2-2015

The Impact of Corruption on Consumer Markets: Evidence From the Allocation of Second-Generation Wireless Spectrum in India

Sandip Sukhtankar
Dartmouth College

The Impact of Corruption on Consumer Markets: Evidence from the Allocation of Second-Generation Wireless Spectrum in India

Sandip Sukhtankar *Dartmouth College*

Abstract

Theoretical predictions of the impact of corruption on economic efficiency are ambiguous, with models allowing for positive, negative, or neutral effects. While much evidence exists on levels of corruption, less is available on its impact, particularly its impacts on consumer markets. This paper investigates empirically the effect of the corrupt sale of spectrum licenses to ineligible firms on the wireless-telecommunications market in India. I find that the corrupt allocation had, at worst, no impact on the number of subscribers, prices, usage, revenues, competition, and measures of quality. I argue that the market-based transfer of licenses to competent firms other than the original awardees, combined with fierce competition in the telecommunications sector, may have mitigated potential deleterious impacts of corruption on consumers. These results suggest that the original corrupt allocation did not matter, which provides support for the Coase theorem.

1. Introduction

Theoretical predictions of the impact of corruption on economic efficiency are ambiguous. One such prediction is that corruption greases the wheels of an economy by allowing firms to bypass inefficient regulations (Leff 1964; Huntington 1968). On the other hand, the illicit nature of corruption could prove distortionary (Murphy, Shleifer, and Vishny 1993; Shleifer and Vishny 1993). A third view

I thank Sam Peltzman, an anonymous referee, Liz Cascio, Taryn Dinkelman, Rema Hanna, Asim Khwaja, Maciej Kotowski, Gabrielle Kruks-Wisner, Stefan Litschig, Karthik Muralidharan, Paul Niehaus, Paul Novosad, Rohini Pande, Andrei Shleifer, Chris Snyder, Doug Staiger, Milan Vaishnav, and seminar participants at Dartmouth College, the University of Pennsylvania, Harvard University, the 2012 North East Universities Development Consortium, the Delhi Centre at the Indian Statistical Institute, and the 2013 American Economic Association annual meeting for comments and helpful discussions. I thank Paulina Karpis, Josh Kornberg, Shotaro Nakamura, Medha Raj, and Kevin Wang for excellent research assistance. This paper previously circulated as "Much Ado about Nothing? Corruption in the Allocation of Wireless Spectrum in India."

[*Journal of Law and Economics,* vol. 58 (February 2015)]
 0022-2186/2015/5801-0003$10.00

that has received less attention in the literature is that corruption could simply represent a transfer from the government to corrupt officials or firms with no impact on efficiency: bribery in the process for allocating licenses may be neutral since the most efficient firms can pay the highest bribes (Lui 1985), or efficient resale implies that the initial allocation may not matter (Coase 1959, 1960).

While much recent empirical work documents the existence of high levels of corruption in developing countries,[1] evidence of the impact of corruption is less voluminous. The studies that exist suggest harmful impacts on firm performance and economic activity (see, for example, Sequeira and Djankov 2010; Fisman and Svensson 2007; Ferraz, Finan, and Moreira 2012; Bertrand et al. 2007),[2] but evidence of the impact on consumer markets remains limited.

This paper investigates empirically the effect of corruption on consumer markets by examining how the corrupt allocation of licenses to ineligible firms affected the wireless-telecommunications market in India. In early 2008, the Department of Telecommunications (DoT) in India allocated lucrative licenses to provide wireless-telecommunications service. Instead of using an auction[3] to limit the number of entrants and discover the market price, the licenses were sold at fixed June 2001 prices using erratic rules designed to favor firms connected to then–Communication and Information Technology minister Andimuthu Raja. Subsequent investigations by the Comptroller and Auditor General of India (CAG) and the Central Bureau of Investigation (CBI) revealed that Raja received bribes of up to US$1 billion to award licenses to companies that otherwise would not have qualified for them. The ensuing scandal almost brought down the ruling United Progressive Alliance (UPA) government (see Yardley and Timmons [2010] for one of many commentaries) and dominated political discourse in India for over 2 years.

This incident of corruption provides a compelling context in which to test for effects of corruption on markets and understand what determines the eventual impact on consumers. The scale of corruption was massive (the most widely cited estimates of the loss to the government are around US$44.2 billion (CAG 2010),[4] which is equivalent to the entire defense budget)[5] and involved an important sec-

[1] Examples of studies estimating the magnitude of bribes paid to government officials for bending or breaking rules include Olken and Barron (2009), Svensson (2003), Bertrand et al. (2007), and Hunt (2007); those documenting embezzlement of funds from public programs include Olken (2006, 2007), Ferraz, Finan, and Moreira (2012), Reinikka and Svensson (2004), and Niehaus and Sukhtankar (2013a, 2013b).

[2] In addition, a large literature using cross-country growth regressions (for example, Mauro 1995) finds a negative effect of corruption on growth.

[3] As Hazlett (2008) suggests, there is widespread consensus that market mechanisms are superior to administrative methods in allocating radio frequency spectrum.

[4] For comparison, the total revenue raised from the sale of all spectrum in the United States was US$53 billion (Hazlett and Muñoz 2009, p. 425), and the sale of third-generation (3G) wireless cellular licenses in the United Kingdom and Germany raised a combined US$80 billion (Klemperer 2002, p. 169).

[5] India's total government spending in 2010–11 was US$247.2 billion (see Government of India, Ministry of Finance, Key Features of Budget 2010–2011 [http://indiabudget.nic.in/ub2010-11/bh/bh1.pdf]). All conversions are calculated at the exchange rate valid on the applicable date; for exam-

tor in India's burgeoning economy (Kotwal, Ramaswami, and Wadhwa 2011) that "typically [has] large and persistent positive spillovers to the entire economy" (Cramton et al. 2011, p. S170). Much information about the corrupt sales was revealed afterward. While the licenses were eventually rescinded—4 years after being awarded—the interim period, especially prior to the widespread coverage of the scandal in late 2010, provides a window in which to observe the impact of the corrupt allocation.

Corruption here maps well into the Shleifer and Vishny (1993, p. 599) framework, as it involved the "sale of government property for private gain" by a government official. I can test whether this sale was distortionary because inefficient firms received licenses through their connections or was productive because eligibility rules were keeping otherwise-efficient firms from receiving them. Of course, if licenses and spectrum could be simply bought and sold on a secondary market, these questions would be moot. But in India—like elsewhere—the direct sale of licenses and spectrum is expressly forbidden, and moreover fairly stringent rules govern mergers and acquisitions as well as foreign direct investment (FDI).[6] Whether corruption in the presence of such transfer restrictions affects efficiency is the focus of this paper.

This debate is not merely academic or theoretical: understanding whether corruption hurts efficiency is important given that the often-draconian responses to corruption in developing countries—with low state capacity, this may involve simply shutting down economic activity—may be worse than the effects of corruption itself.[7] Amid the political furor in India, some have disputed whether the corrupt allocation has hurt the telecommunications market.[8]

To examine the consequences of malfeasance in license allocation, I rely on a simple difference-in-differences approach, using the variation across regions in the number of corruptly awarded licenses and the one-time allocation of licenses on a single day in January 2008. Differences in the number of corruptly awarded licenses appear to be driven by the use of existing spectrum by the defense forces,[9] a plausibly exogenous source of variation in the amount of corruption. The availability of detailed data across time allows me to examine the effect of illicitly

ple, if a currency figure refers to January 2008, I use an exchange rate of 40 rupees to the dollar, the average for the month, from OANDA, Currency Converter (http://www.oanda.com).

[6] Note that there is a current policy debate over whether resale of spectrum should be allowed and over the regulations governing mergers and foreign direct investment (see, for example, TRAI 2013).

[7] In India, for example, numerous key defense purchase decisions were put on hold after a bribery scandal related to helicopter purchases was uncovered; in another case, all construction activity in the city of Mumbai ceased after the discovery of previous malfeasance (see Lakshmi 2013; Bajaj 2012).

[8] For example, the former Communications and Information Technology minister Kapil Sibal suggested that selling licenses at fixed prices benefited consumers because it led to lower prices for wireless service (Government of India 2011).

[9] The total availability of spectrum, which determines the number of licenses awarded in a region, depends on its alternative uses: in the Indian context, the main alternative use was by the defense forces for communication. Below I show that the only factor consistently significantly associated with the number of corruptly allocated licenses is an indicator for regions that are a defense priority.

acquired licenses on the number of wireless telephone subscribers, prices, firm revenues, and quality measures (for example, proportion of calls dropped) aggregated at the regional level. Systematic and comprehensive investigations by two government entities—the CAG and CBI—allow me to examine two separate characterizations of whether a license was corruptly awarded. The CAG determined whether a license was awarded to an ineligible company,[10] while the CBI determined whether evidence of wrongdoing by the company was uncovered.

Separating regions into those with many corrupt licenses and those with fewer corrupt licenses (or, alternatively, those with a greater proportion of corrupt licenses to new licenses awarded) and time periods into those before licenses were allocated and those after, I find that outcomes are, in general, no worse in the more corrupt[11] areas after license allocation. The only consistently significant effect seems to be an improvement in quality measures, while the impacts on the number of subscribers, prices, minutes used, and revenues are statistically indistinguishable from 0, with standard error bounds ruling out large negative impacts. These results are robust to the addition of region-specific time trends to account for differential trends in outcomes prior to the license allocation,[12] to redefining the period after allocation as that after the allocation of spectrum rather than licenses, and to alternative empirical methods using synthetic control groups. Corruption, then, had at worst no impact on consumer markets. To the extent that unobserved factors not absorbed by region and time fixed effects and region-by-time trends may have affected both license allocations and outcomes, these results must be viewed with caution.

In contrast to these results, the existing literature on the impact of corruption on firms finds large negative effects. For example, Fisman and Svensson (2007) find that a 1-percentage-point increase in bribes reduces annual firm growth by 3 percentage points, while Sequeira and Djankov (2010) find that the diversion costs of corruption for each individual firm are on average three to four times higher than bribes paid. In a different context, Ferraz, Finan, and Moreira (2012) find educational outcomes in corrupt areas to be .35 of a standard deviation lower than in those without corruption. In India, and in particular for this scandal, the presumption is that corruption slowed growth; an overview of corruption in India notes that "growth sputtered to a decade low in 2012, with many observers pointing to the corrosive effect of endemic corruption—including a spate of scandals under former prime minister Manmohan Singh—as a culprit" (Xu 2014).

The fact that my results are not in line with the existing empirical evidence suggests that the context in which corruption takes place might matter. Two fea-

[10] A company could be ineligible for two major reasons: because it misrepresented its core business and because it did not have sufficient paid-up capital (equity capital from the sale of shares).

[11] Note that "more corrupt" does not necessarily refer to the magnitude of corruption in these regions; it simply means that in these areas there was a greater number or proportion of corruptly awarded licenses.

[12] Adding region-specific trends can be problematic if they are conflated with dynamic effects of the allocation (Wolfers 2006). Figure 4 shows that such effects, if any, are indistinguishable from 0.

tures of the wireless-telecommunications market in India may help us understand this contrast: the fact that licenses were acquired by firms different from those to which they were allocated and the levels of competition in the market. First, despite restrictions on the direct sale of licenses and spectrum, the firms that eventually obtained access to these licenses were not the firms that were awarded the licenses. While licenses were initially awarded to firms whose ability to efficiently provide wireless service might have been doubtful (for example, real estate companies, vegetable wholesalers, shell companies with no other physical or human capital), these licenses were subsequently acquired—at substantial premia, through complex arrangements of mergers and acquisitions—by firms such as telecommunications giants Telenor (Norway) and Etisalat (United Arab Emirates). Sixty-eight percent of new licenses ended up with an entity distinct from the original licensee; there were also more mergers in the more corrupt areas (29 percent of all license holders merged by December 2010) than in the less corrupt areas (23 percent).

Yet the secondary transfer of licenses is unlikely to explain on its own why corruption did not affect markets in this instance: Milgrom (2004, p. 20) writes, for example, that "the history of the US wireless telephone service offers direct evidence that the fragmented and inefficient initial distribution of rights was not quickly correctable by market transactions." First, there is no guarantee that the secondary transfers went to efficient firms: if efficient firms are also law abiding, they would stay away from corruptly acquired assets.[13] Second, costs incurred by the acquiring firms could be passed on to consumers in the presence of monopoly power; for example, anecdotal evidence suggests that monopoly power wielded by coal-mining companies (which also procured licenses for coal mines in a corrupt allocation process) was responsible for efficiency losses in that sector (Sharma 2012).

Here, the existence of a number of large players[14] and competition in the Indian wireless-telecommunications market also helps explain why negative impacts of corruption were mitigated. With the entry of new firms after the allocation, measures of competitiveness increased dramatically in both corrupt and less corrupt areas: the number of providers almost doubled from an average of 6.6 to 12.2 per region, while the Herfindahl-Hirschman index (HHI) of market share declined by over 500 points.[15] Regressions of the HHI suggest that, if anything, competition increased more in corrupt areas.

These results cast light on ongoing debates over the impact of corrupt activity. In Russia, for example, the privatization of government enterprises was widely accepted to have been characterized by cronyism and sweetheart deals. And yet

[13] Indian and international law prohibits such acquisitions; see, for example, the Prevention of Corruption Act (No. 49 of 1988, ch. 3) in India and the International Anti-bribery and Fair Competition Act (Pub. L. No. 105-366, 112 Stat. 3302 [1998]) and the Foreign Corrupt Practices Act of 1977 (15 U.S.C. 78dd-1) in the United States.

[14] Four large firms held between 55 and 59 percent of the market share in both corrupt and noncorrupt areas.

[15] Author's calculations from TRAI (2012) data.

Shleifer and Treisman (2005) argue that the privatized companies subsequently performed very well. This disagreement points to a broader conundrum in the data: both macroeconomic (Mauro 1995) and microeconomic (Olken and Pande 2012) evidence suggests that efficiency costs of corruption may be high, yet corruption is highest in the fastest-growing middle-income countries. One possible way to reconcile these facts is to argue that perhaps these countries would grow even faster in the absence of corruption. Another possibility is that corruption is simply a way of doing business in countries with weak judicial institutions.[16] Under these conditions, as long as markets are competitive and secondary transfers are possible, corruption is unlikely to impede growth.

This paper is also related to the extensive literature on the allocation of rights over natural resources in general and a large subset of that literature on the allocation of radio frequency spectrum (see, for example, McMillan 1994; Klemperer 2002; Cramton et al. 2011; Hazlett 1990, 2008; Hazlett and Muñoz 2009). Attaining economic efficiency and raising revenue are the key—sometimes conflicting—goals of the allocation process, with other social goals such as reaching underserved communities or promoting minority businesses sometimes prominent. Given the conditions of thin markets, natural monopolies, and the potential for collusion or corruption in the process (particularly in developing countries), much attention is paid to the form of the allocation process: for example, whether a beauty contest, lottery, or particular type of auction should be used and whether resale of rights is permitted. While in the Indian case there was no variation in the form of allocation, and direct resale remains forbidden, the incident provides some evidence that corruption in the initial allocation did not matter, which thus confirms the insight of Coase (1959, 1960).

While there may have been no direct efficiency consequences, the discretionary allocation at fixed prices did involve distributional consequences in the form of a substantial transfer of resources from the government to corrupt officials and companies. Estimates using the premia that the final owners paid suggest that this loss was around US$14.4 billion (CAG 2010).[17] Moreover, this paper examines a particular type of corruption: bribery in the sale of government licenses; other types of corruption could have efficiency as well as distributional costs. Finally, the corrupt allocation may have had deleterious effects on other outcomes that are difficult to measure, for example, the breakdown of trust in government and the discouragement of market actors without political connections.

The rest of the paper is organized as follows: Section 2 presents information on the industry and the license allocation procedure. Section 3 presents the data and empirical strategy, followed by the results in Section 4. Section 5 discusses these results and examines the effects on market structure.

[16] Perhaps this reality is best expressed by an official in Mexico: "If we put everyone who's corrupt in jail, who will close the door?" (Aridjis 2012).

[17] Given that consumer surplus in wireless cellular markets is orders of magnitude higher than producer surplus (Hazlett and Muñoz 2009), many if not all economists suggest that raising revenues should be of secondary consideration to achieving economic efficiency (Cramton et al. 2011). On the other hand, lost government revenues imply inefficiency given that taxation is distortionary.

2. Background

2.1. Market Structure

It is difficult to overstate the importance of the wireless-telecommunications sector in India: the country has the cheapest and possibly the most accessible cell phone service in the world. The wireless-telecommunications market is very large and lucrative, with 900 million subscribers[18] as of January 2012 and a growth rate of 1.1 percent a month. India's absolute growth in number of subscribers in 2010 was twice that of the next closest country (China), with prices per minute, at $.007, over 30 times lower than the most expensive (Japan) (TRAI 2012). Total revenues for global system for mobile communications (GSM)[19] operators (70 percent of the market) in the second quarter of 2011 were approximately US$3.8 billion, which extrapolates to total annual revenues for the entire sector of US$22 billion.[20] The fact that the number of landline subscriptions is tiny in comparison (30 million subscribers) and declining further increases the importance of the wireless segment of the telecommunications sector for communications in India. In their review of India's economic liberalization and subsequent growth, Kotwal, Ramaswami, and Wadhwa (2011) suggest that communications technology facilitated a quantum leap in the growth of the service sector.

Fifteen companies currently provide cellular service, with at least nine providing coverage nationwide and three others providing close to nationwide coverage.[21] Competition for subscribers is fierce, especially since the introduction of mobile number portability. Bharti-Airtel holds the largest market share with 19.6 percent as of February 2012, but there are eight companies with a market share of 5–20 percent. In comparison, the United States has only four large nationwide providers that held almost 95 percent of the market in 2011, with the two largest providers, Verizon (36.5 percent) and AT&T (32.1 percent), reaching almost 70 percent by themselves.[22]

While competitive when compared with other countries, India's wireless-telecommunications market can be best characterized as having oligopolistic

[18] A subscriber corresponds to a telephone number, not an individual. Most measures of telephone density simply report the number of subscribers divided by the total population; hence, it is difficult to know what the penetration—the proportion of the population that has a mobile phone—is. For comparison, in 2010 India had a telephone density of 63 percent, Russia had 166 percent, and the United States had 90 percent (Telecom Regulatory Authority of India 2012).

[19] The global system for mobile communications (GSM) is one of the two major cell phone transmission systems. The other is code division multiple access (CDMA). In India the two systems are allocated slightly different parts of the spectrum. Other than revenues, which are not available for CDMA providers (the CDMA providers' umbrella organization does not make them available), the differences between the two systems do not matter for the practical purposes of this paper.

[20] Author's calculations from TRAI (2012) data.

[21] In descending order of market share, these companies are Bharti-Airtel, Reliance, Vodafone, Idea, BSNL, Tata, Aircel-Dishnet, Uninor, Sistema, Videocon, MTNL, Loop, STel, HFCL, and Etisalat.

[22] Data on market share are from Statista, Market Share Held by Wireless Telecommunications Carriers in the U.S. in 2011 (http://www.statista.com/statistics/219720/market-share-of-wireless-carriers-in-the-us-by-subscriptions).

competition. The average HHI for this sector over the analysis period was 2,093. The US Justice Department considers markets between 1,500 and 2,500 points to be moderately concentrated (US Department of Justice and Federal Trade Commission 2010). The main factor of production is a limited natural resource—spectrum[23]—that is best used in discrete, uninterrupted chunks. Next, there are a number of fixed costs that may serve as barriers to entry—the construction of cell phone towers, the setup of marketing and distribution systems for subscriber services,[24] and technological know-how—many of which are subject to large economies of scale. On the other hand, a firm could conceivably rent a tower from a rival, outsource distribution systems, and license technological know-how, and many large Indian conglomerates have the capital to enter this market.

In this context, the entry of an inefficient firm would result in the underuse or disuse of allocated spectrum. The "wasteful use of the spectrum resource" and "uneconomic stock-piling of spectrum licenses" have long been recognized as problems to avoid in allocating spectrum (Melody 1980, p. 393). A significant proportion—on average 30 percent of existing spectrum—was auctioned in the new allocation described below. If a new entrant were too high cost to effectively use allocated spectrum in a market, slower overall subscriber growth might result. Moreover, the added pressure on the utilized spectrum might lead to problems with quality for existing providers, who may also charge higher prices. Finally, underused spectrum and licenses might reduce competitive pressure on incumbents, which could lead to reduced quality and higher prices (Cramton et al. 2011). The analysis below tests whether corruptly allocated licenses led to negative impacts on the number of subscribers and on quality and also resulted in higher prices. First, however, I describe the allocation procedure and resulting variation in corruption across regions.

2.2. *License and Spectrum Allocation*

The wireless-telecommunications sector was not always as dynamic as described in Section 2.1: prior to 1994, services were provided by a single nationalized monopoly provider and were widely considered to be abysmal. After 1994, private providers were allowed to operate limited services, but it was not until new policies (in 1999 and chiefly in 2002) reduced restrictions on the number of providers and their potential services that the wireless segment started its real growth path. While at the end of 2002 there were a handful of private service providers and only 6 million subscribers, by the end of 2006 the number of private

[23] Spectrum refers to electromagnetic frequency bands, some of which are reserved for the use of wireless telecommunications. In India, the National Frequency Allocation Plan (Government of India 2008) delineates the use of the electromagnetic frequency spectrum among various users such as the defense forces, police, intelligence agencies, radio and TV broadcasting, energy utilities, airlines, and public and private telecommunications operators.

[24] Ninety-five percent of subscribers in India have prepaid connections, which require constant refills via small retail shops. For comparison, only 15 percent of subscribers in the United States use a prepaid connection (TRAI 2012).

service providers had expanded to 10, and there were 150 million wireless subscribers in India.

Given the fast-paced growth, the telecommunications sector was viewed as an attractive investment opportunity, and a large number of firms wished to enter the market. To operate wireless service, firms need a license from the government, which entitles them to obtain spectrum. The licenses and spectrum are region specific, spread over 22 regions (or telecom circles) across India.[25] In 2007, a process of new license and spectrum allocation was initiated by the DoT. Licenses awarded through this new process were incremental to existing ones, and hence new firms had the opportunity to enter the market.[26] Firms could apply for pan-India licenses and for licenses in particular regions and for either code division multiple access (CDMA) or GSM spectrum. Licenses and spectrum awarded could not be sold to other entities.

Given that this was the first round of large-scale allocation of spectrum—over 35 percent of existing capacity was due to be allocated—since the telecommunications market had really started growing in India, it was eagerly anticipated by potential new entrants. Market growth was predicted to skyrocket, and the sector was young and far from saturated: true to predictions, market size quintupled over the next 3 years (Corporate Catalyst India 2006).[27] By October 2007, the DoT had received 575 applications for licenses from 46 companies; although the Telecom Regulatory Authority of India (TRAI) suggested that any applicant who satisfied certain eligibility criteria should receive a license, the amount of spectrum available for distribution was limited, and a rationing mechanism was necessary.

The ensuing process of license allocation led by then–Communication and Information Technology minister Andimuthu Raja was severely criticized for its blatant arbitrariness and disregard for higher authority (including the Ministry of Finance and the prime minister).[28] Instead of using an auction[29] to limit the number of entrants and discover the market price of the spectrum, the licenses were sold at fixed June 2001 prices (in January 2008), with arbitrary rules—designed

[25] There were previously 23 regions in India, with the metropolis of Chennai considered its own region, as were Delhi, Kolkata, and Mumbai; however, by 2007 Chennai was absorbed into the region of Tamil Nadu.

[26] The spectrum band to be allocated allowed for second-generation, or 2G, communications, which generally refer to digital (as opposed to analog) voice services and are basically comparable to first-generation communications in terms of revenue possibilities for firms. Third-generation, or 3G, service generally refers to advanced voice and data networks, with far greater revenue potential (Hazlett 2008).

[27] Incumbents were also extremely worried about new entry, so much so that one (Reliance) tried to set up a fake firm to bid for licenses in order to keep them from competitors (CAG 2010).

[28] Raja is a member of the Dravida Munnetra Kazhagam Party, a key supporter of the Congress Party–led United Progressive Alliance. With elections a year or so away, and his Congress Party with insufficient seats in the national parliament to form a government on its own, Prime Minister Manmohan Singh had little leverage over Raja. Raja could thus ignore the prime minister's questions about equality and transparency in the spectrum allocation process.

[29] As Hazlett (2008) suggests, there is widespread consensus that market mechanisms are superior to administrative methods in allocating spectrum.

to favor firms connected to Raja—used to limit the number of licenses allotted. After not processing a number of applications for almost 2 years, on September 24, 2007, the DoT suddenly announced that October 1, 2007, would be the deadline for accepting applications. However, on January 10, 2008, the deadline was reset to September 25, 2007, which allowed the DoT to rule out a number of applicants. Moreover, licenses and spectrum were meant to be allotted on a first-come-first-served basis given the limited availability of spectrum. However, on January 10 at 2:45 p.m. the DoT posted an announcement saying that the current ordering applied only if payment was made between 3:30 p.m. and 4:30 p.m. that day. Applicants were ordered to show up with bank guarantees worth millions of dollars in a matter of minutes; of course, this was possible only for those parties who had prior intimation of this announcement. Eventually, 122 licenses were allotted to 17 companies across 22 regions; of these, the CAG determined that 85 were allotted to companies that were ineligible on account of either misrepresenting their core business or not having sufficient paid-up capital.[30] The CBI indicted the chairs of companies that received 61 licenses. Links between these ineligible firms and Raja have been well documented (CAG 2010; Patil 2011; *Times of India* 2010).

The upshot of the process was that all companies who received licenses did so at a substantial discount; a large number of companies that received licenses should not have, given current regulations; and many of these companies jumped to the head of the queue for receiving spectrum. For example, Swan Telecom, a shell company with no assets, human capital, or telecommunications expertise, paid US$384 million for 13 licenses but subsequently sold equity worth 50 percent for US$900 million. Extrapolating from this equity dilution, the CAG calculated that the full set of licenses allocated should have been worth US$17.5 billion, as opposed to the US$3.1 billion received by the government.[31] A rather more speculative value of US$44.2 billion, calculated by using amounts spent on the April 2010 auction of third-generation (3G) licenses, has been widely reported in the Indian press and is assumed to be the loss to the government.

Given the amounts involved, as well as the attempts by the government to sweep the controversy under the carpet prior to the May 2009 elections, the ensuing scandal when news of the corruption broke out—only after taped phone conversations between a corporate lobbyist and a telecommunications company chairman were leaked to the press—was massive. Coming as it did among a spate of other scandals, such as corruption during the Commonwealth Games held

[30] Paid-up capital refers to money obtained through the sale of shares by a company as opposed to debt financing.

[31] The assumptions made in the report (CAG 2010) were the following: Swan had no other assets, so the full value of the company (US$1.8 billion, Rs 72 billion) was equivalent to the value of the licenses acquired. This value was adjusted to account for the fact that Swan had 13 high-value licenses (that is, not representative of all licenses) and 35 dual-technology licenses (licenses to operate CDMA services granted to already licensed GSM operators or vice versa) and then extrapolated to the full set of 122 licenses. The precise scaling factors used are not available in the report, but other calculations in the report use reserve prices for subsequent auctions as a guide.

in Delhi in 2010, the 2G scam (in reference to second-generation communications), as it is known in India, has dominated political discourse from late 2010 until national elections in May 2014. It spawned the growth of an anticorruption movement and was presumably a major reason why Raja's Dravida Munnetra Kazhagam Party lost elections in its home state of Tamil Nadu. Some have also argued that corruption scandals led to losses suffered by the Congress Party and its UPA allies in state elections across India. Most recently, a Supreme Court order deemed the licenses allocated in the 2007–8 process void, calling on the TRAI to decide on a new procedure to reallocate the 122 licenses (*Centre for Public Interest Litigation v. Union of India*, W.P. [C.] No. 423 of 2010 and No. 10 of 2011 [February 2, 2012]).

3. Empirical Strategy

3.1. Variation in Corrupt Allocation across Regions

Table 1 presents the distribution of newly allocated licenses across the 22 telecommunications regions. The total number of new licenses awarded ranged from four in Mumbai and Rajasthan to seven in Assam, Jammu and Kashmir, and the Northeast, representing in all cases a substantive proportion of new entrants to the market. Every region had at least one license awarded to an ineligible company, with one region having five. All licensees (except three in Delhi) were eventually allocated spectrum, although this did not necessarily happen immediately; in Section 3.2 I show that the allocation of spectrum, which depended on whether the defense services were able to vacate the spectrum in a given area, was not any faster in more corrupt areas.

Prior to exploring what determined the variation in corrupt allocations across regions, it would be helpful to define "corrupt." The CAG (2010) report documents in detail how individual applicants were ineligible for licenses, either because they misrepresented their primary business—for example, real estate companies with no previous telecommunications experience received a large number of licenses—or because they did not have sufficient paid-up capital. Using the CAG's determination of whether a firm should not have received a license allows me to test whether current regulations were indeed too stringent, in case these firms did improve efficiency. However, it is possible that not all ineligible firms were necessarily corrupt in that they did not pay bribes to receive their licenses. Fortunately, I can use CBI investigations to determine this corruption: these investigations revealed the links between some of the ineligible applicants and Raja, following the money trail of illicit payments to a cable television channel in South India (CAG 2010; Patil 2011; *Times of India* 2010). While two firms receiving 27 licenses were deemed ineligible but were not indicted by the CBI, one firm receiving three licenses was not considered ineligible but was indicted. Hence, I present results below using both CAG and CBI definitions of illegality.

I use these designations of corruptly awarded licenses to determine which regions were more versus less corrupt. Note that these labels do not necessarily re-

Table 1
Licenses Allocated by Region

	New Licenses	Existing Licenses	Defense Priority	CAG Deemed Ineligible			Indicted by CBI			Circle Category
				Licenses	Corrupt	Proportion	Licenses	Corrupt	Proportion	
Andhra Pradesh	6	7	0	4	1	.67	3	1	.50	A
Assam	7	5	1	4	1	.57	3	1	.43	C
Bihar	6	7	0	5	1	.83	3	1	.50	C
Delhi	6	7	1	4	1	.67	3	1	.50	Metro
Gujarat	5	7	1	4	1	.80	3	1	.60	A
Haryana	6	7	0	4	1	.67	3	1	.50	B
Himachal Pradesh	5	7	1	4	1	.80	2	0	.40	C
Jammu and Kashmir	7	5	1	4	1	.57	3	1	.43	C
Karnataka	6	7	0	4	1	.67	3	1	.50	A
Kerala	5	7	0	4	1	.80	3	1	.60	B
Kolkata	5	6	1	3	0	.60	2	0	.40	Metro
Madhya Pradesh	5	6	1	4	1	.80	3	1	.60	B
Maharashtra	6	7	0	4	1	.67	3	1	.50	A
Mumbai	4	8	1	3	0	.75	2	0	.50	Metro
Northeast	7	5	1	4	1	.57	3	1	.43	C
Orissa	6	6	1	4	1	.67	2	0	.33	C
Punjab	5	8	1	3	0	.60	3	1	.60	B
Rajasthan	4	8	1	4	1	1.00	3	1	.75	B
Tamil Nadu	6	6	0	4	1	.67	3	1	.50	A
Uttar Pradesh (East)	5	7	0	4	1	.80	3	1	.60	B
Uttar Pradesh (West)	5	7	0	4	1	.80	3	1	.60	B
West Bengal	5	6	1	3	0	.60	2	0	.40	B

Note. Values are for new licenses awarded for wireless spectrum in the second-generation range across the 22 telecommunications regions in India, as well as the number of these licenses that were deemed illegitimate by the Comptroller and Auditor General of India (CAG) and the Central Bureau of Investigation (CBI). Corrupt is a binary variable indicating whether the region has a high level of corruption on the basis of the number of illegitimate licenses. Defense priority is an indicator for whether the region shares a border with hostile neighbors (Pakistan, China, or Bangladesh), is a metropolitan area subject to terrorist attacks, or has major internal civil conflict led by armed Maoists. The circle category indicates the Telecom Regulatory Authority of India's grouping of telecommunications regions. Bihar includes Jharkhand. Madhya Pradesh includes Chattisgarh. Northeast includes Assam Arunachal Pradesh, Mizoram, Manipur, Tripura, Nagaland, and Meghalaya. Tamil Nadu includes Puducherry and Chennai. Uttar Pradesh (West) includes Uttarakhand. West Bengal includes the Andaman and Nicobar Islands and Sikkim.

flect the underlying levels of corruption in these regions: the allocation of licenses was determined centrally, and the exercise in this paper is to examine the impact of the corrupt central allocation. As Table 1 shows, every region has at least one firm that received a license illegitimately. The number of illegally obtained licenses varies from two to five, depending on the CAG or CBI definition of illegality. There is more variation when the proportion, rather than the raw number, of new licenses that were corruptly awarded is considered: between .57 and 1 for companies determined ineligible by the CAG and between .33 and .75 for companies with officials indicted by the CBI. Hence, I categorize more versus less corrupt regions by the number of corruptly awarded licenses and also by directly using the proportion of corruptly awarded new licenses, and I present results by the two definitions of corruption separately.

Why do some regions have more corruptly awarded licenses than others? A central authority determined the allocation of licenses across regions, conditional on receiving applications. The availability of spectrum in a region determined the overall number of licenses awarded in the region. The total availability of spectrum depends on its alternative uses: in the Indian context, the main alternative use is by the defense forces for communication. In addition, at the time of allocation the amount of available spectrum depended on the amount of spectrum already distributed to preexisting licenses. Table 2 explores the correlates of licenses awarded. The total number of licenses awarded in a region was negatively correlated both with the existing number of operators and with whether the region was a defense priority[32] region. None of the other factors that one might associate with the entry of new firms—market growth, concentration, or population—is consistently significantly associated with higher levels of corruption.

The only factor consistently significantly associated with the number of corruptly allocated licenses is the indicator for defense priority regions. Defense requirements are a plausibly exogenous source of variation in the allocation procedure across regions, particularly since other economic factors that one might expect to matter are not significantly associated with corrupt allocation. Of course, this limited exercise does not rule out other unobserved factors that may have affected license assignment. Below I describe the empirical specifications that build on this variation in corrupt license allocation across regions.

3.2. Data and Econometric Specifications

Economic efficiency in spectrum allocation is defined by Cramton et al. (2011, p. S169) as "assignment of licenses that maximizes the consumer value of wireless services less the cost of producing those services." While it would be difficult to measure precisely whether the corrupt allocation did or did not achieve the best use of spectrum, data available from the telecommunications regulator and in-

[32] This is simply an indicator for whether the region shares a border with hostile neighbors Pakistan, China, or Bangladesh; is a metropolitan area subject to terrorist attacks; or has major internal civil conflict led by armed Maoists.

Table 2
Variation in Illegitimate Licenses across Regions

			Licenses				Proportion Illegitimate			
	New Licenses		CAG Deemed Ineligible		Indicted by CBI		CAG Deemed Ineligible		Indicted by CBI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Existing operators	−.663***	−.524*	−.0578	.0469	.00355	.0306	.0781*	.0840*	.0679*	.0626**
	(.203)	(.210)	(.151)	(.147)	(.143)	(.166)	(.0335)	(.0344)	(.0287)	(.0317)
Defense priority	−.557*	−.880*	−.498*	−.487*	−.420*	−.408	−.00883	.0286	−.0186	.0125
	(.263)	(.304)	(.196)	(.212)	(.186)	(.240)	(.0435)	(.0496)	(.0373)	(.0458)
Existing spectrum	−.0129	.00482	−.0101	.00755	−.00683	−.000548	−.000875	.000966	−.000783	−.000659
	(.0210)	(.0239)	(.0156)	(.0167)	(.0148)	(.0188)	(.00347)	(.00390)	(.00297)	(.00360)
Subscriber growth		.0366		.0229		.0156		.00195		.00121
		(.0344)		(.0241)		(.0271)		(.00562)		(.00518)
HHI		3.242		4.445**		.445		.435		−.206
		(3.065)		(2.144)		(2.419)		(.501)		(.462)
Population		−5.56e−09		2.60e−09		9.82e−10		1.14e−09**		7.38e−10
		(3.67e−09)		(2.57e−09)		(2.90e−09)		(6.00e−10)		(5.54e−10)
R^2	.611	.698	.277	.502	.358	.514	.220	.247	.378	.453

Note. Values are the correlates of different types of licenses allotted in January 2008 in the 22 telecommunications regions across India. Existing operators are licensed cell phone providers in the region in January 2008. Defense priority is an indicator for whether the region shares a border with hostile neighbors (Pakistan, China, or Bangladesh), is a metropolitan area subject to terrorist attacks, or has major internal civil conflict led by armed Maoists. Existing spectrum is the amount of spectrum allotted to current licensed operators. Subscriber growth is the average monthly growth in the region in the year 2007. The Herfindahl-Hirschman index (HHI) is for market share in the region in January 2008. Population is the total population in the region from the 2001 census. Standard errors are in parentheses. $N = 22$. CAG = Comptroller and Auditor General of India; CBI = Central Bureau of Investigation.

* $p < .05$.
** $p < .01$.
*** $p < .001$.

dustry associations provide reasonable proxies for consumer value and producer costs. The main outcome variables I consider are the number of subscribers, the average price per minute (including both origination and ongoing charges), the average number of call minutes per subscriber per month, average revenues per subscriber (or total revenues), and measures of service quality such as the proportion of dropped calls, the proportion of calls that connect on first attempt, a measure of voice quality, and the proportion of customer service calls answered within 60 seconds. The number of subscribers, price per minute, minutes used, and quality of service serve as proxies for consumer surplus, while revenues per subscriber proxy for operator performance. All data are available at the operator level by either month or quarter and are aggregated to region-month or region-quarter depending on the frequency of reporting for the particular variable. The subscriber data are available from 2001 onward; quality, price, and usage data are available from 2004 onward; while revenue data are available only from 2005 onward and are restricted to GSM operators. The price and usage data are available only at a higher level of aggregation for four telecom circles across India.

These data are from the TRAI, the main regulatory body, and the Cellular Operators Association of India and the Association of Unified Telecom Service Providers of India (AUSPI), industry associations of GSM and CDMA providers, respectively. Note that subscriber data are available separately from TRAI and the industry associations and match to a very high degree ($\rho = .9977$). Given security concerns around cell phones—they can be used to set off improvised explosive devices, for example—the last few years have seen strong efforts in tracking subscriber and usage data, and hence the quality of these data is perceived to be very high.

Given that the new 2G license allocation process started in 2007, while the scandal broke in late 2010, I restrict my analysis to the time period between these events.[33] I combine these data on the telecommunications industry with information on the license and spectrum allocation process from the DoT, TRAI, CAG, and CBI and a special report compiled by an ex-Supreme Court justice and commissioned by the government. A DoT press release provides the full list of licenses allotted, while the special report and TRAI document contain the amounts and the dates on which spectrum was allocated. Table 3 presents summary statistics on these outcome variables.

Separating regions into those with a high number and proportion of corrupt licenses (indicated by Corrupt) and those with fewer, as described in Section 3.1, and time periods into those before licenses were allocated and those after (Post), I estimate the following simple regression:

$$Y_{st} = \alpha + \beta(\text{Post} \times \text{Corrupt})_{st} + \sum_t \text{Time}_t + \sum_s \text{Region}_s + \varepsilon_{st}, \qquad (1)$$

[33] Robustness tests that expand and contract this period—for example, ending the period of study in April 2010, when further auctions for the 3G licenses took place, rather than December 2010, when the 2G scandal definitively broke out—find very similar results.

Table 3
Summary Statistics by Regions' Level of Corruption

	Average	More Corrupt	Less Corrupt	Test of Equality (p-Value)
Subscribers	13,200,000	13,500,000	11,600,000	.97
	(12,600,000)	(13,400,000)	(7,978,902)	
ln(Subscribers)	15.86	15.82775	15.98328	.40
	(1.19)	(1.25)	(.84)	
HHI	.23	.23	.2	.08
	(.08)	(.08)	(.03)	
Revenues	132.03	132.63	129.31	.55
	(94.6)	(99.66)	(67.61)	
ln(Revenues)	4.54	4.51	4.69	.41
	(.93)	(.98)	(.67)	
% Calls dropped	1.32	1.37	1.12	.60
	(.55)	(.59)	(.31)	
Voice quality	97.35	97.26	97.78	.24
	(1.2)	(1.28)	(.59)	
Minutes used	431.05	419.69	442.40	.17
	(51.13)	(51.35)	(49.09)	
Price per minute	.77	.82	.71	.55
	(.21)	(.19)	(.22)	

Source. Data compiled from Telecom Regulatory Authority of India, Monthly Press Reports (http://www.trai.gov.in/Content/PressReleases.aspx); Telecom Regulatory Authority of India, Quarterly Performance Indicator Reports (http://www.trai.gov.in/Content/PerformanceIndicatorsReports/1_1_PerformanceIndicatorsReports.aspx); Cellular Operators Association of India, Statistics (http://www.coai.com/statistics/arpu-and-revenuereport); and Association of Unified Telecom Service Providers of India, Subscriber Data (http://www.auspi.in/search-subscriber.asp).
Note. More and less corrupt areas are determined by the number of illegitimate licenses.The p-values are for the difference in outcomes in regions prior to January 2008. Subscribers are total number of wireless subscribers in a telecommunications region (monthly data for 2005–10). The Herfindahl-Hirschman index (HHI) is for monthly market concentration for 2005–10. Revenues are quarterly averages per operator across the global system for mobile communications operators in the region for 2005–10 in tens of millions of rupees. All other variables are subscriber-weighted averages across all operators in the region. Voice quality refers to the clarity of the sound transfer in a call measured by an index from 1 to 100 (quarterly data for 2007–10). Minutes used are the total number of minutes (incoming and outgoing) per subscriber per month averaged across months, while price per minute is the average price in rupees per minute (both quarterly data at the telecom circle level for 2007–10).

where Y_{st} is the number of subscribers, revenues per subscriber, or quality outcomes and indicators for time periods (either months or quarters) and region serve as controls. Region fixed effects account for any time-invariant characteristics that influence outcomes, while time fixed effects account for nationwide time-varying trends.[34] I cluster standard errors along two dimensions (region and time) using the multiway clustering approach suggested by Cameron, Gelbach, and Miller (2008) and Thompson (2011).[35]

[34] Tables A2 and A3 in the online appendix also show the basic difference-in-differences estimate without time or region fixed effects.

[35] Note that the number of clusters in some of the regressions may be low: for example, there are 22 regions, 16 quarters, and only four telecom circles in the data set. As a robustness check, I estimate wild cluster percentile-t bootstraps as suggested by Cameron, Gelbach, and Miller (2008) in all cases. This does not change inferences drawn from clustering on region or quarter dimensions. It does, however, make a large difference to inferences based on clustering at the circle level, which is

One possible confound is that corrupt areas may simply have received spectrum earlier. To check for this, I adapt a procedure first used by Griliches (1957) to estimate the speed of diffusion of hybrid corn and adapted and described in Skinner and Staiger (2007). The idea is to run a logistic estimation of the form

$$\ln(P_{st}/(K_s - P_{st}) = \alpha + \beta \text{Corrupt}_s + \delta \text{Time}_t + \gamma(\text{Time} \times \text{Corrupt}), \quad (2)$$

where P_{st} is the (cumulative) fraction of allocated spectrum received by time t in region s, K_s is the maximum fraction of allotted spectrum received, Corrupt_s indicates a state with a high number and proportion of corrupt licenses and reveals the difference in time to first obtaining spectrum, Time_t is a time trend, and the interaction γ indicates whether more corrupt regions receive their allocations faster. Since K_s is 1 for every state, and the initial fraction of allotted spectrum is 0, I cannot simply run a logistic estimation and instead use generalized least squares estimation with a logistic link. Table A1 in the online appendix suggests that corrupt areas were not likely to receive spectrum any faster, nor was the date of first spectrum release any faster. To be conservative, however, I also control for the amount of spectrum currently allocated in the region with the variable AmtSpectrum_{st}:

$$\begin{aligned} Y_{st} &= \alpha + \beta(\text{Post} \times \text{Corrupt})_{st} + \gamma(\text{AmtSpectrum})_{st} \\ &\quad + \sum_t \text{Time}_t + \sum_s \text{Region}_s + \varepsilon_{st}. \end{aligned} \quad (3)$$

Another potential problem is that preexisting trends within regions may confound the difference-in-differences analysis. For example, graphs of the time trend in subscribers show a divergence between corrupt and less corrupt regions prior to the license allocation process (Figures 1 and 2). This is also true for log subscribers, prices, and revenues—with more corrupt areas growing faster or declining less slowly than less corrupt areas—but not in general true for the quality variables. Moreover, general economic trends do not seem to be different between corrupt and less corrupt areas, as shown in Figures 3 and 4. Nonetheless, to account for this potential confound, I add region-specific time trends as a control:

$$\begin{aligned} Y_{st} &= \alpha + \beta(\text{Post} \times \text{Corrupt})_{st} + \gamma(\text{AmtSpectrum})_{st} + \sum_t \text{Time}_t \\ &\quad + \sum_s \text{Region}_s + \sum_s (\text{Region}_s \times \text{Time}_t) + \varepsilon_{st}. \end{aligned} \quad (4)$$

Note that this estimation might conflate any dynamic effects of the license allocation with the region-specific time trends (Wolfers 2006). To separate out these effects, I include indicators for time periods in the postallocation period in corrupt areas and perform the following estimation:

not surprising since there are only four circle clusters. Hence, for regressions with price and minutes of use as outcomes, I present the p-values from the wild cluster percentile-t bootstraps instead of standard errors.

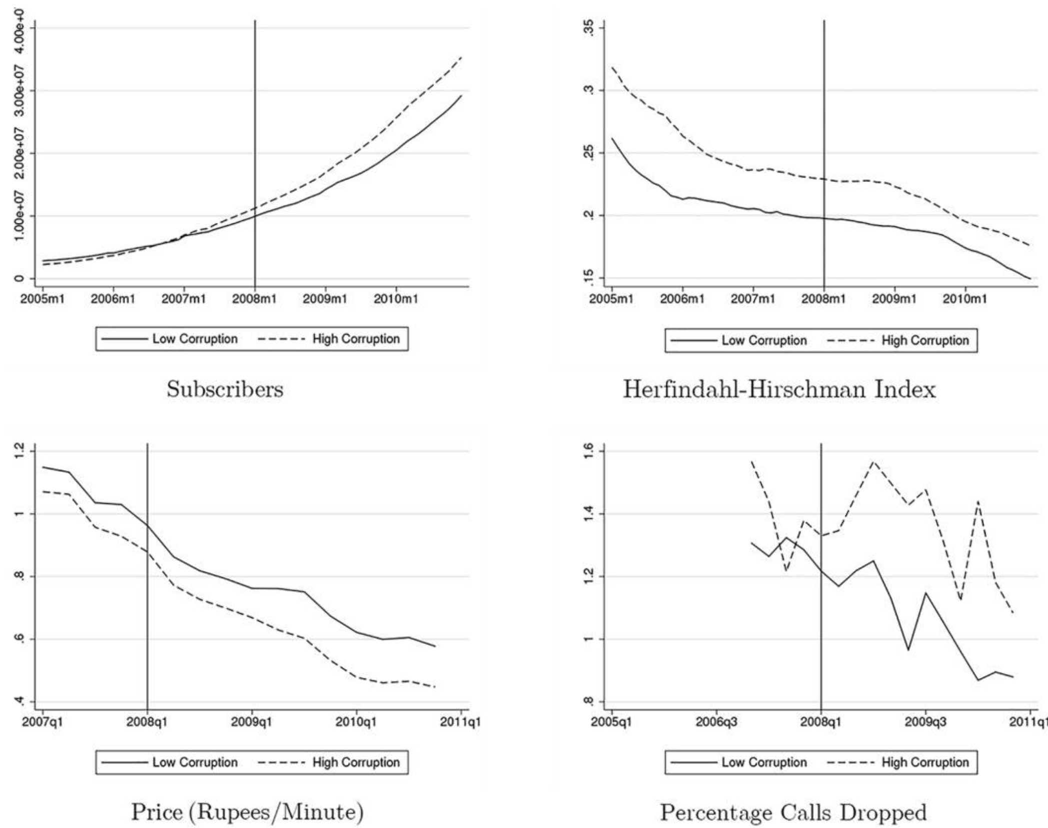


Figure 1. Outcomes over time by level of corruption: licenses to firms declared ineligible by the Comptroller and Auditor General of India

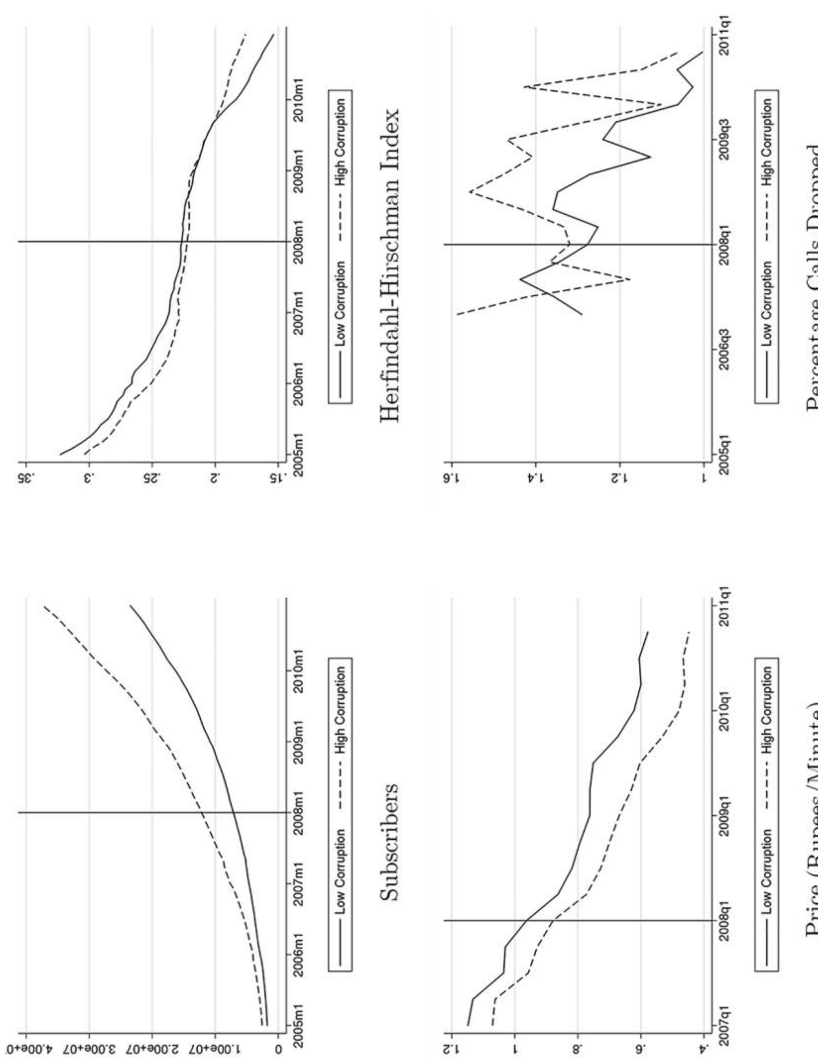
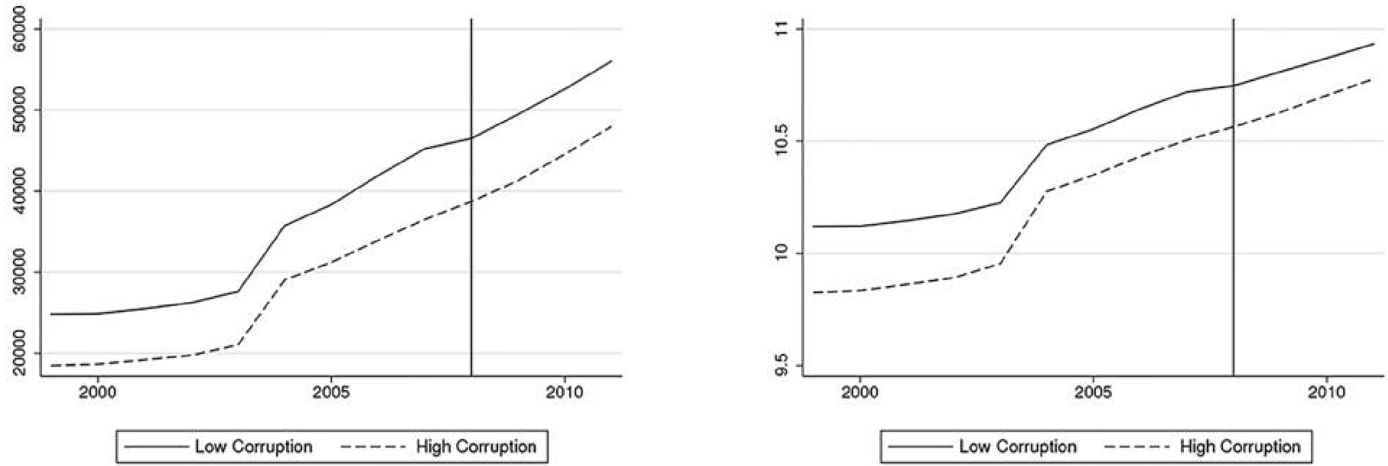


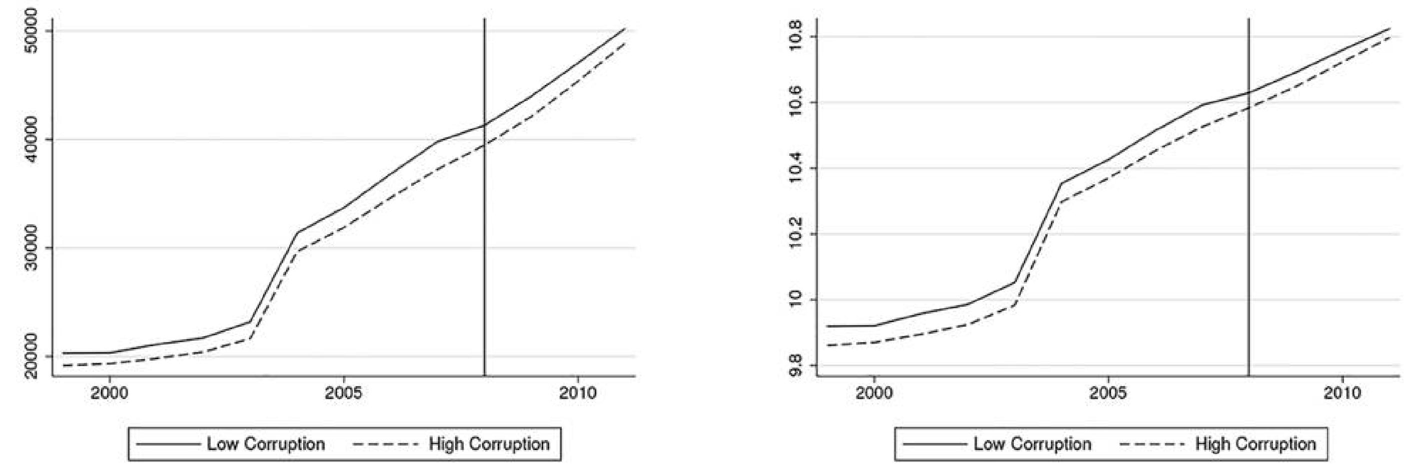
Figure 2. Outcomes over time by level of corruption: licenses to firms indicted by the Central Bureau of Investigation



GDP/capita

Log GDP/capita

Figure 3. Trends in gross domestic product per capita: licenses to firms declared ineligible by the Comptroller and Auditor General of India



GDP/capita

Log GDP/capita

Figure 4. Trends in gross domestic product per capita: licenses to firms indicted by the Central Bureau of Investigation

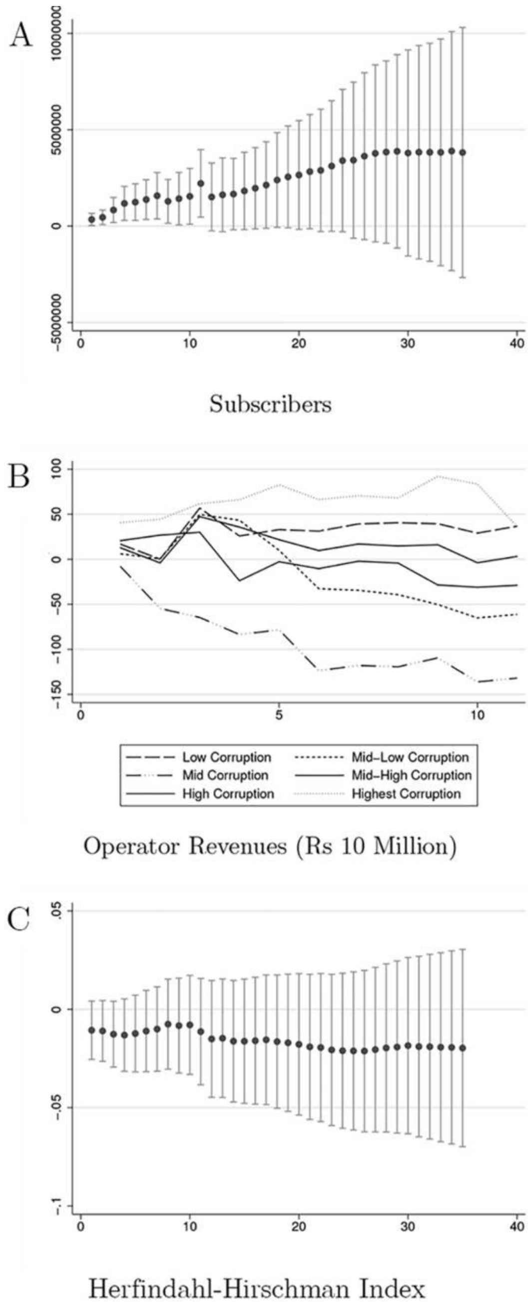


Figure 5. Dynamics of the postallocation period in more corrupt areas: licenses to firms declared ineligible by the Comptroller and Auditor General of India.

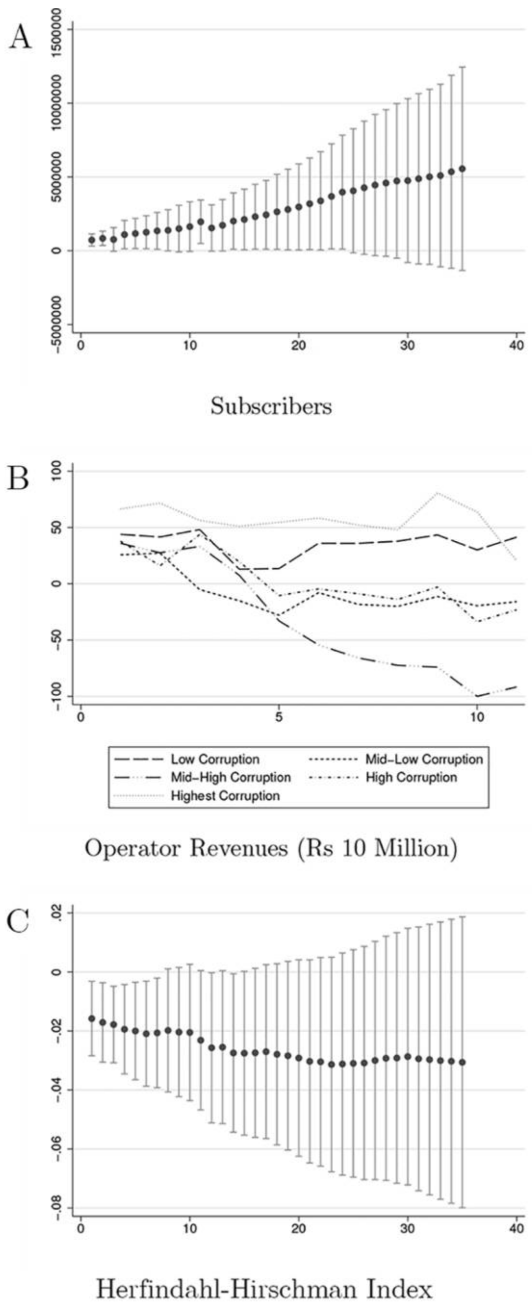


Figure 6. Dynamics of the postallocation period in more corrupt areas: licenses to firms indicted by the Central Bureau of Investigation.

Table 4
Effect of Corruption on Subscribers and Revenues

	Subscribers				Revenues			
	CAG Deemed Ineligible		Indicted by CBI		CAG Deemed Ineligible		Indicted by CBI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of new licenses:								
Corrupt × Post	647,357	71,220	416,778	−22,149	17.99	25.01**	23.86	28.61*
	(414,917)	(304,027)	(457,242)	(338,081)	(13.71)	(13.67)	(15.17)	(13.87)
Adjusted R^2	.988	.999	.988	.999	.958	.974	.958	.975
Proportion of new licenses:								
Corrupt × Post	123,268	−1.469e+06	1.004e+06	−541,195	31.19	39.82	77.46**	89.04**
	(2.993e+06)	(2.355e+06)	(2.915e+06)	(2.220e+06)	(41.98)	(43.56)	(43.39)	(45.83)
Adjusted R^2	.988	.999	.988	.999	.957	.974	.958	.974
Region × Time	No	Yes	No	Yes	No	Yes	No	Yes

Note. Values are the results of difference-in-differences regressions with the total number of wireless-telecommunications subscribers in a region-month and the revenues by log of subscribers as dependent variables. In the first set of regressions, Corrupt is an indicator for whether the region has a high number of illegitimately allotted licenses as determined by the Comptroller and Auditor General of India (CAG) or the Central Bureau of Investigation (CBI), and in the second set of regressions it refers to the proportion of illegitimately allotted licenses to all new licenses. The variable Post is an indicator for months after February 2008. All regressions include region and time fixed effects. Standard errors in parentheses are multiway clustered by month and region. $N = 1{,}584$.

* $p < .05$.
** $p < .01$.

Table 5
Effect of Corruption on Quality

	Dropped Calls				Voice Quality			
	CAG Deemed Ineligible		Indicted by CBI		CAG Deemed Ineligible		Indicted by CBI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of new licenses:								
Corrupt × Post	.263*	.148	.194	.0772	−.431	−.171	−.275	−.00657
	(.106)	(.149)	(.135)	(.147)	(.381)	(.398)	(.368)	(.374)
Adjusted R^2	.117	.488	.100	.487	.087	.568	.117	.588
Proportion of new licenses:								
Corrupt × Post	−1.655*	−1.842*	−1.665*	−1.994**	3.304**	3.652**	3.336*	3.989*
	(.743)	(.926)	(.831)	(1.056)	(1.961)	(2.022)	(1.685)	(2.021)
Adjusted R^2	.112	.511	.102	.508	.097	.568	.083	.586
Region × Time	No	Yes	No	Yes	No	Yes	No	Yes

Note. Values are the results of difference-in-differences regressions with the average percentage of dropped calls in a region-quarter and average voice quality (rated 1–100) in a region-quarter as the dependent variables. In the first set of regressions, Corrupt is an indicator for whether the region has a high number of illegitimately allotted licenses as determined by the Comptroller and Auditor General of India (CAG) or the Central Bureau of Investigation (CBI), and in the second set of regressions it refers to the proportion of illegitimately allotted licenses to all new licenses. The variable Post is an indicator for quarters after the first quarter of 2008. All regressions include region and time fixed effects. Standard errors in parentheses are multiway clustered by quarter and region. $N = 352$.

* $p < .05$.
** $p < .01$.

Table 6
Effect of Corruption on Prices and Usage

	Price per Minute				Minutes Used			
	CAG Deemed Ineligible		Indicted by CBI		CAG Deemed Ineligible		Indicted by CBI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of new licenses:								
Corrupt × Post	−.0221	.0695	−.0221	.0695	52.34	53.36	52.34	53.36
	{.873}	{.583}	{.873}	{.293}	{.063}	{.193}	{.063}	{.193}
Adjusted R^2	.898	.963	.898	.963	.820	.848	.820	.848
Proportion of new licenses:								
Corrupt × Post	2.877	1.360**	1.816**	.711	−474.8	−47.88	−408.5**	−218.7
	{.213}	{.063}	{.063}	{.173}	{.448}	{.908}	{.068}	{.653}
Adjusted R^2	.932	.965	.937	.963	.801	.824	.820	.829
Region × Time	No	Yes	No	Yes	No	Yes	No	Yes

Note. Values are the results of difference-in-differences regressions with the average price per minute in a circle-quarter and the average number of minutes per subscriber per month in a region-quarter as the dependent variable. In the first set of regressions, Corrupt is an indicator for whether the region has a high number of illegitimately allotted licenses as determined by the Comptroller and Auditor General of India (CAG) or the Central Bureau of Investigation (CBI), and in the second set of regressions it refers to the proportion of illegitimately allotted licenses to all new licenses. The variable Post is an indicator for quarters after the first quarter of 2008. All regressions include region and time fixed effects. The p-values from a wild cluster percentile-t bootstrap are in braces. $N = 64$.

** $p < .01$.

$$\begin{aligned} Y_{st} = {} & \alpha + \gamma(\text{AmtSpectrum})_{st} \\ & + \sum_{k \geq 1} \beta_k K \text{ Periods after Allocation in Corrupt Areas}_{st} \\ & + \sum_t \text{Time}_t + \sum_s \text{Region}_s + \sum_s (\text{Region}_s \times \text{Time}_t) + \varepsilon_{st}. \end{aligned} \tag{5}$$

The coefficients β_k are presented in Figures 5 and 6.[36]

Despite the evidence presented in Section 3.1 suggesting that defense requirements drove the license allocation, it is possible that other unobserved factors were involved. For example, corrupt allocation of licenses may have been driven by unobserved future potential for growth. To the extent that this potential was predicted by preexisting trends and fixed regional characteristics—and as the results below suggest, these do indeed have very high predictive power—the inclusion of fixed effects and trends ameliorates some of these concerns. To the extent that unobserved factors beyond these controls may have influenced outcomes, the results below must be interpreted with caution.

4. Results

A glance at Table 4 suggests that the corrupt sale of licenses had no significant effects on the number of wireless telephone subscribers. The results are similar if the proportion of new licenses received illegally in each region is considered rather than a simple categorization into more versus less corrupt regions. When region-specific linear time trends are introduced into the regressions, the coefficients drop dramatically and even turn negative (column 4), although the magnitudes are very small (less than .002 of a standard deviation). The dynamics of the postallocation period, shown in Figures 5*A* and 6*A*, suggest that these trends are not conflating dynamic effects.[37]

While determining whether results are precisely estimated is a somewhat subjective exercise, and the standard errors used are conservative (multiway clustered at the region and time levels), these results suggest that the difference between more and less corrupt regions was a narrowly estimated 0 (standard errors on the order of 200,000, or about 1.5 percent of the standard deviation or 1.2 percent of the mean), at least for the first year after the license allocations. After this period, while the standard errors increase, so does the magnitude of the coefficients. Hence, even 24 months after the new licenses were allotted, the 95 percent confidence intervals allow me to rule out negative effects greater than .01 of a standard deviation.

[36] Figures 5*A*, 5*C*, 6*A*, and 6*C* plot coefficients on indicators for month and include standard errors. Figures 5*B* and 6*B* plot coefficients on indicators for quarter, where the comparison regions indicate the regions with the lowest levels of corruption.

[37] Given that the average number of subscribers in corrupt versus less corrupt areas was quite different prior to the allocation of licenses, difference-in-differences estimations will be sensitive to the functional form. The log results mostly mirror the levels results: corrupt areas do not appear to be significantly different than less corrupt areas after allocation (see Table A8 in the online appendix).

Table 7
Tracing Licenses

Original Recipient	Eventual Operator	New Licenses	CAG Deemed Ineligible	Indicted by CBI
Adonis Projects Pvt. Ltd.	Uninor	6	1	1
Allianz Infratech Pvt. Ltd.	Etisalat	2	1	1
Aska Projects Ltd.	Uninor	3	1	1
Azare Properties Ltd.	Uninor	1	1	1
Datacom Solutions Pvt. Ltd.	Videocon	21	1	0
Hudson Properties Ltd.	Uninor	1	1	1
Idea Cellular Ltd.[a]	Idea Cellular Ltd.	9	0	0
Loop Telecom Private Ltd.[a]	Loop Telecom Private Ltd.	21	1	1
Nahan Properties Pvt. Ltd.	Uninor	6	1	1
Shyam Telelink Limited	Sistema Shyam	21	0	0
Spice Communications Ltd.	Idea Cellular Ltd.	4	0	0
S Tel Ltd.[a]	S Tel Ltd.	6	1	0
Swan Telecom Pvt. Ltd.	Etisalat	13	1	1
Tata Teleservices Ltd.[a]	Tata Docomo	3	0	1
Unitech Builders & Estates Pvt. Ltd.	Uninor	1	1	1
Unitech Infrastructures Pvt. Ltd.	Uninor	1	1	1
Volga Properties Pvt. Ltd.	Uninor	3	1	1

Note. The data are for the 122 licenses granted in 2008. Note that Tata Teleservices and S Tel both sold equity to other entities but retained over 50 percent ownership. CAG = Comptroller and Auditor General of India; CBI = Central Bureau of Investigation.
[a] The original owner of the license and the eventual operator are the same entity.

How did the corrupt allocation affect firm revenues? Revenues might be interpreted as an indicator of profitability of firms in the region. This outcome is available only for GSM providers, so the results must be interpreted with caution. Nonetheless, Table 4 presents some evidence that firms in more corrupt regions seem to have significantly increased revenue levels after the allocation, with increases of 25 percent. This does not seem to be true when the outcome is specified in logs rather than levels (Table A8 in the online appendix). The results also disappear when the dynamics of the post-allocation period are taken into account (Figures 5 and 6).

The corrupt license allocation also does not seem to have negatively affected consumers. As shown in Table 5, data on the quality of service provided, such as the proportion of calls dropped or TRAI measures of average voice quality, suggest that more corrupt areas were again similar to less corrupt areas after the license allocation. The results indicate that, if anything, quality improved in more corrupt areas after the allocation.

Results on prices paid per minute and minutes used must be interpreted with two caveats in mind: first, the data are aggregated at a higher level (to telecom circles), and hence coefficients are not directly comparable; and second, since there are only four region categories, clustered standard errors can be inappropriate. Table 6 thus shows p-values from a wild cluster percentile-t bootstrap (Cameron,

Table 8
Market Shares of Wireless Subscribers in a Region-Month: Herfindahl-Hirshman Index

	CAG Deemed Ineligible		Indicted by CBI	
	(1)	(2)	(1)	(2)
Number of new licenses:				
Corrupt × Post	−.0108	.00478	−.0199*	−.00812
	(.00989)	(.0100)	(.00808)	(.0107)
Adjusted R^2	.926	.974	.927	.974
Proportion of new licenses:				
Corrupt × Post	−.0921	−.0389	−.134**	−.0760***
	(.0642)	(.0272)	(.0698)	(.0282)
Adjusted R^2	.928	.974	.929	.975
Region × Time	No	Yes	No	Yes

Note. Values are the results of difference-in-differences regressions. In the first set of regressions, Corrupt is an indicator for whether the region has a high number of illegitimately allotted licenses as determined by the Comptroller and Auditor General of India (CAG) or the Central Bureau of Investigation (CBI), and in the second set of regressions it refers to the proportion of illegitimately allotted licenses to all new licenses. The variable Post is an indicator for months after February 2008. All regressions include region and time fixed effects. Standard errors in parentheses are multiway clustered by month and region. N = 1,584.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

Gelbach, and Miller 2008) instead of standard errors. The results again suggest that neither prices per minute nor minutes used per subscriber were consistently significantly different in more corrupt circles after allocation.

4.1. Robustness Checks

The results above are robust to a variety of checks. The first check changes the definition of the postallocation period to the period after spectrum, rather than licenses, is assigned. Spectrum was allocated as soon as it was available; some spectrum may have been vacant at the time of license allocation, while other pieces may have been in use by the defense forces. The advantage of this definition is that it better captures when a firm can start operating; moreover, the empirical specification corresponds better to a standard state-level difference-in-differences model based on differential timing of policy changes. The disadvantage is that the timing may be endogenous, given that corrupt firms might have been able to influence the spectrum allocation date. In any case, using either the date when the first firm received new spectrum in a region or the date when all firms had received their allotment does not qualitatively change the results described above, as shown in Tables A4–A7 in the online appendix.

A second robustness check changes the empirical methodology used to the synthetic control method developed by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010). This method for causal inference "provides a data-driven procedure to construct synthetic control units based on a convex combination of comparison units that approximates the characteristics of

the unit that is exposed to the intervention."[38] The synthetic control group is constructed using preintervention characteristics—in this case I use controls including population, literacy, state gross domestic product (GDP), cumulative spectrum availability in various bands, and pre-allocation-period outcomes. Since the method is designed for estimating effects in settings where a single unit is exposed to treatment, and in this case there are more units exposed to treatment rather than controls, I flip the designation of treatment to allow for a larger set of potential control units, and I collapse the new treated units into one using simple averaging as suggested by the method's creators.

Figures A1 and A3 in the online appendix show predicted outcomes for the synthetic control group (the more corrupt areas in this case) versus the treatment group (the less corrupt areas). As is clear from the figures, the outcomes basically line up exactly after allocation of licenses. This is particularly noticeable in cases in which the preallocation outcomes can be precisely predicted. Where preallocation outcomes cannot be precisely predicted, the postallocation outcomes of the groups are not as well aligned.[39]

5. Discussion and Conclusion

Overall, the estimations suggest that the corrupt allocation had, at worst, no measurable impact on activity in wireless-telecommunications markets, which runs counter to much of the macroeconomic and microeconomic evidence on the impact of corruption and the perception (in India at least) of the effect of corruption scandals on growth. For example, Mauro (1995) suggests that improving a country's corruption index score by 1 standard deviation would lead to a .8-percentage-point increase in the annual growth rate of GDP. In the microeconomic literature, Fisman and Svensson (2007) find that a 1-percentage-point increase in bribes reduces annual firm growth by 3 percentage points; Sequeira and Djankov (2010) find that firms suffer costs that are on average three to four times higher than bribes paid for transport to ports with less corruption; and Ferraz, Finan, and Moreira (2012) show educational outcomes to be .35 of a standard deviation lower in corrupt areas than in areas without corruption.

What might explain this discord? First, despite the restrictions on the direct sale and transfer of licenses and spectrum, firms who illegitimately received the licenses transferred them to other firms through a complex series of mergers and acquisitions. Table 7 tracks licenses from initial allocation to eventual user. It shows, for example, that the shell company Swan was acquired by telecommunications giant Etisalat. Licenses held by a group of real estate companies (Adonis and Unitech) were eventually obtained by Uninor, which is a subsidiary of the

[38] Jens Hainmueller, Synth Package (http://web.stanford.edu/~jhain/synthpage.html).

[39] Inference in this method is through the use of placebo tests in which the synthetic control method is applied to areas that did not receive the intervention. The gap between treatment and synthetic control groups is compared with the gaps between the placebo treatment and synthetic control groups. As Figures A2 and A4 in the online appendix show, the actual gap is in fact much smaller than the placebo gaps, which suggests that there is no effect of the corrupt allocation.

Norwegian firm Telenor. Eventually, 83 of the 122 licenses allocated (68 percent) were acquired by other firms through mergers or dilution of equity. Such transfers have occurred in other countries as well when the initial licensee was not necessarily set up to efficiently provide wireless-telecommunications service: for example, McMillan (1994) recounts the case of an obscure group obtaining via lottery a license to provide wireless service on Cape Cod (in the United States) and promptly selling it to Southwestern Bell for a large profit. Since there were more corruptly allocated licenses in more corrupt areas (by definition), there were significantly more mergers in these areas (29 percent of all licensed entities) than in less corrupt areas (23 percent).

However, the transfer of licenses to other firms does not seem sufficient, by itself, to explain why corruption had no impact. There is no guarantee that the firms that obtained licenses through secondary transfers were necessarily efficient: for example, it is possible that efficient yet law-abiding firms may not necessarily wish to obtain corruptly acquired assets. If acquiring licenses confers monopoly power to the new firms, they may pass on costs to customers, as seems to be the case with coal-mining companies in India (Sharma 2012).

In the case of the 2G allocation, the degree of competitiveness in the wireless-telecommunications market may have forced new entrants to provide services efficiently. As described above, wireless-telecommunications markets in India tend to be characterized by aggressive competition for subscribers. There were 6.6 providers on average per region prior to the new allocation, but by December 2010, following new allocation and consolidation, there were 12.2 providers per region. Of course, some of these new providers could be small and inconsequential, but other more reliable measures also suggest large increases in competition. In both corrupt and noncorrupt areas, the four largest firms held only about 55–59 percent of the market share.

Figure 2 suggests that competitiveness, as measured by the HHI of market share, increased dramatically after the new spectrum allocation in both types of regions, following a brief lag possibly related to the handover of spectrum and setting up of new service providers. The HHI decreased from an average of 2,233 points in January 2008 to an average of 1,710 points by December 2010, a drop of 23.4 percent. For context, a merger that would increase concentration by 200 points in already concentrated markets would be presumed likely to enhance market power and hence come under scrutiny by the US Department of Justice and Federal Trade Commission. In comparison, a 513-point decrease appears to be a substantial increase in competition (US Department of Justice and Federal Trade Commission 2010). Meanwhile, the decreases in corrupt and noncorrupt regions appear to be relatively similar.

Regression analysis confirms this story. Table 8 shows that the effect of the new allocation on HHI in corrupt regions was basically indistinguishable from that in less corrupt regions. With the inclusion of region-specific trends, it appears that there was perhaps a small increase in competitiveness, although the effect sizes

are small. Moreover, Figure 6*C* suggests that some of this effect might be a conflation of the dynamics, likely related to the lag in HHI decline after the allocation.

A final piece of evidence on competitiveness is provided by data on telecommunications firm profits around the world (TRAI 2012). A comparison of 31 global telecommunications companies shows that the three Indian companies in the sample are all in the bottom half in terms of profits before taxes, with the best-performing Indian company at number 20 in the rankings. Moreover, the three Indian companies are the top three in the list of companies with the biggest decline in profits in the year 2010.

Thus, the Indian wireless-telecommunications sector was more competitive than wireless-telecommunications sectors in other countries at the outset, and competition increased even more with the allocation of new licenses. The fact that changes in market structure were similar across corrupt and less corrupt regions might at least partly explain why changes in other outcomes were also similar. Overall, in the Indian 2G spectrum case, it appears that the Coase (1959, 1960) theorem applies—the initial misallocation of licenses was corrected through the secondary market.[40]

In summary, then, this paper has investigated the impact of the corrupt allocation of wireless licenses and spectrum on activity in the cellular telecommunications market in India. I find that although many firms that received licenses had no prior experience in providing wireless services, this had, at worst, no measurable impact on the number of wireless subscribers, revenues, prices, usage, or measures of quality. The lack of an effect of corruption on consumer markets may be explained by a combination of factors: one potential explanation is that the licenses were transferred to other firms better equipped to provide wireless-telecommunications services and another may be the presence of existing large players and competition in the wireless-telecommunications market. The same corruption was, however, very costly to the Indian government in terms of lost revenues. Moreover, the ensuing scandal carries with it potential—but not easily measurable—social and political costs associated with decreasing levels of public trust and increasing cronyism. Nonetheless, under the conditions of competitive markets and secondary license transfers, the corrupt allocation of licenses to ill-equipped firms did not result in efficiency costs passed on to the consumer, and the initial allocation of property rights did not matter.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association* 105:493–505.

[40] It is of course possible that despite the apparent efficient reallocation there were large transactions costs in the transfer. One such cost is delay in starting service. However, these delays were no different for licenses that were reallocated than for those that were not and were no different for the corruptly allocated than for noncorruptly allocated licenses.

Abadie, Alberto, and Javier Gardeazabal. 2003. The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review* 93:113–32.

Aridjis, Homero. 2012. The Sun, the Moon, and Walmart. *New York Times*, April 30. http://www.nytimes.com/2012/05/01/opinion/the-sun-the-moon-and-walmart.html.

Bajaj, Vikas. 2012. Indian Official Starts Pulling up Corruption's Roots in Mumbai. *New York Times,* December 4. http://www.nytimes.com/2012/12/05/world/asia/indian-official-starts-pulling-up-corruptions-roots-in-mumbai.html.

Bertrand, Marianne, Simeon Djankov, Rema Hanna, and Sendhil Mullainathan. 2007. Obtaining a Driver's License in India: An Experimental Approach to Studying Corruption. *Quarterly Journal of Economics* 122:1639–76.

CAG (Comptroller and Auditor General of India). 2010. *Performance Audit Report on the Issue of Licenses and Allocation of 2G Spectrum by the Department of Telecommunications.* Report No. 19. New Delhi: Comptroller and Auditor General of India.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2008. Bootstrap-Based Improvements for Inference with Clustered Errors. *Review of Economics and Statistics* 90:414–27.

———. 2011. Robust Inference with Multiway Clustering. *Journal of Business and Economic Statistics* 29:238–49.

Coase, R. H. 1959. The Federal Communications Commission. *Journal of Law and Economics* 2:1–40.

———. 1960. The Problem of Social Cost. *Journal of Law and Economics* 3:1–44.

Corporate Catalyst India. 2006. Telecom Industry in India. Industry Report Series. Corporate Catalyst India, New Delhi.

Cramton, Peter, Evan Kwerel, Gregory Rosston, and Andrzej Skrzypacz. 2011. Using Spectrum Auctions to Enhance Competition in Wireless Services. *Journal of Law and Economics* 54:S167–S188.

Ferraz, Claudio, Frederico Finan, and Diana B. Moreira. 2012. Corrupting Learning: Evidence from Missing Federal Education Funds in Brazil. Working Paper No. 18150. National Bureau of Economic Research, Cambridge, MA.

Fisman, Raymond, and Jakob Svensson. 2007. Are Corruption and Taxation Really Harmful to Growth? Firm Level Evidence. *Journal of Development Economics* 83:63–75.

Government of India. 2008. *National Frequency Allocation Plan.* New Delhi: Government of India, Ministry of Communications and Information Technology, Department of Telecommunications. http://wpc.dot.gov.in/nfap.asp.

Government of India. Ministry of Communications and Information Technology. 2011. Statement given by Kapil Sibal on 2G spectrum issues. Press release. Press Information Bureau, New Delhi. January 7.

Griliches, Zvi. 1957. Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica* 25:501–22.

Hazlett, Thomas W. 1990. The Rationality of U.S. Regulation of the Broadcast Spectrum. *Journal of Law and Economics* 33:133–75.

———. 2008. Property Rights and Wireless License Values. *Journal of Law and Economics* 51:563–98.

Hazlett, Thomas W., and Roberto E. Muñoz. 2009. A Welfare Analysis of Spectrum Allocation Policies. *RAND Journal of Economics* 40:424–54.

Hunt, Jennifer. 2007. How Corruption Hits People When They Are Down. *Journal of Development Economics* 84:574–89.

Huntington, Samuel P. 1968. *Political Order in Changing Societies*. New Haven, CT: Yale University Press.

Klemperer, Paul. 2002. What Really Matters in Auction Design. *Journal of Economic Perspectives* 16(1):169–89.

Kotwal, Ashok, Bharat Ramaswami, and Wilima Wadhwa. 2011. Economic Liberalization and Indian Economic Growth: What's the Evidence? *Journal of Economic Literature* 49:1152–99.

Lakshmi, Rama. 2013. Helicopter Bribe Scandal Threatens India's Defense Modernization. *Washington Post,* February 15. http://www.washingtonpost.com/world/asia_pacific/helicopter-bribe-scandal-threatens-indias-defense-modernization/2013/02/15/05e70f76-775a-11e2-b102-948929030e64_story.html.

Leff, Nathaniel H. 1964. Economic Development through Bureaucratic Corruption. *American Behavioral Scientist* 8:8–14.

Lui, Francis T. 1985. An Equilibrium Queuing Model of Bribery. *Journal of Political Economy* 93:760–81.

Mauro, Paolo. 1995. Corruption and Growth. *Quarterly Journal of Economics* 110:681–712.

McMillan, John. 1994. Selling Spectrum Rights. *Journal of Economic Perspectives* 8:145–62.

Melody, William H. 1980. Radio Spectrum Allocation: Role of the Market. *American Economic Review: Papers and Proceedings* 70:393–97.

Milgrom, Paul. 2004. *Putting Auction Theory to Work*. New York: Cambridge University Press.

Murphy, Kevin M., Andrei Shleifer, and Robert W. Vishny. 1993. Why Is Rent-Seeking So Costly to Growth? *American Economic Review: Papers and Proceedings* 83:409–14.

Niehaus, Paul, and Sandip Sukhtankar. 2013a. Corruption Dynamics: The Golden Goose Effect. *American Economic Journal: Economic Policy* 5:230–69.

———. 2013b. The Marginal Rate of Corruption in Public Programs: Evidence from India. *Journal of Public Economics* 104:52–64.

Olken, Benjamin A. 2006. Corruption and the Costs of Redistribution: Micro Evidence from Indonesia. *Journal of Public Economics* 90:853–70.

———. 2007. Monitoring Corruption: Evidence from a Field Experiment in Indonesia. *Journal of Political Economy* 115:200–249.

Olken, Benjamin A., and Patrick Barron. 2009. The Simple Economics of Extortion: Evidence from Trucking in Aceh. *Journal of Political Economy* 117:417–52.

Olken, Benjamin A., and Rohini Pande. 2012. Corruption in Developing Countries. *Annual Review of Economics* 4:479–509.

Patil, Shivaraj P. 2011. *Report on Examination of Appropriateness of Procedures Followed by Department of Telecommunications in Issuance of Licenses and Allocation of Spectrum during the Period 2001–2009.* January 31. New Delhi: Ministry of Communications and Information Technology, Department of Telecommunications.

Reinikka, Ritva, and Jakob Svensson. 2004. Local Capture: Evidence from a Central Government Transfer Program in Uganda. *Quarterly Journal of Economics* 119:679–705.

Sequeira, Sandra, and Simeon Djankov. 2010. An Empirical Study of Corruption in Ports. Working paper. London School of Economics, London.

Sharma, Supriya. 2012. Secret of Jindal's Success: Cheap Coal, Costly Power. *Times of India,* September 9. http://timesofindia.indiatimes.com/india/Secret-of-Jindals-success-Cheap-coal-costly-power/articleshow/16319069.cms.

Shleifer, Andrei, and Daniel Treisman. 2005. A Normal Country: Russia after Communism. *Journal of Economic Perspectives* 19:151–74.
Shleifer, Andrei, and Robert W. Vishny. 1993. Corruption. *Quarterly Journal of Economics* 108:599–617.
Skinner, Jonathan, and Douglas Staiger. 2007. Technology Adoption from Hybrid Corn to Beta-Blockers. Pp. 545–70 in *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches,* edited by Ernst R. Berndt and Charles R. Hulten. Chicago: University of Chicago Press.
Svensson, Jakob. 2003. Who Must Pay Bribes and How Much? Evidence from a Cross Section of Firms. *Quarterly Journal of Economics* 118:207–30.
TRAI (Telecom Regulatory Authority of India). 2012. *Telecommunications in Select Countries Policies: Statistics*. New Delhi: Telecom Regulatory Authority of India.
———. 2013. *Recommendations on Valuation on Reserve Price of Spectrum.* September 9. New Delhi: Telecom Regulatory Authority of India. http://www.trai.gov.in/WriteReadData/Recommendation/Documents/Recommendations%2009.09.2013.pdf.
Thompson, Samuel B. 2011. Simple Formulas for Standard Errors That Cluster by Both Firm and Time. *Journal of Financial Economics* 99:1–10.
Times of India. 2010. After CBI Raids, Companies Linked to Raja Put Up a Brave Front. December 18. http://timesofindia.indiatimes.com/city/chennai/After-CBI-raids-companies-linked-to-Raja-put-up-a-brave-front/articleshow/7120052.cms.
US Department of Justice and Federal Trade Commission. 2010. Horizontal Merger Guidelines. Washington, DC: US Department of Justice and the Federal Trade Commission.
Wolfers, Justin. 2006. Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results. *American Economic Review* 96:1802–20.
Xu, Beina. 2014. Governance in India: Corruption. Council on Foreign Relations. http://www.cfr.org/corruption-and-bribery/governance-india-corruption/p31823.
Yardley, Jim, and Heather Timmons. 2010. Telecom Scandal Plunges India into Political Crisis. *New York Times,* December 13. http://www.nytimes.com/2010/12/14/world/asia/14india.html.