Does Market Power in Agricultural Markets Hinder Farmer Climate Change Adaptation?*

Rajat Kochhar
University of Chicago

Ruozi Song
World Bank

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Abstract

What role do government policies which distort market competition play in impeding farmers' climate change adaptation? We study this question in the context of India, where longer-run adaptation to climate change has been inadequate — posing a considerable risk to its ∼250 million agricultural workers. We exploit spatial discontinuities in intermediary market power, created by state-level laws that restrict farmer-intermediary transactions to the same state, to determine how spatial competition affects farmers' adaptation. We find that a farmer selling in the 75th percentile of the competition index compared to one that faces the 25th percentile of the competition index achieves a **4.9** percent higher output for each additional day of extreme heat. This effect is driven by increased input usage by farmers in anticipation of higher prices after climate shocks, an effect limited only to high competition areas. We then propose and estimate a quantitative spatial trade model with intermediary market power to examine the welfare implications of higher competition for adaptation. Our structural estimates suggest that the farmer's economic loss due to extreme weather (*i.e.* their climate damage function) could be mitigated by **13.8** percent if government regulation distorting market competition is dismantled. These results highlight the importance of understanding the political economy of reforming these competition-distorting laws to accelerate climate change adaptation.

Keywords: **Climate Change; Adaptation; Market Power; Government Distortions**
JEL Codes: **D43, F18, L13, L81, L88, O13, P1, Q13, Q54, Q56**

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1 Introduction

This paper analyzes whether market distortions induced by a country's institutions inhibit its adaptation to climate change. Though the negative impacts of a departure from perfect competition are well documented (Arrow 1962, Ashenfelter et al. 2014), these detrimental effects risk being exacerbated by the climate crisis. One major source of these distortions is government regulations which can concentrate market power in the hands of a few economic agents. In light of this, do institutional policies, that dictate an agents' market power, impede climate change adaptation? And would eliminating these distortions by establishing free markets enhance welfare by aiding adaptation? In this article, we address these questions in the context of competition in India's agricultural markets, and the role of market power, in facilitating farmer adaptation to climate change.

Our analysis is motivated by a simple observation: in a world where climate change will result in crop production losses and fall in agricultural productivity (IPCC 2022), farmer adaptation is crucial, and critically depends on institutional and policy constraints. A country's agricultural policy can play a dominant role in building resilience and reducing exposure to the impacts of climate change—with the potential to either advance or distort (through the imposition of *soft limits*[1]) adaptation behavior (Mees 2017, Valdivieso et al. 2017, Oo et al. 2017).[2] For instance, Annan & Schlenker (2015) show that federal crop insurance policy in the United States creates a moral hazard problem, disincentivizing adaptation and consequently exacerbating losses. Similarly, agricultural laws in India, which create market power for agricultural intermediaries (Chatterjee 2019), may also disincentivize adaptation. Consider the case where post climate shock adaptation may be dependent on higher input usage, which in turn is contingent on higher expected prices. The market power of intermediaries may, however, constrain farmer prices from rising beyond a level that impels farmers to adapt to climate shocks. Thus, the impact of climate change on agriculture is inherently dependent on the capacity to effectively adapt. But *how* and *to what extent* this capacity is constrained by government-induced distortions to market competition remains an open question.

Addressing these questions empirically poses three challenges: first, competition is not directly observable, making it difficult to credibly measure its intensity (OECD 2021); second, causal identification of competition on adaptation suffers from both potential endogeneity in competition and in adaptation response; and lastly, limited simultaneous varia-

[1] *Soft adaptation limit* is defined as the existence of adaptive options to avoid intolerable risks, but which are currently unavailable.

[2] See Kuruppu & Willie (2015) and Robinson (2018) for a discussion on how the governance architecture can act as a bottleneck to adaptation in small island developing states.

tion in climate shocks and market competition makes it challenging to detect any significant causal effects, should they exist. We tackle these challenges by studying the impact of spatial competition between intermediaries on farmer adaptation in India, focusing on a law that restricts farmers to selling their produce to intermediaries within their own state. The Indian context affords us progress on all three challenges.

Central to our approach are the state-specific Agriculture Produce and Marketing Committee (APMC) Acts which regulate the first sale and purchase of agricultural commodities within each state in India. Two provisions in these laws are noteworthy for our purpose: first, farmers in a state are restricted to sell their produce at government designated physical markets (known as *mandis*) *within* their own state; second, output can only be sold to government-licensed intermediaries, each of whom requires a market-specific license to operate in the respective APMC *mandi*.[3] Importantly, other wholesalers, retail traders, or food processing companies cannot buy directly from the farmer. Therefore, the spatial arbitrage constraints imposed on farmers by the law — restricting access to licensed intermediaries within a state border — reduce the competition faced by intermediaries. In essence, state-specific institutional setup governing the sale of agricultural output generates spatially varying monopsony power for licensed intermediaries, a source of variation which we can exploit to address the empirical challenges.

The context allows us, first, to accurately measure competition at the *mandi* level, offering spatially granular variation in competition intensity between intermediaries. We collect novel microdata from India on the geolocations of *mandis*, and combine it with the daily quantity arrivals and prices of agricultural produce there-within. Subsequently, drawing on the standard measure of market access in trade literature (Donaldson & Hornbeck 2016, Allen & Atkin 2016), we measure the competition intensity faced by each intermediary as the inverse-distance weighted sum of the value of trade at all other markets near a origin market site, but in the same state.[4]

Second, the interstate trade restrictions on farmers help us overcome the potential endogeneity in the location of intermediaries. Potential bias in estimating the impact of market power on adaptation can arise if, for instance, markets were placed in areas with higher

[3]Intermediaries, or middlemen, tend to be the principal buyers of farmers' output in developing countries (Reardon 2015). The license to operate in a *mandi* is provided to them by the APMC board under whose jurisdiction the *mandi* falls. Unlike farmers, there are no sale restrictions on the intermediary, who is free to transport the purchased produce and sell it to retailers all over the country.

[4]Chatterjee (2019) defines spatial competition as the number of markets in the neighborhood of each market weighted by the inverse of their distance. Thus, there is no variable controlling for the size of the markets in his measure. This is similar to the *market potential* measure in Harris (1954), who defines it as the summation of markets accessible to a point divided by their distances from that point. Similarly, Macchiavello & Morjaria (2021) use the number of proximate competitors as a measure of competition. We employ these different measures for testing the robustness of our results.

predisposition for farmer innovation. The APMC Acts establish a discontinuity at the border in the competition faced by intermediaries. This allows us to employ a *hybrid* border-discontinuity design with market pairs, akin to Chatterjee (2019). We form market pairs by matching *mandis* that are in close proximity with each other but lie on different sides of a state border, thereby allowing us to difference out unobserved factors, other than competition, that affect adaptation.

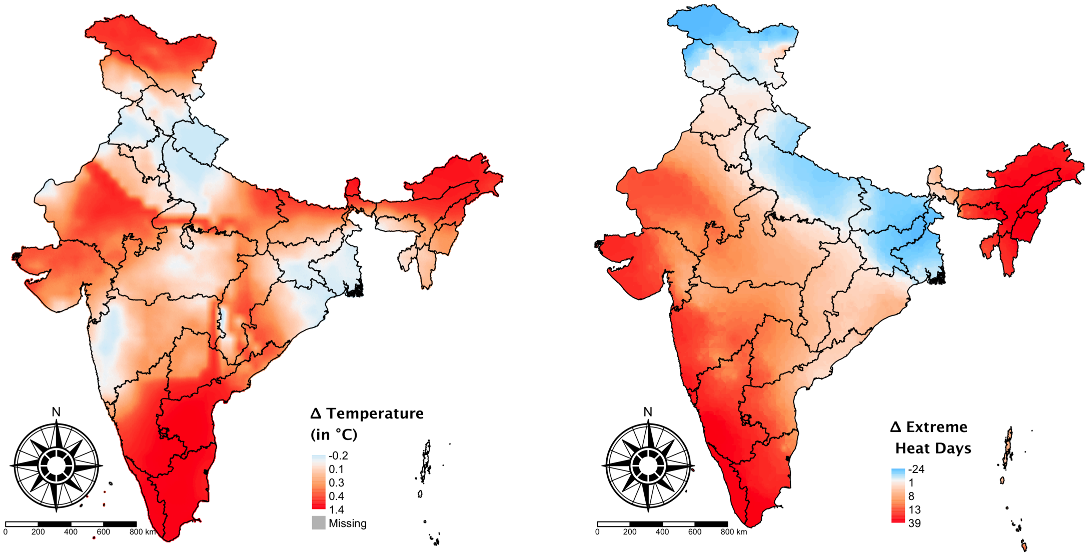
Third, India, with an estimated 263 million agricultural workers (Census of India 2011) spread across 15 agro-climatic regions (Ahmad et al. 2017)—each with substantial spatial heterogeneity in competition intensity—offers significant variation to study the effect of market power on farmer adaptation to climate change.[5] Agricultural households, which account for 48 percent of total households in India (NABARD 2018), have been incentivized to invest in an adaptation portfolio owing to an unprecedented increase over the past several decades in both maximum temperature, and frequency and intensity of extreme heat days (Krishnan et al. 2020; also see Figure 1).[6] Notably, this effect is expected to worsen, with India projected to have the highest climate-change induced increase in heat exposure and vulnerability to crop production losses relative to other nations (Jones et al. 2018, IPCC 2022).[7] This is relevant because it motivates our use of extreme heat (defined as temperatures $\geq 35°$C or 95°F) as a proxy for climate shocks.

The empirical analysis proceeds in three steps. Section 4.A motivates our core question — the role of market power in adaptation — by asking if Indian farmers have adapted in the long-run. Evidence to the contrary would indicate that constraints imposed by distortionary institutional policies on adaptation may be persistent and binding; Section 4.B explores whether intermediary market power mitigates the deleterious impact of climate shocks; Section 4.C investigates the mechanisms.

[5] India has the highest number of agricultural workers in the world. 263 million people (54.6 percent of India's total workforce) are employed in agriculture. The figure of 263 million comprises of 119 million cultivators/farmers and 144 million agricultural laborers. There is, however, some debate about the total farmer population in India, with official figures ranging between 100 and 150 million. The main source of contention is the absence of a standard definition of who constitutes a farmer. See Damodaran (2021) and Narayanan & Saha (2021) for a detailed discussion.

[6] An *agricultural household* is defined as a household that received some value of produce more than ₹5000 (equivalent to US$63 using the average USD-INR exchange rate in calendar year 2021) from agricultural activities (*e.g.*, cultivation of field crops, horticultural crops, fodder crops, plantation, animal husbandry, vermiculture, sericulture, etc.) and had at least one self-employed member in agriculture, either in principal status or in subsidiary status during last 365 days.

[7] India's average temperature has risen by approximately 0.7°C between 1901–2018. By the end of this century, the average temperature across India is projected to rise by 4.4°C relative to the 1976–2005 average, under the RCP8.5 scenario (Krishnan et al. 2020). Furthermore, the frequency of summer heat waves over India is projected to be 3 to 4 times higher by the end of the 21st century under the RCP8.5 scenario, as compared to the 1976–2005 baseline period. The average duration of heat wave events is also projected to approximately double (Rohini et al. 2019). Finally, Mishra et al. (2012) and Turner & Annamalai (2012) project a steady decline in the total precipitation during monsoon months.



(a) Change in Maximum Temperature **(b) Change in Extreme Heat Days**

Notes: The weather data for *Panel* (*a*) comes from Terraclimate (2018), which has a monthly temporal resolution and a 4-km (1/24th degree) spatial resolution. Change in maximum temperature is calculated by taking the average maximum temperature for each grid point within Indian boundaries for two time periods: 1960-70 and 2010-2020; and then differencing the two. The weather data for *Panel* (*b*) is sourced from India Meteorological Department (2009) which uses 395 weather stations to provide a 1×1 degree gridded daily temperature dataset starting from 1951 up until 2020. Extreme heat days were defined for each grid cell as days with maximum temperature greater than the 95th percentile of the temperature distribution in the respective grid cell between 1950-2020. Change in number of extreme heat days is calculated by taking the total number of extreme heat days between 1960-70 and comparing the same to the total number of extreme heat days between 2010-20.

Figure 1: Climatological Changes Over India Between 1960-70 and 2010-20

We begin by documenting evidence of limited long-run yield-stabilizing adaptation in India. Following Burke & Emerick (2016), we measure long-run adaptation as the difference between *panel* and *long-differences* estimates of the effect of extreme heat on yields. The *panel* estimates capture short-run within-year adjustments by farmers, while the *long-differences* estimates encapsulate long-run transformational adaptations. Their difference, thus, reflects the share of the short-run impacts that are offset in the longer run. Using fine geospatial crop yields and weather data from 1968 to 2017, we find that both methods yield significant but similar estimates — each additional day of extreme heat reduces yields by **1.0** to **2.7** percent — indicating that long-run adaptations have likely offset none of the short-run impacts of adverse climate. Therefore, the bottlenecks farmers face in adopting short-run strategies have a direct and cumulative impact on their ability to adapt in the long-term, making it imperative to recognise and address these constraints.

Our core result is that market power of intermediaries arising out of institutional policies acts as a major constraint on the farmers' post-climate shock adaptation efforts. Using a *hybrid* border-discontinuity design, we find that a farmer selling in the 75$^{\text{th}}$ percentile of competition compared to one that faces the 25th percentile of competition achieves a **4.5** to **5.2** percent higher output on average for each additional degree-day of extreme heat. This result is robust to different distance thresholds, ranging from 25 to 50 kilometers, between market pairs. We corroborate these findings using (*i*) a panel approach, and (*ii*) a panel approach but changing the spatial unit of analysis from a *mandi* to a district. As before, the results unequivocally indicate that monopsony power thwarts adaptation — a one standard deviation increase in competition helps a farmers alleviate between **15** and **37** percent of the negative impact of extreme heat.

Next, in order to investigate the mechanisms underlying the relationship between market power and adaptation, we build a simple agricultural household model with incomplete input markets (Aragón et al. 2021). This allows us to derive predictions on *how* and *when* farmers would invest in their adaptation portfolio in the event of an exogenous negative shock. Subsequently, we provide evidence consistent with the predictions highlighted in the model.

The model yields the following prediction — in the event of a negative weather shock, farmers could increase their input usage if the output prices are expected to rise beyond a certain threshold. This could happen, for instance, if extreme heat reduces yields and, hence, aggregate supply. However, the magnitude of increase in prices is likely to be greater in high competition areas as a large set of intermediaries now compete for lower output. Lower spatial competition between intermediaries translates into lower farmer prices (Chatterjee 2019). We hypothesize that climate shocks interact with market power to further exacerbate these pre-existing distortions, thereby incentivizing only the farmers in high competition areas to adjust their input usage as a response to extreme heat. This, in turn, helps alleviate the crop production losses associated with heat stress.

We find evidence consistent with the mechanisms highlighted in the model: (*i*) the positive effect of higher competition on intermediary prices is compounded after a climate shock, and (*ii*) farmers in high competition areas increase their input usage, indicating post climate shock adaptation. Specifically, a one standard deviation increase in competition causes the pre-existing difference in crop prices to increase by **0.5** to **0.6** percentage points, conditional on both areas being exposed to a week of extreme heat. Next, we use household level survey data to show that this rise in prices incentivizes farmers to increase their input use within the growing season. Our estimates suggest that a one standard deviation increase in competition leads to a **1.2** and **1.7** percent increase in land and labor inputs, respectively, for each additional day of extreme heat. Furthermore, input costs associated with labor, irrigation, fertilizers, and farm equipment also experience a significant increase. Consistent with the adaptation portfolio, we also find evidence of crop diversification at a macro-scale (i.e., district-level) in high competition areas, indicating crop-mix as a potential avenue for increased resilience. In summary, productive adjustment, incentivized by increasing prices, attenuates undesirable drops in output, but is limited to high competition areas.

One way to counter the market power distortions generated by archaic institutional policies is to remove the inter-state trade restrictions. However, the welfare impacts of such a policy change cannot be deduced directly from the data, and require a structural model. Specifically, our empirical strategy is inadequate in encapsulating three pivotal general equilibrium effects. First, removing trade restrictions will not only affect prices in *mandis* near the state borders, but also have a knock-on effect on prices in markets that are not in close proximity to state borders. Second, change in intermediary prices will incentivize farmers to re-optimize their choice of crops, intermediate inputs, and market for sale. This will alter supply, thereby impacting retail prices, which will eventually feed back into *mandi* prices. Finally, and more importantly, climate change will influence productivity differences across crops and fields, altering comparative advantage between different regions of India. This evolution of comparative advantage will interact with a change in market power of intermediaries, shaping the adaptation portfolio of farmers. A model, therefore, helps us understand how the policy change aids in mitigating the consequences of climate change.

To estimate adaptation gains from removing interstate trade restriction, we develop a spatial general equilibrium model of trade in the agricultural markets, drawing on the work of Costinot et al. (2016) and Chatterjee (2019). In our framework, every state consists of a large number of fields with heterogeneous productivity across multiple crops. Each field is represented by a farmer who makes two decisions: (*i*) crop and input choice, and (*ii*) intermediary market for sale post-harvest. The former decision is influenced by the relative productivity differences across crops and fields, *i.e.* comparative advantage, which determines the pattern of specialization within and between states. The latter decision relies on the farmers' transportation costs between competing markets — each of which is represented by an intermediary — and determines the level of market power. In order to ensure the model resembles reality, we add three key features. First, farmers cannot cross state border. To incorporate these trade restrictions, we assume transportation costs are infinite if the farm and market lie on different sides of the border. Second, intermediaries are *price makers*. This is modeled through a Bertrand competition which ensures intermediaries act strategically when purchasing crops, internalizing their market power. Third, intermediaries are allowed to sell across state borders. Therefore, geography and trade restrictions create spatial heterogeneity influencing farmers' arbitrage opportunities, and consequently, creating spatial variation in the monopsony power that intermediaries can exert.

The competitive equilibrium of our model and any subsequent counterfactual analysis will depend on five key parameters: (*i*) the elasticity of substitution between different varieties of the same crop; (*ii*) the elasticity of substitution between different crops; (*iii*) within-field heterogeneity in productivity; (*iv*) trade costs and; (*v*) dispersion of idiosyncratic shocks to the trade cost. All these parameters are estimated using a rich micro-level data set on field level crop productivity, inland trade data on agricultural commodities, geolocation of markets, as well as prices and quantity arrivals of different crops in each market. Finally we use the estimated parameters and information on the pattern of comparative advantage across fields and crops to simulate our model under the no–climate change scenario, and compare it to two counterfactual scenarios. In the first, we study the welfare consequences of a decline in crop and field productivity due to climate change, but in the presence of trade restrictions on farmers. In the second counterfactual scenario, we study the welfare consequences of climate change but without trade restrictions. The difference between the two counterfactual helps us ascertain the magnitude of mitigation that transpires once trade restrictions are removed.

Our model suggests that the welfare impact of climate change is substantially mitigated once inter-state trade restrictions are lifted. Specifically, we find that climate change reduces welfare in India by **2.1** percent of total GDP, assuming no policy change. However, increase in competition arising out of abolishing trade barriers enables farmers to receive a higher price, which changes the source and magnitude of adjustment, allowing a **13.8** percent alleviation in the welfare losses. This illustrates how market distortions created by government policies could hinder adaptation, and how removing the same could expand the adaptation portfolio of farmers, thus helping countries mitigate the negative consequences of climate change.

Related Literature: This paper contributes to several strands of literature. First, it contributes to the broader literature on the impact of market concentration on economic outcomes. A large body of research shows that market power has negative consequences for consumer surplus (Dafny et al. 2012, Miller & Weinberg 2017), economic inequality (Comanor & Smiley 1975), employee welfare (Prager & Schmitt 2021), as well as productivity and innovation (Aghion et al. 2001, 2005, Holmes et al. 2012). Interestingly, impeding competition is also linked with anti-democratic outcomes like concentrated economic and political power, political instability, and corruption (Becker 1958, Robinson & Acemoglu 2012). We instead focus on the role of market competition in incentivizing adaptation to climate change. In line with previous studies, we find that (intermediary) market power has harmful implications, and can put soft limits on adaptation in agriculture.

Second, this work relates to the literature on inefficiencies generated by government policies and institutional features. An extensive literature has documented the adverse effects of government regulations: labor regulations hurt output and productivity (Holmes 1998, Besley & Burgess 2004); licensing regulations which restrict firm entry lead to market concentration, decelerate employment growth, and increase corruption (Djankov et al. 2002, Bertrand & Kramarz 2002); product market regulations (*e.g.* trade tariffs) adversely impact competition, average firm size and profits (Blanchard & Giavazzi 2003), and; cost-of-service regulations in the utilities sector reduce efficiency (Fabrizio et al. 2007, Cicala 2022). We complement this literature by finding evidence that regulations governing the sale and purchase of agricultural products can distort competition and disincentivize adaptation. In this regard, our study is closest to Annan & Schlenker (2015) who find that a highly subsidized crop insurance program in the United States, providing coverage to farmers against crop losses, inhibits adaptation. However, the disincentive to adapt in their setup is a result of moral hazard, while the disincentive in our setting is driven by government induced distortions in market power of intermediaries. Thus, our paper documents how government regulations, intended to protect farmers from exploitation by middlemen, have inadvertently distorted competition and hindered adaptation, thereby exacerbating the dead-weight loss arising from climate change.

Third, we contribute to the literature on adaptation to climate change, and the mechanisms that underpin it. There is mounting evidence on the deleterious impact of climate change on several economic indicators like productivity, education, health, *etc.* (Burgess et al. 2017, Park et al. 2020, Somanathan et al. 2021).[8] As a natural progression, subsequent studies have focused on adaptation efforts, *i.e.* how these damaging effects can be mitigated. Researchers have documented the positive role of air conditioners (Barreca et al. 2016, Zivin & Kahn 2016), expansion of bank branches (Burgess et al. 2017), and relocation (Deschenes & Moretti 2009) in combating mortality and productivity losses caused by climate change. Agricultural adaptation has been linked with changing crop-mix (Auffhammer & Carleton 2018, Taraz 2018), using drought-tolerant seeds (Boucher et al. 2021), labor input adjustments (Aragón et al. 2021), and migration (Feng et al. 2015, Hermans & McLeman 2021). In a similar vein, this article finds that farmers rely on input adjustments and changing the crop mix to attenuate losses arising from climate shocks. Importantly, however, this adaptation portfolio is only accessible to farmers in high competition areas — on account of higher expected prices — and not where government policies have distorted market power.

Finally, our paper is related to the growing body of literature focusing on trade and adaptation to climate change (Reilly & Hohmann 1993, Randhir & Hertel 2000, Costinot

[8] There are numerous studies on the potential impact of climate change on agriculture in India (Guiteras 2009, Mall et al. 2006, Economic Survey of India 2018) and the United States (Mendelsohn et al. 1994, Schlenker et al. 2005, Deschênes & Greenstone 2007, Fisher et al. 2012, Schlenker & Roberts 2009). A review of the impact of global warming on agriculture in developing countries is provided by Mendelsohn (2009).

et al. 2016). While the literature has focused on how international trade can help alleviate climate change losses, we show that removing *domestic* trade barriers would also go a long way in accelerating adaptation efforts. In this regard, we build on the quantitative spatial general equilibrium model of Costinot et al. (2016) by moving away from the assumption of perfectly competitive environment, and adding spatial variation in market power of intermediaries. This allows us to quantify the welfare gains from adaptation to climate change through a reduction in intermediary market power, an outcome of dismantling domestic trade barriers.

Roadmap: The organization of the paper is as follows. Section 2 provides an overview of the institutional background of agricultural trade in India, particularly the APMC markets. In Section 3, we describe our data sources and the construction of variables. Section 4 presents the empirical strategy and the results from our econometric analysis. A theoretical model of climate change and trade is laid out in Section 5, its estimation in Section 6, and the counterfactual analysis in Section 7. Conclusions and areas for future research are discussed in Section 8.

2 Background on Agricultural Markets in India

To help understand how government regulations concerning agriculture marketing created spatial competition distortions amongst intermediaries, *i.e.* the paper's specific context, we provide a detailed overview of the origin of these laws. Section 2.A delves into the history, Section 2.B details the provisions, while Section 2.C provides insight into the unintended consequences of these provisions.

A History

The regulation of agricultural marketing in India has its roots in pre-independence policies introduced during the British Raj. The British government wanted to ensure sustained supplies of cotton at reasonable prices for textile mills in the United Kingdom. In order to facilitate this, the first regulated cotton market was set up in Karanja (Maharashtra) in 1886. Subsequently, the *Berar Cotton and Grain Market Act, 1887* was introduced which empowered the British to establish a trading supervisory committee and, thereafter, designate any place as a market for sale and purchase of agricultural produce within a district.

In 1928, under the chairmanship of Lord Linlithgow,[9] the British government's Royal

[9] Lord Linlithgow was Governor General and Viceroy of India from 1936 to 1943.

Commission on Agriculture in India expanded the scope of regulated markets. Simply, the commission recommended: (*i*) extending regulation of marketing practices to all crops, and (*ii*) establishment of regulated markets. To quote from the report:

> "It is only in Berar that the constitution of markets is regulated by special legislation and that the management is in the hands of elected committees. … The most hopeful solution of the cultivator's marketing difficulties seems to lie in the improvement of communications and the **establishment of regulated markets**, and we recommend for the consideration of other provinces, the establishment of regulated markets on the Berar system. … The Bombay Act is, however, definitely limited to cotton markets and the bulk of the transactions in Berar markets is also in that crop. We consider that the system can conveniently be extended to other crops. … We consider that the management of these markets should be vested in a market committee."

In pursuance of these ideals, the British Government in India circulated a Model Bill in 1931 to regulate trade practices and establish market yards in the countryside. However, only a few provinces adopted these laws (Central Provinces, Madras, Baroda, Bombay, Punjab, and Mysore). At its core, however, the establishment of regulated markets under the British was intended to control the price, quantity, buyer, and type of goods sold, with the direct aim of ensuring cheap supplies for England.

Post independence, the focus of the government shifted towards incentivizing farmers to heighten agricultural production. Moreover, the government sought to protect cultivators from exploitative middlemen who often forced farmers to sell at low prices. In pursuit of this objective, government regulation was seen as an effective instrument to facilitate fair and competitive compensation for farmers. Consequently, a large number of states enacted and enforced the Agriculture Produce Marketing Regulation (APMR) Acts from the late 1960s to the early 1980s.[10] The provisions within these Acts, and how they create monopsony power for intermediaries, is explained in the following subsection.

B Agricultural Produce Market Committee: Regulations

Agriculture is a state subject under the Indian constitution, *i.e.* states have the power and responsibility to legislate on agricultural marketing. In accordance with these legislative powers, each state has enacted laws under the APMR Act to regulate agricultural trade within its boundaries. These laws permit state governments to designate certain areas

[10] All states, except Kerala, Jammu and Kashmir and Manipur, enacted such laws.

within the geographical confines of the state as market areas (*mandis*). Each market area is governed by an Agricultural Produce Marketing Committee (APMC) — constituted of elected traders, farmers, and government representatives from the area — which is tasked with framing and enforcing the rules governing agricultural marketing. The committee is also responsible for setting up market yards where agricultural trade takes place.

These state-specific Acts mandate that the sale or purchase of agricultural commodities can only be executed in specified market areas, yards, or sub-yards located within the state (see images in Figure 2). In particular, it requires that all food produce should be brought by the farmers to a market yard in their region and then sold through an auction. Furthermore, intermediaries (*buyers*) who wish to trade in a certain market area are required to obtain a license from the market committee. Additionally, the Act also mandates that sellers and traders pay a market fee on all trade that takes place within the market area. This institutional setup was designed to ensure that farmers had access to organized markets operating under the supervision of the government; such oversight was intended to minimize the risks of exploitation by traders and middlemen. However, the provisions distorted market competition, which we discuss in detail below.

(a) APMC Market in Bhatinda, Punjab **(b) APMC Market in Yavatmal, Maharashtra**

Notes: *Panel* (*a*) and *Panel* (*b*) show two designated APMC market yards, also known as *mandis*, which were established under the state-specific Agricultural Produce Marketing Committee (APMC) Acts. These yards are the first point of contact between the farmers and intermediaries. All agricultural produce must be brought to these *mandis* by farmers in that region, and sales are made through auction. Intermediaries require a license to operate within a *mandi*, but are free to transport the purchased produce and sell it across the country.

Figure 2: APMC Market Yards or *Mandis* in India

C *Monopsony Power*

Though noble in their intentions, the APMC laws introduced an unintended consequence: monopoly power for market committees in their respective area. APMC legislation criminalizes setting up competing markets and buying agricultural produce from outside the designated market yards. Importantly, as the APMC laws are state-specific, their jurisdiction does not stretch beyond state boundaries. This, coupled with the requirement that farmers can only sell their produce in the APMC of their region, implies that farmers cannot cross state boundaries to sell their produce. In essence, jurisdictional boundaries and strict market regulations distort competition. This negatively impacts farmers' bargaining power and, consequently, lowers the probability of receiving fair prices for their produce.

Along with between-market competition, within-market competition is also impacted by collusion amongst traders. Market committees, responsible for granting licenses, are usually dominated by the trader lobby. This creates a conflict of interest as existing traders prevent market entry to preserve their profits. The licensing regime, therefore, artificially reduces the number of buyers in the market. Furthermore, since wholesalers, retail traders, and large processors cannot buy directly from the farmers, they rely on licensed traders to act as intermediaries. This behavior also impacts prices: various studies (Banerji & Meenakshi 2004, Meenakshi & Banerji 2005) document non-transparent price discovery processes resulting from trader collusion. This ultimately renders farmers subject to exploitation by intermediaries who act as financiers, information brokers, and traders. Notably, farmer exploitation creates further opportunities for rent-seeking as intermediaries can buy low and sell high, capturing the difference as profits.

In summary, while the APMC laws were intended to protect farmer exploitation by regulating agricultural marketing, many exploitative conditions have gradually resurfaced, mostly as unintended consequences of these laws. They limit between-market competition by creating legal barriers to entry, prohibiting farmers to sell outside APMC markets, and restricting the set of buyers to licensed intermediaries within the state. One way to counter this would be through within-market competition among intermediaries. However, collusion among traders is rampant, with evidence of price manipulation and restricted buyer entry, effectively creating a monopsony. The net result is an exploitative system of interlocked transactions that robs farmers of discretion across important selling decisions.

3 Data

Our goal is to study the extent of long-run adaptation, and the role of institution-led distortions in market competition on adaptation to climate change. To this end, we need four main types of data, which we draw from varied sources: (*i*) estimates of yields for our sample of crops; (*ii*) weather data to construct estimates of climate shocks; (*iii*) location of intermediary markets (*mandis*) to construct the competition measure, and; (*iv*) daily prices and arrivals (quantity of crop brought to a *mandi*) data for the sample of crops. Below, we provide detailed information on all the data sources.

A Yields

Our agricultural data on yields comes from the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT 2018). In collaboration with the Tata Cornell Institute of Agriculture and Nutrition (TCI), ICRISAT (2018) provides district level data on area (*'000 ha*), production (*'000 tons*), and yields (*kg*/*ha*) for 19 major crops in 313 districts of 20 states of India at an annual level from the year 1966 to 2017.[11] Our unit of analysis is, thus, the crop-district-year. There were 313 districts in 16 states in 1966.[12] Over the next 50 years, four new states were created from the 16 states to make it 20 states, with the number of districts in the 20 states increasing to 571. The database is, therefore, divided into 2 datasets: *apportioned* and *unapportioned*. *Apportioned* includes only the 1966 base districts, with data on districts formed after 1966 given back to their parent district. This has resulted in a consistent and comparable time series data for all the districts since 1966. *Unapportioned*, on the other hand, includes all the districts formed until 2015 in 20 states of India, but it only spans the years 1990 to 2015. We, thus, use the *apportioned* dataset for our analysis given its longer time horizon.[13]

We divide the crops based on the growing season, of which there are two main ones in India: *Kharif* and *Rabi*. The *Kharif* cropping season is from July–October during the southwest monsoon, with crops harvested from the third week of September to October. The *Rabi* cropping season is from October–March during winter, with harvesting in the spring months between April and May. The ICRISAT (2018) database does not separate the agricultural data by growing season (except for sorghum or millets). Therefore, we do not have estimates of what proportion of the crop was grown in each season. This is, however, necessary to ascertain as otherwise there is a risk of yielding spurious estimates of the relationship between climate variables and agricultural production. For instance, modeling yearly yields of a crop as a function of annual number of extreme heat days will be invalid if the production was, predominantly, limited to one growing season. Favorably for us, the production of most crops is concentrated to one of the two seasons, with negligible cultivation in the other. Agricultural Statistics at a Glance (2020), released by the Directorate of Economics and Statistics, Government of India, provides all India estimates of agricultural production of crops by season, averaged between the years 2014 to 2019. We use the share of

[11] As of 2022, India is divided into 28 states and 8 union territories, with the states being further subdivided into 776 districts. Year refers to the agricultural year, *i.e.* June 1st to May 31st (Sanghi et al. 1998).

[12] This excludes northeastern states (except Assam) and Jammu and Kashmir.

[13] For a description of the methodology for apportioning newly formed districts to their parent district, and a list of districts formed after 1966, see Appendices 1 and 2 of ICRISAT (2018).

production in each season to classify commodities into either of the two cropping seasons. For *e.g.*, if a majority of the total production of a crop was condensed to the *Kharif* season, we classify the crop as *Kharif*. Of course, given India's varied topography and climate, there could be variation in the cropping season for the same crop across different regions. We address this issue in Section 3.D.

B Weather

Our climate data are drawn from European Centre for Medium-Range Weather Forecasts (ECMWF), an independent intergovernmental organisation and research institute headquartered in the United Kingdom. We use the fifth generation of ECMWF atmospheric reanalyses of the global climate (ERA5-Land, 2021) dataset that provides gridded temperature (*Kelvin*) and precipitation (*depth in metres*) data at a $0.1^{\circ} \times 0.1^{\circ}$ (9km) horizontal resolution.[14] The data is made available at an hourly temporal resolution with coverage from January 1950 to present.

There was a mismatch in spatial resolution between weather and agricultural data: the former was available at a very high spatial resolution (9km $\times$ 9km grid cells), while the resolution of the latter was coarser and aggregated to a bigger administrative unit (district level). This implies that several weather grid cells fell within the boundaries of each district. To address this, we take a weighted mean of the temperature (weighted sum in case of precipitation) across all cells within the district. In order to calculate weights, note first that districts in India can be fairly large with heterogeneous geographical features, and contain areas with little to no agricultural activity (*e.g.* Himalayas in North and East India, or deserts in Gujarat and Rajasthan). Consequently, weather conditions in such parts of the district may be irrelevant for agricultural production within that unit. Therefore, we rely on fine scale land cover data to use as an aggregation weight. Specifically, we use the Global Food Security-support Analysis Data at 30m resolution (GFSAD30, 2017) which provides satellite-derived cropland extent maps in collaboration with National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS) for South Asia for the year 2015. The database divides land into three categories: water (ocean and water bodies), non-cropland, and cropland. For our purpose, all weather variables were aggregated based on weights proportional to the cropland extent (see Figure A.1).[15]

[14]Temperature of air measured at $2m$ above the surface of land, sea or in-land waters. Temperature measured in *Kelvin* was converted to degrees Celsius ($^{\circ}C$) by subtracting 273.15.

[15]Cropland extent was defined as lands cultivated with plants harvested for food, feed, and fiber, including both seasonal crops (*e.g.*, wheat, rice, corn, soybeans, cotton) and continuous plantations (*e.g.*, coffee, tea, rubber, cocoa, oil palms). Cropland fallows are lands uncultivated during a season or a year but are farmlands and are equipped for cultivation, including plantations (*e.g.*, orchards, vineyards, coffee, tea, rubber). Further details are available at globalcroplands.org.

Next, we provide details on the construction of the weather variables used in the empirical analysis. Schlenker & Roberts (2009) have documented strong non-linearities in the relationship between exposure to weather conditions and agricultural outcomes. To capture this, we use the concept of *Growing Degree Days* (*GDD*), which measures cumulative temperature exposure between two temperature thresholds during a period of time. The process of creating exposure bins for all district-month-year combinations involved the following steps. First, we use the hourly cropland-weighted weather data, aggregated to a district level, to calculate the daily minimum and maximum temperature for each district in India. Next, we derive how much time is spent at each temperature bin for all districts. These bins were $1°$C wide, ranging from $-10°$C to $50°$C. Finding the number of hours a district is exposed to each $1°$C interval requires intra-daily distribution of temperature, which required making assumptions about the temperature-time path. Specifically, the distribution of temperatures within each day was approximated using a sinusoidal curve (Ortiz-Bobea 2021), which generates a series of points at 15-minute intervals, between minimum and maximum temperatures of each day. Following this, we computed the exposure bins (measured in hours) by determining the frequency of these 15-minute interval points throughout the month.[16] As a final step, we compute growing degree days from these exposure bins by converting the number of hours in each exposure bin to days (divide by 24), and subsequently aggregating them between a low threshold $\underline{h}$ and a high threshold $\overline{h}$ using the expression:

$$GDD_{\underline{h}\ to\ \overline{h}} = \sum_{k=\underline{h}}^{\overline{h}-1} z^k \tag{1}$$

where z^k is the exposure in days to the k^{th} temperature bin. Essentially, $GDD_{\underline{h}\ to\ \overline{h}}$ measures the amount of time a crop was exposed to temperatures between a given lower and upper bound.

C *Intermediary Markets*

An empirical analysis of the impact of competition on mitigation of climate shocks requires information on market power, which is a function of the number, size, and location of intermediary markets. Our primary measure of competition is defined at a wholesale market level, and is calculated as an inverse distance weighted sum of total trade across all neighboring markets in the same state (see Section 4.B for details). Given the spatial nature of this statistic, it was important to determine the exact geospatial location of each market. The steps employed to create this dataset are detailed below.

[16]By construction, summing over all bins across a month for a district equals the number of hours in that month.

First, we needed a comprehensive list of all wholesale intermediary markets in the country. For this purpose, we used the *Directory of Wholesale Agricultural Produce Assembling Markets in India* published in 2004 by the Directorate of Marketing and Inspection (DMI), Ministry of Agriculture, Government of India (Chimalwar et al. 2004).[17] The directory lists 5,983 markets in the country, and provides information on the name of the market, name of and distance to the nearest railway station, district and state of each market, and the commodities traded therewith. These 5,983 markets form our universe of wholesale intermediaries (*mandis*) in India.

However, not all of these markets observed active trade and/or reported the daily quantities and prices of commodities arriving in the marketplace. Therefore, as a second step, we remove from our initial sample the subset of markets for which there did not exist any price or quantity data since 2001. The assumption here is that data does not exist because these markets did not see any trade during this time period.[18] For this exercise, we use the *Agmarknet* dataset provided by the Ministry of Agriculture and Farmers Welfare in India, which collates data on daily arrivals and producer prices for all government-regulated agricultural markets in India since 2001.[19] We match the DMI list of 5,983 markets with the list of markets in the *Agmarknet* data, and include a market in our sample if there was even a single day of trading at the market for any of the 19 major commodities (selected from ICRISAT (2018)) from 2001 onwards. Next, we remove all markets in the state of Bihar, which dismantled the APMC markets in 2006, and markets in Kerala, Jammu and Kashmir, and Manipur, which never enacted the APMC Act. We also remove markets in the north-eastern states, certain Union Territories, and islands, where agriculture is not practiced on any substantial scale.[20] This gives us a final sample of 2,938 markets in 20 states.

The third step involved a significant undertaking of finding the exact geolocation of these 2,938 markets. The problems with using a Google API to identify the coordinates of a market in India are manifold. First, India's linguistic diversity means APMC markets are denoted on Google Maps by local names in different states.[21] This implies that there does

[17]We used the latest version published in 2004. There are also three older directories published in the years 1963, 1992 and 2000.

[18]*Mandis* can be of three types: primary, secondary, and non-regulated (Chimalwar et al. 2004). The missing trade data pertains to the latter two. Our analysis is focused on primary markets, which are large yards where the first trade between farmers and intermediaries takes place. In essence, these yards are the first point of contact with the farmers. Secondary and non-regulated markets are smaller with rarely, if any, farmers participating. They are mostly used for further trading of the agricultural produce purchased by the intermediaries from the primary markets. Given that our chief focus is on farmers, and we have data on quantities and prices for all primary markets, the missing data for secondary markets is not a major concern.

[19]The *Agmarknet* data can be accessed at https://agmarknet.gov.in/.

[20]This includes Andaman and Nicobar Islands, Arunachal Pradesh, Chandigarh, Dadra and Nagar Haveli, Daman and Diu, Lakshadweep, Meghalaya, Mizoram, Nagaland, Puducherry, Sikkim, and Tripura. The states included in the final analysis are shown in Figure A.2.

[21]Examples of the most common names in each state include: *Agricultural Market Committee*, *Agriculture Mar-*

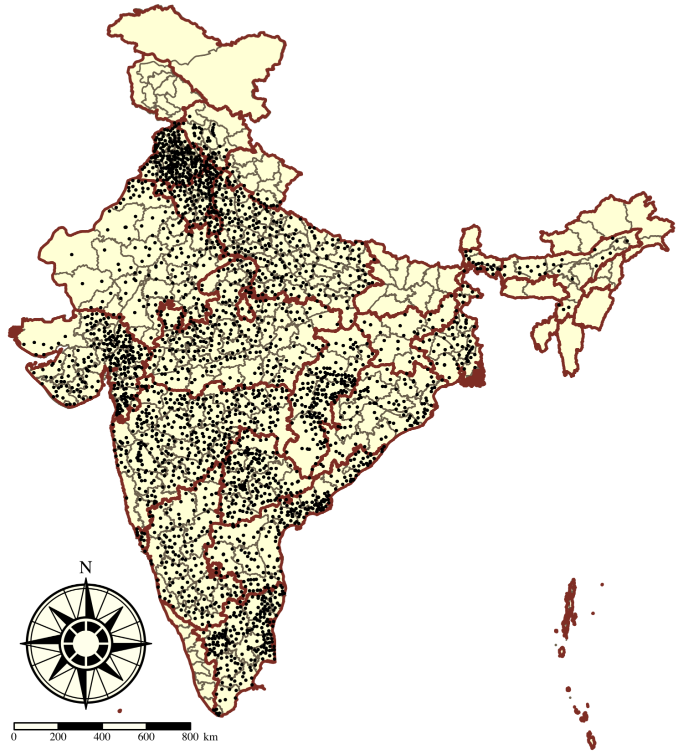
not exist a uniform text string which could be used to search the latitude and longitude coordinates of the markets. Second, though using the coordinates of the village centroid is a potential proxy for the geolocation of markets, Indian towns and villages can be expansive, and sometimes have multiple markets in the vicinity. Ignoring these distances and markets could lead to an erroneous competition measure. Furthermore, various village names are repeated, sometimes even within the same state, which could lead to inaccuracies in the collation of spatial location data. Given these complications, we, therefore, conducted a search on Google Maps using unique keywords for each market. For each market in a state, our keywords included the market name, postal address, and district followed by the commonly used designation for wholesale markets in that state. We replaced the designation with different monikers of APMC markets if our search did not turn up a valid result. In case of uncertainty, we further refined our search by calculating the distance between the market identified by our search results and the nearest railway station mentioned in the directory by DMI. We then compared our figure with the distance to the same railway station given in the directory, and only if the difference was minuscule (less than 10 percent) was the market selected.

As a final step, we corroborated our findings, wherever possible, with a dataset by the Pradhan Mantri Gram Sadak Yojana (PMGSY) which provides information on approximately 770,000 geo-tagged rural facilities, 20 percent of which are agricultural.[22] We did not use this as our primary source for geolocation of markets because the dataset is only available for rural India, and does not cover facilities in urban centers. Moreover, in most states, it classifies smaller retail markets as also *mandis*, making it difficult to differentiate wholesale markets from retail markets. However, it proved useful in validating — and confirming in case of uncertainty — our Google Maps search results in rural areas.

Notwithstanding different searches involving various strings and the use of PMGSY dataset, 13 percent (386 markets) of the markets could not be precisely geocoded. In such cases, we used the centroid coordinates of the village or town. The geographic distribution of all wholesale markets in the country is plotted in Figure 3.

ket Yard, *Rythubazar*, or *Farmer Grain Market* in Andhra Pradesh; *Regulated Market Committee* or *Notified Mandi* in Assam and Orissa; *Krishi Upaj Mandi* or *Galla Mandi* in Chhattisgarh, Rajasthan and Madhya Pradesh; *Khetiwadi Utpadan Samiti Market* in Gujarat; *Anaaj Mandi* or *Grain Market* in Haryana and Punjab; *RMC Yard* in Karnataka; *Krushi Utpanna Bazar Samiti* in Maharashtra; *Regulated Market* or *Weekly Shandi* in Tamilnadu; *Galla Mandi Samiti* or *Naveen Mandi Sthal* in Uttar Pradesh; *Krishak Bajar*, *Anaj Hat Tala* or *Kisan Mandi* in West Bengal.

[22] The dataset is provided by the Online Management, Monitoring and Accounting System (OMMAS) arm of PMGSY and is available at http://omms.nic.in/. The agricultural facilities include cold storages, collection centres, *mandis*, warehouse, etc.



Notes: The map shows the geographic distribution of 2,938 APMC markets by district and state. Each dot represents an APMC market. Geographic coordinates were found through Google Maps, using data from the *Directory of Wholesale Agricultural Produce Assembling Markets in India* published by the Directorate of Marketing and Inspection, Ministry of Agriculture, Government of India Chimalwar et al. (2004), and further corroborated with a dataset on geo-tagged rural facilities provided by the Pradhan Mantri Gram Sadak Yojana (PMGSY).

Figure 3: Geographic Distribution of APMC Markets

D *Quantity Arrivals and Prices*

The Ministry of Agriculture and Farmers Welfare aggregates commodity level, daily quantity arrivals and producer prices received by farmers across government-regulated agricultural markets in India. Information is available starting 2001 for 344 agricultural and livestock commodities from approximately 4,000 markets spread across more than 650 districts of India. Though this data is available on the government's *Agmarknet* portal, we downloaded the same from the portal maintained by the Centre for Economic Data and Analysis (CEDA) of Ashoka University, as they have collated the data in a format that is easily downloadable and also corrected for certain inconsistencies.[23]

Our sample is comprised of 52 major commodities which mirror the 19 crops in the

[23]The data from CEDA can be accessed at https://agmarknet.ceda.ashoka.edu.in/

ICRISAT (2018) dataset.[24] One potential concern with the latter dataset is that it does not classify regional crop production based on season. However, growing season for the same crop may differ across regions.[25] For instance, if we classify an agricultural commodity as a *Kharif* crop in a region where it is, in fact, grown in the winter months, the weather conditions ascribed to the crop yields will be erroneous, leading to spurious results. In this regard, high frequency arrivals data helps us attribute the right growing season for crops traded in a market as we can deduce the time of harvest based on its arrival date in an APMC market. Therefore, to correctly classify the growing season for each crop in each market, we use the following algorithm: for every crop-market pair, we first aggregate all arrivals up to a monthly level, and compute the monthly average across all years (2001 onwards). This gives us the average quantity traded in a market for every month across all years. Second, we use this monthly average to find the proportion of quantity traded in each month. Finally, we determine the growing season based on the month with the maximum proportion of arrivals. Accordingly, if the peak arrivals was between October to February, we classify the crop as *Kharif*, if it was between March to June, we classify it as *Rabi*, and *Zaid* (summer season) otherwise.

The market-wise growing season classification is then used to construct the price and quantity traded variables at a market-crop-year level. For quantity in each year, we sum the daily arrivals in a market across the agricultural season, while for prices, we use the modal price of the crop in the market across the growing season.

4 Empirical Methods and Results

The empirical section is divided into three parts. We start with Section 4.A which motivates our question on the distortionary impact of market power on adaptation by examining if there is any evidence of long-run yield-stabilizing adaptation to extreme heat in India. If farmers were able to neutralize the negative impact of institutional challenges over the long-term, then studying their distortionary impact in the short-run would just be a cursory exercise. This is followed by Section 4.B, which estimates the effect of market competition in mitigating the damaging impact of extreme heat. We approach this question using panel data methods and then proceed to strengthen our identification strategy through a border

[24] ICRISAT (2018) tends to aggregate several crops under a single head. For instance, it contains *minor pulses* as a crop, but this classification includes numerous pulses for which we have disaggregated data at the market level in the *Agmarknet* database. This is the source of discrepancy between the number of crops in ICRISAT (2018) and *Agmarknet* (19 versus 52).

[25] To give an example, rice growing season in India varies depending upon climatic conditions, soil types, and water availability. Eastern and southern regions of the country have favorable temperature for rice cultivation throughout the year, leading to two or three crops of rice every year. Northern and western regions, on the other hand, grow only one crop of rice from May to November (Singh 2009).

regression discontinuity design. Finally, in Section 4.C, we identify the potential mechanisms driving the impact of market competition on adaptation.

A Effect of Climate Shocks on Yields

This subsection estimates the share of the negative short-run impacts of extreme heat that are offset in the longer run. We run two separate regressions. First, Section 4.A.A.1 uses a panel approach, akin to Deschênes & Greenstone (2007), to estimate the effect of random year-to-year variation in district weather conditions on agricultural yields for the time period from 1968 to 2017. Second, Section 4.A.A.2 uses a long-differences approach proposed by Burke & Emerick (2016) to model long-run district-level changes in yields between two different points in time as a function of long-run changes in temperature and precipitation. Finally, in Section 4.A.A.3, we compare panel and long differences coefficients which offers a test of whether the shorter run damages of climatic variation on agricultural outcomes are mitigated in the longer run.

A.1 Panel Approach

The panel approach uses short-run variation in climate, which is plausibly random, within a given area to estimate the effect of extreme heat on agricultural productivity. Our econometric model takes the following form:

$$log(Yields)_{cdsy} = \alpha \; + \; \sum_{j=1}^{6} \beta_j \; GDD_{\{j\}dsy} \; + \; \theta \; Precip_{dsy} \; + \; \delta \; (Precip_{dsy})^2 \; + \; \pi_{cd} \; + \; \gamma_y \; + \; f_s(y) \; + \; \xi_{cdsy} \quad (2)$$

where $log(Yields)_{cdsy}$ refers to the log of yields (in *kg/ha*) for crop c in district d of state s in agricultural year y (July-June). The key explanatory variable is $GDD_{\{j\}dsy}$, which captures the daily distribution of daily temperatures in district d of state s in year y. It denotes the number of days in district d of state s in agricultural year y on which the daily mean temperature fell in the j^{th} of the six temperature bins (in $^{\circ}C$), namely $< 15^{\circ}C$, $> 35^{\circ}C$, and four $5^{\circ}C$ wide bins in between. $Precip_{dsy}$ and $(Precip_{dsy})^2$ denote the linear and quadratic polynomial function of total rainfall (in m of water equivalent per day) for district d in state s and year y. For our main specification, we include crop-district, π_{cd}, and agricultural year, γ_y, fixed effects, while $f_s(y)$ refers to state-specific linear and quadratic time-trend. The fixed effects imply that identification comes only from weather variation across years within a particular district for each crop after differencing out any state-specific time trends and macro variations across all states in a year. ξ_{cdsy} denotes the error term. Note that the model above is run separately for *Kharif* and *Rabi* crops, so agricultural year refers to the particular cropping season in that agricultural year.[26]

We estimate separate coefficients β_j for each of the temperature bin regressors. Since the number of days in a particular standardized cropping season always sums to the same amount, we have to use one bin as a reference category.[27] We use $20-25°C$ as the reference category for *Kharif* crops, and $15-20°C$ as the reference category for *Rabi* crops, with the coefficients for the reference categories consequently normalized to zero.[28] We use two-way clustered robust standard errors, with clustering at the crop-state and year level. Results are presented in columns (1) and (2) of Table 1.

The results from the panel regression indicate that extreme heat has a significant negative impact on productivity, with each additional degree-day of heat above $35°C$ reducing yields by 1 percent and 1.8 percent for *Kharif* and *Rabi* crops, respectively. For *Rabi* crops, an additional degree-day between $30-35°C$ is also detrimental, with yields experiencing a sharp decline by 1 percent in comparison to the yields during the optimal temperature of $15-20°C$ degrees. The larger impact on *Rabi* crops is expected, as they are sown in winter and harvested in early spring and, therefore, will be more sensitive to extreme heat.

Given that panel estimates capture within-year adjustments by farmers (Guiteras 2009) — such as modification of inputs or cultivation techniques — the negative results indicate that short-run adjustment are unable to mitigate the harmful effects of extreme heat.[29] Next, we estimate the effect of climate shocks over the long-run which allows for the possibility of transformational adaptations, for *e.g.* crop switching or exit from farming.

A.2 Long Differences Approach

The *Long Differences* model uses the approach developed by Burke & Emerick (2016) to identify the effect of climate change (as opposed to shocks) on agricultural productivity.

[26]Specifically, the weather variables for *Kharif* crops are defined as the sum of the growing degree days or precipitation in the months of June, July, August, and September for a particular agricultural year, while the weather variables for *Rabi* crops pertain to the months of October, November, December, January, and February of the agricultural year.

[27]For *Kharif* season, the number is 122, calculated as the total number of days between June-September. For *Rabi* season, the number is 151, calculated as the total number of days between October-February.

[28]Reference category was selected based on the optimal temperature during the ripening (grain filling) stage for the key crop in the season — rice for *Kharif*, and wheat for *Rabi*. Grain filling is one of the most sensitive temperature stages for rice and wheat, with a strong bearing on final yields (Krishnan et al. 2011). The mean optimum temperature during this stage is between 21.2 to 24.2 for rice (Sánchez et al. 2014), and 15-20 for wheat (Jenner 1991, Wardlaw 1974)

[29]The ability of panel models to capture long-run climatic adaptation remains a subject of active research. See McIntosh & Schlenker (2006) and Mérel & Gammans (2021) for a discussion.

Table 1: Effect of Temperature on Yields: Panel and Long Difference Estimates

	Panel		Long Differences	
	Kharif	*Rabi*	*Kharif*	*Rabi*
	(*1*)	(*2*)	(*3*)	(*4*)
Bin $<15_{dsy}$	0.005	0.001	0.016	-0.015
	(0.005)	(0.002)	(0.039)	(0.014)
Bin 15-20$_{dsy}$	0.007		0.002	
	(0.004)		(0.018)	
Bin 20-25$_{dsy}$		-0.004		-0.012
		(0.002)		(0.012)
Bin 25-30$_{dsy}$	-0.001	-0.003	0.005	-0.016
	(0.002)	(0.002)	(0.005)	(0.012)
Bin 30-35$_{dsy}$	-0.005^{*}	-0.010^{***}	-0.004	-0.029^{***}
	(0.002)	(0.002)	(0.008)	(0.011)
Bin $>35_{dsy}$	-0.010^{**}	-0.018^{**}	-0.023^{***}	-0.027^{*}
	(0.004)	(0.004)	(0.008)	(0.015)
Fixed Effects				
Crop × District	✓	✓		
Crop × State			✓	✓
Year	✓	✓		
State Time-Trend	✓	✓		
Num. obs.	125,279	56,436	2,189	1,082
Adj. R^2	0.743	0.809	0.563	0.580

Notes: Clustered robust standard errors are in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Columns (*1*) and (*2*) provide estimates of the effect of climate shocks on yields using a panel approach, as specified in Equation (2). The dependent variable is the natural logarithm of yields (in *kg*/*ha*) for crop *c* in district *d* of state *s* in agricultural year y. Columns (*3*) and (*4*) provide estimates of the effect of climate change on agricultural yields from a long-differences approach (Burke & Emerick 2016), as specified in Equation (3). The dependent variable is the change in logged value of yields for crop c in district d of state s between two periods, wherein the two periods are 1970 and 2015, with endpoints calculated as five-year average. Data, sourced from ICRISAT (2018), are for 313 Indian districts of 20 states at an annual level from the year 1966 to 2017. The independent variables, $Bin_{\underline{h}\ to\ \overline{h}}$, measure the amount of time, in days, a crop was exposed to temperatures between a given lower and upper bound. The coefficient of interest is the estimate on *Bin* $>35_{dsy}$, which represents extreme heat. Columns (*1*) and (*3*) provide estimates for *Kharif* crops (July–October), while columns (*2*) and (*4*) provide estimates for *Rabi* crops (October–March). Standard errors for panel estimates are clustered at the crop-state and year level, while standard errors for long-difference estimates are clustered at the district-level.

Long differencing uses variation in longer run climate change and, therefore, helps to account for long run adjustments to temperature. Specifically, we construct longer run yield and weather averages at two different points in time for each location, and calculate changes in average yields as a function of changes in average temperature and precipitation. The model is as follows:

$$\Delta log\left(\overline{Yields}\right)_{cds} = \alpha \;+\; \sum_{j=1}^{6} \beta_j \left(\Delta \overline{GDD}_{\{j\}ds}\right) \;+\; \theta\left(\Delta \overline{Precip}_{ds}\right) \;+\; \delta\left(\Delta \overline{Precip}_{ds}\right)^2 \;+\; \pi_{cs} \;+\; \xi_{cds} \quad (3)$$

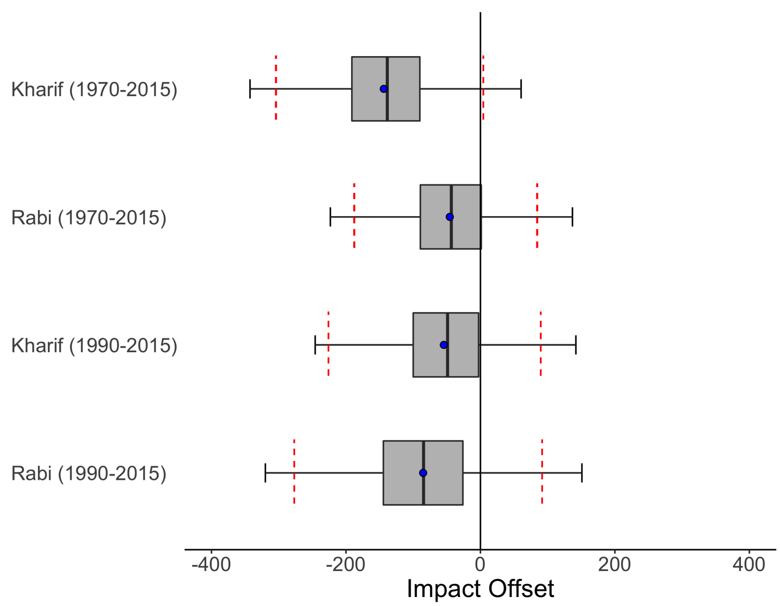
where $\Delta log\left(\overline{Yields}\right)_{cds}$ is the change in logged value of yields for crop c in district d of state s between two periods. In our main specification, the two periods are 1970 and 2015, with endpoints calculated as five-year averages for each variable to smooth out any idiosyncratic noise. $\Delta\overline{GDD}_{\{j\}ds}$ is the average difference in the number of growing degree days in the j^{th} temperature bin in district d between the two periods, while $\Delta\overline{Precip}_{ds}$ refers to the change in average rainfall between the two periods in a given district. We also include crop-state fixed effects, π_{cs}, to account for any crop- and state-specific trends. The identifying variation, therefore, comes from temperature changes within different districts in a state after differencing out crop-specific trends. The key coefficient of interest is β_6, which measures how yields are affected by exposure to extreme heat, *i.e.* $> 35°C$. Like before, the analysis is run separately for *Kharif* and *Rabi* crops, and the coefficients for the reference categories are normalized to zero. Error terms are assumed to be correlated within districts, and consequently, the standard errors are clustered at the district-level. Results are presented in columns (3) and (4) of Table 1.

The long differences estimates are higher in magnitude than estimates from the panel approach, and suggest that one unit increase in exposure to heat above $35°C$ results in a significant 2.3 and 2.7 percent decline in yields for *Kharif* and *Rabi* crops, respectively. As before, exposure to degree days between $30 - 35°C$ are also damaging for crops in the *Rabi* season, with yields dropping by 2.9 percent relative to one additional day in the reference bin of $15 - 20°C$. Note that the magnitude of these effects is net of any transformational adaptations made by farmers over the 45-year estimation period, for *e.g.* crop switching or exit from farming.

A.3 Adaptation

We can compare panel and long differences coefficients, in the style of Burke & Emerick (2016), to estimate adaptation to extreme heat in the long-run. The logic is as follows: panel models identify the short-run responses to weather, while long differences models identify the impact of long-run changes in climate, embodying any adaptation that farmers have undertaken over the estimation period. Comparing the two estimates can, therefore, allow us to test whether the shorter run detrimental effects of extreme heat on agricultural outcomes are in fact mitigated over a longer horizon. We quantify the magnitude of adaptation as $1 - \beta_j^{LD}/\beta_j^{FE}$, with $j = 6$, *i.e.* $> 35°C$ temperature bin, and it gives us the percentage of the negative short-run impact of extreme heat on yields that is offset in the long-run. β_j^{LD} here refers to the estimate of $\beta_{\{j=6\}ds}$ in the long differences model in Equation (3), and β_j^{FE} refers to the estimate of $\beta_{\{j=6\}dsy}$ in the panel model in Equation (2). A positive estimate would signify adaptation, with farmers demonstrating better adjustability to rising temperatures over the long-run, compared to shorter run heat shocks. Contrarily, a null or negative result provides evidence of a failure to alleviate short-term yield losses from exposure to extreme heat through adaptation in the long-run; worse still, this could indicate mitigation measures available in the short-run prove untenable in the long term.

Given that β_j^{FE} and β_j^{LD} are estimated using separate regressions, we need to quantify the uncertainty in the adaptation estimate. We bootstrap our data 5,000 times, sampling districts with replacement to preserve the within-cluster features of the error (Cameron et al. 2008). Therefore, if the d^{th} cluster (district) is selected, then all data (dependent and regressor variables) in that cluster appear in the resample.[30] This procedure is run separately for *Kharif* and *Rabi* crops for two time periods: 1970-2015 and 1990-2015. We then use the distribution of bootstrapped adaptation estimates to test, for each season and time period of interest, the null hypothesis of "no adaptation" to extreme heat—i.e., that $1 - \beta_j^{LD}/\beta_j^{FE} = 0$. Results are presented in Figure 4.



Notes: Figure 4 shows the percentage of the short-run impacts of extreme heat on agricultural productivity for *Kharif* and *Rabi* cropping seasons that are mitigated in the longer run. Each box plot corresponds to a particular season and time period as labeled on the left, and represents 5,000 bootstrap estimates of $1-\beta_j^{LD}/\beta_j^{FE}$ for that time period. The dark line in each distribution is the median, the blue dot the mean, the grey box the interquartile range, and the whiskers represent the fifth to ninety-fifth percentile. The red dashed lines in each box plot represents the 2-sided confidence intervals for the test that $1 - \beta_j^{LD}/\beta_j^{FE} = 0$.

Figure 4: Percentage of Short-Run Impacts Offset by Adaptation

[30] That is, we take a draw of districts with replacement, estimate both long differences and panel model for those districts, compute the extreme heat coefficients for the two models, calculate the adaptation measure, and repeat 5,000 times for a given time period.

Results suggest that long-run adaptation to extreme heat has been absent, and in fact, the deleterious impact of weather shocks over the long-run is higher relative to the short-run when adaptation avenues could be more limited. Median estimates (dark black lines) from the bootstrap distribution are negative for all the cases. Long-run point estimates are higher than short-run estimates by 48 to 132 percent for *Kharif* crops, and by 45 to 85 percent higher for *Rabi* crops. However, even though the estimates are negative, the 2-sided confidence intervals (red dashed lines) for all cases span zero. Thus, longer run adaptations appear to have mitigated none of the large negative short-run impacts of extreme heat on productivity. More likely, short-term adaptation measures mitigate a portion of the damaging effects, but the same measures prove to be unsustainable over the long-run.

In summary, our results on adaptation in the long-run indicate that the bottlenecks farmers face in adopting short-run strategies have a direct and cumulative impact on their ability to adapt in the long-term. It should be noted that various studies document that Indian farmers correctly perceive climatic changes, which makes the lack of adaptation we find in the long-run puzzling (Datta et al. 2022). A clearer understanding of the effect of distortionary policies on year-to-year adaptation is, therefore, crucial to assess their persistent impact and also shed light on heterogeneity in adaptation across regions with high and low competition.

B Effect of Competition on Mitigation of Climate Shocks

We start by constructing a local spatial competition measure in Section 4.B.B.1. This measure is then used in Section 4.B.B.2 to estimate, using a panel regression, the effect of competition on adaptation. In our analysis thus far, adaptation has been measured by the magnitude of the fall in district-wise yields mitigated by competition. We modify this definition in Section 4.B.B.3, where we now use spatially disaggregated market arrivals data to measure adaptation. Finally, in Section 4.B.B.4, to address endogeneity concerns, we implement a border discontinuity design with market pairs to causally identify these effects.

B.1 Measuring Market Power

We construct a measure of local competition at the market level, $Comp_{1m}$, by taking a weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state. The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade (Y_n) refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021. For any market m,

$$Comp_{1m} = \sum_{n \in \mathcal{M} \backslash \{m\}} \left\{ \frac{1}{distance_{mn}} \right\} Y_n \times \mathbb{1} \{\textit{state of m} = \textit{state of n}\} \tag{4}$$

where $\mathcal{M}$ is the set of all markets in India. Competition in any market m is driven by three factors: the number of neighboring markets (n), a farmer's ease of access to alternative markets, which we incorporate through $distance_{mn}$, and the size of the alternative markets, which we proxy using the value of trade over the last two decades (Y_n). Therefore, the $Comp_{1m}$ measure will assign a greater weight to a proximal market. Furthermore, a neighboring market with large trade volumes will lead to a higher competition measure, as opposed to a market with limited trade.

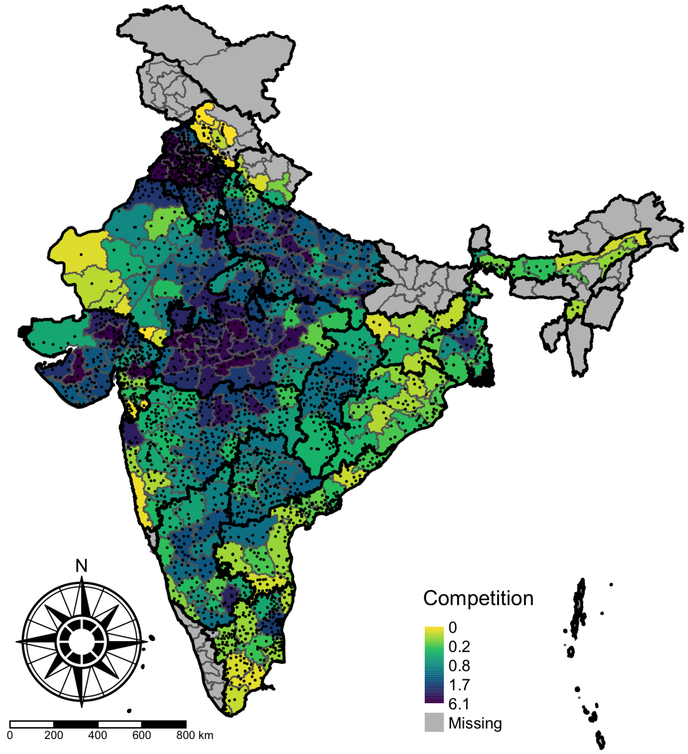
We also create an analogous local competition measure $Comp_{2m}$, similar to Chatterjee (2019), by taking an inverse distance weighted sum of other markets near a particular market site but in the same state. The only difference between the two measures is that we do not include the value of trade (Y_n) in the latter, and competition is only defined by the proximity of markets. Finally, since our unit of analysis is crop-district-year, we aggregate competition to a district level by averaging the competition measure for all markets in a district d of state s. This also gives us an opportunity to define a third, more crude measure of competition, $Comp_{3ds}$, which equals the density of markets, *i.e.* the number of markets per square km in a district d of state s. The geographic distribution of competition using the $Comp_{1m}$ measure, aggregated to a district level, is illustrated in Figure 5.

B.2 Panel Approach

We run a panel model to estimate how market competition, measured at a district level, mitigates the adverse effects of extreme heat on crop yields. Our main specification takes the following form:

$$\begin{aligned} log(Yields)_{cdsy} = \alpha \ + \sum_{j=1}^{6} \eta_j \ GDD_{\{j\}dsy} + \sum_{j=1}^{6} \Omega_j (GDD_{\{j\}dsy} \times Comp_{ds}) \ + \\ \phi \ Precip_{ds} + \delta \ (Precip_{ds})^2 + \lambda_{cy} + \lambda_{dct} + \lambda_{sy} + \xi_{cdsy} \end{aligned} \tag{5}$$

where $Comp_{ds}$ is the aggregate measure of competition at the district level, and equals either the mean value of the market level competition measure, $Comp_{im} \forall \ i \in \{1, 2\}$, for all markets m in district d, or the number of markets per square km in district d of state s $(Comp_{3ds})$. Since our baseline competition measure $(Comp_{1m})$ is calculated as an inverse distance weighted sum of total value of trade across all years in neighboring markets, and



Notes: The map shows the geographic distribution of competition at a district level. Competition is measured for each of the 2,938 APMC markets (represented by black dots) as the weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state (see Equation (4)). The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021. Since our unit of analysis is crop-district-year, we aggregate competition to a district level by averaging the competition measure for all markets in a district d of state s.

Figure 5: Geographic Distribution of Competition Aggregated to District Level

we do not have data on the date of construction of markets, $Comp_{ds}$ is time invariant across the length of our sample. c

To control for confounds, we include multiple fixed effects, including the following in our most rigorous specification: a crop-year fixed effect, λ_{cy}, that controls for changes in national or world prices of the commodity; a district-crop-decade fixed effect, λ_{dct}, that controls for slow-moving changes in crop-specific costs, in the area allocated to the crop, in preferences, or in technologies; and a state-year fixed effect, λ_{sy}, that controls for state-specific cost or demand shocks common to all crops. Certain specifications also include $f_s(y)$, which is a state-specific linear and quadratic time-trend. Note that the inclusion of any form of district fixed effects implies that the level effect of time-invariant district specific competition $(Comp_{ds})$ is swept out and cannot, therefore, be estimated. Finally, we compute robust standard errors clustered at the state-year and crop level to account for cropping decisions and other shocks which are likely to be spatially and serially correlated. Results are presented in Table 2.

Table 2: Competition and Mitigation of Climate Shocks: Panel Approach with Yields

	Dependent Variable: $log(Yields)_{cdsy}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Bin\ 30\text{-}35_{dsy}$	-0.004^{*}	-0.004^{*}	-0.011^{***}	-0.002	-0.013^{***}	-0.010^{***}
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$Bin > 35_{dsy}$	-0.026^{***}	-0.025^{***}	-0.014^{**}	-0.033^{***}	-0.018^{***}	-0.015^{***}
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.004)
$Bin < 15_{dsy} \times Comp_{ds}$	-0.002	-0.002	-0.000	-0.000	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
$Bin\ 15\text{-}20_{dsy} \times Comp_{ds}$	0.003	0.003	0.002	0.002	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
$Bin\ 25\text{-}30_{dsy} \times Comp_{ds}$	-0.000	0.000	0.002	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Bin\ 30\text{-}35_{dsy} \times Comp_{ds}$	-0.001	-0.001	0.001	-0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
$Bin > 35_{dsy} \times Comp_{ds}$	0.004^{***}	0.004^{***}	0.003^{**}	0.005^{**}	0.003^{**}	0.002^{*}
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Fixed Effects						
Crop		✓				
District	✓	✓				
Year		✓	✓			
Crop × District			✓			
Crop × Year	✓			✓	✓	✓
District × Year				✓		
State × Year						✓
District × Crop × Decade					✓	✓
Effect Mitigated (in %)	**18.5**	**20.9**	**31.7**	**18.8**	**20.5**	**15.1**
Num. obs.	59,593	59,593	59,593	59,593	59,593	59,593
Adj. R^2	0.624	0.615	0.805	0.635	0.829	0.844

Notes: Clustered robust standard errors are in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Columns (1) to (6) provide estimates of how market competition, measured at a district level, mitigates the adverse effects of extreme heat on crop yields (Equation (5)). The dependent variable, $log(Yields)_{cdsy}$, refers to the log of yields (in *kg*/*ha*) for crop c in district d of state s in agricultural year y (July-June). Data, sourced from ICRISAT (2018), are for 313 Indian districts of 20 states at an annual level from the year 1966 to 2017. $Comp_{ds}$ is the aggregate measure of competition at the district level. For this purpose, we first calculate competition for each of the 2,938 APMC markets as the weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state. The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021. Second, we aggregate competition to a district level by averaging the competition measure for all markets in a district d of state s. The independent variables related to temperature, $Bin_{\underline{h}\ to\ \overline{h}}$, measure the amount of time, in days, a crop was exposed to temperatures between a given lower and upper bound. The coefficient of interest is the estimate on the interaction term between $Bin > 35_{dsy}$ (extreme heat) and $Comp_{ds}$. It can be interpreted as the supplementary impact of an additional degree day of extreme heat for a given level of competition. The antepenultimate row, titled Effect Mitigated (in %), provides estimates of the impact of extreme heat mitigated by a one standard deviation increase in district competition. Coefficients related to the effect of temperatures less than 30°C on yields have been omitted for brevity. Standard errors are clustered at the state-year and crop level.

Our results suggest that there is significant mitigation of the effect of extreme heat owing to increased competition. Depending on the specification, each additional degree-day of heat above $35°C$ reduces yields by 1.4 to 3.2 percent. Importantly, in areas with lower intermediary market power, this effect is attenuated, with the coefficient on the interaction term between extreme heat and competition significantly positive and ranging from 0.001 to 0.003. To interpret the scale of this number, we can compute the impact of a one standard deviation increase in competition on the effect of heat shocks on yields. Dividing this by η_j

gives us the percentage of impact mitigated. We find that a one standard deviation increase in market competition can help farmers mitigate the impact of extreme heat by 13.2 percent in our most rigorous specification in column (6) with crop-year, state-year and district-crop-decade fixed effects. The effect is substantially larger in column (3), where we control for crop-district and year fixed effects and add in state time trends, with one standard deviation increase in competition leading to an attenuation of 31.3 percent. The rest of the specifications give us a number between these two extreme values.

B.3 Panel Approach: Arrivals Data

To this point in our paper, we have used the attenuation in district-wise crop-specific yields as a measure of adaptation. However, potential concerns could arise regarding mismeasurement of the district level competition variable as the same was constructed by averaging the market competition across all *mandis* in the district. Particularly, if farmers regularly cross district borders within the state boundaries to sell their produce, then the average competition across district mandis may not be a true indicator of the monopsony power faced by farmers. Therefore, we address this by using microdata on the daily quantity *arrivals* of each crop at a market. *Arrivals* reflect the daily quantity traded of a crop in a particular *mandi*, and the sum across the growing season acts as a proxy for the total production of the crop during the agricultural year.

Our econometric specification closely follows Equation (5), except that our unit of analysis is now market-crop-year, and we replace yields at the district level with quantity arrivals at each market. Specifically,

$$log(Arrivals)_{cmdsy} = \alpha \ + \sum_{j=1}^{6} \eta_j \ GDD_{\{j\}dsy} + \sum_{j=1}^{6} \Omega_j (GDD_{\{j\}dsy} \times Comp_{mds}) + \phi \ Precip_{ds} + \delta \ (Precip_{ds})^2 + \lambda_m + \lambda_{cy} + \lambda_{dt} + \lambda_{sy} + \xi_{cmdsy} \quad (6)$$

where $log(Arrivals)_{cmdsy}$ refers to the natural logarithm of the quantity of crop c arriving in market m situated in district d of state s in agricultural year y. $Comp_{mds}$ is the market level measure of competition, calculated as either the weighted sum of the total value of trade at all other markets in the same state near the origin market site ($Comp_{1m}$), or the inverse distance weighted sum of other markets in the same state near a particular market site ($Comp_{2m}$). We include crop-year fixed effects (λ_{cy}) to account for changes in national or world prices of commodities, and district-decade fixed effects (λ_{dt}) to factor out slow moving district-specific technological changes. We also control for state-specific cost or demand shocks common to all crops by including state-year fixed effects (λ_{sy}), and individual market time-invariant idiosyncrasies by adding individual market fixed effects (λ_m). The inclusion of market fixed effects implies that the level effect of time-invariant market specific competition ($Comp_{mds}$) is swept out and cannot, therefore, be estimated.

η_6 can now be interpreted as the effect of an additional degree-day of extreme heat in the district on quantity arrivals, while the coefficient of interest, Ω_6, indicates the magnitude of impact mitigated by competition. We cluster our standard errors two-way, both at the state-decade level and the crop level. Results are presented in Table 3.

Table 3: Competition and Mitigation of Climate Shocks: Panel Approach with Arrivals

	Dependent Variable: $log(Arrivals)_{cmdsy}$			
	(1)	(2)	(3)	(4)
Bin 30-35$_{dsy}$	0.001	0.001	0.002	0.001
	(0.006)	(0.006)	(0.006)	(0.006)
Bin >35$_{dsy}$	−0.023*	−0.023*	−0.030*	−0.023*
	(0.013)	(0.013)	(0.016)	(0.014)
Bin <15$_{dsy}$ × *Comp*$_{mds}$	−0.000	−0.000	−0.001	−0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Bin 15-20$_{dsy}$ × *Comp*$_{mds}$	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.001)
Bin 25-30$_{dsy}$ × *Comp*$_{mds}$	0.000	−0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Bin 30-35$_{dsy}$ × *Comp*$_{mds}$	−0.000	−0.000	−0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.001)
Bin >35$_{dsy}$ × *Comp*$_{mds}$	0.002***	0.002***	0.003**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Fixed Effects				
Market	✓			✓
Crop × Year	✓	✓	✓	✓
District × Decade				✓
Market × Decade		✓		
Market × Year			✓	
State × Year	✓	✓	✓	✓
Effect Mitigated (in %)	**36.9**	**35.4**	**29.6**	**36.2**
Num. obs.	148,814	148,814	148,814	148,814
Adj. R^2	0.433	0.450	0.450	0.437

Notes: Clustered robust standard errors are in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Columns (1) to (4) provide estimates of how market competition mitigates the adverse effects of extreme heat on quantity arrivals at each market (Equation (6)). The dependent variable, $log(Arrivals)_{cmdsy}$, refers to the natural logarithm of the quantity of crop c arriving in market m situated in district d of state s in agricultural year y. Data, sourced from Centre for Economic Data and Analysis (CEDA) of Ashoka University, comprises of quantity arrivals of 52 major commodities in 2,938 APMC markets from 2001 to 2021. $Comp_{mds}$ is the measure of competition at the market level, and equals the weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state. The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021. The independent variables related to temperature, $Bin_{\underline{h}\ to\ \overline{h}}$, measure the amount of time, in days, a crop was exposed to temperatures between a given lower and upper bound. The coefficient of interest is the estimate on the interaction term between $Bin > 35_{dsy}$ (extreme heat) and $Comp_{mds}$. It can be interpreted as the effect of an additional degree-day of extreme heat in the district on quantity arrivals. The antepenultimate row, titled Effect Mitigated (in %), provides estimates of the impact of extreme heat mitigated by a one standard deviation increase in market competition. Coefficients related to the effect of temperatures less than 30°C on quantity arrivals have been omitted for brevity. Standard errors are clustered at the state-decade and crop level.

The results mirror the estimates from the previous subsection — in fact, the mitigation effects are larger. Depending on the specification, each additional degree-day of heat above 35°C reduces quantity arrivals by 2.3 to 3.0 percent. However, as before, this effect is significantly allayed in high-competition areas. A one standard deviation increase in market competition can help farmers mitigate the impact of extreme heat by 36.2 percent in our most rigorous specification in column (4) with market, crop-year, state-year, and district-decade fixed effects. In the remaining columns, the effect sizes range from 29.6 to 36.9 percent. This suggests that our results using district-level yields as a measure of adaptation were biased downwards, and using arrivals data as a proxy helps correct this bias.

B.4 Hybrid Border Discontinuity Design

Although our results are consistent across different empirical specifications, one can still be concerned about other forms of unobserved heterogeneity. For example, if a large number of markets were set up in regions where farmers had a higher potential for innovation, then the coefficient on the interaction between competition and weather could just be capturing the effect of farmer ingenuity. To overcome this issue, we implement a hybrid border discontinuity design with market pairs. We match all markets which are less than x kilometers apart (bandwidth) but lie on different sides of a state boundary. We try different values of the bandwidth ranging from 25 kms to 50 kms, and all multiples of five therein. For each bandwidth, we obtain a sample of market pairs, with markets belonging to a pair lying in close proximity spatially but divided by a state border. The empirical strategy involves regressing — for each market pair — the difference in arrivals on: (*i*) the difference in competition; (*ii*) the average weather conditions across the two markets, and (*iii*) the interaction between the two. We call it *hybrid* because even though there is a discontinuity in competition at the border, the regression involves weather variables which are continuous.

The basic rationale behind employing the border discontinuity design is that other determinants of arrivals like demand, weather, productivity via soil quality, farmer ingenuity, and transportation costs will vary continuously across a state boundary. This should, therefore, help to assuage concerns about unobserved heterogeneity. One could be concerned that geographical conditions change discontinuously at the border. However, post independence in 1947, Indian states were redrawn along linguistic principles, rather than administrative, economic, or geographic factors (Chari 2016, Samaddar 2020).[31] Nevertheless, an important determinant of farmer adaptation which could change discontinuously at the state border is each state's policy on weather shocks. To address this confounding effect, we add market pair-year fixed effects. Thus, the only remaining discontinuity across

[31] The Government of India appointed the States Reorganisation Commission in December 1953 which advocated the following: *To consider linguistic homogeneity as an important factor but not to consider it as an exclusive and binding principle* (Parameswaran & Chattopadhyay 2014). In August 1956, the Indian Parliament enacted the States Reorganisation Act, which remains India's largest collective administrative reorganisation. While due consideration was given to administrative and economic factors, it recognized for the most part the linguistic principle and redrew state boundaries on that basis (Kumar 2019).

state borders which could potentially aid in attenuating the impact of extreme heat is local competition, as farmers are not allowed to sell their output across state borders.[32]

In essence, the advantage of this design is that we can difference out unobserved factors other than competition that affect adaptation by choosing market pairs in close geographical proximity to each other. To better illustrate the design, Figure 6 presents a graphical representation of our hybrid border discontinuity design. Along the same state border, we have two market pairs (*Pair 1* and *Pair 2*), with markets in each pair within 25 kms of each other but lying on different sides of the border. For *Pair 1*, there is no difference in competition, while for *Pair 2*, market C has a higher competition than market D. Now, in the event of extreme heat (bad weather), the difference in arrivals should not change for *Pair 1*, as both markets have the same competition and will be equally affected. However, for *Pair 2*, the difference in arrivals should increase because farmers in Market C have been able to attenuate some of the impact through higher competition. The spatial feature of the design is illustrated in Figure 7, which presents the geographical distribution of all 652 markets selected using the bandwidth of 50 kms.[33] Note that only markets less than 50 kms apart and situated in different states will be considered as a pair. This results in 1,210 market pairs for the said bandwidth.

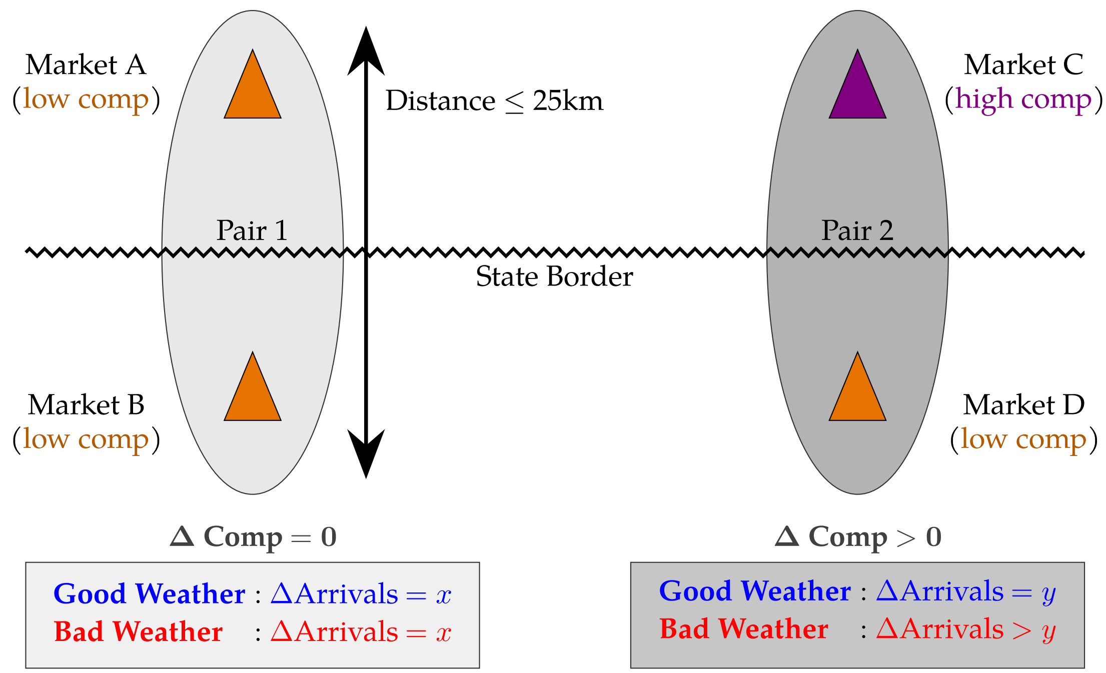
The *hybrid* border discontinuity model linking difference in arrivals to the interaction between differences in competition and weather variables is as follows:

$$\Delta log(Arrivals)_{cmm'y} = \alpha + \sum_{j=1}^{6} \eta_j \, \overline{GDD}_{\{j\}cmm'y} + \sum_{j=1}^{6} \Omega_j (\overline{GDD}_{\{j\}cmm'y} \times \Delta Comp_{mm'}) + \phi \, \overline{Precip}_{mm'y} + \delta \, (\overline{Precip})^2_{mm'y} + \lambda_{cy} + \lambda_{mm'y} + \lambda_{bct} + \xi_{cmm'y} \quad (7)$$

where $\Delta log(Arrivals)_{cmm'y}$ is the difference in the natural log of arrivals of crop c in agricultural year y between markets m and m' which lie on different sides of the state boundary b. $\Delta Comp_{mm'}$ is the time-invariant difference in competition measure $Comp_{1m}$ between markets m and m'. $\overline{GDD}_{\{j\}cmm'y}$ denotes the number of days in the cropping season, for crop c in year y, on which the daily mean temperature fell in the j^{th} of the six temperature bins (in °C) at the district border between m and m'. To arrive at this variable, we average the GDD's in the districts containing the markets which, by design, lie on either sides of the state border. The precipitation variables, too, are constructed in a similar manner.

[32]As Chatterjee (2019) mentions, Indian languages change gradually over distance. Therefore, farmers and intermediaries in close geographical proximity but settled on different sides of a state border should be able to communicate with each other.

[33]Our preferred bandwidth is 25 kms. We illustrate the geographical distribution of markets selected with the 50 kms bandwidth as that leads to more market pairs, offering a vivid visualization.

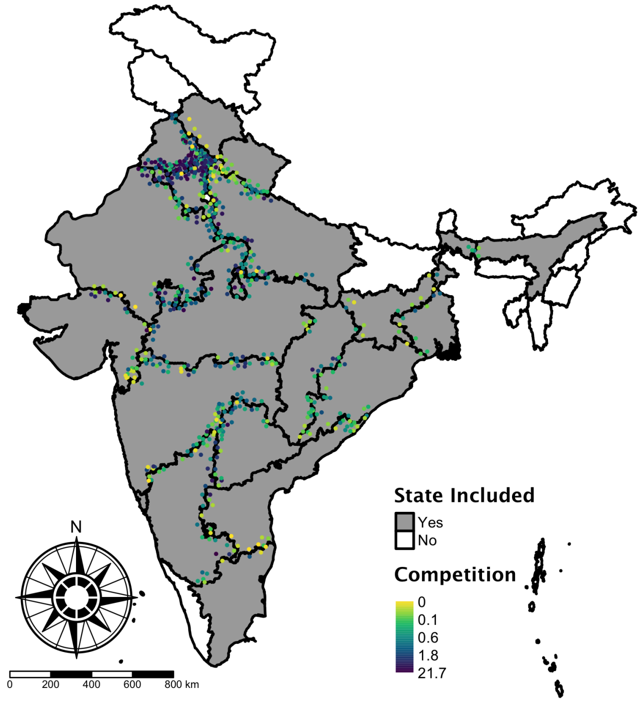


Notes: Figure 6 presents a graphical representation of the *hybrid* border regression discontinuity design in Equation (7); see text for details.

Figure 6: Interpreting the Border Discontinuity Design

We control for confounding factors by adding three fixed effects in our most stringent specification: a crop-year fixed effect (λ_{cy}) that controls for changes in global or national prices of the crop c; a market pair-year fixed effect ($\lambda_{mm'y}$) that controls for differences in market specific infrastructure, policies and cost or demand shocks that are common to all crops; and a state border-crop-decade fixed effect (λ_{bct}) that accounts for differences in slow moving changes in crop-specific costs, in the area allocated to the crop, in preferences, or in technology. As an aside, we can include market pair-year fixed effects as there are multiple crops within that dimension. Importantly, these different crops within the same market pair-year level are not subjected to the same weather. For example, *kharif* and *rabi* arrivals in a market will be exposed to different weather conditions in the same agricultural year.[34] Also note that the data for each market pair only includes crops which had the same cropping season across both markets. Therefore, if rice in market A is a *Kharif* crop and rice in Market B is a *Rabi* crop, we dropped rice as a commodity for market pair A-B. Hence, the identifying variation comes from the differing weather conditions that different crops within a market pair and year were exposed to, after differencing out any crop specific fixed effect. Finally, the inclusion of any form of market pair fixed effects implies that the level

[34] The identification of cropping season for each market-crop is made possible using the time series on arrivals data, and is explained in detail in Section 3.D.



Notes: The map shows the geographic distribution of markets used in the *hybrid* border discontinuity design with a bandwidth of 50 kms. The dots represent the sample of market pairs which lie in close spatial proximity but are divided by a state border. There are 652 markets for the distance threshold of 50 kms. The empirical strategy involves regressing — for each market pair — the difference in arrivals on: (*i*) the difference in competition; (*ii*) the average weather conditions across the two markets, and (*iii*) the interaction between the two. Competition refers to the weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state (see Equation (4)). The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021.

Figure 7: Geographical Distribution of Markets Selected Using 50 kms Bandwidth

effect of time-invariant difference in market competition $(\Delta Comp_{mm'})$ is swept out and cannot, therefore, be estimated.

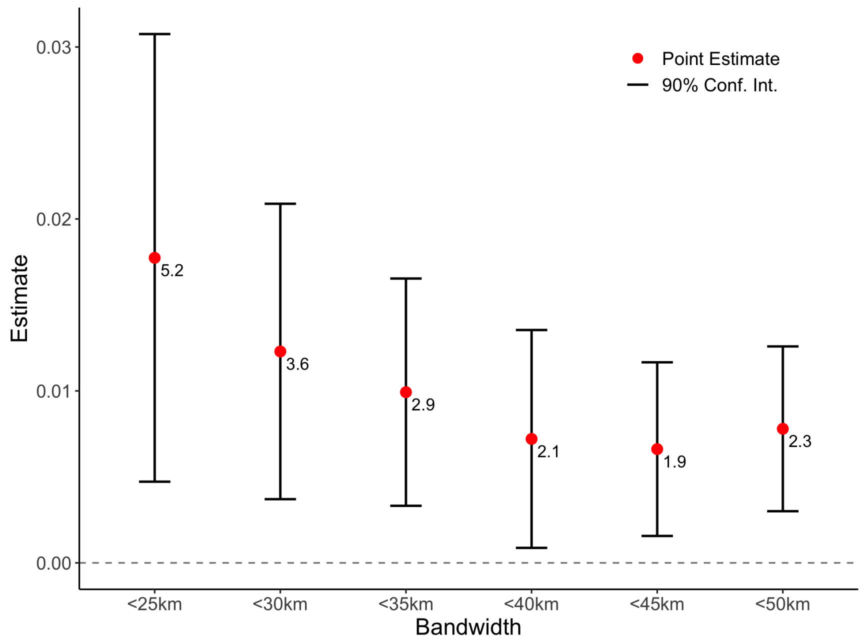
The interpretation of the coefficients changes slightly as compared to previous specifications. Though previously η_j measured the effect of spending an additional day in the j^{th} temperature bin on arrivals, it now measures the effect on the difference in arrivals. If our discontinuity in competition assumption is correct, then the only thing impacting the difference in arrivals during extreme heat should be competition, which is captured by the coefficient Ω_j. In other words, η_6 should not be significantly different from 0. If that is not the case, it would indicate the presence of extraneous factors affecting arrivals during extreme heat which, if correlated with competition, could bias our results. Thus, the coefficient on η_6 acts as a placebo check. However, this implies that we cannot calculate the percentage of impact mitigated by competition, as we do not obtain an estimate of the marginal effect of climate shocks on arrivals. We cluster our standard errors two-way, both at the border-year level and crop level. Results are presented in Table 4 for our preferred bandwidth of 25 kms.

Table 4: Competition and Mitigation of Climate Shocks: Border Discontinuity

	Dependent Variable: $\Delta log(Arrivals)_{c\{mm'\}by}$			
	Markets $\leq$ *25km Apart*			
	(1)	(2)	(3)	(4)
$\overline{Bin}$ *30-35*$_{cmm'y}$	−0.029	−0.016	0.016	0.011
	(0.048)	(0.016)	(0.030)	(0.031)
$\overline{Bin}$ *>35*$_{cmm'y}$	0.029	0.037	0.025	0.036
	(0.034)	(0.026)	(0.031)	(0.027)
$\overline{Bin}$ *<15*$_{cmm'y}$ $\times \Delta Comp_{mm'}$	0.005	0.012	0.012	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)
$\overline{Bin}$ *15-20*$_{cmm'y}$ $\times \Delta Comp_{mm'}$	0.012	0.010	0.010	0.007
	(0.014)	(0.009)	(0.012)	(0.012)
$\overline{Bin}$ *25-30*$_{cmm'y}$ $\times \Delta Comp_{mm'}$	0.011	0.012	0.013	0.012
	(0.008)	(0.008)	(0.009)	(0.009)
$\overline{Bin}$ *30-35*$_{cmm'y}$ $\times \Delta Comp_{mm'}$	0.003	0.007	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.007)
$\overline{Bin}$ *>35*$_{cmm'y}$ $\times \Delta Comp_{mm'}$	0.015**	0.018**	0.018**	0.017**
	(0.007)	(0.006)	(0.008)	(0.008)
Fixed Effects				
Market-Pair × Year	✓	✓	✓	✓
Border × Crop		✓	✓	
Crop × Year			✓	✓
Border × Crop × Decade				✓
75th — 25th Percentile (in %)	**4.5**	**5.2**	**5.2**	**5.1**
Num. obs.	2,899	2,899	2,899	2,899
Adj. R^2	0.454	0.545	0.536	0.534

Notes: Clustered robust standard errors are in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Columns (1) to (4) provide estimates, using a 25 kms *hybrid* border discontinuity approach, of how market competition mitigates the adverse effects of extreme heat on quantity arrivals at each market (Equation (7)). The dependent variable, $\Delta log(Arrivals)_{c\{mm'\}by}$, refers to the difference in the natural log of arrivals of crop c in agricultural year y between markets m and m' which lie on different sides of the state boundary b. Data, sourced from Centre for Economic Data and Analysis (CEDA) of Ashoka University, comprises of quantity arrivals of 52 major commodities in 2,938 APMC markets from 2001 to 2021. $\Delta Comp_{mm'}$ is the time-invariant difference in competition measure between markets m and m'. $\overline{GDD}_{\{j\}cmm'y}$ denotes the number of days in the cropping season, for crop c in year y, on which the daily mean temperature fell in the j^{th} of the six temperature bins (in °C) at the district border between m and m'. The coefficient of interest is the estimate on the interaction term between $\overline{Bin}$ *>35*$_{cmm'y}$ (extreme heat) and $\Delta Comp_{mm'}$. The antepenultimate row, titled 75th — 25th Percentile (in %), provides estimates of the higher yield experienced by a farmer selling in the 75th percentile of competition compared to one that faces the 25th percentile of competition for an additional degree-day of extreme heat. Coefficients related to the effect of temperatures less than 30°C on yields have been omitted for brevity. Standard errors are clustered two-way at the border-year and crop level.

Our results with the border discontinuity design are in harmony with our previous specifications and deliver the same message: competition helps in fostering adaptation to climate shocks. All estimates of the interaction term between extreme heat and difference in competition are positive and significant, irrespective of the fixed effects used. A farmer selling in the 75th percentile of competition compared to one that faces the 25th percentile of competition achieves a 4.5 to 5.2 percent higher yield on average for an additional degree-day of extreme heat. Reassuringly, the estimates on the temperature bins themselves are insignificant, as was expected if the regression was correctly specified. To test the robustness of the adaptation results, we also present the coefficient on Ω_6 from regressions using different bandwidths in Figure 8. Like before, the effect sizes are positive and significant, although smaller in magnitude. One additional degree day in the highest temperature bin leads to a difference in the range of 1.9 to 3.6 percent in yields between farmers in the 75$^{\text{th}}$ percentile of competition relative to farmers in the 25$^{\text{th}}$ percentile. Note that the confidence intervals for the 25 kms bandwidth are larger, which is expected given the low number of market pairs due to the shorter distance.



Notes: Figure 8 provides estimates, using a *hybrid* border-discontinuity design with different distance bandwidths, of how market competition mitigates the adverse effects of extreme heat on quantity arrivals at each market. The distance thresholds used for each estimate are labeled on the X-axis. The point estimates (red dots) on the Y-axis correspond to the coefficient of interest — the estimate on the interaction term between $\overline{Bin} > 35_{cmm'y}$ (extreme heat) and $\Delta\text{Comp}_{mm'}$ — in Equation (7). $\Delta\text{Comp}_{mm'}$ is the time-invariant difference in competition measure between markets m and m'. $\overline{GDD}_{\{j\}cmm'y}$ denotes the number of days in the cropping season, for crop c in year y, on which the daily mean temperature fell in the j^{th} of the six temperature bins (in °C) at the district border between m and m'. To interpret the point estimates, we calculate the difference in yields experienced by a farmer selling in the 75$^{\text{th}}$ percentile of competition compared to one that faces the 25$^{\text{th}}$ percentile of competition, for each additional degree-day of extreme heat. This is indicated by the labels next to the red dots. The whiskers represent the 90$^{\text{th}}$ percentile confidence intervals, with standard errors clustered two-way at the border-year and crop level.

Figure 8: Impact of Extreme Heat Offset by Competition: Border Discontinuity

C Mechanisms

Given the result that market competition leads to higher adaptation, we now turn our attention towards ascertaining the mechanisms behind our findings. Section 4.C.C.1 presents an analytical framework that uses a simple agricultural model to derive predictions on input usage post a climate shock. We then test empirically whether these predictions hold in the data, the results of which are presented in Section 4.C.C.2 and Section 4.C.C.3.

C.1 Analytical Framework

In this subsection, we present a simple agricultural household model to examine how subsistence farmers would adjust their input decisions in the event of an exogenous heat shock. Closely following the work of Taylor & Adelman (2003) and Aragón et al. (2021), we present a framework where production and consumption decisions are linked. This transpires because the farmer is both a producer, choosing the allocation of inputs to crop-production, and a consumer, choosing the allocation of income to consumption.

We start with an agricultural production function with two inputs, land (T) and labor (L). The household has an endowment of land T^e, which can be used for production or non-productive activities like leisure.[35] Household utility $U(c, t)$ is a function of consumption of a market good (c) and land used for leisure (t). Households are price takers and obtain income by renting their land, and selling their produce in the market at price p. The production function is defined by $\mathcal{F}(A, L, T)$, where A is farmer's total factor productivity. Specifically, we use A to capture the productivity shock due to exposure to extreme heat. Consistent with our results on the relationship between crop yields and temperature, we assume that extreme heat has a detrimental effect on productivity. Each growing season, the household maximizes utility by choosing simultaneously the amount of land allocated to productive and nonproductive uses, and the labor to be employed. Finally, we assume that both the utility and the production functions are increasing and strictly concave.

Under the extreme assumption that all input markets exist and are well functioning, the household's production and consumption decisions can be decoupled (Benjamin 1992). This separation result is driven by the possibility of trade in complete markets. In this scenario, the farmer's optimal input usage can simply be inferred by solving the profit maxi-

[35] We follow Aragón et al. (2021) in this regard. The inclusion of land directly in the utility function is a modeling device to create a positive shadow price (i.e., an opportunity cost of using land) and should not be taken literally. Since land cannot be sold or rented out, without this device, the model would predict that farmers will always use all available land. This prediction is inconsistent with the empirical observation that as a proportion of cultivable area, 13.4 percent of the land was left fallow in 2010–2011, an increase from 10.6 per cent in 1970–1971 (Ranganathan & Pandey 2018).

mization problem, $\max_{\{T,L\}} \; \pi = pF(A,T,L) - rK - wL$, where r and w refer to input prices. Under such a setting, a negative productivity shock, such as extreme heat, would always reduce input usage.[36]

The prediction above changes in the case of incomplete markets, which is a more realistic setting in the context of India (Rosenzweig & Wolpin 1993). To illustrate this, we consider a mixed market scenario. Specifically, we assume that there is no input market for land, but there is a well-functioning input market for labor. In this simplified setting, the farmer's problem becomes:

$$\begin{gathered} \max_{\{T,L\}} \; U(c,t) \\ \text{subject to} \\ c \leq pF(A,T,L) - wL \\ T + t \leq T^e \end{gathered} \tag{8}$$

The two first order condition are $U_t = pU_cF_t$ and $pF_L = w$. Taking total derivatives of the first order conditions with respect to A, followed by some algebra, we obtain:

$$\frac{dT}{dA} = \frac{(F_{LA}F_{TL}U_c/F_{LL}) + F_AU_{tc} - pF_AF_TU_{cc} - F_{TA}U_c}{pF_t^2U_{cc} - 2F_TU_{ct} + F_{TT}U_c + (U_{tt}/p) - (F_{TL}^2U_c/F_{LL})} \tag{9}$$

Assuming a Cobb-Douglas technology $F(A,T,L) = AT^\alpha L^\beta$, we can show that the necessary and sufficient condition for $dT/dA < 0$, *i.e.* land usage increases with a negative productivity shock, is:

$$p > \frac{1}{\alpha F}\left[T\frac{U_{tc}}{U_{cc}} - \frac{U_c}{U_{cc}}\right] \tag{10}$$

Intuitively, the inequality suggests that, in the presence of incomplete markets, farmers could increase their input usage post a negative weather shock if the output price is expected to rise. The increase in output prices could occur because of two reasons: first, a negative effect on aggregate supply coupled with inelastic demand could increase prices; and second, local competition in the markets could interact with a fall in supply to drive the prices even higher. The former effect will be common to all areas, but the latter would be restricted to high competition areas.

[36] Assuming a Cobb-Douglas technology $f = AT^\alpha L^\beta$, the optimal T equals $\left[p\ A\left(\frac{\alpha}{r}\right)^{1-\beta}\left(\frac{\beta}{w}\right)^{\beta}\right]^{1/\gamma}$, while the optimal L equals $\left[p\ A\left(\frac{\alpha}{r}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{1-\alpha}\right]^{1/\gamma}$, where $\gamma = (1-\alpha-\beta)$. Differentiating these two terms with respect to A, we get $\frac{dT}{dA} = \left[p\ A^{\alpha+\beta}\left(\frac{\alpha}{r}\right)^{1-\beta}\left(\frac{\beta}{w}\right)^{\beta}\right]^{1/\gamma}/\gamma$, and $\frac{dL}{dA} = \left[p\ A^{\alpha+\beta}\left(\frac{\alpha}{r}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{1-\alpha}\right]^{1/\gamma}/\gamma$. Both of these are positive as long as $\alpha + \beta < 1$.

Another alternative, but not mutually exclusive, mechanism that could cause this phenomenon is high risk aversion amongst farmers. This can be seen in Equation (10) where an increase in the coefficient of absolute risk aversion, $-U_{cc}/U_c$, increases the probability of satisfying the inequality. In this context, high risk aversion would imply that farmers are more likely to use supplementary inputs to attenuate the fall in agricultural output and minimize the drop in consumption. This response is analogous to coping mechanisms to smooth consumption, such as selling disposable assets. The key distinction is that it involves adjustments in productive decisions.

The model predicts that an increase in land usage post a negative productivity shock also increases the likelihood of an increase in the use of labor inputs. To see this, note that the necessary and sufficient condition for labor inputs to increase post a weather shock is:

$$\frac{dT}{dA} < -\frac{T}{\alpha A} \tag{11}$$

Therefore, if the increase in land usage following a negative productivity shock is large enough, labor inputs on the farm will also rise.

With this framework in mind, our empirical analysis focuses on examining the effect of competition on prices, and how the same varies across different weather conditions. We subsequently test whether input usage increases in areas which experience price rise during heat stress, as predicted by the model.

C.2 *Effect of Competition on Prices: Heterogeneous Impact by Weather*

This subsection aims to causally identify the effect of competition on prices during inclement weather. Besides its intrinsic interest, the heterogeneous effect of weather on the correlation between competition and prices could also help inform the mechanism behind the adaptive behavior documented in previous sections. The econometric specification takes the following form:

$$\begin{aligned} log(Prices)_{cmdsy} = \alpha \ + \sum_{j=1}^{6} \eta_j \ GDD_{\{j\}dsy} + \sum_{j=1}^{6} \Omega_j (GDD_{\{j\}dsy} \times Comp_{mds}) + \\ \phi \ Precip_{dsy} + \delta \ (Precip_{dsy})^2 + \lambda_m + \lambda_{cy} + \lambda_{dt} + \lambda_{sy} + \xi_{cmdsy} \end{aligned} \tag{12}$$

where $log(Prices)_{cmdsy}$ refers to the natural logarithm of the price of crop c in market m situated in district d of state s in agricultural year y. This is the price during the main agricultural season pertaining to the crop-market pair, and is calculated as the mean of the daily modal price. The regressors and fixed effects have the exact same definition as in

Equation (6). η_6 can now be interpreted as the effect of an additional degree-day of extreme heat in the district on prices in markets with low competition, while the coefficient of interest, Ω_6, indicates the supplementary impact of high competition on prices during heat stress. As before, the inclusion of market fixed effects (λ_m) implies that the level effect of time-invariant market specific competition ($Comp_{mds}$) is swept out and cannot, therefore, be estimated. However, Chatterjee (2019) shows, in a similar setting, that increasing spatial competition by one standard deviation causes prices received by farmers to increase between 2.7 and 6.4 percent. Though not shown here, we also calculate the difference in prices between high and low competition areas and our results are similar, with a one standard deviation increase in competition leading to a 5.8 to 6.6 percent increase in prices. Thus, there is a positive effect of competition on farmer prices on average, holding constant the weather. Our aim is to establish how this relationship changes during inclement weather. Results on heterogeneous impact by weather are presented in Table 5.

Our results indicate that the positive effect of local competition on prices is exacerbated during periods of extreme heat. The estimate of Ω_6 is positive and significant: markets with higher level of competition experience a larger gain in price with each additional degree day of extreme heat. If the effect was being driven solely by a fall in supply, we would expect prices in low competition markets during heat stress to also increase relative to prices in the same markets during good weather. Nevertheless, as indicated by the coefficient on $Bin > 35_{dsy}$, the effect sizes are positive but not significant, irrespective of the specification. Notably, the effect sizes are large, but the lack of significance most likely stems from low power caused by very few markets with competition tending to zero.

To interpret the coefficients, we calculate the difference in prices between high and low competition areas when exposed to the mean number of extreme heat days during the growing season (7.3 days). Note that this is in addition to the positive difference in prices that exists during good weather. We find that a one standard deviation increase in competition causes the difference in prices to increase by 0.53 to 0.57 percentage points, given that both areas were exposed to a week of extreme heat. Therefore, monopsony power tends to aggravate the already existing price distortions. A simple back of the envelope calculation suggests that this translates to an extra yearly income in the range of ₹172 ($3) and ₹31,642 ($608), depending on the crop being grown by the average farmer.[37] This is equivalent to an increase of 0.4-69 percent in yearly net receipts from crop production for an average agricultural household in India.

We have shown that during extreme heat, the prices received by farmers in high competition areas increase, while prices in low competition areas do not. The analytical frame-

[37] The ₹ to $ conversion was based on the historical average USD-INR exchange rate of 52.004 from 1st January, 2000 to 31st December, 2020, as published by Investing.com.

Table 5: Effect of Competition on Prices Post Climate Shocks

	Dependent Variable: $log(Price)_{cmdsy}$			
	(1)	(2)	(3)	(4)
Bin 30-35$_{dsy}$	0.297	0.248	0.295	0.251
	(0.827)	(0.828)	(0.923)	(0.835)
Bin >35$_{dsy}$	1.180	1.323	1.563	1.297
	(0.758)	(0.796)	(1.071)	(0.774)
Bin <15$_{dsy}$ × *Comp$_{mds}$*	−0.131	−0.134	−0.150	−0.124
	(0.205)	(0.209)	(0.214)	(0.206)
Bin 15-20$_{dsy}$ × *Comp$_{mds}$*	0.188	0.186	0.176	0.190
	(0.117)	(0.114)	(0.122)	(0.118)
Bin 25-30$_{dsy}$ × *Comp$_{mds}$*	0.124	0.125	0.120	0.128
	(0.079)	(0.079)	(0.085)	(0.082)
Bin 30-35$_{dsy}$ × *Comp$_{mds}$*	0.026	0.022	−0.009	0.020
	(0.120)	(0.121)	(0.125)	(0.121)
Bin >35$_{dsy}$ × *Comp$_{mds}$*	0.227**	0.220**	0.230*	0.236**
	(0.111)	(0.106)	(0.115)	(0.107)
Fixed Effects				
Market	✓		✓	✓
Crop × Year	✓	✓	✓	✓
District × Decade				✓
District × Year			✓	
Market × Decade		✓		
State × Year	✓	✓		✓
Increase in Prices (in pp)	**0.555**	**0.538**	**0.563**	**0.577**
Num. obs.	147,005	147,005	147,005	147,005
Adj. R^2	0.877	0.879	0.879	0.878

Notes: Clustered robust standard errors are in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Columns (1) to (4) provide causal estimates of the effect of competition on prices following a period of extreme heat (Equation (12)). The dependent variable, $log(Price)_{cmdsy}$, refers to the natural logarithm of the price of crop c in market m situated in district d of state s in agricultural year y. Data, sourced from Centre for Economic Data and Analysis (CEDA) of Ashoka University, comprises of prices of 52 major commodities in 2,938 APMC markets from 2001 to 2021. $Comp_{mds}$ is the measure of competition at the market level, and equals the weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state. The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021. The independent variables related to temperature, $Bin_{\underline{h}\ to\ \overline{h}}$, measure the amount of time, in days, a crop was exposed to temperatures between a given lower and upper bound. The coefficient of interest is the estimate on the interaction term between $Bin > 35_{dsy}$ (extreme heat) and $Comp_{mds}$. It can be interpreted as the supplementary impact of high competition on prices during heat stress. The antepenultimate row, titled Increase in Prices (in pp), provides estimates of the effect of a one standard deviation increase in competition on the difference in prices, given that both areas were exposed to a week of extreme heat. Coefficients related to the effect of temperatures less than 30°C on prices have been omitted for brevity. All coefficients have been multiplied by 1000 for illustrative purposes. Standard errors are clustered at the state-decade and crop level.

work presented in Section 4.C.C.1 predicts that this increase in prices should lead to higher input usage in high competition areas, which in turn could help alleviate the crop production losses associated with heat stress. The next section tests this hypothesis.

C.3 Changes in Input Use

We examine changes in input use as a potential margin of adjustment to high temperatures, and how this differs between low and high competition areas. We combine household survey with spatial weather and competition data to construct a comprehensive dataset containing agricultural, socioeconomic, competition, and weather variables. The unit of observation is the household-year. The household data is a repeated cross section from the India Human Development Survey (IHDS), a nationally representative multi-topic survey conducted in 2005 and 2011-12 (Desai et al. 2005, 2012). Our primary focus is on the income, social capital and agricultural part of the survey, which asks questions on input usage and expenditure in the last one year. Using the date of interview, we can construct household specific weather variables, *i.e.* the number of growing degree days in each temperature bin and precipitation over the last 12 months is specific to each household.[38]

The generic estimating equation is as follows:

$$Y_{hdsy} = \alpha + \sum_{j=1}^{6} \eta_j \, GDD_{\{j\}hdsy} + \sum_{j=1}^{6} \Omega_j (GDD_{\{j\}hdsy} \times Comp_{ds}) + \phi \, Precip_{dsy} + \delta \, (Precip_{dsy})^2 + \psi \mathbf{Z}_{hdsy} + \lambda_d + \lambda_{sy} + \xi_{hdsy} \quad (13)$$

where Y_{hdsy} refers to either input usage or input costs of household h situated in district d of state s in agricultural year y, $GDD_{\{j\}hdsy}$ refers to the number of growing degree days in the j^{th} temperature bin which the household was exposed to over the course of the 12 months prior to the interview, $Precip_{dsy}$ is the analogous rainfall counterpart, and $Comp_{ds}$ denotes the mean value of the market level competition measure across all *mandis* in the district. $\mathbf{Z}_{hdsy}$ is a vector of household characteristics, and includes religion, caste, main income source, total land endowment, and permanent fallow land of the household, in addition to the occupation and education of the household head. Finally, we control for district and state-year fixed effects to account for, first, district specific determinants of TFP as well as other drivers of input, and second, changes in agricultural prices at the state level. Standard errors are clustered at the state-year level to allow for spatial dependence. If the model prediction is accurate, then we expect the interaction term between high temperature and competition (Ω_6) to be positive and significant, indicating increased input usage in high competition areas during heat stress. Results are presented in Table 6.

As predicted by the model, input usage and expenditure increases in high competition areas during periods of high temperature. Columns (1) and (2) focus on changes in land and labor inputs. For each additional degree day of extreme heat, a one standard deviation increase in competition increases the land cultivated and labor employed by 1.2 and 1.7 percent, respectively. This estimate already controls for household endowments and permanent fallow land, and thus is not simply picking up changes in the size composition of farmers. Columns (3) to (6) relate to input costs, specifically expenditure on labor, irrigation, equipment, and fertilizers over the past 12 months. For each of these categories, the effect sizes on Ω_6 are positive and significant, indicating farmers in high competition areas expend more when faced with inclement weather. A one standard deviation increase

[38] Households in the same district and interviewed in the same month-year will have identical values for the weather variables.

in competition would cause a farmer, experiencing an additional day in the extreme temperature bin, to increase their labor expenditure by ₹122 ($2.3), irrigation expenditure by ₹31 ($0.6), expenditure on farm equipment by ₹98 ($1.9), and expenditure on fertilizers by ₹157 ($3.0).

In addition to adjustments in input usage and costs, we also find evidence of crop diversification at a macro-scale (*i.e.*, district-level) in high competition areas, indicating crop-mix as a potential avenue for increased resilience. To measure crop diversity, we follow Auffhammer & Carleton (2018) and construct an indicator of concentration, the Herfindahl–Hirschman Index (HHI), based on area planted to different crops in a given year and district. The HHI for district d and year y is defined as follows:

$$HHI_{dy} = \sum_{c=1}^{C} s_{dcy}^2 \tag{14}$$

where $s_{dcy} = a_{dcy} / \sum_{c=1}^{C} a_{dcy}$ is the share of total planted area in district d dedicated to crop c in year y. C is the total number of crops, which in our data set comprises the 19 major and minor crops available in ICRISAT (2018). The regression specification in Equation (13) changes slightly, with the unit of observation now district d and agricultural year y. Furthermore, the regressand Y_{dsy} now denotes the crop-mix, while we dispense with the household control variables. Results presented in column (7) imply that each additional day of extreme heat reduces the HHI significantly in areas with higher competition, indicating higher crop diversity. The point estimates suggest that for each additional day of extreme heat, a one standard deviation increase in competition leads to a 0.13 percent fall in HHI. Coupled with the evidence that farmers adjust their land during the growing season, we interpret these findings as suggestive evidence that the additional land is planted with distinct crops in order to diversify the weather risk.

Our main results suggest that farmers adjust input use within the growing season as a mechanism to cope with the negative effects of extreme temperatures, but only in high competition areas. Farmers in these areas adjust their use of land, both in terms of area planted and crop composition, as a response to extreme heat. Furthermore, they increase labor usage, reflected both in the number of workers hired and total wages paid. Additionally, the expenditure on irrigation, equipment hired to work on the farm, and fertilizer and manure also rises. These margins of adjustment attenuate undesirable drops in output and consumption caused by heat. Importantly, the mechanism for these productive adjustments are prices, which rise in high competition areas during heat stress, further inflating the pre-existing monopsony distortions. In this sense, our findings are consistent with models of subsistence farmers in a context of incomplete markets (De Janvry et al. 1991, Taylor &

Adelman 2003), which predict a rise in input usage if prices increase following a negative productivity shock.

Table 6: Heterogeneous Impact of Climate Shocks on Input Usage and Crop Mix

	Inputs		Input Costs (₹)				Crop Mix
	$\log(\text{Land})_{hdsy}$	$\log(\text{Labor})_{hdsy}$	Labor_{hdsy}	Irrigation_{hdsy}	Equipment_{hdsy}	$\text{Fertilizers}_{hdsy}$	HHI_{dsy}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bin 30-35$_{dsy}$	-0.007	-0.026	-186.367	-10.872	67.362	-110.610^{*}	0.511^{*}
	(0.012)	(0.021)	(134.622)	(19.305)	(124.858)	(63.290)	(0.294)
Bin >35$_{dsy}$	-0.020	-0.014	-137.790	-16.740	-60.710	-176.421^{*}	0.480
	(0.012)	(0.015)	(101.053)	(16.826)	(89.583)	(92.065)	(0.481)
Bin <15$_{dsy}$ × *Comp*$_{ds}$	0.012	0.021	100.256^{**}	9.924	-46.148	-76.222	0.000
	(0.009)	(0.013)	(44.907)	(29.171)	(89.536)	(127.411)	(0.000)
Bin 15-20$_{dsy}$ × *Comp*$_{ds}$	0.014^{**}	0.018	-16.132	21.854	8.843	46.186	-0.197
	(0.005)	(0.012)	(48.905)	(26.599)	(90.759)	(105.920)	(0.155)
Bin 25-30$_{dsy}$ × *Comp*$_{ds}$	0.005	0.026^{**}	109.807^{**}	44.160	56.101	-13.769	-0.194
	(0.006)	(0.011)	(55.445)	(29.828)	(67.600)	(100.552)	(0.133)
Bin 30-35$_{dsy}$ × *Comp*$_{ds}$	0.008	0.025^{**}	125.444^{*}	23.881^{*}	-28.514	-98.107	-0.039
	(0.006)	(0.011)	(66.089)	(13.473)	(79.673)	(56.889)	(0.087)
Bin >35$_{dsy}$ × *Comp*$_{ds}$	0.009^{**}	0.014^{*}	93.363^{*}	24.120^{*}	73.561^{*}	122.220^{**}	-0.267^{*}
	(0.004)	(0.008)	(51.790)	(13.887)	(41.445)	(46.165)	(0.142)
Fixed Effects							
District	✓	✓	✓	✓	✓	✓	✓
State × Year	✓	✓	✓	✓	✓	✓	✓
Num. obs.	25,592	20,517	24,652	27,654	28,256	21,179	4,624
Adj. R^2	0.580	0.352	0.243	0.187	0.187	0.380	0.944

Notes: Clustered robust standard errors are in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
All columns represent estimates from different versions of the estimating Equation (13), which examines changes in input use or crop-mix as a potential margin of adjustment to high temperatures, and how this differs between low and high competition areas. The dependent variable in Columns (*1*) and (*2*) represents land and labor inputs used by household h situated in district d of state s in agricultural year y, respectively. The dependent variable in columns (*3*) to (*6*) relates to input costs, specifically expenditure (in ₹) on labor, irrigation, equipment, and fertilizers over the past 12 months. The dependent variable in column (*7*) represents an indicator of crop concentration, the Herfindahl–Hirschman Index (HHI), based on area planted to different crops in a given year and district (Equation (14)). The independent variable related to competition intensity, $Comp_{ds}$, is the measure of competition at the district level. For this purpose, we first calculate competition for each of the 2,938 APMC markets as the weighted sum of the total value of trade at all other markets near the origin market site, provided they are all in the same state. The weights are the inverse of distances of the neighboring markets (n) to the origin market (m), while the total value of trade refers to the sum of the value of agricultural produce traded in the neighboring market n between the years 2000 to 2021. Second, we aggregate competition to a district level by averaging the competition measure for all markets in a district d of state s. The independent variables related to temperature, $Bin_{\underline{h}\ to\ \overline{h}}$, measure the amount of time, in days, a crop was exposed to temperatures between a given lower and upper bound. The coefficient of interest is the estimate on the interaction term between $Bin > 35_{dsy}$ (extreme heat) and $Comp_{ds}$. It can be interpreted as the supplementary impact of high competition on household input usage (for columns (*1*)-(*6*)), or crop mix (for column (*7*)), during heat stress. The household data is a repeated cross section from the India Human Development Survey (IHDS), a nationally representative multi-topic survey conducted in 2005 and 2011-12 (Desai et al. 2005, 2012). Data for crop mix is sourced from ICRISAT (2018), which has data on area under cultivation for 19 crops in 313 Indian districts of 20 states at an annual level from the year 1966 to 2017. Coefficients related to the effect of temperatures less than 30°C on the dependent variable have been omitted for brevity. Standard errors are clustered at the state-year level to allow for spatial dependence.

5 Theory

A *Basic Environment*

Our setup closely follows the environment assumed by Costinot et al. (2016). We consider a national economy comprising multiple states, indexed by $i \in \mathcal{I} \equiv \{1, \ldots, I\}$. Within each state there are two factors of production, labor and land, which can be used to produce multiple crops, indexed by $k \in \mathcal{K} \equiv \{1, \ldots, K\}$, and an outside good. The outside good can be thought of as a composite of manufactured goods and services. Labor is homogeneous, perfectly mobile within a state, and immobile across states. The term N_i denotes the total endowment of labor, and w_{it} denotes the wage in state i at time t. Land comes in the form of heterogeneous fields, indexed by $f \in \mathcal{F}_i \equiv \{1, \ldots, F_i\}$, each comprising a continuum of heterogeneous parcels, indexed by $\omega \in [0,1]$. We let s_i^f denote the area in hectares of field f in state i.

Preferences—Each state i at time t has a representative agent who derives utility from consuming the outside good, C_{it}^0, and a composite of all crops, C_{it}:

$$U_{it} = C_{it}^0 + \beta_i \ \ln (C_{it}) \tag{15}$$

The quasi-linear form of the utility function in Equation (15) implies that there are no income effects. Moreover, the total demand for crops depends only on a state-specific and time-invariant demand shifter, $\beta_i \geq 0$. Assuming that the crops in our analysis account for a small fraction of consumers' expenditure across states, the absence of income effects acts as a minor limitation of our study.

Aggregate crop consumption at time t, C_{it}, depends on the consumption of each crop, C_{it}^k, which itself depends on the consumption of varieties from different origins, C_{jit}^k:

$$C_{it} = \left[\sum_{k \in \mathcal{K}} (\beta_i^k)^{1/\varphi} (C_{it}^k)^{(\varphi-1)/\varphi} \right]^{\varphi/(\varphi-1)} \tag{16}$$

$$C_{it}^k = \left[\sum_{j \in \mathcal{I}} (\beta_{ji}^k)^{1/\sigma} (C_{jit}^k)^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)} \tag{17}$$

where $\varphi > 0$ denotes the elasticity of substitution between different crops (e.g., rice vs wheat), and $\sigma > 0$ denotes the elasticity of substitution between different varieties of a given crop (*e.g.*, West Bengal vs Punjab rice). Finally, $\beta_i^k \geq 0$ denotes crop and state specific demand shocks, whereas $\beta_{ji}^k \geq 0$ denotes crop and origin-destination specific demand shocks. The functional form implies that all states export each crop that they produce to all other states (as long as $\beta_{ji}^k > 0$).

Technology—The outside good is produced under constant returns to scale using labor only. The term $A_{it}^0 > 0$ denotes labor productivity in state i's outside sector at time t. In the agriculture sector, we assume that labor and parcels of land are perfect complements in the production of each crop. Combining $L_{it}^{fk}(\omega)$ hectares of parcel ω with $N_{it}^{fk}(\omega)$ workers enables a representative farmer to produce:

$$Q_{it}^{fk}(\omega) = A_{it}^{fk}(\omega)\ \mathrm{min}\{L_{it}^{fk}(\omega), N_{it}^{fk}(\omega)/\nu_i^f(\omega)\} \tag{18}$$

where $A_{it}^{fk}(\omega) \geq 0$ denotes the total factor productivity (TFP) of parcel ω in field f if allocated to crop k in state i at time t, and $\nu_i^f(\omega) > 0$ measures the time-invariant labor intensity of the production process. Inspired by Eaton & Kortum (2002) gravity model of trade, we assume that TFP and labor intensity are independently drawn for each (i, f, ω, t) from a Fréchet distribution:

$$\begin{aligned} &\Pr\{A_{it}^{f1}(\omega) \leq a^1,\ \ldots,\ A_{it}^{fK}(\omega) \leq a^K, \nu_i^f(\omega) \leq \nu\} \\ &\quad = \exp\left\{-\gamma\left[\sum_{k\in\mathcal{K}}(a^k/A_{it}^{fk})^{-\theta} + (\nu/\nu_i)^{-\theta}\right]\right\} \end{aligned} \tag{19}$$

where the constant γ is set such that $A_{it}^{fk} = \mathbb{E}[A_{it}^{fk}(\omega)]$ and $\nu_i = \mathbb{E}[\nu_i^{fk}(\omega)]$.[39] The term $A_{it}^{fk} \geq 0$ captures the average productivity of field f for growing crop k in state i at time t and is, thus, shared by all plots $\omega \in f$. A high A_{it}^{fk} implies that on average all plots in farm f have high productivity for growing crop k. In other words, it measures the comparative and absolute advantage of a field in producing particular crops. The parameter $\theta > 1$ measures the extent of technological heterogeneity within each field. A higher value of θ will imply higher specialization across different farms. Since we do not have access to disaggregated data on labor intensity, we require average labor intensity $\nu_i > 0$ to be identical across crops, fields, and time. However, agriculture is allowed to be more labor intensive in some states than in others.

Market Choice—This part of the model takes inspiration from the market setup of Chatterjee (2019). Upon harvest, farmers optimally choose the market where they want to sell, indexed by $m \in \mathcal{M} \equiv \{1,\ \ldots,\ M\}$. We assume that farmers are subject to iceberg trade costs, such that the quantity of crop k actually reaching any market m from farm f at time

[39]Formally, we set $\gamma \equiv \Gamma\left(\dfrac{\theta-1}{\theta}\right)^{-\theta}$, where $\Gamma(\cdot)$ denotes the gamma function; i.e., $\Gamma(t) = \int_0^{+\infty} u^{t-1}\exp(-u)du$ for any $t > 0$.

t is:

$$Q_{mit}^{fk}(\omega) = \frac{Q_{it}^{fk}(\omega)}{\tau_{mt}^{f}} \tag{20}$$

Trade costs between farm f and market m at time t are constant for all parcels $\omega \in f$, and are defined as:

$$\tau_{mt}^{f} = (1 + \zeta d_{m}^{f}) \cdot \xi_{mt}^{f} \tag{21}$$

where d_m^f is the geodesic distance between farm f and market m, and ζ is a scale parameter. The shock term, ξ_{mt}^f, represents origin farm-market specific costs like broken roads, availability of a truck, or a strike among intermediaries, which are not observable to the econometrician but are known to the farmers. We follow Barjamovic et al. (2019), and assume for tractability that ξ_{mt}^f is drawn from a Weibull distribution such that:

$$\Pr\left[\xi_{mt}^{f} \leq \xi\right] = 1 - \exp\left(-\Upsilon \xi^{\lambda}\right) \tag{22}$$

$\lambda > 0$ is the shape parameter and can be interpreted as an inverse measure of the dispersion of shocks. $\Upsilon > 0$ is the scale parameter and controls the efficiency of transporting goods to a market. The distribution of shocks is *i.i.d.* across crops and over time, and shocks are independent across markets. To incorporate trade restrictions, τ_{mt}^f is set to ∞ if farm f and market m lie in different states.

Intermediary—Each market m can be thought of as an intermediary, a chain linking the farmer to the consumer. Though each market can have multiple intermediaries, only a few are active and cartelization among intermediaries is common. Incumbent intermediaries also prevent new entrants (Chand 2012). This fact makes our simplifying assumption that each market is served by a single intermediary not too unrealistic.

An intermediary m in state i can purchase multiple crops $k \in \mathcal{K}$ at time t, and sells the same to retailers/consumers at price $\mathcal{P}_{it}^{rk}$. Unlike the farmer, the intermediary is allowed to cross state borders. However, interstate trade in crops may be subject to iceberg trade costs. In order to sell one unit of a crop k in state j, intermediaries from state i must ship Ψ_{ij}^k units. Non-arbitrage therefore requires the price of a crop k produced in state i and sold in state j to be equal to

$$\mathcal{P}_{ijt}^{rk} = \Psi_{ij}^{k} \mathcal{P}_{it}^{rk} \tag{23}$$

where $\mathcal{P}_{it}^{rk}$ denotes the local price of the domestic variety of crop k in state i.

B ***Competitive Equilibrium***

In a competitive equilibrium, all consumers maximize their utility, all farmers and intermediaries maximize their profits, and all markets clear.

Farmer Profit Maximisation—In the outside sector, profit maximization requires that $w_{it} = A^0_{it}$ whenever the outside good is produced. Throughout this model, we assume that labor endowments, N_{it}, are large enough for the outside good to be produced in all states. Thus, we can use A^0_{it} in place of the wage w_{it} and treat it as an exogenous parameter.

In the agricultural sector, profit maximization requires that the farmer first choose a crop k, and subsequent to harvest, choose a market m to sell. The price that farmers get in market m for crop k at time t is denoted by $\mathcal{P}^k_{mit}$. We can use backward induction to solve for the farmer's choice. Let

$$\Omega^{fk}_{mit} \equiv \Pr\{\mathcal{P}^k_{mit} Q^{fk}_{mit}(\omega) = \max\{\mathcal{P}^k_{1it} Q^{fk}_{1it}(\omega), \ldots, \mathcal{P}^k_{Mit} Q^{fk}_{Mit}(\omega)\}\} \tag{24}$$

denote the probability that a farmer, tilling parcel ω of a field f located in state i and growing crop k at time t, chooses market m. Given distributional assumptions:[40]

$$\Omega^{fk}_{mit} = \frac{\left(\dfrac{\mathcal{P}^k_{mit}}{1+\zeta d^f_m}\right)^{\lambda}}{\sum\limits_{m' \in \mathcal{M}} \left(\dfrac{\mathcal{P}^k_{m'it}}{1+\zeta d^f_{m'}}\right)^{\lambda}} \tag{25}$$

This expression has an intuitive explanation. The probability of choosing a market m for crop k depends on how large the distance adjusted price of the crop in m is relative to the distance adjusted price index of the crop. A higher price of crop k in market m increases the probability of farmers selling their output in m, whereas an increase in the price in other markets m' relative to m reduces this probability. Similarly, if the distance to m is large, that will depress the probability of choosing m. Currently, the farmers in state i only take into account the prices in markets situated in i. An opening of trade borders would lead the farmer to also factor in the prices in all other states $j \in \mathcal{I}$.

Conditional on choosing market m, the farmer decides the crop k to grow at time t. Let $\pi^{fk}_{it}(\omega)$ denote the profits from parcel $\omega \in f$ in state i when farmer decides to grow k at

[40] See Appendix C.C.2 for derivation.

time t. It can be expressed as:[41]

$$\pi_{it}^{fk}(\omega) = A_{it}^{fk}(\omega) L_{it}^{fk}(\omega) \overline{\mathcal{P}}_{it}^{fk} - w_{it} N_{it}^{fk}(\omega) \tag{26}$$

where

$$\overline{\mathcal{P}}_{it}^{fk} = \sum_{m' \in \mathcal{M}} \Omega_{m'it}^{fk} \mathcal{P}_{m'it}^{k} = \frac{\sum\limits_{m' \in \mathcal{M}} \dfrac{(\mathcal{P}_{m'it}^{k})^{\lambda+1}}{\left(1+\zeta d_{m'}^{f}\right)^{\lambda}}}{\sum\limits_{m' \in \mathcal{M}} \left(\dfrac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^{f}}\right)^{\lambda}} \tag{27}$$

denotes a probability weighted price of crop k for farmer f at time t, aggregated across all markets. Profit maximisation requires that all parcels of land are (i) allocated to the crop that maximizes the value of their marginal product if such value is greater than the wage bill associated with operating that parcel, or (ii) left unused if the maximum value of their marginal product is less than the wage bill. Given the production function in Equation (18), the land allocation can be solved as a simple discrete choice problem.[42] Let

$$\Delta_{it}^{fk} \equiv \Pr\{A_{it}^{fk}(\omega)\overline{\mathcal{P}}_{it}^{fk} = \max\{A_{it}^{0}\nu_i^{f}(\omega), A_{it}^{f1}(\omega)\overline{\mathcal{P}}_{it}^{f1}, \ \ldots, A_{it}^{fK}(\omega)\overline{\mathcal{P}}_{it}^{fK}\}\} \tag{28}$$

denote the probability that a parcel ω of a field f located in state i is allocated to crop k at time t. Since there is a continuum of parcels within each field, Δ_{it}^{fk} also corresponds to the share of parcels allocated to that crop.

Given our distributional assumptions, standard algebra implies:[43]

$$\Delta_{it}^{fk} = \frac{(A_{it}^{fk}\overline{\mathcal{P}}_{it}^{fk})^{\theta}}{(\alpha_{it})^{\theta} + \sum\limits_{k'}(A_{it}^{fk'}\overline{\mathcal{P}}_{it}^{fk'})^{\theta}} \tag{29}$$

where $\alpha_{it} \equiv A_{it}^{0}\nu_i$ parameterizes cross-state differences in labor costs, because of differences in either wages or labor intensity. The higher α_{it} is, the more costly it is to hire workers to produce crops, and the smaller the share of a field f allocated to any given crop k. Likewise, the higher the average value of the marginal product of land, $A_{it}^{fk}\overline{\mathcal{P}}_{it}^{fk}$, the higher the share of field f allocated to crop k. In our model, the extent of technological heterogeneity, θ, determines the elasticity of the relative supply of land to various crops. When θ is higher, parcels are more homogeneous within a field, which makes the supply of land more

[41] See Appendix C.C.3 for derivation.

[42] See Appendix C.C.4 for derivation.

[43] We use the property that given n draws $\{z_1, ..., z_n\}$, where z_i is distributed Fréchet with $F_i(z) = \exp\{-(T_i z^{-\theta})\}$, the probability that $z_i = \max\{z_1, ..., z_n\}$ is $\Delta_i = T_i / \sum_{j=1}^{n} T_j$ (Turner 2019).

sensitive to changes in prices, $\overline{\mathcal{P}}_{it}^{fk}$, or productivity, A_{it}^{fk}.

Let $\mathcal{Q}_{mit}^{k} = \sum_{f\in\mathcal{F}_i} \Omega_{mit}^{fk} \int_0^1 Q_{it}^{fk}(\omega)d\omega$ denote the total output of crop k supplied to market m in state i at time t. Intuitively, it is the expected output of crop k across all parcels of land in f, weighted by the probability of choosing market m, and this expression is then summed across all the fields f in state i. Using the production function in Equation (18) and the law of iterated expectations, we must have:[44]

$$\begin{aligned}\mathcal{Q}_{mit}^{k} &= \sum_{f\in\mathcal{F}_i} s_i^f \Delta_{it}^{fk} \Omega_{mit}^{fk} \mathbb{E}[A_{it}^{fk}(\omega)|A_{it}^{fk}(\omega)\overline{\mathcal{P}}_{it}^{fk} \\ &= \max\{A_{it}^{0}\nu_i^f(\omega), A_{it}^{f1}(\omega)\overline{\mathcal{P}}_{it}^{f1}, \ldots, A_{it}^{fK}(\omega)\overline{\mathcal{P}}_{it}^{fK}\}]\end{aligned} \tag{30}$$

Given our distributional assumptions, one can also check that:[45]

$$\begin{aligned}\mathbb{E}[A_{it}^{fk}(\omega)|A_{it}^{fk}(\omega)\overline{\mathcal{P}}_{it}^{fk} &= \max\{A_{it}^{0}\nu_i^f(\omega), A_{it}^{f1}(\omega)\overline{\mathcal{P}}_{it}^{f1}, \ldots, A_{it}^{fK}(\omega)\overline{\mathcal{P}}_{it}^{fK}\}] \\ &= A_{it}^{fk} \times (\Delta_{it}^{fk})^{-1/\theta}\end{aligned} \tag{31}$$

Note that because of the endogenous selection of fields into crops, the average productivity conditional on a crop being produced is strictly greater than the unconditional average, i.e. $A_{it}^{fk} \times (\Delta_{it}^{fk})^{-1/\theta} > A_{it}^{fk}$

Combining the above two equations, we obtain the following expression for the supply of crop k in market m in state i at time t:

$$\begin{aligned}\mathcal{Q}_{mit}^{k} &= \sum_{f\in\mathcal{F}_i} s_i^f A_{it}^{fk} \Omega_{mit}^{fk} (\Delta_{it}^{fk})^{(\theta-1)/\theta} \\ &= \sum_{f\in\mathcal{F}_i} s_i^f A_{it}^{fk} \left[\frac{\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta d_m^f}\right)^{\lambda}}{\sum_{m'\in\mathcal{M}}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^f}\right)^{\lambda}}\right]\left[\frac{(A_{it}^{fk}\overline{\mathcal{P}}_{it}^{fk})^{\theta}}{(\alpha_{it})^{\theta} + \sum_{k'}(A_{it}^{fk'}\overline{\mathcal{P}}_{it}^{fk'})^{\theta}}\right]^{(\theta-1)/\theta}\end{aligned} \tag{32}$$

The quantity supplied of crop k at market m is, thus, a function of the average TFP of the crop, the price of the crop in other markets within the state, and also the productivity and price of crops other than k.

Intermediary Price Setting—Each intermediary m can purchase multiple crops $k' \in \mathcal{K}$, offering price $\mathcal{P}_{mit}^{k'}$. They purchase $Q_{mit}^{k'}$ units of crop k' from the farmer, and sell the same

[44]See Appendix C.C.5 for derivation.
[45]See Appendix C.C.6 for derivation.

to retailers/consumers in different parts of the country at a price $\mathcal{P}^{rk'}_{ijt}$. We assume that there is no restriction on where the intermediary can sell, but transportation costs are incurred only if the produce is sold outside the state.

Every intermediary exerts market power over farmers, which we model as Bertrand competition for crops.[46] When deciding what price to offer for a crop, intermediaries form expectations about how farmers respond. In other words, they internalize the upward sloping crop supply curve in Equation (32): each additional unit they purchase increases the price of every other unit. Zavala (2020) has a similar setting but models exporters instead of local intermediaries. Additionally, he assumes that each exporter only buys a single crop, whereas in our case, we assume that an intermediary can purchase all crops supplied in the market.

An intermediary m maximises the following profit function

$$\max_{\{\mathcal{P}^{k'}_{mit} \forall\, k'\}} \sum_{k' \in \mathcal{K}} \left(\mathcal{P}^{rk'}_{it} - \mathcal{P}^{k'}_{mit}\right) Q^{k'}_{mit} \tag{33}$$

subject to the supply curve in Equation (32), where $\mathcal{P}^{rk'}_{it}$ represents the retail price of commodity k' in state i at time t. The first order condition for price $\mathcal{P}^{k}_{mit}$ can be expressed as:

$$\left(\mathcal{P}^{rk}_{mit} - \mathcal{P}^{k}_{mit}\right) \underbrace{\left[\sum_{f \in \mathcal{F}_i} Q^{fk}_{mit} \left[\lambda \left(\frac{1 - \Omega^{fk}_{mit}}{\mathcal{P}^{k}_{mit}}\right) + (\theta - 1)\Omega^{fk}_{mit} \left(\frac{\lambda + 1}{\overline{\mathcal{P}}^{fk'}_{it}} - \frac{\lambda}{\mathcal{P}^{k}_{mit}}\right)\right]\right]}_{\partial Q^{k}_{mit}/\partial \mathcal{P}^{k}_{mit}} -$$

$$(\theta - 1) \sum_{k' \in \mathcal{K}} \sum_{f \in \mathcal{F}_i} \left(\mathcal{P}^{rk'}_{mit} - \mathcal{P}^{k'}_{mit}\right) \underbrace{\left[Q^{fk'}_{mit} \Omega^{fk}_{mit} \Delta^{fk}_{it} \left(\frac{\lambda + 1}{\overline{\mathcal{P}}^{fk'}_{it}} - \frac{\lambda}{\mathcal{P}^{k}_{mit}}\right)\right]}_{-\partial Q^{k'}_{mit}/\partial \mathcal{P}^{k}_{mit}} = Q^{k}_{mit} \tag{34}$$

Rubens (2021) states that the extent of oligopsony power of an intermediary m over an input k can be parametrized through an inverse input supply elasticity η^{k}_{mit}, defined as:

$$\eta^{k}_{mit} \equiv \frac{\partial \mathcal{P}^{k}_{mit}}{\partial Q^{k}_{mit}} \times \frac{Q^{k}_{mit}}{\mathcal{P}^{k}_{mit}}$$

If an intermediary has oligopsony power over input k, the input price $\mathcal{P}^{k}_{mit}$ increases if more inputs are purchased. This, thus, has the interpretation of an input price '*markdown ratio*'.

[46] Market power can also be modeled as Cournot competition, but Equation (32) does not lend itself to a closed form inverse supply curve.

Also, we can define inverse cross input supply elasticity as:

$$\eta^{kk'}_{mit} \equiv \frac{\partial \mathcal{P}^k_{mit}}{\partial Q^{k'}_{mit}} \times \frac{Q^{k'}_{mit}}{\mathcal{P}^k_{mit}}$$

which reflects how the price of commodity k in market m changes if there is a change in the supply of commodity k' to the said market.

Additionally, we define markup μ as the ratio of retail prices over marginal costs:

$$\mu^k_{mit} \equiv \frac{\mathcal{P}^{rk}_{mit}}{\mathcal{P}^k_{mit}}$$

Using these three definitions, Equation (34) can be rewritten as:

$$\mathcal{P}^k_{mit} = \left[\sum_{k' \neq k} \left(\frac{\mu^{k'}_{mit} - 1}{\eta^{kk'}_{mit}}\right) \mathcal{P}^{k'}_{mit} Q^{k'}_{mit}\right] \left[\frac{\eta^k_{mit}}{1 + \eta^k_{mit} - \mu^k_{mit}}\right] \frac{1}{Q^k_{mit}} \tag{35}$$

Thus, the price for crop k paid by an intermediary m is a function of the markdown for not only k, but also the markdown for k caused by quantity supplied of other crops. It also depends on the markup the intermediary may expect to receive in the retail market.

Finally, the intermediaries sell the produce to the consumer/retailer, with the retail price of crop k in state i, $\mathcal{P}^{rk}_{it}$, set such that all the intermediaries selling in state i (including from state $j \neq i$) sell at the same price, i.e. $\mathcal{P}^{rk}_{jit} = \mathcal{P}^{rk}_{it} \quad \forall j \in \mathcal{I}$. ***Utility Maximisation***—Given equations (15), (16), (17) and (23), utility maximization by the representative agent in each state requires that:[47]

$$C^k_{jit} = \beta_i \frac{\beta^k_i (\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rk}}_{\boldsymbol{it}})^{1-\varphi}}{\sum\limits_{l \in \mathcal{K}} \beta^l_i (\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rl}}_{\boldsymbol{it}})^{1-\varphi}} \frac{\beta^k_{ji} (\Psi^k_{ji} \mathcal{P}^{rk}_{jt})^{-\sigma}}{\sum\limits_{n \in \mathcal{I}} \beta^k_{ni} (\Psi^k_{ni} \mathcal{P}^{rk}_{nt})^{1-\sigma}} \quad \forall \ i, j \in \mathcal{I}, k \in \mathcal{K} \tag{36}$$

where

$$\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rk}}_{\boldsymbol{it}} \equiv \left[\sum_{n \in \mathcal{I}} \beta^k_{ni} \left(\Psi^k_{ni} \mathcal{P}^{rk}_{nt}\right)^{1-\sigma}\right]^{1/1-\sigma} \tag{37}$$

denotes the CES retail price index associated with crop k in state i at time t.

Market Clearing—Define Q^k_{it} as the total output of crop k produced in state i at time t. Since farmers are only allowed to sell their produce in state i, $Q^k_{it} = \sum\limits_{m \in \mathcal{M}} Q^k_{mit}$. Trade in

[47] See Appendix C.C.7 for derivation.

crops is subject to iceberg trade costs, which implies market clearing for all varieties of all crops requires

$$Q_{it}^{k} = \sum_{j \in \mathcal{I}} \Psi_{ij}^{k} C_{ijt}^{k} \;\; \forall \, \{i, j\} \in \mathcal{I} \text{ and } k \in \mathcal{K} \tag{38}$$

Parcels of land may remain idle if the value of their marginal product is below the labor cost required to produce on these parcels. Thus, by construction, land demand is weakly less than land supply at all locations. Finally, under the assumption that the outside good is produced in all states, the amount of labor demanded by the outside sector adjusts to guarantee labor market clearing at the wage equal to A_{it}^{0}.

DEFINITION 1. Given parameters $\beta_i, \beta_i^k, \beta_{ji}^k$ (demand shifters), φ, σ (elasticities of substitution), $\lambda_t, \zeta, \Psi_{ij}^k$ (trade cost for farmers and intermediaries), θ (technological heterogeneity), and μ (intermediary markup), a competitive equilibrium consists of, for each state $i \in \mathcal{I} \equiv \{1, \;\ldots, \; I\}$ and each time period t:

1. inputs for crops $\{L_{it}^{fk}(\omega), N_{it}^{fk}(\omega)\}_{k \in \mathcal{K}, f \in \mathcal{F}_i}$, and outside good $\{N_{it}^{0}\}$,
2. output of crops $\{Q_{it}^{fk}(\omega)\}_{k \in \mathcal{K}, f \in \mathcal{F}_i}$, and outside good $\{Q_{it}^{0}\}$,
3. optimal market choice at each farm $\{m(f)\}$,
4. domestic trade flows $\{X_{ijt}^{k}\}_{k \in \mathcal{K}, j \in \mathcal{I}}$, which is the total value of exports of crop $k \in \mathcal{K}$ from state i to state j, expressed in ₹,
5. consumer prices $\{\mathcal{P}_{it}^{rk}\}_{k \in \mathcal{K}}$, intermediary prices, $\{\mathcal{P}_{mit}^{k}\}_{k \in \mathcal{K}, m \in \mathcal{M}}$, and outside good price $\{\mathcal{P}_{it}^{0}\}$,
6. final crop consumption $\{C_{it}^{k}\}_{k \in \mathcal{K}}$ and outside good consumption $\{C_{it}^{0}\}$,

such that:

1. farmers maximise their profits by choosing the optimal crop (Equation (29)) and market (Equation (25));
2. intermediaries maximise their profits according to Equation (34)
3. consumers maximise their utility to solve Equation (36)
4. market for all crops clears, which requires:

$$\sum_{f \in \mathcal{F}_i} Q_{it}^{fk} = \sum_{j \in \mathcal{I}} \Psi_{ij}^{k} C_{ijt}^{k} \; \forall \; i \in \mathcal{I} \text{ and } k \in \mathcal{K} : \tag{39}$$

In the remainder of this paper we will use the model outlined in this section to study the consequences of climate change. We will compute competitive equilibria for states with contemporary agricultural productivities and trade restrictions, compute competitive equilibria for counterfactual economies with post–climate change productivities and open trade borders, and then compare welfare levels across equilibria. However, we first need to estimate the unknown structural parameters of our model, and we describe below the methodology and data used.

6 Estimation

To simulate the model described in Section 5 and run counterfactual, we require estimates of demand- and supply-side parameters. Section 6.A details the estimation methodology for demand side parameters, while Section 6.B focuses on the supply side parameters.

A Demand

We follow Costinot et al. (2016) closely for our demand side estimation. Similar to their methodology, it involves three steps, each pertaining to a different level of the nested demand system. The first step uses data on bilateral shipment flows (total quantity and not total value) of crops between states (N^k_{ijt}), retail prices ($\mathcal{P}^{rk}_{it}$), and crop yields at the district level (A^k_{dit}) to estimate the elasticity of substitution between different state varieties of a given crop, σ. In addition, it allows us to estimate a composite of the lower-level demand shifters (β^k_{ijt}) and trade costs for intermediaries (ψ^k_{ijt}). Second, we use the estimates from the previous step to construct crop-specific retail price indices, $\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rk}}_{\boldsymbol{it}}$. This, combined with data on crop quantity, $N^k_{jt} = \sum_{i \in \mathcal{I}} N^k_{ijt}$, allows us to estimate φ — the elasticity of substitution between different crops — and mid-level demand shifters, β^k_{jt}. Finally, we construct data on total crop expenditures, $X_{jt} = \sum X^k_{jt}$, to estimate the upper-level demand shifters, β_{jt}.

Step 1—Define the value of exports of crop k at time t from state i to state j, $X^k_{ijt} = P^{rk}_{ijt} C^k_{ijt}$. Using the non-arbitrage condition in Equation (23), we can rewrite the value of exports as:

$$\begin{aligned} X^k_{ijt} &= \left(\Psi^k_{ijt} P^{rk}_{it}\right) C^k_{ijt} \\ &= \beta_{jt} \frac{\beta^k_{jt} \left(\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rk}}_{\boldsymbol{jt}}\right)^{1-\varphi}}{\sum_{l \in \mathcal{K}} \beta^l_{jt} \left(\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rl}}_{\boldsymbol{jt}}\right)^{1-\varphi}} \frac{\beta^k_{ijt} \left(\Psi^k_{ijt} \mathcal{P}^{rk}_{jt}\right)^{1-\sigma}}{\sum_{n \in \mathcal{I}} \beta^k_{njt} \left(\Psi^k_{njt} \mathcal{P}^{rk}_{nt}\right)^{1-\sigma}} \quad \forall \, \{i, j\} \in \mathcal{I} \text{ and } k \in \mathcal{K} \end{aligned} \tag{40}$$

When estimating the lower level of our demand system, we consider the cases of zero and nonzero inter-state trade flows separately. If $X_{ijt}^k = 0$, we simply set $\beta_{ijt}^k \left(\Psi_{ijt}^k\right)^{1-\sigma} = 0$. If $X_{ijt}^k > 0$, we take logs and rearrange equation Equation (40) as:

$$\ln\left(X_{ijt}^k / X_{jt}^k\right) = M_{jt}^k + (1-\sigma)\ln\left(\mathcal{P}_{it}^{rk}\right) + \varepsilon_{ijt}^k \tag{41}$$

where the first term on the right-hand side,

$$M_{jt}^k \equiv -\ln\left[\sum_{n\in\mathcal{I};X_{njt}^k>0} \beta_{njt}^k \left(\mathcal{P}_{nt}^{rk}\Psi_{njt}^k\right)^{1-\sigma}\right]$$

can be treated as an importer-crop-year fixed effect while the final term $\varepsilon_{ijt}^k \equiv \ln\left[\beta_{ijt}^k\left(\Psi_{ijt}^k\right)^{1-\sigma}\right]$ reflects idiosyncratic year-specific demand shocks across varieties of different crops as well as trade costs. Without loss of generality, we normalize these shocks such that

$$\sum_{i\in\mathcal{I};X_{ijt}^k>0} \varepsilon_{ijt}^k = 0 \tag{42}$$

Equilibrium retail prices of crop ($\mathcal{P}_{it}^{rk}$) depend on demand shocks, ε_{ijt}^k. To address this endogeneity in Equation (41), we need exogenous supply shocks that are correlated with $\mathcal{P}_{it}^{rk}$ but uncorrelated with ε_{ijt}^k. We construct the following instrument based on the ICRISAT (2018) data,

$$Z_{it}^{rk} = \ln\left(\frac{1}{D_i}\sum_{d\in\mathcal{D}_i} A_{dit}^k\right) \tag{43}$$

which corresponds to the log of the arithmetic average of crop k's yields across all districts in state i at time t. Our exclusion restriction is that $\mathbb{E}\left[Z_{it}^{rk}\varepsilon_{ijt}^k\right] = 0$.

Note that our data contains information on quantity of crops traded between states, and not their value. However, our use of the Eaton & Kortum (2002) model allows us to overcome this missing data problem. This is because their model predicts that the fraction of quantity imported by j originating from i, $\frac{N_{ijt}^k}{\sum\limits_{i\in\mathcal{I}} N_{ijt}^k}$, should equal the fraction of j's value of imports from i, $\frac{X_{ijt}^k}{\sum\limits_{i\in\mathcal{I}} X_{ijt}^k}$, in expectation. This implies that we can replace the left-hand side of Equation (41) with $\ln\left(N_{ijt}^k \middle/ \sum\limits_{i\in\mathcal{I}} N_{ijt}^k\right)$ to estimate the model.

The results from the instrumental variable regression are reported in xxx. Our estimate of the elasticity of substitution between different varieties of the same crop, σ, is **25.66**, with a standard error of 14.6 when clustered at the crop-importer and crop-exporter levels. Furthermore, our instrument has a strong first stage (F-stat of 34.28) and has the expected negative sign with a coefficient of **-0.052** — implying a one percent increase in yields leads to a 5.2 percent fall in retail prices. Though our elasticity estimate is higher than Costinot et al. (2016), this is expected given we are looking at substitution between different varieties of a crop but produced in the same country. Therefore, the quality differentiation across varieties will be lower, making it easier to substitute between them.

Having estimated σ, we subsequently solve for $\beta_{ijt}^{k}\left(\Psi_{ijt}^{k}\right)^{1-\sigma}$ as residuals. Specifically, we find $\beta_{ijt}^{k}\left(\Psi_{ijt}^{k}\right)^{1-\sigma}$ for all $i,j\in\mathcal{I}$ and $k\in\mathcal{K}$ for which $X_{ijt}^{k}>0$ so that equations (41) and (42) simultaneously hold for all crops, states and years. This estimation procedure does not allow us to identify separately lower-level demand shifters, β_{ijt}^{k}, from trade costs, Ψ_{ijt}^{k}. However, the composite shock, $\beta_{ijt}^{k}\left(\Psi_{ijt}^{k}\right)^{1-\sigma}$, is sufficient to construct equilibria in Section 7.

Step 2—The second step of our demand estimation is similar to the first one: the retail price index, $\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rk}}$, plays the role of the individual crop price, $\mathcal{P}_{it}^{rk}$, whereas crop expenditure, X_{jt}^{k}, plays the role of bilateral trade flows, X_{ijt}^{k}. Note that unlike $\mathcal{P}_{it}^{rk}$, we do not observe $\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rk}}$ in the data and construct it as

$$\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rk}}=\left[\sum_{i\in\mathcal{I}}\beta_{ijt}^{k}\left(\Psi_{ijt}^{k}\mathcal{P}_{it}^{rk}\right)^{1-\sigma}\right]^{1/1-\sigma}$$

using data on crop prices, $\mathcal{P}_{it}^{rk}$, as well as our estimates of σ and $\beta_{ijt}^{k}\left(\Psi_{ijt}^{k}\right)^{1-\sigma}$ from ***Step 1***.

For all crops and states with positive quantity traded in year t, $X_{jt}^{k}>0$, we can again use Equation (40) and take logs to get

$$\ln\left(X_{jt}^{k}/X_{jt}\right)=M_{jt}+(1-\varphi)\ln\left(\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rk}}\right)+\varepsilon_{jt}^{k} \tag{44}$$

where the first term on the right-hand side,

$$M_{jt}\equiv-\ln\left[\sum_{l\in\mathcal{K};X_{jt}^{l}>0}\beta_{jt}^{l}\left(\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rl}}\right)^{1-\varphi}\right]$$

can now be treated as an importer-time fixed effect, and the final term, $\varepsilon_{jt}^{k}\equiv\ln\left(\beta_{jt}^{k}\right)$, reflects idiosyncratic year-specific demand shocks across crops. Without loss of generality, we again normalize these shocks such that

$$\sum_{k\in\mathcal{K};X_{jt}^k>0} \varepsilon_{jt}^k = 0 \tag{45}$$

There still exists endogeneity issues between demand shocks (ε_{jt}^k) and prices ($\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rk}}$) at this higher level of aggregation, which could potentially bias our estimates of φ. To address this, we now instrument $\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{jt}}^{\boldsymbol{rk}}$ with Z_{jt}^{rk}. The exclusion restriction now equals $\mathbb{E}\left[Z_{jt}^{rk}\varepsilon_{jt}^k\right] = 0$. As before, since we do not have data on either the value of specific crops imported from all exporters or the total value of crops imported, we replace $ln\left(X_{jt}^k/X_{jt}\right)$ with $ln\left(N_{jt}^k/N_{jt}\right)$.

Results, reported in xxx, indicate that the IV estimate for the elasticity of substitution between crops, φ, equals **9.39** with standard errors of 2.3 when clustered at the importer level. Also, the first stage estimate equals **-0.055**, which can be interpreted as a one percent increase in yields leading to a 5.5 percent fall in prices. As in ***Step 1***, once the elasticity of substitution, φ, is known, we can solve for β_{jt}^k for all $j \in \mathcal{I}$ and $k \in \mathcal{K}$ such that $X_{jt}^k > 0$, as residuals using equations (44) and (45).

Step 3—The final step of our procedure estimates the upper-level demand shifters, β_{jt}. The assumption of log preferences at the upper level implies that β_{jt}'s can be read directly from data on total expenditure across crops. Specifically, using Equation (40), we can show that $\beta_{jt} = X_{jt}$ for all $j \in \mathcal{I}$ at time t.

Since we only have data on the quantity of crops imported, and not on the value of imports, we need a proxy for the price of imports to construct X_{jt}. To this end, we assume that the value of exports of crop k from i to j, X_{ijt}^k, equals the average price of k across all the markets m within state i, multiplied by the quantity exported from i to j, N_{ijt}^k. Summing this value across all $i \in \mathcal{I}$ and $k \in \mathcal{K}$ for state j provides us with X_{jt} for year t.

B Supply

There are four supply side parameters we need to estimate: the inverse measure of the dispersion of shocks (λ), the scale parameter for the trade costs (ζ), the extent of technological heterogeneity (θ), and the state-specific labor cost shifters (α_i). We proceed in two steps. First, we use data on crop prices in different markets ($\mathcal{P}_{mit}^k$), distance between farms and markets (d_m^f), and crop quantity produced in each state (Q_{it}^k) to estimate λ and ζ using a generalized method of moments (GMM) estimation procedure. Then, we use the previous estimates along with data on farm productivity (A_i^{fk}) in a nonlinear least squares (NLS) framework to estimate θ and α_i.

Step 1—We know that Ω^{fk}_{mit} from Equation (25) represents the probability that a farmer f located in state i and growing crop k at time t, chooses market m. This probability can be used to calculate the share of crop k produced in state i that reaches a market m at time t. Denoting the same by $\mathcal{S}^k_{mit}$, we can calculate it as the share of crop k that each farmer takes to market m at time t ($\mathcal{Q}^{fk}_{it}$), summed across all farmers, and divided by the total quantity of crop k produced in state i at time t ($\mathcal{Q}^k_{it}$). The expression takes the following form:

$$\begin{aligned}
\mathcal{S}^k_{mit} &= \frac{\sum\limits_{f \in \mathcal{F}_i} \Omega^{fk}_{mit} \mathcal{Q}^{fk}_{it}}{\mathcal{Q}^k_{it}} \\
&= \sum_{f \in \mathcal{F}_i} \left[\frac{\left(\frac{\mathcal{P}^k_{mit}}{1 + \zeta d^f_m} \right)^{\lambda} \mathcal{Q}^{fk}_{it}}{\sum\limits_{m' \in \mathcal{M}} \left(\frac{\mathcal{P}^k_{m'it}}{1 + \zeta d^f_{m'}} \right)^{\lambda}} \right] \Big/ \mathcal{Q}^k_{it}
\end{aligned} \tag{46}$$

Now, we use Equation (46) to carry out a GMM procedure to estimate λ and ζ. In particular, we choose $\Theta = \{\lambda, \zeta\}$, with true parameter value Θ_0, to minimize the distance between moments of the data and their estimated counterparts. Let $g(Y_m, \theta)$ be a continuous and continuously differentiable function of θ and Y_m, where the latter is a market-specific vector of parameters like prices and distance to farms. Then the population moment conditions are such that:

$$\mathbb{E}\left[g(Y_m, \Theta_0)\right] = \mathbb{E}\left[\mathcal{S}^k_{mit} - \frac{\sum\limits_{f \in \mathcal{F}_i} \Omega^{fk}_{mit} \mathcal{Q}^{fk}_{it}}{\mathcal{Q}^k_{it}} \right] = 0$$

The corresponding sample moments are given by:

$$g_m(\Theta) = \frac{1}{M} \sum_{m \in \mathcal{M}} g(Y_m, \Theta) = 0$$

Our GMM estimator can, therefore, be written as:

$$\hat{\Theta} = \arg \min_{(\Theta)} \left(\frac{1}{M} \sum_{m \in \mathcal{M}} g(Y_m, \Theta) \right)^T \hat{W} \left(\frac{1}{M} \sum_{m \in M} g(Y_m, \Theta) \right) \tag{47}$$

where $\hat{W}$ is the optimal weighting matrix. We use numerical methods to find the required gradients. Note that we do not have data on total crop produced per farm in any year, so we proxy that using ICRISAT (2018) data on district level yearly output of crops (Q^k_{dit}).

Specifically, we assume that all the farms f that fell within the district had the same output, which we can calculate as follows:

$$Q_{it}^{fk} = \frac{Q_{dit}^{k}}{F_i}$$

Finally, Q_{it}^{k} is the sum of output of crop k across all districts d in state i at time t.

Our estimates of λ and ζ equal **1.84** and **0.07**, respectively. Since λ is inversely related to the dispersion of transportation cost shocks, a low value of λ implies that farmers face substantial heterogeneity in trade costs across different states. To interpret the scale parameter ζ, we use Equation (21) to calculate the elasticity of trade costs with respect to distance:

$$\frac{\partial \tau}{\partial d} \times \frac{d}{\tau} = \frac{\zeta d}{1 + \zeta d}.$$

The equation above implies that the change in trade costs with respect to change in distance is not uniform, and depends on the original distance being traversed. For instance, if the distance between the farm and the market is 10 kms, a 10 percent increase in distance — or 1 km — leads to a 4.1 percent increase in trade costs for the farmer. On the other hand, if the distance was 100 kms, increasing the same by 10 percent will increase the transportation costs by approximately 8.7 percent.

Step 2—The remaining supply-side parameters that need to be estimated are the extent of technological heterogeneity, θ, as well as the state-specific labor cost shifters in different years, α_{it}. We do not need to estimate the productivity of fields for different crops, A_i^{fk} — the main variable that changes in our model under a climate change scenario — as it is directly observable in the GAEZ data. However, GAEZ data is not available at a yearly level; rather there is only one observation per field for the time period 1980-2010. Therefore, we only use data pertaining to the year 2010 for estimating the supply parameters in this step.[48] Naturally, the labor cost shifters too will only pertain to the year 2010. Henceforth, we remove the time subscript (t) in this subsection.

Using Equation (32), we can denote the predicted supply of crop k in state i as a function of the unknown parameters θ and α_i:

$$\mathcal{Q}_i^k\left(\theta, \alpha_i\right) = \sum_{m \in \mathcal{M}_i} \sum_{f \in \mathcal{F}_i} s_i^f A_i^{fk} \left[\frac{\left(\frac{\mathcal{P}_{mi}^k}{1 + \zeta d_m^f} \right)^{\lambda}}{\sum_{m' \in \mathcal{M}} \left(\frac{\mathcal{P}_{m'i}^k}{1 + \zeta d_{m'}^f} \right)^{\lambda}} \right] \left[\frac{(A_i^{fk} \overline{\mathcal{P}}_i^{fk})^{\theta}}{(\alpha_i)^{\theta} + \sum_{k' \in \mathcal{K}} (A_i^{fk'} \overline{\mathcal{P}}_i^{fk'})^{\theta}} \right]^{(\theta - 1)/\theta} \tag{48}$$

[48] We could have used yields data from ICRISAT (2018) but GAEZ is more accurate and spatially disaggregated (district versus farm).

Next, let $L_i(\theta, \alpha_i)$ denote the predicted land allocated to all crops in state i as a function of θ and α_i. This is calculated as the share of field f which is allocated to crop k (Δ_i^{fk} from Equation (28)), multiplied by the field size, s_i^f, and sum across all crops and fields. Specifically,

$$L_i(\theta, \alpha_i) \equiv \sum_k \sum_f s_i^f \left[\frac{(A_i^{fk} \overline{\mathcal{P}}_i^{fk})^\theta}{(\alpha_i)^\theta + \sum_{k' \in \mathcal{K}} (A_i^{fk'} \overline{\mathcal{P}}_i^{fk'})^\theta} \right] \tag{49}$$

To estimate θ and α_i, we follow the same procedure as Costinot et al. (2016), *i.e.* choose a value of θ, and conditional on it, find the vector of labor cost shifters, α_i, such that the total amount of land allocated to crops as predicted by the model, $L_i(\theta, \alpha_i)$, exactly matches the total amount of land allocated to crops in the data, L_i, for all states. Next, given the vector of labor cost shifters (α_i) for all states, we search for θ such that the difference between the output predicted by the model, $Q_i^k(\theta, \alpha_i)$, and output observed in the data, Q_i^k, is minimised. This algorithm can be formally expressed as the following non-linear least squares problem:

$$\min_{\theta, \alpha_i} \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} \left[\ln \mathcal{Q}_i^k(\theta, \alpha_i) - \ln \mathcal{Q}_i^k \right]^2$$

subject to

$$L_i(\theta, \alpha_i) = L_i \;\; \text{for all} \;\; i \in \mathcal{I}.$$

Our estimate of θ equals 1.82, which suggests that within-field, within-crop productivity dispersion in Indian agriculture is large. This is reassuringly close to the estimate of Sotelo (2020), who finds a value of 1.658 for θ using data from Peru.

7 Counterfactual Analysis

We now use the estimated parameters to simulate our model and run policy counterfactuals that involve climate change, with and without inter-state trade barriers. Specifically, we can use the model to run the following two counterfactuals: (*i*) welfare impact of climate change under a policy with inter-state trade restrictions, and; (*ii*) welfare impact of climate change under a policy without inter-state trade restrictions. Under both counterfactuals, we allow for production and trade patterns to fully adjust.

To run either of these counterfactuals, we first need to solve for the competitive equilibrium before climate change. This equilibrium is characterized by the market supply curve in Equation (32), and the following three conditions: (*i*) intermediary profit maximization in

Equation (34); (*ii*) consumer utility maximisation in Equation (36), and; (*iii*) market clearing in Equation (38). Crop productivity for different farms, A_i^{fk}, is the structural parameter which will change under the climate change scenario. Therefore, for the first equilibrium, we use pre-climate change GAEZ data. Subsequently, for the counterfactual equilibrium with climate change, we use the exact same equations and structural parameters except for crop yields, which is replaced with post-climate change productivity, $(A_i^{fk})'$, as measured by GAEZ.

The key mechanism driving any differences between the equilibrium with and without climate change is the change in productivity across different farms and crops caused by global warming. Climate change will affect comparative advantage in crop yields across different regions of the country. This, in turn, alters supply as farmers change the use of intermediate inputs and substitute between crops, which then impacts *mandi* and retail prices — an effect that feeds back into the prices farmers can get.

It is worth noting that the welfare consequences of changes in comparative advantage will also depend crucially on the spatial competition faced by farmers, as it directly incentivizes farmer adaptation. To see this, consider the following example: a farmer near a state border grows rice, but climate change shifts their comparative advantage towards wheat. The price offered to wheat farmers in the nearby *mandi*, however, is not competitive due to intermediary market power. Thus, despite rice yields falling, the farmer does not substitute. Lifting border restrictions would necessarily improve the welfare outcome by increasing the farmer's choice set, both in terms of accessible markets and crop choices.

The channel for this welfare improvement is intuitive. First, opening state borders directly impacts the probability of the farmer choosing a market, as seen in Equation (25). This occurs because reducing distance — and, thus, transportation costs — between farms and potential markets increases farmers' arbitrage opportunities. Second, the change in market choice probability subsequently affects farmers' probability of allocating land to a crop through changes in the average value of the marginal product of the field (Equation (29)). These changes in farmer input decisions, in turn, change quantities supplied to each market (Equation (32)). Now, the prices received by farmers will be affected through two sources: the change in quantity, and the change in bargaining power, as the intermediary faces increased competition now from across the border. This increase in competition affects each intermediaries share in the market, which will affect the markdowns. Importantly, the changes in intermediary market power near the borders has ripple effects across interior markets through this change in quantity Equation (34). Finally, changes in production, market choice of farmers and intermediary market power could also adjust retail prices which in turn will feed back into the prices farmers' receive. This change would eventually incentivize the farmer at the border to substitute from rice to wheat, as predicted by comparative advantage. Therefore, change in production and incomes brought about by opening trade borders could aid in mitigating the climate change impact.

Our assumption of quasi-linear preferences allows us to compute welfare changes as changes in social surplus, expressed as a fraction of GDP in the initial equilibrium:

$$\Delta W_i = \frac{(Y_i)' - Y_i + (\beta \ln C_i - P_i C_i)' - (\beta \ln C_i - P_i C_i) + (\pi)' - \pi}{Y_i} \tag{50}$$

where Y_i and π_i are the GDP and intermediary profits in the initial equilibrium, respectively, while primes denote the analogous variable in the counterfactual equilibrium.

We find that climate change reduces welfare in India by 2.1 percent of total GDP, assuming border restrictions for farmers remain in place. Note that up until now, we have set the distance between farms in state i and markets in state j, for $i \neq j$, as ∞. In the subsequent counterfactual where we remove the trade barriers, the distance is set to the actual geodesic distance, similar to if farms and markets were in the same state. Under this counterfactual, where farmers can access markets across state borders, the country still experiences a 1.81 percent fall in GDP. However, this is 13.8 percent lower, implying a mitigation of the negative impacts. This illustrates how market distortions created by government policies could hinder adaptation, and how removing the same could expand the adaptation portfolio of farmers, thus helping countries mitigate the negative consequences of climate change.

8 Discussion and Conclusion

Extreme and frequent heat events, induced by climate change, are predicted to accelerate crop failures, leading to increased food prices and greater food insecurity (IPCC 2022). Given this portentous scenario, a higher magnitude and rate of farmer adaptation are crucial to flatten the slope of the climate damage function. However, to what extent does the effectiveness of adaptation responses depend on a country's institutional framework? We offer an insight into this question by studying the impact of institution-led distortions in market competition on farmer climate-change adaptation in India. Using spatial variation in intermediary market power — an unintended consequence of regulations governing agricultural marketing — we show that higher competition among buyers of agricultural produce helps farmers alleviate the detrimental impact of extreme heat. This effect is primarily driven by an increase in input usage in more competitive areas, a response to higher expected prices post climate shocks. Subsequently, we structurally estimate a spatial trade equilibrium model to test the implications of eliminating these market distortions under a climate change scenario. Our results indicate that there is potential for substantial welfare gains if government policies distorting market competition are removed, highlighting the positive role of free markets in facilitating adaptation.

Though our setting — distortions in intermediary competition emanating from Indian agricultural laws — is a specific one, we believe that many of its characteristics, and the lessons derived from it, apply more broadly. First, we show that well-intended government policies can distort adaptation behavior. A similar result is outlined by Annan & Schlenker (2015), who show that federal crop insurance can lead to moral hazard, and thus, discourage private adaptation efforts. Similarly, Kahn & Lall (2021) hypothesize that government investment in resilience infrastructure can encourage migration into risky areas, increasing the population's overall risk exposure. Second, intermediary power in agricultural value chains is ubiquitous in developing economies, for *e.g.* Ecuador (Zavala 2020), Kenya (Dhingra & Tenreyro 2020), and Rwanda (Macchiavello & Morjaria 2021), among others. Our results indicate that adaptation to climate change in such countries will therefore, be rendered more challenging as farmers would also need to overcome the distortions to adaptation incentives caused by market power.

While *State* intervention in case of market failures is valuable, there needs to be recognition that government and private individuals respond to each other (Kousky et al. 2006). Therefore, these strategic interactions need to be internalized when designing policies, else the resulting distortions arising from unintended consequences could have negative implications in a world afflicted by climate change.

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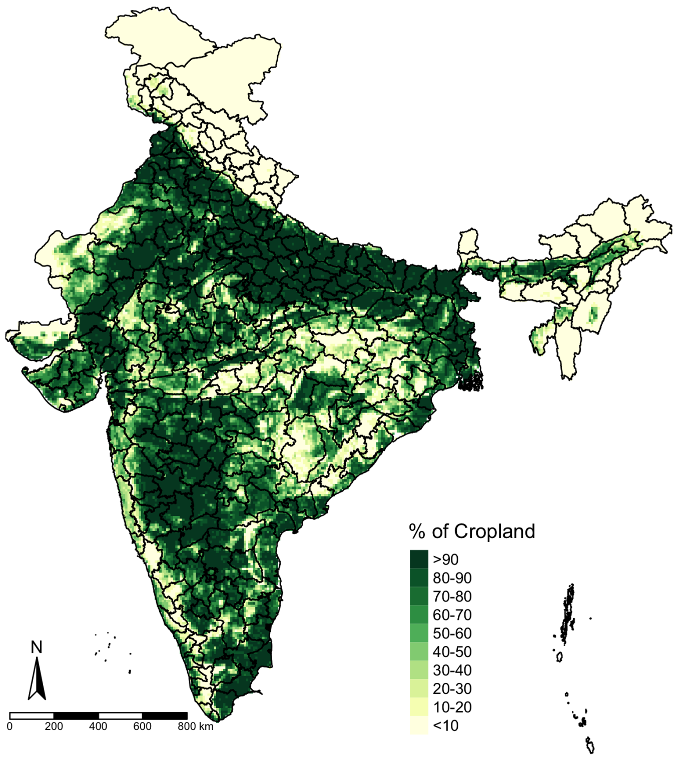
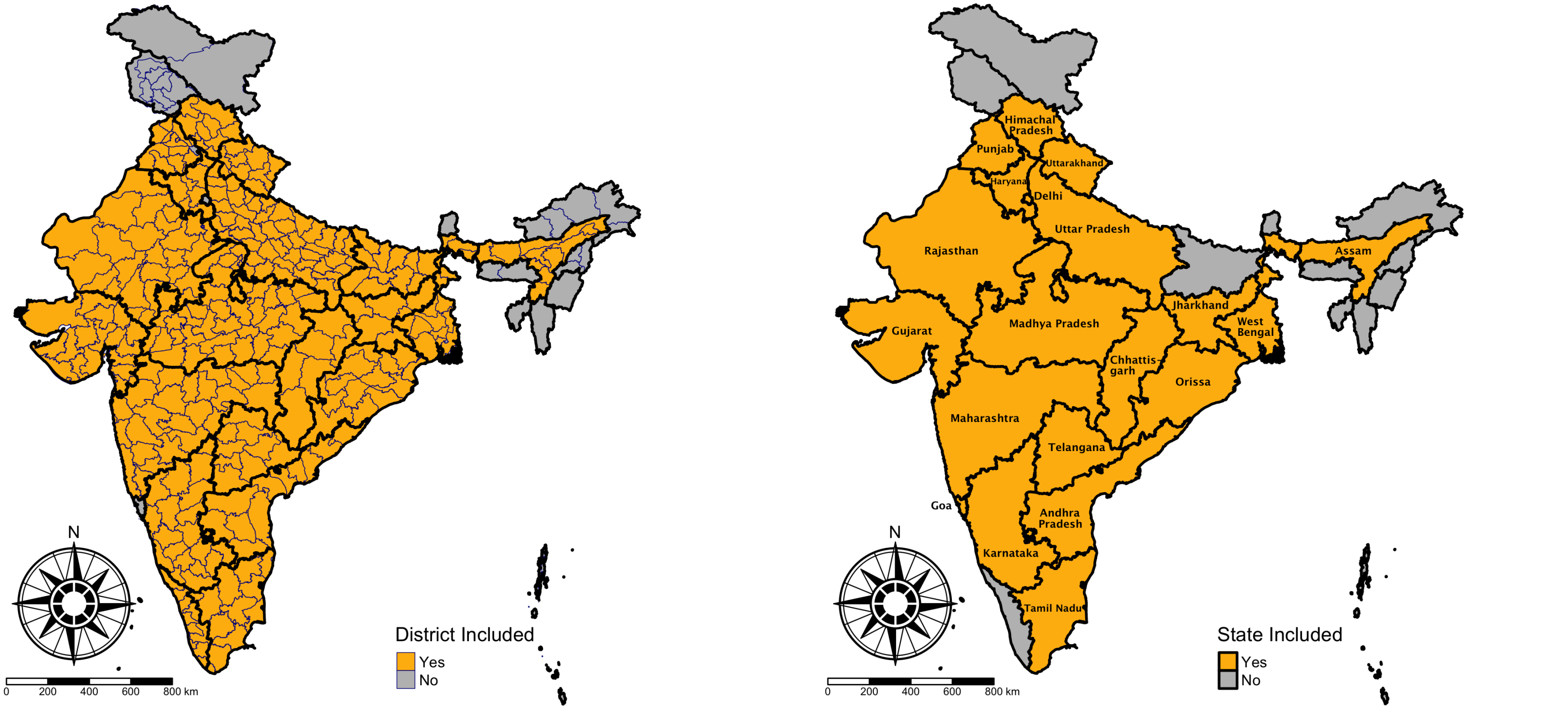
Appendices

A Figures



Notes: The cropland shares are computed based on 30m land cover data from the Global Food Security-support Analysis Data 2015 (GFSAD30, 2017).

Figure A.1: Fraction of Cropland in each ECMWF (Weather) Gridcell

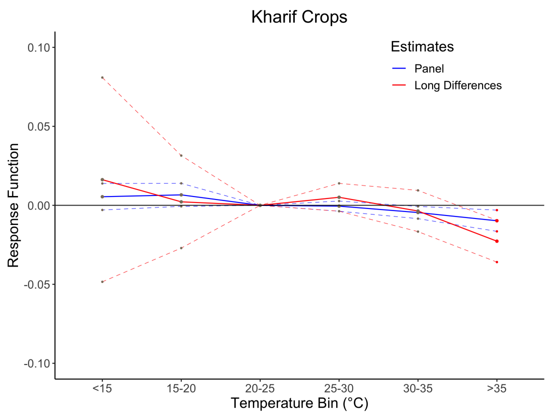


(a) Districts in Sample for Analysing Effect of Extreme Heat **(b) States in Sample for Analysing Effect of Competition**

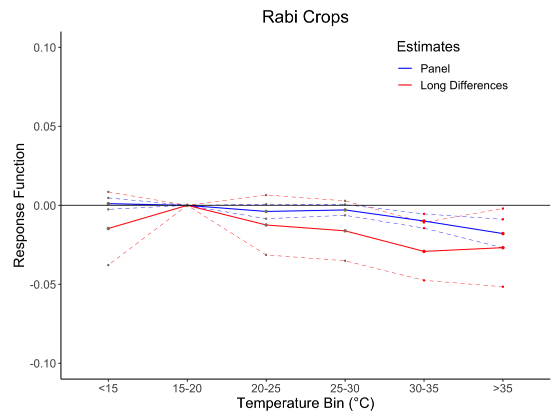
Notes: Panel (a) shows the 313 districts (filled in *goldenrod* color) covered in ICRISAT (2018)'s *Apportioned* database, which provides yields for 25 major crops district-wise from 1966-2017. The district boundaries pertain to the year 1966. There were a total of 349 districts in 1966. Therefore, the 36 districts not included in the ICRISAT (2018) database are filled in *grey*. Panel (b) shows the 19 states (filled in *goldenrod* color) which constitute the sample used to analyse the effect of competition on various economic outcomes. These states include 2,938 wholesale intermediary *Mandis* geolocated within their boundaries, which forms our final sample of markets. The state boundaries pertain to the year 2020. 9 States and 8 Union Territories not included in the sample are filled in *grey*.

Figure A.2: ICRISAT Districts and APMC States in Sample

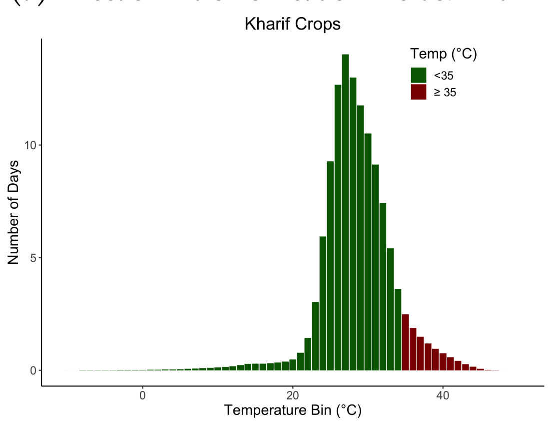
B Tables



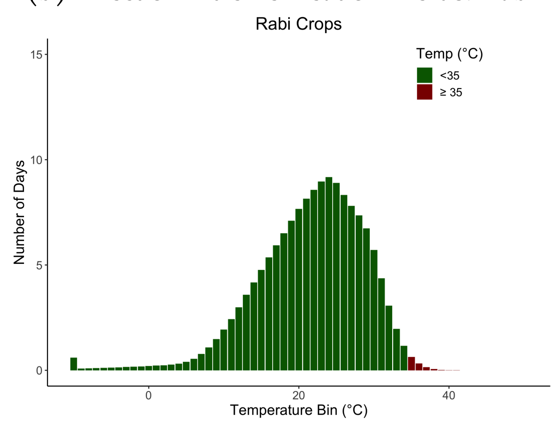
(a) Effect of Extreme Heat on Yields: Kharif



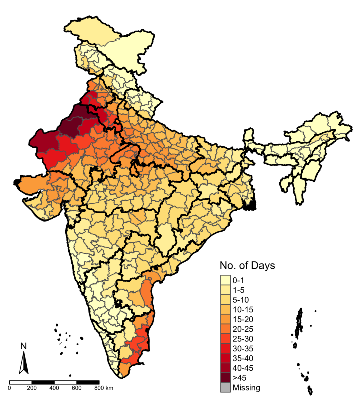
(b) Effect of Extreme Heat on Yields: Rabi



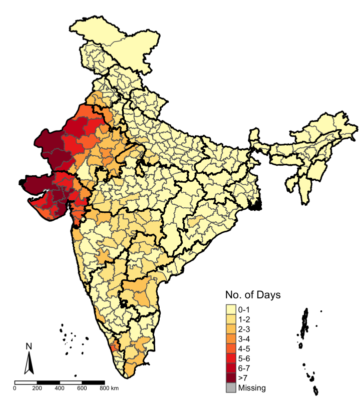
(c) Growing Season Distribution: Kharif



(d) Growing Season Distribution: Rabi



(e) Map of Extreme Heat Exposure: Kharif



(f) Map of Extreme Heat Exposure: Rabi

Notes:

Figure A.3: Coefficient Plot, GDD Distribution, and Extreme Heat Exposure by Season

Table B.1: Effect of Temperature on Yields (Panel Approach): Robustness Tests

	Dependent Variable: $log(Yields)_{cdsy}$									
	Kharif					Rabi				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bin <15$_{dsy}$	0.010***	0.002	0.011	0.004	0.004	0.002	0.004*	0.002	0.004***	0.003*
	(0.003)	(0.006)	(0.007)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)
Bin 15-20$_{dsy}$	0.007**	0.000	0.008	0.004	0.003					
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)					
Bin 20-25$_{dsy}$						−0.002	−0.001	−0.004	0.000	0.001
						(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
Bin 25-30$_{dsy}$	−0.001	−0.003**	−0.002	−0.004***	−0.004**	−0.001	−0.002	−0.002	−0.002*	−0.001
	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Bin 30-35$_{dsy}$	−0.005**	−0.005***	−0.005	−0.006***	−0.006***	−0.009***	−0.005**	−0.009***	−0.006***	−0.006***
	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Bin >35$_{dsy}$	−0.011***	−0.011***	−0.011**	−0.011***	−0.011***	−0.017***	−0.014**	−0.018***	−0.014***	−0.014***
	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Fixed Effects										
District	✓	✓	✓			✓	✓	✓		
Crop × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Crop × State			✓					✓		
State × Year		✓		✓	✓		✓		✓	✓
District × Decade				✓					✓	
District × Crop × Decade					✓					✓
State Time-Trend	✓					✓				
Num. obs.	125,279	125,279	125,279	125,279	125,279	60,429	60,429	60,429	60,429	60,429
Adj. R^2	0.599	0.622	0.701	0.628	0.836	0.724	0.742	0.754	0.754	0.871

Notes: two-way clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.2: Effect of Temperature on Yields (Long-Differences): Robustness Tests

	Dependent Variable: $log(\overline{Yields})_{cds}$					
	Cross Section		2-Period Panel		3-Period Panel	
	Kharif	*Rabi*	*Kharif*	*Rabi*	*Kharif*	*Rabi*
Bin <15$_{dst}$	-0.038^{*}	-0.006	-0.007	-0.019^{*}	0.036	0.006
	(0.021)	(0.018)	(0.018)	(0.010)	(0.027)	(0.015)
Bin 15-20$_{dst}$	-0.003		0.016		0.027	
	(0.019)		(0.012)		(0.022)	
Bin 20-25$_{dst}$		-0.005		-0.039^{***}		-0.015
		(0.012)		(0.009)		(0.009)
Bin 25-30$_{dst}$	-0.001	-0.008	-0.006	-0.035^{***}	-0.018^{***}	0.001
	(0.008)	(0.016)	(0.005)	(0.010)	(0.005)	(0.012)
Bin 30-35$_{dst}$	-0.016^{**}	-0.011	-0.017^{***}	-0.031^{***}	-0.021^{***}	0.000
	(0.008)	(0.014)	(0.006)	(0.007)	(0.005)	(0.008)
Bin >35$_{dst}$	-0.017^{*}	-0.034^{*}	-0.019^{***}	-0.037^{***}	-0.044^{***}	-0.050^{***}
	(0.009)	(0.019)	(0.006)	(0.013)	(0.006)	(0.017)
Time Period						
Period 1	1990-2015	1990-2015	1970-1990	1970-1990	1970-1980	1970-1980
Period 2			1995-2015	1995-2015	1985-1995	1985-1995
Period 3					2000-2015	2000-2015
Fixed Effects						
Crop × State	✓	✓	✓	✓	✓	✓
Time Period			✓	✓	✓	✓
Num. obs.	2,636	1,267	4,877	2,397	7,283	3,547
Adj. R^2	0.510	0.382	0.219	0.227	0.185	0.121

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.3: Effect of Out-of-State Competition on Mitigation of Climate Shocks

	Dependent Variable: $log(Yields)_{cdsy}$					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Bin 30-35$_{dsy}$	-0.004^{**}	-0.004	-0.011^{***}	-0.002	-0.014^{***}	-0.010^{***}
	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Bin >35$_{dsy}$	-0.022^{***}	-0.020^{***}	-0.011^{*}	-0.029^{***}	-0.015^{**}	-0.014^{***}
	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.004)
Bin <15$_{dsy}$ $\times$ *Comp'*$_{ds}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Bin 15-20$_{dsy}$ $\times$ *Comp'*$_{ds}$	0.000	0.001	0.000	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Bin 25-30$_{dsy}$ $\times$ *Comp'*$_{ds}$	-0.000	-0.000	0.001	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bin 30-35$_{dsy}$ $\times$ *Comp'*$_{ds}$	-0.000	-0.000	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bin >35$_{dsy}$ $\times$ *Comp'*$_{ds}$	0.000	0.000	0.001	0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Fixed Effects						
Crop		✓				
District	✓	✓				
Year		✓	✓			
Crop × District			✓			
Crop × Year	✓			✓	✓	✓
District × Year				✓		
State × Year						✓
District × Crop × Decade					✓	✓
Num. obs.	59,593	59,593	59,593	59,593	59,593	59,593
Adj. R^2	0.623	0.614	0.805	0.635	0.829	0.844

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.4: Competition and Mitigation of Climate Shocks: Robustness Tests

	Dependent Variable: $log(Yields)_{cdsy}$							
	Comp$_{2m}$				**Comp**$_{3ds}$			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Bin 30-35$_{dsy}$	-0.002	-0.002	-0.001	-0.006^{*}	-0.002	-0.003	-0.001	-0.011^{***}
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bin >35$_{dsy}$	-0.038^{***}	-0.037^{***}	-0.043^{***}	-0.023^{**}	-0.034^{***}	-0.032^{***}	-0.040^{***}	-0.021^{**}
	(0.010)	(0.006)	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.007)
Bin <15$_{dsy}$ $\times$ *Comp*$_{ds}$	-0.004	-0.003	-0.001	-0.005	-2.752	-2.399	-0.874	-0.723
	(0.003)	(0.003)	(0.003)	(0.004)	(2.416)	(2.394)	(2.847)	(2.055)
Bin 15-20$_{dsy}$ $\times$ *Comp*$_{ds}$	0.005	0.005	0.004	0.000	3.383	2.851	3.571	1.456
	(0.004)	(0.003)	(0.004)	(0.002)	(2.918)	(2.954)	(3.692)	(2.545)
Bin 25-30$_{dsy}$ $\times$ *Comp*$_{ds}$	-0.002	-0.001	-0.001	-0.003	-1.209	-1.327	0.683	-3.176
	(0.003)	(0.003)	(0.003)	(0.003)	(2.781)	(2.817)	(3.638)	(2.189)
Bin 30-35$_{dsy}$ $\times$ *Comp*$_{ds}$	-0.003	-0.004	-0.003	-0.004	-2.321	-2.544	-2.490	-0.957
	(0.004)	(0.004)	(0.003)	(0.003)	(1.957)	(1.971)	(2.401)	(1.829)
Bin >35$_{dsy}$ $\times$ *Comp*$_{ds}$	0.014^{**}	0.015^{***}	0.015^{***}	0.007^{*}	9.973^{***}	9.926^{***}	11.719^{***}	5.048^{*}
	(0.005)	(0.004)	(0.005)	(0.004)	(2.733)	(2.752)	(3.185)	(2.843)
Fixed Effects								
Crop		✓				✓		
District	✓	✓			✓	✓		
Year		✓				✓		
Crop $\times$ Year	✓		✓	✓	✓		✓	✓
District $\times$ Year			✓				✓	
District $\times$ Crop $\times$ Decade				✓				✓
State Time-Trend	✓	✓		✓	✓	✓		✓
Effect Mitigated (in %)	**24.5**	**26.2**	**23.2**	**19.6**	**22.3**	**23.6**	**21.9**	**18.2**
Num. obs.	59,783	59,783	59,783	59,783	59,783	59,783	59,783	59,783
Adj. R^2	0.627	0.618	0.637	0.831	0.626	0.617	0.636	0.831

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table B.5: Competition and Mitigation of Climate Shocks—Arrivals: Robustness Tests

	Dependent Variable: $log(Arrivals)_{cmdsy}$			
	(1)	(2)	(3)	(4)
Bin 30-35$_{dsy}$	-0.009	-0.008	-0.013	-0.007
	(0.008)	(0.010)	(0.012)	(0.010)
Bin >35$_{dsy}$	-0.035^{*}	-0.036^{**}	-0.056^{**}	-0.030^{*}
	(0.019)	(0.016)	(0.023)	(0.015)
Bin <15$_{dsy}$ $\times$ *Comp*$_{mds}$	0.003	0.003	0.008	0.002
	(0.004)	(0.005)	(0.006)	(0.004)
Bin 15-20$_{dsy}$ $\times$ *Comp*$_{mds}$	0.012^{*}	0.012	0.019^{**}	0.009
	(0.006)	(0.007)	(0.008)	(0.007)
Bin 25-30$_{dsy}$ $\times$ *Comp*$_{mds}$	0.008^{**}	0.008^{**}	0.013^{**}	0.006
	(0.004)	(0.004)	(0.006)	(0.004)
Bin 30-35$_{dsy}$ $\times$ *Comp*$_{mds}$	0.006^{*}	0.006	0.010	0.004
	(0.004)	(0.004)	(0.007)	(0.004)
Bin >35$_{dsy}$ $\times$ *Comp*$_{mds}$	0.013^{*}	0.013^{**}	0.023^{**}	0.010^{*}
	(0.007)	(0.006)	(0.010)	(0.006)
Fixed Effects				
Market	✓			✓
Crop × Year	✓	✓	✓	✓
District × Decade				✓
Market × Decade		✓		
Market × Year			✓	
State × Year		✓	✓	✓
Effect Mitigated (in %)	**65.2**	**65.4**	**74.8**	**60.2**
Num. obs.	156,724	156,724	156,724	156,724
Adj. R^2	0.434	0.451	0.449	0.429

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

C Derivations

C.1 *Joint Distribution of TFP and Labor Intensity*

Assume that the total factor productivity (TFP) of parcel ω in field f if allocated to crop k in state i at time t, $A_{it}^{fk}(\omega) \geq 0$, is Fréchet distributed with

$$\Pr[A_{it}^{fk}(\omega) \leq a^k] = \exp\left\{-\left(a^k/s^k\right)^{-\theta}\right\} \quad \forall\, k \in \mathcal{K} \tag{51}$$

where $\theta > 0$ is a shape parameter, and $s > 0$ is the scale parameter. Denote $\mathbb{E}\left[A_{it}^{fk}(\omega)\right] = A_{it}^{fk}$, which is given by

Table B.6: Effect of Out-of-State Competition on Mitigation—Arrivals

	Dependent Variable: $log(Arrivals)_{cmdsy}$			
	(1)	(2)	(3)	(4)
Bin 30-35$_{dsy}$	0.001	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)
Bin >35$_{dsy}$	−0.019	−0.019	−0.025*	−0.019
	(0.012)	(0.012)	(0.014)	(0.012)
Bin <15$_{dsy} \times$ *Comp'*$_{mds}$	0.000	0.000	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Bin 15-20$_{dsy} \times$ *Comp'*$_{mds}$	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Bin 25-30$_{dsy} \times$ *Comp'*$_{mds}$	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Bin 30-35$_{dsy} \times$ *Comp'*$_{mds}$	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Bin >35$_{dsy} \times$ *Comp'*$_{mds}$	0.001	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Fixed Effects				
Market	✓			✓
Crop × Year	✓	✓	✓	✓
District × Decade				✓
Market × Decade		✓		
Market × Year			✓	
State × Year		✓	✓	✓
Num. obs.	148,814	148,814	148,814	148,814
Adj. R^2	0.433	0.450	0.449	0.437

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

$$A_{it}^{fk} = s^k \Gamma\left((\theta - 1)/\theta\right) \text{ for } \theta > 1, \ \forall\, k \in \mathcal{K}$$

where $\Gamma(\cdot)$ denotes the Gamma function, i.e. $\Gamma(t) = \int\limits_0^{+\infty} u^{t-1}\exp(-u)du$ for any $t > 0$.

Using the above definition, and setting $\gamma \equiv \Gamma\left((\theta-1)/\theta\right)^{-\theta}$, Equation (51) becomes

$$\Pr[A_{it}^{fk}(\omega) \leq a^k] = \exp\left\{-\gamma\left(a^k/A_{it}^{fk}\right)^{-\theta}\right\} \quad \forall\, k \in \mathcal{K} \tag{52}$$

Also, assume labor intensity, $\nu_i^f(\omega)$, which is constant across crops and time, is distributed Fréchet such that

$$\Pr[\nu_i^f(\omega) \leq \nu] = \exp\left\{-\gamma\left(\nu/\nu_i\right)^{-\theta}\right\} \tag{53}$$

where ν_i denotes $\mathbb{E}\left[\nu_i^f(\omega)\right]$. Given that TFP and labor intensity are independently drawn for each (i, f, ω, t), and using Equation (52) and (53), the joint CDF can, therefore, be written as

$$\begin{aligned}
&\Pr\{A_{it}^{f1}(\omega) \leq a^1, \ \ldots, \ A_{it}^{fK}(\omega) \leq a^K, \nu_i^f(\omega) \leq \nu\} \\
&= \prod_{k \in \mathcal{K}} \exp\left\{-\gamma \left(a^k / A_{it}^{fk}\right)^{-\theta}\right\} \cdot \exp\left\{-\gamma \left(\nu/\nu_i\right)^{-\theta}\right\} \\
&= \exp\left\{-\gamma \left[\sum_{k \in \mathcal{K}} (a^k / A_{it}^{fk})^{-\theta} + (\nu/\nu_i)^{-\theta}\right]\right\}
\end{aligned}$$

C.2 ***Probability of Choosing Market***

Derivation of probability of choosing market m for crop k, Equation (24) in text.

A farmer in state i chooses market $m \in \mathcal{M}$ at time t if:

$$\mathcal{P}_{mit}^k Q_{mit}^{fk}(\omega) \geq \mathcal{P}_{m'it}^k Q_{m'it}^{fk}(\omega) \ \ \forall \ \ m' \in \mathcal{M} \backslash \{m\} \tag{54}$$

Our assumption of iceberg trade costs for farmers (Equation (20) in text) implies that $Q_{mit}^{fk}(\omega) = Q_{it}^{fk}(\omega)/\tau_{mt}^f$. Using this, we can rewrite the condition above. Therefore, a farmer chooses market $m \in \mathcal{M}$ at time t if:

$$\frac{\tau_{mt}^f}{\mathcal{P}_{mit}^k} = \min\left\{\frac{\tau_{1t}^f}{\mathcal{P}_{1it}^k}, \ \ldots, \ \frac{\tau_{mt}^f}{\mathcal{P}_{mit}^k}, \ \ldots, \ \frac{\tau_{Mt}^f}{\mathcal{P}_{Mit}^k}\right\} \tag{55}$$

Our assumption of Weibull distributed trade cost shocks (Equation (22)), and the distribution's property of being closed under scale transformations implies:

$$\frac{\tau_{mt}^f}{\mathcal{P}_{mit}^k} \sim \text{Weibull}\left(\lambda, \frac{\Upsilon^{-1/\lambda}(1 + \zeta d_m^f)}{\mathcal{P}_{mit}^k}\right)$$

Let G_{mt}^f denote the c.d.f. of $\frac{\tau_{mt}^f}{\mathcal{P}_{mit}^k}$. Then:

$$\begin{aligned}
\mathsf{G}_{mt}^f(\epsilon) &= \Pr\left[\frac{\tau_{mt}^f}{\mathcal{P}_{mit}^k} \leq \epsilon\right] \\
&= 1 - \exp\left(-\Upsilon \epsilon^\lambda \left(\frac{\mathcal{P}_{mit}^k}{1 + \zeta d_m^f}\right)^\lambda\right)
\end{aligned}$$

The probability of choosing market m for crop k can now be written as:

$$\Omega_{it}^{fmk} = \Pr\left[\frac{\tau_{mt}^{f}}{\mathcal{P}_{mit}^{k}} \leq \min_{m'}\left\{\frac{\tau_{m't}^{f}}{\mathcal{P}_{m'it}^{k}}\right\}\right] = \Pr\left[\frac{\tau_{mt}^{f}}{\mathcal{P}_{mit}^{k}} \leq \min_{m'\neq m}\left\{\frac{\tau_{m't}^{f}}{\mathcal{P}_{m'it}^{k}}\right\}\right]$$
$$= \int_0^\infty \prod_{m'\neq m}\left(1 - G_{m't}^{f}(\epsilon)\right) dG_{mt}^{f}(\epsilon)$$

We can use the c.d.f. $\mathsf{G}_{m't}^{f}(\epsilon) = 1 - \exp\left(-\Upsilon\epsilon^{\lambda}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^{f}}\right)^{\lambda}\right)$, and the corresponding p.d.f. $d\mathsf{G}_{mt}^{f}(\epsilon) = \lambda\epsilon^{\lambda-1}\Upsilon\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta d_{m}^{f}}\right)^{\lambda}\exp\left(-\Upsilon\epsilon^{\lambda}\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta d_{m}^{f}}\right)^{\lambda}\right) d\epsilon$ to get,

$$\Omega_{mit}^{fk} = \lambda\Upsilon\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta d_{m}^{f}}\right)^{\lambda}\int_0^\infty \prod_{m'}\exp\left(-\Upsilon\epsilon^{\lambda}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^{f}}\right)^{\lambda}\right)\epsilon^{\lambda-1}d\epsilon$$
$$= \lambda\Upsilon\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta d_{m}^{f}}\right)^{\lambda}\int_0^\infty \exp\left(-\left(\sum_{m'}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^{f}}\right)^{\lambda}\right)\Upsilon\epsilon^{\lambda}\right)\epsilon^{\lambda-1}d\epsilon$$
$$= \lambda\Upsilon\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta d_{m}^{f}}\right)^{\lambda}\left[\frac{-\exp\left(-\left(\sum_{m'}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^{f}}\right)^{\lambda}\right)\Upsilon\epsilon^{\lambda}\right)}{\lambda\Upsilon\sum_{m'}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta d_{m'}^{f}}\right)^{\lambda}}\right]_0^\infty$$
$$= \frac{\left(\frac{\mathcal{P}_{mit}^{k}}{1+\zeta\cdot d_{m}^{f}}\right)^{\lambda}}{\sum_{m'\in\mathcal{M}}\left(\frac{\mathcal{P}_{m'it}^{k}}{1+\zeta\cdot d_{m'}^{f}}\right)^{\lambda}}\square$$

C.3 ***Profit Function of Farmer***

Derivation of profits for a farmer growing crop k in farm f at time t, Equation (26) in text.

Given the production function in Equation (18), the profit for a farmer from parcel

$\omega \in f$ in state i who grows crop k at time t is given by:

$$\begin{aligned}
\pi_{it}^{fk}(\omega) = & \ (\mathcal{P}_{1it}^{k} A_{it}^{fk}(\omega) L_{it}^{fk}(\omega) - w_{it} N_{it}^{fk}(\omega)) \cdot \Omega_{1it}^{fk} \ + \ \ldots \\
& + \ (\mathcal{P}_{Mit}^{k} A_{it}^{fk}(\omega) L_{it}^{fk}(\omega) - w_{it} N_{it}^{fk}(\omega)) \cdot \Omega_{Mit}^{fk} \\
= & \left(\sum_{m' \in \mathcal{M}} \Omega_{m'it}^{fk} \mathcal{P}_{m'it}^{k} \right) (A_{it}^{fk}(\omega) L_{it}^{fk}(\omega)) - \underbrace{\left(\sum_{m' \in \mathcal{M}} \Omega_{m'it}^{fk} \right)}_{=1} (w_{it} N_{it}^{fk}(\omega))
\end{aligned}$$

Using the expression for the probability of choosing a market (Ω_{mit}^{fk}) in Equation (25), we can write the above as:

$$\pi_{it}^{fk}(\omega) = A_{it}^{fk}(\omega) L_{it}^{fk}(\omega) \underbrace{\left(\frac{\sum_{m' \in \mathcal{M}} \frac{(\mathcal{P}_{m'it}^{k})^{\lambda+1}}{\left(1 + \zeta d_{m'}^{f}\right)^{\lambda}}}{\sum_{m' \in \mathcal{M}} \left(\frac{\mathcal{P}_{m'it}^{k}}{1 + \zeta d_{m'}^{f}} \right)^{\lambda}} \right)}_{= \overline{\mathcal{P}}_{it}^{k}} - w_{it} N_{it}^{fk}(\omega) \square \tag{56}$$

C.4 *Land Allocation Problem*

Derivation of probability that a parcel ω of a field f located in state i is allocated to crop k at time t, Equation (28) in text.

Conditional on choosing to grow a crop, farmer in farm f and state i chooses crop k at time t if:

$$\pi_{it}^{fk}(\omega) > \pi_{it}^{fk'}(\omega) \quad \forall \ \ (k' \neq k) \in \mathcal{K}$$

We can use the profit function in Equation (56) to write the above condition as:

$$\begin{aligned}
A_{it}^{fk}(\omega) L_{it}^{fk}(\omega) \overline{\mathcal{P}}_{it}^{k} - \ w_{it} N_{it}^{fk}(\omega) > A_{it}^{fk'}(\omega) L_{it}^{fk'}(\omega) \overline{\mathcal{P}}_{it}^{k'} - w_{it} N_{it}^{fk'}(\omega) \\
\forall \ \ (k' \neq k) \in \mathcal{K}
\end{aligned} \tag{57}$$

The Leontief production function in Equation (18) implies $L_{it}^{fk}(\omega) = \dfrac{N_{it}^{fk}(\omega)}{\nu_i^f(\omega)}$ $\forall k \in \mathcal{K}$. Also, once a farmer decides to grow a crop, they will use the entire land area available since profits are an increasing function of production inputs. Thus, $L_{it}^{fk}(\omega) = L_{it}^{fk'}(\omega) \ \forall \ k' \in \mathcal{K}$. Equation (57) can then be written as:

$$A_{it}^{fk}(\omega) \overline{\mathcal{P}}_{it}^{k} > A_{it}^{fk'}(\omega) \overline{\mathcal{P}}_{it}^{k'} \quad \forall \ \ (k' \neq k) \in \mathcal{K} \tag{58}$$

The farmer in state i also has an outside option which entails working in state i's outside sector and producing the outside good. With labor productivity denoted by A^0_{it}, and production under constant returns to scale using only labor, the profit maximisation problem of state i's outside sector can be written as:

$$\max_{\{N^0_{it}\}} \quad \pi^0_{it} = A^0_{it} N^0_{it} - w_{it} N^0_{it}$$

Differentiating the above w.r.t. $\{N^0_{it}\}$, we find that profit maximisation in state i's outside sector requires $w_{it} = A^0_{it}$. Therefore, a farmer chooses to grow crop k over working in state i's outside sector if:

$$A^{fk}_{it}(\omega)\overline{\mathcal{P}}^k_{it} > A^0_{it}\nu^f_i(\omega) \tag{59}$$

Combining Equation (58) and Equation (59), we can deduce that a farmer in state i will grow crop k in parcel $\omega \in f$ at time t if:

$$A^{fk}_{it}(\omega)\overline{\mathcal{P}}^k_{it} = \max\{A^0_{it}\nu^f_i(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^1_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^K_{it}\}\square \tag{60}$$

C.5 ***Quantity Supplied to Market***

Derivation of quantity of crop k supplied to market m in state i at time t, Equation (30) in text. Let $\mathcal{Q}^k_{mit}$ denote the quantity of crop k supplied to market m in state i at time t. Then

$$\mathcal{Q}^k_{mit} = \sum_{f \in \mathcal{F}_i} \Omega^{fk}_{mit} \int_0^1 Q^{fk}_{it}(\omega) d\omega \tag{61}$$

Assume that $\omega \sim \mathcal{U}_{[0,1]}$. Thus, the probability density function of ω is:

$$f(\omega) = \begin{cases} 1 & \text{for} \quad 0 \leq \omega \leq 1 \\ 0 & \text{for} \quad \omega < 0 \ \text{ or } \ \omega > 1 \end{cases}$$

Also, by law of iterated expectations,

$$\begin{aligned} \mathbb{E}[Q^{fk}_{it}(\omega)] &= \mathbb{E}_k[\mathbb{E}[Q^{fk}_{it}(\omega)|A^{fk}_{it}(\omega)\overline{\mathcal{P}}^k_{it} \\ &= \max\{A^0_{it}\nu^f_i(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^1_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^K_{it}\}]] \end{aligned}$$

Equation (61) can, therefore, be written as

$$
\begin{aligned}
\mathcal{Q}^k_{mit} = \sum_{f \in \mathcal{F}_i} \Omega^{fk}_{mit} \Delta^{fk}_{it} \mathbb{E}[Q^{fk}_{it}(\omega) | A^{fk}_{it}(\omega) \overline{\mathcal{P}}^k_{it} \\
= \max\{A^0_{it}\nu^f_i(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^1_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^K_{it}\}]
\end{aligned} \tag{62}
$$

Furthermore, note that

$$
\begin{aligned}
\mathbb{E}[L^{fk}_{it}(\omega) | A^{fk}_{it}(\omega) \overline{\mathcal{P}}^k_{it} = \max\{A^0_{it}\nu^f_i(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^1_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^K_{it}\}] \\
= \mathbb{E}[L^{fk}_{it}(\omega)] \\
= \int_0^1 L^{fk}_{it}(\omega) f(\omega) d\omega \\
= s^f_i
\end{aligned}
$$

Using (i) the production function in Equation (18); (ii) the fact that conditional on choosing crop k, $A^{fk}_{it}(\omega) \perp L^{fk}_{it}(\omega)$, and; ($iii$) the previous expression, Equation (62) can be expressed as:

$$
\begin{aligned}
\mathcal{Q}^k_{mit} = \sum_{f \in \mathcal{F}_i} s^f_i \Omega^{fk}_{mit} \Delta^{fk}_{it} \mathbb{E}[A^{fk}_{it}(\omega) | A^{fk}_{it}(\omega) \overline{\mathcal{P}}^k_{it} \\
= \max\{A^0_{it}\nu^f_i(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^1_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^K_{it}\}]
\end{aligned} \tag{63}
$$

C.6 Average Conditional Productivity

Derivation of average productivity conditional on a crop being produced, Equation (31) in text.

Using the definition of a c.d.f. and formula for conditional probability, we can write:

$$
\begin{aligned}
&\Pr\{A^{fk}_{it}(\omega) \leq a | A^{fk}_{it}(\omega) \overline{\mathcal{P}}^k_{it} = \max\{A^0_{it}\nu^f_i(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^1_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^K_{it}\}\} \\
&= \frac{1}{\Delta^{fk}_{it}} \Pr\{A^{fk}_{it}(\omega) \leq a, A^0_{it}\nu^f_i(\omega) \leq \overline{\mathcal{P}}^k_{it} A^{fk}_{it}(\omega), \overline{\mathcal{P}}^l_{it} A^{fl}_{it}(\omega) \leq \overline{\mathcal{P}}^k_{it} A^{fk}_{it}(\omega) \ \forall \ l \neq k\} \\
&= \frac{1}{\Delta^{fk}_{it}} \Pr\left\{ \frac{A^0_{it}\nu^f_i(\omega)}{\overline{\mathcal{P}}^k_{it}} \leq A^{fk}_{it}(\omega) \leq a, \frac{\overline{\mathcal{P}}^l_{it}}{\overline{\mathcal{P}}^k_{it}} A^{fl}_{it}(\omega) \leq A^{fk}_{it}(\omega) \leq a \ \forall \ l \neq k \right\}
\end{aligned}
$$

Define $A^{fk}_{it}(\omega) = \chi$ as a Fréchet distributed random variable. Then,

$$
\begin{aligned}
&\Pr\{A^{fk}_{it}(\omega) \le a | A^{fk}_{it}(\omega)\overline{\mathcal{P}}^{k}_{it} = \max\{A^{0}_{it}\nu^{f}_{i}(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^{1}_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^{K}_{it}\}\} \\
&= \frac{1}{\Delta^{fk}_{it}}\int_0^a \Pr\left\{\frac{A^{0}_{it}\nu^{f}_{i}(\omega)}{\overline{\mathcal{P}}^{k}_{it}} \le \chi, \frac{\overline{\mathcal{P}}^{l}_{it}}{\overline{\mathcal{P}}^{k}_{it}}A^{fl}_{it}(\omega) \le \chi \ \forall \ l \neq k\right\} f(\chi)d\chi \\
&= \frac{1}{\Delta^{fk}_{it}}\int_0^a \prod_{l\neq k}\Pr\left\{\frac{\overline{\mathcal{P}}^{l}_{it}}{\overline{\mathcal{P}}^{k}_{it}}A^{fl}_{it}(\omega) \le \chi\right\} \Pr\left\{\frac{A^{0}_{it}\nu^{f}_{i}(\omega)}{\overline{\mathcal{P}}^{k}_{it}} \le \chi\right\} f(\chi)d\chi
\end{aligned}
\tag{64}
$$

Given the p.d.f. for Fréchet distributed TFP and labor intensity in Equation (19), we can derive the following c.d.f's:

$$
\begin{aligned}
Pr\left(A^{fk}_{it}(\omega)\overline{\mathcal{P}}^{k}_{it} \le x\right) &= \exp\left\{-\gamma\left[x/A^{fk}_{it}\overline{\mathcal{P}}^{k}_{it}\right]^{-\theta}\right\} \\
Pr\left(A^{0}_{it}(\omega)\nu^{f}_{i}(\omega) \le \nu\right) &= \exp\left\{-\gamma\left[\nu/A^{0}_{it}\nu_{i}\right]^{-\theta}\right\}
\end{aligned}
$$

Using the above, Equation (64) can be written as

$$
\begin{aligned}
&\Pr\{A^{fk}_{it}(\omega) \le a | A^{fk}_{it}(\omega)\overline{\mathcal{P}}^{k}_{it} = \max\{A^{0}_{it}\nu^{f}_{i}(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^{1}_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^{K}_{it}\}\} \\
&= \int_0^a \exp\left\{-\gamma\chi^{-\theta}\frac{(A^{fk}_{it})^{\theta}}{\Delta^{fk}_{it}}\right\}\frac{\theta\gamma}{\Delta^{fk}_{it}}(\chi)^{-1-\theta}(A^{fk}_{it})^{\theta}d\chi \\
&= \exp\left\{-\left[\frac{a}{A^{fk}_{it}(\Delta^{fk}_{it})^{-1/\theta}\gamma^{1/\theta}}\right]^{-\theta}\right\}
\end{aligned}
$$

Thus, the c.d.f. is Fréchet distributed with shape parameter θ and scale parameter equivalent to $A^{fk}_{it}(\Delta^{fk}_{it})^{-1/\theta}\gamma^{1/\theta}$. Then,

$$
\begin{aligned}
\mathbb{E}[A^{fk}_{it}(\omega)|A^{fk}_{it}(\omega)\overline{\mathcal{P}}^{k}_{it} = \max\{A^{0}_{it}\nu^{f}_{i}(\omega), A^{f1}_{it}(\omega)\overline{\mathcal{P}}^{1}_{it}, \ \ldots, A^{fK}_{it}(\omega)\overline{\mathcal{P}}^{K}_{it}\} &= A^{fk}_{it}(\Delta^{fk}_{it})^{-1/\theta}\gamma^{1/\theta}\,\Gamma\left(1-\frac{1}{\theta}\right) \\
&= A^{fk}_{it} \times (\Delta^{fk}_{it})^{-1/\theta}
\end{aligned}
$$

where $\Gamma(\cdot)$ denotes the gamma function

C.7 *Consumers Utility Maximisation*

Derivation of representative consumers' consumption of crop k, imported from j to i, at time t; Equation (36) *in text.*

Consumer solves the following maximisation problem:

$$\max_{\{C^{it}, C^k_{it}, C^k_{jit}\}} \quad U_{it} = C^0_{it} + \beta_i \ln C_{it}$$

$$\text{subject to}$$

$$C_{it} = \left[\sum_{k \in \mathcal{K}} (\beta^k_i)^{1/\varphi} (C^k_{it})^{(\varphi-1)/\varphi} \right]^{\varphi/(\varphi-1)}$$

$$C^k_{it} = \left[\sum_{j \in \mathcal{I}} (\beta^k_{ji})^{1/\sigma} (C^k_{jit})^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)}$$

$$E_{it} \geq \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{I}} \left[\mathcal{P}^{rk}_{jit} C^k_{jit} \right] + C^0_{it}$$

$$\mathcal{P}^{rk}_{jit} = \Psi^k_{ji} \mathcal{P}^{rk}_{jt}$$

where E_{it} is household income for the representative consumer in state i at time t.

Setting up the Lagrangian and solving, we get

$$C^k_{jit} = (\beta_i)^\sigma \frac{(C_{it})^{(1-\varphi)\sigma/\varphi}}{\left(C^k_{it}\right)^{(\sigma-\varphi)/\varphi}} \frac{\left(\beta^k_i\right)^{\sigma/\varphi} \beta^k_j i}{\left(\Psi^k_{ji} \mathcal{P}^{rk}_{jt}\right)^\sigma} \tag{65}$$

Defining the CES price index associated with crop k in state n at time t as:

$$\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rk}}_{\boldsymbol{it}} \equiv \left[\sum_{n \in \mathcal{I}} \beta^k_{ni} \left(\Psi^k_{ni} \mathcal{P}^{rk}_{nt} \right)^{1-\sigma} \right]^{1/1-\sigma} \tag{66}$$

Using Equation (65) and (66) in Equation (17) gives us:

$$C^k_{it} = (\beta_i)^\varphi \beta^k_i \frac{(C_{it})^{1-\varphi}}{\left(\hat{\boldsymbol{\mathcal{P}}}^{\boldsymbol{rk}}_{\boldsymbol{it}}\right)^\varphi} \tag{67}$$

Substituting Equation (67) in Equation (16) implies:

$$C_{it} = \beta_i \left[\sum_{k \in \mathcal{K}} \beta_i^k \left(\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{it}}^{\boldsymbol{rk}} \right)^{1-\varphi} \right]^{1/(\varphi-1)} \tag{68}$$

Finally, use Equation (66), (67) and (68) in Equation (65) to get:

$$C_{jit}^k = \beta_i \, \frac{\beta_i^k (\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{it}}^{\boldsymbol{rk}})^{1-\varphi}}{\sum\limits_{l \in \mathcal{K}} \beta_i^l (\hat{\boldsymbol{\mathcal{P}}}_{\boldsymbol{it}}^{\boldsymbol{rl}})^{1-\varphi}} \, \frac{\beta_{ji}^k (\Psi_{ji}^k \mathcal{P}_{jt}^{rk})^{-\sigma}}{\sum\limits_{n \in \mathcal{I}} \beta_{ni}^k (\Psi_{ni}^k \mathcal{P}_{nt}^{rk})^{1-\sigma}} \quad \forall \;\; i, j \in \mathcal{I}, k \in \mathcal{K}$$