is often weak. For example, in our empirical context of India, politicians’ personal wealth plays an outsized role in the electoral process because parties are weak and the scope for transparent campaign finance is limited (Sircar 2018). Though Indian voters disapprove of politicians’ wealth accumulation, disapproval does not affect vote choice (Chauchard et al. 2019).

Our Argument

Our central claim is that politicians in developing democracies are motivated to attract FDI to extract rents from MNCs. We define rents broadly as the use of public office for private gain, encompassing both illegal and legal forms (Krueger 1974). Prior scholarship argues that FDI engenders corruption in the presence of formal entry barriers. MNCs are willing to pay bribes to access monopoly profits, creating rent seeking opportunities for host country

officials who enforce restrictive FDI policies (Malesky et al. 2015; Zhu 2017). These findings imply that when countries liberalize FDI inflows, corruption should decline, all else equal.

We articulate an alternative logic in which FDI liberalization increases rent seeking. The most common type of FDI entry barrier restricts MNCs to minority ownership, effectively forcing joint ventures with domestic companies. Although ownership restrictions may create monopoly profits, forced joint ventures introduce a variety of contractual risks that diminish the value of MNCs' proprietary technologies (Henisz 2000). These risks deter MNCs: on average, countries with higher ownership restrictions receive less FDI (Pandya 2014).

Liberalization increases total FDI inflows and, as a larger proportion of MNCs operate without local partners, MNCs have more direct and ongoing contact with local officials (Chen and Xu 2023). Though liberalization eliminates or streamlines government approval for market entry, firms must still engage with local government to establish and operate production facilities. In most countries, subnational governments enforce regulations, issue permits, and provide access to public goods and infrastructure, creating contact points between MNCs and government. Many developing countries exhibit ambiguity in rules and procedures, and firm surveys document large gaps between *de jure* rules and *de facto* experience (Hallward-Driemeier and Pritchett 2015). Prominent measures of political risk emphasize the consequences of these gaps (Dollar et al. 2006; Kinda 2010).

These contact points provide opportunities to seek rents from MNCs in exchange for completion of governance tasks. Rents can take several forms. Illegal payments, such as bribes, are the most direct form of rent seeking. For example, Wal-Mart admitted to paying bribes to government officials in Mexico, Brazil, and India.⁸ Legal manifestations of rent seeking include business decisions favorable to officials regarding employment and contracting opportunities for politicians' kin groups (Vaishnav 2017).

An obvious question is why MNCs would tolerate rent seeking amid intense competition

⁸See <https://www.nytimes.com/2019/06/20/business/walmart-bribery-settlement.html>.

to attract investment. Indeed, not all MNCs do. Host governments have greater leverage over MNCs who invest to produce and sell within the host market (market-oriented FDI) (Vernon 1971; Kobrin 1987). For these investments, MNCs are effectively limited to large markets, which can support production on an efficient scale. While rent seeking imposes some cost, it generally does not present the contractual hazards of forced joint ventures. Politicians have less scope to extract rents from MNCs who invest to produce goods and services for export (export-oriented FDI). Countries can more readily compete to reduce firms' production costs to attract these footloose investments. Export-oriented investors are also more sensitive to the quality of public goods including infrastructure.

Bureaucratic Transfers Reveal Politicians' FDI Motives

Politicians' motives to attract FDI cannot be directly observed. Thus, we turn to an observable implication of these motives: how politicians manage bureaucrats in FDI-exposed areas. The politician-bureaucrat relationship embodies that of a principal and agent (P-A) in which the politician (principal) must delegate implementation to the bureaucrat (agent) who possesses necessary resources (information, skill, or time) (Kiewiet and McCubbins 1991). Bureaucrats exhibit a range of material and non-material motives, only some of which are consistent with politicians' goals (Niskanen 1971; Dal Bó et al. 2013; Iyer and Mani 2012). A P-A problem emerges when the two parties' objectives are misaligned and the politician can only imperfectly observe bureaucrats' actions (Strøm 2000; Aghion and Tirole 1997).

Our focus is politicians' use of a specific tool to overcome the P-A problem: bureaucratic transfers. Even in merit-based bureaucracies, politicians often retain some discretion to transfer bureaucrats across posts. Politicians can use this discretion to reward (punish) bureaucrats with desirable (undesirable) posts. Transfers are an insightful proxy for politicians' motives to attract FDI since FDI does not change the structure or rules of bureaucracy.⁹ In our empirical setting of India, lateral transfers, transfers within the same pay grade, are at

⁹Long-term, FDI may create new opportunities that influence selection into the bureaucracy.

state politicians' discretion and occur in real time.

We argue that politicians use transfers to pressure bureaucrats into facilitating their rent seeking. In a seminal study, Wade (1985) documents how Indian politicians used transfers to pressure bureaucrats to extract bribes from farmers. Brierley (2020) finds that bureaucrats in Ghana are more likely to engage in corruption on behalf of politicians who can credibly threaten to transfer them to undesirable posts. This pattern is consistent with politicians using bureaucratic oversight for electoral gain in other ways including the distribution of public services (Gulzar and Pasquale 2017) and selective law enforcement (Holland 2016).

Bureaucrats are uniquely positioned to extract rents from MNCs. MNCs rely on bureaucrats to help secure land, permits, and access to critical infrastructure (Levien 2013; Kaufmann and Wei 1999). This rent seeking undermines at least some of FDI's economic benefits. It likely detracts from bureaucrats' other tasks, many of which improve countries' capacity to absorb productivity spillovers from FDI (Alfaro 2017). More frequent transfers correlate with worse quality public services (Akhtari et al. 2022) and reduce bureaucrats' motives to develop specialized substantive expertise. MNCs adapt to rent seeking by curtailing voluntary joint ventures and other channels for productivity spillovers to local firms (Rodriguez et al. 2005; Sartor and Beamish 2018).

We infer politicians' motives to attract FDI from which bureaucrats they transfer in FDI-exposed areas. For our purposes, bureaucrats differ in their career concerns. In merit-based bureaucracies, recruitment and promotion standards help motivate bureaucrats to perform their jobs efficiently (Bekke et al. 1996). Bureaucrats can, however, vary in their motivation to meet the merit-based criteria for career advancement. Career-constrained bureaucrats, those with weaker prospects for merit-based promotion, are more likely to facilitate politicians' rent seeking in exchange for desirable posts. Bertrand et al. (2020) show that IAS officers constrained by the IAS's mandatory retirement age are perceived by their peers as less effective and more susceptible to illegitimate political pressure. Iyer and Mani (2012) document spikes in post-election IAS transfers, driven by politicians transferring

loyal but less competent officers into important posts.

In sum, we argue that politicians seek FDI to extract rents from MNCs. An observable implication of this motive is that in FDI-exposed districts, transfers of career-constrained bureaucrats increase. We briefly note an alternative explanation for increased transfers: politicians may increase transfers in FDI-exposed areas to curb constrained bureaucrats' personal rent seeking (Grindle 2012). We address this alternative below.

3 Empirical Context: India

Our empirical context is India, the world's largest electoral democracy and fifth largest economy. In India's decentralized federal system, the central government sets FDI regulations but states oversee key issues for MNCs including taxation, labor regulations, and environmental standards. During our sample period, states were the locus of India's FDI promotion efforts, which included tax breaks, expedited approvals, subsidized production inputs, and firm-specific infrastructure upgrades (Phillips et al. 2021). State Chief Ministers (CMs) personally dedicate extensive effort to negotiate with foreign companies.¹⁰ While many question whether such measures attract investment (Jensen and Malesky 2018), they resolve common information asymmetries in developing countries (Harding and Javorcik 2011).

India is organized into 28 states that hold elections for legislative assemblies every five years using a first-past-the-post parliamentary system. Voters elect members of legislative assemblies (MLAs) in single-member districts. Constituencies nest within districts, the level of local government that is our unit of analysis.¹¹ State parties are weak and fragmented, incumbents often face an electoral disadvantage, and politicians frequently switch parties between elections, obscuring responsibility for economic performance (Chhibber et al. 2014; Verma 2012; Jensenius and Suryanarayan 2022). Distributive payments to voters are promi-

¹⁰“How India's states compete for investment.” The Economist, 13 May 2023.

¹¹The average district has approximately 2 million residents, with substantial variation.

nent (Ravishankar 2009; Suri 2009; Uppal 2009; Verma 2012). Ethnic, caste, and religious identities also play an outsized role in vote choice (Chandra 2005). The parliamentary system and frequent emergence of coalition government means that the political survival of the CM depends directly on the reelection of MLAs within the coalition. As a result, CMs are incentivized to satisfy the political needs of MLAs. Legitimate campaign finance is weak such that it is a leading driver of politicians’ rent seeking (Vaishnav 2017).

2005 FDI Liberalization

Our empirical strategies leverage India’s extensive 2005 FDI liberalization to identify FDI’s effects on bureaucratic transfers. India regulates industry-level FDI inflows on two dimensions: the percent foreign ownership allowed in a single firm, and whether government approval is required (“government route”) or not (“automatic route”). Before 2005, India allowed up to 51 percent foreign ownership through the automatic route in 35 industries.

On December 23, 2005, India’s Department of Industrial Promotion and Planning (DIPP) issued guidance that “FDI up to 100% is permitted under the automatic route in most sectors/activities.” The guidance explains “[i]t has been observed that sometimes proposals are submitted for prior Government approval even though the cases are eligible for the automatic route. The investors are hereby advised to access the automatic route where the policy so permits” (DIPP 2005). This was the first legally binding policy statement that, unless stated otherwise, foreign firms can hold 100% ownership without government approval. It effectively liberalized ownership and entry in 110 industries. Figure 2 disaggregates official Indian FDI data by entry route and shows new (“greenfield”) FDI via the automatic route drove post-2005 FDI growth. We infer from this context that liberalization was not biased towards certain industries and was unrelated to other policy reforms.

Our two research designs build on FDI’s strong tendency to agglomerate in close proximity to other firms in the same industry (Head et al. 1995; Bobonis and Shatz 2007). Agglomeration produces knowledge spillovers, especially important for firms operating in

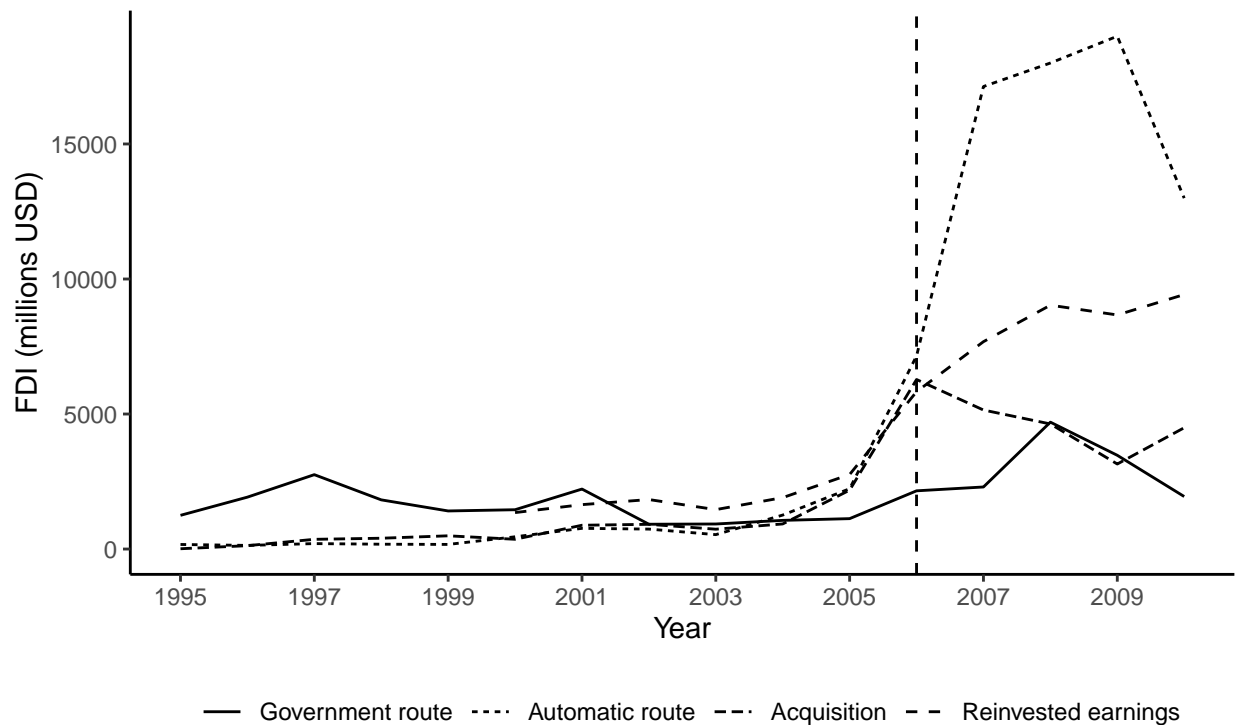


Figure 2: FDI in India Over Time by Entry Route. Source: 2012 RBI Bulletin.

an unfamiliar country. Agglomeration also allows MNCs to more readily access specialized parts suppliers and workers with industry-specific skills.

Our DID approach compares outcomes across two sets of Indian states. Six states received most of India’s FDI surge: Maharashtra, Karnataka, National Capital Region (NCR) of Delhi, Tamil Nadu, Andhra Pradesh, and Gujarat. Consistent with geographic agglomeration, Figure 3 shows that pre-liberalization FDI was concentrated in these six states (“treatment”) and they received nearly all of the post-liberalization FDI growth. India’s remaining states (“control”) had low levels of FDI before and after liberalization. An obvious concern is that districts in treated states may have other underlying traits that correlate with FDI, bureaucratic transfers, or politicians’ rent seeking. We analyze state- and district-level correlates of treatment status for 1962-2001 and find only modest differences between

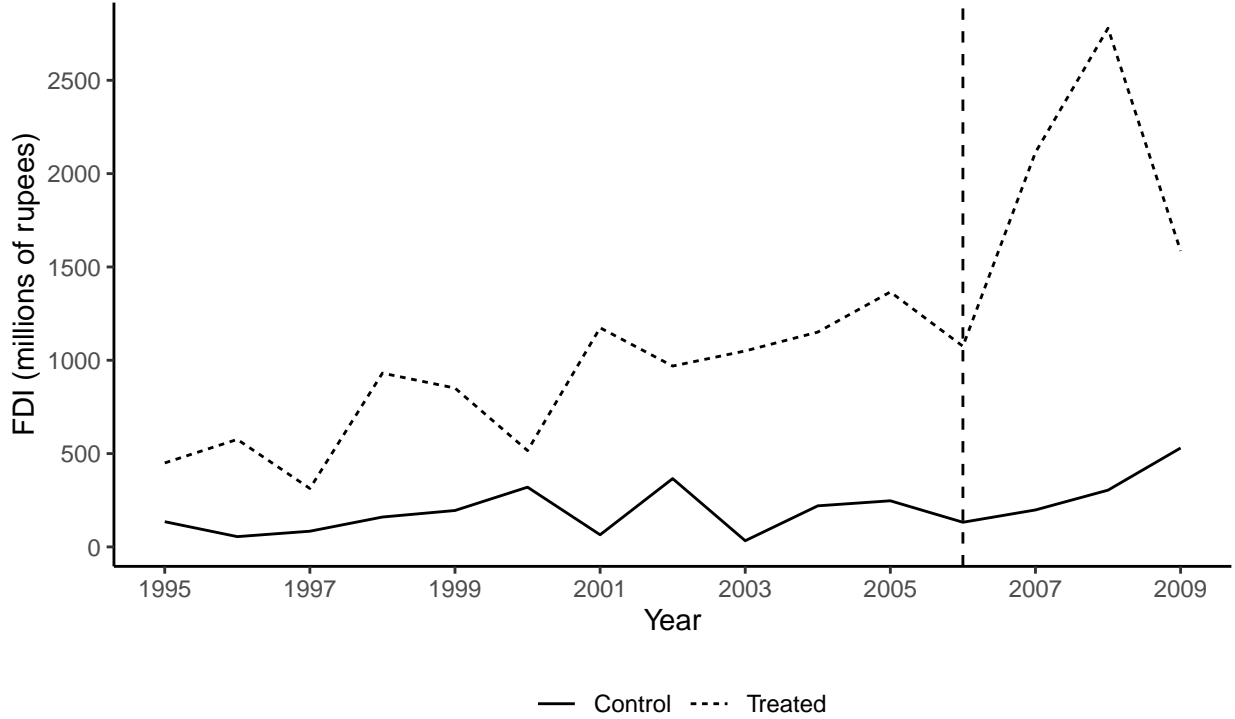


Figure 3: FDI in India Over Time in Treated vs. Control States. Source: CapEx.

treatment and control areas.¹² Our use of district fixed effects accounts for unobserved, time-invariant characteristics that may correlate with FDI and our outcomes. Additionally, we control for time-varying district characteristics that may correlate with relevant omitted district characteristics and employ district-specific time trends in estimations.

Our instrumental variable (IV) approach is a finer-grained analysis that does not rely on this treatment/control classification. We use district-year exposure to liberalization to instrument for exposure to FDI.¹³ This approach rests on the identifying assumption that national FDI regulations influence FDI inflows but are otherwise uncorrelated with district-year bureaucratic transfers or politicians' rent seeking.

¹²See Appendix B, including Tables B.1 and B.2, for full results and discussion.

¹³Topalova (2010) uses an analogous measure of district trade exposure.

Indian Administrative Service

The roughly 5,000 officers of India’s IAS oversee key functions of district, state, and central governments and government-owned companies.¹⁴ Our research designs exploit recruitment and promotion rules that produce variation in career constraints across officers. Of the less than 200 people who join the IAS annually, two-thirds are “direct recruits,” selected through a highly competitive national process and quasi-randomly assigned to a state for the duration of their IAS career. Applicants must be 21-30 years old; average entry age is 26 years old. The remaining one-third are “state recruits,” state-level civil servants nominated by their state to be an IAS officer in that state.¹⁵ State recruits are ostensibly the state’s most talented civil servants but they are widely viewed as patronage appointments (Krishnan and Somanathan 2017). The average state recruit is 43 years old at entry.

The IAS mandates retirement at 60, which constrains state recruits’ prospects for merit-based career advancement. All officers face the same evaluation and promotion structure, which is uniform nationwide. They begin their careers as deputies to the district magistrate, the chief district-level bureaucrat. District IAS officers are powerful administrators who, among other things, supervise revenue collection, law enforcement, and infrastructure (Vaishnav and Khosla 2016). The IAS has seven tiers of seniority and promotion eligibility is at fixed intervals. Promotions are subject to vacancies and strict merit criteria, and confer higher pay and prestige. After 20 years of service, officers are eligible for appointment to central government posts, which offer as much as a 60 percent raise and open up lucrative post-retirement job opportunities. By virtue of their age, state recruits rarely reach this level before retirement: in our data, state recruits hold less than five percent of central posts.

CMs have limited authority to transfer officers across posts within the state. They can make lateral transfers, transfers within the same seniority tier, at will. Transfers are common: 57 percent of district-level officers were transferred at least once annually, most laterally. CMs

¹⁴See Appendix C for detailed description of IAS.

¹⁵These recruits are often called “promotees.”

have limited influence on promotions subject to national IAS rules and merit assessments by a panel of senior officers. In practice, they can influence low-level promotions but promotions at higher levels, which are more competitive, are merit-based. CMs cannot fire officers and demotions are rare. Though the central government decides how many officers each state receives, CMs can create or eliminate posts and reshuffle posts’ substantive portfolios. MLAs work closely with IAS officers assigned to the district in which their constituency is located. When MLAs are from a party in the state’s ruling coalition, they can influence transfers. For example, Iyer and Mani (2012) show that when a new CM takes office, transfers increase in districts with a higher proportion of MLAs from the CM’s party.

MLAs use transfers to incentivize IAS officers. Desirable posts are those that confer power, influence, and prestige; are geographically desirable; or allow officers to engage in their own rent seeking. Career-constrained direct recruits are perceived by their peers as more susceptible to political pressure and are more likely to occupy prestigious posts when they exhibit loyalty to politicians (Bertrand et al. 2020; Iyer and Mani 2012). State recruits are perceived to be unduly influenced by MLAs, who are said to prefer working with state recruits because they are easier to “mould” (Banik 2001; Ramashankar 2011).¹⁶

Politicians leverage transfer authority to extract rents in multiple ways. Officers may bribe MLAs to secure plumb posts, paying more for posts with opportunities for bureaucrats’ own rent seeking. This pattern is among the most criticized aspects of the IAS (Saxena 2010; Krishnan and Somanathan 2017). Officers can also use their posts in ways that enrich MLAs. For example, Lehne et al. (2018) find that IAS officers awarded road construction contracts to contractors connected to local MLAs. Asher and Novosad (2017) demonstrate that politicians influence bureaucrats’ regulatory enforcement in ways that improve per-

¹⁶Given that CMs appoint state recruits, they may also share politicians’ preferences.

Though a P-A problem is absent, politicians would still transfer state recruits in the same manner to maximize rent extraction. State recruits remain IAS officers after their appointing politicians leave office so transfers should remain an important motivator.

formance of politically connected firms. Agnihotri et al. (2022) find that politicians use transfers to coerce bureaucrats in charge of local land administration into making decisions that generate windfalls to politicians from lucrative land deals. Politicians can either reward officers who make favorable decisions or threaten officers with transfers to undesired posts.

Bureaucracy and FDI in India

MNCs operating in India rely on district-level IAS officers for regulatory approvals and access to public infrastructure (e.g., electricity, water, communications), providing contact points to extract rents (PERC 2010; Dutta and Fischer 2021). Investment climate reports and firm executives cite bureaucracy as the largest source of political risk in South Asia (Jones and Comunale 2018; Santander 2021). Liberalization changed, but did not reduce, MNCs' interactions with bureaucrats. With the demise of central planning, local bureaucrats assumed greater importance (Sinha 2004).

MNCs often require bureaucrats' assistance to interpret ambiguous rules and regulation. No issue illustrates this challenge more than industrial land acquisition. IAS officers play a prominent and often controversial role in brokering land acquisitions for MNCs' plants (Levien 2013; Alkon 2018). Due to poor public record keeping, bureaucrats are often called upon to certify title, valuation, and influence other central aspects of transactions. Liberalization gave states responsibility for negotiating with existing landholders on behalf of private parties. This is especially true of converting agricultural land for industrial use, transactions that lack transparency and are rife with rent seeking (Chandra 2015).

4 Research Design

Data and Measurement

We measure bureaucratic transfers and other IAS officer characteristics using records from India’s Ministry of Personnel, Public Grievances, and Pensions.¹⁷ Records contain detailed biographical information and IAS career history. Our data cover 1995-2009, during which we have essentially universal coverage of serving officers. Because direct recruits complete two years of training after entry, post-liberalization applicants are excluded. State recruits undergo only eight weeks of training, so new state recruits may enter post-liberalization. This change in composition of state recruits has no straightforward implication for our argument.¹⁸ Consistent with our focus on local governance, we limit our sample to district-level officers, whose responsibilities are uniform throughout India. These data unfortunately do not report district officers’ substantive portfolios so we are unable to test hypotheses related to substantive aspects of posts. One exception is that we identify district magistrates, the chief district-level IAS officer. We use this information to create an officer-year panel dataset.

Transfer Our dependent variable, $Transfer_{ijt}$, equals one if officer i in district j is posted in a different position in year t than in year $t - 1$ and zero otherwise. $Lateral_{ijt}$ equals one if officer i in district j holds a new position at the same rank in year t as in year $t - 1$ and zero otherwise. $Promotion_{ijt}$ is an analogous measure that captures transfer to a higher rank in year t .¹⁹ The probability of transfer in a given year is 0.57.

Recruitment Source $StateRecruit_i$ is a time-invariant indicator equal to one if bureaucrat i entered the IAS from a state civil service and zero otherwise. One-third of all IAS

¹⁷These data are available at <https://supremo.nic.in/KnowYourOfficerIAS.aspx>.

¹⁸State recruit positions may become marginally more appealing as a result of liberalization, but this possibility has no straightforward implications for politicians’ transfer decisions.

¹⁹Some officers experience multiple transfers within the same year. Following Iyer and Mani (2012), we code them as transferred only once, creating a conservative measure of transfer.

officers are state recruits. This is our central measure of career constraints.

Officer Quality For all officers regardless of entry pathway, *FirstClassDegree_i* equals one if officer *i* attained a first class university degree and zero otherwise. *ForeignDegree_i* indicates whether officer *i* received a degree from a foreign university. 80 percent of direct recruits hold first class degrees and 20 percent hold foreign degrees, compared to just 20 and three percent, respectively, for state recruits. Two additional measures are relevant only for direct recruits. *ExamRank_i* is the rank earned by direct recruit *i* on the competitive national IAS entrance exam.²⁰ State recruits did not take this exam during the sample period. *SameDomicile_i* equals one if direct recruit *i* serves in their home state and zero otherwise. Highest-scoring direct recruits receive limited consideration of location preference, which is almost always their home state. State recruits always serve in their home state.

FDI FDI data are from CapEx, a database published by the Centre for Monitoring Indian Economy (CMIE). CapEx’s project-level level FDI data reports the district in which the project is located, industry, and date of operation.²¹ To the best of our knowledge, these data are the most granular and accurate Indian FDI data available for the sample period. Official FDI data are based on intended investment, a portion of which never materializes, whereas CapEx identifies completed investments.²² We measure FDI as the count of completed greenfield FDI projects in a district-year. Valuation data are missing for more than 25 percent of projects. The industry distribution of projects pre- and post-liberalization indicates that

²⁰Data are from the IAS’s Empanelment and Appraisal System (<https://easy.nic.in/civilListIAS/YrCurr/AppendixQryCL.htm>). Data are available for only current officers so we lack data for approximately 30 percent of officers who served during 1995-2009 but retired prior to 2020 when we retrieved the data.

²¹CMIE obtains this information through press reports, government filings, and correspondence with firms.

²²CapEx data are also less likely to capture Indian firms’ use of foreign tax havens, which inflates official FDI estimates.

no specific industries drive topline FDI growth.

Our IV approach uses original FDI regulations data to construct an instrument for district-level FDI exposure. For each 4-digit industry in the 2008 Indian National Industrial Classification, we code the percent foreign ownership allowed in a firm and whether investment required government authorization (government route) or not (automatic route) in a given year. For each industry-year, we measure liberalization as the percent foreign ownership allowed via the automatic route.

We use these data to measure district-year exposure to FDI liberalization. Exposure is a function of districts’ pre-liberalization industrial composition, which we measure using employment data from the 2001 Indian National Sample Survey (NSS). The measure averages district exposure to liberalization, weighted by industrial employment composition. To illustrate, if a district-year has five industries, each accounting for 20 percent of employment in 2001, and one industry is open to 100 percent foreign ownership via the automatic route, exposure is 0.2. If, in the following year, a second industry is fully liberalized, the value increases to 0.4. On average, 35 percent of a district’s economy is open to FDI.

Control variables We use data from the 1991 and 2001 Indian Census to construct district controls: logged population, Scheduled Caste rate, adult literacy rate, employment rate, and gender ratio. We interact these decennial variables with year indicators – we use 1991 census values from 1995-2000 and 2001 values for subsequent years. Summary statistics for all variables are available in Appendix Table A.1.

5 Empirical Analysis

Our DID analysis compares transfers in treated states’ districts before and after FDI liberalization to districts in India’s other states. We estimate the following empirical model:

$$Transfer_{ijt} = \alpha_0 + \alpha_1 Treated_{ij} * Post_t + \alpha_2 Rank_{it} + \alpha_3 X_{jt} * \kappa_t + \theta_j + \kappa_t + \theta_j * Year_t + \epsilon_{ijt} \quad (1)$$

where $Treated_{ij}$ is an indicator variable equal to one if officer i is located in a treated district j ; $Post_t$ is an indicator variable equal to one for years 2006 and beyond; $Rank_{it}$ corresponds to IAS rank for officer i at time t ; and $X_{jt} * \kappa_t$ is a vector of controls for district j interacted with year indicators κ_t . θ_j and κ_t are district and year fixed effects. $\theta_j * Year_t$ represents district-specific linear time trends. ϵ_{ijt} is the error term. α_1 is the parameter of interest. We estimate all models using OLS and report robust standard errors clustered by state.²³

We leverage a triple difference design to analyze sources of heterogeneity including the differential movement of state recruits, ex ante state corruption, and investment characteristics. We discuss these specifications later.

Table 1 shows the estimation of Equation 1.²⁴ $Transfer_{ijt}$ is the dependent variable in Columns (1), (2), and (3). Column (1) includes no controls, Column (2) controls for population only, and Column (3) includes the full set of controls. India's FDI liberalization caused significantly increased transfers in exposed districts. Officers located in districts most exposed to liberalization had a 23.7 percentage point increase in the probability of transfer. The results in Columns (4) and (5), in which the dependent variable is $Lateral_{ijt}$ and $Promotion_{ijt}$ respectively, show that this topline result is primarily driven by increased probability of lateral transfer (i.e., within rank), which can reflect use of transfers as both carrots and sticks. The absence of detailed data on the substantive portfolios of posts motivates our triple difference analysis of heterogeneity in transfers across bureaucrats with varying levels of career constraint.

²³Results are robust to clustering by district.

²⁴We also estimate these models with officer fixed effects and present the results in Appendix Table A.2.

Table 1: FDI and Bureaucratic Transfers

	<i>Dependent variable:</i>				
	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Lateral_{ijt}</i>	<i>Promotion_{ijt}</i>
	(1)	(2)	(3)	(4)	(5)
<i>Treated_{ij} * Post_t</i>	0.121*** (0.043)	0.138*** (0.044)	0.237*** (0.053)	0.195*** (0.067)	0.036 (0.031)
Observations	11,091	10,399	10,399	10,399	10,399
Number of districts	556	497	497	497	497
Control for district pop.	X	✓	✓	✓	✓
Other district controls	X	X	✓	✓	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Full results in Appendix Table E.1.

Event Study

We evaluate the plausibility of the parallel trends assumption in our DID design by estimating the following event study model:

$$Transfer_{ijt} = \alpha_0 + \sum_{l=1996}^{2009} \gamma_l(Treated_{ij} * d_l) + \alpha_2 Rank_{it} + \alpha_3 X_{jt} * \kappa_t + \theta_j + \kappa_t + \theta_j * Year + \epsilon_{ijt} \quad (2)$$

where notation remains the same as in Equation 1. γ_l are year-specific estimates of the interaction of $Treated_{ij}$ and year indicators d_l .

We present the results of our event study estimation in Figure 4. 2005 is the excluded reference year; we also omit the first year, 1995, due to the inclusion of district-specific trends. The figure plots the coefficients of the interaction term between treatment and year indicators with 95 percent confidence intervals. For each year between 1996 and 2004, the estimates are small and statistically insignificant.²⁵ We observe a sharp, statistically significant increase

²⁵An F-test for joint significance of the pre-period coefficients fails to reject the null hypothesis that the coefficients are equal to zero ($F = 0.212, p = 0.64$).

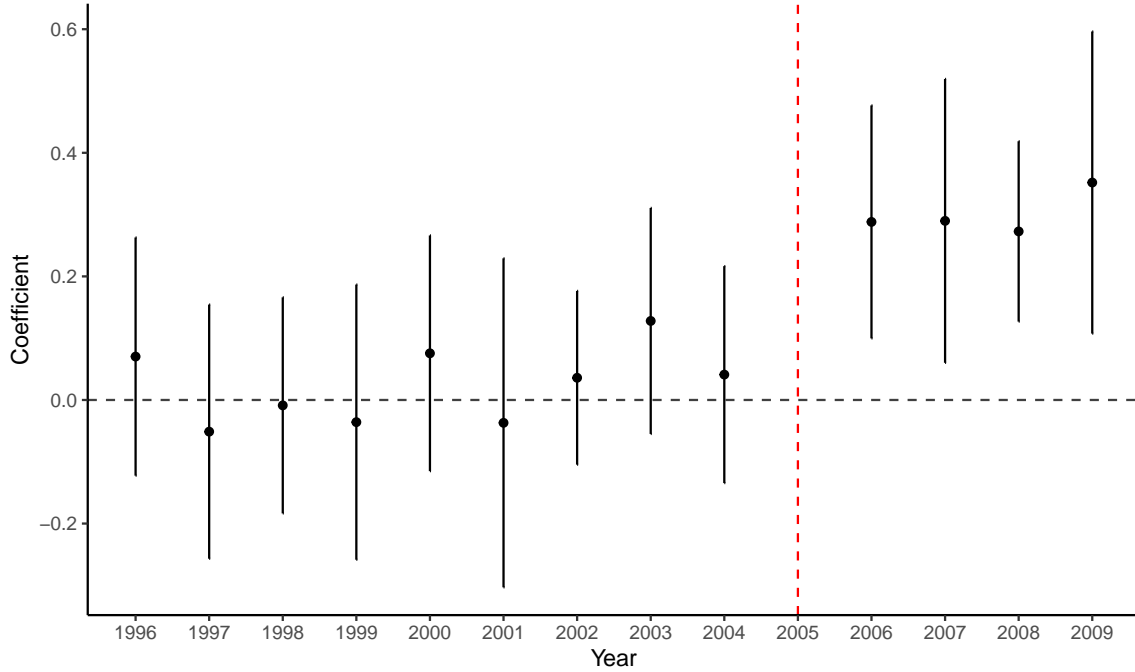


Figure 4: Year-by-Year Treatment Estimates. Notes: year-by-year coefficient of interaction between treatment and year indicators on transfers with 95 percent confidence intervals. Standard errors clustered by state. 2005 omitted as reference period. Model includes district and year fixed effects and district-specific time trends.

in the probability of transfer in 2006, the year following FDI liberalization; the effect stays relatively constant thereafter.²⁶ We do not observe differential pre-trends by treatment status, and the timing of increased transfer corresponds with liberalization. These results further suggest that FDI liberalization increased transfers.

We address the possibility that heterogeneous treatment effects bias our results using the estimator developed by de Chaisemartin and D’Haultfœuille (2020).²⁷ We present these results in Appendix Table A.3. The estimated effect is virtually identical to our baseline

²⁶An F-test for joint significance of the post-period coefficients rejects the null hypothesis that the coefficients are equal to zero ($F = 15.67, p = 0.00008$).

²⁷Our design does not leverage differential treatment timing.

results. Appendix Figure A.1 presents a placebo test to check for evidence of differential pretrends using this estimator; there is little evidence to this effect.

Instrumental Variables Estimation

We also directly estimate the relationship between FDI and bureaucratic transfers using a two-stage least-squares (2SLS) IV model with district and year fixed effects. We use our previously discussed measure of district-year exposure to FDI liberalization. This strategy addresses the possibility that MNCs' district location decisions within India are non-random with respect to outcomes. The first-stage regression is as follows:

$$FDI_{jt-1} = \beta_0 + \beta_1 LiberalizationExposure_{jt-2} + \beta_2 Rank_{it} + \beta_3 X_{jt} * \kappa_t + \theta_j + \kappa_t + u_{jt} \quad (3)$$

where FDI_{jt-1} is the count of new FDI projects district j receives at time $t - 1$; $LiberalizationExposure_{jt-2}$ is exposure to liberalization in district j at time $t - 2$; and u_{jt} is the error term. All other notation is the same as in Equation 1.

The second-stage regression is estimated as follows:

$$Transfer_{ijt} = \alpha_0 + \alpha_1 \widehat{FDI_{jt-1}} + \alpha_2 Rank_{it} + \alpha_3 X_{jt} * \kappa_t + \theta_j + \kappa_t + \epsilon_{ijt} \quad (4)$$

where $\widehat{FDI_{jt-1}}$ is the instrumented number of new FDI projects from Equation 3 and ϵ_{ijt} is the error term. We report robust standard errors clustered by state and utilize a linear specification to estimate our 2SLS model.

We show the estimated effect of FDI liberalization on transfers using our 2SLS estimation in Table 2. Column (1) presents the first-stage results for receipt of new FDI, while Column (2) presents the second-stage results for the probability of transfer. We find that increased liberalization causes a significant increase in the number of new FDI projects. This increase in FDI exposure leads to a 36 percentage point increase in the probability of transfer.

Table 2: Instrumental Variables (2SLS) Estimation

	<i>Dependent variable:</i>	
	<i>FDI_{jt-1}</i>	<i>Transfer_{ijt}</i>
	1st stage	2nd stage
	(1)	(2)
<i>AvgFDIAllowed_{jt-2}</i>	0.017*** (0.005)	
<i>FDI_{jt-1}</i>		0.363** (0.183)
First stage F-statistic	10.6	
Observations	9,787	9,787
Number of districts	488	488

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using two-stage least-squares (2SLS) with district and year fixed effects. Full results in Appendix Table E.2.

Which Bureaucrats Do Politicians Transfer?

We extend our DID analysis to analyze whether this topline result reflects the systematic transfer of state recruits – career-constrained bureaucrats who are most likely to facilitate politicians’ rent seeking. We estimate the following triple difference model:

$$\begin{aligned}
Y_{ijt} = & \alpha_o + \alpha_1 Treated_{jt} * Post_t + \alpha_2 Treated_{jt} * Post_t * StateRecruit_i + \\
& \alpha_3 Post_t * StateRecruit_i + \alpha_4 Treated_{jt} * StateRecruit_i + \\
& \alpha_5 Rank_{it} + \alpha_6 X_{jt} * \kappa_t + \theta_j + \kappa_t + \theta_j * Year_t + \epsilon_{ijt}
\end{aligned} \tag{5}$$

where the parameter of interest is α_2 , the coefficient on the interaction between liberalization exposure and whether officer i is a state recruit.

Table 3 presents the results.²⁸ Liberalization-induced transfers primarily involved the

²⁸All constituent interactions are included but suppressed due to space constraints.

Table 3: FDI and Transfers of State Recruits

	<i>Dependent variable:</i>				
	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Lateral_{ijt}</i>	<i>Promotion_{ijt}</i>
	(1)	(2)	(3)	(4)	(5)
<i>Treated_{ij} * Post_t</i>	0.168***	0.178***	0.173***	0.037	0.130**
<i>StateRecruit_i</i>	(0.045)	(0.047)	(0.049)	(0.068)	(0.057)
<i>Treated_{ij} * Post_t</i>	0.049	0.060	0.164***	0.176***	−0.016
	(0.050)	(0.050)	(0.058)	(0.068)	(0.034)
Observations	11,098	10,406	10,406	10,406	10,406
Number of districts	556	497	497	497	497
Control for district pop.	X	✓	✓	✓	✓
Other district controls	X	X	✓	✓	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Full results in Appendix Table E.3.

transfer of state recruits, who are an additional 17.2 percentage points more likely to experience transfers in FDI-exposed areas. This increased probability of transfer is primarily driven by *promotions* of state recruits – in other words, the movement of state recruits to higher-rank district-level positions. The double interaction ($Treated_{jt} * Post_t$) continues to be positive and statistically significant. Figure 5 shows the results of an identical event study model expressed in Equation 2 for state recruits only. For each year between 1996 and 2004, the estimates for state recruits are small and statistically insignificant.²⁹ We again observe a sharp and statistically significant increase in the probability of transfer for state recruits immediately following liberalization; this effect stays relatively constant thereafter. One year in the post-liberalization period (2008) is statistically insignificant, while all others are significant at $p < .05$.³⁰

²⁹An F-test for joint significance of the pre-period coefficients fails to reject the null hypothesis that the coefficients are equal to zero ($F = 0.0.185, p = 0.67$).

³⁰An F-test for joint significance of the post-period coefficients rejects the null hypothesis

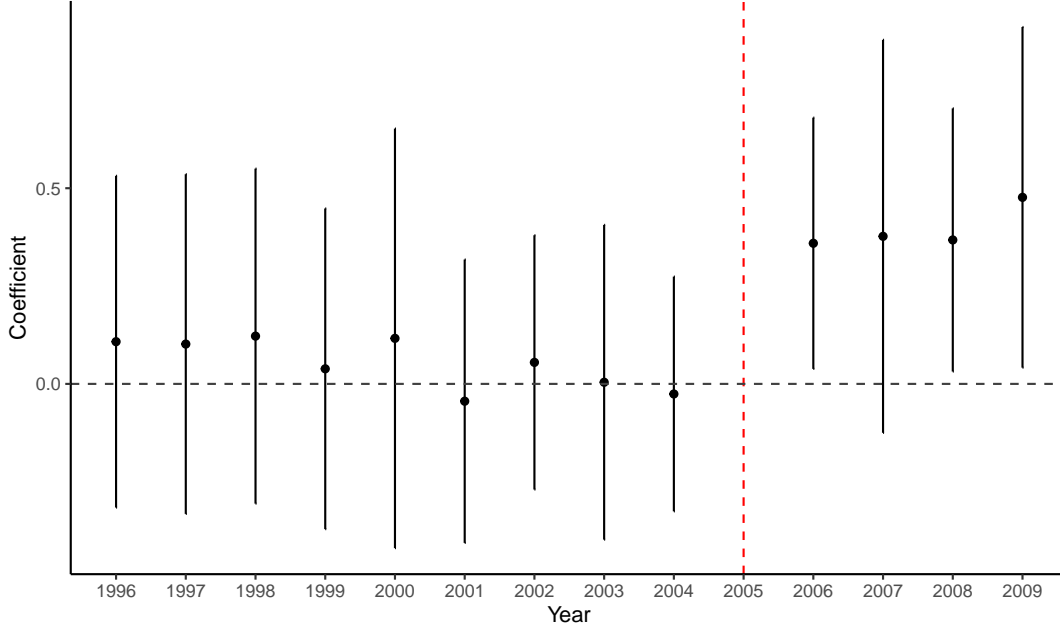


Figure 5: Year-by-Year Treatment Estimates for State Recruits. Notes: year-by-year coefficient of interaction between treatment and year indicators on transfers with 95 percent confidence intervals. Standard errors clustered by state. 2005 omitted as reference period. Model includes district and year fixed effects and district-specific time trends.

No Differential Transfer of Competent Bureaucrats

One alternative explanation is that politicians transfer state recruits because they are more competent by virtue of greater contextual knowledge of their home state. We disentangle the potential role of competence by estimating triple difference models with four indicators of ex ante competence we defined earlier: *Top20Exam_i*, *SameDomicile_i*, *FirstClassDegree_i*, and *ForeignDegree_i*. The first two measures are relevant only for direct recruits.

Table 4 displays the results. Models (1), (2), (3), and (5) are estimated for direct recruits, while models (4) and (6) are estimated for state recruits. Using multiple proxies for competence, more competent officers in FDI-exposed areas are not more likely to be transferred. Direct recruits posted to their home state are no more likely to experience transfers,

that the coefficients are equal to zero ($F = 6.39, p = 0.012$).

Table 4: FDI and Transfers of Competent Bureaucrats

	<i>Dependent variable: Transfer_{ijt}</i>					
	Direct recruits (1)	Direct recruits (2)	Direct recruits (3)	State recruits (4)	Direct recruits (5)	State recruits (6)
$Treated_{ij} * Post_t *$ $Top20Exam_i$	-0.098 (0.101)					
$Treated_{ij} * Post_t *$ $SameDomicile_i$		-0.021 (0.053)				
$Treated_{ij} * Post_t *$ $FirstClassDegree_i$			0.045 (0.072)	-0.341* (0.182)		
$Treated_{ij} * Post_t *$ $ForeignDegree_i$					-0.144* (0.079)	-0.299 (0.191)
$Treated_{ij} * Post_t$	0.103 (0.111)	0.138** (0.066)	0.097 (0.095)	0.408*** (0.131)	0.150** (0.066)	0.399*** (0.131)
Observations	4,692	6,683	6,683	3,294	6,683	3,294
Number of districts	479	489	489	457	489	457

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Full results in Appendix Table E.4.

suggesting that promotion of state recruits is not due to their superior local knowledge.

Transfers Into Powerful Posts

Our framework has obvious implications for the types of posts into which politicians transfer state recruits: powerful positions that allow state recruits to facilitate rent seeking. Though we lack detailed data on the portfolios of district IAS officers, we can identify officers appointed as district magistrates. Often described as the “kingpin” of district governance, magistrates enjoy both prestige and unmatched rent seeking opportunities (Vaishnav and Khosla 2016). In Table 5, we extend our triple difference strategy to analyze the outcome

Table 5: FDI and State Recruits in Top District Positions

	<i>Dependent variable: DistrictMagistrate_{ijt}</i>		
	(1)	(2)	(3)
$Treated_{ij} * Post_t *$ $StateRecruit_i$	0.150** (0.064)	0.128** (0.061)	0.131** (0.060)
$Treated_{ij} * Post_t$	0.055 (0.042)	0.071* (0.042)	0.088* (0.045)
Observations	9,666	9,063	9,063
Number of districts	551	495	495
Control for district pop.	X	✓	✓
Other district controls	X	X	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Sample includes only bureaucrats eligible for district magistrate positions. Full results in Appendix Table E.5.

$DistrictMagistrate_{ijt}$, an indicator equal to one if officer i is district j has been appointed as a district magistrate at time t . We find that in FDI-exposed districts, state recruits are about 12 percentage points more likely to be district magistrates.

This finding also addresses the alternative explanation that politicians transfer state recruits to prevent entrenchment and personal rent seeking (McCubbins et al. 1987). Two further pieces of evidence are inconsistent with this alternative. Direct recruits posted to their home states are perceived as more entrenched (Bhavnani and Lee 2018; Xu et al. 2023). However, in Table 4, we show that these officers are no more likely to be transferred in FDI-exposed areas. Politicians often use geographically distant reassignment to prevent entrenchment (Brierley 2020) but roughly 75 percent of district-level transfers are across posts within the same district.

Additional Sources of Heterogeneity

We document additional sources of heterogeneity in FDI exposure and transfers consistent with politicians' rent seeking motives. Further details are available in Appendix D.

An observable implication of our framework is that FDI-driven transfers should be concentrated in more corrupt states. Using pre-liberalization Transparency India state corruption rankings, we estimate a triple difference model similar to Equation 5, interacting FDI exposure with state corruption rank in 2005. We find that transfers of state recruits are almost entirely concentrated in ex ante more corrupt states (Appendix Table D.1). Related, if MNCs from more corrupt countries pay rents more readily, then transfers of state recruits should be pronounced in the presence of FDI from relatively corrupt countries. Using V-Dem data on home country corruption, we find support for this implication (Appendix Table D.2).

Another implication of our framework is that MNCs making market-oriented investments should be more tolerant of politicians' rent-seeking. Accordingly, transfers of state recruits should be more likely in the presence of market-oriented FDI. We measure market orientation using data on related party exports from India to the US. Industries in which related party exports are relatively low are more likely to have market-oriented FDI. We use these data to measure average district-level FDI market orientation. Using this measure, we estimate a triple difference model, interacting liberalization exposure with average export orientation of FDI inflows. Appendix Table D.3 presents the results. We split the sample by recruitment source and find that state recruits are less likely to be transferred as investment becomes more export-oriented; transfers of direct recruits do not systematically vary with FDI orientation.

FDI and Private Returns to Office

We evaluate FDI's consequences for politicians' personal assets, a proxy for rent seeking. We draw on candidate-level asset disclosure data collected by the Election Commission of

India (ECI) and provided by India’s Association for Democratic Reform (ADR).³¹ Following a 2002 Supreme Court ruling, all candidates for state and national office are required to disclose the value of their personal assets. Misstatement is punishable with financial penalties, imprisonment up to six months, and disqualification from holding office. Disclosures include candidates’ assets, their dependents’ assets, education, criminal activity, and age.

We use these data in an empirical strategy pioneered by Fisman et al. (2014) that models the private returns to office using a subset of state legislative candidates (MLAs) who were involved in close elections. For each candidate, some of whom won and some lost, we observe the total value of personal assets at two points in time – at elections that occur both pre- and post-liberalization. The exact time points at which we observe their assets depends on the particular state’s election cycle. The asset data are further broken down by the value of *movable* (e.g., cash, vehicles) vs. *immovable* (e.g., real estate) assets.³² We conjecture that rent seeking should have a relatively larger effect on movable assets, whereas changes in immovable asset values are more likely to reflect FDI-related changes in local economic prosperity. We match each candidate to the cumulative amount of FDI received in their district between the two time points. We also match each candidate to the share of district IAS officers who are state recruits in the year prior to their second election. Recall that MLA constituencies are nested within districts.

³¹See <https://adrindia.org/about-adr/who-we-are> for asset disclosure records for elections since 2003.

³²Summary statistics for politicians’ financial assets is available in Appendix Table A.1.

We model politicians' asset growth as:

$$\begin{aligned}
Assets_{pjt} = & \gamma_0 + \gamma_1 CumulFDI_{jt} + \gamma_2 Incumbent_{pjt-} + \gamma_3 StateRecruit_{jt-1} + \\
& \gamma_4 CumulFDI_{jt} * Incumbent_{pjt-} + \gamma_5 StateRecruit_{jt-1} * Incumbent_{pjt-} + \\
& \gamma_6 CumulFDI_{jt} * StateRecruit_{jt-1} + \\
& \gamma_7 CumulFDI_{jt} * StateRecruit_{jt-1} * Incumbent_{pjt-} + \\
& \gamma_8 Assets_{pjt-} + \gamma_9 X_{pt} + \tau_{t-} + \mu_{pjt}
\end{aligned} \tag{6}$$

where $Assets_{pjt}$ is the logged value of assets of politician p in district j at time t , the year of the politician's post-liberalization election; $CumulFDI_{jt}$ is the cumulative count of FDI projects in district j that were completed between the pre-liberalization election at time $t-$ and the post-liberalization election at time t ; $Incumbent_{pjt-}$ is an indicator for whether politician p in district j won the pre-liberalization election at time $t-$ and therefore holds office at the time of the post-liberalization election t ; $StateRecruit_{jt-1}$ is the share of bureaucrats in district j that are state recruits at time $t - 1$, the year prior to the post-liberalization election; $Assets_{pjt-}$ is the logged value of assets of politician p in district j at the time of the pre-liberalization election, $t-$; and X_p is a vector of candidate p characteristics at time t including age, gender, education, and criminal convictions. τ_{t-} represent pre-liberalization election fixed effects. We estimate these models using OLS and cluster standard errors by state.

Table 6 presents our results. Panel A shows the results for total logged assets, while Panels B and C show the results for movable and immovable assets, respectively. Recall that we restrict the sample to politicians who narrowly won or lost their pre-liberalization election, in line with Fisman et al. (2014), to address potential endogeneity concerns with respect to candidate selection. In Column (1) we analyze all candidates, while in Columns (2) and (3) we disaggregate politicians by whether they formed a part of the state's ruling government.

Table 6: FDI, Bureaucratic Reorganization, and Private Returns to Office

Panel A: $Assets_{pjt}$	All (1)	In govt. (2)	Out of govt. (3)
$CumulFDI_{jt} * Incumbent_{ijt-} * StateRecruit_{jt-1}$	0.084** (0.034)	0.119* (0.067)	0.057 (0.052)
$CumulFDI_{jt} * Incumbent_{ijt-}$	-0.023* (0.013)	-0.059 (0.035)	-0.002 (0.033)
$CumulFDI_{jt}$	0.021 (0.012)	0.027** (0.011)	0.005 (0.029)
Observations	716	315	401
Panel B: $MovableAssets_{pjt}$	All (1)	In govt. (2)	Out of govt. (3)
$CumulFDI_{jt} * Incumbent_{ijt-} * StateRecruit_{jt-1}$	0.056 (0.084)	0.214** (0.082)	-0.063 (0.080)
$CumulFDI_{jt} * Incumbent_{ijt-}$	-0.081 (0.011)***	-0.141*** (0.038)	-0.009 (0.024)
$CumulFDI_{jt}$	0.051 (0.021)**	0.073*** (0.015)	-0.014 (0.026)
Observations	706	310	396
Panel C: $ImmovableAssets_{pjt}$	All (1)	In govt. (2)	Out of govt. (3)
$CumulFDI_{jt} * Incumbent_{ijt-} * StateRecruit_{jt-1}$	0.041 (0.033)	0.100 (0.077)	0.020 (0.048)
$CumulFDI_{jt} * Incumbent_{ijt-}$	0.004 (0.053)	-0.076* (0.095)	0.026 (0.107)
$CumulFDI_{jt}$	0.032*** (0.010)	0.033*** (0.010)	0.020 (0.031)
Observations	677	295	382

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with first election fixed effects. Candidate controls include: years of education, criminal record, gender, age, previous incumbency status, and logged net assets at time of prior election. Full results in Appendix Table E.6.

We first note that greater cumulative numbers of FDI projects are unconditionally associated with increased asset growth for MLAs, and this result is driven entirely by politicians whose party controls the state government. These politicians have more influence over IAS transfers because their co-partisans in the state government control transfers.

The more relevant comparison, however, is between incumbent politicians in FDI-exposed areas with relatively more or less state recruits in their district. In these areas, incumbents whose districts have no state recruits immediately preceding the election experience negative asset growth (Panel A, second row). But in FDI-exposed districts with a higher share of state recruits, incumbents whose party control the state government see a substantial increase in their assets. This gain is especially concentrated in *movable* rather than *immovable* assets: the triple interaction estimated in Column (2) of Panel B indicates a 24 percent increase in assets in between the pre- and post-liberalization elections. The average FDI-exposed district received approximately four new projects during the politician’s term. Growth in politicians’ movable assets is roughly 12 percent of the average value of new district FDI during their term. Taken together, these findings are consistent with politicians using transfer discretion to motivate career-constrained bureaucrats to facilitate their rent seeking from MNCs.

6 Conclusion

Politicians in developing democracies take costly measures to attract FDI. Even when voters do not reward politicians for attracting new investment, FDI can be an attractive source of rents. We introduce a novel measure of politicians’ revealed motives to attract FDI: bureaucratic transfers in FDI-exposed areas. When bureaucrats have weaker prospects for merit-based career advancement, they more likely to facilitate politicians’ rent seeking in exchange for desirable posts. We find that after FDI liberalization in India, FDI-exposed districts saw more transfers of career-constrained IAS officers and higher likelihood that a constrained officer occupied desirable posts. Additionally, we show that the personal assets of state legislators in FDI-exposed areas grow but only when a high proportion of districts IAS officers are constrained and copartisans control transfers.

We note possible extensions of this research. One promising line of inquiry is the electoral consequences of FDI-derived rents. These rents may be distinctive with respect to their size,

frequency, and availability. For example, MNCs are often resilient to negative economic shocks that can reduce domestic firms' capacity to pay rents. Another set of potential questions pertain to the allocation of bureaucrats' limited time and attention. To the extent that local bureaucrats' engagement with MNCs, rent seeking or otherwise, detracts from other responsibilities, politicians must weigh the electoral value of rents against bureaucrats' provision of electorally salient public services. Alternatively, bureaucrats' efforts on behalf of MNCs, including provision of public goods, may have positive spillovers.

References

- Aghion, Philippe and Jean Tirole. 1997. Formal and Real Authority in Organizations. *Journal of Political Economy* 105(1), 1–29.
- Agnihotri, Anustubh, Aditya Dasgupta, and Devesh Kapur. 2022. The Political Economy of Capture: Micromotives and Macrobehavior in India’s Land Bureaucracy. Working paper.
- Akhtari, Mitra, Diana Moreira, and Laura Trucco. 2022. Political Turnover, Bureaucratic Turnover, and the Quality of Public Services. *American Economic Review* 112(2), 442–93.
- Alfaro, Laura. 2017. Gains from Foreign Direct Investment: Macro and Micro Approaches. *The World Bank Economic Review* 30, S2–S15.
- Alkon, Meir. 2018. Do Special Economic Zones Induce Developmental Spillovers? Evidence from India’s States. *World Development* 107, 396–409.
- Alt, James E., David D. Lassen, and John Marshall. 2016. Credible Sources and Sophisticated Voters: When Does New Information Induce Economic Voting? *The Journal of Politics* 78(2), 327–342.
- Anderson, Christopher J.. 2007. The End of Economic Voting? Contingency Dilemmas and the Limits of Democratic Accountability. *Annual Review of Political Science* 10(1), 271–296.
- Asher, Sam and Paul Novosad. 2017. Politics and Local Economic Growth: Evidence from India. *American Economic Journal: Applied Economics* 9(1), 229–273.
- Auerbach, Adam and Tariq Thachil. 2020. Cultivating Clients: Reputation, Responsiveness, and Ethnic Indifference in India’s Slums. *American Journal of Political Science* 64(3), 471–487.
- Auerbach, Adam Michael and Tariq Thachil. 2018. How Clients Select Brokers: Competition and Choice in India’s Slums. *American Political Science Review* 112(4), 775–791.

- Banik, Dan. 2001. The Transfer Raj: Indian Civil Servants on the Move. *European Journal of Development Research* 13(1), 106–134.
- Bekke, Hans A., Theo A. Toonen, and James L. Perry (Eds.). 1996. *Civil Service Systems in Comparative Perspective*. Bloomington: Indiana University Press.
- Bertrand, Marianne, Robin Burgess, Arunish Chawla, and Guo Xu. 2020. The Glittering Prizes: Career Incentives and Bureaucrat Performance. *Review of Economic Studies* 87(2), 626–655.
- Bhavnani, Rikhil and Alexander Lee. 2018. Local Embeddedness and Bureaucratic Performance: Evidence from India. *Journal of Politics* 80(1), 71–87.
- Bloom, Nicholas and John Van Reenen. 2007. Measuring and Explaining Management Practices Across Firms and Countries. *The Quarterly Journal of Economics* 122(4), 1351–1408.
- Bobonis, Gustavo J., Paul J. Gertler, Marco Gonzalez-Navarro, and Simeon Nichter. 2022. Vulnerability and Clientelism. *American Economic Review* 112(11), 3627–3659.
- Bobonis, Gustavo J. and Howard J. Shatz. 2007. Agglomeration, Adjustment, and State Policies in the Location of Foreign Direct Investment in the United States. *Review of Economics and Statistics* 89(1), 30–43.
- Brierley, Sarah. 2020. Unprincipled Principals: Co-opted Bureaucrats and Corruption in Ghana. *American Journal of Political Science* 64(2), 209–222.
- Bussell, Jennifer. 2012. *Corruption and Reform in India: Public Services in the Digital Age*. Cambridge: Cambridge University Press.
- Calvo, Ernesto and Maria Victoria Murillo. 2004. Who Delivers? Partisan Clients in the Argentine Electoral Market. *American Journal of Political Science* 48(4), 742–757.
- Chandra, Kanchan. 2005. Ethnic Parties and Democratic Stability. *Perspectives on Politics* 3(2), 235–252.

- Chandra, Kanchan. 2015. The New Indian State: The Relocation of Patronage in the Post-Liberalisation Economy. *Economic and Political Weekly* 50(41), 46–58.
- Chauchard, Simon, Marko Klašnja, and S.P. Harish. 2019. Getting Rich Too Fast? Voters’ Reactions to Politicians’ Wealth Accumulation. *The Journal of Politics* 81(4), 1197–1209.
- Chen, Frederick R and Jian Xu. 2023. Partners with Benefits: When Multinational Corporations Succeed in Authoritarian Courts. *International Organization* 77(1), 144–178.
- Chhibber, Pradeep, Francesca Jensenius, and Pavithra Suryanarayan. 2014. Party Organization and Party Proliferation in India. *Party Politics* 20(4), 489–505.
- Dal Bó, Ernesto, Frederico Finan, and Martín A. Rossi. 2013. Strengthening State Capabilities: The Role of Financial Incentives in the Call to Public Service. *The Quarterly Journal of Economics* 128(3), 1169–1218.
- de Chaisemartin, Clément and Xavier D’Haultfoeuille. 2020. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review* 110(9), 2964–2996.
- DIPP. 2005. DIPP Press Release Archive, S No. 50, December 23. Technical report, Government of India, Ministry of Commerce & Industry.
- Dollar, David, Mary Hallward-Driemeier, and Taye Mengistae. 2006. Investment Climate and International Integration. *World Development* 34(9), 1498–1516.
- Duch, Raymond M. and Randolph T. Stevenson. 2008. *The Economic Vote: How Political and Economic Institutions Condition Election Results*. Cambridge: Cambridge University Press.
- Dutta, Anwesha and Harry W. Fischer. 2021. The Local Governance of COVID-19: Disease Prevention and Social Security in Rural India. *World Development* 138, 105234.

- Evans, Peter B. 1995. *Embedded Autonomy: States and Industrial Transformation*. Princeton: Princeton University Press.
- Feng, Yilang, Andrew Kerner, and Jane L. Sumner. 2021. Quitting Globalization: Trade-Related Job Losses, Nationalism, and Resistance to FDI in the United States. *Political Science Research and Methods* 9(2), 292–311.
- Fisman, Raymond, Florian Schulz, and Vikrant Vig. 2014. The Private Returns to Public Office. *Journal of Political Economy* 122(4), 806–862.
- Gingerich, Daniel W. 2013. *Political Institutions and Party-Directed Corruption in South America: Stealing for the Team*. Cambridge: Cambridge University Press.
- Golden, Miriam and Brian Min. 2013. Distributive Politics Around the World. *Annual Review of Political Science* 16(1), 73–99.
- Grindle, Merilee S. 2012. *Jobs for the Boys: Patronage and the State in Comparative Perspective*. Cambridge: Harvard University Press.
- Gulzar, Saad and Benjamin T. Pasquale. 2017. Politicians, Bureaucrats, and Development: Evidence from India. *American Political Science Review* 111(1), 162–183.
- Haggard, Stephan. 2018. *Developmental States*. Cambridge: Cambridge University Press.
- Hallward-Driemeier, Mary and Lant Pritchett. 2015. How Business is Done in the Developing World: Deals versus Rules. *Journal of Economic Perspectives* 29(3), 121–140.
- Harding, Torfinn and Beata S. Javorcik. 2011. Roll Out the Red Carpet and They Will Come: Investment Promotion and FDI Inflows. *The Economic Journal* 121(557), 1445–1476.
- Head, Keith, John Ries, and Deborah Swenson. 1995. Agglomeration Benefits and Location Choice: Evidence from Japanese Manufacturing Investments in the United States. *Journal of International Economics* 38(3-4), 223–247.

- Helpman, Elhanan, Marc J. Melitz, and Stephen R. Yeaple. 2004. Export Versus FDI with Heterogeneous Firms. *American Economic Review* 94(1), 300–316.
- Henisz, Witold J. 2000. The Institutional Environment for Multinational Investment. *The Journal of Law, Economics, and Organization* 16(2), 334–364.
- Hicken, Allen. 2011. Clientelism. *Annual Review of Political Science* 14(1), 289–310.
- Holland, Alisha C. 2016. Forbearance. *American Political Science Review* 110(2), 232–246.
- Iyer, Lakshmi and Anandi Mani. 2012. Traveling Agents: Political Change and Bureaucratic Turnover in India. *Review of Economics and Statistics* 94(3), 723–739.
- Javorcik, Beata S.. 2015. Does FDI Bring Good Jobs to Host Countries? *The World Bank Research Observer* 30(1), 74–94.
- Jensen, Nathan M., Michael G. Findley, and Daniel L. Nielson. 2020. Electoral Institutions and Electoral Cycles in Investment Incentives: A Field Experiment on Over 3,000 U.S. Municipalities. *American Journal of Political Science* 64(4), 807–822.
- Jensen, Nathan M. and Edmund J. Malesky. 2018. *Incentives to Pander: How Politicians Use Corporate Welfare for Political Gain*. Cambridge: Cambridge University Press.
- Jensenius, Francesca R. and Pavithra Suryanarayan. 2022. Party System Institutionalization and Economic Voting: Evidence from India. *The Journal of Politics* 84(2), 814–830.
- Jones, Geoffrey and Rachael Comunale. 2018. Business, Governments, and Political Risk in South Asia and Latin America since 1970. *Australian Economic History Review* 58(3), 233–264.
- Kaufmann, Daniel and Shang-Jin Wei. 1999. Does “Grease Money” Speed Up the Wheels of Commerce? Working Paper 7093, National Bureau of Economic Research.

- Kayser, Mark A. 2014. Comparing Democracies: Elections and Voting in a Changing World. In *Comparing Democracies: Elections and Voting in a Changing World*, pp. 112–132. London: SAGE.
- Kiewiet, D. Roderick and Mathew D. McCubbins. 1991. *The Logic of Delegation*. Chicago: University of Chicago Press.
- Kinda, Tidiane. 2010. Investment Climate and FDI in Developing Countries: Firm-Level Evidence. *World Development* 38(4), 498–513.
- Kobrin, Stephen J. 1987. Testing the Bargaining Hypothesis in the Manufacturing Sector in Developing Countries. *International Organization* 41(4), 609–638.
- Krishnan, K.P. and T.V. Somanathan. 2017. The Civil Service. In *Rethinking Public Institutions in India*. Oxford University Press.
- Krueger, Anne O. 1974. The Political Economy of the Rent-Seeking Society. *The American Economic Review* 64(3), 291–303.
- Lehne, Jonathan, Jacob N. Shapiro, and Oliver Vanden Eynde. 2018. Building Connections: Political Corruption and Road Construction in India. *Journal of Development Economics* 131, 62–78.
- Levien, Michael. 2013. Regimes of Dispossession: From Steel Towns to Special Economic Zones. *Development and Change* 44(2), 381–407.
- Levitsky, Steven. 2007. From Populism to Clientelism? The Transformation of Labor-Based Party Linkages in Latin America. In Herbert Kitschelt and Steven I. Wilkinson (Eds.), *Patrons, Clients and Policies: Patterns of Democratic Accountability and Political Competition*, pp. 206–226. Cambridge: Cambridge University Press.

- Lewis-Beck, Michael S. and Mary Stegmaier. 2019. Economic Voting. In Roger D. Congleton, Bernard Grofman, and Stefan Voigt (Eds.), *The Oxford Handbook of Public Choice*. Oxford: Oxford University Press.
- Malesky, Edmund J. 2008. Straight Ahead on Red: How Foreign Direct Investment Empowers Subnational Leaders. *The Journal of Politics* 70(1), 97–119.
- Malesky, Edmund J., Dimitar D. Gueorguiev, and Nathan M. Jensen. 2015. Monopoly Money: Foreign Investment and Bribery in Vietnam, a Survey Experiment. *American Journal of Political Science* 59(2), 419–439.
- McCubbins, Mathew D., Roger G. Noll, and Barry R. Weingast. 1987. Administrative Procedures as Instruments of Political Control. *Journal of Law, Economics, & Organization* 3(2), 243–277.
- Moehlecke, Carolina. 2020. The Chilling Effect of International Investment Disputes: Limited Challenges to State Sovereignty. *International Studies Quarterly* 64(1), 1–12.
- Mosley, Layna. 2010. *Labor Rights and Multinational Production*. Cambridge Studies in Comparative Politics. Cambridge: Cambridge University Press.
- Niskanen, William A. 1971. *Bureaucracy and Representative Government*. New Brunswick, NJ: Routledge.
- Owen, Erica. 2013. Unionization and Restrictions on Foreign Direct Investment. *International Interactions* 39(5), 723–747.
- Owen, Erica. 2019. Foreign Direct Investment and Elections: The Impact of Greenfield FDI on Incumbent Party Reelection in Brazil. *Comparative Political Studies* 52(4), 613–645.
- Pandya, Sonal S. 2014. *Trading Spaces: Foreign Direct Investment Regulation, 1970-2000*. Cambridge: Cambridge University Press.

- Pandya, Sonal S. 2016. Political Economy of Foreign Direct Investment: Globalized Production in the Twenty-First Century. *Annual Review of Political Science* 19, 455–475.
- Pepinsky, Thomas B., Jan H. Pierskalla, and Audrey Sacks. 2017. Bureaucracy and Service Delivery. *Annual Review of Political Science* 20, 249–268.
- PERC. 2010. Asian Risk Prospects – 2010. Political and Economic Risk Consultancy Technical Report.
- Phillips, Joe, Armando Heilbron, and Priyanka Kher. 2021. Lessons in Investment Promotion: The Case of Invest India. Equitable Growth, Finance & Institutions Notes, World Bank.
- Potter, David C. 1996. *India's Political Administrators: From ICS to IAS*. Oxford: Oxford University Press.
- Poulsen, Lauge N. Skovgaard and Emma Aisbett. 2013. When the Claim Hits: Bilateral Investment Treaties and Bounded Rational Learning. *World Politics* 65(2), 273–313.
- Rains, Emily and Erik Wibbels. 2023. Informal Work, Risk, and Clientelism: Evidence from 223 Slums across India. *British Journal of Political Science* 53(1).
- Ramashankar. 2011. Govt Grapples with Babu Crisis. *The Telegraph India*.
- Rauch, James E. and Peter B. Evans. 2000. Bureaucratic Structure and Bureaucratic Performance in Less Developed Countries. *Journal of Public Economics* 75(1), 49–71.
- Ravishankar, Nirmala. 2009. The Cost of Ruling: Anti-Incumbency in Elections. *Economic and Political Weekly* 44(10), 92–98.
- Rodriguez, Peter, Klaus Uhlenbruck, and Lorraine Eden. 2005. Government Corruption and the Entry Strategies of Multinationals. *Academy of Management Review* 30(2), 383–396.

- Santander. 2021. Foreign Investment in India. Accessed via <https://santandertrade.com/en/portal/establish-overseas/india/foreign-investment>.
- Sartor, Michael A. and Paul W. Beamish. 2018. Host Market Government Corruption and the Equity-Based Foreign Entry Strategies of Multinational Enterprises. *Journal of International Business Studies* 49(3), 346–370.
- Saxena, N.C. 2010. The IAS Officer – Predator or Victim? *Commonwealth & Comparative Politics* 48(4), 445–456.
- Simmons, Beth A. 2014. Bargaining over BITs, Arbitrating Awards: The Regime for Protection and Promotion of International Investment. *World Politics* 66(1), 12–46.
- Sinha, Aseema. 2004. The Changing Political Economy of Federalism in India: A Historical Institutional Approach. *India Review* 3(1).
- Sircar, Neelanjan. 2018. Money in Elections: The Role of Personal Wealth in Election Outcomes. In Devesh Kapur and Milan Vaishnav (Eds.), *Costs of Democracy*. Delhi: Oxford University Press.
- Stokes, Susan C., Thad Dunning, Marcelo Nazareno, and Valeria Brusco. 2013. *Brokers, Voters, and Clientelism: The Puzzle of Distributive Politics*. Cambridge: Cambridge University Press.
- Strange, Susan. 1996. *The Retreat of the State: The Diffusion of Power in the World Economy*. Cambridge: Cambridge University Press.
- Strøm, Kaare. 2000. Delegation and Accountability in Parliamentary Democracies. *European Journal of Political Research* 37(3), 261–290.
- Suri, K C. 2009. The Economy and Voting in the 15th Lok Sabha Elections. *Economic and Political Weekly* 44(39), 64–70.

- Tomashevskiy, Andrey. 2017. Investing in Violence: Foreign Direct investment and Coups in Authoritarian Regimes. *The Journal of Politics* 79(2), 409–423.
- Topalova, Petia. 2010. Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India. *American Economic Journal: Applied Economics* 2(4), 1–41.
- Tucker, Joshua A. 2002. The First Decade of Post-Communist Elections and Voting. *Annual Review of Political Science* 5(1), 271–304.
- Uppal, Yogesh. 2009. The Disadvantaged Incumbents: Estimating Incumbency Effects in Indian State Legislatures. *Public Choice* 138(1), 9–27.
- Vaishnav, Milan. 2017. *When Crime Pays: Money and Muscle in Indian Politics*. New Haven: Yale University Press.
- Vaishnav, Milan and Saksham Khosla. 2016. The Indian Administrative Service Meets Big Data. Technical report, Carnegie Endowment for International Peace.
- Verma, Rahul. 2012. What Determines Electoral Outcomes in India?: Caste, Class, or Voters’ Satisfaction with Government Performance? *Asian Survey* 52(2), 270–297.
- Vernon, Raymond. 1971. *Sovereignty at Bay: The Multinational Spread of US Enterprises*. Basic Books.
- Wade, Robert. 1985. The Market for Public Office: Why the Indian State is Not Better at Development. *World Development* 13(4), 467–497.
- Wang, Xiaonan, Margaret M Pearson, and John F. McCauley. 2022. Foreign Direct Investment, Unmet Expectations, and the Prospects of Political Leaders: Evidence from Chinese Investment in Africa. *The Journal of Politics* 84(3), 1403–1419.

Xu, Guo, Marianne Bertrand, and Robin Burgess. 2023. Organization of the State: Home Assignment and Bureaucrat Performance. *The Journal of Law, Economics, and Organization* 39(2), 371–419.

Zhu, Boliang. 2017. MNCs, Rents, and Corruption: Evidence from China. *American Journal of Political Science* 61(1), 84–99.

A Appendix for Bartering Bureaucrats

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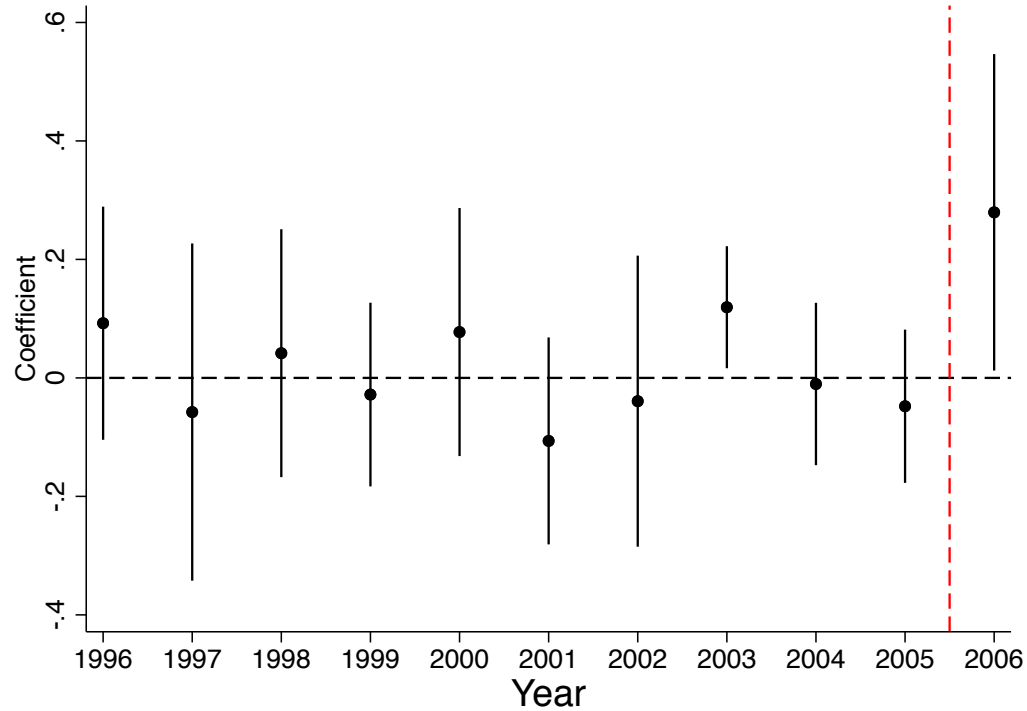
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A Summary Statistics and Robustness Checks

Appendix Figure A.1: Placebo Test Robust to Heterogeneous Treatment Effects



Notes: Pre-trend placebo estimates robust to heterogeneous treatment effects using estimator from de Chaisemartin and D'Haultfœuille (2020). Implemented using *did_multiplegt* command in Stata. Robust standard errors clustered by state. Model includes district and year fixed effects and district-specific time trends.

Appendix Table A.1: Summary Statistics

Variable	Observations	Mean	SD	Min.	Max.
IAS Data					
<i>Transfer_{ijt}</i>	10,406	0.572	0.495	0	1
<i>Lateral_{ijt}</i>	10,406	0.370	0.483	0	1
<i>Promotion_{ijt}</i>	10,406	0.192	0.394	0	1
<i>StateRecruit_i</i>	10,406	0.317	0.465	0	1
<i>Top20Exam_i</i> (direct recruits)	4,697	0.277	0.447	0	1
<i>SameDomicile_i</i> (direct recruits)	6,690	0.275	0.446	0	1
<i>FirstClassDegree_i</i> (direct recruits)	6,690	0.792	0.406	0	1
<i>FirstClassDegree_i</i> (state recruits)	3,294	0.112	0.315	0	1
<i>ForeignDegree_i</i> (direct recruits)	6,690	0.196	0.397	0	1
<i>ForeignDegree_i</i> (state recruits)	3,294	0.029	0.167	0	1
FDI Data					
<i>FDI_{jt-1}</i>	9,794	0.200	0.999	0	22
<i>AvgFDIAllowed_{jt}</i>	9,794	35.33	10.164	13.98	72.05
Census Data					
<i>Log(population)_{j1991}</i>	10,406	14.56	0.605	11.88	16.11
<i>Log(population)_{j2001}</i>	10,406	14.44	0.692	11.52	16.30
<i>ScheduledCaste_{j1991}</i>	10,406	0.164	0.078	0	0.518
<i>ScheduledCaste_{j2001}</i>	10,406	0.163	0.081	0	0.501
<i>Literacy_{j1991}</i>	10,406	0.426	0.129	0.145	0.851
<i>Literacy_{j2001}</i>	10,406	0.547	0.115	0.242	0.854
<i>Employment_{j1991}</i>	10,406	0.377	0.068	0.239	0.540
<i>Employment_{j2001}</i>	10,406	0.399	0.064	0.241	0.570
<i>Female_{j1991}</i>	10,406	0.481	0.015	0.441	0.547
<i>Female_{j2001}</i>	10,406	0.484	0.014	0.434	0.504
Politician Asset Data					
<i>Log(NetAssets)_{pt}</i>	741	15.980	1.44	11.945	20.923
<i>Log(NetAssets)_{pt-}</i>	741	15.118	1.400	11.695	20.607
<i>Log(MovableAssets)_{pt}</i>	731	14.550	1.494	9.616	20.768
<i>Log(MovableAssets)_{pt-}</i>	731	13.534	1.618	6.215	18.966
<i>Log(ImmovableAssets)_{pt}</i>	697	15.774	1.493	11.462	20.112
<i>Log(ImmovableAssets)_{pt-}</i>	697	14.904	1.438	10.309	20.606
<i>StateRecruit_{jt-1}</i>	741	0.314	0.411	0	1
Miscellaneous Data					
<i>OriginCountryCorruption_{jt-1}</i>	699	0.054	0.073	0.005	0.678
<i>RelatedParty_{jt}</i>	1,069	2.4	9.4	0	99.6

Appendix Table A.2: FDI and Bureaucratic Transfers - Including Officer Fixed Effects

	<i>Dependent variable:</i>				
	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Lateral_{ijt}</i>	<i>Promotion_{ijt}</i>
	(1)	(2)	(3)	(4)	(5)
<i>Treated_{ij} * Post_t</i>	0.091* (0.050)	0.102* (0.052)	0.275*** (0.066)	0.198** (0.080)	0.081** (0.034)
Observations	11,091	10,399	10,399	10,399	10,399
Number of districts	556	497	497	497	497
Control for district pop.	X	✓	✓	✓	✓
Other district controls	X	X	✓	✓	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with officer, district, and year fixed effects and district-specific time trends. Full results in Appendix Table E.7.

Appendix Table A.3: Robustness to Heterogeneous Treatment Effects

	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>	
	(1)	(2)
<i>Treated_{ij} * Post_t</i>	0.262** (0.130)	0.280** (0.136)
Observations	722	722
District time trends	X	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using procedure from de Chaisemartin and D'Haultfœuille (2020) and implemented with *did_multiplegt* command in Stata.

B Historical Correlates of FDI Distribution Across Indian States

We analyze the historical roots of FDI agglomeration in India using state-level data for 1962-1992 and 1992-2001.³³ These data provide an unbalanced panel of state characteristics including media coverage, labor regulations, industrial base, taxes, and poverty. We estimate a probit model of treatment (e.g., status as high FDI recipient state) based on these state characteristics and state geographic features in 1991; year indicators are also included.³⁴ Treatment correlates positively with state land area, stamps and registration fees, excise duties on commodities and services, number of registered factories, and number of industrial regulations. Rural poverty, population, and labor regulations are negatively correlated.³⁵

In more recent decades (1991-2001) leading up to the FDI liberalization, we assess agglomeration using a linear model of how demographic characteristics, climatic characteristics, and infrastructure expenditure on features such as roads and transportation influence the location of FDI using district level data. The infrastructure data comes from the CapEx data collected by the Center for Monitoring Indian Economy and the demographic data comes from the Indian Census.³⁶ Rainfall and temperature data are from the University of Delaware series.³⁷ Results are in Appendix Table B.2. Size of transportation infrastructure positively influences location choice whereas investment in transport infrastructure negatively correlates with treatment albeit to a very small extent. Investment in water, electricity, and welfare infrastructure (schools, dispensaries, hospitals) is uncorrelated with treatment but number of water projects is positively correlated. Literacy rates, employment rates, and female population are correlated with treatment. However, important confounders can be trends. We observe a negative correlation with trends. Areas with better emergent trends in literacy, employment, and gender ratio are less likely to receive treatment. Precipitation is negatively and temperature is positively correlated with the treatment status.

³³State data are from the Economic Opportunities and Public Policy Programme, STICERD-LSE. http://sticerd.lse.ac.uk/eopp/_new/data/indian_data/default.asp. We consider state-level FDI correlates because analogous district-level data are unavailable.

³⁴Model estimates in Appendix Table B.1.

³⁵We find no correlation between treatment and total factory workers, newspaper circulation, urban poverty, public expenditures on education/art/culture, scientific services and research.

³⁶Data is used for 1991 and 2001.

³⁷Spatial tools have been used to extract the data for the Indian districts.

Appendix Table B.1: Historical Correlates of State-Level FDI Agglomeration 1962-1992

Dependent Variable: Treated

Variables	Probit Estimation marginal effects (in %)
Number of total newspapers in all languages	-0.0043 (0.0064)
Cumulative Regulatory Change	4.96*** (1.08)
Labor Regulation Index	-14.09*** (2.69)
No. of Factories covered under Payment of Wages Act 1936	0.0054*** (0.0005)
Factory Sector total workers	0.0000 (0.0017)
Mean per capita expenditure rural (1973-74 prices)	-1.74*** (0.33)
Mean per capita expenditure urban (1973-74 prices)	-0.2938 (0.2299)
Stamps and registration fees	0.0206*** (0.0034)
State Excise duty on commodities and services	0.0013** (0.0005)
Education, art and culture, scientific services, and research expenditure	0.0002 (0.0005)
Population	-1.64e-06*** (2.48e-07)
Area (sq KM)	0.0001*** (0.0000)
Observations	494
No. of States	15

Notes: ***p<0.01, **p<0.05, *p<0.1; Year fixed effects controlled. District-clustered standard errors parentheses.

Appendix Table B.2: District-Level Correlates of FDI, 1991-2001

Dependent Variable: Treated

Variables	Linear Probability Estimates
Percentage of Schedule Caste Population 1991	-0.324 (0.248)
Percentage of Literate Population 1991	1.304*** (0.171)
Employment rate 1991	2.959*** (0.259)
Percentage of Female Population 1991	-4.444** (2.124)
Change in Percentage of Schedule Caste Population 1991-2001	-0.940 (0.783)
Change in Percentage Literate Population 1991-2001	-0.886*** (0.291)
Change in Employment Rate 1991-2001	-1.008** (0.501)
Change in Percentage of Female Population 1991-2001	-6.025*** (1.893)
Electricity Infrastructure Investment	-2.49e-06 (4.07e-06)
Number of Electricity Infrastructure projects	0.0541 (0.0340)
Water Infrastructure Investment	-0.000979 (0.000878)
Number of Water Infrastructure Projects	0.392*** (0.102)
Transport Infrastructure Investment	-4.38e-05*** (1.55e-05)
Number of Transport Infrastructure Projects	0.0398*** (0.0120)
Welfare Infrastructure Investment	0.00118 (0.00103)
Number of Welfare Infrastructure Projects	0.0292 (0.252)
Rainfall (average annual in mm)	-0.000143*** (3.99e-05)
Temperature (average annual)	0.0391*** (0.00921)
Constant	0.127 (0.907)
Observations	488
R-squared	0.494

Notes: ***p<0.01, **p<0.05, *p<0.1; standard errors clustered by district in parentheses.

C Indian Administrative Service

Often described as the “steel frame” of India (Potter 1996), the IAS supplies key bureaucrats for district, state, and central governments, and state-owned enterprises. Much of the IAS’s structure and rules originate from the colonial-era Indian Civil Service, the merit-based civil service that Great Britain established in India during the 19th century. Roughly 5,000 IAS officers serve at a given time, a remarkably small number in comparison to the size of the population they govern.

Entry Officers enter the IAS via one of two pathways. Two-thirds are direct recruits, selected through a highly competitive nationwide process that includes exams and interviews. This centralized process is administered by the Union Public Service Commission, a federal entity. Of the roughly 450,000 applicants in the average year, fewer than 150 are selected. Applicants must be 21-30 years of age. Members of reserved groups, Scheduled Castes and Tribes (SC/ST) and Other Backward Castes (OBC), are eligible until 35. The average entry age for direct recruits is 26.

The remaining one-third of IAS officers are state recruits. State politicians nominate individuals from their state-level civil service to join the IAS. Until 2013, state recruits were not required to take IAS exams.³⁸ State recruits are also exempt from age restrictions. The average entry age for state recruits is 43, consistent with their prior work history.

CMs ostensibly nominate their most talented state civil servants to the IAS, but allegations of patronage appointments are common. Some suggest that ruling politicians send direct recruits to the central government so that they can be replaced with state recruits in key rent seeking positions (Tribune News Service 2003; Times of India 2012). News reports suggest that the selection of provincial officers of the CM’s choice allows politicians to establish a grip on the IAS even though its design is supposed to prevent undue political influence (Mishra and Mohanty 2012).

Assignment Once admitted, direct recruits are quasi-randomly assigned to one of 24 “cadres,” which correspond to states and three groups of smaller territories. For ease of exposition, we use the term “states” to encompass both states and the three groupings.

Assignment of direct recruits is a centralized process. States provide some input on the number of vacancies in that year but have no control over which officers are assigned to them. An idiosyncratic rule divides Indian states into four groups based on alphabetical order and rotates their rank annually. For example, if groups A,B,C,D are ranked 1-4, respectively in year t , in year $t+1$ the rank order shifts to B,C,D,A. This rotation is designed to ensure a

³⁸<https://www.hindustantimes.com/delhi/govt-for-change-in-rules-for-promotion-in-ias-ips/story-ysn6EtDi4D98fFQ390CuVL.html>

roughly equal distribution of quality. In a given year, direct recruits are sequentially assigned to states based on exam rank. Within this allocation rule, assignments further reflect the number of state vacancies and affirmative action for reserved groups. Direct recruits with the highest exam rankings can indicate a preference. Most choose their home state but placement is subject to available vacancies. State assignments are career-long; transfers across states are exceedingly rare and are usually associated with marriage of two officers. State recruits always become IAS officers in their home state.

Career advancement All direct recruits undergo two years of training consisting of one year of coursework at the Lal Bahadur Shastri National Academy of Administration and one year of hands-on district level training. State recruits receive eight weeks of training at the National Academy or another training institute. After training, IAS officers begin their careers as deputies to the district magistrate, the chief district-level bureaucrat.³⁹ District-level IAS officers oversee a wide range of governance functions, including revenue collection, infrastructure development, implementation of government welfare programs, law enforcement, and crisis administration. After four years, officers are eligible for promotion to district magistrate. Officers are eligible for further promotion to state positions at fixed intervals: 9, 13, 16, 25, and 30 years following their entry. Higher levels of promotion have a significant merit component rather than solely relying on seniority (Vaishnav and Khosla 2016).

Chief ministers (CM), states' highest-ranked elected official, have no control over which direct recruits are assigned to their state, nor can they fire IAS officers.⁴⁰ Salaries associated with pay grades and minimum requirements for promotion are also out of their control. CMs do, however, control officers' job postings and many aspects of officers' career advancement, and they also control the state recruit selection process. Transfer refers to IAS officers' reassignment to another post. With respect to the standardized IAS pay scale, transfer can reflect lateral transfer, promotion, or demotion. Transfer is frequent: 57 percent of district-level officers experience transfer at least once annually. On average, most transfer is lateral (64.4 percent), followed by promotion (33.8 percent). Demotions comprise less than two percent of transfer.

Career incentives IAS officers are motivated by a range of career incentives. After the first promotion, which is based on years of service, all further promotions are merit-based. Senior IAS officers in the state confidentially evaluate each officer annually and

³⁹In some states, the title is district inspector or collector but the job description is identical.

⁴⁰Firing IAS officers is extremely difficult and rare. Temporary suspensions do infrequently occur for serious misconduct or non-performance.

make recommendations to the CM. This process incentivizes competence, as promotion is associated with more prestigious postings and higher pay. After at least 20 years of service, officers are eligible for appointment to prestigious central government posts. In a process called empanelment, the state evaluates officers at the highest state-level pay grade for their suitability for central government posts. If deemed suitable, officers are appointed to central government positions as they become available.⁴¹ Empanelment is a strong signal of competence within the IAS, corresponds to the highest pay grade, and carries considerable social prestige. Officer pensions are based on their pay grade at retirement and empaneled officers can leverage prestige for post-retirement job opportunities.

The IAS has a mandatory retirement age of 60, which has differential effects on career incentives of direct versus state recruits.⁴² State recruits are significantly older than direct recruits. From the outset of their IAS careers, they know they will not achieve the highest levels of service. On average, less than five percent of officers in empaneled positions are state recruits.

References

- Mishra, Ashutosh and Subhashish Mohanty. 2012. Babu Shortfall Boon for Govt - Adversity to Benefit State Rulers. *The Telegraph India*.
- Times of India. 2012. Babus Seek Probe into Irregularities in IAS Promotions. *The Times of India*.
- Tribune News Service. 2003. Govt Prefers Promotee Officers, Posting of Deputy Commissioners, SPs. *Tribune India*.
- Vaishnav, Milan and Saksham Khosla. 2016. The Indian Administrative Service Meets Big Data. Technical report, Carnegie Endowment for International Peace.

D Additional Sources of Heterogeneity

In this appendix, we further discuss analyses that explore additional sources of heterogeneity in our main results. These sources include state corruption, corruption of the investment origin country, and motivation of the investment.

⁴¹Officers continue to serve in state-level positions after being empaneled until they are selected for a posting.

⁴²The age was 58 prior to 1998.

State-Level Corruption

An observable implication of our proposed rent seeking mechanism is that FDI's effects on transfers should be greater in more corrupt states. We leverage pre-liberalization (2005) data from Transparency International India on the rankings of Indian states by their level of corruption (Transparency International India 2005).⁴³ Higher numerical ranks reflect greater corruption. We have notable variation in ex ante levels of corruption among treated states.⁴⁴

We estimate a triple difference model similar to Equation 5, but instead interact liberalization exposure with state corruption rank in 2005. The sample is restricted only to state recruits. These results are displayed in Panel A of Appendix Table D.1. We find that transfers of state recruits are almost entirely concentrated in states that are ex ante more corrupt. For a relatively clean state such as Gujarat, state recruits are an additional 13.5 percentage points more likely to experience transfers. This jumps to 54 percentage points for a more corrupt state such as Tamil Nadu. By contrast, as shown in Panel B, transfers of direct recruits do not systematically vary by state corruption.

Origin Country Corruption

We also examine if transfers vary by corruption levels in MNCs' country of origin.⁴⁵ If MNCs that originate in more corrupt countries are more comfortable engaging in rent-seeking behavior, then transfers of state recruits should be pronounced in the presence of FDI from relatively corrupt countries.

We estimate an additional triple difference model where we limit the sample to districts that received any FDI, measuring origin-country corruption as the average of public sector corruption according to V-Dem, weighted by the number of projects received from each

⁴³These rankings are based on surveys of people on their personal corruption experiences that Transparency India conducts in each state, calculating an overall corruption score and ranking states accordingly.

⁴⁴Gujarat is ranked 3rd, Andhra Pradesh 4th, Maharashtra 5th, Delhi 11th, Tamil Nadu 12th, and Karnataka 17th.

⁴⁵CapEx does not report firms' country of origin. Using firm names and industry, we matched CapEx project data to project data in fDi Markets, a proprietary database of greenfield FDI announcements. We matched approximately seventy percent of firms using fastLink, an R package for probabilistic record linkage (Enamorado et al. 2019) and the remainder through online searches. We assigned projects to the home country of the firm's ultimate beneficial owner to minimize bias caused by MNCs routing investments through low-tax jurisdictions.

country of origin.⁴⁶ Projects originate from 29 unique countries of origin.⁴⁷ In Appendix Table D.2, we find that state recruits are significantly more likely to be transferred in districts that received FDI from relatively more corrupt countries of origin.

Market- vs. Export-Oriented FDI

Large countries such as India are attractive FDI destinations because they allow MNCs to produce for sale in the local market at a profitable scale. We argue that MNCs are, all else equal, more tolerant of rent seeking in these countries because they have few alternatives. By contrast, when MNCs produce for export, their primary concern is cost, a dimension on which countries can compete regardless of market size. MNCs making export-oriented investments should be less tolerant of rent seeking, all else equal.

We test this implication by creating a yearly district-level measure of the extent to which FDI is designed to produce for export. Our measure uses data on related party exports from India to the US. Data are from the US Census Related Party Trade Database, which defines related party trade as trade between entities in which one party holds a five percent or greater ownership in the other party.⁴⁸ We take US related-party trade patterns as representative of all MNCs' motives to invest in India. We first match individual FDI projects to their Harmonized System 4 digit (HS-4) industry code. For each HS-4 industry, we then calculate the share of exports from India to the US that are between related parties. We calculate average values during 2003-2005 to capture pre-liberalization levels of related party trade.⁴⁹ This measure proxies for the extent to which FDI in an industry that tends to invest to produce for export. Finally, for each district-year, we calculate the average of industry-level FDI export orientation, weighted by the number of FDI projects in each industry. The sample is limited only to district-years that received FDI.

Using this measure, we estimate a triple difference model, interacting liberalization exposure with the average export orientation of FDI inflows. Appendix Table D.3 presents the

⁴⁶The V-Dem public sector corruption measure is bounded by zero and one, with higher values representing greater public sector corruption. We standardize this variable for ease of interpretation.

⁴⁷Origin countries with the highest levels of corruption include China, Malaysia, Mexico, Brazil, and Greece. Origin countries with the lowest levels of corruption include Denmark, Singapore, Sweden, Germany, and New Zealand. The most common countries of origin, the US and UK, also have relatively low corruption scores.

⁴⁸See https://www.census.gov/foreign-trade/Press-Release/related_party/index.html.

⁴⁹For non-traded industries, this percentage equals zero.

main results. We split the sample by recruitment source, analyzing state and direct recruits in Columns (1) and (2), respectively. In districts with a higher proportion of export-oriented FDI, we find that state recruits are less likely to be transferred.

References

- Enamorado, Ted, Benjamin Fifield, and Kousuke Imai. 2019. Using a Probabilistic Model to Assist Merging of Large-Scale Administrative Records. *American Political Science Review* 113 (2), 353–371.
- Transparency International India. 2005. India Corruption Study 2005. Technical report, Transparency International India, New Delhi.

Appendix Table D.1: More Bureaucratic Transfers in Corrupt States

Panel A: State Recruits	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>		
	(1)	(2)	(3)
<i>Treated_{ij} * Post_t * StateCorruptionRank_j</i>	0.027*** (0.009)	0.029*** (0.011)	0.045*** (0.013)
<i>Treated_{ij} * Post_t</i>	0.022 (0.103)	0.014 (0.134)	−0.021 (0.185)
Observations	3,357	3,223	3,223
Number of districts	476	447	447
Panel B: Direct Recruits	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>		
	(1)	(2)	(3)
<i>Treated_{ij} * Post_t * StateCorruptionRank_j</i>	−0.002 (0.009)	−0.003 (0.009)	0.003 (0.010)
<i>Treated_{ij} * Post_t</i>	0.043 (0.107)	0.049 (0.113)	0.103 (0.130)
Observations	6,862	6,568	6,568
Number of districts	511	477	477
Control for district pop.	X	✓	✓
Other district controls	X	X	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Sample includes only state recruits. Full results in Appendix Table E.8.

Appendix Table D.2: FDI Origin Country Corruption Increases Bureaucratic Transfers

	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>		
	(1)	(2)	(3)
<i>StateRecruit_i * Post_t * OriginCountryCorruption_{jt-1}</i>	0.130*** (0.034)	0.140*** (0.040)	0.192*** (0.036)
<i>Post_t * OriginCountryCorruption_{jt-1}</i>	-0.089 (0.104)	-0.061 (0.095)	-0.240*** (0.080)
Observations	717	697	697
Number of districts	95	89	89
Control for district pop.	X	✓	✓
Other district controls	X	X	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. Models estimated using OLS with district and year fixed effects and district-specific time trends. Full results in Appendix Table E.9.

Appendix Table D.3: Market-Oriented FDI Increases Bureaucratic Transfers

	<i>Dependent variable:</i>	
	<i>Transfer_{ijt}</i> State recruits	<i>Transfer_{ijt}</i> Direct recruits
	(1)	(2)
<i>Treated_{ij} * Post_t * RelatedParty_{jt}</i>	-0.150** (0.051)	0.008 (0.019)
<i>Treated_{ij} * Post_t</i>	0.842 (0.752)	0.172 (0.398)
Observations	328	706
Number of districts	80	118

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Full results in Appendix Table E.10.

E Results with Control Variables

Appendix Table E.1: FDI and Bureaucratic Transfers - with Control Variables

	<i>Dependent variable:</i>				
	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Lateral_{ijt}</i>	<i>Promotion_{ijt}</i>
	(1)	(2)	(3)	(4)	(5)
<i>Treated_{ij} * Post_t</i>	0.121*** (0.043)	0.138*** (0.044)	0.237*** (0.053)	0.195*** (0.067)	0.036 (0.031)
<i>SalaryLevel2_{it}</i>	0.087*** (0.029)	0.087*** (0.030)	0.089*** (0.031)	-0.035 (0.035)	0.137*** (0.010)
<i>SalaryLevel3_{it}</i>	0.130*** (0.033)	0.133*** (0.034)	0.133*** (0.034)	-0.082*** (0.027)	0.238*** (0.018)
<i>SalaryLevel4_{it}</i>	0.221*** (0.051)	0.222*** (0.053)	0.225*** (0.056)	-0.140*** (0.044)	0.391*** (0.021)
<i>SalaryLevel5_{it}</i>	0.123*** (0.042)	0.127*** (0.044)	0.128*** (0.044)	-0.052 (0.043)	0.208*** (0.016)
<i>SalaryLevel6_{it}</i>	0.284** (0.131)	0.284** (0.135)	0.290** (0.133)	-0.040 (0.155)	0.355*** (0.065)
<i>log(population)_{j1991} * 1995</i>		0.087 (0.065)	0.104 (0.068)	0.032 (0.080)	0.099* (0.053)
<i>log(population)_{j1991} * 1996</i>		0.068 (0.051)	0.079 (0.053)	0.024 (0.066)	0.075 (0.061)
<i>log(population)_{j1991} * 1997</i>		-0.015 (0.047)	-0.003 (0.051)	-0.015 (0.057)	0.040 (0.053)
<i>log(population)_{j1991} * 1998</i>		-0.009 (0.048)	-0.003 (0.046)	-0.015 (0.054)	0.040 (0.040)
<i>log(population)_{j1991} * 1999</i>		0.040 (0.054)	0.026 (0.059)	0.063 (0.069)	-0.005 (0.040)
<i>log(population)_{j1991} * 2000</i>		0.018 (0.062)	0.018 (0.060)	0.041 (0.057)	-0.004 (0.040)
<i>log(population)_{j2001} * 2001</i>		0.044 (0.045)	0.028 (0.048)	0.072** (0.031)	-0.029 (0.034)
<i>log(population)_{j2001} * 2002</i>		-0.033 (0.053)	-0.068 (0.047)	-0.013 (0.037)	-0.051 (0.038)
<i>log(population)_{j2001} * 2003</i>		0.030 (0.055)	0.008 (0.064)	0.105** (0.049)	-0.079* (0.042)
<i>log(population)_{j2001} * 2004</i>		0.017 (0.066)	-0.004 (0.071)	0.086 (0.055)	-0.090 (0.069)

$\log(\text{population})_{j2001} * 2005$	-0.035 (0.074)	-0.064 (0.090)	0.047 (0.061)	-0.105* (0.062)
$\log(\text{population})_{j2001} * 2006$	-0.003 (0.074)	-0.086 (0.084)	0.040 (0.067)	-0.097** (0.049)
$\log(\text{population})_{j2001} * 2007$	-0.039 (0.095)	-0.112 (0.101)	0.040 (0.079)	-0.145** (0.057)
$\log(\text{population})_{j2001} * 2008$	-0.012 (0.096)	-0.078 (0.108)	0.102 (0.085)	-0.162** (0.070)
$\log(\text{population})_{j2001} * 2009$	-0.040 (0.097)	-0.100 (0.110)	0.113 (0.090)	-0.189** (0.082)
$\text{ScheduledCaste}_{j1991} * 1995$		-1.299 (1.537)	-1.882 (1.844)	0.561 (0.915)
$\text{ScheduledCaste}_{j1991} * 1996$		-0.586 (1.329)	-0.829 (1.514)	0.307 (0.870)
$\text{ScheduledCaste}_{j1991} * 1997$		-0.687 (1.142)	-0.552 (1.258)	-0.080 (0.684)
$\text{ScheduledCaste}_{j1991} * 1998$		-0.728 (1.154)	-0.001 (1.113)	-0.614 (0.655)
$\text{ScheduledCaste}_{j1991} * 1999$		-0.639 (1.043)	0.658 (0.862)	-1.249* (0.689)
$\text{ScheduledCaste}_{j1991} * 2000$		-0.501 (1.280)	1.337 (1.033)	-1.736** (0.718)
$\text{ScheduledCaste}_{j2001} * 2001$		0.853 (1.295)	2.169** (0.950)	-1.189 (0.830)
$\text{ScheduledCaste}_{j2001} * 2002$		0.596 (1.565)	2.469** (1.111)	-1.648 (1.044)
$\text{ScheduledCaste}_{j2001} * 2003$		0.530 (1.787)	2.408* (1.232)	-1.539 (1.268)
$\text{ScheduledCaste}_{j2001} * 2004$		0.797 (1.946)	3.343** (1.511)	-2.466** (1.167)
$\text{ScheduledCaste}_{j2001} * 2005$		0.306 (2.366)	3.564* (1.903)	-3.044** (1.521)
$\text{ScheduledCaste}_{j2001} * 2006$		1.164 (2.630)	4.714** (1.988)	-3.278* (1.739)
$\text{ScheduledCaste}_{j2001} * 2007$		0.690 (2.839)	4.667** (2.378)	-3.571* (1.940)

$ScheduledCaste_{j2001} * 2008$	1.090 (3.153)	5.510** (2.631)	-3.944* (2.103)
$ScheduledCaste_{j2001} * 2009$	1.115 (3.440)	5.636* (2.965)	-4.095* (2.400)
$Literacy_{j1991} * 1995$	-0.433 (0.698)	0.061 (0.412)	-0.488 (0.535)
$Literacy_{j1991} * 1996$	-0.305 (0.539)	-0.015 (0.449)	-0.282 (0.427)
$Literacy_{j1991} * 1997$	-0.812 (0.579)	-0.425 (0.451)	-0.388 (0.413)
$Literacy_{j1991} * 1998$	-0.479 (0.523)	-0.197 (0.560)	-0.319 (0.422)
$Literacy_{j1991} * 1999$	-1.032* (0.571)	-0.763 (0.658)	-0.241 (0.375)
$Literacy_{j1991} * 2000$	-0.649 (0.594)	-0.506 (0.622)	-0.076 (0.378)
$Literacy_{j2001} * 2001$	-0.392 (0.859)	-0.273 (0.902)	-0.072 (0.383)
$Literacy_{j2001} * 2002$	-0.509 (1.083)	-0.363 (1.034)	-0.009 (0.436)
$Literacy_{j2001} * 2003$	-0.274 (1.147)	-0.434 (1.128)	0.286 (0.453)
$Literacy_{j2001} * 2004$	-0.642 (1.294)	-0.661 (1.270)	0.127 (0.465)
$Literacy_{j2001} * 2005$	-0.635 (1.393)	-0.361 (1.396)	-0.031 (0.476)
$Literacy_{j2001} * 2006$	-0.803 (1.473)	-0.780 (1.466)	0.133 (0.571)
$Literacy_{j2001} * 2007$	-0.838 (1.860)	-0.606 (1.731)	-0.117 (0.615)
$Literacy_{j2001} * 2008$	-1.026 (1.905)	-0.919 (1.723)	0.079 (0.664)
$Literacy_{j2001} * 2009$	-0.594 (2.063)	-0.717 (1.886)	0.284 (0.740)
$Employment_{j1991} * 1995$	-1.330 (1.061)	-1.094 (1.040)	-0.478 (0.841)

$Employment_{j1991} * 1996$	-1.132 (0.903)	-1.217 (0.863)	-0.342 (0.770)
$Employment_{j1991} * 1997$	-1.176 (0.899)	-0.252 (0.752)	-1.175* (0.603)
$Employment_{j1991} * 1998$	-1.318 (0.848)	-0.307 (0.861)	-1.236** (0.493)
$Employment_{j1991} * 1999$	-2.568*** (0.776)	-1.747** (0.753)	-0.986* (0.557)
$Employment_{j1991} * 2000$	-1.999* (1.052)	-1.183 (0.861)	-1.162** (0.580)
$Employment_{j2001} * 2001$	-1.335* (0.789)	-0.375 (0.671)	-1.218** (0.560)
$Employment_{j2001} * 2002$	-2.397** (0.960)	-1.323* (0.761)	-1.401** (0.657)
$Employment_{j2001} * 2003$	-1.886* (1.065)	-0.674 (0.955)	-1.430** (0.693)
$Employment_{j2001} * 2004$	-2.227* (1.184)	-1.028 (1.127)	-1.518* (0.868)
$Employment_{j2001} * 2005$	-2.822* (1.496)	-0.866 (1.352)	-2.051** (0.993)
$Employment_{j2001} * 2006$	-3.812*** (1.333)	-1.410 (1.500)	-2.459*** (0.944)
$Employment_{j2001} * 2007$	-4.136*** (1.528)	-2.014 (1.453)	-2.259* (1.350)
$Employment_{j2001} * 2008$	-3.979** (1.587)	-1.700 (1.613)	-2.387* (1.311)
$Employment_{j2001} * 2009$	-3.676** (1.736)	-1.565 (1.866)	-2.200* (1.330)
$Female_{j1991} * 1995$	1.276 (3.394)	2.680 (2.746)	-1.934 (2.800)
$Female_{j1991} * 1996$	2.953 (2.471)	3.315 (2.774)	-0.340 (2.127)
$Female_{j1991} * 1997$	-3.186 (2.777)	-2.419 (2.681)	-0.643 (2.691)
$Female_{j1991} * 1998$	0.408 (1.874)	-0.751 (2.426)	1.259 (1.462)
$Female_{j1991} * 1999$	-0.493	1.315	-2.047

			(2.235)	(2.511)	(1.485)
<i>Female_{j1991}</i> * 2000			2.700 (2.475)	2.576 (1.631)	−0.113 (2.081)
<i>Female_{j2001}</i> * 2001			−1.070 (2.605)	0.544 (1.777)	−1.741 (1.520)
<i>Female_{j2001}</i> * 2002			−6.411*** (2.280)	−3.993** (1.666)	−2.114 (2.111)
<i>Female_{j2001}</i> * 2003			−5.627 (3.846)	−3.893 (2.630)	−1.288 (2.335)
<i>Female_{j2001}</i> * 2004			−5.979* (3.583)	−3.189 (2.151)	−3.103 (2.986)
<i>Female_{j2001}</i> * 2005			−8.380** (4.072)	−2.608 (2.137)	−5.905** (2.644)
<i>Female_{j2001}</i> * 2006			−6.006* (3.307)	−2.498 (2.760)	−2.776 (2.554)
<i>Female_{j2001}</i> * 2007			−13.595*** (4.967)	−6.223** (3.128)	−6.975* (4.043)
<i>Female_{j2001}</i> * 2008			−11.457** (4.991)	−6.719* (3.827)	−3.517 (3.716)
<i>Female_{j2001}</i> * 2009			−13.256** (6.057)	−7.008 (4.352)	−5.601 (3.861)
Observations	11,091	10,399	10,399	10,399	10,399
Number of districts	556	497	497	497	497
Control for district pop.	X	✓	✓	✓	✓
Other district controls	X	X	✓	✓	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends.

Appendix Table E.2: Instrumental Variables (2SLS) Estimation - with Control Variables

	<i>Dependent variable:</i>	
	<i>FDI_{jt-1}</i>	<i>Transfer_{ijt}</i>
	1st stage	2nd stage
	(1)	(2)
<i>AvgFDIAllowed_{jt-2}</i>	0.017*** (0.005)	
<i>FDI_{jt-1}</i>		0.363** (0.183)
<i>SalaryLevel2_{it}</i>	-0.017 (0.015)	0.098*** (0.030)
<i>SalaryLevel3_{it}</i>	-0.031* (0.019)	0.150*** (0.034)
<i>SalaryLevel4_{it}</i>	-0.008 (0.024)	0.225*** (0.057)
<i>SalaryLevel5_{it}</i>	-0.059** (0.025)	0.165*** (0.049)
<i>SalaryLevel6_{it}</i>	-0.127 (0.176)	0.290** (0.137)
<i>log(population)_{j1991} * 1995</i>	-0.210 (0.148)	0.016 (0.131)
<i>log(population)_{j1991} * 1996</i>	-0.116 (0.094)	0.079 (0.055)
<i>log(population)_{j1991} * 1997</i>	-0.049 (0.070)	-0.035 (0.056)
<i>log(population)_{j1991} * 1998</i>	-0.100 (0.086)	0.012 (0.053)
<i>log(population)_{j1991} * 1999</i>	0.123* (0.064)	-0.038 (0.057)
<i>log(population)_{j1991} * 2000</i>	-0.066 (0.111)	0.021 (0.073)
<i>log(population)_{j2001} * 2001</i>	0.147* (0.081)	-0.033 (0.064)
<i>log(population)_{j2001} * 2002</i>	0.222* (0.131)	-0.170** (0.072)
<i>log(population)_{j2001} * 2003</i>	0.064 (0.046)	-0.023 (0.051)

$\log(\text{population})_{j2001} * 2004$	0.131 (0.110)	-0.062 (0.090)
$\log(\text{population})_{j2001} * 2005$	0.110 (0.096)	-0.128 (0.078)
$\log(\text{population})_{j2001} * 2006$	0.029 (0.058)	-0.037 (0.058)
$\log(\text{population})_{j2001} * 2007$	0.111** (0.054)	-0.101* (0.058)
$\log(\text{population})_{j2001} * 2008$	0.145** (0.072)	-0.078 (0.071)
$\log(\text{population})_{j2001} * 2009$	0.157** (0.078)	-0.102 (0.070)
$\text{ScheduledCaste}_{j1991} * 1995$	1.600 (1.015)	-0.711 (1.005)
$\text{ScheduledCaste}_{j1991} * 1996$	0.491 (0.820)	0.116 (0.681)
$\text{ScheduledCaste}_{j1991} * 1997$	0.176 (0.811)	-0.005 (0.643)
$\text{ScheduledCaste}_{j1991} * 1998$	0.176 (0.877)	-0.093 (0.740)
$\text{ScheduledCaste}_{j1991} * 1999$	-0.262 (0.900)	0.178 (0.725)
$\text{ScheduledCaste}_{j1991} * 2000$	-0.040 (0.879)	0.118 (0.868)
$\text{ScheduledCaste}_{j2001} * 2001$	-0.871 (1.007)	1.366** (0.588)
$\text{ScheduledCaste}_{j2001} * 2002$	-1.034 (0.964)	1.075** (0.532)
$\text{ScheduledCaste}_{j2001} * 2003$	-0.453 (0.843)	0.744 (0.608)
$\text{ScheduledCaste}_{j2001} * 2004$	-0.782 (0.994)	1.082 (0.857)
$\text{ScheduledCaste}_{j2001} * 2005$	-0.635 (0.860)	0.528 (0.643)
$\text{ScheduledCaste}_{j2001} * 2006$	-0.670 (0.864)	0.954 (0.696)

$ScheduledCaste_{j2001} * 2007$	-0.397 (0.922)	0.310 (0.693)
$ScheduledCaste_{j2001} * 2008$	-0.812 (0.942)	0.846 (0.742)
$ScheduledCaste_{j2001} * 2009$	-0.728 (0.908)	0.791 (0.541)
$Literacy_{j1991} * 1995$	-1.661 (1.026)	1.155* (0.663)
$Literacy_{j1991} * 1996$	-1.038 (0.645)	1.004** (0.420)
$Literacy_{j1991} * 1997$	-0.895* (0.508)	0.392 (0.402)
$Literacy_{j1991} * 1998$	-0.890 (0.690)	0.847** (0.417)
$Literacy_{j1991} * 1999$	-0.054 (0.443)	0.037 (0.355)
$Literacy_{j1991} * 2000$	-0.501 (0.733)	0.435 (0.452)
$Literacy_{j2001} * 2001$	0.180 (0.423)	0.606 (0.397)
$Literacy_{j2001} * 2002$	0.519 (0.549)	0.202 (0.573)
$Literacy_{j2001} * 2003$	-0.421 (0.432)	0.784* (0.455)
$Literacy_{j2001} * 2004$	-0.135 (0.396)	0.377 (0.392)
$Literacy_{j2001} * 2005$	0.279 (0.497)	0.277 (0.422)
$Literacy_{j2001} * 2006$	-0.249 (0.663)	0.526 (0.348)
$Literacy_{j2001} * 2007$	-0.267 (0.561)	0.491 (0.566)
$Literacy_{j2001} * 2008$	-0.447 (0.473)	0.317 (0.410)
$Literacy_{j2001} * 2009$	-0.269 (0.432)	0.632** (0.305)
$Employment_{j1991} * 1995$	0.360	-0.895

	(1.556)	(1.172)
$Employment_{j1991} * 1996$	1.102 (1.241)	-0.605 (0.881)
$Employment_{j1991} * 1997$	1.122 (1.361)	-0.787 (0.940)
$Employment_{j1991} * 1998$	1.083 (1.168)	-0.570 (0.767)
$Employment_{j1991} * 1999$	1.990* (1.065)	-1.992** (0.821)
$Employment_{j1991} * 2000$	0.392 (0.976)	-0.679 (0.897)
$Employment_{j2001} * 2001$	1.698 (1.219)	-0.380 (0.863)
$Employment_{j2001} * 2002$	1.515 (1.381)	-1.189* (0.703)
$Employment_{j2001} * 2003$	1.246 (1.253)	-0.312 (0.691)
$Employment_{j2001} * 2004$	2.097* (1.224)	-0.811 (0.817)
$Employment_{j2001} * 2005$	1.730 (1.249)	-1.117 (0.872)
$Employment_{j2001} * 2006$	1.904 (1.449)	-0.993 (0.870)
$Employment_{j2001} * 2007$	2.010 (1.410)	-1.205 (0.815)
$Employment_{j2001} * 2008$	2.280* (1.380)	-0.887 (0.880)
$Employment_{j2001} * 2009$	1.836 (1.283)	-0.287 (0.899)
$Female_{j1991} * 1995$	13.955* (7.431)	-7.423 (4.695)
$Female_{j1991} * 1996$	8.589* (4.649)	-0.261 (2.639)
$Female_{j1991} * 1997$	8.126** (3.915)	-4.120* (2.397)
$Female_{j1991} * 1998$	8.884** (3.945)	-2.013 (2.803)

$Female_{j1991} * 1999$	4.793 (3.522)	-1.498 (2.635)
$Female_{j1991} * 2000$	7.831** (3.809)	1.499 (2.814)
$Female_{j2001} * 2001$	2.791 (3.767)	1.832 (3.087)
$Female_{j2001} * 2002$	3.437 (5.348)	-2.585 (2.330)
$Female_{j2001} * 2003$	2.429 (3.838)	-0.409 (3.256)
$Female_{j2001} * 2004$	2.812 (4.388)	-0.073 (2.184)
$Female_{j2001} * 2005$	5.061 (3.936)	-1.439 (3.469)
$Female_{j2001} * 2006$	3.025 (3.087)	2.164 (1.901)
$Female_{j2001} * 2007$	3.180 (2.755)	-4.151* (2.287)
$Female_{j2001} * 2008$	-1.467 (2.629)	0.864 (1.758)
$Female_{j2001} * 2009$	-0.078 (2.744)	-0.246 (2.325)
First stage F-statistic	10.6	
Observations	9,787	9,787
Number of districts	488	488

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using two-stage least-squares (2SLS) with district and year fixed effects.

Appendix Table E.3: FDI and Transfers of State Recruits - with Control Variables

	<i>Dependent variable:</i>				
	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Lateral_{ijt}</i>	<i>Promotion_{ijt}</i>
	(1)	(2)	(3)	(4)	(5)
<i>Treated_{ij} * Post_t * StateRecruit_i</i>	0.168*** (0.045)	0.178*** (0.047)	0.173*** (0.049)	0.037 (0.068)	0.130** (0.057)
<i>Treated_{ij} * Post_t</i>	0.049 (0.050)	0.060 (0.050)	0.164*** (0.058)	0.176*** (0.068)	-0.016 (0.034)
<i>Treated_{ij} * StateRecruit_i</i>	-0.008 (0.030)	-0.015 (0.033)	-0.012 (0.033)	0.049 (0.037)	-0.047 (0.036)
<i>Post_t * StateRecruit_i</i>	-0.026 (0.025)	-0.029 (0.026)	-0.032 (0.029)	0.013 (0.027)	-0.050* (0.027)
<i>StateRecruit_i</i>	-0.128*** (0.029)	-0.126*** (0.032)	-0.126*** (0.031)	-0.108*** (0.015)	-0.039** (0.017)
<i>SalaryLevel2_{it}</i>	0.108*** (0.031)	0.109*** (0.031)	0.112*** (0.033)	-0.022 (0.035)	0.149*** (0.011)
<i>SalaryLevel3_{it}</i>	0.164*** (0.033)	0.166*** (0.034)	0.166*** (0.034)	-0.059** (0.028)	0.254*** (0.019)
<i>SalaryLevel4_{it}</i>	0.259*** (0.048)	0.257*** (0.050)	0.260*** (0.053)	-0.115*** (0.042)	0.408*** (0.019)
<i>SalaryLevel5_{it}</i>	0.140*** (0.043)	0.143*** (0.044)	0.144*** (0.044)	-0.043 (0.042)	0.218*** (0.017)
<i>SalaryLevel6_{it}</i>	0.271** (0.132)	0.268** (0.136)	0.275** (0.135)	-0.048 (0.157)	0.344*** (0.064)
<i>log(population)_{j1991} * 1995</i>		0.087 (0.065)	0.103 (0.065)	0.034 (0.080)	0.098* (0.056)
<i>log(population)_{j1991} * 1996</i>		0.065 (0.053)	0.075 (0.054)	0.024 (0.067)	0.072 (0.064)
<i>log(population)_{j1991} * 1997</i>		-0.012 (0.051)	-0.0003 (0.054)	-0.012 (0.057)	0.041 (0.055)
<i>log(population)_{j1991} * 1998</i>		-0.011 (0.050)	-0.005 (0.046)	-0.015 (0.053)	0.038 (0.041)
<i>log(population)_{j1991} * 1999</i>		0.037 (0.056)	0.023 (0.060)	0.063 (0.069)	-0.007 (0.040)
<i>log(population)_{j1991} * 2000</i>		0.018 (0.062)	0.017 (0.060)	0.042 (0.057)	-0.005 (0.041)
<i>log(population)_{j2001} * 2001</i>		0.041	0.025	0.071**	-0.030

	(0.044)	(0.046)	(0.031)	(0.033)
$\log(population)_{j2001} * 2002$	-0.036 (0.053)	-0.072 (0.046)	-0.015 (0.037)	-0.053 (0.038)
$\log(population)_{j2001} * 2003$	0.028 (0.054)	0.004 (0.061)	0.102** (0.047)	-0.081* (0.041)
$\log(population)_{j2001} * 2004$	0.020 (0.067)	-0.003 (0.069)	0.087 (0.057)	-0.090 (0.067)
$\log(population)_{j2001} * 2005$	-0.033 (0.068)	-0.065 (0.083)	0.048 (0.061)	-0.106* (0.058)
$\log(population)_{j2001} * 2006$	-0.002 (0.068)	-0.087 (0.077)	0.041 (0.066)	-0.100** (0.046)
$\log(population)_{j2001} * 2007$	-0.039 (0.094)	-0.115 (0.097)	0.040 (0.081)	-0.149*** (0.053)
$\log(population)_{j2001} * 2008$	-0.009 (0.092)	-0.080 (0.102)	0.101 (0.085)	-0.164** (0.067)
$\log(population)_{j2001} * 2009$	-0.036 (0.096)	-0.104 (0.106)	0.112 (0.094)	-0.193** (0.079)
$ScheduledCaste_{j1991} * 1995$		-1.063 (1.509)	-1.707 (1.858)	0.642 (0.962)
$ScheduledCaste_{j1991} * 1996$		-0.373 (1.303)	-0.675 (1.512)	0.385 (0.919)
$ScheduledCaste_{j1991} * 1997$		-0.520 (1.098)	-0.440 (1.238)	-0.014 (0.708)
$ScheduledCaste_{j1991} * 1998$		-0.621 (1.118)	0.068 (1.106)	-0.571 (0.656)
$ScheduledCaste_{j1991} * 1999$		-0.600 (0.996)	0.675 (0.841)	-1.231* (0.679)
$ScheduledCaste_{j1991} * 2000$		-0.494 (1.203)	1.326 (0.991)	-1.724** (0.697)
$ScheduledCaste_{j2001} * 2001$		0.763 (1.213)	2.088** (0.904)	-1.216 (0.805)
$ScheduledCaste_{j2001} * 2002$		0.505 (1.465)	2.391** (1.062)	-1.676* (1.016)
$ScheduledCaste_{j2001} * 2003$		0.341 (1.689)	2.249* (1.200)	-1.597 (1.238)
$ScheduledCaste_{j2001} * 2004$		0.597	3.169**	-2.522**

	(1.874)	(1.500)	(1.149)
<i>ScheduledCaste_{j2001} * 2005</i>	0.129 (2.281)	3.402* (1.907)	-3.084** (1.496)
<i>ScheduledCaste_{j2001} * 2006</i>	0.871 (2.541)	4.472** (2.001)	-3.369** (1.716)
<i>ScheduledCaste_{j2001} * 2007</i>	0.386 (2.720)	4.407* (2.387)	-3.659* (1.913)
<i>ScheduledCaste_{j2001} * 2008</i>	0.737 (3.055)	5.214** (2.660)	-4.048* (2.092)
<i>ScheduledCaste_{j2001} * 2009</i>	0.747 (3.333)	5.318* (3.003)	-4.193* (2.387)
<i>Literacy_{j1991} * 1995</i>	-0.519 (0.691)	-0.017 (0.416)	-0.504 (0.542)
<i>Literacy_{j1991} * 1996</i>	-0.361 (0.540)	-0.076 (0.463)	-0.285 (0.436)
<i>Literacy_{j1991} * 1997</i>	-0.841 (0.582)	-0.465 (0.459)	-0.382 (0.416)
<i>Literacy_{j1991} * 1998</i>	-0.524 (0.507)	-0.247 (0.566)	-0.321 (0.422)
<i>Literacy_{j1991} * 1999</i>	-1.036* (0.573)	-0.782 (0.665)	-0.228 (0.378)
<i>Literacy_{j1991} * 2000</i>	-0.650 (0.578)	-0.522 (0.622)	-0.063 (0.374)
<i>Literacy_{j2001} * 2001</i>	-0.382 (0.843)	-0.277 (0.901)	-0.059 (0.375)
<i>Literacy_{j2001} * 2002</i>	-0.490 (1.073)	-0.358 (1.035)	0.004 (0.423)
<i>Literacy_{j2001} * 2003</i>	-0.211 (1.128)	-0.401 (1.123)	0.320 (0.433)
<i>Literacy_{j2001} * 2004</i>	-0.568 (1.279)	-0.619 (1.269)	0.163 (0.446)
<i>Literacy_{j2001} * 2005</i>	-0.578 (1.366)	-0.341 (1.383)	0.003 (0.449)
<i>Literacy_{j2001} * 2006</i>	-0.740 (1.448)	-0.747 (1.460)	0.161 (0.536)
<i>Literacy_{j2001} * 2007</i>	-0.774 (1.821)	-0.571 (1.719)	-0.094 (0.572)

$Literacy_{j2001} * 2008$	−0.894 (1.880)	−0.839 (1.722)	0.135 (0.624)
$Literacy_{j2001} * 2009$	−0.431 (2.038)	−0.616 (1.883)	0.356 (0.694)
$Employment_{j1991} * 1995$	−1.032 (1.009)	−0.895 (1.032)	−0.326 (0.794)
$Employment_{j1991} * 1996$	−0.877 (0.880)	−1.051 (0.857)	−0.211 (0.748)
$Employment_{j1991} * 1997$	−0.925 (0.885)	−0.109 (0.725)	−1.033* (0.577)
$Employment_{j1991} * 1998$	−1.156 (0.859)	−0.221 (0.869)	−1.136** (0.493)
$Employment_{j1991} * 1999$	−2.430*** (0.776)	−1.668** (0.774)	−0.906* (0.548)
$Employment_{j1991} * 2000$	−1.918* (1.063)	−1.144 (0.879)	−1.111* (0.577)
$Employment_{j2001} * 2001$	−1.339* (0.776)	−0.398 (0.670)	−1.204** (0.559)
$Employment_{j2001} * 2002$	−2.441** (0.956)	−1.374* (0.755)	−1.403** (0.665)
$Employment_{j2001} * 2003$	−1.966* (1.053)	−0.746 (0.942)	−1.454** (0.703)
$Employment_{j2001} * 2004$	−2.348** (1.132)	−1.137 (1.114)	−1.555* (0.861)
$Employment_{j2001} * 2005$	−2.966** (1.465)	−0.985 (1.349)	−2.103** (0.981)
$Employment_{j2001} * 2006$	−4.035*** (1.273)	−1.594 (1.485)	−2.539*** (0.944)
$Employment_{j2001} * 2007$	−4.411*** (1.478)	−2.233 (1.440)	−2.363* (1.351)
$Employment_{j2001} * 2008$	−4.308*** (1.532)	−1.958 (1.596)	−2.514* (1.305)
$Employment_{j2001} * 2009$	−4.075** (1.693)	−1.875 (1.863)	−2.351* (1.311)
$Female_{j1991} * 1995$	1.038 (3.443)	2.589 (2.804)	−2.092 (2.832)

$Female_{j1991} * 1996$			2.771 (2.444)	3.299 (2.896)	-0.504 (2.178)
$Female_{j1991} * 1997$			-3.370 (3.006)	-2.432 (2.734)	-0.808 (2.819)
$Female_{j1991} * 1998$			0.534 (1.999)	-0.634 (2.479)	1.287 (1.521)
$Female_{j1991} * 1999$			-0.615 (2.310)	1.252 (2.558)	-2.123 (1.512)
$Female_{j1991} * 2000$			2.656 (2.514)	2.569 (1.665)	-0.151 (2.092)
$Female_{j2001} * 2001$			-1.226 (2.543)	0.433 (1.748)	-1.812 (1.495)
$Female_{j2001} * 2002$			-6.397*** (2.207)	-3.946** (1.653)	-2.144 (2.073)
$Female_{j2001} * 2003$			-5.828 (3.704)	-4.056 (2.584)	-1.368 (2.234)
$Female_{j2001} * 2004$			-6.302* (3.502)	-3.420 (2.167)	-3.255 (2.901)
$Female_{j2001} * 2005$			-8.278** (3.885)	-2.536 (2.098)	-5.886** (2.541)
$Female_{j2001} * 2006$			-6.316** (3.199)	-2.773 (2.690)	-2.891 (2.489)
$Female_{j2001} * 2007$			-13.829*** (4.731)	-6.478** (3.024)	-7.038* (3.892)
$Female_{j2001} * 2008$			-11.613** (4.701)	-6.926* (3.652)	-3.534 (3.621)
$Female_{j2001} * 2009$			-13.534** (5.691)	-7.328* (4.169)	-5.671 (3.757)
Observations	11,091	10,399	10,399	10,399	10,399
Number of districts	556	497	497	497	497
Control for district pop.	X	✓	✓	✓	✓
Other district controls	X	X	✓	✓	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends.

Appendix Table E.4: FDI and Transfers of Competent Bureaucrats - with Control Variables

	<i>Dependent variable: Transfer_{ijt}</i>					
	Direct recruits (1)	Direct recruits (2)	Direct recruits (3)	State recruits (4)	Direct recruits (5)	State recruits (6)
<i>Treated_{ij} * Post_t * Top20Exam_i</i>	-0.098 (0.101)					
<i>Treated_{ij} * Post_t * SameDomicile_i</i>		-0.021 (0.053)				
<i>Treated_{ij} * Post_t * FirstClassDegree_i</i>			0.045 (0.072)	-0.341* (0.182)		
<i>Treated_{ij} * Post_t * ForeignDegree_i</i>					-0.144* (0.079)	-0.299 (0.191)
<i>Treated_{ij} * Post_t</i>	0.103 (0.111)	0.138** (0.066)	0.097 (0.095)	0.408*** (0.131)	0.150** (0.066)	0.399*** (0.131)
<i>Treated_{ij} * Top20Exam_i</i>	0.028 (0.049)					
<i>Post_t * Top20Exam_i</i>	0.073 (0.060)					
<i>Top20Exam_i</i>	-0.020 (0.027)					
<i>Treated_{ij} * SameDomicile_i</i>		-0.035 (0.047)				
<i>Post_t * SameDomicile_i</i>		-0.034 (0.045)				
<i>SameDomicile_i</i>		0.029 (0.025)				
<i>Treated_{ij} * FirstClassDegree_i</i>			-0.108*** (0.042)	0.104 (0.067)		
<i>Post_t * FirstClassDegree_i</i>			-0.076* (0.043)	0.066 (0.142)		
<i>FirstClassDegree_i</i>			0.061** (0.027)	-0.014 (0.049)		
<i>Treated_{ij} * ForeignDegree_i</i>					0.035 (0.048)	0.163 (0.168)
<i>Post_t * ForeignDegree_i</i>					0.089* (0.055)	0.144 (0.157)
<i>ForeignDegree_i</i>					-0.011 (0.030)	-0.239 (0.149)

<i>SalaryLevel2_{it}</i>	0.158*** (0.038)	0.145*** (0.036)	0.148*** (0.035)	0.086 (0.078)	0.145*** (0.036)	0.088 (0.081)
<i>SalaryLevel3_{it}</i>	0.171*** (0.043)	0.152*** (0.035)	0.156*** (0.034)	0.263*** (0.095)	0.152*** (0.035)	0.266*** (0.098)
<i>SalaryLevel4_{it}</i>	0.266*** (0.060)	0.225*** (0.060)	0.232*** (0.057)	0.401*** (0.112)	0.225*** (0.060)	0.403*** (0.116)
<i>SalaryLevel5_{it}</i>	0.250*** (0.058)	0.101** (0.048)	0.106** (0.046)	0.345*** (0.109)	0.095* (0.049)	0.344*** (0.114)
<i>SalaryLevel6_{it}</i>		0.252* (0.142)	0.252* (0.146)		0.237 (0.152)	
<i>log(population)_{j1991} * 1995</i>	0.159 (0.148)	0.182** (0.087)	0.175* (0.090)	0.062 (0.155)	0.178** (0.087)	0.077 (0.160)
<i>log(population)_{j1991} * 1996</i>	0.254** (0.122)	0.183** (0.077)	0.179** (0.080)	-0.086 (0.141)	0.181** (0.079)	-0.079 (0.142)
<i>log(population)_{j1991} * 1997</i>	0.095 (0.095)	0.072 (0.073)	0.068 (0.077)	-0.170 (0.108)	0.070 (0.075)	-0.167 (0.112)
<i>log(population)_{j1991} * 1998</i>	0.084 (0.107)	0.036 (0.076)	0.034 (0.076)	-0.136* (0.078)	0.035 (0.078)	-0.130 (0.082)
<i>log(population)_{j1991} * 1999</i>	0.004 (0.103)	0.036 (0.077)	0.037 (0.076)	-0.062 (0.098)	0.037 (0.079)	-0.052 (0.100)
<i>log(population)_{j1991} * 2000</i>	0.086 (0.072)	0.011 (0.069)	0.012 (0.068)	-0.022 (0.135)	0.010 (0.070)	-0.012 (0.139)
<i>log(population)_{j2001} * 2001</i>	0.072 (0.060)	-0.013 (0.060)	-0.012 (0.060)	0.050 (0.117)	-0.011 (0.060)	0.051 (0.118)
<i>log(population)_{j2001} * 2002</i>	-0.007 (0.090)	-0.078 (0.070)	-0.077 (0.069)	-0.120 (0.113)	-0.076 (0.069)	-0.126 (0.117)
<i>log(population)_{j2001} * 2003</i>	0.102 (0.119)	0.042 (0.091)	0.043 (0.090)	-0.085 (0.179)	0.046 (0.089)	-0.088 (0.183)
<i>log(population)_{j2001} * 2004</i>	0.031 (0.112)	-0.066 (0.083)	-0.066 (0.082)	0.033 (0.196)	-0.062 (0.081)	0.031 (0.201)
<i>log(population)_{j2001} * 2005</i>	-0.076 (0.119)	-0.159* (0.087)	-0.158* (0.086)	0.010 (0.252)	-0.154* (0.084)	0.003 (0.261)
<i>log(population)_{j2001} * 2006</i>	-0.126 (0.151)	-0.167 (0.133)	-0.168 (0.131)	-0.012 (0.249)	-0.163 (0.128)	-0.019 (0.256)
<i>log(population)_{j2001} * 2007</i>	-0.157 (0.160)	-0.207 (0.128)	-0.207* (0.125)	-0.068 (0.309)	-0.200 (0.123)	-0.075 (0.318)

$\log(population)_{j2001} * 2008$	-0.139 (0.169)	-0.225* (0.132)	-0.225* (0.130)	-0.006 (0.304)	-0.221* (0.127)	-0.015 (0.313)
$\log(population)_{j2001} * 2009$	-0.140 (0.210)	-0.232 (0.160)	-0.233 (0.159)	-0.132 (0.353)	-0.228 (0.155)	-0.140 (0.364)
$ScheduledCaste_{j1991} * 1995$	2.206 (3.167)	0.634 (2.602)	0.695 (2.600)	-7.562* (3.928)	0.686 (2.606)	-6.874* (3.789)
$ScheduledCaste_{j1991} * 1996$	1.258 (2.884)	0.905 (2.331)	0.945 (2.329)	-4.732 (3.331)	0.945 (2.342)	-4.142 (3.239)
$ScheduledCaste_{j1991} * 1997$	1.408 (2.221)	1.065 (2.024)	1.099 (2.039)	-5.635** (2.581)	1.101 (2.045)	-5.159** (2.488)
$ScheduledCaste_{j1991} * 1998$	1.120 (2.294)	0.438 (2.092)	0.456 (2.096)	-3.841* (2.048)	0.480 (2.117)	-3.453* (1.950)
$ScheduledCaste_{j1991} * 1999$	1.590 (2.169)	0.880 (1.777)	0.869 (1.795)	-4.143** (1.758)	0.913 (1.811)	-3.878** (1.701)
$ScheduledCaste_{j1991} * 2000$	0.692 (2.540)	0.725 (1.996)	0.693 (2.025)	-2.802 (1.827)	0.754 (2.033)	-2.639 (1.779)
$ScheduledCaste_{j2001} * 2001$	1.331 (2.755)	1.153 (1.824)	1.095 (1.882)	1.460 (1.644)	1.179 (1.868)	1.486 (1.599)
$ScheduledCaste_{j2001} * 2002$	0.754 (3.462)	0.875 (2.157)	0.819 (2.223)	2.099 (1.970)	0.904 (2.198)	2.031 (1.935)
$ScheduledCaste_{j2001} * 2003$	0.874 (4.048)	0.880 (2.437)	0.788 (2.511)	2.424 (2.835)	0.898 (2.469)	2.276 (2.819)
$ScheduledCaste_{j2001} * 2004$	0.423 (4.676)	0.741 (2.616)	0.606 (2.694)	4.750 (3.211)	0.736 (2.644)	4.492 (3.175)
$ScheduledCaste_{j2001} * 2005$	0.206 (5.585)	0.306 (3.138)	0.165 (3.226)	5.261 (4.029)	0.304 (3.176)	4.906 (4.018)
$ScheduledCaste_{j2001} * 2006$	0.721 (6.183)	1.033 (3.509)	0.873 (3.608)	7.225 (4.762)	1.013 (3.539)	6.754 (4.721)
$ScheduledCaste_{j2001} * 2007$	-0.423 (6.901)	0.013 (3.891)	-0.171 (3.984)	8.782* (5.125)	0.009 (3.918)	8.192 (5.113)
$ScheduledCaste_{j2001} * 2008$	-0.576 (7.635)	-0.033 (4.308)	-0.251 (4.414)	10.666* (6.082)	-0.037 (4.340)	10.003* (6.047)
$ScheduledCaste_{j2001} * 2009$	0.229 (8.288)	0.661 (4.745)	0.435 (4.866)	11.561* (6.611)	0.634 (4.789)	10.798 (6.581)
$Literacy_{j1991} * 1995$	-0.990 (1.507)	-1.240 (1.384)	-1.269 (1.393)	1.806 (1.824)	-1.244 (1.394)	2.028 (1.753)

$Literacy_{j1991} * 1996$	0.318 (1.287)	-0.899 (1.146)	-0.913 (1.156)	1.449 (1.360)	-0.902 (1.152)	1.637 (1.275)
$Literacy_{j1991} * 1997$	-0.778 (1.091)	-1.356 (0.971)	-1.363 (0.981)	0.818 (1.108)	-1.362 (0.971)	0.976 (1.068)
$Literacy_{j1991} * 1998$	-0.328 (1.046)	-0.844 (0.755)	-0.845 (0.766)	0.319 (0.770)	-0.842 (0.756)	0.465 (0.743)
$Literacy_{j1991} * 1999$	-0.928 (0.921)	-1.117 (0.749)	-1.108 (0.759)	-0.902 (0.573)	-1.117 (0.755)	-0.769 (0.546)
$Literacy_{j1991} * 2000$	-0.899 (0.791)	-0.807 (0.617)	-0.783 (0.625)	-0.612 (0.877)	-0.803 (0.619)	-0.504 (0.869)
$Literacy_{j2001} * 2001$	-0.772 (1.132)	-0.371 (0.913)	-0.328 (0.916)	-1.105 (1.225)	-0.360 (0.926)	-1.040 (1.276)
$Literacy_{j2001} * 2002$	-1.062 (1.228)	-0.291 (1.166)	-0.241 (1.163)	-1.711 (1.488)	-0.275 (1.182)	-1.660 (1.517)
$Literacy_{j2001} * 2003$	-0.909 (1.232)	-0.098 (1.275)	-0.056 (1.274)	-1.899 (1.827)	-0.091 (1.288)	-1.856 (1.849)
$Literacy_{j2001} * 2004$	-1.265 (1.413)	-0.247 (1.429)	-0.193 (1.430)	-2.806 (2.313)	-0.242 (1.445)	-2.776 (2.315)
$Literacy_{j2001} * 2005$	-1.272 (1.585)	-0.060 (1.597)	0.003 (1.595)	-3.362 (2.448)	-0.048 (1.611)	-3.361 (2.449)
$Literacy_{j2001} * 2006$	-1.076 (1.665)	-0.037 (1.799)	0.008 (1.801)	-4.260 (2.877)	-0.056 (1.812)	-4.276 (2.865)
$Literacy_{j2001} * 2007$	-1.312 (2.139)	-0.184 (2.126)	-0.127 (2.128)	-4.136 (3.273)	-0.203 (2.137)	-4.189 (3.254)
$Literacy_{j2001} * 2008$	-1.452 (2.131)	-0.040 (2.232)	0.041 (2.238)	-4.833 (3.756)	-0.043 (2.252)	-4.897 (3.727)
$Literacy_{j2001} * 2009$	-0.849 (2.366)	0.639 (2.526)	0.735 (2.529)	-5.074 (4.070)	0.651 (2.543)	-5.165 (4.025)
$Employment_{j1991} * 1995$	-0.779 (1.972)	-1.791 (1.740)	-1.872 (1.768)	4.805** (1.963)	-1.983 (1.775)	5.018*** (1.929)
$Employment_{j1991} * 1996$	-0.951 (1.770)	-1.533 (1.350)	-1.592 (1.361)	3.641** (1.732)	-1.690 (1.370)	3.725** (1.741)
$Employment_{j1991} * 1997$	-0.491 (1.632)	-1.477 (1.263)	-1.534 (1.287)	2.471 (2.345)	-1.601 (1.297)	2.524 (2.354)
$Employment_{j1991} * 1998$	-1.191 (1.279)	-1.975* (1.009)	-2.013** (1.027)	1.557 (1.513)	-2.060** (1.038)	1.633 (1.499)
$Employment_{j1991} * 1999$	-1.493	-2.219***	-2.236***	-1.240	-2.288***	-1.161

	(1.100)	(0.754)	(0.767)	(1.988)	(0.768)	(1.984)
$Employment_{j1991} * 2000$	-2.121 (1.375)	-2.178* (1.123)	-2.193** (1.112)	-1.203 (2.975)	-2.226** (1.126)	-1.191 (2.992)
$Employment_{j2001} * 2001$	-1.148 (1.752)	-1.464 (1.099)	-1.516 (1.088)	-1.027 (2.314)	-1.494 (1.093)	-1.167 (2.361)
$Employment_{j2001} * 2002$	-2.387 (1.972)	-2.648* (1.403)	-2.710* (1.406)	-2.796 (2.784)	-2.648* (1.396)	-3.080 (2.861)
$Employment_{j2001} * 2003$	-0.878 (2.702)	-1.432 (1.697)	-1.504 (1.665)	-3.378 (3.036)	-1.403 (1.691)	-3.763 (3.137)
$Employment_{j2001} * 2004$	-1.391 (2.819)	-2.125 (1.743)	-2.213 (1.697)	-4.084 (3.879)	-2.085 (1.737)	-4.566 (3.993)
$Employment_{j2001} * 2005$	-3.349 (3.143)	-3.125 (2.117)	-3.211 (2.063)	-4.116 (5.207)	-3.077 (2.106)	-4.686 (5.394)
$Employment_{j2001} * 2006$	-3.949 (3.642)	-3.871* (2.161)	-3.943* (2.110)	-6.696 (5.282)	-3.764* (2.153)	-7.433 (5.465)
$Employment_{j2001} * 2007$	-4.045 (4.189)	-4.137* (2.450)	-4.209* (2.412)	-7.394 (5.813)	-4.024* (2.422)	-8.168 (6.038)
$Employment_{j2001} * 2008$	-3.710 (4.211)	-4.254 (2.749)	-4.345 (2.690)	-7.353 (6.101)	-4.127 (2.725)	-8.187 (6.323)
$Employment_{j2001} * 2009$	-3.373 (4.422)	-3.328 (2.737)	-3.419 (2.679)	-8.619 (7.040)	-3.211 (2.700)	-9.545 (7.287)
$Female_{j1991} * 1995$	3.884 (6.330)	1.827 (5.256)	2.098 (5.401)	0.437 (8.383)	1.835 (5.346)	1.103 (8.544)
$Female_{j1991} * 1996$	5.392 (5.702)	3.236 (3.822)	3.478 (3.976)	2.666 (4.917)	3.276 (3.883)	3.567 (5.018)
$Female_{j1991} * 1997$	-5.992 (4.793)	-1.350 (5.051)	-1.210 (5.093)	-8.641** (4.350)	-1.315 (5.074)	-8.114* (4.285)
$Female_{j1991} * 1998$	-0.331 (3.410)	3.871 (3.278)	3.854 (3.382)	-2.335 (4.428)	3.890 (3.371)	-2.082 (4.505)
$Female_{j1991} * 1999$	0.629 (4.088)	0.124 (3.515)	-0.061 (3.519)	-2.833 (4.010)	0.151 (3.556)	-3.008 (4.157)
$Female_{j1991} * 2000$	2.589 (3.905)	2.422 (3.547)	2.140 (3.445)	2.712 (4.425)	2.373 (3.516)	2.610 (4.620)
$Female_{j2001} * 2001$	-3.262 (2.950)	-1.485 (2.963)	-1.586 (2.919)	-1.771 (8.824)	-1.585 (2.910)	-1.771 (8.882)
$Female_{j2001} * 2002$	-5.075 (3.646)	-4.037 (2.516)	-4.068 (2.496)	-15.534** (7.055)	-3.971 (2.534)	-15.577** (7.041)

$Female_{j2001} * 2003$	-5.911 (4.240)	-5.548** (2.587)	-5.601** (2.533)	-14.608 (11.781)	-5.459** (2.604)	-14.819 (11.865)
$Female_{j2001} * 2004$	-7.534 (5.965)	-6.231 (4.210)	-6.377 (4.226)	-17.856 (11.237)	-6.154 (4.152)	-18.015 (11.371)
$Female_{j2001} * 2005$	-4.395 (4.336)	-5.189** (2.458)	-5.432** (2.492)	-28.036** (13.112)	-5.073** (2.444)	-28.499** (13.176)
$Female_{j2001} * 2006$	-2.575 (5.588)	-4.281 (3.053)	-4.568 (3.079)	-25.382** (12.312)	-4.006 (3.056)	-25.842** (12.482)
$Female_{j2001} * 2007$	-11.094 (6.827)	-12.757*** (3.986)	-13.120*** (4.065)	-29.792* (16.716)	-12.449*** (3.948)	-30.433* (16.849)
$Female_{j2001} * 2008$	-9.311 (7.247)	-10.393*** (3.922)	-10.858*** (3.945)	-32.376* (17.863)	-10.067*** (3.862)	-32.938* (18.069)
$Female_{j2001} * 2009$	-7.791 (7.962)	-10.966** (4.427)	-11.377** (4.491)	-33.952* (19.114)	-10.683** (4.505)	-34.562* (19.181)
Observations	4,692	6,683	6,683	3,294	6,683	3,294
Number of districts	479	489	489	457	489	457

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends.

Appendix Table E.5: FDI and State Recruits in Top District Positions - with Control Variables

	<i>Dependent variable:</i> <i>DistrictMagistrate_{ijt}</i>		
	(1)	(2)	(3)
$Treated_{ij} * Post_t * StateRecruit_i$	0.150** (0.064)	0.128** (0.061)	0.131** (0.060)
$Treated_{ij} * Post_t$	0.055 (0.042)	0.071* (0.042)	0.088* (0.045)
$Treated_{ij} * StateRecruit_i$	-0.150* (0.081)	-0.149* (0.084)	-0.152* (0.082)
$Post_t * StateRecruit_i$	-0.085* (0.044)	-0.079* (0.047)	-0.083* (0.046)
$StateRecruit_i$	0.011 (0.044)	0.010 (0.048)	0.012 (0.047)
$log(population)_{j1991} * 1995$		-0.059 (0.069)	-0.058 (0.074)
$log(population)_{j1991} * 1996$		-0.054 (0.059)	-0.057 (0.062)
$log(population)_{j1991} * 1997$		-0.045 (0.046)	-0.040 (0.051)
$log(population)_{j1991} * 1998$		-0.023 (0.040)	-0.024 (0.042)
$log(population)_{j1991} * 1999$		-0.008 (0.030)	-0.003 (0.036)
$log(population)_{j1991} * 2000$		-0.008 (0.021)	-0.001 (0.028)
$log(population)_{j2001} * 2001$		-0.014 (0.017)	-0.012 (0.020)
$log(population)_{j2001} * 2002$		-0.011 (0.026)	-0.019 (0.023)
$log(population)_{j2001} * 2003$		0.008 (0.053)	-0.023 (0.036)
$log(population)_{j2001} * 2004$		0.020 (0.051)	-0.006 (0.033)
$log(population)_{j2001} * 2005$		0.033 (0.059)	0.011 (0.047)

$\log(\text{population})_{j2001} * 2006$	0.032 (0.068)	-0.00005 (0.053)
$\log(\text{population})_{j2001} * 2007$	0.045 (0.083)	0.013 (0.065)
$\log(\text{population})_{j2001} * 2008$	0.049 (0.095)	0.015 (0.075)
$\log(\text{population})_{j2001} * 2009$	0.057 (0.102)	0.022 (0.079)
$\text{ScheduledCaste}_{j1991} * 1995$		-4.239* (2.414)
$\text{ScheduledCaste}_{j1991} * 1996$		-3.370 (2.051)
$\text{ScheduledCaste}_{j1991} * 1997$		-2.493 (1.702)
$\text{ScheduledCaste}_{j1991} * 1998$		-1.741 (1.363)
$\text{ScheduledCaste}_{j1991} * 1999$		-1.061 (0.980)
$\text{ScheduledCaste}_{j1991} * 2000$		-0.134 (0.668)
$\text{ScheduledCaste}_{j2001} * 2001$		0.651 (0.454)
$\text{ScheduledCaste}_{j2001} * 2002$		1.195** (0.584)
$\text{ScheduledCaste}_{j2001} * 2003$		2.038** (0.916)
$\text{ScheduledCaste}_{j2001} * 2004$		2.718** (1.300)
$\text{ScheduledCaste}_{j2001} * 2005$		3.175* (1.629)
$\text{ScheduledCaste}_{j2001} * 2006$		3.809* (1.978)
$\text{ScheduledCaste}_{j2001} * 2007$		4.783** (2.364)
$\text{ScheduledCaste}_{j2001} * 2008$		5.318* (2.810)
$\text{ScheduledCaste}_{j2001} * 2009$		6.325**

	(3.205)
$Literacy_{j1991} * 1995$	0.118 (0.847)
$Literacy_{j1991} * 1996$	0.155 (0.660)
$Literacy_{j1991} * 1997$	0.150 (0.525)
$Literacy_{j1991} * 1998$	0.244 (0.429)
$Literacy_{j1991} * 1999$	0.308 (0.400)
$Literacy_{j1991} * 2000$	0.313 (0.340)
$Literacy_{j2001} * 2001$	0.465 (0.396)
$Literacy_{j2001} * 2002$	0.518 (0.402)
$Literacy_{j2001} * 2003$	0.632 (0.560)
$Literacy_{j2001} * 2004$	0.628 (0.692)
$Literacy_{j2001} * 2005$	0.807 (0.791)
$Literacy_{j2001} * 2006$	0.795 (0.952)
$Literacy_{j2001} * 2007$	0.725 (1.031)
$Literacy_{j2001} * 2008$	0.879 (1.236)
$Literacy_{j2001} * 2009$	1.044 (1.364)
$Employment_{j1991} * 1995$	0.777 (1.255)
$Employment_{j1991} * 1996$	0.400 (1.155)
$Employment_{j1991} * 1997$	0.733 (0.905)

$Employment_{j1991} * 1998$	0.440 (0.628)
$Employment_{j1991} * 1999$	0.638 (0.464)
$Employment_{j1991} * 2000$	0.770 (0.505)
$Employment_{j2001} * 2001$	0.459 (0.693)
$Employment_{j2001} * 2002$	0.075 (0.875)
$Employment_{j2001} * 2003$	-0.648 (1.024)
$Employment_{j2001} * 2004$	-0.656 (1.275)
$Employment_{j2001} * 2005$	-0.651 (1.452)
$Employment_{j2001} * 2006$	-1.027 (1.692)
$Employment_{j2001} * 2007$	-1.113 (2.062)
$Employment_{j2001} * 2008$	-1.248 (2.372)
$Employment_{j2001} * 2009$	-1.109 (2.615)
$Female_{j1991} * 1995$	-3.993* (2.397)
$Female_{j1991} * 1996$	-1.597 (2.164)
$Female_{j1991} * 1997$	-1.171 (2.086)
$Female_{j1991} * 1998$	0.294 (1.384)
$Female_{j1991} * 1999$	0.757 (1.559)
$Female_{j1991} * 2000$	0.417 (1.116)

$Female_{j2001} * 2001$	1.873** (0.914)
$Female_{j2001} * 2002$	1.919* (1.102)
$Female_{j2001} * 2003$	3.847*** (1.406)
$Female_{j2001} * 2004$	2.456** (1.152)
$Female_{j2001} * 2005$	1.316 (1.495)
$Female_{j2001} * 2006$	1.437 (1.830)
$Female_{j2001} * 2007$	1.643 (2.408)
$Female_{j2001} * 2008$	0.419 (2.273)
$Female_{j2001} * 2009$	2.404 (2.739)

Observations	9,666	9,063	9,063
Number of districts	551	495	495
Control for district pop.	X	✓	✓
Other district controls	X	X	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Sample includes only bureaucrats eligible for district magistrate positions.

Appendix Table E.6: FDI, Bureaucratic Reorganization, and Private Returns to Office - with Control Variables

Panel A: $Assets_{pjt}$	All (1)	In govt. (2)	Out of govt. (3)
$CumulFDI_{jt} * Incumbent_{ijt-} * StateRecruit_{jt-1}$	0.084** (0.034)	0.119* (0.067)	0.057 (0.052)
$CumulFDI_{jt} * Incumbent_{ijt-}$	-0.023* (0.013)	-0.059 (0.035)	-0.002 (0.033)
$CumulFDI_{jt} * StateRecruit_{jt-1}$	-0.0313 (0.0282)	0.00396 (0.0480)	-0.0141 (0.0444)
$Incumbent_{ijt-} * StateRecruit_{jt-1}$	-0.0829 (0.129)	-0.132 (0.138)	-0.105 (0.208)
$CumulFDI_{jt}$	0.021 (0.012)	0.027** (0.011)	0.005 (0.029)
$Incumbent_{ijt-}$	0.205** (0.0720)	0.312*** (0.0999)	0.149 (0.106)
$StateRecruit_{jt-1}$	0.164 (0.143)	0.157 (0.190)	0.151 (0.168)
$Assets_{pjt-}$	0.804*** (0.0248)	0.766*** (0.0320)	0.840*** (0.0425)
$Log(Education)_j$	-0.185** (0.0877)	-0.213 (0.207)	-0.105 (0.104)
$CriminalRecord_j$	-0.0338 (0.0811)	-0.0573 (0.104)	-0.0435 (0.0946)
$Female_j$	-0.324* (0.155)	-0.403** (0.189)	-0.207 (0.181)
Age_j	0.00743 (0.0141)	0.0601* (0.0340)	-0.0369 (0.0228)
Age_j^2	-0.000135 (0.000135)	-0.000681** (0.000324)	0.000330 (0.000212)
$PriorIncumbent_j$	0.0299 (0.0709)	0.151* (0.0845)	-0.0446 (0.0896)
$Constant$	3.980*** (0.764)	3.364** (1.470)	4.264*** (0.978)
Observations	716	315	401

Panel B: <i>MovableAssets_{pjt}</i>	All (1)	In govt. (2)	Out of govt. (3)
<i>CumulFDI_{jt} * Incumbent_{ijt-} * StateRecruit_{jt-1}</i>	0.056 (0.084)	0.214** (0.082)	-0.063 (0.080)
<i>CumulFDI_{jt} * Incumbent_{ijt-}</i>	-0.081 (0.011)***	-0.141*** (0.038)	-0.009 (0.024)
<i>CumulFDI_{jt} * StateRecruit_{jt-1}</i>	-0.0406 (0.0440)	-0.0759 (0.0591)	0.0511 (0.0504)
<i>Incumbent_{ijt-} * StateRecruit_{jt-1}</i>	-0.0715 (0.193)	-0.367 (0.364)	0.122 (0.204)
<i>CumulFDI_{jt}</i>	0.051 (0.021)**	0.073*** (0.015)	-0.014 (0.026)
<i>Incumbent_{ijt-}</i>	0.458*** (0.108)	0.744*** (0.147)	0.201* (0.103)
<i>StateRecruit_{jt-1}</i>	0.187 (0.139)	0.381 (0.295)	0.0719 (0.147)
<i>MovableAssets_{pjt-}</i>	0.684*** (0.0248)	0.693*** (0.0372)	0.679*** (0.0333)
<i>Log(Education)_j</i>	0.00599 (0.128)	0.224 (0.270)	-0.170 (0.209)
<i>CriminalRecord_j</i>	0.0146 (0.0911)	-0.0174 (0.0974)	-0.0212 (0.130)
<i>Female_j</i>	-0.189 (0.167)	0.0559 (0.210)	-0.326 (0.200)
<i>Age_j</i>	-0.0184 (0.0193)	0.0117 (0.0424)	-0.0265 (0.0269)
<i>Age_j²</i>	0.000112 (0.000194)	-0.000186 (0.000404)	0.000178 (0.000290)
<i>PriorIncumbent_j</i>	-0.0526 (0.0926)	0.119 (0.128)	-0.113 (0.144)
<i>Constant</i>	5.446*** (0.623)	3.997** (1.724)	6.224*** (1.242)
Observations	706	310	396

Panel C: <i>ImmovableAssets_{pjt}</i>	All (1)	In govt. (2)	Out of govt. (3)
<i>CumulFDI_{jt} * Incumbent_{ijt-} * StateRecruit_{jt-1}</i>	0.041 (0.033)	0.100 (0.077)	0.020 (0.048)
<i>CumulFDI_{jt} * Incumbent_{ijt-}</i>	0.004 (0.053)	-0.076* (0.095)	0.026 (0.107)
<i>CumulFDI_{jt} * StateRecruit_{jt-1}</i>	-0.0587** (0.0240)	-0.00635 (0.0477)	-0.0479 (0.0387)
<i>Incumbent_{ijt-} * StateRecruit_{jt-1}</i>	0.0930 (0.146)	0.142 (0.202)	0.00938 (0.259)
<i>CumulFDI_{jt}</i>	0.032*** (0.010)	0.033*** (0.010)	0.020 (0.031)
<i>Incumbent_{ijt-}</i>	0.0775 (0.0751)	0.133 (0.134)	0.0711 (0.107)
<i>StateRecruit_{jt-1}</i>	0.0961 (0.152)	-0.0189 (0.223)	0.105 (0.175)
<i>ImmovableAssets_{pjt-}</i>	0.778*** (0.0337)	0.795*** (0.0444)	0.768*** (0.0599)
<i>Log(Education)_j</i>	-0.226 (0.137)	-0.433* (0.246)	-0.0199 (0.171)
<i>CriminalRecord_j</i>	-0.0387 (0.0966)	0.0219 (0.126)	-0.0967 (0.147)
<i>Female_j</i>	-0.409** (0.145)	-0.415** (0.181)	-0.386* (0.212)
<i>Age_j</i>	0.0129 (0.0202)	0.0442 (0.0414)	-0.0132 (0.0228)
<i>Age_j²</i>	-0.000224 (0.000205)	-0.000541 (0.000400)	0.000045 (0.000196)
<i>PriorIncumbent_j</i>	-0.0430 (0.0692)	0.00363 (0.105)	-0.0819 (0.0835)
<i>Constant</i>	4.516*** (0.750)	4.191*** (1.411)	4.668*** (0.859)
Observations	677	295	382

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with first election fixed effects.

Appendix Table E.7: FDI and Bureaucratic Transfers - Including Officer Fixed Effects, with Control Variables

	<i>Dependent variable:</i>				
	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Transfer_{ijt}</i>	<i>Lateral_{ijt}</i>	<i>Promotion_{ijt}</i>
	(1)	(2)	(3)	(4)	(5)
<i>Treated_{ij} * Post_t</i>	0.091* (0.050)	0.102* (0.052)	0.275*** (0.066)	0.198** (0.080)	0.081** (0.034)
<i>SalaryLevel2_{it}</i>	0.380*** (0.049)	0.388*** (0.051)	0.385*** (0.054)	-0.433*** (0.048)	0.820*** (0.043)
<i>SalaryLevel3_{it}</i>	0.675*** (0.055)	0.690*** (0.057)	0.683*** (0.060)	-0.893*** (0.062)	1.580*** (0.077)
<i>SalaryLevel4_{it}</i>	1.032*** (0.086)	1.039*** (0.089)	1.040*** (0.096)	-1.266*** (0.080)	2.303*** (0.118)
<i>SalaryLevel5_{it}</i>	1.162*** (0.104)	1.175*** (0.109)	1.159*** (0.115)	-1.707*** (0.114)	2.845*** (0.154)
<i>SalaryLevel6_{it}</i>	1.674*** (0.229)	1.563*** (0.257)	1.568*** (0.275)	-2.464*** (0.279)	4.021*** (0.202)
<i>log(population)_{j1991} * 1995</i>		0.134 (0.125)	0.151 (0.134)	0.155* (0.077)	-0.001 (0.100)
<i>log(population)_{j1991} * 1996</i>		0.116 (0.109)	0.137 (0.116)	0.151** (0.071)	-0.015 (0.085)
<i>log(population)_{j1991} * 1997</i>		0.004 (0.099)	0.019 (0.097)	0.068 (0.049)	-0.045 (0.079)
<i>log(population)_{j1991} * 1998</i>		0.011 (0.083)	0.013 (0.083)	0.042 (0.063)	-0.016 (0.059)
<i>log(population)_{j1991} * 1999</i>		0.035 (0.064)	0.013 (0.071)	0.067 (0.061)	-0.036 (0.055)
<i>log(population)_{j1991} * 2000</i>		0.036 (0.066)	0.027 (0.063)	0.035 (0.053)	-0.0004 (0.051)
<i>log(population)_{j2001} * 2001</i>		0.048 (0.053)	0.047 (0.050)	0.055 (0.048)	0.005 (0.040)
<i>log(population)_{j2001} * 2002</i>		-0.060 (0.080)	-0.073 (0.064)	-0.026 (0.067)	-0.043 (0.050)
<i>log(population)_{j2001} * 2003</i>		-0.036 (0.091)	-0.029 (0.083)	0.104 (0.084)	-0.122** (0.052)
<i>log(population)_{j2001} * 2004</i>		-0.060 (0.108)	-0.054 (0.094)	0.073 (0.107)	-0.117 (0.075)

$\log(\text{population})_{j2001} * 2005$	-0.155 (0.118)	-0.159 (0.108)	0.005 (0.106)	-0.147* (0.072)
$\log(\text{population})_{j2001} * 2006$	-0.132 (0.129)	-0.187 (0.121)	-0.007 (0.124)	-0.149* (0.080)
$\log(\text{population})_{j2001} * 2007$	-0.214 (0.175)	-0.271* (0.141)	-0.029 (0.135)	-0.227** (0.093)
$\log(\text{population})_{j2001} * 2008$	-0.209 (0.177)	-0.263 (0.165)	0.030 (0.151)	-0.273** (0.120)
$\log(\text{population})_{j2001} * 2009$	-0.282 (0.179)	-0.336* (0.178)	0.041 (0.175)	-0.339** (0.130)
$\text{ScheduledCaste}_{j1991} * 1995$		-3.651 (2.669)	-1.385 (2.327)	-2.478 (1.648)
$\text{ScheduledCaste}_{j1991} * 1996$		-2.456 (2.268)	-0.357 (1.922)	-2.197 (1.454)
$\text{ScheduledCaste}_{j1991} * 1997$		-2.092 (1.633)	-0.215 (1.504)	-1.954 (1.262)
$\text{ScheduledCaste}_{j1991} * 1998$		-1.539 (1.462)	0.499 (1.186)	-2.008 (1.193)
$\text{ScheduledCaste}_{j1991} * 1999$		-1.266 (1.096)	0.724 (1.081)	-1.980* (1.095)
$\text{ScheduledCaste}_{j1991} * 2000$		-0.580 (1.389)	0.996 (1.000)	-1.463 (1.327)
$\text{ScheduledCaste}_{j2001} * 2001$		1.490 (1.500)	2.236** (1.055)	-0.552 (1.419)
$\text{ScheduledCaste}_{j2001} * 2002$		1.501 (1.951)	2.530* (1.361)	-0.692 (1.716)
$\text{ScheduledCaste}_{j2001} * 2003$		1.784 (2.378)	2.641 (1.688)	-0.457 (2.001)
$\text{ScheduledCaste}_{j2001} * 2004$		2.187 (2.877)	3.314 (2.120)	-0.818 (2.189)
$\text{ScheduledCaste}_{j2001} * 2005$		2.212 (3.454)	3.380 (2.577)	-0.613 (2.683)
$\text{ScheduledCaste}_{j2001} * 2006$		3.703 (4.026)	4.698 (2.861)	-0.474 (3.045)
$\text{ScheduledCaste}_{j2001} * 2007$		3.702 (4.338)	4.733 (3.263)	-0.299 (3.385)

$ScheduledCaste_{j2001} * 2008$	4.669 (4.998)	5.416 (3.657)	0.041 (3.781)
$ScheduledCaste_{j2001} * 2009$	5.636 (5.680)	6.106 (4.179)	0.363 (4.162)
$Literacy_{j1991} * 1995$	-0.323 (1.432)	-0.912 (0.826)	0.804 (1.134)
$Literacy_{j1991} * 1996$	-0.084 (1.136)	-0.749 (0.755)	0.832 (0.934)
$Literacy_{j1991} * 1997$	-0.765 (0.974)	-1.141 (0.737)	0.555 (0.812)
$Literacy_{j1991} * 1998$	-0.514 (0.816)	-0.797 (0.673)	0.432 (0.701)
$Literacy_{j1991} * 1999$	-1.144* (0.663)	-1.389* (0.684)	0.385 (0.559)
$Literacy_{j1991} * 2000$	-1.009 (0.670)	-1.161* (0.665)	0.307 (0.445)
$Literacy_{j2001} * 2001$	-1.104 (0.923)	-0.921 (0.876)	-0.047 (0.436)
$Literacy_{j2001} * 2002$	-1.432 (1.283)	-1.113 (1.191)	-0.128 (0.461)
$Literacy_{j2001} * 2003$	-1.197 (1.435)	-1.065 (1.352)	-0.061 (0.500)
$Literacy_{j2001} * 2004$	-1.851 (1.620)	-1.286 (1.496)	-0.519 (0.631)
$Literacy_{j2001} * 2005$	-1.963 (1.821)	-1.021 (1.587)	-0.859 (0.659)
$Literacy_{j2001} * 2006$	-2.693 (2.049)	-1.584 (1.762)	-1.117 (0.862)
$Literacy_{j2001} * 2007$	-2.795 (2.528)	-1.361 (2.085)	-1.463 (0.954)
$Literacy_{j2001} * 2008$	-2.851 (2.635)	-1.485 (2.089)	-1.323 (1.159)
$Literacy_{j2001} * 2009$	-2.545 (2.916)	-1.204 (2.355)	-1.302 (1.291)
$Employment_{j1991} * 1995$	-1.711 (1.990)	-0.620 (1.916)	-1.012 (1.227)
$Employment_{j1991} * 1996$	-0.635	-0.197	-0.685

	(1.763)	(1.748)	(1.083)
$Employment_{j1991} * 1997$	-0.509 (1.518)	0.637 (1.361)	-1.120 (0.966)
$Employment_{j1991} * 1998$	-0.601 (1.378)	0.796 (1.346)	-1.414* (0.814)
$Employment_{j1991} * 1999$	-2.049* (1.104)	-1.200 (1.102)	-0.874 (0.873)
$Employment_{j1991} * 2000$	-1.546 (1.131)	-1.161 (1.072)	-0.630 (0.806)
$Employment_{j2001} * 2001$	-0.715 (0.979)	-0.338 (0.868)	-0.685 (0.824)
$Employment_{j2001} * 2002$	-1.557 (1.311)	-1.095 (1.016)	-0.923 (0.904)
$Employment_{j2001} * 2003$	-0.864 (1.578)	-0.153 (1.352)	-1.088 (1.054)
$Employment_{j2001} * 2004$	-1.483 (1.759)	-0.643 (1.570)	-1.348 (1.136)
$Employment_{j2001} * 2005$	-2.187 (2.195)	-1.021 (1.866)	-1.464 (1.482)
$Employment_{j2001} * 2006$	-3.062 (2.192)	-1.635 (2.050)	-1.795 (1.591)
$Employment_{j2001} * 2007$	-3.680 (2.662)	-2.799 (2.259)	-1.427 (1.794)
$Employment_{j2001} * 2008$	-3.341 (2.959)	-2.140 (2.618)	-1.886 (1.899)
$Employment_{j2001} * 2009$	-2.717 (3.199)	-1.280 (2.771)	-1.964 (2.104)
$Female_{j1991} * 1995$	-0.654 (4.662)	-2.613 (3.560)	2.291 (2.844)
$Female_{j1991} * 1996$	-0.949 (3.483)	-3.315 (2.692)	3.266 (2.232)
$Female_{j1991} * 1997$	-6.665 (4.611)	-7.442*** (2.414)	0.657 (3.248)
$Female_{j1991} * 1998$	-0.287 (3.254)	-3.708 (2.521)	2.992 (1.982)
$Female_{j1991} * 1999$	-1.524 (3.237)	-0.838 (2.471)	-1.638 (2.361)

$Female_{j1991} * 2000$	1.423 (2.624)	1.433 (1.687)	-0.791 (2.057)
$Female_{j2001} * 2001$	-2.531 (2.170)	-0.247 (1.983)	-2.621 (1.740)
$Female_{j2001} * 2002$	-6.995** (2.797)	-4.949** (2.172)	-2.321 (2.336)
$Female_{j2001} * 2003$	-6.555 (4.158)	-4.586 (3.879)	-2.532 (3.511)
$Female_{j2001} * 2004$	-6.628 (5.576)	-3.155 (5.146)	-4.560 (3.448)
$Female_{j2001} * 2005$	-9.466* (4.957)	-3.838 (5.060)	-6.436 (3.754)
$Female_{j2001} * 2006$	-7.104 (5.199)	-3.028 (5.532)	-5.129 (4.691)
$Female_{j2001} * 2007$	-15.707** (7.217)	-9.939 (6.276)	-7.234 (6.090)
$Female_{j2001} * 2008$	-12.642* (7.311)	-10.161 (7.749)	-2.947 (6.409)
$Female_{j2001} * 2009$	-11.690 (7.521)	-8.012 (6.509)	-4.778 (6.436)

Observations	11,091	10,399	10,399	10,399	10,399
Number of districts	556	497	497	497	497
Control for district pop.	X	✓	✓	✓	✓
Other district controls	X	X	✓	✓	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with officer, district, and year fixed effects and district-specific time trends.

Appendix Table E.8: More Bureaucratic Transfers in Corrupt States - with Control Variables

Panel A: State Recruits	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>		
	(1)	(2)	(3)
<i>Treated_{ij} * Post_t * StateCorruptionRank_j</i>	0.027*** (0.009)	0.029*** (0.011)	0.045*** (0.013)
<i>Treated_{ij} * Post_t</i>	0.022 (0.103)	0.014 (0.134)	-0.021 (0.185)
<i>Post_t * StateCorruptionRank_j</i>	-0.009 (0.007)	-0.010 (0.009)	-0.020*** (0.007)
<i>StateCorruptionRank_j</i>	-0.128*** (0.017)	-0.136*** (0.014)	-0.135*** (0.015)
<i>SalaryLevel2_{it}</i>	0.122 (0.087)	0.108 (0.089)	0.094 (0.087)
<i>SalaryLevel3_{it}</i>	0.301*** (0.109)	0.284*** (0.110)	0.274*** (0.105)
<i>SalaryLevel4_{it}</i>	0.436*** (0.117)	0.419*** (0.117)	0.409*** (0.123)
<i>SalaryLevel5_{it}</i>	0.353*** (0.119)	0.330*** (0.115)	0.342*** (0.118)
<i>Log(population)_{j1991} * 1995</i>		0.052 (0.193)	0.031 (0.187)
<i>Log(population)_{j1991} * 1996</i>		-0.062 (0.162)	-0.126 (0.161)
<i>Log(population)_{j1991} * 1997</i>		-0.179 (0.112)	-0.224** (0.114)
<i>Log(population)_{j1991} * 1998</i>		-0.135 (0.087)	-0.190** (0.084)
<i>Log(population)_{j1991} * 1999</i>		-0.020 (0.088)	-0.099 (0.096)
<i>Log(population)_{j1991} * 2000</i>		-0.006 (0.108)	-0.054 (0.137)
<i>Log(population)_{j2001} * 2001</i>		0.041 (0.115)	-0.019 (0.132)
<i>Log(population)_{j2001} * 2002</i>		-0.126 (0.122)	-0.191 (0.139)
<i>Log(population)_{j2001} * 2003</i>		-0.088	-0.160

	(0.160)	(0.206)
$Log(population)_{j2001} * 2004$	-0.017 (0.193)	-0.056 (0.233)
$Log(population)_{j2001} * 2005$	-0.070 (0.230)	-0.084 (0.295)
$Log(population)_{j2001} * 2006$	-0.023 (0.245)	-0.102 (0.310)
$Log(population)_{j2001} * 2007$	-0.110 (0.288)	-0.207 (0.368)
$Log(population)_{j2001} * 2008$	-0.038 (0.307)	-0.111 (0.379)
$Log(population)_{j2001} * 2009$	-0.193 (0.364)	-0.287 (0.431)
$ScheduledCaste_{j1991} * 1995$		-8.742* (4.581)
$ScheduledCaste_{j1991} * 1996$		-6.159 (3.777)
$ScheduledCaste_{j1991} * 1997$		-6.484** (2.931)
$ScheduledCaste_{j1991} * 1998$		-4.347* (2.285)
$ScheduledCaste_{j1991} * 1999$		-4.949** (1.943)
$ScheduledCaste_{j1991} * 2000$		-3.258* (1.953)
$ScheduledCaste_{j2001} * 2001$		1.166 (1.870)
$ScheduledCaste_{j2001} * 2002$		2.029 (2.251)
$ScheduledCaste_{j2001} * 2003$		2.476 (3.174)
$ScheduledCaste_{j2001} * 2004$		4.878 (3.679)
$ScheduledCaste_{j2001} * 2005$		5.546 (4.595)
$ScheduledCaste_{j2001} * 2006$		6.967

	(5.322)
$ScheduledCaste_{j2001} * 2007$	8.556 (5.843)
$ScheduledCaste_{j2001} * 2008$	10.817 (6.875)
$ScheduledCaste_{j2001} * 2009$	11.692 (7.614)
$Literacy_{j1991} * 1995$	1.594 (1.950)
$Literacy_{j1991} * 1996$	1.203 (1.403)
$Literacy_{j1991} * 1997$	0.465 (1.202)
$Literacy_{j1991} * 1998$	-0.068 (0.851)
$Literacy_{j1991} * 1999$	-1.263* (0.673)
$Literacy_{j1991} * 2000$	-1.038 (0.982)
$Literacy_{j2001} * 2001$	-1.645 (1.517)
$Literacy_{j2001} * 2002$	-2.238 (1.812)
$Literacy_{j2001} * 2003$	-2.502 (2.197)
$Literacy_{j2001} * 2004$	-3.504 (2.760)
$Literacy_{j2001} * 2005$	-4.100 (2.888)
$Literacy_{j2001} * 2006$	-5.463 (3.443)
$Literacy_{j2001} * 2007$	-5.348 (3.899)
$Literacy_{j2001} * 2008$	-6.061 (4.398)
$Literacy_{j2001} * 2009$	-6.412

	(4.753)
$Employment_{j1991} * 1995$	4.924** (2.411)
$Employment_{j1991} * 1996$	3.574* (2.106)
$Employment_{j1991} * 1997$	2.301 (2.798)
$Employment_{j1991} * 1998$	1.503 (1.741)
$Employment_{j1991} * 1999$	-1.095 (2.081)
$Employment_{j1991} * 2000$	-1.184 (3.088)
$Employment_{j2001} * 2001$	-0.958 (2.440)
$Employment_{j2001} * 2002$	-2.814 (2.966)
$Employment_{j2001} * 2003$	-3.482 (3.229)
$Employment_{j2001} * 2004$	-4.288 (4.189)
$Employment_{j2001} * 2005$	-4.337 (5.627)
$Employment_{j2001} * 2006$	-6.942 (5.752)
$Employment_{j2001} * 2007$	-7.925 (6.255)
$Employment_{j2001} * 2008$	-7.772 (6.720)
$Employment_{j2001} * 2009$	-9.245 (7.759)
$Female_{j1991} * 1995$	0.475 (9.363)
$Female_{j1991} * 1996$	3.323 (6.038)
$Female_{j1991} * 1997$	-8.061*

	(4.898)
$Female_{j1991} * 1998$	-2.357 (4.024)
$Female_{j1991} * 1999$	-3.652 (3.915)
$Female_{j1991} * 2000$	2.428 (4.441)
$Female_{j2001} * 2001$	-1.136 (8.979)
$Female_{j2001} * 2002$	-14.314* (7.305)
$Female_{j2001} * 2003$	-12.605 (12.552)
$Female_{j2001} * 2004$	-15.756 (12.065)
$Female_{j2001} * 2005$	-25.127* (14.302)
$Female_{j2001} * 2006$	-25.057* (13.837)
$Female_{j2001} * 2007$	-28.293 (18.432)
$Female_{j2001} * 2008$	-30.450 (19.887)
$Female_{j2001} * 2009$	-30.866 (21.188)

Observations	3,357	3,223	3,223
Number of districts	476	447	447
Panel B: Direct Recruits	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>		
	(1)	(2)	(3)
$Treated_{ij} * Post_t * StateCorruptionRank_j$	-0.002 (0.009)	-0.003 (0.009)	0.003 (0.010)
$Treated_{ij} * Post_t$	0.043 (0.107)	0.049 (0.113)	0.103 (0.130)
$Post_t * StateCorruptionRank_j$	-0.001 (0.008)	-0.001 (0.008)	-0.005 (0.008)

<i>StateCorruptionRank_j</i>	−0.012*** (0.004)	−0.011*** (0.004)	−0.012 (0.008)
<i>SalaryLevel2_{it}</i>	0.147*** (0.035)	0.150*** (0.035)	0.150*** (0.036)
<i>SalaryLevel3_{it}</i>	0.157*** (0.036)	0.156*** (0.036)	0.154*** (0.035)
<i>SalaryLevel4_{it}</i>	0.227*** (0.059)	0.225*** (0.059)	0.228*** (0.061)
<i>SalaryLevel5_{it}</i>	0.100** (0.047)	0.104** (0.048)	0.101** (0.049)
<i>SalaryLevel6_{it}</i>	0.252* (0.140)	0.247* (0.145)	0.252* (0.145)
<i>log(population)_{j1991} * 1995</i>		0.087 (0.096)	0.094 (0.093)
<i>log(population)_{j1991} * 1996</i>		0.102 (0.079)	0.110 (0.080)
<i>log(population)_{j1991} * 1997</i>		0.008 (0.063)	0.008 (0.076)
<i>log(population)_{j1991} * 1998</i>		−0.011 (0.078)	−0.012 (0.073)
<i>log(population)_{j1991} * 1999</i>		0.010 (0.073)	0.002 (0.073)
<i>log(population)_{j1991} * 2000</i>		−0.007 (0.067)	−0.014 (0.069)
<i>log(population)_{j2001} * 2001</i>		−0.015 (0.070)	−0.016 (0.059)
<i>log(population)_{j2001} * 2002</i>		−0.035 (0.088)	−0.075 (0.075)
<i>log(population)_{j2001} * 2003</i>		0.046 (0.095)	0.056 (0.101)
<i>log(population)_{j2001} * 2004</i>		−0.021 (0.105)	−0.025 (0.089)
<i>log(population)_{j2001} * 2005</i>		−0.056 (0.093)	−0.096 (0.103)
<i>log(population)_{j2001} * 2006</i>		−0.019 (0.134)	−0.105 (0.156)

$\log(\text{population})_{j2001} * 2007$	-0.074 (0.138)	-0.125 (0.133)
$\log(\text{population})_{j2001} * 2008$	-0.053 (0.138)	-0.114 (0.151)
$\log(\text{population})_{j2001} * 2009$	-0.077 (0.182)	-0.120 (0.195)
$\text{ScheduledCaste}_{j1991} * 1995$		0.162 (2.727)
$\text{ScheduledCaste}_{j1991} * 1996$		0.412 (2.438)
$\text{ScheduledCaste}_{j1991} * 1997$		0.549 (2.093)
$\text{ScheduledCaste}_{j1991} * 1998$		-0.060 (2.132)
$\text{ScheduledCaste}_{j1991} * 1999$		0.509 (1.809)
$\text{ScheduledCaste}_{j1991} * 2000$		0.338 (2.019)
$\text{ScheduledCaste}_{j2001} * 2001$		0.837 (1.855)
$\text{ScheduledCaste}_{j2001} * 2002$		0.568 (2.224)
$\text{ScheduledCaste}_{j2001} * 2003$		0.654 (2.557)
$\text{ScheduledCaste}_{j2001} * 2004$		0.549 (2.762)
$\text{ScheduledCaste}_{j2001} * 2005$		0.225 (3.339)
$\text{ScheduledCaste}_{j2001} * 2006$		0.913 (3.791)
$\text{ScheduledCaste}_{j2001} * 2007$		-0.031 (4.213)
$\text{ScheduledCaste}_{j2001} * 2008$		-0.027 (4.678)
$\text{ScheduledCaste}_{j2001} * 2009$		0.711 (5.159)
$\text{Literacy}_{j1991} * 1995$		-1.230

	(1.432)
$Literacy_{j1991} * 1996$	-0.909 (1.202)
$Literacy_{j1991} * 1997$	-1.359 (1.008)
$Literacy_{j1991} * 1998$	-0.882 (0.807)
$Literacy_{j1991} * 1999$	-1.197 (0.813)
$Literacy_{j1991} * 2000$	-0.893 (0.676)
$Literacy_{j2001} * 2001$	-0.509 (1.009)
$Literacy_{j2001} * 2002$	-0.460 (1.261)
$Literacy_{j2001} * 2003$	-0.281 (1.371)
$Literacy_{j2001} * 2004$	-0.515 (1.512)
$Literacy_{j2001} * 2005$	-0.352 (1.679)
$Literacy_{j2001} * 2006$	-0.488 (1.902)
$Literacy_{j2001} * 2007$	-0.713 (2.232)
$Literacy_{j2001} * 2008$	-0.595 (2.335)
$Literacy_{j2001} * 2009$	0.085 (2.627)
$Employment_{j1991} * 1995$	-1.486 (1.821)
$Employment_{j1991} * 1996$	-1.389 (1.379)
$Employment_{j1991} * 1997$	-1.220 (1.359)
$Employment_{j1991} * 1998$	-1.890* (0.999)

$Employment_{j1991} * 1999$	-2.105*** (0.778)
$Employment_{j1991} * 2000$	-2.103* (1.158)
$Employment_{j2001} * 2001$	-1.466 (1.147)
$Employment_{j2001} * 2002$	-2.683* (1.464)
$Employment_{j2001} * 2003$	-1.552 (1.759)
$Employment_{j2001} * 2004$	-2.206 (1.839)
$Employment_{j2001} * 2005$	-3.242 (2.230)
$Employment_{j2001} * 2006$	-4.156* (2.325)
$Employment_{j2001} * 2007$	-4.396* (2.555)
$Employment_{j2001} * 2008$	-4.508 (2.926)
$Employment_{j2001} * 2009$	-3.698 (2.914)
$Female_{j1991} * 1995$	2.034 (5.913)
$Female_{j1991} * 1996$	3.747 (4.383)
$Female_{j1991} * 1997$	-1.732 (5.610)
$Female_{j1991} * 1998$	4.020 (3.627)
$Female_{j1991} * 1999$	-0.083 (3.810)
$Female_{j1991} * 2000$	2.008 (3.808)
$Female_{j2001} * 2001$	-1.875 (3.092)

$Female_{j2001} * 2002$	−4.378*
	(2.518)
$Female_{j2001} * 2003$	−5.756**
	(2.580)
$Female_{j2001} * 2004$	−7.060
	(4.472)
$Female_{j2001} * 2005$	−6.053**
	(2.539)
$Female_{j2001} * 2006$	−5.150*
	(2.994)
$Female_{j2001} * 2007$	−13.931***
	(4.219)
$Female_{j2001} * 2008$	−11.876***
	(4.056)
$Female_{j2001} * 2009$	−12.241***
	(4.403)

Observations	6,862	6,568	6,568
Number of districts	511	477	477
Control for district pop.	X	✓	✓
Other district controls	X	X	✓

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends. Sample includes only state recruits.

Appendix Table E.9: FDI Origin Country Corruption Increases Bureaucratic Transfers - with Control Variables

	<i>Dependent variable:</i> <i>Transfer_{ijt}</i>		
	(1)	(2)	(3)
<i>StateRecruit_i * Post_t * OriginCountryCorruption_{jt-1}</i>	0.130*** (0.034)	0.140*** (0.040)	0.192*** (0.036)
<i>Post_t * OriginCountryCorruption_{jt-1}</i>	-0.089 (0.104)	-0.061 (0.095)	-0.240*** (0.080)
<i>StateRecruit_i * Post_t</i>	0.155 (0.154)	0.130 (0.147)	0.123 (0.157)
<i>StateRecruit_i * OriginCountryCorruption_{jt-1}</i>	-0.111*** (0.025)	-0.111*** (0.028)	-0.129*** (0.032)
<i>StateRecruit_i</i>	-0.167*** (0.033)	-0.168*** (0.030)	-0.202*** (0.029)
<i>OriginCountryCorruption_{jt-1}</i>	-0.018 (0.025)	-0.038* (0.021)	0.043 (0.038)
<i>SalaryLevel2_{it}</i>	0.024 (0.054)	0.043 (0.067)	0.057 (0.077)
<i>SalaryLevel3_{it}</i>	0.188*** (0.060)	0.189*** (0.068)	0.182*** (0.065)
<i>SalaryLevel4_{it}</i>	0.159* (0.084)	0.165* (0.084)	0.181** (0.090)
<i>SalaryLevel5_{it}</i>	0.101 (0.079)	0.097 (0.078)	0.092 (0.090)
<i>SalaryLevel6_{it}</i>	0.069 (0.152)	0.065 (0.166)	0.101 (0.161)
<i>log(population)_{j1991} * 1996</i>		-1.297*** (0.345)	-2.921*** (1.100)
<i>log(population)_{j1991} * 1997</i>		-0.664** (0.261)	-1.212 (0.873)
<i>log(population)_{j1991} * 1998</i>		-1.003*** (0.248)	-1.107** (0.491)
<i>log(population)_{j1991} * 1999</i>		-0.718*** (0.231)	-0.392 (0.341)
<i>log(population)_{j1991} * 2000</i>		-0.413 (0.261)	-0.008 (0.557)

$\log(\text{population})_{j2001} * 2001$	-0.209 (0.453)	0.928 (0.630)
$\log(\text{population})_{j2001} * 2002$	0.028 (0.409)	1.335 (0.999)
$\log(\text{population})_{j2001} * 2003$	0.321 (0.535)	1.834 (1.265)
$\log(\text{population})_{j2001} * 2004$	0.488 (0.736)	2.506* (1.496)
$\log(\text{population})_{j2001} * 2005$	0.736 (0.796)	3.022* (1.772)
$\log(\text{population})_{j2001} * 2006$	1.151 (0.989)	4.139* (2.208)
$\log(\text{population})_{j2001} * 2007$	1.335 (1.038)	4.355* (2.484)
$\log(\text{population})_{j2001} * 2008$	1.463 (1.170)	4.792* (2.539)
$\log(\text{population})_{j2001} * 2009$	1.476 (1.228)	4.606 (3.133)
$\text{ScheduledCaste}_{j1991} * 1996$		0.638 (18.621)
$\text{ScheduledCaste}_{j1991} * 1997$		-1.130 (15.545)
$\text{ScheduledCaste}_{j1991} * 1998$		0.498 (11.186)
$\text{ScheduledCaste}_{j1991} * 1999$		3.728 (10.751)
$\text{ScheduledCaste}_{j1991} * 2000$		3.973 (8.469)
$\text{ScheduledCaste}_{j2001} * 2001$		15.045 (11.498)
$\text{ScheduledCaste}_{j2001} * 2002$		11.549 (16.387)
$\text{ScheduledCaste}_{j2001} * 2003$		16.273 (19.911)
$\text{ScheduledCaste}_{j2001} * 2004$		22.467 (24.305)

<i>ScheduledCaste</i> _{j2001} * 2005	26.435 (30.609)
<i>ScheduledCaste</i> _{j2001} * 2006	36.468 (33.804)
<i>ScheduledCaste</i> _{j2001} * 2007	35.790 (40.878)
<i>ScheduledCaste</i> _{j2001} * 2008	37.235 (45.347)
<i>ScheduledCaste</i> _{j2001} * 2009	44.612 (48.739)
<i>Literacy</i> _{j1991} * 1996	14.215*** (4.364)
<i>Literacy</i> _{j1991} * 1997	7.347* (4.457)
<i>Literacy</i> _{j1991} * 1998	5.528 (4.049)
<i>Literacy</i> _{j1991} * 1999	3.787* (2.165)
<i>Literacy</i> _{j1991} * 2000	4.775 (2.899)
<i>Literacy</i> _{j2001} * 2001	3.021 (4.547)
<i>Literacy</i> _{j2001} * 2002	−0.398 (5.011)
<i>Literacy</i> _{j2001} * 2003	0.168 (6.727)
<i>Literacy</i> _{j2001} * 2004	−4.770 (8.495)
<i>Literacy</i> _{j2001} * 2005	−4.512 (9.929)
<i>Literacy</i> _{j2001} * 2006	−10.799 (11.211)
<i>Literacy</i> _{j2001} * 2007	−7.992 (12.949)
<i>Literacy</i> _{j2001} * 2008	−9.418 (13.916)
<i>Literacy</i> _{j2001} * 2009	−4.923

	(17.456)
$Employment_{j1991} * 1996$	15.586* (8.696)
$Employment_{j1991} * 1997$	9.583 (5.988)
$Employment_{j1991} * 1998$	17.909** (8.319)
$Employment_{j1991} * 1999$	5.632 (4.325)
$Employment_{j1991} * 2000$	3.740 (2.956)
$Employment_{j2001} * 2001$	8.118** (3.777)
$Employment_{j2001} * 2002$	6.514 (5.525)
$Employment_{j2001} * 2003$	10.804* (6.512)
$Employment_{j2001} * 2004$	10.791 (7.278)
$Employment_{j2001} * 2005$	14.487 (8.850)
$Employment_{j2001} * 2006$	15.332 (10.563)
$Employment_{j2001} * 2007$	20.184* (11.729)
$Employment_{j2001} * 2008$	23.257* (13.645)
$Employment_{j2001} * 2009$	29.803** (14.856)
$Female_{j1991} * 1996$	-30.844* (18.565)
$Female_{j1991} * 1997$	-36.883*** (13.118)
$Female_{j1991} * 1998$	-67.960*** (16.063)
$Female_{j1991} * 1999$	-22.739*** (5.959)

$Female_{j1991} * 2000$	3.314 (8.882)
$Female_{j2001} * 2001$	6.141 (21.946)
$Female_{j2001} * 2002$	11.713 (27.713)
$Female_{j2001} * 2003$	15.886 (31.617)
$Female_{j2001} * 2004$	48.325 (40.510)
$Female_{j2001} * 2005$	49.831 (44.188)
$Female_{j2001} * 2006$	72.424 (51.133)
$Female_{j2001} * 2007$	36.034 (62.440)
$Female_{j2001} * 2008$	46.713 (61.709)
$Female_{j2001} * 2009$	56.986 (72.492)

Observations	717	697	697
Number of districts	95	89	89
Control for district pop.	X	✓	✓
Other district controls	X	X	✓

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Robust standard errors clustered by state in parentheses. Models estimated using OLS with district and year fixed effects and district-specific time trends.

Appendix Table E.10: Market-Oriented FDI Increases Bureaucratic Transfers - with Control Variables

	<i>Dependent variable:</i>	
	<i>Transfer_{ijt}</i> State recruits	<i>Transfer_{ijt}</i> Direct recruits
	(1)	(2)
<i>Treated_{ij} * Post_t * RelatedParty_{jt}</i>	−0.150** (0.051)	0.008 (0.019)
<i>Treated_{ij} * Post_t</i>	0.842 (0.752)	0.172 (0.398)
<i>Treated_{ij} * RelatedParty_{jt}</i>	0.011 (0.029)	−0.004 (0.013)
<i>Post_t * RelatedParty_{jt}</i>	0.111* (0.059)	0.004 (0.016)
<i>RelatedParty_{jt}</i>	−0.012 (0.016)	−0.016 (0.011)
<i>SalaryLevel2_{it}</i>	−0.151* (0.086)	0.107 (0.082)
<i>SalaryLevel3_{it}</i>	0.148 (0.114)	0.145*** (0.054)
<i>SalaryLevel4_{it}</i>	0.095 (0.106)	0.003 (0.054)
<i>SalaryLevel5_{it}</i>	0.208* (0.119)	0.102 (0.066)
<i>SalaryLevel6_{it}</i>		0.017 (0.145)
<i>log(population)_{j1991} * 1995</i>	−3.821 (12.031)	0.732 (0.547)
<i>log(population)_{j1991} * 1996</i>	−10.597* (5.813)	−0.032 (0.846)
<i>log(population)_{j1991} * 1997</i>	−2.993 (2.999)	−0.754 (0.593)
<i>log(population)_{j1991} * 1998</i>	−6.381 (4.300)	−0.180 (0.445)
<i>log(population)_{j1991} * 1999</i>	−6.675* (3.318)	−0.762 (0.486)
<i>log(population)_{j1991} * 2000</i>	−4.906** (2.188)	−1.008* (0.554)

$\log(\text{population})_{j2001} * 2001$	-4.793** (1.727)	-1.155** (0.472)
$\log(\text{population})_{j2001} * 2002$	-1.979 (1.677)	-1.409** (0.678)
$\log(\text{population})_{j2001} * 2003$	-0.007 (2.553)	-1.749** (0.775)
$\log(\text{population})_{j2001} * 2004$	-0.278 (2.866)	-1.485* (0.772)
$\log(\text{population})_{j2001} * 2005$	0.690 (3.614)	-2.336*** (0.837)
$\log(\text{population})_{j2001} * 2006$	1.294 (4.645)	-1.908* (1.042)
$\log(\text{population})_{j2001} * 2007$	1.601 (5.635)	-2.363** (1.117)
$\log(\text{population})_{j2001} * 2008$	2.826 (6.340)	-2.788** (1.280)
$\log(\text{population})_{j2001} * 2009$	2.693 (7.345)	-2.762** (1.334)
$ScheduledCaste_{j1991} * 1995$	142.292*** (47.467)	-5.620 (14.441)
$ScheduledCaste_{j1991} * 1996$	151.435*** (27.049)	-4.643 (10.515)
$ScheduledCaste_{j1991} * 1997$	75.471** (29.742)	-1.628 (12.196)
$ScheduledCaste_{j1991} * 1998$	91.130*** (11.357)	3.761 (10.503)
$ScheduledCaste_{j1991} * 1999$	94.667*** (16.534)	12.245 (9.783)
$ScheduledCaste_{j1991} * 2000$	83.701*** (16.831)	9.820 (13.629)
$ScheduledCaste_{j2001} * 2001$	68.511*** (12.437)	14.530 (12.607)
$ScheduledCaste_{j2001} * 2002$	50.165*** (11.028)	15.049 (17.021)
$ScheduledCaste_{j2001} * 2003$	43.883*** (9.331)	21.684 (18.666)

$ScheduledCaste_{j2001} * 2004$	39.470*** (9.130)	26.460 (21.754)
$ScheduledCaste_{j2001} * 2005$	32.162*** (7.100)	25.222 (22.965)
$ScheduledCaste_{j2001} * 2006$	24.580*** (6.366)	31.270 (26.566)
$ScheduledCaste_{j2001} * 2007$	32.352*** (2.888)	33.209 (28.969)
$ScheduledCaste_{j2001} * 2008$	23.458*** (3.321)	35.532 (31.649)
$ScheduledCaste_{j2001} * 2009$	(0.000)	41.075 (34.355)
$Literacy_{j1991} * 1995$	82.549 (48.614)	-11.664 (12.002)
$Literacy_{j1991} * 1996$	105.643*** (30.477)	-11.894 (8.314)
$Literacy_{j1991} * 1997$	60.037** (24.811)	-4.074 (7.846)
$Literacy_{j1991} * 1998$	80.293*** (26.021)	-5.641 (6.351)
$Literacy_{j1991} * 1999$	73.330*** (22.713)	-1.828 (4.922)
$Literacy_{j1991} * 2000$	54.412** (21.301)	-0.151 (3.420)
$Literacy_{j2001} * 2001$	82.011*** (22.954)	6.480 (5.099)
$Literacy_{j2001} * 2002$	49.750** (18.949)	6.374 (5.362)
$Literacy_{j2001} * 2003$	26.102 (25.457)	9.937 (7.110)
$Literacy_{j2001} * 2004$	30.469** (10.906)	11.682 (8.603)
$Literacy_{j2001} * 2005$	21.334** (9.701)	17.329 (10.940)
$Literacy_{j2001} * 2006$	13.713 (8.305)	17.029 (12.866)

$Literacy_{j2001} * 2007$	10.403 (6.605)	18.775 (15.441)
$Literacy_{j2001} * 2008$	-0.204 (3.751)	21.816 (17.593)
$Literacy_{j2001} * 2009$	(0.000)	24.505 (20.670)
$Employment_{j1991} * 1995$	127.605 (79.020)	-19.771* (11.843)
$Employment_{j1991} * 1996$	149.184*** (41.587)	-15.016* (8.277)
$Employment_{j1991} * 1997$	77.918** (30.726)	-15.432 (9.951)
$Employment_{j1991} * 1998$	104.229*** (32.407)	-9.662 (6.007)
$Employment_{j1991} * 1999$	91.612*** (29.666)	-5.113 (4.354)
$Employment_{j1991} * 2000$	70.660** (25.982)	-3.876 (4.401)
$Employment_{j2001} * 2001$	58.148** (22.068)	5.139 (4.210)
$Employment_{j2001} * 2002$	41.119* (19.630)	-1.003 (6.866)
$Employment_{j2001} * 2003$	39.556* (19.797)	10.504* (5.414)
$Employment_{j2001} * 2004$	25.202 (18.907)	9.988 (6.816)
$Employment_{j2001} * 2005$	16.995 (20.887)	14.383* (8.508)
$Employment_{j2001} * 2006$	6.481 (24.276)	20.227** (9.801)
$Employment_{j2001} * 2007$	-2.622 (29.940)	20.353* (11.410)
$Employment_{j2001} * 2008$	-16.092 (31.721)	25.229** (11.988)
$Employment_{j2001} * 2009$	-24.782 (36.182)	27.397* (14.283)
$Female_{j1991} * 1995$		-11.954

	(0.000)	(14.978)
<i>Female</i> _{j1991} * 1996		−27.651**
	(0.000)	(11.117)
<i>Female</i> _{j1991} * 1997		−11.763
	(0.000)	(18.063)
<i>Female</i> _{j1991} * 1998	−115.075	−20.930**
	(78.623)	(10.236)
<i>Female</i> _{j1991} * 1999	−2.409	−21.479*
	(22.280)	(12.299)
<i>Female</i> _{j1991} * 2000	−21.207*	−11.357
	(10.288)	(9.177)
<i>Female</i> _{j2001} * 2001	−173.929***	−45.884**
	(55.569)	(20.031)
<i>Female</i> _{j2001} * 2002	−120.482**	−20.594
	(46.120)	(25.031)
<i>Female</i> _{j2001} * 2003	33.924	−29.272
	(89.078)	(27.213)
<i>Female</i> _{j2001} * 2004	−52.810	−12.321
	(37.477)	(25.252)
<i>Female</i> _{j2001} * 2005	−37.491	−18.919
	(57.438)	(43.457)
<i>Female</i> _{j2001} * 2006	−45.124	−27.319
	(42.009)	(49.851)
<i>Female</i> _{j2001} * 2007	−87.608*	−43.518
	(48.403)	(52.653)
<i>Female</i> _{j2001} * 2008	−113.934**	−38.608
	(53.524)	(61.779)
<i>Female</i> _{j2001} * 2009	−131.306**	−40.463
	(56.902)	(64.068)
Observations	328	706
Number of districts	80	118

Notes: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered by state in parentheses. All models estimated using OLS with district and year fixed effects and district-specific time trends.