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Essays on Development, Ownership Structure, and Agriculture

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of the requirements for the degree
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by

Aravind Moorthy

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Abstract of the Dissertation

Essays on Development, Ownership Structure, and Agriculture

by

Aravind Moorthy

Doctor of Philosophy in Economics

University of California, Los Angeles, 2012

Professor Adriana Lleras-Muney, Chair

This thesis examines how ownership structure and climate change issues affect farmers in developing countries in three chapters. The first chapter surveys the theoretical and empirical literature on how ownership structure and industry competitiveness interact. The second chapter examines the role of sugar mill ownership and regulations on farmers in one region of India. The third chapter studies how climate change has affected agricultural yields over a 50-year period in India, accounting for the role that farmer adaptations may play in mitigating these effects. This thesis finds substantial ownership effects on farmer outcomes, due ultimately to the unexpected ways in which regulatory restrictions affect the incentives of privately-owned firms. It does not find that climate change impacted crop yields during the period of study, perhaps due to farmer adaptations that mitigated any adverse climate effects.

The dissertation of Aravind Moorthy is approved.

Ariel Burstein

Edward E. Leamer

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Adriana Lleras-Muney, Committee Chair

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2012

To my wife, Anjali da Victoria Lobo, whose patience and understanding allowed me to undertake this degree; and, to my son, Elan Siddharth Lobo-Moorthy, whose impending birth encouraged me to get moving on it.

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CHAPTER 1

Firm Ownership, Efficiency, and Competition

Chapter Abstract:

While the majority of recent publications conclude that privately-owned firms are more efficient than state-owned firms, there are important and unexplained exceptions, and large differences in the extent of efficiency gains attributed to private ownership. In this chapter, I posit that the effect of ownership on firm efficiency may interact significantly with the level of competition in an industry, and review the theoretical and empirical literature on firm ownership, efficiency, and competition. I find evidence that the relative efficiency of private firms attenuates with increasing competition levels, and that the underlying components of competition that interact with relative efficiency are not strictly related to common measures of industry competitiveness.

1.1 Introduction

The relative efficiency of private and state-owned enterprises has been a subject of interest throughout recent history, and has gained attention in recent decades following a wave of privatizations that began with the Thatcher government in the UK in the 1980s, and escalated after the collapse of the Soviet Union. While theoretical literature in the last 3 decades has been nearly unequivocal in favoring the productive efficiency of private firms, results in the empirical literature have been less conclusive. Boardman and Vining (1989) survey 54 studies that examine the effects of ownership on performance, and find that 32 of them conclude that private firms outperform state-owned firms, and 22 of them are either inconclusive, or find that public firms outperform private firms. More recently, Megginson and Netter (2000) find greater evidence that the empirical literature favors the efficiency of private firms, but cite important exceptions. In addition, measures of efficiency vary greatly between studies, and may have important implications to findings.

In this paper, I explore whether the variation in findings on the effect of firm ownership on productive efficiency can be partially explained by differences in the level of industry competition faced in each setting. In addition, I identify the elements of "competitiveness"that theoretically matter in determining efficiency differences between state-owned and private firms, to shed light on what elements seem to matter most, and how strongly these elements are tied to standard measures of competitiveness.

Several authors discuss the theoretical importance of the competitive environment in determining the extent of efficiency differences between public and private firms, including Sheshinski and López-Calva (2003), Shirley and Walsh (2000), Allen and Gale (1999), Vickers and Yarrow (1988), Willig (1985), and Hart (1983). In addition, several authors have reviewed the empirical literature on performance and ownership, amongst which the aforementioned Megginson and Netter (2000) and Boardman and Vining (1989) articles stand out for their comprehensiveness.

However, these studies provide limited evidence on factors such as competition that may influence the relative efficiency of ownership types, and do not separate productive efficiency from other measures of performance that are affected by price-setting behavior. Many empirical studies comment on how the level of competition affects their efficiency results,[1]but view competitiveness as a single characteristic, although theory suggests that specific elements of competition drive the efficiency results, and those elements may only be loosely correlated with measures of the overall level of competition. By examining, when possible, these elements of competition, I hope to clarify the context of the literature's results.

It is worth noting that this paper does not directly address the *allocative* efficiency of state-owned and private firms, which is also potentially affected by the level of competition within a market.[2] While allocative efficiency is undoubtedly of interest to policymakers when considering policies of privatization, nationalization, or regulation, I instead focus on how competition affects the *productive* or "internal"efficiency of firms, typically measured as the average cost per unit of output. One reason for this choice is that empirical literature on the productive efficiency of private and state-owned firms is much larger and well-identified than that which describes the welfare effects of firm ownership, presumably because of the difficulty in identifying how individual firms affect social surplus.

Productive efficiency is not just important to firms, but can affect social welfare: When firms produce outputs at the lowest possible cost, welfare gains accrue both to firms and, potentially, to their customers, through lowered prices. Also, in general equilibrium, cost efficiency ensures that inputs are being used in their most valued capacity, and therefore improves the allocative efficiency of input markets.

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[1]Ros (1999), La Porta and Lopez-de-Silanes (1999), and Vining and Boardman (1992) are examples.

[2]Birdsall and Nellis (2002) provide some coverage of this topic in their review of the distributional impacts of privatization.

Vickers and Yarrow (1998) emphasize that competition, in influencing productive efficiency, can have strong effects on welfare:

> One of the main virtues of competition emphasized by proponents of privatization and liberalization is its role as a mechanism that stimulates *internal* efficiency. Indeed, despite the emphasis of textbook competition theory on *allocative* efficiency in a static environment, it has long been recognized that much of the effect of competition on welfare is due to its role as an incentive system and discovery mechanism in a world of imperfect information...

Section 1.2 proceeds by presenting the relevant theoretical differences between private and state-owned enterprises, and discusses how competition might affect the efficiency of these firms differently. In Section 1.3, I review empirical findings on the productive efficiency differences between state-owned and private firms in different competitive environments, and attempt to determine whether competition levels have mattered in practice.

1.2 Theory

1.2.1 Efficiency Differences Between State-Owned and Private Firms

In this section, I discuss the relevant theoretical differences between private and state-owned enterprises that affect a firm's productive efficiency. While the focus of my discussion will be the effects that change as the level of competition changes, I include a brief discussion of the most important factors that affect level differences between public and private firm efficiency, but are insensitive to the competitive environment. These factors are helpful in explaining why different empirical studies find level differences in the productive efficiencies of different ownership structures, regardless of competition levels.

I begin with a discussion of two themes: the differing extent of agency problems faced by firm owners in private and state-owned firms, and the soft budget constraints of public firms that may adjust to offset profit levels.

1.2.1.1 Agency Problems

Both private and state-owned firm owners potentially face agency problems in persuading firm managers to be efficient, when the managers of a firm are separate from the firm's owners. These problems result from the inability of owners to gauge the effort level of managers, the fact that owners cannot completely contract with managers to achieve their goals, and the potential for managers to pursue personal goals that interfere with efficiency (Sheshinski and López-Calva (2003) ans Shleifer (1998) discuss these issues in greater detail). When combined, imperfect knowledge of managerial effort means that owners cannot identify appropriate benchmarks for optimal performance, and are therefore unable to specify contracts that reward the attainment of these benchmarks. Since these issues imply that managers are, at best, imperfect agents in carrying out the goals of firm owners, they imply that a discussion of firm efficiency should consider managerial incentives separately from the intentions of owners.

Vining and Boardman (1992) survey the empirical literature on firm efficiency under manager-controlled and owner-controlled organizational structures, and find strong evidence that owner-controlled firms are more efficient. They further argue that the problem of having management carried out by agents other than firm owners is more acute in the public sector, where firm owners - the citizens of a nation - are necessarily uninvolved in management decisions. By contrast, the private sector may possess a mix of manager-controlled and owner-controlled firms, and is therefore more efficient on average.

Shleifer (1998) argues that the agency problem is more acute in state-owned firms even when they are compared to private firms that are manager-controlled, because a nation's citizens are an intrinsically diffuse group who have limited ability to specify and monitor the behaviors of firm managers. Shapiro and Willig (1990) additionally suggest that public managers may be more likely to have personal goals that conflict with efficiency, as they tend to pursue political careers that benefit from goals such as maximizing the employment of the firm.

Hart (1983) and Willig (1985) illustrate how agency problems are mitigated by competition: As the level of industry competition increases, owners gain useful information from observing other similar firms in the market, and are better able to gauge the extent to which their own managers are exerting efforts to reduce costs. They can then more precisely contract with managers to reward effort or punish slack.

If public firms suffer from greater information deficiencies in the absence of competition, due to their relatively poor ability to monitor firms, then the gains from observing other firms should be greater to them. Consequently, an increase in the level of industry competition due to an increase in the number of firms should increase the efficiency of state-owned firms relative to private firms.

It is important to note that the effects of competition in mitigating agency problems are driven by information gleaned from comparable firms. Thus, as both the similarity and number of direct competitors increases, efficiency gains should be realized. By contrast, if a market is perceived to be competitive solely because of *potential* competition that has not manifested in direct competitors (after, for example, a recent market liberalization), or solely because of *indirect* competition from substitute markets where firms have different cost structures, then one would not expect efficiency gains through the agency channel.

1.2.1.2 Soft Budget Constraints

Kornai (1986) documents the existence of "soft" budget constraints among state-owned firms in a variety of contexts, wherein firms are provided with funding from the government that compensates any losses and prevents them from failing. By contrast, a private firm cannot indefinitely make losses without facing shutdown, creating strong incentives for managers and other employees to perform efficiently in such circumstances.

While not all state-owned firms may face soft budget constraints, Sheshinski and López-Calva (2003) cite a reason for the existence of these subsidies that may be widely applicable:

> In any situation in which the firms have engaged in unwise investments, it will be in the interest of the central government to bail the firm out using the public budget. The rationale for this relies on the fact that the bankruptcy of the firm would have a high political cost, whose burden would be distributed within a well-defined political group, like unions. On the other hand, the cost of the bailout can be spread over the taxpayers, a less organized, larger group in society, with diversified interests and preferences.

This argument is strengthened if central government term limits prevent repeated interactions with firms, so that politicians do not have a long-term interest in avoiding the moral hazard problem of public firms by punishing them for inefficient behavior.

As competition levels rise, soft budget constraints may reduce the relative efficiency of state firms to private firms in two ways: First, if firm profits are reduced as the level of competition increases, then the danger of shutdown for a private firm increases with competition. Thus, private managers and employees faced with the prospect of unemployment and may increase their efficiency, regardless of whether contracting problems misalign their incentives when the threat of shutdown is less imminent.

Second, public firms with soft budget constraints may not only be less responsive to losses brought on by competitive forces because they do not face a credible threat of shutdown, they may actually perform more poorly once they are subsidized by the government. Beyond the point when a firm relies on the government for support, its managers have little incentive to improve efficiency, as reductions in profit will be offset by increases in government funding, and increases in profit will be offset by reductions in government support.

Note that the incentive problems created by soft budget constraints may be mitigated through contracting: both firm owners (the nation's citizens) and the government bodies who fund state-owned firms have incentives to avoid managerial slack, since supporting a firm that makes losses detracts from other potentially beneficial projects. It is thus possible that governments could at least partially reduce the effects of soft budget constraints by rewarding managers for efficient behavior. However, as described in Section 1.2.1.1, specifying contracts may be especially challenging in public enterprises.

1.2.1.3 Differences Unaffected By Competition

Aside from agency problems and soft budget constraints, several other differences between private and state-owned firms are put forth in the literature. While these differences do not appear to be affected by the level of competition faced by firms, and are therefore not the focus of this paper, they are imporant because they affect level differences between public and private firms, and provide some context for the fact that the empirical literature largely finds private firms to be more efficient than private firms, independent of competition.

In this section, I briefly describe the most important differences between state-owned and private firms that affect productive efficiency, but are not affected by the level of competition faced by firms.

Transferability. A key tenet of the theory of property rights is summarized by De Alessi (1980):

> The crucial difference between private and political [state-owned] firms is that ownership in the latter effectively is nontransferable. Since this rules out specialization in their ownership, it inhibits the capitalization of future consequences into current transfer prices and reduces owners' incentives to monitor managerial

behavior.

The lack of ownership transferability does not only reduce the value of state-owned firms to their owners, potentially weakening their interest in costly monitoring to ensure managerial efficiency - it also means that managers do not risk being replaced in a takeover, and reduces their incentives to be efficient relative to managers in private firms that are subject to a market for corporate control.

Political interference. Shleifer and Vishny (1996) suggests that politicans may distort the efficiency incentives of firm managers by providing covered subsidies to firms to achieve their own political goals. They argue that the politicians' cost of such interference increases as the government's share of ownership decreases, so that a fully divested private firm is the least likely to encounter such distortions.[3]

Other Government Goals. Governments commonly and explicitly set goals for public firms other than profit maximization, and a subset of these goals may conflict with productive efficiency.

An example can be found in public works programs and other government projects intended to provide employment opportunities: a government might employ more workers than are strictly necessary to produce a given level of output, if it is more committed to increasing employment than to minimizing costs. Similarly, a government may be more reluctant than a private firm to reduce the size of its workforce, should efficiency demand such reductions.[4]

It is worth observing that a large set of government goals are perfectly consistent with minimizing costs. For example, a common goal of public firm ownership is to address market

[3]Note that this result is grounded in the assumption that a government's intentions in intervening are socially malevolent. Williamson (1985) reaches a different conclusion regarding the effects of government intervention, by assuming that a government's intentions are benevolent, rather than malevolent, with regard to efficiency.

[4]See Shapiro and Willig (1990) or Shleifer and Vishny (1996) for a more detailed discussion of the distortionary effects of government goals.

failures caused by issues such as natural monopoly conditions.[5] While a public firm designed to address monopoly problems would typically reduce prices and increase quantities relative to a private firm under imperfectly competitive circumstances, the direction of average cost changes is generally unclear as quantities are increased from the point of maximal profit. Moreover, such goals do not affect the underlying cost *function* that the firm follows, as a function of quantity. Similarly, a public firm with the goal of providing goods or services that are deemed to be underprovided by the private sector need not be cost-inefficient in providing those goods or services.

1.2.2 Ownership and Competition are Not Independent

Vickers and Yarrow point out that, while the effects of privatization and competition are quite different, the two may go together in many circumstances for theoretical reasons. And, empiricially, they very often do, perhaps for political reasons. Could describe this here, or at the end of the analysis, when looking at anomalies.

1.2.3 Implications

In summarizing the theoretical literature on efficiency differences between state-owned and private firms, a few points emerge:

- The theoretical arguments presented unanimously suggest that private firms will be more productively efficient than state-owned firms.
- Diminished agency problems in the public sector may cause the efficiency gap between private and state-owned firms to *attenuate* in more competitive markets, ceteris paribus.

[5] See, for example, Lewis (1949), or Simons (1948).

- However, soft budget constraints may cause the efficiency gap to *widen* in more competitive markets, ceteris paribus.

- The underlying elements of competitiveness matter: agency problems will only be alleviated as the number of comparable firms increases, while soft budget constraints will reduce the relative efficiency of public firms any time overall competitive pressure reduces profit margins.

Because agency problems and soft budget constraint problems exert opposing influences on efficiency as the level of competition rises, the overall effect of industry competition on the relative efficiency of private and public firms will depend, in practice, on the extent to which agency problems and failure threats exist in the state-owned and private firms being studied.

Additionally, there may be a great deal of heterogeneity in the agency problems faced by private and public firms, and some public firms may not face soft budget constraints. The definition of a "competitive" market is also important: as the last point suggests, some markets that are considered competitive may not experience the gains of mitigated agency problems, if those markets do not provide firm owners the opportunity to observe the performance of comparable firms.

With these considerations in mind, Section 1.3 reviews the empirical evidence.

1.3 Empirical Evidence

1.3.1 Constraints

To accurately examine the literature on how competition affects the relative efficiency of state-owned and private firms, this study imposes a few constraints on the papers reviewed: First, I limit my survey to studies that compare ownership effects in non-transition economies, and therefore omit examples from China, the former Soviet Union, and parts of central and Eastern Europe. The main reason for this constraint is that economies transitioning from Communist structures simultaneously made many economy-wide changes, and separating the effects of regulatory changes, increased competition, and privatization programs is particularly challenging. In addition, as Megginson and Netter (2000) observe, "the data from transition economies is much worse and much more limited than from non-transition economies."

Second, I generally avoid studies that measure productive efficiency solely with metrics that combine revenue and cost data. Many influential studies on private and state-owned firm differences use statistics that depend on output prices to measure "efficiency"- such as marginal profit, return on assets, or the ratio of revenue to costs. While these measures are clearly important in gauging performance differences, they pose issues in measuring productive or cost efficiency that are compounded when efficiency is being compared across different competitive environments. As Boles de Boer and Evans (1996) point out: "profits and rates of return may not be good indicators of efficiency as they will reflect any departures from Ramsey pricing which may be possible because of the dominant position of the company."

Private and public firms might also be expected to exhibit different price-setting behaviors as the level of industry competition varies, which affect any measures of efficiency that depend on prices. In particular, private firms with market power can profitably increase prices relative to the social optimum, while state-owned firms that have allocative efficiency goals might not.[6] Then, measures of efficiency that are sensitive to output prices would overstate the relative cost efficiency of private firms in imperfectly competitive settings - since they would rise when revenues increased - and relative efficiency gains would attenuate as conditions approached perfect competition.

Empirical evidence supports this expectation: Bonin, Hasan, and Wachtel (2003) use a

[6] See Vickers and Yarrow (1988) for a more detailed description of these behaviors.

number of measures to compare public and private bank performance, and find that public banks outperformed private banks in all measures that used costs alone. When measures that incorporated revenues and costs were instead used, private banks outperformed public banks. Both Caves and Christiansen (1980) and Laurin and Bozec (2000) study “TFP”differences between two Canadian railroads and use the same data, but reach different conclusions about their relative efficiencies. Laurin and Bozec use a TFP calculation that depends on revenue shares, and find that the private railroad is more efficient than the state-owned one. Caves and Christiansen intentionally choose a measure that uses output cost elasticitices instead of revenue shares due to the issues cited above, and find no differences between the efficiency of the public and private railroad after 1987. Their conclusions differ presumably because of price differences, and not cost efficiency differences, between the railroads.

Since it is ambiguous whether whether price-inclusive measures of relative efficiency are adjusting due to cost reductions or revenue increases, I focus on studies that include measures of efficiency based on output per unit of cost. However, I also consider evidence from studies that use price-inclusive efficiency measures in highly competitive environments, since price-setting behavior should be limited or non-existent in these contexts.

1.3.2 An Overview of Findings

Table A.1 lists 21 studies that estimate the relative efficiency of private and state-owned enterprises, and that give indications of the level (or levels) of competition studied. Of these, 9 studies examine firms in non-competitive environments; 7 studies examine competitive environments; 4 studies examine firms in monopolistically competitive or oligopolistic environments; and, 1 study examines firms in a variety of competitive environments separately.

The competition levels in each study were established using the evidence available in each case. Where possible, I used four-firm concentration ratios for each industry to establish the competition level[7]: Firms operating in industries with four-firm concentration ratios under 20% were deemed competitive; those with ratios between 30% and 80% were monopolistically competitive or oligopolistic; those with ratios above 80% were considered to be non-competitive. When four-firm ratios were not available, I used the number of industry competitors faced by firms, along with descriptions and assessments of the competitive environments provided by authors. Aside from establishing the appropriate competitition category for each study, author descriptions provided additional relevant details about the competitive environment, such as levels of indirect competition faced from substitute markets, any potential but unrealized competition faced from recently lowered barriers to entry, the extent to which firms competed internationally or regionally, the regulatory environment within which firms operated, and the extent of product differentiation within the industry.

Because of the variance in methodologies and measures of efficiency, comparable measures of the extent of the efficiency gap between private and public firms were not available across studies. Nonetheless, by examining the porportion of studies that find significant differences between ownership types at each level of competition, a pattern emerges. Figure A.1 separates the 21 studies according to the level of competition they examine, and their findings on the relative efficiency of ownership types. 7 of the 10 studies (70%) that take place in monopolistic settings find that private firms are more efficient than state-owned firms, while the other 3 find no significant differences in ownership types. In monopolistically competitive or oligopolistic environments, 3 of 5 (60%) of studies find private firms more efficient, and 2 find no differences; and, in competitive environments, only 4 of 8 (50%) studies find gains to private firms, 3 studies report no differences, and 1 study finds that public firms are more efficient.

Clearly, no conclusions can be drawn from these coarse results alone. The studies vary

[7] A four-firm concentration ratio is the percent of an industry's market share captured by the four largest firms in an industry. Although it is widely used as a measure of market competitiveness, Weiss (1963) provides a discussion of its merits and drawbacks.

widely in the number of firms they consider, the data they examine, and the methods they use. Additionally, contextual differences likely play a large role in explaining the variation in findings: Some studies examine static environments where state-owned and private firms co-exist, while others look at privatization programs that often occured along with market liberalization measures and regulatory changes. The governments running state-owned firms had a variety of stated and observed goals for their firms, different policies regarding subsidization of public firms, and may have differed in their abilities to monitor firm managers. Private firms may have been more or less efficient depending on the regulatory constraints under which they operated.

To gain some insight into how competition might affect ownership differences, Section 1.3.3 reviews in greater detail the findings of the literature.

1.3.3 A More Detailed Review

While most studies considered in this paper examine firms within a single (broadly-defined) level of competition, I begin with the single study that separately examines ownership effects across both competitive and non-competitive environments. La Porta and Lopez-de-Silanes (1999) study the effects of privatization for 218 state-owned enterprises in Mexico. Measuring costs per unit of output, the authors find that privatization increased the efficiency of firms operating in both competitive and non-competitive environments, and that the efficiency gains from privatization were significantly greater in non-competitive environments than in competitive ones.

These results provide a uniquely controlled setting in which to study the effect of competition on relative efficiency, and also the relative importance of agency issues and soft budget constraint issues in publicly-owned firms. Since public firms should become less relatively *less* efficient than prive firms as competition increases, because soft budget constraints shield them from competitive pressures, and relatively *more* efficient as competition increases, because the observable performance of other firms reduces agency issues, the fact that efficiency gains from privatization attenuated with the level of competition provides evidence that the effects of agency issues dominated the effects of soft budget constraints in this study.[8] The study also documents the existence of subsidies to public firms prior to privatization - amounting to 12.7% of GDP in Mexico - suggesting that reductions in agency-related issues due to competition had to surmount substantial soft budget constraint issues that presumably increased with the level of competition that firms faced. Because La Porta and Lopez-de-Silanes (1999) separates ownership effects by competition level, examines a large number of firms, and is exceptionally careful and thorough in its approach, it is one of the most persuasive studies in providing evidence of the effects of competition on ownership efficiency.

1.3.3.1 Studies in Non-Competitive Settings

The vast majority of studies that examine public and private efficiency differences in non-competitive settings are studies of privatization efforts that compare the performance of enterprises before and after state ownership. A complication in studying privatization programs is that ownership effects could take place gradually, and might not be adequately captured just after privatization takes place. Additionally, the announcement of a government's intentions to privatize sometimes preceded the actual transfer of ownership by several years, during which the perception of ownership transferrability and a period of "shake-out" could

[8] In their main specification, the authors define "competitive" and "non-competitive" based on the (potentially subjective) opinions of financial consultants who reviewed the privatization of each firm, which deemed any firm operating in conditions other than monopoly or oligopoly to be competitive. In alternate specifications, the authors redefine "competitive" to refer to industries with more than 10 competitors, and find no significant difference between the efficiency gains in competitive and non-competitive environments. While this may appear to be evidence that agency concerns did not, in fact, dominate soft budget constraint concerns, most of the gains from alleviating agency concerns are likely to be realized when a few comparable firms enter the market, so that many of the firms in the "non-competitive" group may be indistinguishable from those in the "competitive" group in this specification.

increase public firm efficiency. Lastly, privatization programs are typically accompanied by other regulatory changes - in particular, many governments shielded state-owned firms from competition, and undertook market liberalization measures either concurrently with privatization, or after a grace period during which newly privatized firms are shielded from competition.[9] Unless these liberalization effects are separated, studies may compare public monopolies to private firms operating with limited competition, and thus conflate the effects of competition and ownership on effiency.

Of the 9 studies in non-competitive environments in our review, 5 study privatizations of telecommunications firms. Within this industry, Wallsten (2001) and Boylaud and Nicoletti (2000) both find no ownership effects from privatization, while Ros (1999), Ramamurti (1996), and Boles de Boer and Evans (1996) find that private firms are more efficient than state-owned firms.

Wallsten (2001) studies the privatization of telecom monopolies in 30 countries across Africa and Latin America, from 1984 to 1997. Controlling for competition changes and other concurrent programs that may have affected firm efficiency, he finds no effect of privatization on labor productivity (output per employee) in the absence of additional regulatory measures.[10] When privatized firms are faced with price regulation from an independent regulator, though, privatization yields efficiency benefits. This result is consistent with theory: By keeping prices low, regulators essentially create the pressure for efficiency that competition does, which differentially affects private firms if public firms face soft budget constraints.

Boylaud and Nicoletti (2000) study telecom privatizations in 23 OECD countries from 1991 to 1997, and similarly conclude that ownership did not affect labor productivity, when

[9] Wallsten (2001) and Vickers and Yarrow (1988) describe of these issues.

[10] Wallsten also finds that competition is independently associated with a 6% *decrease* in labor productivity. While this result appears contrary to theory, the author explains that competition may have brought about new investment, which required hiring new workers potentially unrelated to sales. He concludes that the effect of competition was generally positive, due to overall increased output.

controlling for the level of competition and also the time to liberalization. However, both the number of competitors and decreases in the time to liberalization are associated with increases in productivity. The authors interpret the effects of time to liberalization as being due to the effects of potential competition, which may have stimulated managers and employees in public firms to increase efforts to avoid unemployment as profit margins were reduced. Such responses may be partially attributable to an anticipated reduction in cross-subsidization across internal groups, which the authors describe as common prior to privatization.[11] However, diminished agency issues would only occur when actual competitors emerged, and the separately significant effect of the number of competitors provides evidence that agency issues are important. Notable in this study is the fact that the government "generally maintained the largest single share of the PTOs capital and sometimes retained special voting rights in the privatised enterprises." The limited extent of ownership change may have limited the effects found in this study. Indeed, some studies (see, for example, Ehrlich, Gallais-Hamonno, Liu, and Lutter (1994)) find that ownership change is only effective when firms are fully privatized.

Ros (1999), Ramamurti (1996), and Boles de Boer and Evans (1996) all find productivity improvements in telecom firms following privatization. Ros studies a mix of firms that were either privatized during the period from 1986 to 1995, or were private throughout the period, and measures ownership effects on labor productivity while controlling for competition. Ramamurti (1996) finds significant ownership effects in 3 of 4 telecoms studied, but does not separate competition and ownership effects, and acknowledges that the level of competition may have changed after privatization.

Boles de Boer and Evans (1996) provide a case study of the 1990 privatization of Telecom New Zealand, and study efficiency changes during the period from 1987, when the market

[11] The authors mention that profitable telecom groups within a firm, such as long-distance service, often subsidized loss-incurring groups, such as local service. Such cross-subsidization activities would have a similar effect to soft budget constraints on the incentives of the loss-incurring groups.

was liberalized, to 1993, when the first actual competitors entered. As a case study, the evidence the auhtors present is inherently less generalizable than that of other studies. On the other hand, the authors are less restricted to use variables that are common across all firms being studied, and can be precise about the levels of competition and other contextual details of the privatization. The study measures productivity as the level of output per cost of inputs, where inputs include labor, material inputs, and capital. They find that productivity increased by 10% per year during the study period, and that unit costs reduced by 5.8% per year. Like Ramamurti (1996), the authors do not separate the effects of competition and ownership in their examination; however, competitors only emerged in the final year of the study, and potential competition due to deregulation was present throughout.

A concern permeating all the telecom studies is that the effects of ownership are averaged across both the monopoly conditions and conditions of limited competition following market liberalization, making it impossible to isolate the precise market conditions under which these effects occur.

Caves and Christiansen (1980) provides some evidence on ownership effects in a static competitive environment, by comparing two Canadian railroads - one private, one state-owned - who were each other's sole competitors for many decades. Measuring the cost of inputs per unit of output, they find that the state-owned railroad was initially less productive than the private one, but find no significant differences between the two by the end of the 19-year study period. Since the railroads began to compete 30 years prior to the study period, their findings suggest that efficiency improvements may take a very long time to adjust to a change in the level of competition. Assuming this is true, the privatization studies that average efficiency effects across short periods of time during which monopolies were exposed to competition may be best placed as studies reporting relative efficiencies under monopoly conditions.

Both Caves and Christiansen (1980) and Ramamurti (1997) make another contribution to the analysis: While they both study railroads that faced little or no direct competition (Ramamurti studies the privatization of a state-owned monopoly), both argue that the railroads they study faced substantial indirect presure from other forms of transportation that competed for both passengers and freight. Ramamurti explicitly documents the market share of the Argentinian railroad he studies, and finds that only 8% of freight and intercity travel were handled by the railroad, along with 15-20% of suburban travel.

Since ameliorating agency issues requires the observation of direct competitors, both studies exist in a non-competitive environment for agency purposes. However, indirect competitive pressure reduced prices and profit margins, and thus expand the efficiency gap between public and private firms due to soft budget constraints. With both unmitigated agency issues and exacerbated soft budget constraint issues, theory would predict the efficiency gap between these railroads to be at their largest.

Indeed, Ramamurti (1997) finds that privatization resulted in a 370% increase in labor productivity, and explicitly documents the existence of railroad subsidies to the state-owned Argentinian railroad prior to privatization. Caves and Christiansen, who paradoxically find no significant differences by the end of their study, also point out that the state's role was "restricted to that of a stockholder"in their study - no subsidies were provided to the state-owned railroad. Both of these studies point to the potential relevance of state subsidies in reducing efficiency gains, particularly in environments where firms face substantial competitive pressure.

1.3.3.2 Studies in Oligopolistic or Monopolistically Competitive Settings

The four studies that examine efficiency differences in oligopolistic or monopolistically competitive environments are evenly split: Ehrlich et al (1994) and Boardman and Vining (1989) both find that private firms are more efficient than state-owned firms, while Cullinane, Song, and Gray (2001) and Funkhouser and MacAvoy (1979) find no differences attributable to ownership.

Ehrlich et al (1994) conduct a very careful study of 23 airlines with varying (and also changing) ownership types, and estimate a model wherein productivity is endogenously and separately determined for each airline. The authors include several robustness checks using alternate specifications, and do not consistently find level differences between the cost efficiencies of private and public airlines across all specifications. However, they find that private firms have a relatively higher rate of cost reduction over time in each specification that they test.

To examine whether ownership effects vary with competition levels, the authors separately test the efficiency of the subset of airlines in the US, Canada, France, and the UK, arguing that that they exist in competitive environments because there are more domestic competitors within these nations. Although the authors find qualitatively similar results for these airlines, it is unclear whether airlines in those four countries might not face very different competitive environments from airlines that are the sole carriers for their countries, to the extent that airlines compete internationally, and also because - as the authors themselves point out - the International Air Transport Association (IATA) coordinated fares and erected barriers to entry for all airlines during the period of study.

Also notable in this study is the fact that both private and public airlines have historically been subject to soft budget constraints via "bailouts",[12], so that state-owned airlines may not be subject to a widened efficiency gap at higher competition levels in this industry.

Funkhouser and MacAvoy (1979) study firms in a variety of industries in Indonesia, and compare their efficiencies by computing the ratio of each firm's average costs to the appropriate industry average. Although they find no differences at the 5% level, private firms are significantly more efficient at the 10% level.

[12]As examples, the Japanese government bailed out a private carrier, JAL, in 2010; and, the US government extended bailouts to both private and public carriers in 2001.

Cullinane, Song, and Gray (2001) use a method that is increasingly popular in the recent literature to estimate cost efficiency: stochastic production frontier function estimation. Rather than looking at the cost of producing a unit of each output separately, or creating an index to evaluate the cost of all outputs simultaneously, the method establishes an efficient frontier of production using the data available, and evaluates each firm's efficiency based on its distance from the frontier. The authors study 15 container ports in Asia, and find no significant differences in efficiency based on ownership.

1.3.3.3 Studies in Competitive Environments

Of the 7 studies reviewed that study competitive environments, only 3 found that private firms were more efficient than state-owned firms. Of those 3, Vining and Boardman (1992) and Diboky (2007) both used measures of efficiency that are sensitive to revenue gains; it is unclear whether the measures used in Chen and Yeh (2000) are price-sensitive or not. As the evidence in Section 1.3.1 suggests, the efficiency of private firms may be overstated using price-sensitive measures, when markets are not highly competitive.

Diboky (2007) and Chen and Yeh (2000) are similar in other respects. Both studies use Data Envelopment Analysis (DEA) to estimate the technical efficiency of public and private firms that contemporaneously exist over the study period.[13] Diboky studies results for 300 insurance firms in Germany that compete directly with each other; Chen and Yeh examine 34 domestic banks in Taiwan that face additional competition from 67 banks that are partially foreign-owned. Diboky (2007) measures firm "outputs"as gross premiums and net income, while Chen and Yeh measure quantities of loan services and portfolio investment. Chen and Yeh (2000) find that private banks outperform public banks; Diboky (2007) finds that public

[13]DEA establishes a frontier of efficient output allocation and evaluates each firm's proximity to the frontier, much like stochastic frontier function estimation, but does so non-parametrically, instead of using specified relationships between variables in the production function.

banks were substantially less efficient than either private or "mutual" banks of mixed public and private ownership.

Vining and Boardman (1992) study a variety of industries whose four-firm concentration ratios vary from 14% to 43%, suggesting that the competitive environment in their study bordered on monopolistic competition, by the standards of this review (see Section 1.3.2). In such an environment, their use of efficiency metrics such as sales per employee and sales per asset may have caused private firms to appear more efficient than state-owned firms for reasons of higher prices, rather than lower unit costs.

Goldar, Renganathan, and Banga (2003), Altunbas, Evans, and Molyneux (2001), and Kole and Mulherin (1997) all find no differences between public and private firm efficiency in their studies. Kole and Mulherin (1997) present a novel study of public ownership, wherein the US government assumed ownership of firms that had substantial German or Japanese ownership during World War II. The authors report that the US government had no intentions for the firms other than as investors, and intended from the beginning to sell off the firms. Because subsidies and other soft budget constraints were not applied to these firms, and firm ownership was perceived to be transferrable, efficiency differences between ownership types were likely diminished relative to other cases in competitive markets. The authors further argue that the state-owned firms were monitored using mechanisms comparable to those in the private sector firms comprising their comparison group, reducing any agency issues that may have already been mitigated by the competitive markets within which the firms operated.

Isik and Hassan (2003) are unique in being the only study to report that public firms were more efficient than private firms. The authors use measures of cost and technical efficiency to evaluate ownership effects among Turkish banks, and use non-traditional outputs to construct their measures, such as the number of letters of guarantee issued, and the number of loan commitments provided, thereby avoiding price sensitive data in their calculations.

However, the study acknowledges that public banks had priveleged access to lower factor costs than private banks, which likely contributed to the results found.

1.3.4 Explaining The Findings

A broad overview of the empirical literature across the spectrum of competitive environments suggests that ownership differences appear to diminish in more highly competitive environments.

Detailed examination reveals complexities that both sharpen this result, and provide a more nuanced understanding of the theoretical issues that drive efficiency differences between ownership types. Boylaud and Nicoletti (2000) provide an example of how, because privatizations may be announced at one time and executed at another time, some "ownership"effects may occur prior to actual ownership. Additionally, a closer look at Wallsten (2000) shows that price regulation common in monopolies can create effects similar to competition, so that firms existing in a non-competitive environment can display some of the efficiency characteristics of competitive firms. While both of these studies find no efficiency effects to ownership alone, they each provide evidence that the entire process of privatization provides efficiency benefits, some of which occur prior to the the ownership transfer and after typical regulations are applied.

In competitive environments, although 3 of the 7 studies reviewed find that private firms outperform state-owned firms, none of the 3 studies that avoided price-sensitive measures found this result. While this is by no means conclusive, it may suggest that this study's criteria for competitive environments are not so stringent as to prevent a certain amount of price-setting behavior, so that price-sensitive measures of efficiency in this environment could reflect revenue increases.

Accounting for these details strengthens the evidence that increased competition reduces efficiency differences between public and private ownership. According to theory, this implies that, as competition increases, reductions in agency issues have a positive effect on the relative efficiency of state-owned firms that dominates the negative effect from increasing reliance on soft budget constraints.

However, the evidence suggests that this may be true only because soft budget constraints are *not* increasingly relied upon as competition increases, rather than because their effects are insignificant. Amongst non-competitive firms, there is evidence of soft budget constraints in 3 of the 7 studies; in competitive firms, none report any evidence of soft budget constraints. The reason for this deviation from theoretical expectations may be the prevalence of price regulations among monopolies in our sample of studies, which compel both private and public firms to supply at prices and quantities that might otherwise be found at much higher levels of competition.

1.4 Conclusions

This review seeks to determine whether some of the variation in the literature's findings on the effect of ownership on productive efficiency can be explained by an interaction between competition and ownership effects. It finds that studies which report that private firms are more efficient than public firms are more prevalent in non-competitive settings than in competitive settings, perhaps because competition alleviates agency issues: increases in the number of competitors allow public firm owners to acquire useful information about the efforts that their managers are exerting, and to thereby establish more incentive-aligned contracts with them.

Perhaps more importantly, this review finds that some of the underlying factors that influence the relative efficiency of public and private firms are not firmly related to the conventional measures of industry competition levels that I employ. Whenever firms face reduced prices - whether because of direct competition, indirect competition from substitutes, or price regulations - private firms face an increased threat of failure, and may be compelled to improve their efficiencies. By contrast, state-owned firms that are sheltered from failure by subsidies or other soft budget constraints may not experience this threat as keenly. A corollary to this finding is that regulations and substitute markets matter, as they can influence firm behavior in ways that are not captured by standard measures of industry competitiveness, such as four-firm concentration ratios.

This review does find that diminished agency issues seem to follow the measures of industry competitiveness established. Indeed, the strength of this relationship appears to drive the fundamental result that efficiency differences diminish with competition. The relationship between agency issues and the competition measures I use - four-firm competition ratios, and the number of direct competitors - is unsurprising: four-firm concentration ratios are strongly related to the number of competitors in an industry, and the ability to observe direct competitors is pivotal in diminishing agency issues.

These results are cause for optimism that the variation in the literature's results on ownership and efficiency can, indeed, be explained, through careful identification of the underlying causes of efficiency differences, and the real-world conditions under which those causes manifest.

CHAPTER 2

Private Firms, Regulations, and Unintended Consequences: Evidence from Sugar Mills and Farmers in India

Chapter Abstract:

In this chapter, I examine how state-owned and private sugar mills differentially affect farmer profits in Tamil Nadu, India, by exploiting a discontinuity in ownership structure created by a zoning system in the state. I find that private sugar mills substantially reduce profits and raise costs for crops other than sugar cane, while sugar cane outcomes are not significantly affected by sugar mill ownership structure. A closer look suggests that private sugar mills intentionally discourage farmers from farming crops other than sugar cane, in order to increase the supply of inputs to mills. My findings broadly suggest that private firms in highly regulated markets may influence less-restricted related markets to maximize profits, with consequences that may not be anticipated by regulators. This presents a challenge to the literature that contends that regulated private firms are similar to state-owned firms in their abilities to carry out a state's distributional goals, and differ only in their efficiency.

2.1 Introduction

The relative merits of private and state-owned enterprises have been debated throughout recent history. When assessing whether private or public firm ownership is more beneficial to society, the consensus has shifted over time. In the early and mid-20th century, both theoreticians and policymakers emphasized the potential for social losses in privatized markets due to market failures such as monopolistic pricing and externalities, and saw state ownership as a cure for these problems.[1] In the last few decades, the argument that private firms are more innovative and efficient has held sway. Moreover, the theoretical foundations for state ownership have been weakened by the notion that regulation can solve market failures and achieve any distributional goals of the state by controlling the undesirable actions of private firms, while still allowing them sufficient freedom to innovate.[2] However, unless policymakers can fully anticipate the behaviors of private firms, regulations may alter incentives for profit maximization in ways that lead to unintended consequences.

In this paper, I study how private and state-owned sugar mills differentially affect the outcomes of farmers who grow both sugar cane and other crops, in Tamil Nadu, India. Because the activities of sugar mills are highly monitored and regulated within the market for sugar cane, I posit that private sugar mills may pursue profits through less-regulated channels, such as discouraging substitute activities for their vendors by making it less profitable to grow other crops.

In the setting of this study, private firms have both a motive and a potential means to affect the profitability of substitute activities. Sugar mills have high returns to scale, and benefit from increasing the quantity of raw sugar cane they receive from farmers (Mul-

[1] See, for example, Lewis (1949), and Simons (1934).

[2] Shleifer (1998) discusses this evolution of thought, along with the literature on public and private efficiency.

lainathan and Sukhtankar 2011). In addition, a regulatory system in the state assigns a zone to each sugar mill, within which it has exclusive rights to purchase sugar cane from farmers, and outside of which it cannot purchase sugar cane. While the zoning system is intended to provide an incentive for mills to increase the productivity of existing sugar cane farmers within its zone[3], it also increases incentives for mills to discourage farmers in their zones from growing other crops in lieu of sugar cane. Because private mills typically have relationships with large agricultural conglomerates that supply inputs to crops other than sugar cane, they may plausibly act on these incentives by influencing the costs or availability of inputs to grow other crops.

Tamil Nadu's zoning system not only provides a case study of how private firms react to regulatory constraints differently from state-owned firms; it also serves as the source of identification in this paper. By studying households who grow crops near the borders between state-owned and private mill zones, I am able to compare the effects of public and private mills on farmers who otherwise exist in the same geographic and policy environments. I employ a regression discontinuity design to identify outcome differences that occur at the border, and test soil quality and other determinants of farming outcomes to verify that borders are not endogenously placed. I find that crops other than sugar cane have substantially higher costs and lower profits in private zones than in state-owned zones, although sugar cane outcomes are not significantly affected by sugar mill ownership differences. My findings suggest that private sugar mills discourage farmers from pursuing substitute activities to growing sugar cane, in order to increase the supply of inputs to mills.

Only a handful of papers examine the differential impacts of private and state-owned firms empirically, perhaps because of the difficulty of finding settings in which ownership effects can be identified.[4] Frydman et al (1999) find that private firms are associated with higher

[3]This intention is made explicit in descriptions of the zoning system. See, for example, Baru (1990).

[4]The majority of papers studying private and state-owned firms assess firm *performance*, rather than

employment levels, using data on state and privatized firms across transitional economies in Central Europe. Duggan (2000) studies private for-profit, private not-for-profit, and state-owned hospitals, and finds no difference in low-income patient health outcomes between ownership types. The closest study to this paper is conducted by Mullainathan and Sukhtankar (2011), who study how public and private sugar mills differentially impact sugar cane growers using the same identification strategy, and find small consumption gains among sugar cane growers who sell to private mills. However, none of these studies examine the effects of ownership differences on other related markets, and thus potentially overlook impacts resulting from private firms' attempts to avoid regulatory scrutiny.

This paper makes a unique contribution to the literature by examining the differential effects of state-owned and private firms on substitute markets for their vendors, and finds evidence that ownership structure can, indeed, have large impacts on vendors in these markets. This suggests that papers studying the effects of ownership on the economy may neglect important outcomes by constraining their analysis to the market of treatment. The study also employs an unusually clean identification of public and private ownership effects, as it compares the effects of publicly- and privately-owned firms on farmers who grow crops in otherwise similar environments, but must sell sugar cane only to a state-owned or private mill, respectively. In addition, the paper examines the consequences of a zoning policy common in India and other developing countries, and presents findings that broadly demonstrate how private firms might respond differently to regulations than state-owned firms. Lastly, the survey conducted to gather data for this paper contributes a novel dataset of farmer characteristics, growing practices, crop choices, and outcomes in rural India.

The paper proceeds as follows: In Section 2.2, I discuss relevant theoretical differences between state-owned and private enterprises, and how they affect predicted outcomes in

firm impacts on other stakeholders in society. For a review of the literature and a summary of identification challenges, see Megginson and Netter (2001).

related markets. I also provide contextual information about farming in Tamil Nadu, and about sugar cane in particular. In Section 2.3, I describe my data and the regression discontinuity design I use for identification, along with identification concerns and how I address them. Section 2.4 discusses my analysis and results, and provides some explanations for what I find.

2.2 Background

2.2.1 Theoretical Differences Between State-Owned and Private Firms

How might private and state-owned enterprises differentially affect other markets? To answer this question, I begin with a discussion of theoretical differences between private and state-owned firms.

It is commonly held that the goal of private firms is the maximal attainment of profits, while state-owned firms may have a variety of bottom lines, such as maximizing total gains to society, redistributing wealth amongst their stakeholders, or providing services that would not otherwise be provided by private enterprise. The arguments for state-owned firms are as varied as their potential goals: they may be intended to reduce social losses due to market failures, to promote social values, or to provide services deemed essential that may otherwise be neglected by the private sector. However, these arguments - along with the distinction between private and state-owned firms - are dimmed somewhat by the ability of governments to regulate industries. If governments are able to perfectly specify their goals in contracts or regulations, then private firms that abide by their stipulations would fulfill any goals that state-owned firms are intended to accomplish (Shleifer 1998).

In practice, contracts and regulations may be incomplete, if governments cannot anticipate exactly what they wish to accomplish, or cannot completely specify how a firm must achieve these goals. Grossman, Hart, and Moore develop a theory of incomplete contracts that observes that the gaps in an incompletely specified contract allow firms the flexibility to make decisions that serve their own ends (Grossman and Hart 1986, Hart and Moore 1990, and Hart 1995). Analogously, incomplete regulations give leeway to firms wherever laws do not specify how they must conduct business.

These observations can be adapted to provide a more nuanced distinction between public and private sector firms in a regulated environment: While private firms are free to pursue profit maximization wherever regulations or government contracts do not specify how they must behave, state-owned firms can be thought of as completely regulated, and thus forced to act narrowly within the expectations of the government. Then, the difference between private and state-owned firms is the scope of activities that each can undertake to maximize profits, while fulfilling the regulatory obligations imposed upon it by a government.

While this flexibility afforded to private firms can encourage innovation and efficiency, it may also lead to outcomes that were not envisioned by the government. In particular, since firms can profit from influencing related markets such as the substitute markets for their vendors, private firms may respond to regulations that constrain their within-market operations by increasing their activities in related markets, if they are less regulated.

2.2.2 State-Owned and Private Sugar Mills in Tamil Nadu

Several features of Tamil Nadu's sugar cane market make it an appropriate environment to study how private and state-run firms react differently to regulations, and how private firms may affect related markets in doing so. In this section, I describe the relevant features of the market, and provide a foundation for why we might expect differences in how private and state-owned sugar mills affect crops other than sugar cane.

1. *The sugar cane industry contains a mix of private and state-run mills, with explicitly*

stated goals for state-run mills. Before India became independent in 1947, all sugar mills in Tamil Nadu were privately owned, and mill owners typically held large sugar cane plantations that ensured an integrated and cheap source of cane input. After independence, a government-imposed cap on land ownership effectively prevented mills and sugar cane plantations from being owned by the same entities, and led to a decline in private investment (Baru 1990). To ensure that domestic cane production would not be threatened, the central government began the Cane Growers Programme, which fostered the creation of new cooperative sugar mills that purchased sugar cane from independent farmers[5].

In January 2011, there were 17 cooperative sugar mills active in Tamil Nadu, along with two separately owned government mills, and 19 private mills. Cooperatives in the state are publicly owned and managed, and serve the goals of maintaining domestic sugar production, providing employment opportunities, and increasing productivity by assisting sugar cane farmers in obtaining loans and crop inputs. The two other government mills are administered by the same government body and have the same stated goals, but are managed separately.[6] Since the government has clearly stated goals that may not directly align with profit maximization, this setting provides an opportunity to see how private and state mill outcomes differ when the state directly controls some mills, and uses regulations to steer the behavior of private mills.

2. *Regulations in the market for sugar cane increase the incentives of mills to discourage substitute activities for their vendors.* The sugar mill zoning system assigns exclusive sugar cane purchasing rights to each sugar mill within a designated zone, and prevents mills from purchasing sugar cane from farmers outside of their zone. These zones are assigned to all

[5]These events are discussed in Kansal (2011), and on the website for the National Federation of Cooperative Sugar Factories, http://coopsugar.org/history.php (accessed on October 10, 2011)

[6]Both cooperative and non-cooperative government mills are administered by the Tamil Nadu Co-Operative Sugar Federation. However, the non-cooperative mills are directly managed by the Tamil Nadu Sugar Corporation, while the cooperatives are not. See the Tamil Nadu Co-Operative Sugar Federation website for details: http://www.tn.gov.in/sugar/sugarcorp.htm (accessed on July 28, 2011).

mills by the Directorate of Sugar, a state government body, and are intended to equate the farming populations within each zone, and to minimize the distance and difficulty of transporting cane from harvested land to the designated mill.[7] [8]

The zoning system was designed to create incentives for mills to encourage regional sugar cane development. Since sugar mills run factories with high fixed costs and increasing returns to scale, mills generally run below capacity, and have a strong interest in increasing the amount of sugar cane they source (Mullainathan and Sukhtankar 2011). Because the system constrains the area from which they can purchase sugar cane, mills must focus on increasing sugar cane production within their zones. These incentives were an explicit intention of the system, and were expected to result in mill-led programs to increase sugar cane productivity (Baru 1990). However, mills may also increase cane production by decreasing the profitability of substitute activities amongst farmers, if they can feasibly influence these markets.

3. *The clearest substitute activity for sugar cane farmers in Tamil Nadu is to grow other crops.* 70% of the state's population is engaged in activities related to agriculture, and most non-agricultural activities are concentrated in urban areas.[9] Even when other economic activites exist in the rural communities in which most farmers live, non-farming activities are costly for existing farmers to undertake: Farmers in this study typically own their own agricultural land, and this land is often situated away from main roads and commercial thoroughfares. Selling land can be difficult in rural India because land ownership records are typically informal, and laws restrict the maximum amount of agricultural land that can be owned. Also, land used for sugar cane development is suitable for several other locally grown crops - including rice paddy, peanuts, pearl millet, sorghum, and coconuts. Taken

[7] In practice, this is achieved somewhat roughly, and zone borders are not changed over time to account for demographic changes.

[8] Appendix C provides a more complete discussion of the zoning system.

[9] See the Tamil Nadu Agriculture Department website, http://www.tn.gov.in/departments/agri.html, and the Tamil Nadu Statistical Handbook, http://www.tn.gov.in/deptst/.

together, we may expect strong substitution effects between growing sugar cane and growing these other crops, and commensurately strong incentives for private firms to discourage the growth of non-cane crops.

4. *Mills also have a potential means for affecting the markets for crops other than sugar cane.* Both private and state-owned[10] mills provide several goods and services to sugar cane farmers in their zones, including loans, crop inputs, and transportation services to bring harvested sugar cane to their factories. To do so, state-owned mills typically partner with other state-administered "cooperative societies" that provide loans and inputs, while private mills partner with banks, and are often co-owned by large agricultural conglomerates that sell crop inputs.[11]

Relationships with conglomerates may feasibly allow mills to affect the prices farmers pay for the inputs to other crops, without affecting input prices for sugar cane: Although most inputs to sugar cane - including pesticide, fertilizer, unskilled labor - are common to other crops grown in Tamil Nadu, farmers of crops other than sugar cane purchase their inputs to crops through village stores, where they are re-sold from conglomerates. Because farmers have strong social capital investments within their villages, they may be relatively inelastic to price increases in these stores. Sugar cane farmers, on the other hand, have direct relationships with their mills, and have access to loans and inputs from mills after registering their land with the sugar mill within their zone (Mullainathan and Sukhtankar 2011).

Taken together, Tamil Nadu presents an environment where the motivations of private and state-owned mills in Tamil Nadu might differ, and where profit-driven private mills

[10]Henceforth, I refer to cooperative and non-cooperative government-owned mills collectively as "state-owned" or "public" mills.

[11]As an illustrative example, 5 private sugar mills in Tamil Nadu are owned by EID Parry Limited, which also owns Coromandel International, a company that sells fertilizer, pesticide, and other products related to agriculture.

have both an incentive and a mechanism to differentially affect growers of other crops in Tamil Nadu. While these elements are specific to agriculture in Tamil Nadu, they provide examples of the means by which large private firms may more broadly innovate in reaction to regulations in other contexts, and correspond to the predictions of theory.

2.3 Data and Identification Strategy

To study the differential outcomes of farmers in state-owned and private zones, I employ a regression discontinuity design that identifies any shift in outcomes that occurs at the borders dividing public sugar mills from private sugar mills. I compare farmers within pairs of neighboring villages that lie along the border, where one village in each pair is in a private sugar mill zone, and the other is across the border in a state-owned zone. Identifying the effects of mill ownership structure on farmer outcomes is therefore dependent on the characteristics of villages within each pair being different only due to the differences in ownership structure, on average.

2.3.1 Data

Two original datasets were collected for this project. The primary dataset consists of a survey of farmers who own land along the borders between public and private sugar mill zones, and examines their land usage, crop growing activities, income sources, and expenditures between March 2010 and February 2011. The second dataset is a collection of soil samples that were collected in the villages that were included in the survey, and analyzed to reveal fixed characteristics of the soil that are relevant for crop growth.

In addition, I rely on a pilot survey dataset collected prior to my study by Mullainathan and Sukhtankar (2011), which establishes that zone borders do, indeed, constitute a discontinuity, by confirming that farmers near a border sell their cane overwhelmingly to the mill within their zone.

2.3.1.1 Sampling

The sampling strategy used for the primary dataset was twofold: First, a stratified random sample of villages was selected from each border between a public and private mill in the state of Tamil Nadu. Then, a stratified random sample of farmers was picked from each of these villages, to include both sugar cane and non-sugar cane farmers.

For the village sample, all borders between state-owned and private mills were initially considered, and any borders that coincided with major administrative boundaries or natural barriers were eliminated. This was done to ensure that village pairs would have similar geographic and climatic conditions, and be subject to the same policy environments. Each village on one side of the border was paired with the closest village on the opposite side of the border, and villages were drawn from the pool as pairs. The strata were chosen to ensure that an equal number of villages were chosen from each border, to ensure that the sample represented a variety of borders and geographic regions.

After the sample of villages was drawn, lists of farmers who owned land within 1 km of each zone border were compiled from Village Administrative Office records in each selected village. Then, a random sample was drawn from each list with strata to include farmers who grew sugar cane, and farmers who grew other crops. My econometric analysis uses probability weights to adjust for both levels of stratification.

The resulting dataset surveys farmers in 64 villages that own land within 1 km of zone borders between public and private sugar mills in Tamil Nadu. Because villages were chosen in pairs, each public mill village in the survey neighbors one private mill village in the survey that lies directly across a zone border from it. Hence, 32 of the villages are in public zones, and each is paired with one of 32 villages that lie in private zones. This design allowed me to compare private and public zone outcomes within pairs of neighboring villages, eliminating geographical and climatic variation along zone boundaries from my analysis.

The villages surveyed lie along 20 distinct zone borders, and come from 11 private zones, and 12 public zones. Of the public mills, 10 are cooperatives, and 2 are directly administered by the state government. Figure B.2 shows a map of the border areas that were surveyed, and their geographic distribution within Tamil Nadu.

2.3.1.2 Data Losses

A sample of 2,935 farming households were initially drawn to be surveyed. Of these, only 1,565 households were actually surveyed, and 912 were used in the analysis. Table B.1 reports these losses, and also compares characteristics of the original sample to those surveyed and those used.

Households that were not be surveyed were overwhelmingly households that could not be found.[12] Although the lists of farmers compiled from Village Administrative Office records were found to accurately associate households with the land they grew along zone borders, they gave little indication of how to locate these households. Because "villages" in our study are delineated by state administrative boundaries that frequently encompass several communities, locating a farmer within a village could mean searching through multiple communities separated by several kilometers. In addition, names were often not unique within a village, so that identifying the correct household required verifying that the land owned by a given household matched the land of the household included in our sample.

These losses could potentially bias the estimation of ownership effects, if the probability of being found and surveyed differed between private and state-owned mill areas, and was

[12] Fewer than 10 households refused to be surveyed, or could not be surveyed for other reasons once located.

correlated with characteristics that affected household outcomes. However, Table B.1 indicates that the rate of success in surveying households did not differ substantially between private and state-owned mill areas, and there is little cause to believe that the groups surveyed within each ownership type differ in characteristics that affect their outcomes, aside from those characteristics affected by ownership type itself.

Of the 1,565 households surveyed, only 912 were used in the final sample for analysis. Households were omitted from the final sample for two reasons: Some were found to have been surveyed along the border of a mill that was not operational. Others did not provide valid information about either their sugar cane revenues, sugar cane costs, non-cane revenues, or non-cane costs, and were omitted to ensure that the analysis was conducted for the same groups of people in specifications that examined costs and revenues separately. While Table B.1 shows that those used in the analysis were slightly more educated, and owned more land, these differences did not differ between private and state-owned mill zones. Moreover, the results I present are not sensitive to including observations who omitted data in other key fields.

2.3.2 Estimation

To determine the differential effects of public and private mills on farmer outcomes, I estimate the following equation:

$$Y_{ivm} = \alpha_0 + \sum_p I(v \in p) * \beta_p + \alpha_1 * DistanceToMill_v + \alpha_2 * Private_m + \epsilon_{ivm} \tag{2.1}$$

where: i indexes households; v indexes villages; p indexes village pairs; and, m indexes sugar mills. $I()$ is an indicator function that equals 1 if village v is part of village pair p, and 0 otherwise; β_p is the fixed effect of village pair p; $DistanceToMill_v$ is the distance from village

v to the mill within its zone; and, $Private_m$ is 1 if mill m is private, and is 0 otherwise. Y_{ivm} represents an outcome of interest for household i, such as the profits they received from crops other than sugar cane during the past 12 months.

The coefficient α_1 absorbs the effects of increasing distance between a village and its mill on outcome Y_{ivm}, so that any continuous and linear effects of changing geography are identified separately from mill ownership structure effects that occur at the zone border. The inclusion of village pair dummies β_p effectively compares characteristics of villages within pairs, to reduce sampling variability that may arise because of geographic and climatic variations along borders. The coefficient of interest is α_2, which estimates the effect of being in a private mill area, relative to a public mill area, on outcome Y_{ivm}. Since $Private_m$ varies per sugar mill, I cluster all standard errors at the mill level.

Because farmers may grow multiple crops during the 12-month period studied, farmers who grow sugar cane can also receive non-cane income. Since I posit that private and state-owned sugar mills may differently provide incentives for farmers to grow cane, they may have different effects on the non-cane profits of farmers who grow both sugar cane *and* other crops compared to those who *only* grow non-cane crops. To estimate effects on these two subgroups separately, I estimate Equation 2.1 with interaction terms, when analyzing outcomes for non-cane crops:

$$\begin{aligned} Y_{ivm} =& \theta_0 + \sum_p I(v \in p) * \beta_p + \theta_1 * DistanceToMill_v + \theta_2 * Private_m \\ &+ \theta_3 * GrowsCane_i + \theta_4 * (GrowsCane_i) * (Private_m) + \epsilon_{ivm} \end{aligned} \tag{2.2}$$

where: $GrowsCane_i$ is 1 if individual i has harvested cane in the last season, and is 0 otherwise.

Here, θ_2 captures the effect of being in a private area on an outcome Y_{ivm} for those who do not grow any sugar cane, relative to being in a public area and not growing any sugar cane. θ_3 captures the effect of growing sugarcane; and, θ_4 captures the incremental effect of being in a private zone for those who grow at least some sugar cane. Thus, $(\theta_2 + \theta_4)$ is the effect of being in a private zone for those who *do* grow at least some sugar cane, relative to being in a public zone and growing at least some sugar cane; and, $(\theta_3 + \theta_4)$ is the differential effect of being in a private area and growing at least some sugar cane, relative to being in a private area and growing *no* sugar cane.

To obtain unbiased estimates of α_2, θ_2, and θ_4 in the above equations, it is necessary to ensure that characteristics of individuals and villages that affect Y_{ivm} are uncorrelated with $Private_v$, except when those characteristics are *caused* by $Private_v$. In other words, the estimation procedure outlined in this section will only correctly estimate the effect of ownership structure on a given outcome if the households studied are identical on both sides of the border except for the ways in which ownership structure has affected them.

Since ownership structure may have subtle impacts on individuals and villages in our sample, many differences in observable characteristics could either be the effects of ownership structure, or of other causes that bias the study's results, and are thus not useful in verifying that ownership structure has been correctly identified. Moreover, an ownership discontinuity must actually exist at the border for *any* differences to be attributable to private and state-owned mills. In the next section, I discuss some specific identification concerns, and how this study addresses them.

2.3.3 Identification Concerns

In their survey of the same households I study, Mullainathan and Sukhtankar (2011) verify that farmers living along the borders between mills do, indeed, sell sugar cane to the mill on their side of the border. Figure B.1 aggregates data on sugar cane farmers living near sugar mill borders and shows, on the left, the proportion of those living in a mill zone who have *ever* sold sugar cane to the mill on the opposite side of the border. On the right, the figure shows the proportion of households in the opposing mill's zone who have *only* sold sugar cane to their own mill. Even given this strict method of accounting[13], it is clear that the vast majority of sugar cane farmers sell only to their own mill, and that an ownership discontinuity exists.

Lee and Lemieux (2010) identify several additional conditions required for identification in geographic regression discontinuity designs, and corresponding concerns to be addressed by researchers. In the remainder of this section, I discuss these concerns in the context of this study.

To identify the effects of mill ownership structure on farmer outcomes, it is essential that sugar mill boundaries were placed randomly with respect to characteristics of the land and population that could affect farmer welfare. If borders were drawn in specific locations that marked geographic or demographic differences, to favor either public or private mills, then the analysis might attribute differences in outcomes to mills, when the differences were actually inherent to the regions demarcated by the borders.

The decision to survey borders that did not coincide with natural boundaries such as rivers or hills partially alleviates this concern. In addition, soil sample tests conducted in each of the villages in this survey reveal no significant differences between private and state-owned zones in fixed soil characteristics that affect crop outcomes.[14]

Lastly, Table B.3 shows that villages on either side of the border are not significantly different in observable characteristics. In particular, there are no significant differences in

[13]In any given season, the discontinuity is likely to be even sharper.

[14]Table B.2 shows the results of regressing *Private* on various soil characteristics. Although nitrogen, phosphorus, and potassium levels may be affected by fertilizers, texture and "quality"measure characteristics that are unlikely to have been affected by mill ownership type.

land ownership: While other measures of wealth may be affected by income levels, and are plausibly altered by ownership structure differences between private and state-owned mills, land ownership is a relatively persistent measure of historic wealth in rural India, due to the difficulties in selling land that were previously mentioned.

Another identification concern would arise if mill ownership structure were correlated with regional characteristics that pre-dated the mills and affected farmer outcomes. If, for example, state-owned mills were only created to accommodate areas where private mills had not chosen to establish themselves, we might expect to see a continuous decrease in outcomes at greater distances from a private mill. Then, public villages in our sample could have poorer outcomes for reasons that were not caused by ownership structure.

A related problem would arise if public or private mills were systematically located in a manner that was correlated with geographic characteristics that affected farmer outcomes. For example, if all public mills were in the east of the state, nearer to the coast, we might expect different outcomes for farmers on the public sides of each border, for reasons unrelated to ownership structure.

Features of the regression discontinuity design explicitly address these concerns. If public and private mills emerged in land that was differently disposed to crop development, one would expect outcomes to become poorer with increasing distance from mills of the favored ownership structure, and not to experience a sudden discontinuity at mill borders. Because I compare effects within village pairs, and only amongst farmers with land less than 1 km from the border, differences between land in private and state-owned zones that increase with distances to mills are likely to be very small.[15] Moreover, by controlling for distance to the mill in my analysis, I identify ownership structure separately from any mill effects that increase smoothly with distance.

Lee and Lemieux (2010) raise a third concern about identification in geographic regression

[15] For comparison, the average distance between land and mill in this study was 39.8 km.

discontinuity designs: If sorting occurs across borders, this could alter the observed impact of the discontinuity. A mitigating factor, here, is the aforementioned difficulty of selling property in rural India. In addition, strong social ties within Indian villages make relocation costly. Empirically, I find that about 3/4 of the farmers in our sample own *no* land other than that which they have inherited, making it unlikely for any of these farmers to have moved within their lifetimes (see Table B.3). Nonetheless, if villagers were to have relocated because of favorable conditions across the border, this could increase the border effect sizes found.

Similarly, if farmers who are more productive alter the proportion of sugar cane that they grow in systematically different ways across public and private areas, the effect sizes measured might be altered. This type of selection might occur if mills make differential efforts to entice the best farmers into growing sugar cane, for example; or, if farmer productivity is correlated positively with ambition, so that the best farmers are more sensitive to differences in the benefits of growing sugar cane across public and private zones, and are therefore more likely to increase the proportion of cane they grow if sugar cane presents greater benefits.

These types of farmer adjustments are arguably an effect of the border itself, and not a threat to internal validity; moreover, adjustments that take advantage of differential benefits in public and private zones are indicative that an initial effect did, indeed, occur. Still, caution should be used in applying the magnitudes of effect sizes found in this study to other populations, to the degree that systematic migration and growing adjustments may be specific to this setting.

I proceed by presenting summary statistics, and then estimate Equations 2.1 and 2.2 using farming profits as the dependent variable of interest, Y_{ivm}. Next, I decompose the profit results to examine how they may have arisen, and provide explanations for my findings.

2.4 Results

Tables B.3 presents a summary of farmer characteristics in our sample, and shows results separately for those who farm land in public and private mill zones. Standard deviations for the sample are shown in parentheses[16]. Columns 1 and 2 pool results for both sugar cane and non-cane farmers, and show that farmers in public and private zones do not appear very different in their characteristics.

Columns 3 - 6 show results separately for two subgroups: those that harvested sugar cane in the last 12 months are shown in columns 3 and 4, and those that did not are shown in columns 5 and 6. Results in these columns show that sugar cane farmers own more land than non-cane farmers, and have slightly higher literacy rates. They also suggest a degree of persistence in sugar cane farming: over 85% of farmers who harvested sugar cane in the past 12 months grow it currently, while less than 5% of farmers who did *not* grow sugar cane in the past 12 months currently grow it.

Table B.4 shows means for profits, revenues, and costs across farmers in public and private zones, and again splits farmers into subgroups based on whether or not they have recently harvested sugar cane. Here, we see notably lower incomes in private zones than in state-owned zones, which appear to come mostly from differences in farm profits. Also evident are income differences between sugar cane and non-cane farmers: sugar cane farmers earn much higher profits from farming than non-cane farmers, although this difference is dampened somewhat when net income across all activities is considered. Lastly, columns 3 and 4 show price and productivity differences for sugar cane between public and private zones. Both yields per acre and prices appear slightly higher in public zones, although these differences are not statistically significant.

[16]As a general rule, standard deviations were quite high in the sample. This is due to large demographic variations across different regions of Tamil Nadu. Much of this variation is absorbed by the fixed effects for village pairs that are included in regression results.

Table B.5 uses the estimation equations from Section 2.3.2 to compare income and profit results for farmers in public and private zones.[17] Columns 1 and 3 display income and farming profits for all farmers, and show that private zones are associated with lower net incomes that are largely explained by lower farming profits. Columns 5 and 6 separate farming profits into sugar cane and non-sugar cane profits, respectively, and reveal that non-cane profits decline in private zones, while sugar cane profits are not significantly different across ownership structures. Non-cane profit declines are economically significant, as well, accounting for about 18% of average net income in private areas.

Columns 2, 4, and 7 include interaction terms that show how mill ownership structures affect profits for two mutually exclusive subgroups: those who do not farm any sugar cane, and those who farm at least some sugar cane. In these columns, the coefficient for the $Private$ variable is the effect of private zones on farmers who do not grow any sugar cane, while the sum of the coefficients for $Private$ and $(Private) * (GrowsCane)$ is the effect of private zones on farmers who grow at least some sugar cane. Column 7 shows that those who farm no sugar cane earn lower profits from their crops in private zones, by statistically and economically significant margins. However, the non-cane profits of farmers who grow both sugar cane *and* other crops do not differ from their counterparts in public zones by a significant margin.[18]

Taken together, the results in Table B.5 present a paradox: Sugar mill ownership differences appear to have no effect on those who grow sugar cane, but have large and significant effects on those who do not.

[17] It is perhaps worth noting that the probability weights used in regressions to adjust within-village oversampling of sugar cane farmers reveal different correlations between the degree of oversampling and outcomes across public and private zones. This causes some differences between means presented in the summary statistics tables, which do not use probability weights to correct oversampling, and those in the regressions, which do.

[18] That is, the sum of the coefficients for $Private$ and $(Private) * (GrowsCane)$ in Column 7 is not significantly different from 0 at a 0.10 level.

Table B.6 provides robustness checks for the non-cane profit results in Table B.5 by showing the results of alternate model specifications. Column 1 duplicates the results of Column 7 in Table B.5, where households are clustered at the mill level. In Column 2, standard errors are clustered at the village level. In Columns 3 and 4, $DistanceToMill$ is added as a control variable both linearly and quadratically, to absorb any continuous effects that increase as farmers are located further from the center of a state-owned or private zone. The coefficients for $DistanceToMill$ and $(DistanceToMill)^2$ are small and insignificant, and its inclusion does not affect the magnitudes of other coefficients substantially, suggesting that it is not strongly correlated with mill ownership structure. Column 5 removes all observations from the sample along borders with either of the two public mills that are managed separately[19], to ensure that differences between these mills and the state-owned cooperative mills did not influence the results shown. Lastly, Column 6 specifies non-cane profits in log terms, after shifting profit observations by a constant to ensure that they are all positive. The statistical significance of the coefficient for *Private* demonstrates that the results in Column 1 are insensitive to the log specification. However, there is little intuitive value to the magnitude of the coefficient, due to the shift in profit values needed to ensure that all profit values were positive prior to the log transformation.

The alternate specifications in Columns 2 - 5 of Table B.6 show the same result as Column 1: profits for non-cane crops were lower in private mill zones than in state-owned mill zones, by economically and statistically significant margins. Similar robustness checks were performed for the regression models used in other tables, and did not affect results substantially. For the sake of brevity, I present subsequent results using the baseline specification in Column 1.

[19]See Section 2.2.2 for a description of how state-owned mills are managed.

2.4.1 Decomposing Profits

What factors cause non-cane crops to have lower profits in private zones? Was less land devoted to non-cane crops, or were per acre profits lower? Were revenues lower, or costs higher?

Table B.7 examines how mill ownership affects profits per acre, and finds similar results to those in Table B.5: On a per acre basis, non-cane crop profits are significantly lower in private mill zones, except amongst those who also grow sugar cane. Thus, profit effects in private zones were not caused solely by shifts in land use away from non-cane crops. Cane profits per acre are not significantly affected by mill ownership, but appear slightly lower in private zones. Since aggregate cane profits are slightly higher in private zones than state-owned zones, this suggests that more land is devoted to growing cane in private zones.

Table B.8 examines land use changes explicitly. Because data entry errors in the primary data set caused some land usage data to be misreported[20], I additionally report more reliable results from the pilot survey dataset collected by Mullainathan and Sukhtankar to verify the border discontinuity. Despite errors in the primary dataset, the two datasets show generally consistent ownership effects: Columns 1 and 3 report how the percentage of each farmer's land used to grow cane differed between private and state-owned mill zones, from the primary and pilot datasets, respectively. These columns show that the proportion of farmed land used for cane development is higher in private zones - by 8%, in Column 3. Columns 2 and 4 examine land use changes solely on the extensive margin, by showing the effect of mill ownership on the total number of households growing any amount of sugar cane. While ownership effects are not significantly different from zero, Column 4 shows that about 7%

[20]Two surveyors appear to have used the tenths and hundredths columns for cane acreage on the questionnaire to report whole units. These errors were caught by consistency checks of the data, and do not appear to occur in other parts of the dataset. There is no evidence that the errors differently affected data in private and state-owned zones, but they increase the variance of results that examine ownership results.

more households grew sugar cane in private zones than in state-owned zones, on average.

Table B.9 decomposes profits a different way, by examining differences in revenues and costs per acre between public and private mill zones. Columns 1 - 3 show no statistically significant changes in revenue for either cane or non-cane crops between ownership structures, although cane revenues rise in private areas, on average, while non-cane revenues fall. Column 4 shows that cane costs rise along with cane revenues in private areas, although results are again not statistically significant. The most striking results are in Column 5 and 6: costs for crops other than sugar cane rise substantially and significantly in private areas. This implies that higher costs are the reason for decreased non-cane profits in private zones. Column 6 shows that this result only holds for farmers that grow non-cane crops exclusively; those that also grow cane have only slightly lower non-cane costs in private zones than in state-owned zones.

Columns 3 and 6 also show another notable result: the coefficients for *GrowsCane* are significant and positive in both columns. Thus, regardless of whether farmers live in private or state-owned mill zones, their non-cane revenues and costs are affected by whether they grow sugar cane. This suggests that farmers who grow both sugar cane and other crops either conflate the costs of different crops, or use inputs for one crop to grow another. Since most crop inputs are common to both sugar cane and other crops grown in Tamil Nadu, both scenarios are plausible.

Table B.10 repeats the analyses in Table B.9 for revenues and costs per acre, and finds similar results: Costs for non-cane crops are higher in private zones for those who do not grow any sugar cane, while those who grow cane do not appear to be affected by mill ownership differences.

Table B.11 examines costs in greater detail, and reveals that fertilizer, labor, and harvesting costs are all substantially and significantly higher for non-cane crops in private zones. Again, the models that include interaction terms show that farmers growing non-cane crops who also grow sugar cane do not appear to be affected by ownership structure. Unfortunately, sugar cane costs were not categorized in the same way as non-cane costs in our data, so a direct comparison of sugar cane and non-cane cost components is only possible for fertilizer and pesticide. In neither of these categories do costs for sugar cane differ significantly between private and public zones.

2.4.2 Explaining The Results

The results of this analysis suggest that differences in sugar mill ownership have strong effects on profits and costs for those who do not farm sugar cane, while the profits of those who farm sugar cane seem to be largely unaffected by ownership. Specifications that separately estimate effects on those who farm *no* cane and those who farm at least *some* cane reveal that the cost hikes found in private areas for non-cane crops are isolated to those who do not farm any cane. This suggests that the higher costs are defrayed for those who have some relationship with the sugar mill in a private zone.

One theory to explain the cost findings is that more efficient farmers in private areas are drawn to farming sugar cane; thus, those who remain to farm crops other than sugar cane are less efficient, and therefore have higher costs. This type of selection is broadly consistent with the theoretical implications of incomplete regulation detailed in Section 2.2.1: if private sugar mills are more free to find innovative ways of maximizing profits than their public counterparts, they may entice farmers who are more productive to switch to sugar cane in ways that public mills cannot. However, if this were the case, we would expect to see greater profits per acre for cane farmers in private areas due to their higher productivity, along with some evidence of enticement. Instead, Table B.7 reveals that cane farmers in private areas have lower profits per acre than their public counterparts, on average.

Another theory that explains why non-cane costs are higher in private mill zones is that private sugar mills deliberately raise the costs of non-cane crops, while keeping sugar cane costs low.

Because sugar mills can increase their profits by encouraging sugar cane development within their zones, they have an incentive to discourage farmers from growing other crops. In addition, the ties that sugar mills have to large suppliers of crop inputs gives them a potential means to influence these markets by raising input costs. Although most inputs are common to both sugar cane and other crops, mills can sell inputs directly to sugar cane growers, and thereby keep their costs low relative to those of non-cane farmers who purchase in the open market.[21] If private mills are more profit-motivated than state-owned firms, or are more free to act where regulations do not restrict them than state-owned firms with clearly stipulated goals, then we might expect these opportunities to be taken up to a greater degree in private mill zones.

This explanation is consistent with the key results of the analysis: Farmers who do not sell sugar cane have substantially higher costs in private zones than state-owned zones, while cane costs are not significantly different. The fact that private zone farmers selling sugar cane have lower costs even for non-cane crops may be due to cross-subsidization - that is, these farmers may use inputs obtained from mills to grow crops other than sugar cane.

However, the type of mill behavior described in this theory is only optimal under certain conditions, since raising input costs above their equilibrium levels reduces profits for those selling inputs. While identifying whether these optimality conditions hold is beyond the scope of this paper, two key factors are a sufficiently low elasticity of demand for the non-cane inputs whose prices are raised by private sugar mills, and a sufficiently high propensity for farmers to substitute between growing cane and other crops.

Demand elasticities for the inputs whose prices are raised by mills are plausibly quite low.

[21] A more complete discussion of the incentives and channels by which sugar mills can influence crop costs is provided in Section 2.2.2.

Anecdotal evidence suggests that the agricultural conglomerates which co-own or partner with private mills are large, and have regional market power. Moreover, farmers in rural Tamil Nadu have strong social ties to their villages, and may be unlikely to purchase inputs outside of their local store, even if prices are higher. A high propensity to substitute between growing cane and non-cane crops is also plausible, given that most local crops can be grown on the same land, and that there is a lack of occupational alternatives to farming for most farmers.

In addition, results for land use changes in Table B.8 show an economically and statistically significant increase in the proportion of sugar cane planted in private zones relative to state-owned zones, although the number of additional farmers growing sugar cane is not statistically significantly higher.[22] Such land shifts lend credibility to the idea that growing non-cane crops is a strong occupational substitute for growing sugar cane, and also suggests that private firms were successful indiscouraging non-cane crops, under this theory.

Regardless of the mechanism by which costs are raised for non-cane farmers in private zones, the findings of this study have important implications to our understanding of the differential impacts of state-owned and private firms in regulated policy environments. I conclude with a summary of these implications.

2.5 Conclusions

This paper examines the differential impacts of state and private firm ownership by looking not only at direct stakeholders of these firms, but also at those in related markets that firms could profitably influence. It takes advantage of an unusually clean setting for identifying ownership effects - the sugar mill zoning system in Tamil Nadu, India - and examines how

[22] The fact that land use changes were only significant on the intensive margin may indicate that a degree of specialized knowledge is required to farm sugar cane.

private and state-owned mills affect both farmers who grow sugar cane, and those who grow other crops that serve as substitute activities for growing sugar cane.

The study's findings provide several insights into how state-owned and private firms can differently impact the economies in which they exist, and about how regulations affect the incentives of private firms.

Most directly, the paper finds that private mills substantially reduce profits and raise costs for those who do *not* sell to them - growers of other crops. By contrast, the profits of those who sell sugar cane to mills are not materially affected by mill ownership type. While most studies focus on the efficiency differences between private and state-owned enterprises, these results highlight relevant consequences of ownership structure on other stakeholders in society, including those operating in separate but related markets.

These findings also illustrate how regulations can create incentives for private firms to act in ways that were not anticipated by policymakers. Although the intention of the Tamil Nadu's zoning policy was to create incentives for mills to increase sugar cane productivity, it also increased incentives for firms to discourage farmers from pursuing alternatives to sugar cane farming. The fact that state-owned mills do not appear to act on these incentives may suggest that they are more bound to fulfill the goals of the state explicitly, or are otherwise less motivated by profits.

This presents a challenge to the theory that regulated private firms and state-owned firms are equal in their ability to achieve the goals of the state, and differ only in their efficiencies of operation. Indeed, the same forces of innovation that cause private firms to outperform state-owned firms may lead to unanticipated consequences for regulators.

CHAPTER 3

The Impact of Climate Change on Crop Yields in India from 1961 to 2010

With Wolfgang Buermann and Deepak Rajagopal

Chapter Abstract:

The study of climate change impacts on Indian agriculture has gained recent attention, due to the size of India's agricultural sector, and reports suggesting that developing countries are more vulnerable to negative climate change effects. Studies in India have focused on predicting future trends using standard climate change scenarios from externally developed models. However, these studies are not generally able to provide accurate error estimates of their predictions, and are limited in their consideration of farmer adaptations that may offset climate change impacts. This study examines the impact of historic climate change trends over a 50-year period, and develops a model that accommodates a number of farmer adaptation possibilities. We are unable to find that temperature and precipitation trends have had a significant impact on major crop yields over our period of study, under any of the specifications we test. Our results emphasize the importance of error measurement when predicting outcomes, and suggest that adaptation may play a role in mitigating adverse climate change effects.

3.1 Introduction

Much attention has been given to the effects of climate change on agricultural output, because of the relevance of agriculture to the world economy, and the sensitivity of crop yields to climate conditions. Historically, much of the work on climate change impacts has focused on US outcomes, but recent work has increasingly studied developing countries, following predictions that the greatest short-term consequences of climate change may exist in the developing world.[1]

A small but growing literature studies impacts in India, where the agricultural sector is a critical component of the economy. In 2011, agriculture accounted for 18.1% of India's GDP, and 52% of employment, compared to 1.2% and less than 0.7% in the US, respectively.[2] Climate change impacts on India can have far-reaching consequences, as well: India is the world's second largest producer of of agricultural outputs[3], and any changes in production due to climate change could materially impact global agricultural imports and exports.

Recent studies on climate change impacts in India project future outcomes under a variety of scenarios.[4] These studies typically estimate yield sensitivity coefficients from existing data, and then use climate change predictions from external climate change models to project yield changes. One drawback of this approach is that these studies are generally unable to provide accurate standard errors of their final predictions, since their results depend on the accuracies of specific scenarios that make assumptions about future policies and behaviors. Another drawback is that most of these studies make few allowances for farmer adaptations to climate

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[1] Stern (2006), Rosenzweig and Parry (1994)

[2] CIA World Factbook (2012)

[3] FAO Statistical Yearbook (2012)

[4] Guiteras (2009), Aggarwal and Mall (2002), Kumar and Parikh (2001), Saseendran et al (2000), Lal et al (1998), and Aggarwal and Sinha (1993) are all examples.

change.[5]

When considering adaptation, studies in the global literature broadly fall into four categories. Crop modeling studies typically study the reactions of plants to varying climate conditions in controlled environments.[6] The advantage of these studies is their ability to experimentally assess how plants respond to climate adjustments in the absence of other confounding factors. However, farmer adaptations to climate change are difficult to consider in these settings. While some studies attempt to test specific adaptive responses such as planting time adjustments[7], these may differ from the actual range of responses that take place.

Other studies use time-series data in a single region to examine how climate changes have affected yields in practice. While these studies accommodate any responses that farmers can make on a year-to-year basis, they are unable to account for longer-term adaptations that farmers may make, particularly if changes in technology over time occur simultaneously.

Cross-sectional studies mitigate these concerns by studying the effects of climate change over geographically and climatically diverse regions. Because those who farm in statically different environments will have adapted their technologies and crop choices to suit their region, these studies account for some long-term adjustments to climate changes.[8] Nonetheless, such studies may fail to take into account other regional differences that are correlated with climate differences and affect yields, leading to bias in their estimates.

Recently, panel data studies have emerged that attempt to correct the limitations of both cross-sectional and time-series studies, by accounting for fixed regional effects, and

[5]Exceptions are Guiteras (2009) and Kumar and Parikh (2001), who consider some adaptation possibilites.

[6]Iglesias, Erda, and Rosenzweig (1996) review crop modeling studies in Asia.

[7]See, for example, Matthews et al (1995).

[8]Mendelsohn, Nordhaus, and Shaw (1994) is an influential example in this category; Kumar and Parikh (2001) apply this approach in India.

estimating the effects of climate change variable changes non-linearly over a diversity of regions and climates.

This study aims to contribute to this last category of the literature by assessing how climate changes have affected the yields of major crops in India, over a 50-year time period from 1961-2010. We relax several modeling assumptions of the existing literature that restrict the ways in which farmers can adapt to changes, and exploit the considerable climatic diversity across regions of India to determine how yields respond not only to short-term weather fluctuations, but to long-term temperature and precipitation level differences. We find that there has been no clear impact of climate change on the yields of crops we study, over the 50-year period.

Our paper is most closely related to two recent papers, Lobell et al (2011) and Guiteras (2009). Lobell et al (2011) examines a 20-year country-level panel to estimate historical global impacts of temperature and precipitation trends on crop yields, and find that changes have reduced yields for some crops. However, using country-level data may overlook climatic differences within each country, and could overstate yield losses if farmers in regions more prone to harmful climate changes for affected crops are less likely to grow those crops, or employ differential production processes. Guiteras (2009) studies temperature and precipitation effects in India, and uses a 40-year district-level panel to estimate the sensitivity of yields to climate changes. The study then predicts climate change effects beyond 2010 under a variety of climate change scenarios generated by external models. However, these results are averaged over the crops studied, and evidence suggests that crops differ in their sensitivities to climate changes.[9] Thus, if farmers make crop choices partly in response to their suitability to regional climate conditions, these results may overestimate yield reductions.

By considering region-specific panel data on climate variables and crop outcomes, and es-

[9]Schlenker and Roberts (2008) show, for example, that the point beyond which temperatures become harmful to yields differs amongst crops.

timating effects separately across crops, we hope to overcome some of the limitations of previous work. In addition, we consider region- and crop-specific technology trends, temperature-precipitation interaction terms, seasonal yield variations, and season- and region-specific climate trends, to avoid any potential bias from averaging across these dimensions.

Lastly, our study differs from Guiteras (2009) and other studies of climate change impacts on crop yields in India in that we estimate historical impacts, and not future predictions. Because we calculate climate trend estimates and yield sensitivity estimates within a dataset of realized observations for the same regions and years, we are able to determine the precision with which our impacts are estimated.

3.2 Data and Methodology

3.2.1 Data

Our study makes use of state-level data on seasonal crop yields for 5 major Indian crops - rice, wheat, sorghum, cotton, and sugarcane - during the period from 1961 to 2010, obtained from the IndiaStat database.[10] For the same period, we use state-level monthly temperature and precipitation data for 32 regions of India, obtained from the University of Delaware Terrestrial Air Temperature and Precipitation dataset.[11]

Crops are grown in three seasons in India. The *Kharif* growing season takes place from June to October, and encompasses the bulk of aggregate production. The *Rabi* growing season is from November to May, and is important for crops such as wheat. The *Annual* growing season encompasses the entire year, and is associated with crops that have year-long production cycles, such as sugarcane. In this study, we average climate data over the months

[10] Available at `http://www.indiastat.com`

[11] Available at `http://climate.geog.udel.edu/~climate/`

corresponding to each of the three yearly growing seasons in India, so that each crop yield is matched to the mean temperature and precipitation for its growing season.

Table E.1 provides information about the states and seasons in which each of the crops we study were grown in our sample. Of the crops studied, rice and sorghum are grown in multiple seasons in some states, while cotton, wheat, and sugarcane are grown exclusively in one season. While rice, a staple food throughout India, is grown in nearly every state, there is considerable geographic variation amongst other crops. Table E.2 reports the average yields of each crop in each state, and reveals considerable heterogeneity in the yields of different crops, and also in the yields of a single crop across regions. Differences in yields across regions may point to varietal differences in crops not captured in our data, but may also be linked to regionally disparate technologies for crop production, and varying climate conditions.

Tables E.3 and E.4 show how climate conditions vary across regions and seasons. Again, there is considerable variation across regions: In mountainous northern regions such as Sikkim, Jammu, and Kashmir, average *Rabi* (November - May) season temperatures are near 0 degrees Celsius, while southern states such as Kerala and Tamil Nadu have averages above 26 degrees during the same season. For these reasons, increases in temperature over time may be beneficial in some regions, by limiting the number of days with extreme cold weather, and harmful in others, by increasing the number of days with extreme hot weather. Precipitation patterns are also diverse, across both seasons and regions. In the typically wetter *Kharif* season, states such as Meghalaya bear an increased risk of flood damage to crops as precipitation levels rise, while drier states like Rajasthan may benefit from increased rainfall.

Climate conditions also influence the crops that are produced in various regions. Cotton production is sensitive to frost, and is avoided in the colder regions of India's north and northeast; on the other hand, wheat is grown in much of the north, as it is relatively less sensitive to cooler temperatures (Table E.1).

These factors suggest a model of climate change and yield that accommodates heterogeneity across seasons, regions, and crop choices, when estimating effects. Section 3.2.2 proceeds by discussing how our model addresses these needs.

3.2.2 Methodology

To estimate how climate trends have affected crop yields in India, we model the effects of temperature and precipitation on yields across all regions of India for the 50-year period, controlling for yield trends owing to technological improvements, and the fixed effects of each region-season-crop combination (the yield model). We separately estimate how climate conditions changed over time, and construct a de-trended set of climate data that preserves the variance of the original data, but keeps climate conditions constant, on average, over the period of our study (the climate change model). We then compare the yields that were observed in the data with counterfactual yields that would have been observed in the absence of climate trend by fitting the de-trended set of climate data to our yield model.

In using a fixed effects estimation with a time trend to estimate climate change effects on yield, our yield model broadly follows Deschênes and Greenstone (2007). The value of this approach is that it exploits year-to-year fluctuations in climate conditions to estimate climate effects on yield, while controlling for regional productivity differences and any long-term trends. If year-to-year fluctuations are essentially random, then, our estimates of the effects of temperature and precipitation on yields should be free of any omitted variable bias.

Our yield model allows substantially more flexibility in assessing the effects of climate in yields than Deschênes and Greenstone (2007), by including separate temperature and precipitation effects for each crop; interacting temperature and precipitation effects; allowing level yield differences for each region, crop, and season combination; and, allowing region- and crop-specific technology trends. This flexibility is afforded by the resolution of our data and the length of time over which we calculate our effects, and allows climate change effects to emerge in the data without restrictive assumptions or averaging across heterogeneous crops, regions, and seasons.[12]

In fitting our yield model to de-trended climate data, we follow Lobell et al (2011). Like the Lobell et al study, we allow climate variables to affect yields quadratically, so that level differences in climate conditions can have different effects on yields. This allows us to account both for the fact that temperature and precipitation effects may change direction, and for long-term adaptations that farmers may make in response to climate trends, using information about how farmers in various regions have adapted to level climate differences.

3.2.2.1 Farmer Adaptations

Farmers may adapt to both short- and long-term changes in climate conditions, when choosing crops and production technologies. In addition, exit and entry into farming may differ under different climate conditions. Because the effects of climate variation on yield are estimated in our yield model using the yields realized under varying year-to-year climate conditions, we accommodate any within-year adjustments that farmers make in advance of a growing season based on anticipated temperature or rainfall, along with any adaptations made during a growing season, as actual temperature and rainfall levels are observed.

To accommodate crop choices that are adapted to regional climate characteristics, our model estimates a separate set of climate effects on each crop's yields, and considers the crops grown in each region and season separately. This poses advantages over models that pool crops or regions when estimating the effects of climate change on yield, since these models can overstate the impacts of harmful climate changes on crop yields, if farmers choose hardier crops in regions with extreme temperatures. Because we observe crop choices

[12] Sections 3.2.2.2 and 3.2.2.3 discuss these features of the model in greater detail.

and temperatures at the state level, and apply our de-trended temperature set at the same level, estimated yield impacts are derived only from the crops that are actually grown within each region.

Additionally, because we use non-linear climate effects on yield and observe farmer responses in regions with diverse climates, wherein farmers have had time to adjust to changes in level, our yield model captures how yields may differ in climates with different average temperature and precipitation levels. To this extent, our estimates of counterfactual yield levels account for long-term farmer adaptations.

However, two potential issues exist in our consideration of long-term adaptations: First, shifts in production across crops, and to alternate economic activities, are not captured in our de-trended counterfactuals. In practice, there are several reasons why these adaptations may occur very gradually in India. Difficulties in transferring land rights, along with the dominance of the agricultural sector in rural regions, could effectively prevent responsive exits from farming occupations in adverse conditions.[13] Additionally, low rates of technological investment and adoption are commonly observed in India and other developing countries, and are often attributed to uncertainty in returns on investment due to short-term climate variability, credit constraints, and limited access to information.[14] Lastly, farmers may not be able to detect the signal of climate change amidst the "noise"of climate variability.[15] These issues may be particularly relevant in our study, as Figures E.1 and E.2 indicate that long term climate patterns in India have been complex, and year-to-year variations are large relative to trends.

Empirical evidence also suggests that long-term adaptations are limited, even in developed countries. Schlenker and Roberts (2009) find that maize yield responses to extreme

[13] Moorthy (2012)

[14] Giné et al (2010), Guiteras (2009), and Feder, Just, and Zilberman (1985) all discuss these issues.

[15] Kelly, Kolstad, and Mitchell (2005), and Reilly and Schimmelpfennig (2000)

weather do not differ between time-series and cross-sectional models, suggesting that long-term adaptations are not different from year-to-year adaptations.[16]

A second issue in our model is that long-term yield responses may be mixed with short-term responses in our model, to some degree. At a given temperature and precipitation level, yield observations may arise from a spectrum of groups: at one end, farmers who, on average, receive those levels of temperature and precipitation, and whose growing practices have adapted to those conditions; and, at the other end, farmers who are experiencing very anomalous weather, and are able only to make short-term adjustments to accommodate these conditions.

This issue is less likely to occur when deviations within regions are small relative to differences between regional averages. In our sample, the standard deviation of temperatures within a region was never greater than 0.61 degrees Celsius, except in one case,[17] and the range of temperatures across regions was large (see Table E.3). Similarly, the standard deviation of precipitations was never greater than 38.38 mm, except in one case,[18] despite large differences between states. More formally, F tests of climate differences across regions reveal an F-statistic of 1352.52 for temperature and 110.46 for precipitation, indicating that variance between states was substantially greater than variance within states.

3.2.2.2 The Yield Model

Our yield model specifies how climate change variables affect crop yields, while controlling for technological changes over time, and the fixed effects of crops, regions, and seasons. It assumes the following:

[16]A corollary to these arguments is that our use of static climate differences across regions may *too greatly* account for long-term adaptations. We discuss this possibility further in our conclusions.

[17]Jammu and Kashmir had a standard deviation of 1.15 degrees.

[18]For precipitations, the exception is Meghalaya, with a standard deviation of 87.66 mm.

$$Y_i = \alpha_{rcs} + \beta_{1,rc} * Year_i + \beta_{2,rc} * Year_i^2 + ClimateVars_i * \theta_c + \epsilon_i \tag{3.1}$$

where: i indexes each observation of a region, crop, season, and year; r indexes regions; c indexes crops; and, s indexes seasons.

Yields. Y_i, the dependent variable in Equation 3.1, is a measure of crop yield (output per unit of area). In our primary specification, we estimate log yields:

$$Y_i = Ln(\frac{Production_i}{Area_i}) \tag{3.2}$$

This assumes that unit increases in temperature and precipitation incur a percentage change in yield, and follows previous work in the field[19] However, other papers use unmodified yield as a dependent variable, assuming a linear relationship between climate changes and yield.[20] To account for both possibilities, we additionally test specifications using unmodified yields, and report coefficients and results from these variants.

Fixed effects. For each region, crop, and season combination, we allow the model to estimate a separate base yield, α_{rcs}. Separating base yields along these dimensions allow our model to capture the substantial level differences in yields among crops and regions (see Table E.2), along with any seasonal effects on yields that are not captured by our climate variables. Fixed effects not only absorb variance to gain clearer estimates of the effects of climate on yield; they also remove any bias in our climate coefficients resulting from correlations between regional characteristics and climate variables.

Climate effects on yield. θ_c is a vector of the main parameters of interest in the model, which capture the effects of each climate variable in the vector $ClimateVars_i$ on Y_i.

[19]See, for example, Lobell et al (2011), or Schlenker and Roberts (2008).

[20]Deschênes and Greenstone (2007) is an example.

In our primary specification, $ClimateVars_i$ includes a quadratic specification for temperature and precipitation:

$$ClimateVars_i = [Temp_i, Temp_i^2, Precip_i, Precip_i^2] \quad (3.3)$$

Correspondingly:

$$\theta_c = [\theta_{c,1}, \theta_{c,2}, \theta_{c,3}, \theta_{c,4}]' \quad (3.4)$$

This specification assumes that temperature and precipitation affect Y_i quadratically, so that increasing temperatures and precipitations can have positive effects at some levels, and negative effects at others.

While models allowing level effects of climate variable increases to vary are common in the literature, papers vary in their approaches to accommodating this variation. Ritchie and NeSmith (1991) suggests that crops have cutoff temperatures, above which increases are harmful, and a few papers explicitly model such cutoffs. However, evidence suggests that cutoff temperatures may vary from crop to crop[21], so that models adopting this approach may be misspecified if they average results across several crops, or otherwise apply the wrong cutoff to the wrong crop. Additionally, crop cutoff values may be correlated with regional climate characteristics that affect yields: for example, farmers may choose to grow crops that are more heat-tolerant in warmer regions. Thus, any misspecifications could lead to bias when estimating the effects of climate changes on yield.

The quadratic specification we use has benefits in this respect, as the data for each crop determine the temperatures and precipitations beyond which yield effects become harmful or beneficial. Additionally, the quadratic specification allows a different marginal effect at

[21] Schlenker and Roberts (2008)

all levels, so that farmer adaptations across regions with different temperature levels can be captured in the climate effects we estimate.

To accommodate the fact that crops may differ in their sensitivities to climate conditions, the vector of climate effects, θ_c, specifies a unique set of parameters for each crop. This allows temperature and precipitation changes to have a unique quadratic relationship with yield for each crop, and prevents bias in our yield impact results from correlations between regional crop choices and regional climate conditions.

Temperature-precipitation interactions. Temperature and precipitation may not have independent effects on yield. For example, temperature increases may be detrimental to yields beyond a certain point in a dry season, but beneficial until a later point during a wet season.[22] To allow precipitation levels to affect the relationship between temperature and yield, and vice versa, we additionally estimate the specification:

$$\begin{aligned} ClimateVars_i = [&Temp_i, Temp_i^2, Precip_i, Precip_i^2, \\ &Temp_i * Precip_i, Temp_i * Precip_i^2, Precip_i * Temp_i^2] \end{aligned} \tag{3.5}$$

Technology trends. Because technology improvements can affect crop yields, and technology trends may be correlated superficially with climate trends, the model controls for quadratic technology trends, whose effects are captured in $\beta_{1,rc}$ and $\beta_{2,rc}$. The quadratic specification of these trends broadly follows the specification in Lobell et al (2011), who allow a separate trend for each region they study. Because technology improvements may occur at different rates not only in different regions, but also for different crops, we calculate a separate trend for each region and crop.

[22] Runge (1968) discusses the relevance of these interactions for corn crops.

3.2.2.3 The Climate Trend Model

The climate trend model estimates the trends in temperature and precipitation over the 50-year period separately for each region and season. Our general specification is:

$$\begin{bmatrix} Temp_i \\ Precip_i \end{bmatrix} = \gamma_{rs} + TimeVars_i * \omega_{rs} + \mu_i \tag{3.6}$$

where: $TimeVars_i$ is a vector of variables specifying the functional form of the trend; and, γ_{rs} and ω_{rs} are parameters that separately estimate the effects of time for each region and season.

Season- and region-specific climate trends have three benefits: they allow for more precise calculations of the effects of climate change on yield; they absorb geographic and within-year variations to clarify climate change trends; and, they reduce any bias in our overall estimates resulting from correlation between region-specific climate trends and region-specific yield trends.

To determine the appropriate functional form for the effect of time on climate change, we tested three specifications of $TimeVars_i$ to estimate a linear, quadratic, and cubic fit for a variant of Equation 3.6:

$$\begin{bmatrix} Temp_i \\ Precip_i \end{bmatrix} = \gamma_{rs} + TimeVars_i * \omega + \mu_i \tag{3.7}$$

Note that while fixed effects γ_{rs} are included in this specification, Equation 3.7 differs from Equation 3.6 in estimating a single parameter for each climate variable, ω. This allowed us to summarize the goodness of fit of each specification across all regions and seasons.

Our test results suggest that the quadratic form best fits the temperature data, while a cubic form best fits the precipitation data. Tables E.5 and E.6 show the parameter estimates under each functional form for temperature and precipitation trends, respectively.

Column (1) of Table E.5 implies that temperatures increased by slightly less than 0.5 degrees over the 50-year study period, after accounting for fixed regional and seasonal effects. Figure E.1 shows a more nuanced trend, using the quadratic fit in Column (2) of Table E.5: temperatures decreased initially, from 1961 - 1975, and then increased from 1975 - 2010.

Although Column (1) of Table E.6 suggests an overall decrease in precipitation over the study period, the cubic fit in Column (3) shows a more complex pattern of initial increases, followed by decreases, followed by increases. Figure E.2 depicts a graph of the cubic trend, and shows the underlying average monthly precipitation values for each year of data.

3.2.2.4 Estimating Climate Trend Impacts

To determine how climate trends have affected realized crop yields over the last 50 years in India, we use parameters obtained from the climate trend model to de-trend the realized observations of temperature and precipitation:

$$\hat{Temp}_{detr,i} = \hat{Temp}_{1961,rs} + (Temp_i - \hat{Temp}_i) \tag{3.8}$$

$$\hat{Precip}_{detr,i} = \hat{Precip}_{1961,rs} + (Precipi - \hat{Precip}_i) \tag{3.9}$$

The resulting de-trended climate variables preserve the residual variation of the original variables, but maintain constant average values across time that are equal to the predicted values for 1961, $\hat{Temp}_{1961,rs}$ and $\hat{Precip}_{1961,rs}$. A separate pair of base values is calculated for each region and season, so that each de-trended climate variable is sensitive to regional and seasonal fixed effects.

Next, the yield model is estimated using realized observations of temperature and precipitation, and the de-trended climate data are fitted to the estimated yield model to obtain predictions of what yields would have occurred in the absence of climate changes:

$$\hat{Y}_{detr,i} = \hat{\alpha}_{rcs} + \hat{\beta}_{1,rc} * Year_i + \hat{\beta}_{2,rc} * Year_i^2 + ClimateVars_{detr,i} * \hat{\theta}_c \tag{3.10}$$

To separate the effects of temperature and precipitation, we estimate $\hat{Y}_{detr,i}$ with three separate specifications for $ClimateVars_{detr,i}$: In the first specification, temperature variables are replaced with their de-trended values from Equation 3.8, but precipitation values are the values realized in the data. The resulting yield estimates reflect a counterfactual scenario in which average temperatures did not change during the last 50 years, but any precipitation trends still occurred. The difference between these yield estimates and the estimates from non-detrended data can thus be attributed to temperature trends. In the second specification, precipitation values are de-trended as per Equation 3.9, but temperature values come from the data. Here, yield estimates describe a scenario in which only temperature trends occurred, and differ from non-detrended estimates due to precipitation trends over the last 50 years. In the third specification, de-trended values are used for both temperature and precipitation, so that resulting yield estimates reflect a scenario in which neither temperature nor precipitation averages changed over the last 50 years.

To compare realized yields with estimated yields from each of these counterfactuals, we compute the percentage difference between each non-detrended estimate and its counterfactual value:

$$\%\widehat{Change}Yield_i = \frac{(\hat{Y}_i - \hat{Y}_{detr,i})}{\hat{Y}_i} \tag{3.11}$$

The resulting values, $\%\widehat{Change}Yield_i$, can be viewed as the estimated percentage changes in yield due to climate trends over the last 50 years. To obtain standard errors for these estimates, we employ a nonparametric bootstrap, and resample our data 5,000 times for each specification.

3.3 Results

3.3.1 Yield Model Results

Tables E.7 - E.11 show estimates of the effects of temperature and precipitation changes on the yields for different crops from the yield model. In each table, Columns (1) and (2) show results for the primary specification in Equation 3.2, where the dependent variable is $Ln(Yield)$. Specifications in Column (1) show very diverse effects of temperature on the crops studied - the level effect of temperature on cotton yields is over 100 times that of wheat. The range of precipitation effects is somewhat less diverse, although rice appears less sensitive to precipitation than other crops.

At the sample mean level of temperature, 22.13 degrees Celsius, Column (1) indicates that marginal temperature increases have a positive effect on yields for all crops but rice. Similarly, at the sample mean level of precipitation, 130.45 mm, precipitation increases have a positive effect on yields for all crops but wheat. Increases in temperature have diminishing effects on crop yields for cotton, sorghum, sugarcane, and wheat. Beyond a certain point (27.4 degrees Celsius, for cotton), temperature increases are detrimental for each of these crops. Results for precipitation show a similarly concave relationship between increased rainfall and crop yields. Beyond a certain precipitation level (an average monthly precipitation of 340.5 mm, for cotton), increases are harmful, presumably due to an increased probability of flooding. These results are statistically significant at a 0.01 level, and are broadly consistent with other estimates of climate impacts on crop yields in the literature, which show diminishing marginal effects of temperature and precipitation on yields, and negative effects beyond the same approximate levels.[23]

[23] See, for example, Schlenker and Roberts (2008).

Results for rice show a convex relationship between temperature and yields, and between precipitation and yields. Temperature increases have a detrimental effect on yield *until* 23.7 degrees Celsius, after which yields increased. While these effects are different from those of other crops, they are not inconsistent with the literature: Welch et al (2010) finds that rice crops in tropical and subtropical Asia have higher yields as maximum daily temperatures increase, and lower yields as minimum daily temperatures increase. Although our data report monthly average temperatures, and do not distinguish maximum and minimum temperatures, the effects found by Welch et al could plausibly explain our findings. In addition, the coefficients for both temperature and precipitation effects on rice yields are very small, though significant - for example, the level temperature and precipitation coefficients for rice are less than 1/10th of those for sugarcane, sorghum, and cotton. Temperature coefficients for wheat are similarly very small, indicating that the range of temperatures observed had little impact on yields for both crops.

Column (2) includes interaction terms between temperature and precipitation that allow level differences in precipitation to affect the relationship between temperature and yield, and vice versa. For sorghum, rice, and sugarcane, the interaction terms reveal that temperature effects on yield were relatively less detrimental as precipitation levels increased. For cotton, increasing precipitation levels have the opposite effect - they cause temperatures to be relatively more harmful to yields, and decrease the temperature beyond which increases are harmful. For wheat, Column (2) suggests that any precipitation level beyond about 30 mm of average rainfall per month causes the temperature function to become convex. However, because coefficient values for wheat are extremely low (though statistically significant) in both Columns (1) and (2), any changes in yield due to temperature effects are minor, regardless of the precipitation level. Most of the coefficients in Column (2) are significant at a 0.01 level, although the level precipitation effect for wheat and the precipitation-temperature interaction effect for rice are exceptions.

Results in Columns (1) and (2) demonstrate that temperature and precipitation changes have significant effects on yields, but that these effects vary greatly across crops. In columns (3) and (4), the dependent variable is changed to $Yield$, following the specifications of Deschênes and Greenstone (2007). Results are qualitatively similar, but less statistically significant for cotton, sorghum, and rice.

3.3.2 Climate Model Results

The climate model estimates temperature and precipitation trends for each of the 32 states and 3 seasons in our sample for which we have data. As Tables E.5 and E.6 show, when a single trend is estimated across the entire sample, trends are significant for the quadratic temperature trend and cubic precipitation trends that we use in our primary specification.[24]

When quadratic temperature trends were separated by state and season, the coefficients for many state-season combinations were insignificant. Of the 25 state-seasons with statistically significant temperature coefficients, all showed similar convex trends to the pooled quadratic trend in Column (2) of Table E.5, with temperatures initially declining over the period, and then rising.

Figure E.3 compares temperature data for the *Rabi* season in the state of Uttarakhand, which had statistically significant temperature trend coefficients, to that of the *Rabi* season in the state of Chhattisgarh, which did not. The graphs demonstrate that significance differences were not due to different amounts of data used to estimate the two trends - indeed, all state-seasons had temperature and precipitation data for at least 47 of the 50 years in the study.

Few precipitation trends had significant coefficients for all of the 3 cubic parameters, when separated by state and season. All of the 6 state-seasons for which coefficients were

[24] Because of the large number of coefficients estimated, we do not display results for individual state-season climate trends in this paper. These results can be obtained from the authors upon request.

significant showed a similar pattern to the pooled trend in Column (3) of Table E.6, with precipitation levels rising early in the period, then falling, then rising again. The larger number of insignificant state-season trends for precipitation may be partially due to the increased data demands of estimating a cubic trend, but also to a less clear pattern of precipitation change in the data. Figure E.4 compares the precipitation patterns for the *Kharif* season in the state of Meghalaya, which had significant trend coefficients, to patterns for the *Annual* season in the state of Maharashtra, which did not. Keeping the scales of both graphs constant, the comparison reveals stark differences in precipitation levels, trends, and in variance across state-seasons that underlie the overall sample trends in Table E.6.

To ensure that our estimations of climate trend impacts are not affected by the polynomial specifications we employ, we include linear trend lines in our alternate specifications for yield impacts.

3.3.3 How Climate Trends Have Affected Yields

To determine how climate trends affected yields during the period of our study, we create a set of de-trended climate variables from our climate model results that simulate temperatures and precipitations in the absence of any climate trends. When fitted to our yield model, the resulting yield estimates reflect yields in the absence of climate trends.

Table E.12 shows percentage changes in yield when de-trended data are fitted to the yield model. Positive percentage values indicate that realized yields were greater than their counterfactual values in no-trend scenarios. Negative percentage values indicate that realized yields were lower than their counterfactual values, and suggest that trends were harmful. Column (1) shows changes in yield when de-trended temperatures are used along with non-detrended precipitations, so that figures in this column depict the impact of temperature trends in isolation. Column (2) shows changes in yield when de-trended precipitation values are used with non-detrended temperatures, and decribes the impact of precipitation trends in isolation. Column (3) uses both sets of detrended climate variables, and shows the aggregate impact of both climate trends on crop yields.

No values in this table are statistically significant for cotton, sorghum, rice, and wheat, suggesting that climate trends did not have a measurable impact on these crops. For sugarcane, climate trends appear to have increased yields by about 1%, owing primarily to precipitation trends during the study period. These results are perhaps unsurprising, given climate and yield model results. Although our yield model shows that climate changes have significant effects on yields, and that yields decline beyond certain temperature and precipitation thresholds, effects are small at the mean values of temperatures and precipitations for most states in the sample (see Tables E.3 and E.4). In addition, climate changes during the period of study do not consistently increase or decrease. In overall sample calculations temperatures first decrease, and then increase after 1975 (Figure E.1). However, in most of the individual state-seasons for which trends are calculated, trends are insignificant. Precipitation patterns are even less clear. Overall sample trends first increase, then decrease, then increase again (Figure E.2), and individual state-seasons show considerable heterogeneity, and are largely without significant trends.

Table E.13 - E.15 show yield differences under alternate model specifications, to determine whether our results are sensitive to our specifications. In Table E.13, the interaction terms and coefficients shown in Column (2) of Tables E.7 - E.11 are used when fitting de-trended climate data. To determine whether our results are sensitive to the functional form of yield, Table E.14 uses the coefficients in Column (3) of Tables E.7 - E.11 when fitting the yield model, wherein $Yield$ is the dependent variable instead of $Ln(Yield)$. Finally, Table E.15 shows yield changes when linear temperature and precipitation trends are estimated in the climate model, instead of the quadratic and cubic fits used in other models, respectively.

None of these models show qualitatively different results from our original specification, except that sugarcane is no longer significantly affected by climate trends in most alternate specifications.

3.4 Conclusions

This study seeks to examine whether climate trends during the past 50 years have affected 5 major crop yields in India. By taking advantage of a panel data set that spans 32 regions within India, we construct a model that accommodates a variety of short- and long-term farmer adaptations, and that flexibly determines how climate variables affect yields.

We identify clear effects of climate variables on yields that suggest that temperature and precipitation increases can be harmful in some ranges, and helpful in others. However, we find that observed climate trends over the past 50 years have had almost no measurable effects on the crop yields we study, under any of the specifications we test.

Our inability to find any yield differences owing to climate trends is likely due to two factors: First, any farmer adaptations to varying regional climate conditions are expressed in our yield sensitivity coefficients (Tables E.7 - E.11), and may have offset the effects of climate change on crop yields in our analysis. These adaptations reflect long-term adjustments that the agricultural sector has made to level differences across regions, and could overstate the extent to which farmers were actually able to adjust to climate trends. On the other hand, some types of adjustments, such as shifts to hardier crop types, are not captured in our model, and could cause us to overstate climate trend effects on yields if such adaptations took place.

Second, the trends we estimate for each state and season over the past 50 years are relatively weak. Less than a third of the temperature trends estimated were statistically significant, and less than one tenth of precipitation trends were significant. Also, precipitation levels lost only 0.049 mm per year on average, or about 2.45 mm over the entire period (Table E.6). Our climate trend results are not inconsistent with other findings. Lobell et al

(2011) finds that temperature and precipitation trends in India were between 0 and 1 standard deviation of year-to-year fluctuations in most regions, and their maps show an even mix of positive and negative trends across regions.

It is important to stress that these results do not directly bear on predictions of the *future* impacts of climate change. The Intergovernmental Panel on Climate Change (IPCC) climate model projects that South Asia will experience an increase of 0.5 degrees Celsius along with a 4% precipitation increase from 2010 to 2039 during *Kharif* season months, in certain scenarios.[25] By 2100, some scenarios predict a 2 degree temperature increase, and a 7% precipitation increase.[26] Depending on regional variations, technology advances, and farmer adjustments, these changes could have significant positive or negative impacts on Indian agricultural output.

However, our results shed light on the importance of uncertainty in future impacts. Projections of future trends are estimated with considerable error, and do not benefit from realized year-to-year data for the periods they study, as our study does. Thus, studies reporting point estimates of climate change impacts without accurate error predictions can be misleading, with potentially costly implications to policymakers that rely on these estimates.

Moreover, the agricultural sector may adapt to any climate changes, and models that do not account for adaptations may overstate impacts. In our accounting of India's past, we find considerable heterogeneity in climate levels and trends amongst regions, and large differences in yield sensitivities to climate change across crop types. Studies projecting future implications of climate change may benefit from these considerations, since estimating average effects across regions and crops may bias climate change effects downward, if crop choices across regions are responsive to climate differences.

[25] Guiteras (2009)

[26] Kumar and Parikh (2001)

APPENDIX A

Chapter 1: Tables and Figures

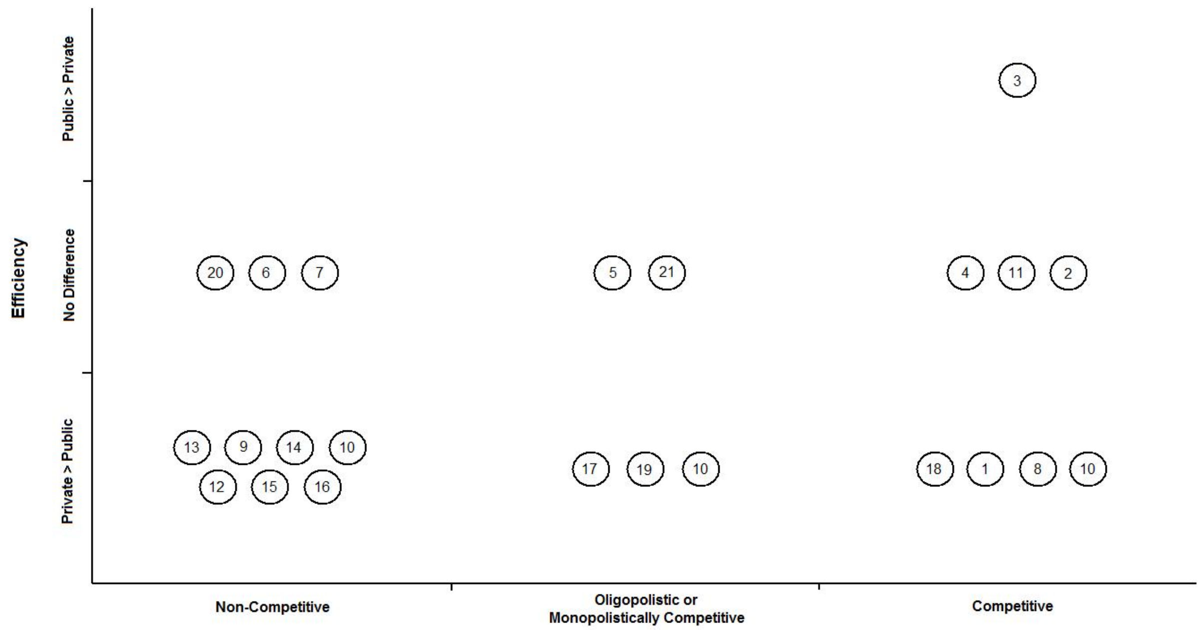
Table A.1: Empirical Literature

Study #	Study	Sector	Competition Level	Efficiency Findings	Measures	Comments
1	Diboky (2007)	Insurance in Germany	Highly Competitive	Private and "Mutual" > Public	Data Envelopment Analysis with a cost efficiency frontier; "output" includes gross premiums, which are sensitive to prices	
2	Goldar, Renganathan, Banga (2003)	Engineering in India	Highly Competitive	No Differences	Stochastic frontier function with a technical efficiency frontier	
3	Isik and Hassan (2003)	Banking in Turkey	Competitive	Public > Private	Technical efficiency (outputs / inputs)	The authors note that public banks enjoy lower factor costs than others
4	Altunbas, Evans, and Molyneux (2001)	Banking in Germany	Highly Competitive	No Differences	Stochastic frontier function with a cost efficiency frontier	
5	Cullinane, Song, and Gray (2001)	Container Ports in Asia	Oligopoly or Monopolistic Competition (15 ports that do not directly compete)	No Differences	Stochastic frontier function with a productive efficiency frontier	
6	Wallsten (2001)	Telecom in 30 countries in Africa and Latin America	Likely Non-Competitive: based on author's descriptions, and industry character. No indications of whether environment changed after privatization.	No Differences from ownership alone; with independent regulation, private firms are more efficient.	Labor productivity (output / employees)	Separates ownership from competition and regulatory effects
7	Boylaud and Nicoletti (2000)	Telecom in 23 OECD countries	Monopoly to Oligopoly	No Differences	Labor productivity (output / employees)	
8	Chen and Yeh (2000)	Banking in Taiwan	Competitive	Private > Public	Data Envelopment Analysis with a technical efficiency frontier; uncertain whether output definitions were price-sensitive	
9	Ros (1999)	Telecom in "approximately" 130 countries	Likely Non-Competitive, based on author's descriptions and industry character	Private > Public	Labor productivity (output / employees)	

Study #	Study	Sector	Competition Level	Efficiency Findings	Measures	Comments
10	La Porta and Lopez-de-Silanes (1999)	Multiple industries - Study 218 Privatizations	Both "Competitive" and "Non-Competitive", by authors' descriptions	Private > Public in both competitive and non-competitive settings; in competitive settings, the gap is significantly smaller	Costs per unit, and the share of profitability attributable to productivity	Evidence of subsidies to public firms equal to 12.7% of GDP
11	Kole and Mulherin (1997)	Multiple industries	Competitive: based on authors' assertion	No Differences	Return on assets, return on sales, sales per employee (all price-sensitive)	Authors report that the government had no agenda in ownership other than as a passive investor; firms were re-sold after an average of 7 years
12	Ramamurti (1997)	Railroads in Argentina	Monopoly, but faced high indirect pressure from other transport forms	Private > Public	Labor productivity (output / employees)	
13	Newberry and Pollitt (1997)	Electricity in UK	Monopoly before privatization; 4 firms after	Private > Public	Labor productivity (output / employees)	The study does not separate the effects of ownership and competition
14	Ramamurti (1996)	Telecom	Monopoly	Private > Public	Labor productivity (output / employees)	
15	Boles De Boer and Evans (1996)	Telecom in New Zealand	Monopoly, though two competitors in the last year; no entry barriers throughout study period	Private > Public	Rate of technical efficiency change (output per value of inputs)	Authors do not separate competition from ownership effects, though competition did not change until the last year of the study
16	Martin and Parker (1995)	Multiple industries	Low; Several case studies of firms that are primarily monopolies	Mixed results	Profitability and Value-Added (both price-sensitive)	Price-sensitive measures may have affected results
17	Ehrlich et al (1994)	Airlines	Oligopoly or Monopolistic Competition: trade association coordinated fares and restricted entry	Private > Public	Rate of unit cost change	Attempt to check whether ownership effects change with competition, and find that they don't

Study #	Study	Sector	Competition Level	Efficiency Findings	Measures	Comments
18	Vining and Boardman (1992)	Multiple industries	Borderline Competitive: 4-firm concentration varies from 14% to 43%	Private > Public	Sales per employee, sales per asset (price-sensitive)	Separates ownership from competition; price-sensitive measures may have affected results
19	Boardman and Vining (1989)	Mining and Manufacturing	Oligopoly to Monopolistic Competition (4-firm concentration is about 50%)	Private > Public	Sales per employee, sales per asset (price-sensitive)	Separates ownership from competition; price-sensitive measures may have affected results
20	Caves and Christiansen (1980)	Railroads in Canada	Duopoly, but faced high indirect pressure from other transport forms	Initially, Private > Public; later: No Differences	"TFP" (output per unit of real resources expended)	
21	Funkhouser and MacAvoy (1979)	Multiple in Indonesia	Mostly Non-Competitive, with the exception of a few agricultural sectors	Private > Public at 10% level; No Differences at 5% level	Average cost	Averages ownership effects across multiple sectors with different competition levels

Figure A.1: Studies by Competition Level and Relative Efficiency



Study numbers correspond to those listed in Table A.1.

Paper 10 appears in all three categories, as it explicitly studies ownership effects in varying competition environments.

APPENDIX B

Chapter 2: Tables and Figures

Table B.1: Sample Data Losses

	Original Sample	Those Surveyed	Those Used in Analysis
N	2935	1565	912
% Private	0.500	0.530	0.534
% Can Read		0.704	0.730
% Can Write		0.681	0.708
# Acres Owned		4.219	4.801

Table B.2: Soil Characteristics

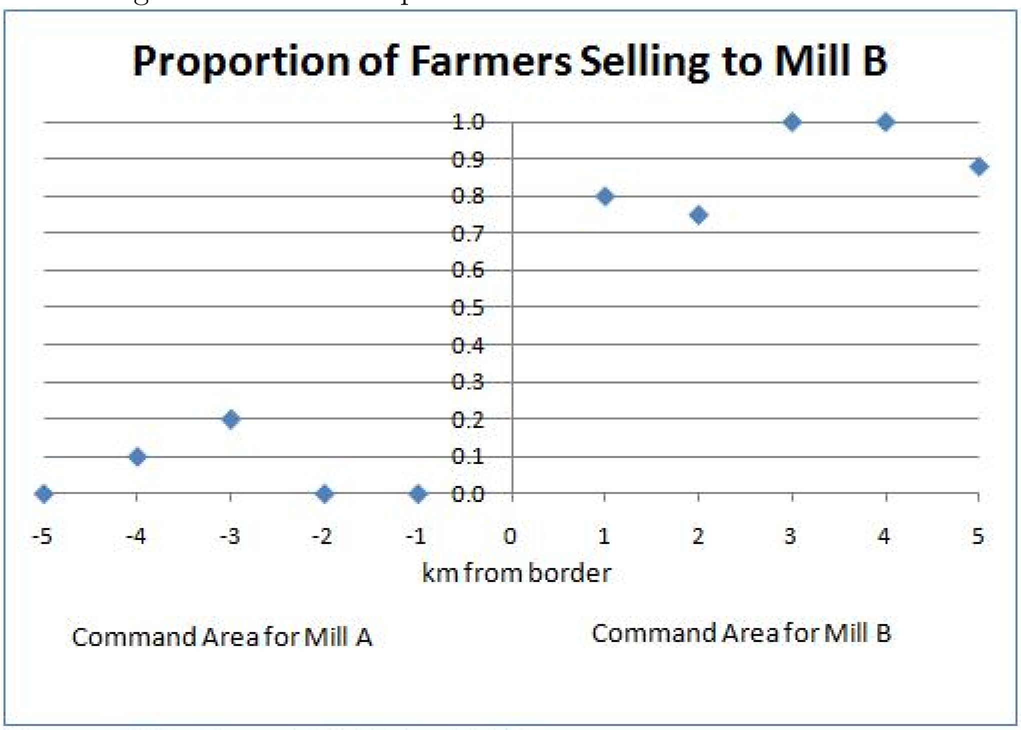
	Texture	Quality	Nitrogen	Phosphorus	Potassium
	(1)	(2)	(3)	(4)	(5)
private	0.1	0.1	-2.8	9.2	20.5
	(0.2)	(0.1)	(15.8)	(6.3)	(15.4)
Mean	2.4	-0.1	261.0	43.9	209.4
R^2	0.507	0.379	0.234	0.705	0.317
N	180	180	180	180	180

Standard errors in parentheses

Texture and *Soil Quality* refer to indices. *Texture* ranks the coarseness of each soil sample on a discrete scale from 1 - 5; *Soil Quality* ranks the quality of soil for each sample on a discrete scale from -1 to +1.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure B.1: Ownership Discontinuities at Mill Zone Borders



Source: Mullainathan and Sukhtankar (2011)
On the left: those who have ever sold to Mill B
On the right: those who have only sold to Mill B

Table B.3: Summary Statistics - Farmer Characteristics

	All Farmers		Grew Cane		Didn't Grow Cane	
	(1) Public	(2) Private	(3) Public	(4) Private	(5) Public	(6) Private
Years of Education	6.845	6.834	7.110	6.915	6.812	6.833
	(4.05)	(3.84)	(4.17)	(3.36)	(4.04)	(3.88)
Can Read	0.720	0.738	0.754	0.830	0.707	0.730
	(0.45)	(0.44)	(0.43)	(0.38)	(0.46)	(0.44)
Can Write	0.701	0.715	0.712	0.798	0.695	0.704
	(0.46)	(0.45)	(0.45)	(0.40)	(0.46)	(0.46)
Harvested Cane In The Last 12 Months	0.344	0.378				
	(0.48)	(0.49)				
Currently Grows Sugar Cane	0.326	0.349	0.872	0.882	0.044	0.022
	(0.47)	(0.48)	(0.34)	(0.32)	(0.21)	(0.15)
Owns Any Uninherited Land	0.211	0.287	0.231	0.266	0.212	0.316
	(0.41)	(0.45)	(0.42)	(0.44)	(0.41)	(0.47)
Acres Owned	4.635	4.940	5.680	6.675	4.054	4.187
	(4.20)	(4.50)	(4.24)	(5.35)	(4.17)	(4.11)
Acres Rented	0.597	1.089	1.107	0.265	0.368	1.504
	(4.26)	(11.28)	(6.99)	(0.79)	(2.07)	(14.22)
Acres Farmed	1.731	1.628	3.550	3.688	1.352	1.241
	(2.18)	(1.98)	(2.44)	(2.68)	(1.95)	(1.47)
Observations	375	431	118	94	249	270

Table B.4: Summary Statistics - Farmer Outcomes

	All Farmers		Grew Cane		Didn't Grow Cane	
	(1) Public	(2) Private	(3) Public	(4) Private	(5) Public	(6) Private
Total Net Income	114,351	77,739	198,460	143,982	95,974	65,163
	(188,122)	(193,977)	(175,128)	(185,503)	(186,777)	(196,753)
Total Farm Profits	48,009	18,723	134,170	105,063	24,066	3,103
	(138,489)	(115,530)	(151,927)	(160,529)	(102,450)	(102,043)
Total Farm Revenue	96,984	72,569	220,253	194,800	59,808	47,966
	(161,562)	(128,806)	(181,958)	(192,963)	(105,885)	(89,035)
Total Non-Cane Revenue	63,497	53,850	41,943	42,885	59,808	47,966
	(118,695)	(97,350)	(86,167)	(104,578)	(105,885)	(89,035)
Total Cane Revenue	33,667	19,163	169,644	145,529		
	(99,905)	(68,291)	(151,174)	(114,355)		
Total Farm Costs	48,975	53,845	84,366	85,603	35,742	44,863
	(65,693)	(93,159)	(70,642)	(105,348)	(52,190)	(92,760)
Total Non-Cane Costs	37,971	45,443	30,215	29,481	35,742	44,863
	(50,763)	(80,816)	(47,883)	(48,584)	(52,190)	(92,760)
Total Cane Costs	11,063	8,601	53,765	56,122		
	(34,493)	(39,002)	(42,691)	(72,031)		
Cane Yield (tons)			36.8	33.2		
			(11.2)	(14.2)		
Cane Produced (tons)			107.0	98.0		
			(91.1)	(70.5)		
Cane Price (per ton)			1,577.1	1,465.4		
			(342.3)	(377.0)		
Observations	375	431	118	94	249	270

Figure B.2: Zone Borders Included in the Survey

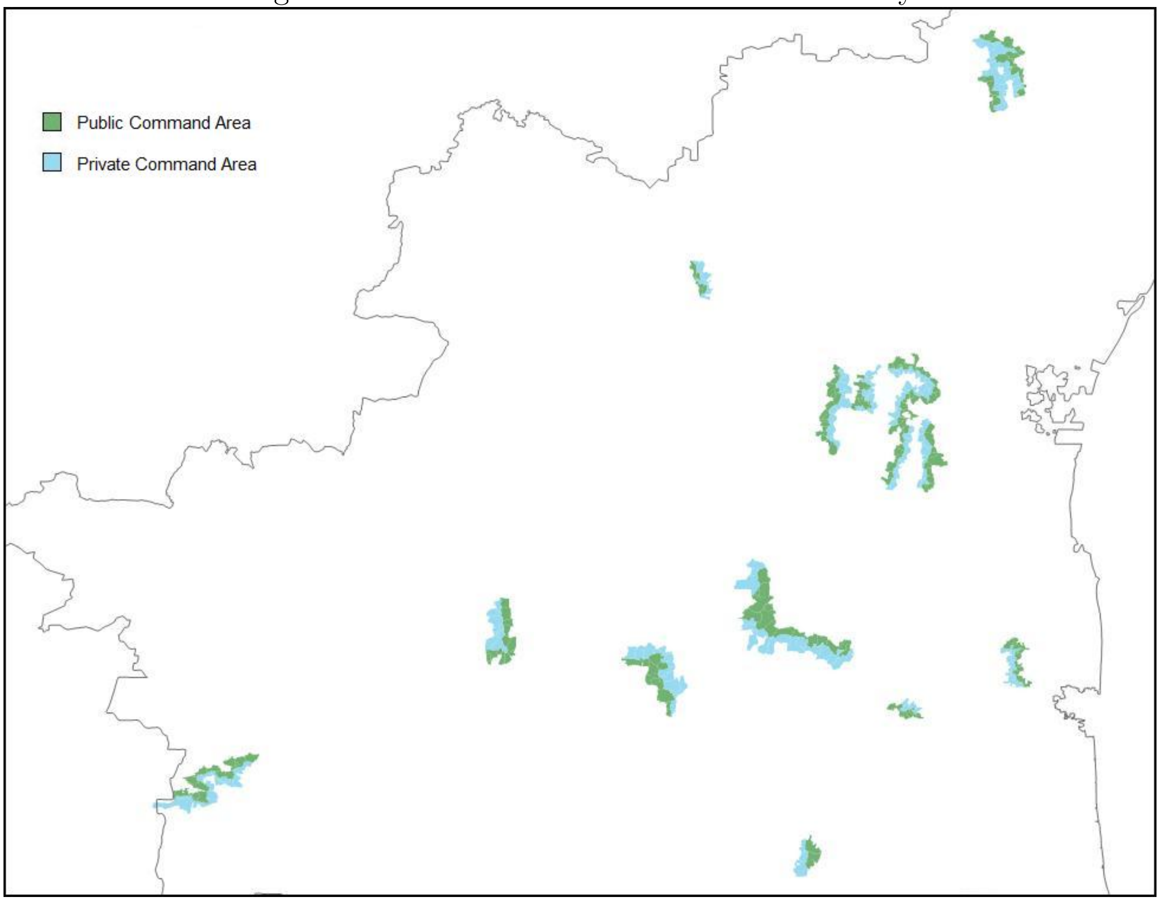


Table B.5: Net Income and Farming Profits

	Net Income		Farming Profit		Cane Profit	Non-Cane Profit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Private	-24,458.6***	-22,876.6***	-20,866.0***	-18,010.8***	3,409.1	-14,137.8***	-18,224.9***
	(7,296.1)	(7,293.5)	(4,269.3)	(3,671.7)	(15,602.3)	(3,185.0)	(3,269.7)
Grows Cane		54,148.7***		59,010.1***			3,005.3
		(12,537.9)		(15,181.6)			(9,879.8)
(Private) *		-1,393.7		-6,273.4			16,938.2
(Grows Cane)		(18,922.3)		(20,770.1)			(11,045.0)
Mean	85,241.9	85,241.9	21,220.4	21,220.4	96,995.2	9,368.8	9,368.8
R^2	0.061	0.074	0.081	0.123	0.098	0.076	0.081
N	806	806	806	806	216	824	824

Standard errors in parentheses.
All currency values are in Indian Rupees.
Each observation is a household.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Non-Cane Profit: Alternate Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Private	-18,225***	-18,225***	-19,221***	-19,409***	-20,396***	-.00773***
	(3,270)	(4,795)	(4,256)	(4,251)	(3,481)	(.00129)
Grows Cane	3,005	3,005	2,755	2,510	1,245	.000614
	(9,880)	(8,678)	(9,927)	(10,022)	(10,221)	(.00389)
(Private) *	16,938	16,938	17,490	17,752	19,418	.00716
(Grows Cane)	(11,045)	(10,621)	(11,102)	(11,272)	(11,464)	(.00436)
Distance to Mill			59.5	-57.1		
			(95.3)	(283)		
(Distance to Mill)^2				.805		
				(1.66)		
Mean	9,368.8	9,368.8	9,368.8	9,368.8	9,395.7	14.7
R^2	0.081	0.081	0.081	0.082	0.083	0.070
N	824	824	824	824	791	824

Standard errors in parentheses.
Column 1 shows results for the baseline specification, where *Non-Cane Profit* is the dependent variable, and standard errors are clustered at the mill level.
Column 2 shows results when the model is clustered at the village level.
Columns 3 and 4 add linear and quadratic terms for *Distance To Mill* to the specification in Column 1.
Column 5 omits the 2 public mills that are managed separately from the results.
Column 6 shows results when Log(Non-Cane Profit + K) is the dependent variable. *K* is used to shift the range of Non-Cane Profit values so that all values are positive.
All currency values are in Indian Rupees.
Each observation is a household.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Profit Per Acre

	All Crops		Cane	Non-Cane	
	(1)	(2)	(3)	(4)	(5)
Private	-7,399.3*	-8,778.5**	-4,304.2	-6,532.0	-11,158.8**
	(4,188.4)	(3,943.6)	(6,535.6)	(4,074.9)	(4,180.5)
Grows Cane		11,605.7			672.7
		(9,714.6)			(8,281.1)
(Private) * (Grows Cane)		6,923.2			18,898.6
		(12,663.2)			(11,089.5)
Mean	9,796.7	9,796.7	33,156.1	8,608.5	8,608.5
R^2	0.066	0.075	0.093	0.074	0.080
N	806	806	215	824	824

Standard errors in parentheses
All currency values are in Indian Rupees.
Each observation is a household.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Land Use

	This Survey		Pilot Survey	
	(1) % Land Cane	(2) # Hhds Grew Cane	(3) % Land Cane	(4) # Hhds Grew Cane
Private	.0248	.0546	.0805*	.0695
	(.0649)	(.124)	(.042)	(.045)
Mean	.143	.318	.40	.38
R^2	0.002	0.003	0.227	0.484
N	815	812	989	1,037

Standard errors in parentheses
Each observation is a household.
% Land Cane is the percentage of farmed land devoted sugar cane.
Land use data from *This Survey* was subject to surveyor errors that do not appear to have occurred in the *Pilot Survey*.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Total Revenue and Costs

	Cane Revenue	Non-Cane Revenue		Cane Costs	Non-Cane Costs	
	(1)	(2)	(3)	(4)	(5)	(6)
Private	19,895.1	-2,894.8	-4,304.0	16,149.1	11,243.0***	13,920.8***
	(13,411.8)	(3,855.9)	(4,312.6)	(9,297.1)	(3,388.9)	(3,598.6)
Grows Cane			24,189.7***			21,184.5***
			(8,045.8)			(4,169.9)
(Private) * (Grows Cane)			8,183.2			-8,755.0
			(8,249.0)			(6,738.4)
Mean	151,476.4	50,570.7	50,570.7	54,301.5	41,201.9	41,201.9
R^2	0.145	0.161	0.179	0.187	0.118	0.128
N	215	824	824	215	824	824

Standard errors in parentheses
All currency values are in Indian Rupees.
Each observation is a household.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Revenue and Costs Per Acre

	Cane Revenue	Non-Cane Revenue		Cane Costs	Non-Cane Costs	
	(1)	(2)	(3)	(4)	(5)	(6)
Private	-4,412	-6,126	-7,950*	-311	782	3,651**
	(5,508)	(3,746)	(4,307)	(2,253)	(1,633)	(1,532)
Grows Cane			7,704			9,450**
			(6,712)			(3,621)
(Private) * (Grows Cane)			7,377			-10,967**
			(9,322)			(4,161)
Mean	55,866.4	42,034.3	42,034.3	22,554.5	33,425.8	33,425.8
R^2	0.249	0.104	0.108	0.150	0.250	0.260
N	215	824	824	215	824	824

Standard errors in parentheses
All currency values are in Indian Rupees.
Each observation is a household.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Cost Details

	Private	Grows Cane	(Private)*(Grows Cane)	N	R^2
Fertilizer - Cane	739			215	.066
	(1,794)				
Fertilizer - Non-Cane	2,620**			824	.11
	(1,252)				
	3,780**	5,976***	-4,116*	824	.11
	(1,418)	(1,498)	(2,106)		
Pesticide - Cane	9,110			215	.079
	(8,740)				
Pesticide - Non-Cane	-290			824	.13
	(258)				
	37	1,977***	-1,130*	824	.14
	(283)	(517)	(557)		
Irrigation - Non-Cane	-697			824	.13
	(541)				
	-1,074	-866*	1,446**	824	.13
	(634)	(468)	(678)		
Labor - Non-Cane	7,650***			824	.068
	(2,074)				
	9,121***	10,550***	-4,921	824	.074
	(2,156)	(1,850)	(3,219)		
Harvesting - Non-Cane	1,732***			824	.14
	(347)				
	1,634***	2,457***	646	824	.15
	(539)	(788)	(1,622)		
Other - Non-Cane	228			824	.047
	(204)				
	422	1,091	-679	824	.049
	(282)	(801)	(706)		

Standard errors in parentheses
For Labor, Harvesting, and Other Costs, no comparable categories exist for cane farmers.
Only 3 cane farmers reported irrigation costs, so regression results are not reported for them.
All currency values are in Indian Rupees.
Each observation is a household.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Non-Cane Profit and Crop Composition

	Non-Cane Profit			
	(1)	(2)	(3)	(4)
Private	-14,137.8***	-12,057.9***	-18,224.9***	-16,377.3***
	(3,185.0)	(3,438.4)	(3,269.7)	(3,167.8)
Grows Cane			3,005.3	1,078.4
			(9,879.8)	(9,988.1)
(Private) *			16,938.2	17,897.3*
(Grows Cane)			(11,045.0)	(9,668.8)
Acres Per Crop Type	No	Yes	No	Yes
Mean	9,368.8	9,368.8	9,368.8	9,368.8
R^2	0.076	0.089	0.081	0.094
N	824	824	824	824

Standard errors in parentheses
All currency values are in Indian Rupees.
Each observation is a household.
Acres Per Crop Type adds a set of variables showing the number of acres that each household used to farm specific types of non-cane crops.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX C

Chapter 2: The Zoning System

Zoning systems for sugar mills were historically implemented within several states in India as a response to the "overcrowding" of mills following the Indian Sugar Cane Protection Act (Baru 1990). Concerned that a relatively large number of high-cost mills competing for cane grown on a fixed amount of land would cause steep sugar price increases, zones were assigned to mills following a 1933 meeting of the central Sugar Committee,

> ...so as not only to eliminate competition among factories for cane and thereby create a stake in cane development for each factory in its zone, but also to ensure adequate cane supply to each factory (Baru 1990).

The zoning system assigned exclusive sugar cane purchasing rights to each of the sugar mills operating within a state in India: Farmers who grew sugar cane could not sell to any mill except the one in whose zone they grew cane, and mills could not purchase raw sugar cane from farmers outside of their zone.

At the same meeting, minimum price controls for sugar cane were recommended, and thereafter implemented, in order to prevent mills from using the monopsony power granted by the zoning system to lower sugar cane prices and thereby "exploit" the farmers who sold cane to the mills.

Since sugar mills have strongly increasing returns to scale, they have incentives to enforce the government regulations that require farmers within their borders not to sell to other mills.

Mullainathan and Sukhtankar (2011) conduct a survey in the same state that verifies that farmers on one side of a border truly sell to their zone's mill. Returns to scale, combined with a fixed supply of arable land, also create reasons for mills to invest in cane farming productivity within their borders, and to discourage the growth of other crops.

While versions of the zoning system exist in most of India - and are sometimes described as "cane area reservation"or "command area"systems - Tamil Nadu is unique in having an even mix of publicly- and privately- owned mills, with 19 mills administered by the government, and 19 owned privately. Of the public mills, 17 are cooperatives, and 2 are non-cooperative.[1] While all 19 are administered by the Tamil Nadu Co-Operative Sugar Federation, the two non-cooperative government mills are directly managed by the Tamil Nadu Sugar Corporation, a government entity that operates within the Federation.[2]

The borders of the sugar mills are determined centrally by the Directorate of Sugar, a state government body. When determining border placement, consideration is given only to equating the populations within each zone, and to minimizing the distance and difficulty of transporting cane from harvested land to the designated mill. If a new mill is to be added to the system, it must demonstrate that its inclusion will increase sugar cane production. It is then granted a zone that either replaces an existing and non-operational mill, or is newly carved from the land of existing zones, after the populations of each zone the distances from border to mills are re-balanced.[3] Since adherence to these border placement processes is easily verified using maps and census data, it is unlikely to be manipulated, in practice. Also, while these allocation processes leave some room for manipulation, they restrict the ways in which political interference and patronage can be used to give some mills preferential

[1]An additional non-cooperative mill, Madura Sugars, is not considered, because it is inactive.

[2]See http://www.tn.gov.in/sugar/sugarcorp.htm for details on this division.

[3]These details come from an interview with Dr. A. Sekhar, Chief Cane Development Officer at the Tamil Nadu Directorate of Sugar, on February 12, 2010.

treatment.

APPENDIX D

Chapter 2: Growing Sugar Cane in Tamil Nadu

Of the crops grown in Tamil Nadu, sugar cane is the third largest by area, after rice paddy and peanuts[1]. Sugar cane is grown by small[2] independent farmers, and is typically planted once a year, around early March. Once mature, a small amount of cane is consumed domestically or used to create *jaggery*, an unrefined sugar; however, the vast majority of harvested sugar cane is sold to the sugar mill within the farmer's zone, to be pressed and processed into refined crystallized sugar (Baru 1990).

Sugar cane is flood and pest resistant relative to most other crops grown in Tamil Nadu, and is also more lucrative (see Table B.4). However, it takes 9 months to grow, while crops such as rice can be harvested 3 months after planting. Thus, cane farmers must have sufficient savings or access to loans to last through the growing season, since sugar cane profits are only realized after the harvest.

It is common for farmers with larger amounts of land to grow different crops simultaneously on separate plots of land, and to use the same land to grow several different crops per year, when possible. However, because the sugar cane harvest cycle takes up to a full year, land devoted to sugar cane cannot be used for any other crop during a 12-month period.

Farmers who grow sugar cane have strong relationships with the mills in their zones.

[1] 2011 Tamil Nadu Statistical Handbook, available online at: http://www.tn.gov.in/deptst/

[2] In our sample, no farmer grew sugar cane on more than 15 acres of land, and the average farmer used less than 3 acres of land. See Table B.3).

Mills provide loans to farmers during the growing season that are deducted from their harvest proceeds. They also sell seeds, fertilizer, and pesticide to farmers, and, in some cases, provide harvesting and transportation services. Farmers intending to sell sugar cane must register their land with the sugar mill each season, and receive several visits from mill representatives during the season.

Since the rollers that mills use to press sugar cane are costly to operate, mills function most efficiently when receiving a steady supply of sugar cane through the harvesting season (Mullainathan and Sukhtankar 2011). Hence, mills issue “cutting orders”to farmers at different times during the harvesting season. Once cutting orders are received, a farmer’s sugar cane is transported to the mill, the cane is weighed, and the farmer is paid according to the weight of the cane at that time.

National and state price regulations dictate a minimum price that mills must pay for sugar cane it purchases from farmers, although the prices paid by mills generally exceed this minimum, and vary with each mill. Mills are required to announce their own minimum prices at the beginning of the sugar cane harvesting season, reducing opportunities for holdup at the end of a harvest. Nonetheless, farmers face uncertainty in the value of their crops even after these prices are announced, since all prices are per ton of sugar cane weighed, and cane weight is affected by any delays in receiving cutting orders.

APPENDIX E

Chapter 3: Tables and Figures

Table E.1: Crops Grown by State and Season

State	Season: Kharif (June - Oct)	Rabi (Nov - May)	Annual
Andhra Pradesh	Rice, Cotton, Sorghum	Sorghum, Wheat	Sugarcane
Arunachal Pradesh	Rice	Wheat	Sugarcane
Assam	Rice, Cotton	Rice, Wheat	Sugarcane
Bihar	Rice, Sorghum	Rice, Wheat	Sugarcane
Chhattisgarh	Rice, Cotton, Sorghum	Wheat	Sugarcane
Dadra and Nagar Haveli	Rice		
Daman and Diu	Rice		
Delhi	Rice, Sorghum	Wheat	
Goa			Sugarcane
Gujarat	Rice, Cotton, Sorghum	Sorghum, Wheat	Sugarcane
Haryana	Rice, Cotton, Sorghum	Wheat	Sugarcane
Himachal Pradesh	Rice, Cotton	Wheat	Sugarcane
Jammu and Kashmir	Rice, Sorghum	Wheat	Sugarcane
Jharkhand	Sorghum	Wheat	Sugarcane
Karnataka	Rice, Cotton, Sorghum	Rice, Sorghum, Wheat	Sugarcane
Kerala	Rice, Cotton, Sorghum	Rice	Sugarcane
Madhya Pradesh	Rice, Cotton, Sorghum	Sorghum, Wheat	Sugarcane
Maharashtra	Rice, Cotton	Rice, Sorghum, Wheat	Sugarcane
Manipur	Rice		Sugarcane
Meghalaya	Rice	Wheat	Sugarcane
Mizoram	Rice		Sugarcane
Nagaland	Rice, Sorghum	Wheat	Sugarcane
Orissa	Rice, Cotton, Sorghum	Rice, Wheat	Sugarcane
Pondicherry	Rice, Cotton, Sorghum	Rice	
Punjab	Rice, Cotton	Wheat	Sugarcane
Rajasthan	Rice, Cotton, Sorghum	Wheat	Sugarcane
Sikkim	Rice	Wheat	
Tamil Nadu	Rice, Cotton, Sorghum	Rice, Sorghum	Sugarcane
Tripura	Rice, Cotton	Rice, Wheat	Sugarcane
Uttar Pradesh	Rice, Cotton, Sorghum	Rice, Wheat	Sugarcane
Uttarakhand	Rice	Wheat	Sugarcane
West Bengal	Rice, Cotton, Sorghum	Rice, Wheat	Sugarcane

Crops are shown when more than 3 years of data exist in our sample for a given state and season. Some crops may be omitted because of a lack of data, and not because those crops are not grown in a given state and season.

Table E.2: Mean Yields by State and Crop

State	Cotton	Sorghum	Rice	Sugarcane	Wheat
Andhra Pradesh	0.39	0.70	2.04	74.50	0.58
Arunachal Pradesh			1.08	18.78	1.50
Assam	0.11		1.22	39.21	1.05
Bihar		0.96	1.17	38.85	1.52
Chhattisgarh	0.29	0.91	1.19	2.52	1.01
Dadra and Nagar Haveli			1.63		
Daman and Diu			1.99		
Delhi		0.85	1.60		2.23
Goa				52.60	
Gujarat	0.47	0.69	1.23	65.55	1.92
Haryana	0.51	0.24	2.38	49.41	2.84
Himachal Pradesh	0.27		1.21	15.03	1.21
Jammu and Kashmir		0.52	1.83	7.54	1.14
Jharkhand		0.79		37.78	1.66
Karnataka	0.26	0.85	2.16	82.40	0.60
Kerala	0.24	0.49	1.80	67.63	
Madhya Pradesh	0.23	0.82	0.84	32.71	1.19
Maharashtra	0.24	0.75	1.47	80.23	0.94
Manipur			1.76	38.02	
Meghalaya			1.35	2.29	1.74
Mizoram			1.16	8.84	
Nagaland		1.22	1.06	46.25	1.86
Orissa	0.38	0.68	1.42	58.96	1.43
Pondicherry	0.53	1.00	2.27		
Punjab	0.61		2.91	53.58	3.15
Rajasthan	0.31	0.38	1.11	40.31	1.87
Sikkim			1.29		1.32
Tamil Nadu	0.33	0.93	2.30	93.63	
Tripura	0.23		1.32	47.96	2.27
Uttar Pradesh	0.16	0.76	1.22	49.26	1.83
Uttarakhand			1.93	58.07	1.95
West Bengal	0.36	0.48	2.02	59.53	1.91
Total	0.33	0.73	1.61	54.29	1.60

Yields are shown in tons per hectare.

Table E.3: Mean Temperatures by State and Season

State	Season			Total
	Annual (Jan - Dec)	Kharif (June - Oct)	Rabi (Nov - May)	
Andhra Pradesh	11.66	27.99		22.83
Arunachal Pradesh	12.90	17.39	9.70	12.80
Assam	23.19	26.87	20.58	23.22
Bihar	25.38	28.83	22.92	25.30
Chhattisgarh	25.77	27.22	24.73	25.77
Dadra and Nagar Haveli		25.97	23.94	24.96
Daman and Diu		28.37	25.24	26.81
Delhi	25.24	30.06	21.79	25.12
Goa	25.21	24.87	25.46	25.22
Gujarat	26.86	29.08	25.28	26.87
Haryana	24.76	29.84	21.14	24.79
Himachal Pradesh	11.34	15.89	8.12	11.38
Jammu and Kashmir	3.46	11.15	-2.02	3.28
Jharkhand	25.08	27.61	23.27	25.02
Karnataka	25.24	24.85	25.53	25.24
Kerala	26.00	25.43	26.43	26.01
Madhya Pradesh	25.59	27.74	24.06	25.60
Maharashtra	26.12	26.67	25.73	26.12
Manipur	19.31	22.47	17.06	19.24
Meghalaya	22.26	25.14	20.20	22.19
Mizoram	22.56	24.59	21.12	22.52
Nagaland	18.80	22.89	15.88	18.70
Orissa	25.96	27.39	24.94	25.96
Pondicherry	28.06	28.94	27.43	28.06
Punjab	24.16	29.68	20.22	24.18
Rajasthan	26.08	30.13	23.20	26.10
Sikkim	4.67	8.64	1.84	4.58
Tamil Nadu	26.91	27.61	26.43	26.92
Tripura	24.79	27.46	22.89	24.81
Uttar Pradesh	25.42	29.35	22.63	25.45
Uttarakhand	11.96	16.05	9.03	11.86
West Bengal	25.68	28.30	23.80	25.69
Total	21.68	25.18	20.16	22.17

Temperatures are in degrees Celsius.

Table E.4: Mean Monthly Precipitation by State and Season

	Season			
State	Annual (Jan - Dec)	Kharif (June - Oct)	Rabi (Nov - May)	Total
Andhra Pradesh	61.66	148.17		120.88
Arunachal Pradesh	229.59	404.17	104.89	225.43
Assam	199.56	340.23	97.82	199.57
Bihar	95.37	204.27	17.59	92.78
Chhattisgarh	107.75	236.50	16.16	108.50
Dadra and Nagar Haveli		474.64	6.56	240.60
Daman and Diu		172.61	3.59	110.94
Delhi	48.63	101.20	11.09	47.38
Goa	214.02	483.07	21.84	207.61
Gujarat	55.89	131.19	3.44	56.87
Haryana	46.00	91.61	12.65	45.83
Himachal Pradesh	128.85	197.39	79.69	129.05
Jammu and Kashmir	56.27	57.24	55.57	56.25
Jharkhand	105.89	224.84	20.92	103.06
Karnataka	93.10	188.44	24.80	93.42
Kerala	233.60	434.10	90.99	234.78
Madhya Pradesh	83.07	184.44	10.11	83.25
Maharashtra	94.44	211.11	11.60	95.20
Manipur	164.25	290.50	74.07	161.25
Meghalaya	328.70	610.86	127.15	321.98
Mizoram	227.65	410.52	97.03	223.29
Nagaland	180.94	313.10	86.54	177.79
Orissa	120.51	250.37	29.00	121.69
Pondicherry	142.65	234.62	77.29	143.22
Punjab	51.95	98.53	18.22	51.93
Rajasthan	34.94	75.04	5.74	34.84
Sikkim	167.01	318.21	59.01	163.41
Tamil Nadu	85.93	121.98	60.70	86.34
Tripura	174.94	293.08	90.50	175.43
Uttar Pradesh	77.90	167.71	13.00	77.93
Uttarakhand	125.91	233.21	49.27	123.36
West Bengal	145.01	292.06	40.93	146.13
Total	129.40	245.48	48.57	131.09

Precipitation amounts are in mm.

Table E.5: Temperature Trend Specifications

	(1)	(2)	(3)
Year	.00941***	-.0134***	-.0171***
	(.000373)	(.00152)	(.00391)
Year^2		.000473***	.000659***
		(.0000304)	(.000188)
Year^3			-2.58e-06
			(2.57e-06)
R^2	0.995	0.996	0.996
N	8,698	8,698	8,698

Standard errors in parentheses

Temperatures are seasonal averages in degrees Celsius.

Fixed effects for each region-season combination are included, but not displayed.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.6: Precipitation Trend Specifications

	(1)	(2)	(3)
Year	-.049*	-.0365	1.41***
	(.0262)	(.108)	(.278)
$Year^2$		-.000258	-.0747***
		(.00216)	(.0133)
$Year^3$			.00103***
			(.000182)
R^2	0.932	0.932	0.933
N	8,678	8,678	8,678

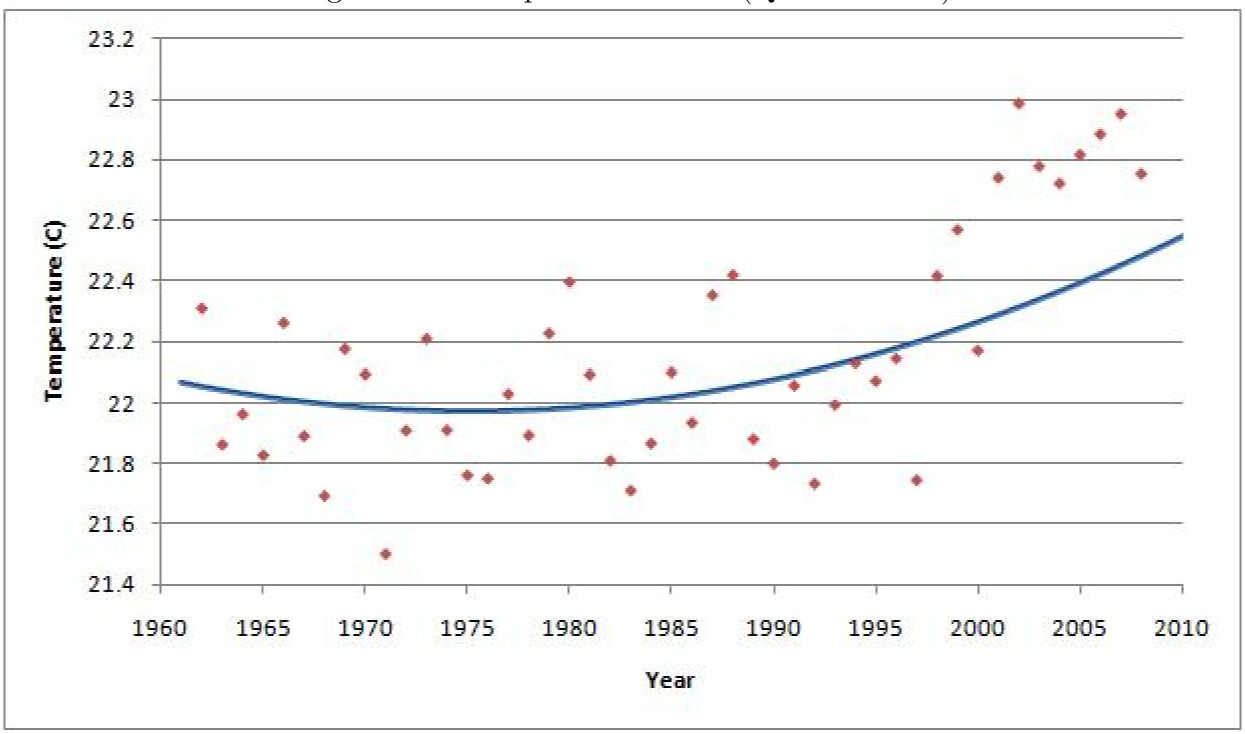
Standard errors in parentheses
Precipitation amounts are monthly averages in millimeters.
Fixed effects for each region-season combination are included, but not displayed.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.7: Temperature and Precipitation Effects on Yield - Cotton

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	1.71***	4.45***	.834	2.5
	(.0915)	(.186)	(4.19)	(8.54)
$Temp^2$	-.0312***	-.0726***	-.0151	-.0415
	(.00158)	(.00311)	(.0722)	(.143)
Precip	.00365***	.117***	.000923	.135
	(.000128)	(.0153)	(.00585)	(.701)
$Precip^2$	-5.36e-06***	-.000363***	-6.96e-07	-.000217
	(3.45e-07)	(.0000116)	(.0000158)	(.00053)
Temp*Precip		-.00276***		-.00697
		(.000997)		(.0457)
$Temp^2$*Precip		-.0000389**		.0000788
		(.0000163)		(.000749)
Temp*$Precip^2$		.0000124***		7.69e-06
		(4.10e-07)		(.0000188)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

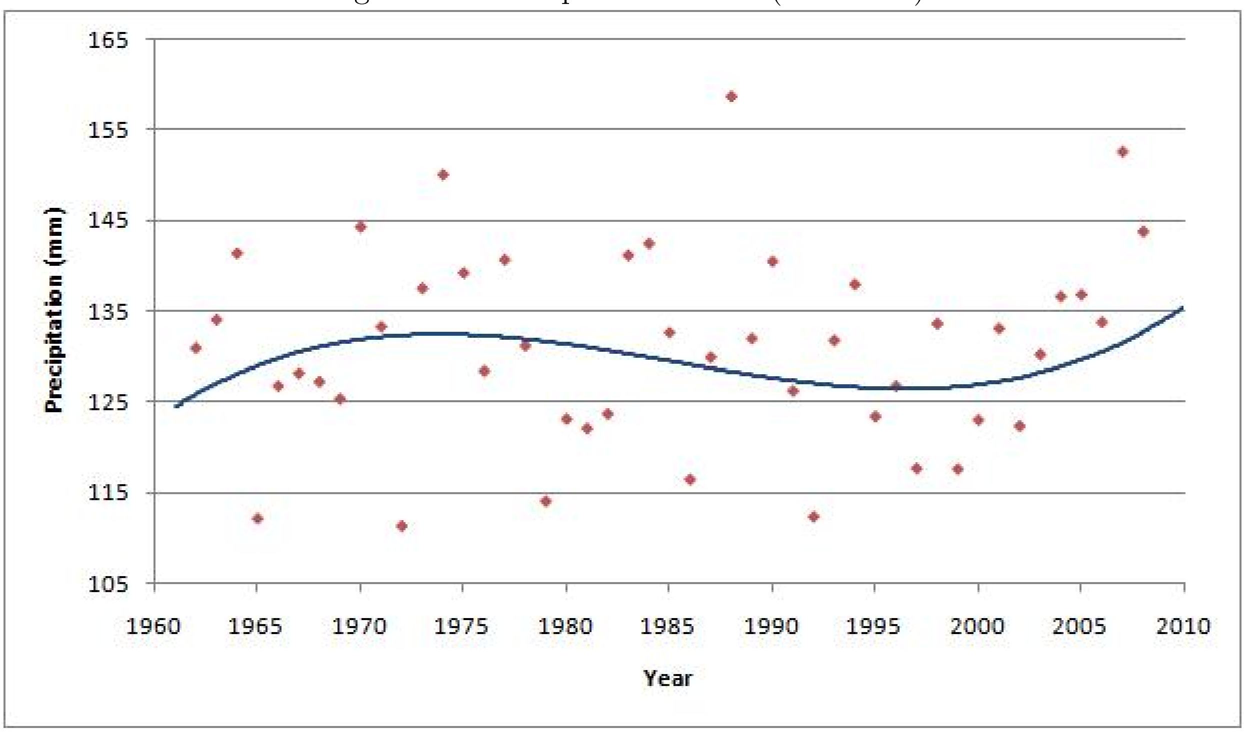
Figure E.1: Temperature Trend (Quadratic Fit)



The temperature trend is predicted using the quadratic specification in Table E.5.

Temperature markers are the average temperature values for each year of data, across all regions and seasons.

Figure E.2: Precipitation Trend (Cubic Fit)



The precipitation trend is predicted using the cubic specification in Table E.6.

Precipitation markers are the average monthly precipitation values for each year of data, across all regions and seasons.

Table E.8: Temperature and Precipitation Effects on Yield - Sorghum

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	.567***	.533***	.0706	-.206
	(.00977)	(.0126)	(.448)	(.577)
$Temp^2$	-.0105***	-.0115***	-.00121	.0034
	(.000179)	(.000238)	(.00822)	(.0109)
Precip	.00358***	-.183***	.00227	-.186
	(.0000386)	(.00347)	(.00177)	(.159)
$Precip^2$	-8.71e-06***	.000151***	-5.11e-06	.0000788
	(1.03e-07)	(2.52e-06)	(4.72e-06)	(.000116)
Temp*Precip		.0118***		.0129
		(.000244)		(.0112)
$Temp^2$*Precip		-.000181***		-.00022
		(4.27e-06)		(.000196)
Temp*$Precip^2$		-5.87e-06***		-3.14e-06
		(9.42e-08)		(4.32e-06)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.9: Temperature and Precipitation Effects on Yield - Rice

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	-.0473***	-.0492***	-.294**	-.42***
	(.00257)	(.0033)	(.118)	(.152)
$Temp^2$	.000999***	.000955***	.00597**	.00824***
	(.0000533)	(.0000677)	(.00244)	(.0031)
Precip	-.000168***	-.00102***	-.000388	-.0183
	(9.21e-06)	(.00027)	(.000422)	(.0124)
$Precip^2$	1.34e-06***	3.51e-06***	2.79e-06*	.0000207
	(3.33e-08)	(2.82e-07)	(1.53e-06)	(.0000129)
Temp*Precip		-.0000288		.00108
		(.0000203)		(.000934)
$Temp^2$*Precip		2.58e-06***		-.0000142
		(3.92e-07)		(.000018)
Temp*$Precip^2$		-9.05e-08***		-7.20e-07
		(1.14e-08)		(5.23e-07)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.10: Temperature and Precipitation Effects on Yield - Sugarcane

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	.474***	.496***	17.6***	15.7***
	(.00391)	(.00437)	(.179)	(.2)
$Temp^2$	-.0094***	-.0104***	-.354***	-.333***
	(.0000764)	(.0000864)	(.0035)	(.00397)
Precip	.00193***	.00254***	.13***	-.388***
	(8.33e-06)	(.00035)	(.000382)	(.016)
$Precip^2$	-3.78e-06***	3.45e-06***	-.000282***	.000478***
	(3.09e-08)	(5.55e-07)	(1.42e-06)	(.0000255)
Temp*Precip		-.000385***		.0288***
		(.0000267)		(.00123)
$Temp^2$*Precip		.0000136***		-.000339***
		(5.32e-07)		(.0000244)
Temp*$Precip^2$		-2.31e-07***		-.0000292***
		(2.21e-08)		(1.01e-06)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.11: Temperature and Precipitation Effects on Yield - Wheat

	Ln(Yield)		Yield	
	(1)	(2)	(3)	(4)
Temp	.013***	.021***	.0789*	.0696
	(.000899)	(.00115)	(.0412)	(.0526)
$Temp^2$	-.000131***	-.000658***	-.00101	-.00184
	(.0000206)	(.0000256)	(.000942)	(.00117)
Precip	.00215***	-.0000686	.00175*	-.0191**
	(.0000201)	(.000211)	(.000919)	(.00969)
$Precip^2$	-.0000276***	-5.38e-06***	-.0000328**	.00015**
	(3.13e-07)	(1.43e-06)	(.0000143)	(.0000656)
Temp*Precip		-.000705***		-.00082
		(.0000153)		(.0007)
$Temp^2$*Precip		.0000352***		.0000789***
		(3.37e-07)		(.0000155)
Temp*$Precip^2$		-1.30e-07*		-7.21e-06**
		(7.07e-08)		(3.25e-06)
R^2	0.996	0.996	0.978	0.978
N	3924	3924	3924	3924

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.12: Climate Change Impacts by Crop: Main Specification

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	-0.01333	0.00990	-0.00343
	(0.06010)	(0.03349)	(0.06688)
Sorghum	-0.00104	0.00569	0.00465
	(0.00508)	(0.00664)	(0.00972)
Rice	0.00024	-0.00197	-0.00173
	(0.00232)	(0.00378)	(0.00465)
Sugarcane	0.00368	0.00729*	0.01098**
	(0.00348)	(0.00411)	(0.00555)
Wheat	-0.00004	0.00021	0.00017
	(0.00127)	(0.00385)	(0.00399)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:

- ln(yield) is the dependent variable
- no interaction terms
- polynomial climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.13: Climate Change Impacts by Crop: With Interaction Terms

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	0.00441	0.01037	0.01454
	(0.07696)	(0.04754)	(0.08549)
Sorghum	-0.00083	0.00386	0.00263
	(0.00666)	(0.00769)	(0.01238)
Rice	0.00099	-0.00217	-0.00116
	(0.00381)	(0.00446)	(0.00611)
Sugarcane	0.00537	0.00780	0.01313*
	(0.00481)	(0.00536)	(0.00789)
Wheat	-0.00035	0.00422	0.00420
	(0.00138)	(0.00466)	(0.00486)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:

- ln(yield) is the dependent variable
- includes interaction terms
- polynomial climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.14: Climate Change Impacts by Crop: Yield as the Regressand

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	-0.01751	0.02571	0.00820
	(0.08614)	(0.05117)	(0.09560)
Sorghum	0.00068	0.00347	0.00415
	(0.00774)	(0.01068)	(0.01448)
Rice	-0.00095	-0.00266	-0.00362
	(0.00390)	(0.00501)	(0.00650)
Sugarcane	0.00822	0.01248	0.02071
	(0.01888)	(0.02642)	(0.03153)
Wheat	-0.00040	-0.00276	-0.00316
	(0.00231)	(0.00496)	(0.00547)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

Standard errors in parentheses.

T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:

- yield is the dependent variable
- no interaction terms
- polynomial climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.15: Climate Change Impacts by Crop: Linear Climate Trends

	T_d, P	T, P_d	T_d, P_d
	(1)	(2)	(3)
Cotton	-0.01303	-0.00452	-0.01755
	(0.05526)	(0.02460)	(0.05694)
Sorghum	0.00224	0.00311	0.00536
	(0.00489)	(0.00319)	(0.00653)
Rice	0.00005	-0.00312	-0.00307
	(0.00479)	(0.00338)	(0.00623)
Sugarcane	0.00632	0.00063	0.00694
	(0.00586)	(0.00164)	(0.00594)
Wheat	0.00268	-0.00027	0.00241
	(0.00334)	(0.00225)	(0.00466)

Values shown are percentage changes in yield when de-trended climate data are fitted to the yield model.

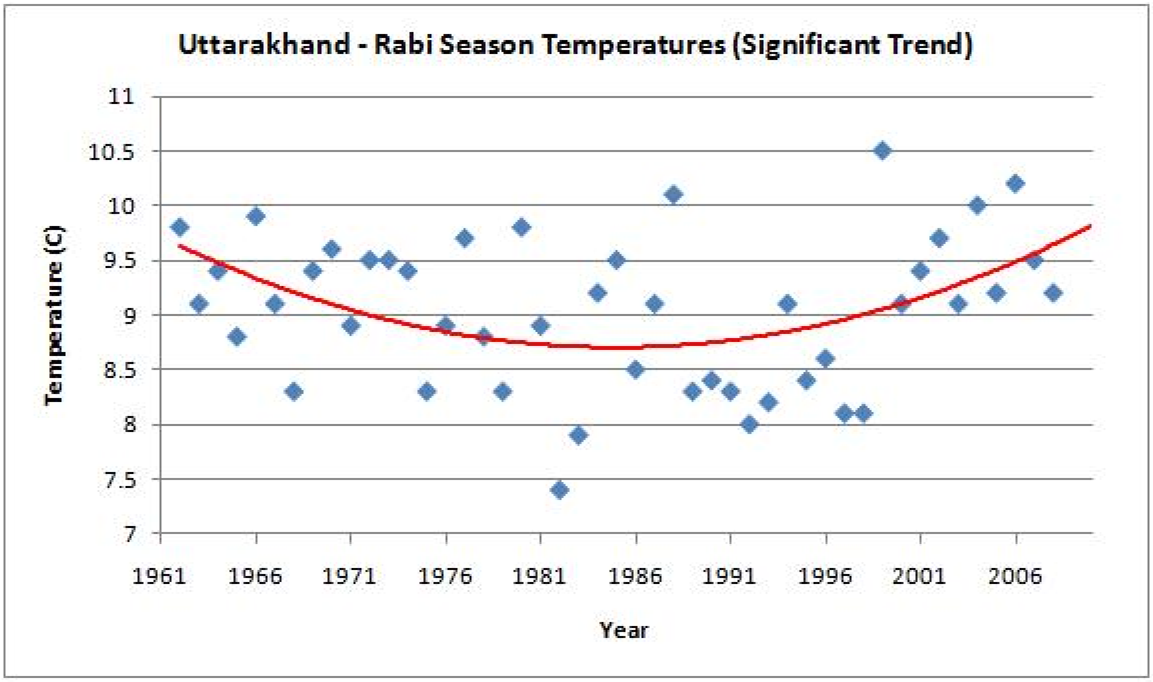
Standard errors in parentheses.

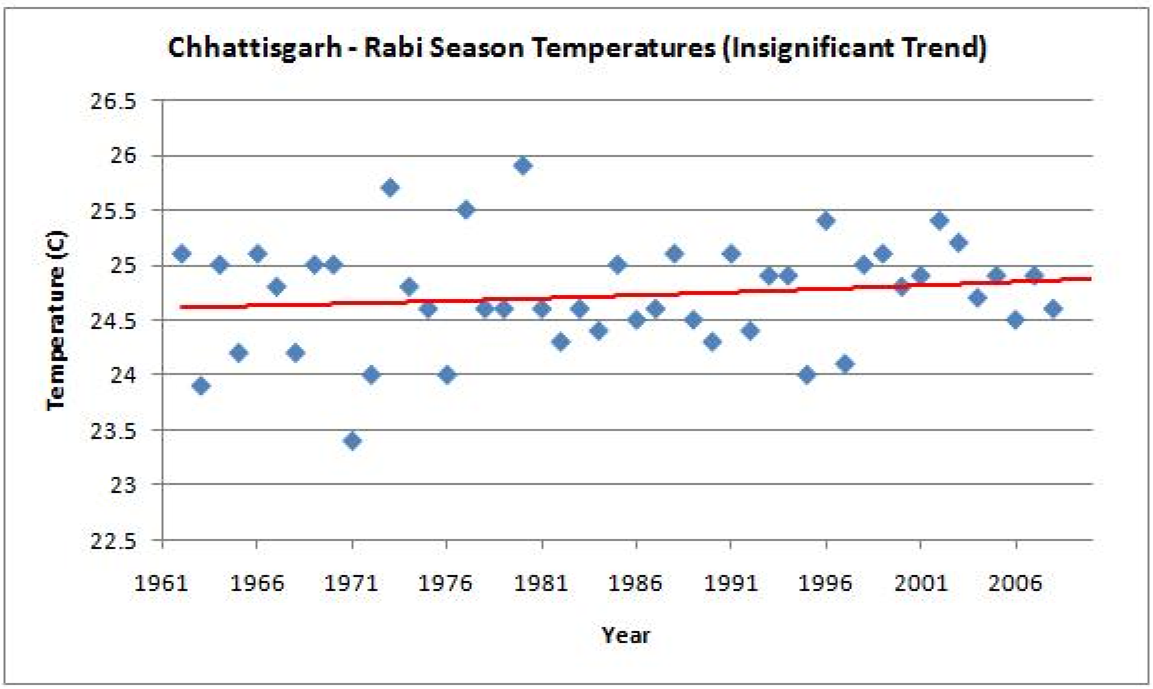
T_d and P_d refer to de-trended data for temperature and precipitation, respectively.

Specification:
- ln(yield) is the dependent variable
- no interaction terms
- linear climate trends

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

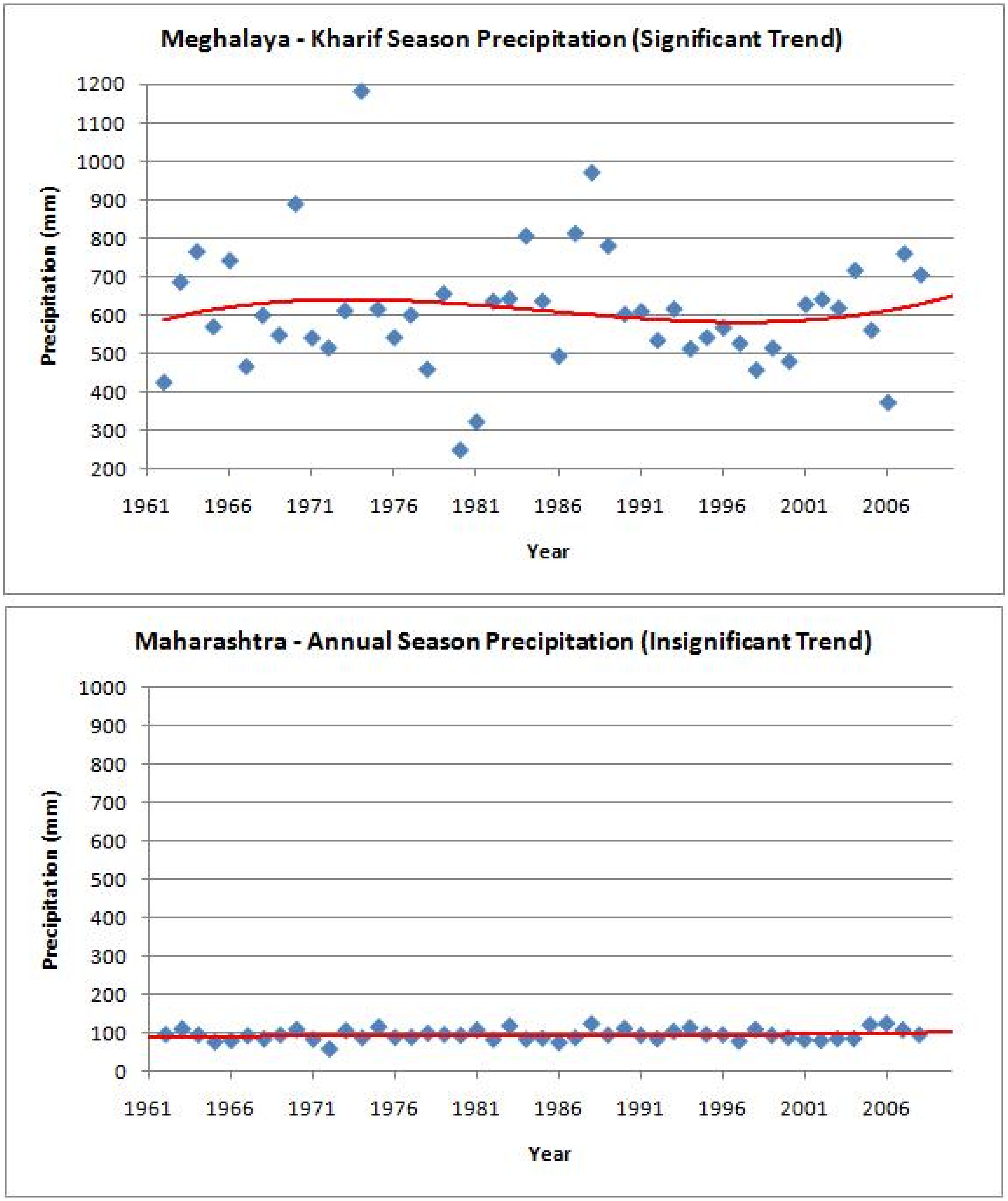
Figure E.3: State-Season Temperature Trend Comparisons





Temperature trends are predicted using the quadratic specification of Equation 3.6. Vertical axis ranges are kept the same in both graphs.

Figure E.4: State-Season Precipitation Trend Comparisons



Precipitation trends are predicted using the cubic specification of Equation 3.6.
Vertical axis ranges are kept the same in both graphs.

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