

AGRICULTURAL PRODUCTIVITY AND CLIMATE ADAPTATION: INSIGHTS FROM
PASTURE TECHNOLOGY AND THE HUMAN WELFARE IMPACTS OF RISING
TEMPERATURES

By

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ABSTRACT

Productive sustainability and climate adaptation strategies in agriculture and development are key goals of global public policy. Understanding how agricultural technology can boost productivity in sectors like cattle ranching, and how rising temperatures directly and indirectly affect human well-being is essential for shaping effective policies in both developed and developing countries. The first chapter examines the impact of introduced pastures on lowland ranching productivity in Latin America. The final two chapters evaluate how rising temperatures influence human capital accumulation and crop yields in Colombia and the US, respectively, and how students' and farmers' behaviors modify these effects.

The first chapter examines three critical questions about introduced pasture adoption in Colombian lowland ranching. First, it estimates the impact of using *Brachiaria* grass, a high-nutrient grass forage variety, on farm-level carrying capacity and livestock revenues. Second, it assesses whether combining complementary practices like fertilization and weed control boosts the impact of using these pastures. Third, it evaluates the potential reduction in land demands for cattle ranching attributable to introduced grasses. The study follows an instrumental variable framework, combining a cross-sectional representative sample of Colombian lowland ranchers, historical data on violence and weather, and spatial information on the location of R&D centers that disseminate knowledge about intensive grazing systems. The use of pastures significantly increases farms' carrying capacities, although at levels below those suggested by agronomic trials. In addition, our analysis suggests that gains from productivity are more significant when combined with complementary practices and that, in the absence of these introduced pastures, reaching similar output levels would have potentially required twice as much land as currently used.

The second chapter studies the impact of exposure to increasing temperatures on human capital accumulation, with particular attention to the potentially differentiated effects between rural and urban settings. Combining rich microdata from a high-stakes, national-level high-school exit exam in Colombia (Saber 11) between 2014 and 2019 with weather-station-level information, we use a fixed-effect estimation to measure the effect of increasing average temperatures on student

success. We find that a 1°C significantly decreases math and overall test scores in urban settings, while there is an apparent positive effect among rural students. Leveraging time-use data, we find evidence of individuals in rural areas responding to increases in temperature by reallocating time towards off-farm activities, which are human capital intensive. Finally, we use information from the announcement of a national scholarship program that introduced exogenous variation in the stakes of Saber 11, to find that the impact of the scholarship policy decreases as temperatures increase. Our analysis underscores how the effectiveness of incentive-based policies may be hindered in the context of a warming world.

The third chapter explores the impacts of heat on crop yields and crop production decisions among sorghum farmers in Kansas, U.S. This analysis addresses a two-part question often overlooked in climate econometrics. Specifically, we examine whether (a) the unbalanced nature of yield panel data likely reflects strategic behavior by farmers when deciding whether to grow sorghum, and (b) whether this leads to estimation bias from sample selection. Our results suggest that (1) a farm's decision to produce sorghum in a given year is likely a climate-sensitive response, indicating an underlying climate adaptation strategy, and (2) accounting for this response as a driver of sample selection results in lower estimates of heat impacts on yields compared to the existing literature. Our results highlight the need to further consider how farm data discontinuity in long-term panels can affect the consistency of traditional fixed-effect estimates.

In conclusion, livestock farming still needs to boost productivity, and the first chapter offers insights into how agricultural technologies, like introduced pastures, can help achieve this. Meanwhile, the second and third chapters emphasize the importance of accurately assessing the impacts of rising temperatures on human welfare—specifically in terms of human capital and food production—and contribute to the broader policy discussion on global climate adaptation strategies.

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To my wife and my sister.
I love you.

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CHAPTER 1

IMPACT OF INTRODUCED PASTURES IN COLOMBIAN LOWLAND RANCHING

1.1 Introduction

Cattle production in Latin America is at a crossroads. Accounting for the largest share of agricultural land, the sector is highly vulnerable to climate change, faces a need for scaling up efforts to increase its productivity, and is in dire need of mitigating its greenhouse gas (GHG) emissions (Arango et al., 2020; Bravo-Parra, 2021; Tapasco, LeCoq, Ruden, Rivas, & Ortiz, 2019). In the case of lowland ranching, which is largely allocated in marginal lands, the challenge of increasing intensification has met the difficulties of providing high-nutrient feed to animals under poor soil conditions (Burkart, 1975; Lane, 1981; Toledo & Nores, 1986). In this context, the use of introduced pastures¹ has been promoted as a first-choice solution, as these have been able to deliver sustainable production (Bogaerts et al., 2017), with agronomic trials suggesting they can assist in increasing productivity (Holmann, Argel, & Pérez, 2008; Rivas & Holmann, 2004), facilitating intensification (González-Quintero et al., 2021; Mazzetto, Feigl, Schils, Cerri, & Cerri, 2015), reducing animal-based GHG emissions (Congio et al., 2021; Gerssen-Gondelach et al., 2017), and serving as carbon sinks (Fisher et al., 1994; Hyman et al., 2022).

Despite well-documented evidence on introduced pasture adoption levels (ISPC, 2018), the factors behind this adoption and its field-level impacts remain unexplored (Baltenweck et al., 2020). Efforts from both National and International Agricultural Research Systems have focused extensively on the development of production technologies (Vaccaro, 1997), while major limitations remain in understanding the institutional and individual factors that shape the landscape of cattle ranching and how farmers make decisions about technological adoption at the farm level (Enciso, Triana, Diaz, & Burkart, 2019). On the other hand, most studies focused on the effect of using introduced pastures are either agronomic experiments related to gains in cattle live weight (Holmann et al., 2008; Pérez-López & Afanador-Tellez, 2017; Rivas & Holmann, 2004), ex-ante evaluations

¹These grass forages varieties (mostly from the *Brachiaria* or *Megathyrus* genera) are not native to Latin America, and are either selected or improved germplasm lines from materials first brought into the continent from Africa (ISPC, 2018)

(Enciso, Charry, Rincón, & Burkart, 2021), and aggregate economic valuations (Fuglie, Peters, & Burkart, 2021), but there are no studies assessing this impact with representative farm-level data. As the literature finds that agronomic analysis can deliver estimates of the effect of using improved practices that may not be achievable in real-world farm conditions (Laajaj, Macours, Masso, Thuita, & Vanlauwe, 2020), providing impact estimates based on farm-level data is of the utmost relevance for effective policymaking.

What is the impact of introduced pasture adoption on productivity? How does it affect revenues? What does this impact translate to for a traditionally land-intensive sector? Taking Colombia as a study case, we build a novel dataset combining information from a cross-sectional farm-level survey, weather data, and official information on violent events and illegal shocks to transport and trade experienced at the Municipality level. We use linear regression and optimal instrumental variables methods to provide meaningful estimates of the effect of introduced pastures on carrying capacity (i.e., kilograms of livestock per ha) and livestock-related revenues.

Among our sampled ranchers, the adoption rate of introduced pastures is estimated to be 66% of pasture acreage. Our findings indicate that the distance to centers of technological dissemination is significantly and negatively correlated with the adoption of introduced pasture varieties, whereas education and other technological endowments are positively correlated. Also, introduced pasture adoption negatively correlates with the number of violent guerrilla incursions that occurred at the Municipality level. The latter is also the case for the number of illegal checkpoints enforced by guerillas and other criminal groups. Our estimates suggest that introduced pastures matter for productivity, with an average increase of 1.34% in carrying capacity for each additional 1% increase in the share of introduced grass varieties. However, the effect is seemingly heterogeneous, conditional on different pasture management practices, with potentially larger gains in carrying capacity for those implementing practices such as weed control or fertilization. In addition, we find a strong effect on sales: for each additional 1% of pasture adoption, there is an expected increase of 2.05% in livestock-related revenues, on average.

Early introduction, dissemination, and adoption of African-native pastures in the Americas

started in the nineteenth century. Yet, in the absence of renovation schemes or proper management practices, these pastures were rapidly naturalized, and their nutritional superiority decayed (Campuzano, Triana-Angel, & Burkart, 2022; Van Ausdal, 2009), which further pushed livestock as a large mechanism of deforestation and rapid degradation of soils (Dale, 1981; Faminow, 1997). The first selected lines of introduced pastures (e.g., *Brachiaria decumbens*) were brought into South America in the early 1950s, although modern selected varieties with better adaptation were released in the 1990s (ISPC, 2018), which were the result of large scales of cross-validation through the region (Rao, Zeigler, Vera, & Sarkarung, 1993; Toledo & Nores, 1986). In the case of Colombia, pasture seed traders were established in the early 1970s (Hurtado, Diaz, Enciso, Gallo, & Burkart, 2020), along with research on the selection and dissemination of introduced materials following the establishment of the tropical forages germplasm bank at the International Center for Tropical Agriculture (CIAT), its subsequent *Brachiaria* improvement program in the late 1980s (Fuglie et al., 2021), and transversal efforts from the Colombian NARS through the Colombian Agricultural Institute and the Colombian Corporation of Agricultural Research AGROSAVIA (formerly Corpoica). The drivers of adoption remain unexplored, though, with breeders acknowledging a need to better understand its dynamics for successfully improving strategies to link research with farmers (Enciso et al., 2019; Peters, Lascano, Roothaert, & de Haan, 2003).

Several studies have explored the effects of the adoption of introduced pasture on livestock productivity and farmers' incomes. Based on agronomic trials controlling cattle feed, Holmann et al. (2008) find that a switch from native savanna to *Brachiaria* grasses can increase animal live weight gains (kg/ha/year) by between 40 and 70 percent. In addition, given that introduced pastures are high-nutrient and are tolerant to several biotic and abiotic stressors in comparison to native savannas, studies reveal that they can significantly increase productive efficiency of ranching in the Americas (Herrero et al., 2013; Jank, Barrios, Do Valle, Simeão, & Alves, 2014; Mazzetto et al., 2015; Pérez-López & Afanador-Tellez, 2017). Based on these findings, ex-ante analyses project that a transition from native grasslands to introduced pastures can boost farmers' revenues (Enciso et al., 2021), especially when complementary practices like fertilization are enforced. Moreover,

when used in combination with trees for forage and shadow provision, they can bring significant co-benefits in terms of GHG mitigation in addition to economic gains (Sandoval, Florez, Enciso Valencia, Sotelo Cabrera, & Burkart, 2023). However, as mentioned earlier, these studies rely on agronomic evaluations and non-probabilistic samples, which may lead to large estimated impacts from pasture adoption that are unlikely to replicate in real-world field settings.

Our contribution is threefold. First, we contribute to the literature on pasture adoption, showing that closeness to technology dissemination centers matters. Since these centers are not sellers of seeds, this reveals that there is an important transaction cost to be considered for accessing information about these pasture varieties. Moreover, we study how the history of violent groups' attacks on population centers and shocks to trade and transportation affect observed technology adoption rates, highlighting how shocks to infrastructure and value chains can affect technology dissemination. Second, we benchmark an econometric approach based on representative data to provide consistent estimates of the effect of introduced pastures on carrying capacity vis à vis common methods in the field. In line with the literature, our impact estimates fall short from those suggested by agronomic trials, which ultimately would suggest the presence an upward bias in expected gains measures in the currently available literature (e.g., ex-ante studies). Third, we extend the analysis of impact directly into welfare metrics. Converse to previous studies that relied on agronomic trials' impact estimates to derive welfare implications, our framework allows us to directly test for any relationships between adoption and livestock-related revenues.

The remainder of the manuscript is organized as follows: Section 1.2 introduces our theoretical framework and empirical strategy, and discusses what covariates are included in the analysis. Section 1.3 presents the data and descriptive statistics. Results are summarized in Section 1.4, while Section 1.5 concludes.

1.2 Methods

1.2.1 Theoretical background and technology of interest

We consider an agricultural household model where a farmer aims to maximize their profits, conditional on resource endowments, time allocation, and production technology constraints. Given

the strong historical frictions in Colombian rural land and labor markets (UPRA, 2016), this allows for an intertwining between consumption and production decisions, including technological adoption (Bardhan & Udry, 1999). We are interested in the farmer's decision about what share of their pastures will be allocated to introduced varieties.

Lowland ranching in Latin America is based on foraging systems, which follow one of (or a combination of) two production schemes, namely extensive grazing on native savannas (i.e., traditional system) or intensive grazing based on sown, introduced pastures (i.e., improved system). Traditional production largely relies on savanna burning practices, which increase the availability of digestible plants for cattle, but at the cost of a high incidence of forest clearing (Fisher, Lascano, Vera, & Rippstein, 1992). However, the low nutrient levels of native savannas lead to low carrying capacities, with averages ranging between 0.2 and 0.5 animal units per hectare (90 and 225 kg of livestock/ha) in Colombia. Meanwhile, introduced pastures work as a perennial crop of sown grasses that provide high-nutrient content to grazing animals, allowing average carrying capacities ranging between 1.5 and 4 animal units per hectare (675 and 1800 kg of livestock/ha) (Hyman et al., 2022), although evaluations of pasture systems based on commercially available varieties suggest that average long-term carrying capacities are in the lower end of this range (Vera & Hoyos Garcés, 2019). Therefore, these figures point to an average increase in carrying capacity between 200% and 650% upon transitioning from a traditional system to an improved system based on introduced pastures.²

To summarize, switching from native savannas to an introduced pasture system is expected to increase carrying capacity by providing more biomass with higher nutrient levels in the same amount of land. Under profit maximization, farmers' use of introduced pastures leads to either an increase in the stock of animals or a reduction in the amount of land dedicated to pastures. Nevertheless, ranchers may not necessarily attach themselves to one system exclusively. For instance, Ospina, Rusch, Pezo, Casanoves, and Sinclair (2012) find that in seasonally dry climates,

²Calculated as a simple percent increase. For instance, assuming 0.5 and 1.5 animal units per ha for the traditional and improved systems, respectively, the percentage increase is $\Delta \times 100\% = ((1.5 - 0.5) / 0.5) \times 100\% = 200\%$. Under an assumption of linearity in elasticity, this suggests that each additional 1% in the share of introduced pastures should lead to at least a 2% increase in productivity.

semi-natural grasslands can be competitive to sown, introduced pastures, especially when tree covers and fertilization schemes are absent. Ultimately, the impact on productivity from the use of introduced pastures can be captured through the observed weights of livestock per hectare (i.e., the reported carrying capacity of the farm). Our setting acknowledges that the level of introduced pasture adoption is likely endogenous with productivity.

1.2.2 Identification strategy

We are interested in determining the elasticity of cattle productivity (and revenues) with respect to the adoption of introduced pastures. To model this, let S_{ijk} be the share of introduced pastures of farmer i in Department j and Municipality k , $\mathbf{m}_{ijk}$ and $\mathbf{G}_k$ vectors of farm- and Municipality-level covariates, $\mathbf{\Gamma}$ and $\boldsymbol{\eta}$ vectors of unknown parameters, and γ_j a Department-level unobserved effect. With our outcome of interest y_{ijk} set as the carrying capacity of the farm in the last year, we are interested in fitting a model that follows

$$\log(y_{ijk}) = \tau S_{ijk} + \mathbf{m}_{ijk}\mathbf{\Gamma} + \mathbf{G}_k\boldsymbol{\eta} + \gamma_j + e_{ijk}, \quad (1.1)$$

where e_{ijk} is an error term, and τ is the effect of interest.

In general, the decision to adopt a new technology (and the extent of adoption) is likely correlated with unobservables also affecting observed yields. For instance, farmers with greater (unobserved) abilities may be more likely to achieve larger-than-average yields out of varietal adoption, which in turn will make them more likely to adopt (Larochele, Alwang, Norton, Katungi, & Labarta, 2015). In the case of lowland regions, especially in a setting like rural Colombia where property rights are poorly defined (UPRA, 2016), ranching also serves a purpose of signaling land tenure and control (Triana Ángel, Burkart, & Pazos Cárdenas, 2024). Hence, unobserved factors like a latent need to signal land ownership can hinder the adoption of introduced pastures as these tend to make cattle concentrate (i.e., potentially reducing animal roaming). Therefore, such an unobserved factor could lead to a downward bias in linear regression,³ and ordinary least squares (OLS) estimates of coefficients in (1) are likely inconsistent (Angrist & Pischke, 2008). To overcome the latter, we follow an instrumental variables approach, using plausibly exogenous sources of variation that

³A situation that could lead to a similar outcome is one where the treatment effects are heterogeneous, and one's identification strategy retrieves a local average treatment effect (LATE) larger than the average treatment effect (ATE).

can directly affect adoption, but that only affect yields through their effect on adoption (exclusion restriction). We will expand on this in the following subsection.

While selection-on-observables approaches, such as those leveraging Oster (2019) bounds, are valuable for addressing endogeneity concerns in some contexts, they present notable challenges in the case of livestock adoption. Unlike settings where adoption decisions can be largely explained by observable factors (e.g., soil characteristics in direct planting decisions, as in Assunção, Bragança, and Hemsley (2019)), pasture adoption is heavily influenced by unobserved farmer characteristics, such as managerial ability, risk aversion, and long-term investment capacity. These factors introduce biases that may not be fully accounted for through an extensive set of observable controls.

Additionally, in our context, financial constraints and land tenure security—two key determinants of technology adoption—are not fully captured by available data, making it challenging to ensure that all relevant confounders are addressed. Given these limitations, an instrumental variable (IV) approach provides a more robust strategy to mitigate endogeneity concerns by leveraging exogenous variation in information access and conflict-related disruptions. Nonetheless, we acknowledge that no identification strategy is without limitations, and we recognize the importance of sensitivity analyses in strengthening causal claims. Future research could explore complementary approaches, such as structural modeling or quasi-experimental designs with longitudinal farm and policy data, to further validate these findings.

Unlike other studies that treat adoption as a binary treatment, we focus on the adoption of introduced pastures a fractional-response variable. The latter follows that most sampled farmers are adopters, but their extent of adoption (i.e., the share of pastures on introduced varieties) reveals an important degree of variation. The latter also has important implications in our empirical approach to address endogeneity concerns. As proven by Xu (2021), there is a drawback to using approaches like two-stage least squares (2SLS) when addressing limited endogenous explanatory variables: waving the non-linear nature of the true conditional mean in the first stage will render a problem of artificially weak instrumentation. The latter means that, in a case like ours, measures like the calculated effective F statistic (Montiel & Pflueger, 2013) are potentially misleading after

2SLS. Therefore, we further follow Xu (2021) and Wooldridge (2010) and use a two-step optimal instrument approach, estimating a first-stage model with fractional regression by quasi-maximum likelihood (QMLE) (Papke & Wooldridge, 1996), and then using the non-linear prediction as an instrument for both IV and control function estimation. Measuring the effect of introduced pastures on revenues is straightforward, as we can estimate a model like that of equation (1.1) with log-revenues as a response variable, also by IV methods.

In addition, we account for possible differences in the effect due to pasture management by fitting an extended specification that follows

$$\log(y_{ijk}) = \tau S_{ijk} + \rho_1(S_{ijk} \times WC_{ijk}) + \rho_2(S_{ijk} \times F_{ijk}) + \rho_3(S_{ijk} \times WCF_{ijk}) + \mathbf{m}_{ijk}\dot{\mathbf{\Gamma}} + \mathbf{G}_k\boldsymbol{\eta} + \gamma_j + e_{ijk}, \quad (1.2)$$

where WC_i , F_i , and WCF_i are mutually exclusive binary variables indicating, respectively, whether the farmer manages their pastures only with weed control, only with fertilization, or both. Each separate binary variable is added into the vector of remaining covariates $\mathbf{m}_{ijk}$. This flexible structure allows to measure how the impact of introduced pastures may vary across possible groups of complementary practices adopted in the farm, but it also implies a potential issue of bias in estimating ρ_1 , ρ_2 , and ρ_3 by OLS. Therefore, for the case of estimating equation (1.2), we follow a control function approach as it is a straightforward strategy to account for the potential endogeneity of S and its interactions with a single added covariate (Wooldridge, 2015). In addition, we provide bootstrap standard errors to account for regression error (Wooldridge, 2010, 2015).

A caveat from this heterogeneity analysis is worth noting. The use of pasture-complementary practices like fertilization, is considered a potentially endogenous decision that can impact productivity (Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Martinez, Labarta, & Gonzalez, 2023; Teklewold, Kassie, & Shiferaw, 2013). However, any adoption or feasible impact is conditional to a prior decision on the adoption of introduced pastures. The latter follows that the use of fertilization on native savanna leads to relatively insignificant increases of this grass's availability (Fisher et al., 1992), a fact that is also reflected in our sample, where the use of fertilization and weed control only occurs among those using introduced pastures. Nevertheless, we acknowledge

this potential limitation and interpret any heterogeneity as a difference in the average impact of the use of introduced pastures, but not as an impact from the use of complementary practices.

1.2.3 Sources of exogenous variation and threats to validity

1.2.3.1 Proximity to centers of R&D and use of other technologies

We consider the distance from the farm to agricultural R&D centers (i.e., CIAT or AGROSAVIA) with extensive focus on ranching systems as an exogenous variation affecting the access to information about technological innovations like introduced pastures. On the one hand, CIAT is a not-for-profit center that develops and deploys agricultural technologies,⁴ while AGROSAVIA is a non-profit, decentralized public entity, focused on scientific research, technology adaptation, transfer, and advice.⁵ These institutions provide technological solutions and recommendations with unrestricted access for the population, through open access to gene banks, data-and-research repositories, and demonstration plots.⁶ Nevertheless, Colombia has historically experienced bottlenecks in its public extension system, including a lack of funding and disconnectedness between extensionists and scientists (Enciso, Triana, Díaz, & Burkart, 2022; Rodríguez, Ramírez-Gómez, Aguilar-Gallegos, & Aguilar-Ávila, 2016). This institutional gap suggests that proximity to R&D centers is most relevant as a proxy for direct access to the pasture-related knowledge and technologies, rather than a broad-based exposure to all livestock management recommendations.⁷

A potential threat to the validity of this exogenous variation arises from whether farmers are strategically locating themselves close to these R&D centers. Yet, land is an essentially fixed asset, which, combined with the high frictions of the Colombian agricultural land market (UPRA,

⁴See <https://www.cgiar.org/research/center/alliance-bioversity-ciat/>

⁵See <https://www.agrosavia.co/en/what-we-do>

⁶Demonstration plots have been a key component of the dissemination strategy, with selected sites established in collaboration with local research stations, producer associations, and select lead farmers to showcase the benefits of improved pastures. However, the geographic placement of these plots has been largely opportunistic rather than systematically distributed, reducing concerns that they correlate with broader agricultural infrastructure or productivity-enhancing factors.

⁷We also acknowledge that complementary practices such as animal health interventions could theoretically be influenced by proximity to R&D centers. However, practices such as cattle vaccination are unlikely to be a major confounding factor. While vaccinations for diseases like Foot-and-Mouth Disease, Brucellosis, and Rabies are crucial for cattle productivity, these vaccines are already widely adopted in Colombia, with compliance rates exceeding 98% according to data from the National Federation of Cattle Ranchers (FEDEGAN). Given this near-universal adoption, it is unlikely that proximity to an R&D center significantly alters vaccination behavior in a way that would bias our estimates.

2016), makes it unlikely that farmers can credibly choose their location strategically close to these technology dissemination hotspots. Further, it could be argued that these centers provide access to other means of technology, like improved cattle breeds, which in fact increase the demand for introduced pastures. Nonetheless, although these institutions do some research on improved cattle breeds, these efforts are only applicable to the Andean region, which is outside our area of study. Therefore, we do not foresee any reverse causality. Finally, it could also be argued that this measure of distance could be partially capturing a proximity to other kinds of infrastructure that could affect productivity (e.g., roads, ports, input markets). However, our data analysis suggests that (a) farms' distance to R&D centers is, for instance, uncorrelated with the distance to the closest agricultural input market,⁸ and (b) when considering both these variables as factors affecting adoption, only the distance to R&D centers remains statistically significant, and with a virtually unchanged partial effect.

In summary, having the presence of CIAT and AGROSAVIA centers as a shock of knowledge dissemination outside of the farmers' decision-making, is arguably a weak assumption. Therefore, with these centers continuously providing recommendations for intensification based on pastures, we assume that the proximity to these centers affects observed cattle intensity only through its effect on pasture adoption. Finally, as technologies and practices usually follow joint patterns of adoption (Kassie et al., 2013; Martinez, Labarta, Gonzalez, & Lopera, 2021; Teklewold et al., 2013), we use an index of ownership of farming durable goods (e.g., water pumps, sprayers, harrows, or tractors) as a factor influencing adoption only.

1.2.3.2 Historical (indirect) shocks of violence

In addition, we use historical Municipality-level data on guerilla violent events and the presence of illegal checkpoints by criminal groups as shock variables affecting access to introduced pastures and their use but not cattle intensity. We consider these variables as exogenous shocks to the historical seed availability and expansion in the adoption of introduced pastures. In our application, we bring in official information from the Colombian National Center of Historical Memory (Centro

⁸In this case, a farm-level linear regression of the distance to the closest R&D on the distance to the closest ag-input market and Department-level dummies, yields a statistically insignificant partial correlation of 0.0083 (Table 1A.1).

Nacional de Memoria Histórica, 2015) on the total number of attacks on the population that occurred in the Municipalities during the 1988-2012 period,⁹, and from the CEDE Municipality Panel Data (Acevedo & Bornacelly, 2014) on the number of illegal checkpoints set up by criminal groups during the 2002-2016 period.¹⁰

Guerrilla attacks are concentrated in the *cabeceras* (downtowns) of each Municipality, which are also the center of input trade in each location. However, these attacks are not targeted directly on civilian (individual or group) property. Instead, they account for impacts on civilian infrastructure resulting from attacks where the main targets were military (or police). Hence, it could be argued that while these attacks may have affected a wider set of socioeconomic outcomes in the short-term, their long-term effect may be of prominence in the stability of markets—thus in the distribution of technologies. Conversely, other forms of violence (e.g., massacres) that are directly targeted to civilians are more likely to affect property rights and human capital in the long run. This is consistent with some correlational evidence from our data, where there is no significant correlation between attacks on population and massacres.¹¹ Likewise, illegal checkpoints imply a direct shock to transportation and inter-municipal trade, which follow the same rationale as a historical plausibly exogenous shock.

The period of violence considered for these variables largely coincide with the period where most introduced grasses have been released and commercialized, namely 1987-2013 (Enciso et al., 2019). Combined, we expect increases in these variables to reflect both weaker value chains and a lower willingness to invest in technologies, which ultimately lead to lower rates of introduced

⁹These are defined as “[A]ny transitory military operation that consists of a temporary penetration of the territory and that seeks to devastate adversaries and their material and symbolic environment, enhancing the devastating effect of military action with the use of unconventional weapons and the attack against civilian targets. The temporary nature of the penetration of the territory does not mean that it is ephemeral, but implies the deployment of a large armed contingent with the capacity to sustain a medium-duration action, which is why it should not be confused with disturbance (or baiting) or an attack that exclusively impacts a military target” (Centro Nacional de Memoria Histórica, 2015; Grupo de Memoria Histórica, 2013). These kinds of attacks ceased in 2012 following the beginning of peace negotiations between the Colombian Government and FARC.

¹⁰This measure combines reported illegal checkpoints set by guerrillas, gangs, and paramilitary groups to commit land piracy and other criminal acts.

¹¹With a Municipality-level regression of the number of massacres on the number of attacks on populations and Department-level controls and robust standard errors, we retrieve a partial correlation of 0.326 and a 95% CI [-0.581;1.235]. Using weights to account for the number of observations per Municipality yields a partial correlation of 0.174 and a 95% CI [-0.771;1.119].

pasture adoption.

1.2.4 Additional covariates

As control variables (or covariates) in our model, we include several farm and farmer-level characteristics shown by previous studies to be correlated with technology adoption decisions, including farm size, access to credit, membership in a farmers' association, education of the household head, house- and farm-assets, and whether the household head is female. Educational attainment by the head of the household is connected to an increased ability to access (and process) knowledge and new information, hence increasing technological adoption. However, at increasing levels, education can be a path to off-farm income that can reduce the odds of dependence on farming (Martey, Al-Hassan, & Kuwornu, 2012). Meanwhile, evidence on gender gaps suggests that women face tighter restrictions to access credit and tend to possess fewer financial endowments (Ouma, Jagwe, Obare, & Abele, 2010), hence adding a control for whether the head of the household is female can reveal if there are important differences in pasture adoption or cattle yields to account for. Finally, we use the average maximum daily temperature and average daily precipitation in the year as variables potentially affecting productivity. In the context of the low-altitude, tropical production system of our study area, increases in temperature can negatively affect productivity due to the heat stress on cattle (Bravo-Parra, 2021), while additional rain can favor animal health and weight gain (Ospina et al., 2012).

1.3 Data

We use data collected by CIAT between October 2016 and early February 2017. The data is representative of beef and dual-purpose production for the Caribbean and Eastern Plains – Amazon Piedmont regions. It contains information on 1,021 farmers distributed across the departments of Arauca, Casanare, Meta, Vichada (Eastern Plains), Caquetá, Guaviare, Putumayo (Amazon Piedmont), Bolívar, Cesar, Córdoba, La Guajira, Magdalena, and Sucre (Caribbean). The sampling followed a two-stage clustered procedure adjusted by potential intraclass correlation, selecting a group of primary sampling units (PSU) and then defining the number of households to be randomly

sampled within each PSU¹². Figure 1.1 presents the spatial distribution of the sample and the location of CIAT and AGROSAVIA Research Centers with programs of influence to our regions of interest. In addition, we retrieved weather information from open-access databases by the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM) for the 2016 agricultural season, and violence data from Centro Nacional de Memoria Histórica (2015).

1.3.1 Descriptive statistics

We summarize the variables used in this study in Table 1.1. An average farm reports around 536 kilograms of livestock per hectare. Hence, relative to an animal unit (roughly 450 kg), an average rancher has slightly above an animal unit per hectare, although there is considerable dispersion. Meanwhile, the average livestock-related revenues over the previous year were COP 684,415 (approximately USD 225 at 2016 prices), also with a considerable degree of variance. The average share of pastures with introduced varieties among sampled farmers is 78%, while the sample overall adoption (i.e., total acreage with introduced pastures over total acreage of pastures) for the lowlands is 66%. Reflecting the spatial distribution displayed in figure 1.1, the average farm is located within 226.2 km from a technological dissemination center. This distance is calculated as the road distance from the farm to the closest R&D center.¹³

The largest share of farmers only does weed control in their grasslands (46%), while 39% do no pasture management. On the other hand, 7% of farmers only do fertilization as a practice of pasture management, while the remaining 8% do both fertilization and weed control. Participation in farmers' associations is low, with a reported level of 22 percent. Low access to specialized knowledge and network support can constrain the odds of improving cattle production systems. Access to credit is only reported in 22% of the farms, further revealing that households may not find means to overcome liquidity constraints in the short-run. This is consistent with the results

¹²We use the unweighted sample for the regression analysis due to unavailability of weight data for the Caribbean part of the dataset, but account for cluster correlation among observations.

¹³For each farm, we use DIVA-GIS open-access data on Colombia's road network to calculate the path distance from each farm to CIAT and each of the AGROSAVIA centers that have a research program in livestock, and then keep the minimum distance. This approach will leave us with 994 observations for our main specification, due to the exclusion of farms that are significantly away from any primary and secondary road, especially those from Puerto Leguizamo, Putumayo (southernmost cluster of observations in Figure 1) as this Municipality is only accessible via boat or airplane. Thus, later we test the robustness of our analysis using geodesic distances for all 1,021 datapoints.

in Mejía, Diaz, Enciso, and Burkart (2021), showing how most agricultural credit institutions are clustered in the Andean region. The average number of household durable goods is 5.94 (out of 11), the figure is 3.81 (out of 9) for farming durable goods. Hence, the average farm is relatively more endowed with household wealth than technological wealth.

Farm sizes vary widely, ranging from 1.5 to 7,000 hectares (roughly 3.7 to 17,300 acres), with an average size of 200 hectares (495 acres). Nevertheless, it is worth noting that introduced pasture adoption and the use of complementary practices are not exclusive to certain scales of production. Table 1.2 disaggregates some of these measures by quintiles of farm size and reveals a certain degree of homogeneity in terms of pasture adoption and use of complementary practices. Conversely, there is an apparent correlation between productivity (and revenues, both at per-hectare levels) and farm size, which emphasizes the need to control for this attribute in our impact analysis.

Circling back to Table 1.1, in terms of education, we found that a majority of heads of household have completed primary education (71%), while only 15% report having completed secondary education. Tertiary education was found in only 6% of the household heads, whereas the share of those without any level of education is 8%. We use the latter as the base category to test whether increasing achieved education systematically increases adoption. The participation of females as household heads is reported in only 7% of the cases, initially suggesting that the sector will vastly reflect male decision-making. Across the 45 municipalities, on average, at least one attack on the population led by guerrillas, paramilitary groups, or other violent actors occurred in the 1988-2012 period. On the other hand, the average municipality experienced 1.64 illegal checkpoints between 2002 and 2016. Average precipitation across municipalities was 5.66 mm/day, with a low of 1.43 mm/day and a maximum of 16 mm/day. Finally, the 2016 average daily maximum temperature was 31.78°C (89.2°F), so the average farm and cattle are exposed to rather high levels of heat stress, which can negatively affect cattle productivity (Bravo-Parra, 2021).

1.4 Results

1.4.1 First-stage results

We summarize the average partial effects' estimates for our first-stage analysis in Table 1.3. First, without additional controls, we find a statistically significant correlation between the share of introduced pastures and (a) the distance to technology dissemination centers, (b) the number of attacks on the population that occurred in the Municipality between 1988-2012, and (c) the number of illegal checkpoints that were present at the Municipality (columns one and three). These are robust to the addition of further factors (columns two and four). On average, and following an OLS (QMLE) approach, a ten-percent increase in the distance between the farm and the closest research and dissemination center is connected to a reduction of approximately 1.15 (1.23) percentage points in the share of adoption of introduced pastures, which highlights the relevance of CIAT and AGROSAVIA research centers in the cattle ranching system of Colombia. Also, on average, each additional attack on the population registered in the 1988-2012 period is connected to a reduction of pasture adoption of 4.28 (3.08) percentage points, while an additional illegal checkpoint relates to an average decrease in adoption of 2.86 (2.57) percentage points. These findings go in line with the literature on the relationship between land use and conflict: disruptions in access to intensification technologies (i.e., introduced pastures) will lead ranchers to rely to a greater extent on extensive traditional grazing, with the latter ultimately leading to increased rates of deforestation (Bautista-Cespedes, Willemen, Castro-Nunez, & Groen, 2021).

We find no statistical differences attributable to educational status of the household head, access to credit, a farmers' association membership, or having a female-led household. Our results suggest that household wealth, as captured in the household assets index, seems unrelated to adoption. Conversely, technological endowment proxies reveal a relevant relationship with adoption intensity. The average effect from an additional durable farming asset is connected to an additional 2.1 (1.96) percentage points in the share of introduced pastures from each additional durable farming asset, which is significant at the 1% level. Finally, we note that the (log) farm size appears statistically significantly correlated with the adoption of pastures, with an increase of 10%

of the farm size related to a decrease of 0.17 (0.13) percentage points of adoption.

1.4.2 Effects of introduced pasture adoption on productivity

We observe a strong unconditional correlation between the adoption of introduced pastures and the farm's carrying capacity (Figure 1.2), which we further disaggregate in our main impact analysis results in Table 1.4. Using only Department-level controls (column 1), this simple correlation suggests that for each additional one percentage point increase in the adoption of introduced pastures, the number of animals that can be sustained per hectare increases by 0.377%. Equivalently, due to the linearity of the estimate, this translates into an increase of 37.7% in carrying capacity by transitioning from native savannas to introduced pastures. Adding further controls in the OLS specification (Column 2) reveals this correlation to be robust to the inclusion of further covariates. After including farm-, farmer- and Municipality-level controls, our estimation suggests that the transition from native savannas into introduced pastures implies an average increase of 33.68% in livestock weight per hectare.

As mentioned in our methods section, we acknowledge the likely endogeneity of the adoption of pastures and our measure of yield, so we extend our analysis with instrumental variable methods. In columns three, four, and five, we report the 2SLS, two-step optimal IV, and control function (CF) estimates for equation (1.1), respectively. All three estimates for the effect of introduced pastures on carrying capacity are significantly larger than that of OLS—in line with our expectation of a presence of downward bias—and statistically equivalent to each other. In both 2SLS and optimal IV, the robust regression endogeneity tests (Wooldridge, 1995) suggest that there was an underlying endogeneity problem in the case of OLS, which is further confirmed by the statistical significance of the control function coefficient estimate. Resembling the findings of Xu (2021), we see that despite having similar estimates and precision levels, the 2SLS approach would suggest a potential problem of weak instruments, unlike the two-step optimal IV approach, which renders an effective F statistic well above the thumb-rule of 23 from Montiel and Pflueger (2013).

We will focus on estimates using the optimal IV and control function approaches (the latter in parentheses). Our estimates suggest that carrying capacity strongly responds to the adoption of

introduced pastures. On average, for each additional 1% point of adoption, cattle yields increase by 1.34% (1.44%). Per the linearity of the model, this implies that transitioning from native savannas to introduced pastures can more than double productivity, i.e., it would increase carrying capacity by 134 (144) percent on average. While the sizeable difference between OLS and optimal IV (or CF) estimates may be concerning at face value, note that the latter estimates are still below the expected increase in carrying capacity suggested by the agronomic literature, which is in the order of 200 percent and above (Fisher et al., 1992; Vera & Hoyos Garcés, 2019). Therefore, these initial results are of high relevance on two contrasting points. First, they highlight that a correlational analysis of the effect of introduced pastures on carrying capacities can significantly underestimate their impact and thus their potential for intensification of cattle systems in lowlands.¹⁴ Second, our analysis also indicates that the on-farm impact of introduced pastures is still below to that suggested by agronomic trials. The latter goes in line with the literature which suggests that while these trials are rigorous, their external validity remains a concern (Laajaj et al., 2020). Our findings further emphasize the need for farm-level analysis impacts of agricultural technologies to inform policy decisions.

Finally, we detect a significant difference in productivity between male and female-led reported households. On average, when households report a female head, this is linked to a decrease in carrying capacity by 20.89% (23.23%), likely reflecting the limitations in access to production resources and implications of structural gender discrimination (Gumucio, Mora-Benard, Twyman, & Hernández-Ceballos, 2016). In addition, we find that being member of a farmers' association is related to an increase of 14.41 (15.16) percent in carrying capacities, pointing to the relevance of ranchers' networking in improving the productivity of cattle systems in lowlands. The magnitude and significant effect reveal that more institutional work should be put into the national research system to tackle these disparities. From the Municipality-level variation, we detect a statistically

¹⁴It is also likely that the marginal adopters identified by the instrument (i.e., those whose adoption decisions are influenced by exposure to information through proximity to dissemination centers or conflict disruption) may experience much larger productivity gains than the average adopter—i.e., as mentioned in Footnote 3, we may be identifying a LATE larger than the ATE. This could occur if these marginal adopters previously faced significant knowledge or resource constraints that limited their ability to transition to improved pasture systems, making the returns to adoption particularly high for them.

significant effect from the average daily precipitation registered during the last agricultural season, although only for the optimal IV specification. We find that an increase in precipitation of 1 mm/day is correlated with an increase in livestock weight per hectare of 2.8%.

1.4.2.1 Testing for identification assumptions and robustness

We begin by providing correlational evidence in support for our exclusion restriction assumptions. First, we find a statistically insignificant correlation between the farm's distance to the closest R&D dissemination center and the distance to the closest input market (Table 1A.1). Additionally, we evaluate whether the proximity to this infrastructure affects adoption by adding it as a regressor in our first-stage specification (Table 1A.2). We find that this new distance variable holds no significant correlation with our adoption measure, while our main inference remains unchanged. Furthermore, we run Poisson regressions where the dependent variables were: (a) the number of complementary practices adopted on the farm, and (b) a farm assets index, while including both distance to the closest R&D center and distance to the closest input market as covariates (Table 1A.3). We find that proximity to R&D centers has no significant effect on the number of complementary practices adopted, but proximity to input markets significantly affects farm asset accumulation.¹⁵ Therefore, these suggest that R&D centers do not systematically drive broader agricultural intensification beyond their specific role in knowledge transfer for improved pasture adoption.¹⁶

Meanwhile, in the case of our violence variables we evaluate whether these variables are correlated with key socioeconomic variables such as household wealth or education levels (Table 1A.4), and do not find any statistically significant association. The latter further supports our argument that their primary channel of influence is through information availability rather than direct effects on productivity. This is expected, as our selection of conflict measures is deliberate,

¹⁵We further include specifications that add farmers' self-reported distance to the closest extension services in Tables REF, finding that our inference regarding the distance to R&D dissemination centers does not change. However, this additional testing is only available for a subset of the sample where the additional covariate is available.

¹⁶Another potential robustness check would consider a placebo test using the distances to non-cattle-focused CGIAR centers in the country. Yet, to our knowledge, there are no alternative CGIAR institutions in Colombia, hence implementing this test within our dataset is unfeasible. Future research could consider using a geolocation of non-cattle-focused demonstration plots established by CIAT to define a comparable placebo.

focusing on likely disruptions of civilian life as a collateral consequence, rather than violence that directly alters land tenure or governance structures in the long run.¹⁷

Now, in terms of the estimation strategy, although the optimal IV approach relies on a first-stage analysis that warrants a non-linear estimation, some concerns may arise as to whether one is incurring in identifying an effect off a non-linearity alone. We provide additional evidence that, in our analysis, instrument strength is not caused by identification from a non-linearity (Table 1A.5), showing that in the absence of exogenous sources of variation, the problem of weak instrumentation would reemerge even with a non-linear first stage. Therefore, as in Xu (2021), we confirm that it is the combination of exogenous variation and a proper conditional mean that circumvents the problem of artificially weak instrumentation.

Furthermore, we evaluate the sensitivity of our estimates considering three separate analyses using each of our main sources of exogenous variation (i.e., distance to R&D, attacks on populations, and illegal checkpoints), and summarize the results in Tables 1A.6 and 1A.7. Our inference remains unchanged in such a case: the partial average effects from first stage analyses are within a standard error from those of our main specification, and so is the case for our estimates of impact of introduced pastures on carrying capacity. Moreover, using each source of exogenous variation separately under our optimal-IV approach, we reject a null hypothesis of weak instruments across all specifications. We further test whether using a geodesic distance to R&D, which allows us to use the full sample, has any significant effect on our main inference (see Tables 1A.8, 1A.9, and 1A.10), but find qualitatively equivalent results.

A potential concern with using a log-linear model lies in the non-negative nature of the carrying capacity measure, atop a potential endogeneity problem. To that purpose, we present a brief summary of the case of an exponential model estimated by Poisson QMLE in Table 1A.11, whose estimates are directly comparable to those from Table 1.4. Consistent with our findings from OLS and IV estimation under a log-linear model, we encounter significant differences between Poisson

¹⁷Future studies in this context could follow an alternative and perhaps more robust testing, having dependent variables related to farm infrastructure (which our data, unfortunately, does not possess), to assess whether other sources of violence (e.g., massacres) are likely correlated with them but not our preferred measures of conflict.

and IV-Poisson estimates (either relying on linear or non-linear estimates in the first step of the analysis). Without acknowledging the likely endogenous nature of the context, estimates would point to an increase in carrying capacity of 21.9% by transitioning from native savanna to introduced pasture, yet this figure goes up to 127.8 (122.8) percent under an IV (optimal IV) approach. Finally, we also test whether our impact estimates are sensitive to excluding non-adopters (Table 1A.12), finding that all estimates are statistically equivalent to those of our baseline estimates, so the effect does not depend solely on the intensive margin.

1.4.2.2 Land use implications

Our estimates have important implications for land use in lowland ranching and its relationship with the adoption of introduced pastures. Leaving aside equilibrium effects, we can calculate a counterfactual measure of productivity for users of introduced pastures had they not adopted these varieties and then project how much more land would be required to keep the same level of output without using introduced pastures. Following similar approximations done in Larochelle et al. (2015) and Larochelle and Alwang (2022) for the case of improved bean varieties and welfare measures in Sub-Saharan Africa, we use our optimal IV estimate¹⁸ of τ from Equation (1.1) to derive a counterfactual yield measure (again in kg/ha), such that

$$y^{CF} = y \times \exp[-\hat{\tau}S], \quad (1.3)$$

where y and S are the observed levels of productivity and pasture adoption. The average counterfactual additional need for land is calculated straightforwardly as

$$\psi = \frac{\bar{y}^{CF} - \bar{y}}{\bar{y}}. \quad (1.4)$$

The average observed carrying capacity (yield) among adopters of pastures is 545.28 kg/ha, while we predict an average counterfactual yield of 192.25 kg/ha had they not adopted these pastures. To put these figures in perspective, in the absence of introduced pastures, land use in pastures would have had to increase by 183% to reach the same level of production, which would have potentially led to a dramatic increase in deforestation. These findings further highlight how introduced pasture varieties have been key to increasing productive efficiency (Herrero et al., 2013; Jank et al., 2014)

¹⁸More specifically, we use the estimate of τ from Poisson IV with optimal instruments mentioned above, since using directly the estimates from linear regression would be a violation of Jensen's inequality.

and are a crucial element to achieving sustainable intensification (González-Quintero et al., 2021; Mazzetto et al., 2015).

1.4.3 Heterogeneity by pasture management

Following the literature, we check for differences in the effect of productivity across different kinds of pasture management, fitting the model in equation (1.2) by OLS and CF. We present the average partial effects of the share of introduced pastures conditional on different pasture management schemes in Figure 1.3. Under an OLS framework, our estimates would suggest that without pasture management, there are no effects from the adoption of introduced pastures on cattle intensity, with statistically significant effects only when pasture management practice occurs. Nevertheless, after accounting for the endogeneity in pasture adoption via a control function approach, our analysis suggests that there are significant gains in yields regardless of whether pasture management practices take place, but that they do increase the impact of pastures¹⁹. In terms of point estimates, a 1% point increase in the use of introduced pastures alone will increase productivity by 1.26%. However, when a farm's pastures are managed by making weed control only, a 1 percentage point increase in the adoption of introduced pastures implies an increase of 1.54% in cattle intensity. The figure is 1.87% for the case of only fertilization and 1.53% whenever both practices occur together. Nevertheless, caution should be advised when arguing different levels of impact based on our control function estimates; note that we cannot reject the hypothesis that these heterogeneous effects are statistically equivalent to one another, evidenced by their overlapping confidence intervals.²⁰

Overall, our results hold even when considering different settings of pasture management observed at the farm level. It is worth highlighting that our analysis builds upon the working assumption that practices like fertilization and weed control are taken as given. Nevertheless, among pasture adopters, these practices may reflect an underlying decision-making process by

¹⁹The associated point estimates are summarized in Table 1A.13.

²⁰Having a point estimate of combined practices being lower than that of only using fertilization has a likely agronomic driver. Specifically, common weed control practices usually remove some plants that serve as an important soil coverage, which, combined with fertilization, can lead to accelerated soil degradation and thus limit the average gains from using introduced pastures.

the farmer that could benefit from economic modeling, as suggested by previous studies on other crops²¹ (Kassie et al., 2013; Martinez et al., 2021; Teklewold et al., 2013). While addressing the dual endogeneity of introduced pasture adoption and pasture management practices is beyond the scope of this paper, it will likely be of the utmost crucial for future studies on the adoption of sustainable livestock systems, which typically integrate various practices.

1.4.4 Introduced pasture adoption and revenues per hectare

We plot the relationship of revenues per hectare with the share of introduced pastures in Figure 1.4, revealing that without any controls there is a relevant correlation, although slightly noisier as noted by the wider confidence intervals than those in the case of carrying capacity. However, just as in the case of yields, we must consider a potential problem of endogeneity from self-selection if trying to estimate an impact. We replicate this analysis with revenues as the response variable in Table 1.5. Under an OLS framework, we detect a robust correlation between revenues per ha and introduced pastures, even after considering additional controls, such that each additional 1% point in adoption implies an average 0.31% increase in revenues per ha. However, we find that considering potential endogeneity significantly alters our inference. Under an optimal IV approach, the average response goes up to 2.05%. In transition terms, switching from native savannas to introduced pastures has the potential to increase average revenue per hectare by roughly 205%. Unfortunately, due to a systematic lack of recordkeeping of costs among surveyed households, we have no available information on costs to provide an analysis based on profit rather than revenues. A back-of-the-envelope calculation based on data from Enciso et al. (2021) would suggest that going from native grasslands to improved pastures with standard management would increase costs per hectare by 130% in the year when pastures are established, and by 45% in subsequent years. Therefore, in reference to a potential increase in revenues in the order of 205%, profits per hectare could potentially increase by a significant margin (up to 75%). However, given the lack of proper cost data in our sample, a specific figure cannot be ascertained from our statistical analysis.

²¹For example, an ordered regression analysis on the number of pastures observed in the farm (Table 1A.14) suggests that factors like membership in a farmers' association, education, and access to credit are correlated with the adoption of these complementary practices, resembling the results of Martinez et al. (2021) for complementary technologies in rice farming.

We can derive further relevant insights when exploring possible heterogeneities across various groups of complementary practices (Figure 1.5) for the impact of introduced pastures on revenues.²² For instance, note that under an OLS specification, transitioning into an improved grazing system would only lead to a statistically significant gain in revenues among farmers that only use weed controls. Conversely, there appear to be significant gains in revenue across all groups of complementary-practice adoption from the use of introduced pastures, even in the case of no other complements. However, we are cautious of any back of the envelope calculations for each case, given both the unavailability of cost information at the farm-level or any representative average figures per each specific practice. Therefore, yet again, these projected increases in revenue do not necessarily imply a direct increase in profit.

1.5 Discussion

The sustainability of ranching based on foraging systems remains at the center of debates surrounding their land use and productive efficiency. Yet, impacts from using improved systems based on introduced pastures remained largely unexplored (Baltenweck et al., 2020). Our research on the adoption of introduced pastures in ranching systems examined whether using these materials increases farm-level productivity at the farm level, based on a case study for two macro-regions of Colombia: the Caribbean and Eastern Plains – Amazon Piedmont. Our results suggest that the adoption of introduced pastures is strongly correlated with the proximity to technological research and dissemination centers, other technological endowments, education, farm size, and historical events of violence at the Municipality level. Also, our findings indicate a statistically significant gain in carrying capacity from using introduced pastures. We find a gain in productivity when introduced pastures are implemented, although gains in productivity are larger when weed control or fertilization regimes take place. Our estimates of potential gains in productivity (carrying capacity) from adoption are below those suggested by agronomic trials (Fisher et al., 1992; Hyman et al., 2022). Nonetheless, they coincide with the literature that points to proper pasture management as a necessary action to guarantee the largest average increases in productivity (González-Quintero et

²²The associated point estimates are summarized in Table 1A.15.

al., 2021; Pérez-López & Afanador-Tellez, 2017). In addition, our findings point to a significant reduction in ranching's land demand, which is attributable to improved systems based on introduced pastures.

Our findings are crucial for understanding current conditions and shaping the future of ranching technology research in the Latin American lowlands, particularly in Colombia. First, they highlight the historical role of the National and International Agricultural Research Systems in enhancing ranching productivity through the selection and introduction of higher-nutrient pasture varieties in the seed system. Second, they reveal how past violence and conflict have constrained the agricultural sector's potential, with our study showing that each additional violent attack on the population and each additional illegal checkpoint experienced at the Municipality level decreased the share of introduced pastures by an average of 3.08 and 2.57 percentage points, respectively. Third, the significant productivity increase from adopting introduced pastures suggests that strategies aimed at increasing perceived prices through product differentiation, by signaling the use of more sustainable production (Charry, Narjes, Enciso, Peters, & Burkart, 2019), could incentivize the adoption of low-emission grazing systems with introduced pastures. Fourth, the notable productivity gains from well-managed pastures imply that farmers' benefits could be coupled with social co-benefits, such as ground carbon storage (Fisher et al., 1994; Hyman et al., 2022). This underscores the desirability of programs aiming at intensification (Arango et al., 2020; Tapasco et al., 2019), which farmers have shown a willingness to pursue with better technical support systems (Carriazo, Labarta, & Escobedo, 2020). Finally, additional productivity per hectare of land suggests that pasture-based intensification programs could effectively reduce the deforestation pressure, contributing positively to sustainability goals.

Production solely under introduced pastures is not a silver bullet for achieving optimal productivity levels, particularly in seasonally dry climates, where maintaining a share of grasses as semi-natural pastures or savannas can be more strategic (Ospina et al., 2012). However, given their widespread adoption in Colombia and Latin America (ISPC, 2018), introduced pastures are arguably more appealing as a primary public policy target vis à vis other intensive schemes like

silvopastoral systems. Although the latter may offer the most desirable traits in terms of circularity and climate mitigation (Murgueitio, Chará, Barahona, Cuartas, & Naranjo, 2014; Parodi et al., 2022; Silva-Parra, Trujillo-González, & Brevik, 2021), their adoption remains dramatically low, with roughly 55,000 ha in LAC after years of regional promotion (Chará et al., 2019). In contrast, introduced pastures have not only achieved broader adoption, but have also proven successful for intensification and sustainable, climate-adapted production in Latin America (Bogaerts et al., 2017; Mazzetto et al., 2015), and have been historically (and within our sample) used by farmers of all scales (Campuzano et al., 2022; Van Ausdal, 2009).

Notwithstanding these potential gains from the use of introduced pastures, Latin America still needs larger efforts at the national scale toward sustainable intensification in ranching. In our case of Colombia, the regions under analysis are the ones putting the largest pressure on the agricultural frontier and forests, particularly in the Amazon Piedmont and Eastern Plains. Nevertheless, association membership and access to credit services among producers remain severely low, highlighting the unmet demands of knowledge (Carriazo et al., 2020) and credit (Mejía et al., 2021) in this population. Although the so-called burger connection²³ has not yet impacted deforestation in Colombia (Dávalos, Holmes, Rodríguez, & Armenteras, 2014), the anticipated entry of Colombian beef into the US beef market (Vargas-Cuéllar, 2022) could trigger a significant demand shock. If unmanaged, this could lead to increased land pressures (Jank et al., 2014) and substantial deforestation, similar to what has occurred in Brazil over the past five years (McCoy & Ledur, 2022). This surge in demand might also boost the incentives for illegal production, which is already harming Colombian forests (Murillo-Sandoval et al., 2023).

1.6 Conclusion

Using cross-sectional, geographical, weather, and historical data, we investigate the factors driving the adoption of introduced pastures in Colombian lowland ranching. By leveraging historical information on violence and conflict events and a measure of proximity to centers of technological R&D and promotion, we implement an instrumental variable approach to measure the impact of

²³This relates to the connection between national-or regional-level demands for beef and observed rates of deforestation (McAlpine, Etter, Fearnside, Seabrook, & Laurance, 2009).

introduced pasture adoption on land-carrying capacity (kg of livestock per ha) and livestock-related revenues.

Our results reveal that proximity to research dissemination significantly influences pasture adoption, underscoring the vital role that National and International Agricultural Research Systems play in reaching intensification goals. Additionally, historical violence and alterations to transit and transportation, which disrupt supply chains, also affect the observed levels of adoption. More importantly, we provide impact estimates suggesting that transitioning from native savannas to introduced pastures can potentially increase the weight-carrying capacity of ranching by more than a 100%, with even larger gains when complementary practices like weed control and fertilization are in place. Likewise, livestock-related revenues are positively and significantly increased with adoption. While we find that correlational approaches are likely underestimating the true impact from the use of these pastures, we still detect productivity gains below those suggested by agronomic trials, revealing that the latter are unlikely to materialize under real farm conditions.

While we provide important insights on how introduced pastures affect productivity and factors associated with welfare, our findings could be expanded in at least two areas. First, future studies should focus on determining a representative on-farm measure of GHG emissions and its relationship with grazing systems based on introduced pastures. Given the low levels of spontaneous adoption of alternative intensification methods like silvopastoral systems, enhancing and intensifying grazing systems with introduced pastures could significantly improve the sector's sustainability and help reduce the pressure on the agricultural frontier driven by the increasing global demand for beef. Additionally, detailed information about animal weight gain and associated costs is needed to fully assess the impact on profitability.

Second, our analysis is limited by the cross-sectional nature of the main dataset, so future studies should focus on longitudinal data. Incorporating time variability would enable the analysis of spillover effects and provide clearer identification strategies of the impacts of adopting introduced pastures. In addition, having access to more recent, representative information is crucial for understanding how the violence de-escalation and peacebuilding efforts influence ranching

intensification. Our main dataset was collected in 2016-2017, shortly after the Colombian Peace Accords, which may have introduced a structural change in value chains, seed systems, and the decision-making processes of agricultural households. Future research should utilize more recent data to determine if the observed impacts are not merely an artifact of this structural change.

Figures and Tables

Figure 1.1 Location of surveyed farms, CIAT, and AGROSAVIA Research Centers with relevant dissemination of cattle ranching technologies.

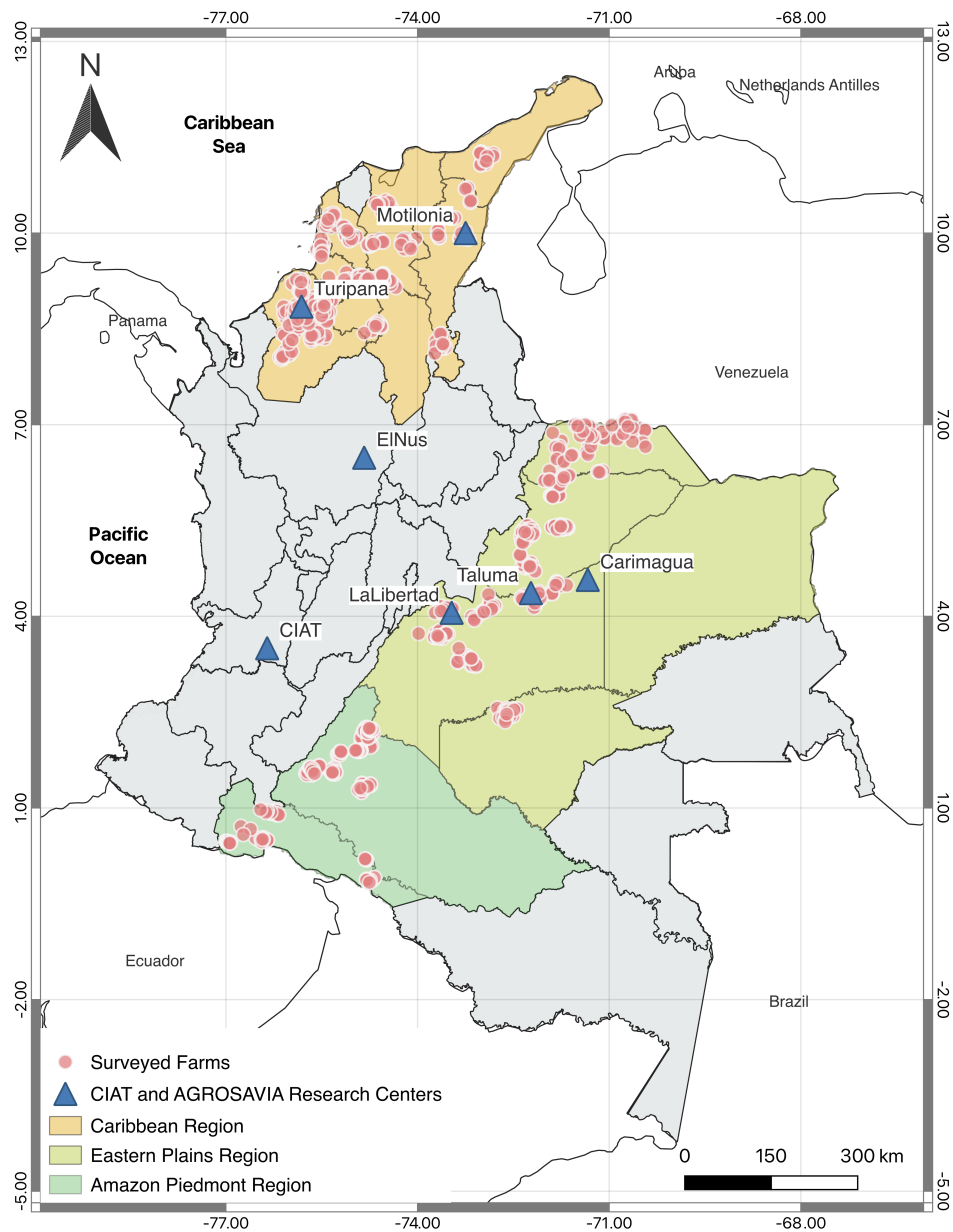


Figure 1.2 Relationship between the share of introduced pastures and cattle yield. Linear prediction and 95% confidence intervals.

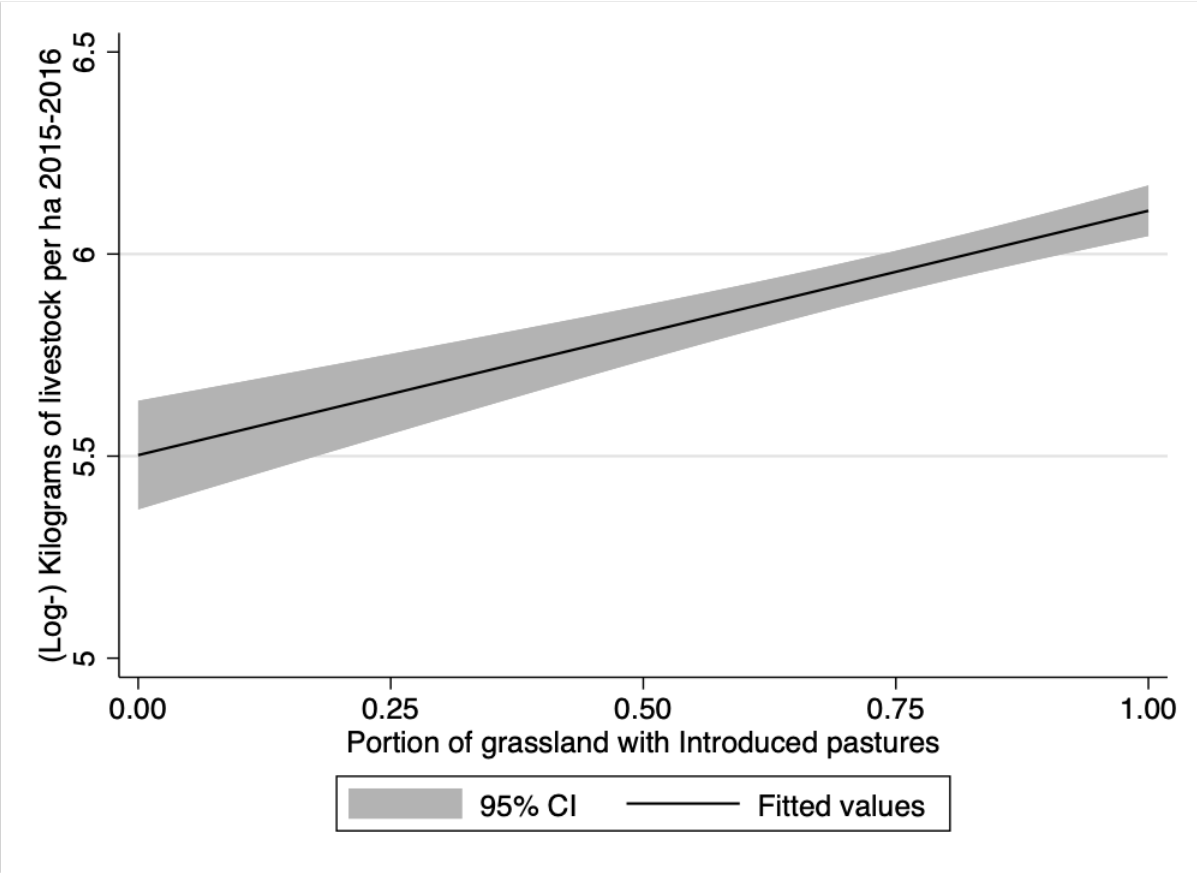


Figure 1.3 Ordinary least squares (OLS) and Control function (CF) estimates of heterogeneity of the average effect of adopting an additional 1% of introduced pastures on cattle yield by pasture management practices used in the farm (95% CI).

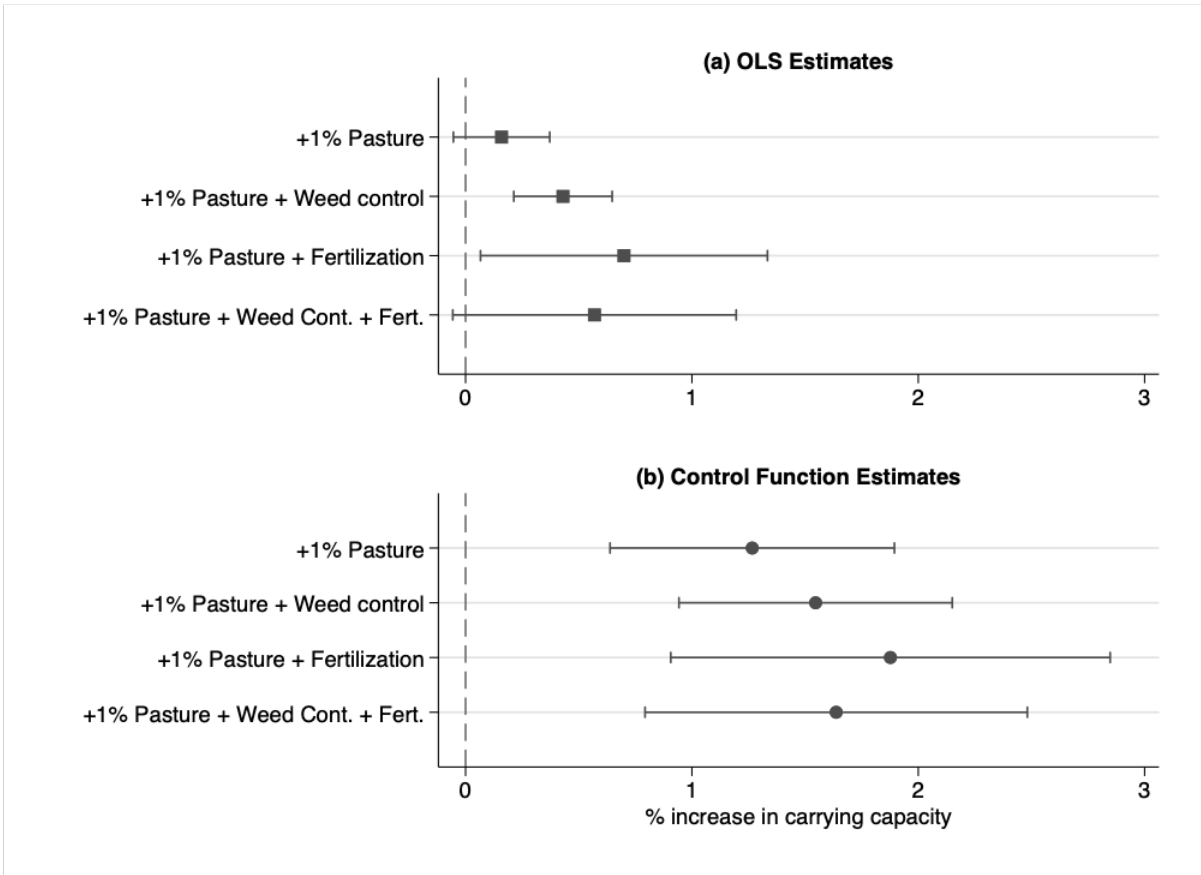


Figure 1.4 Relationship between the share of introduced pastures and livestock-related revenue.
Linear prediction and 95% confidence intervals.

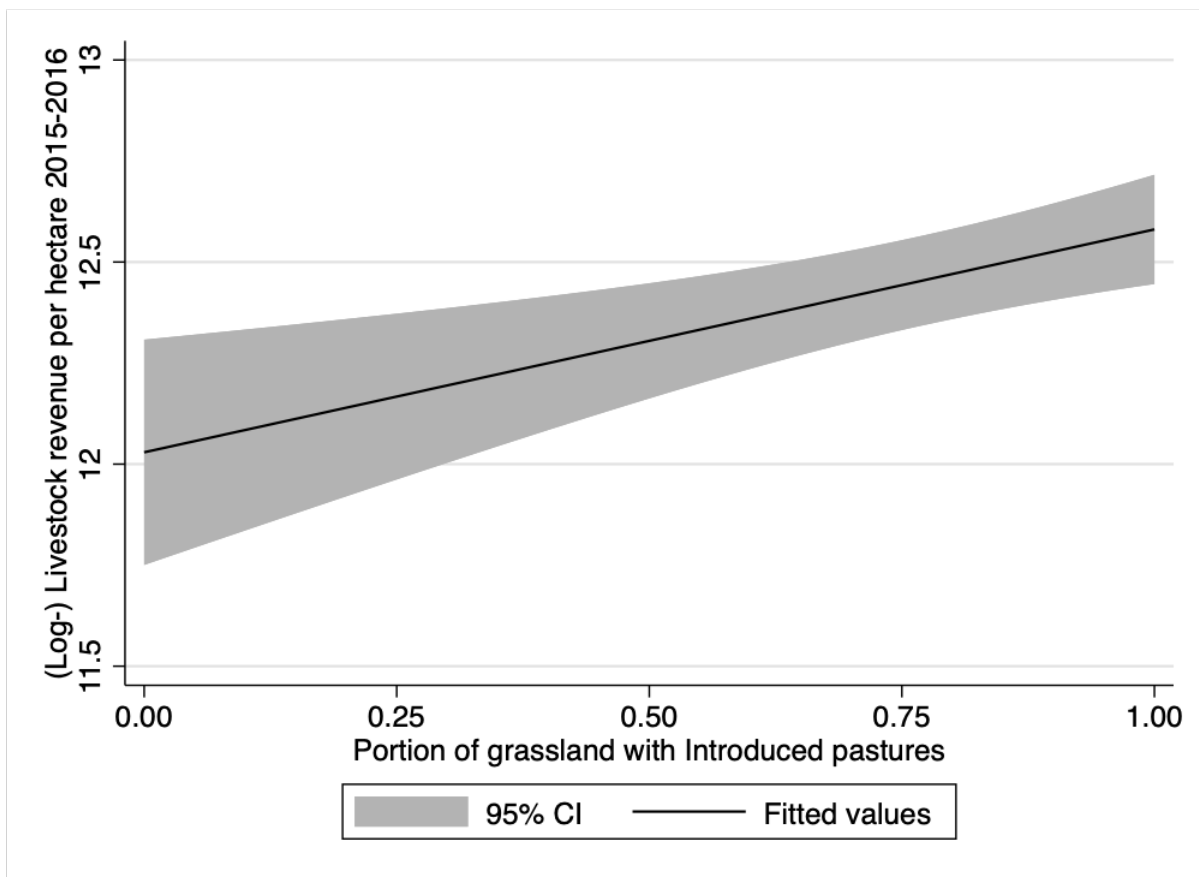


Figure 1.5 Ordinary least squares (OLS) and Control function (CF) estimates of heterogeneity of the average effect of adopting an additional 1% of introduced pastures on livestock-related revenue by pasture management practices used in the farm (95% CI).

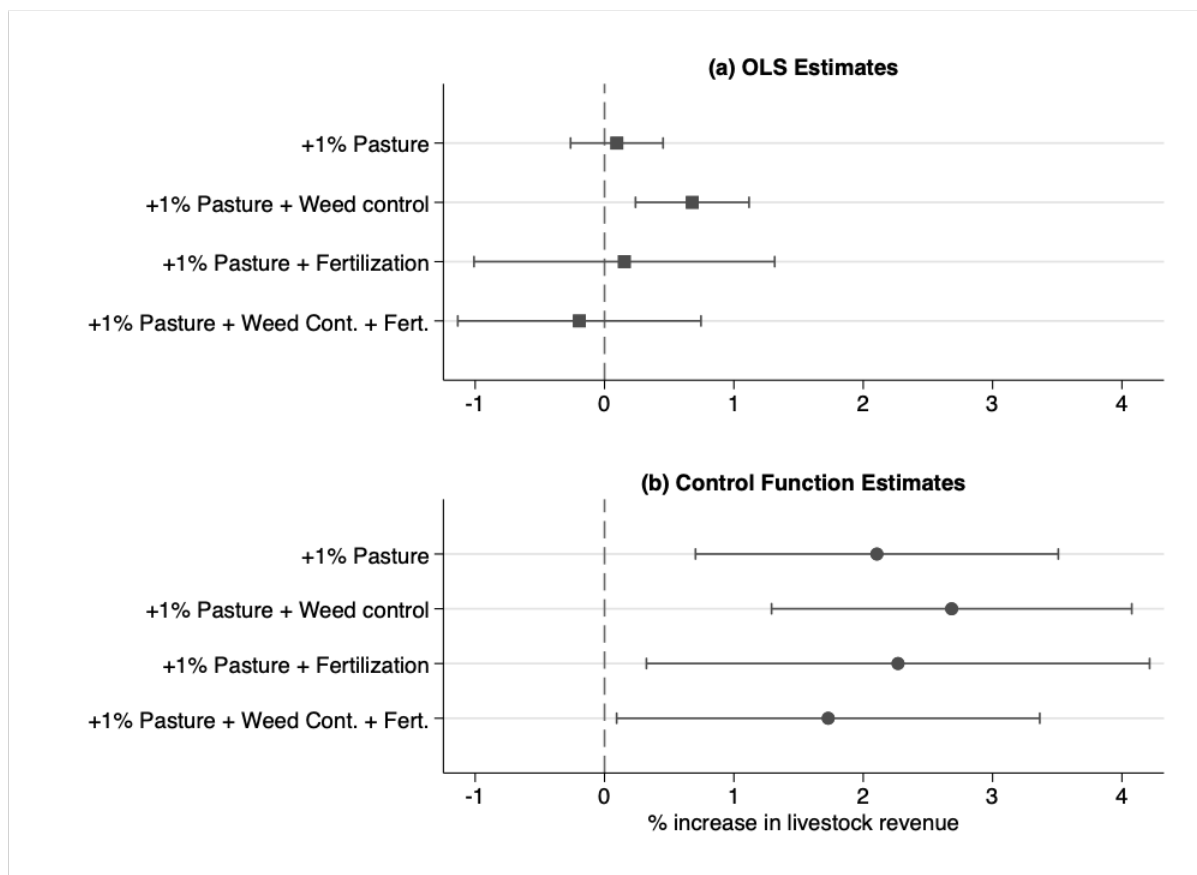


Table 1.1 Descriptive statistics of the sample and Municipality-level variables.

FARM-LEVEL VARIABLES (N=1,021)	Unit	Mean	S.D.	Min	Max
Bovine kilograms per hectare	Kg/ha	536.98	478.80	11.67	4,648.89
Revenue per hectare	COP(1,000)/ha	684.4	1,531.7	0.4	25,864.8
Share of pastures with introduced varieties	Avg./farm ^(a)	0.78	0.32	0	1
	Pooled Avg. ^(b)	0.66			
Distance to closest dissemination center	Km	226.2	139.3	6.2	551.5
Distance to closest input market	Km	17.9	16.1	0.9	89.9
Grass management					
No management	1 = Yes	0.39	0.49	0	1
Only weed control	1 = Yes	0.46	0.50	0	1
Only fertilization	1 = Yes	0.07	0.26	0	1
Fertilization and weed control	1 = Yes	0.08	0.27	0	1
Associativity and credit					
Member of a farmers' association	1 = Yes	0.22	0.41	0	1
Access to credit	1 = Yes	0.22	0.42	0	1
Assets Indices					
Household assets index (Total)	Count	5.97	2.40	0	11
Farming assets index (Total)	Count	3.81	2.02	0	9
Other controls					
Size of the farm	Ha	200.91	467.08	1.5	7,000
Female household head	1 = Yes	0.07	0.26	0	1
Education level of HH: No education	1 = Yes	0.08	0.26	0	1
Education level of HH: Primary	1 = Yes	0.71	0.45	0	1
Education level of HH: Secondary	1 = Yes	0.15	0.36	0	1
Education level of HH: Tertiary	1 = Yes	0.06	0.24	0	1
MUNICIPALITY-LEVEL VARIABLES (N=45)					
Attacks on population (Total, 1988-2012)	Count	1.09	1.55	0	5
Illegal checkpoints (Total, 2002-2016)	Count	1.64	3.09	0	17
Precipitation (avg. daily, 2016)	mm/day	5.66	3.35	1.43	16
Maximum temperature (avg. daily, 2016)	Celsius	31.78	3.36	18.37	35.37

Note — (a) This reports the average per farm share of pastures with introduced varieties. (b) Pooled average sums the total in-sample area with introduced pastures and divides it by the total in-sample area in all pastures.

Table 1.2 Mean values of pasture adoption, complementary practices, and outcomes of interest by quintiles of farm size.

VARIABLES	Unit	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Observations	<i>N</i>	208	206	215	194	198
Bovine kilograms per hectare	Kg/ha	909.95	561.02	438.24	423.48	342.89
Revenue per hectare	COP(1,000)/ha	1,189.62	571.07	658.92	480.25	528.24
Share of pastures with introduced varieties	Avg./farm ^(a)	0.79	0.77	0.78	0.84	0.73
Does fertilization	1 = Yes	0.20	0.13	0.11	0.15	0.18
Does weed control	1 = Yes	0.34	0.47	0.69	0.58	0.62

Note — (a) This reports the average per farm share of pastures with introduced varieties.

Table 1.3 First-stage analysis of factors associated with the share of introduced pastures in the farm.

VARIABLES	(1)	(2)	(3)	(4)
Log-Distance to closest dissemination center ^(a)	-0.1215*** (0.039)	-0.1157*** (0.038)	-0.1320*** (0.042)	-0.1234*** (0.041)
Attacks on population ^(a)	-0.0469*** (0.018)	-0.0428** (0.018)	-0.0355** (0.016)	-0.0308** (0.015)
Illegal checkpoints ^(a)	-0.0309*** (0.011)	-0.0286** (0.012)	-0.0279*** (0.010)	-0.0257** (0.010)
Log-Area of the farm ^(a)		-0.0179** (0.009)		-0.0139* (0.008)
Education of HH (Primary)		0.0571 (0.041)		0.0557 (0.036)
Education of HH (Secondary)		0.0383 (0.049)		0.0317 (0.039)
Education of HH (Tertiary)		-0.0079 (0.060)		0.0011 (0.052)
Female HH (1 = Yes)		-0.0180 (0.038)		-0.0193 (0.036)
Access to Credit (1 = Yes)		0.0083 (0.024)		0.0044 (0.024)
Household Assets Index		0.0061 (0.005)		0.0051 (0.005)
Farm Assets Index		0.0210*** (0.007)		0.0196*** (0.006)
Observations	994	994	994	994
Method	OLS	OLS	QMLE	QMLE
Dept Controls	Yes	Yes	Yes	Yes
Cluster (village) standard errors in parentheses				
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				

Notes — Response variable is the share of pastures with introduced varieties. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1.4 Effect of introduced pasture adoption on cattle yield.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Share of Improved Pastures	0.3770*** (0.091)	0.3368*** (0.072)	1.3701*** (0.261)	1.3470*** (0.247)	1.4456*** (0.303)
Log-Area of the farm ^(a)		-0.2782*** (0.020)	-0.2721*** (0.020)	-0.2722*** (0.020)	-0.2698*** (0.021)
Education of HH (Primary)		0.0881 (0.074)	0.0004 (0.091)	0.0024 (0.091)	-0.0119 (0.098)
Education of HH (Secondary)		0.1217 (0.092)	0.0383 (0.109)	0.0402 (0.108)	0.0334 (0.120)
Education of HH (Tertiary)		0.1292 (0.116)	0.1042 (0.128)	0.1048 (0.127)	0.0839 (0.132)
Female HH (1 = Yes)		-0.2507*** (0.078)	-0.2079** (0.088)	-0.2089** (0.088)	-0.2312** (0.091)
Member of Farmers' Assoc. (1 = Yes)		0.1295** (0.052)	0.1444** (0.058)	0.1441** (0.057)	0.1516** (0.059)
Access to Credit (1 = Yes)		-0.0765 (0.047)	-0.0839 (0.054)	-0.0837 (0.054)	-0.0788 (0.055)
Average precip. in the past year		0.0186 (0.012)	0.0282** (0.013)	0.0280** (0.013)	0.0123 (0.012)
Avg. max. temp. in the past year		-0.0157 (0.013)	0.0005 (0.016)	0.0001 (0.015)	-0.0187 (0.015)
Control Function (ν)					-1.205*** (0.313)
Observations	994	994	994	994	994
Method	OLS	OLS	2SLS	Opt-IV	CF
Dept Controls	Yes	Yes	Yes	Yes	Yes
Effective F			6.664	53.99	
Montiel-Pflueger: 5% Bias Critical value			24.38	37.42	
Montiel-Pflueger: 10% Bias Critical value			14.15	23.11	
Robust reg. endogeneity Test (p -value)			0.000	0.000	
Cluster (village) standard errors in parentheses					
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$					

Notes — Response variable is (log) Kilograms of livestock per hectare. Two-step control function (CF) regression estimates report cluster bootstrapped standard errors. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1.5 Effect of introduced pasture adoption on livestock-related revenues per hectare.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Share of Improved Pastures	0.4376*** (0.165)	0.3081** (0.135)	1.9849*** (0.568)	2.0551*** (0.563)	2.2676*** (0.705)
Log-Area of the farm ^(a)		-0.6613*** (0.046)	-0.6436*** (0.050)	-0.6428*** (0.050)	-0.6446*** (0.052)
Education of HH (Primary)		0.2409 (0.170)	0.0312 (0.207)	0.0224 (0.208)	0.0624 (0.222)
Education of HH (Secondary)		0.3778* (0.229)	0.1639 (0.264)	0.1550 (0.265)	0.2102 (0.282)
Education of HH (Tertiary)		0.4429* (0.240)	0.3553 (0.291)	0.3516 (0.294)	0.3528 (0.300)
Female HH (1 = Yes)		-0.1992 (0.161)	-0.0999 (0.175)	-0.0957 (0.178)	-0.1734 (0.185)
Member of Farmers' Assoc. (1 = Yes)		0.1731 (0.121)	0.1729 (0.130)	0.1729 (0.131)	0.2216* (0.134)
Access to Credit (1 = Yes)		-0.0158 (0.108)	-0.0410 (0.113)	-0.0421 (0.114)	-0.0325 (0.117)
Average precipitation in the past year		0.0460 (0.033)	0.0696* (0.036)	0.0706** (0.036)	0.0315 (0.034)
Avg. max. temp. in the past year		-0.0147 (0.034)	0.0136 (0.034)	0.0148 (0.034)	-0.0255 (0.038)
Control Function (ν)					-2.1363*** (0.726)
Observations	786	786	786	786	786
Method	OLS	OLS	2SLS	Opt-IV	CF
Dept Controls	Yes	Yes	Yes	Yes	Yes
Effective F Statistic			6.208	43.81	
Montiel-Pflueger: 5% Bias Critical value			24.71	37.42	
Montiel-Pflueger: 10% Bias Critical value			14.33	23.11	
Robust reg. endogeneity test (p -value)			0.0010	0.0002	
Cluster (village) standard errors in parentheses					
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$					

Notes — Response variable is (log) Revenue from livestock-related sales per hectare. Two-step control function (CF) regression estimates report cluster bootstrapped standard errors. (a) Regression included the variable and its square, and the table reports the full average partial effect.

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APPENDIX

Table 1A.1 Testing for distance to R&D centers and its relationship with the distance to input markets and extension services.

VARIABLES	(1)	(2)
Distance to closest input market	0.0084 (0.025)	0.0457 (0.037)
Distance to closest extension services		0.0056 (0.040)
Observations ^(a)	993	611
R-squared	0.781	0.682
Method	OLS	OLS
Dept Controls	Yes	Yes
Cluster (village) standard errors in parentheses.		
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Notes — Response variable is the road distance from the farm to the closest R&D dissemination center. (a) Reduced number of observations in Column 2 responds to data limitations in the sample. We only have available data on the distance to extension services for Eastern Plains and Amazon Piedmont.

Table 1A.2 Alternate first-stage analysis of factors associated with the share of introduced pastures in the farm, including distance to closest input market and closest extension services.

VARIABLES	(1)	(2)
Log-Distance to closest dissemination center ^(a)	-0.1196*** (0.041)	-0.1151* (0.063)
Log-Distance to closest input market ^(a)	0.0106 (0.013)	0.0653 (0.047)
Log-Distance to closest extension services ^(a)		-0.0511 (0.046)
Attacks on population ^(a)	-0.0310** (0.015)	-0.0200 (0.014)
Illegal checkpoints ^(a)	-0.0270*** (0.010)	-0.0302*** (0.010)
Log-Area of the farm ^(a)	-0.0153* (0.008)	-0.0441*** (0.011)
Education of HH (Primary)	0.0525 (0.036)	-0.0205 (0.044)
Education of HH (Secondary)	0.0287 (0.039)	-0.0370 (0.053)
Education of HH (Tertiary)	-0.0024 (0.052)	-0.0843 (0.070)
Female HH (1 = Yes)	-0.0176 (0.036)	-0.0154 (0.040)
Member of a Farmer's Association (1 = Yes)	-0.0417 (0.026)	-0.0374 (0.039)
Access to Credit (1 = Yes)	0.0039 (0.023)	0.0513* (0.030)
Household Assets Index	0.0056 (0.005)	0.0239*** (0.007)
Farm Assets Index	0.0200*** (0.006)	0.0130 (0.008)
Observations	993	611
Method	QMLE	QMLE
Dept Controls	Yes	Yes
Cluster (village) standard errors in parentheses		
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Notes — Response variable is the share of pastures with introduced varieties. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.3 Additional testing of distance to R&D and distance to alternate infrastructures in broader agricultural intensification.

VARIABLES	(1) Comp.Pract.	(2) Comp.Pract.	(3) Farm Assets	(4) Farm Assets
Log-Distance to closest dissemination center ^(a)	-0.0294 (0.065)	-0.0742 (0.086)	-0.0633 (0.043)	-0.1053 (0.069)
Log-Distance to closest input market ^(a)	-0.0453 (0.030)	0.1548** (0.077)	-0.0545*** (0.019)	0.0015 (0.046)
Log-Distance to closest extension services ^(a)		-0.193*** (0.074)		-0.0734 (0.045)
) Log-Area of the farm ^(a)	-0.0069 (0.023)	-0.0167 (0.023)	0.1397*** (0.013)	0.1490*** (0.022)
Observations ^(b)	993	611	993	611
Method	Poisson	Poisson	Poisson	Poisson
Dept Controls	Yes	Yes	Yes	Yes
Cluster (village) standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				

Notes — Reporting semi-elasticity estimates from Poisson regression. Response variables are (1-2) the number of complementary practices for pasture management and (3-4) the number of durable farming assets in the farm. (a) Regression included the variable and its square, and the table reports the full average partial effect. (b) Reduced number of observations in Column 2 responds to data limitations in the sample. We only have available data on the distance to extension services for Eastern Plains and Amazon Piedmont.

Table 1A.4 Additional testing of selected violence variables and correlation with measures of wealth and education.

VARIABLES	(1) House Asset Index	(2) High-Ed (1 = Yes)
Attacks on population ^(a)	-0.0179 (0.020)	-0.0158 (0.021)
Illegal checkpoints ^(a)	-0.0043 (0.013)	-0.0192 (0.016)
Log-Area of the farm ^(a)	0.0117 (0.009)	0.0157* (0.008)
Observations	994	994
Method	Poisson	OLS
Dept Controls	Yes	Yes
Cluster (village) standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Notes — Reporting semi-elasticity estimates for Poisson regression and average partial effects for ordinary least squares (OLS). Response variables are (1) the number of complementary house valuable assets and (2) an index variable equal to one when the head of the household has completed either secondary or tertiary education, and zero otherwise. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.5 Additional testing on instrument strength by non-linearity.

VARIABLES	(1) Share of IP	(2) Log-Kg/Ha
Share of Introduced Pastures		1.6768** (0.721)
Log-Area of the farm ^(a)	-0.0033 (0.008)	-0.2667*** (0.020)
Education of HH (Primary)	0.0936** (0.038)	-0.0347 (0.120)
Education of HH (Secondary)	0.0812** (0.035)	-0.0230 (0.139)
Education of HH (Tertiary)	0.0430 (0.046)	0.1017 (0.139)
Female HH (1 = Yes)	-0.0245 (0.038)	-0.1924* (0.101)
Average precipitation in the past year		0.0354** (0.018)
Average maximum temperature in the past year		-0.0010 (0.016)
Observations	1,021	1,021
Method	QMLE	Opt-IV
Dept Controls	Yes	Yes
Effective F Statistic		10.56
Montiel-Pflueger: 5% Bias Critical value		37.42
Montiel-Pflueger: 10% Bias Critical value		23.11
Robust reg. endogeneity test (<i>p</i> -value)		0.0369
Cluster (village) standard errors in parentheses		
*** <i>p</i> <0.01, ** <i>p</i> <0.05, * <i>p</i> <0.1		

Notes — (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.6 Alternate first-stage analysis of factors associated with the share of introduced pastures in the farm, using each main source of exogenous variation separately.

VARIABLES	(1)	(2)	(3)
Log-Distance to closest dissemination center ^(a)	-0.1297*** (0.039)		
Attacks on population ^(a)		-0.0327** (0.014)	
Illegal checkpoints ^(a)			-0.0294*** (0.008)
Log-Area of the farm ^(a)	-0.0174** (0.009)	-0.0110 (0.008)	-0.0106 (0.008)
Education of HH (Primary)	0.0613 (0.038)	0.0773** (0.038)	0.0735* (0.038)
Education of HH (Secondary)	0.0379 (0.039)	0.0592 (0.038)	0.0593 (0.037)
Education of HH (Tertiary)	-0.0082 (0.053)	0.0235 (0.049)	0.0106 (0.052)
Female HH (1 = Yes)	-0.0272 (0.037)	-0.0115 (0.036)	-0.0263 (0.037)
Member of Farmers' Association (1 = Yes)	-0.0396 (0.026)	-0.0301 (0.025)	-0.0269 (0.025)
Access to Credit (1 = Yes)	0.0088 (0.024)	0.0060 (0.024)	0.0056 (0.024)
Household Assets Index	0.0058 (0.005)	0.0070 (0.005)	0.0074 (0.005)
Farm Assets Index	0.0193*** (0.006)	0.0183*** (0.006)	0.0182*** (0.006)
Observations	994	1,021	1,021
Method	QMLE	QMLE	QMLE
Dept Controls	Yes	Yes	Yes

Notes — Response variable is the share of pastures with introduced varieties. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.7 Alternate estimation of the effect of introduced pasture adoption on cattle yield, using each main source of exogenous variation separately.

VARIABLES	(1)	(2)	(3)
Share of Improved Pastures	1.8097*** (0.348)	1.5705*** (0.403)	1.7259*** (0.344)
Log-Area of the farm ^(a)	-0.2695*** (0.021)	-0.2709*** (0.020)	-0.2700*** (0.021)
Education of HH (Primary)	-0.0369 (0.102)	-0.0166 (0.100)	-0.0298 (0.102)
Education of HH (Secondary)	0.0028 (0.119)	0.0221 (0.117)	0.0096 (0.120)
Education of HH (Tertiary)	0.0936 (0.141)	0.0994 (0.134)	0.0956 (0.139)
Female HH (1 = Yes)	-0.1897* (0.099)	-0.1996** (0.093)	-0.1932** (0.097)
Member of Farmers' Association (1 = Yes)	0.1507** (0.063)	0.1473** (0.060)	0.1495** (0.063)
Access to Credit (1 = Yes)	-0.0871 (0.060)	-0.0854 (0.056)	-0.0865 (0.059)
Average precipitation in the past year	0.0322** (0.015)	0.0300** (0.015)	0.0315** (0.015)
Average maximum temperature in the past year	0.0074 (0.017)	0.0036 (0.017)	0.0061 (0.017)
Source of exogenous variation ^(b)	Distance to R&D	Attacks on Pop.	Illegal Checkp.
Observations	994	994	994
Method	Opt-IV	Opt-IV	Opt-IV
Dept Controls	Yes	Yes	Yes
Effective F Statistic	35.8	27.08	41.24
Montiel-Pflueger: 5% Bias Critical value	37.42	37.42	37.42
Montiel-Pflueger: 5% Bias Critical value	23.11	23.11	23.11
Robust reg. endogeneity test (<i>p</i> -value)	7.83e-08	0.00158	3.81e-06
Cluster (village) standard errors in parentheses			
*** <i>p</i> <0.01, ** <i>p</i> <0.05, * <i>p</i> <0.1			

Notes — Response variable is (log) Kilograms of livestock per hectare. (a) Regression included the variable and its square, and the table reports the full average partial effect. (b) Describes the source of exogenous variation used in the first-stage analysis. The optimal IV estimation uses the non-linear conditional mean from the first-stage QMLE analysis.

Table 1A.8 Alternate first-stage analysis of factors associated with the share of introduced pastures in the farm.

VARIABLES	(1)	(2)	(3)	(4)
Distance to closest dissemination center (10 km) ^(a,b)	-0.0888** -0.04	-0.0759* -0.039	-0.0876** -0.034	-0.0727** -0.033
Attacks on population (1988-2012) ^(a)	-0.0522*** -0.017	-0.0492*** -0.017	-0.0410*** -0.015	-0.0370** -0.014
Illegal checkpoints (2002-2016) ^(a)	-0.0375*** -0.012	-0.0336** -0.013	-0.0334*** -0.01	-0.0296*** -0.011
Log-Area of the farm ^(a)		-0.0166** -0.008		-0.0128 -0.008
Education of HH (Primary)		0.0678* -0.04		0.0622* -0.035
Education of HH (Secondary)		0.0606 -0.048		0.0488 -0.037
Education of HH (Tertiary)		0.0192 -0.06		0.0234 -0.048
Female HH (1 = Yes)		-0.0131 -0.037		-0.0154 -0.035
Member of Farmers' Association (1 = Yes)		-0.032 -0.026		-0.0381 -0.025
Access to Credit (1 = Yes)		0.012 -0.023		0.01 -0.023
Household Assets Index		0.0068 -0.005		0.0059 -0.005
Farm Assets Index		0.0193*** -0.007		0.0178*** -0.006
Observations	1,021	1,021	1,021	1,021
Method	OLS	OLS	QMLE	QMLE
Dept Controls	No	Yes	No	Yes

Notes — Response variable is the portion of pastures with introduced varieties. (a) Regression included the variable and its square, and the table reports the full average partial effect. (b) Using distance variable based on the geodesic distance from farm to closest dissemination center on a per 10 kilometer scale.

Table 1A.9 Alternate estimation of the effect of introduced pasture adoption on cattle yield.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Share of Introduced Pastures	0.3580*** (0.091)	0.3386*** (0.072)	1.0865*** (0.252)	1.0846*** (0.276)	1.1477*** (0.296)
Log-Area of the farm ^(a)		-0.2718*** (0.019)	-0.2690*** (0.019)	-0.2690*** (0.019)	-0.2680*** (0.020)
Education of HH (Primary)		0.0917 (0.074)	0.0211 (0.085)	0.0212 (0.083)	0.0128 (0.085)
Education of HH (Secondary)		0.1113 (0.090)	0.0362 (0.102)	0.0364 (0.104)	0.0316 (0.106)
Education of HH (Tertiary)		0.1452 (0.115)	0.1209 (0.121)	0.1210 (0.125)	0.1065 (0.125)
Female HH (1 = Yes)		-0.2443*** (0.077)	-0.2153*** (0.082)	-0.2154** (0.085)	-0.2307*** (0.087)
Average precipitation in the past year		0.0166 (0.012)	0.0271** (0.013)	0.0271** (0.013)	0.0145 (0.012)
Avg. max. temp. in the past year		-0.0113 (0.012)	-0.0056 (0.013)	-0.0056 (0.014)	-0.0169 (0.013)
Control Function (ν)					-0.8893*** (0.297)
Observations	1,021	1,021	1,021	1,021	1,021
Method	OLS	OLS	2SLS	Opt-IV	CF
Dept Controls	Yes	Yes	Yes	Yes	Yes
Effective F			6.619	60.92	
Montiel-Pflueger: 5% Bias Critical value			25	37.42	
Montiel-Pflueger: 10% Bias Critical value			14.37	23.11	
Robust reg. endogeneity Test (p -value)			0.001	0.0005	
Cluster (village) standard errors in parentheses					
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$					

Notes — Response variable is (log) Kilograms of livestock per hectare. Two-step optimal IV (Opt-IV) and control function (CF) regression estimates report cluster bootstrapped standard errors. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.10 Alternate estimation of the effect of introduced pasture adoption on livestock-related revenues per hectare.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Share of Introduced Pastures	0.3988** (0.164)	0.3167** (0.134)	1.7840*** (0.520)	1.8617*** (0.571)	1.9932*** (0.608)
Log-Area of the farm ^(a)		-0.6610*** (0.045)	-0.6502*** (0.047)	-0.6496*** (0.047)	-0.6524*** (0.047)
Education of HH (Primary)		0.2611 (0.169)	0.0688 (0.202)	0.0587 (0.211)	0.1066 (0.212)
Education of HH (Secondary)		0.3806* (0.224)	0.1867 (0.255)	0.1764 (0.271)	0.2291 (0.274)
Education of HH (Tertiary)		0.4783** (0.239)	0.3984 (0.283)	0.3941 (0.292)	0.4088 (0.297)
Female HH (1 = Yes)		-0.2046 (0.157)	-0.1123 (0.167)	-0.1074 (0.177)	-0.1875 (0.176)
Average precipitation in the past year		0.0430 (0.032)	0.0669* (0.035)	0.0682* (0.036)	0.0343 (0.033)
Avg. max. temp. in the past year		-0.0054 (0.032)	0.0133 (0.031)	0.0143 (0.033)	-0.0201 (0.034)
Control Function (ν)					-1.8302*** (0.632)
Observations	796	796	796	796	796
Method	OLS	OLS	2SLS	Opt-IV	CF
Dept Controls	Yes	Yes	Yes	Yes	Yes
Effective F Statistic			5.549	42.54	
Montiel-Pflueger: 5% Bias Critical value			24.71	37.42	
Montiel-Pflueger: 10% Bias Critical value			14.2	23.11	
Robust reg. endogeneity test (p -value)			0.002	0.001	
Cluster (village) standard errors in parentheses					
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$					

Notes — Response variable is (log) Revenue from livestock-related sales per hectare. Two-step optimal IV (Opt-IV) and control function (CF) regression estimates report cluster bootstrapped standard errors. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.11 Effect of introduced pasture adoption on cattle yield with exponential model.

VARIABLES	(1)	(2)	(3)	(4)
Share of Improved Pastures	0.2198*** (0.084)	0.2180*** (0.076)	1.2789*** (0.278)	1.2283*** (0.262)
Log-Area of the farm ^(a)		-0.2657*** (0.024)	-0.2896*** (0.020)	-0.2726*** (0.020)
Education of HH (Primary)		0.0819 (0.084)	0.0797 (0.076)	0.0158 (0.079)
Education of HH (Secondary)		0.0725 (0.107)	0.0888 (0.104)	0.0489 (0.104)
Education of HH (Tertiary)		0.1841 (0.125)	0.1477 (0.115)	0.1453 (0.113)
Female HH (1 = Yes)		-0.2774*** (0.073)	-0.3055*** (0.075)	-0.2816*** (0.074)
Average precipitation in the past year		0.0014 (0.016)	-0.0044 (0.013)	-0.0062 (0.013)
Average maximum temperature in the past year		0.0017 (0.016)	-0.0129 (0.016)	-0.0113 (0.016)
Observations	1,021	1,021	1,021	1,021
Method	Poisson QMLE	Poisson QMLE	IV Poisson	Opt-IV Poisson
Dept Controls	Yes	Yes	Yes	Yes
Cluster (village) standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$				

Notes — Response variable is Kilograms of livestock per hectare. IV Poisson with optimal instrument (Opt-IV Poisson) regression estimates report cluster bootstrapped standard errors.

Table 1A.12 Effect of introduced pasture adoption on cattle yield with sample limited to adopters (only including farms with $S_i > 0$).

VARIABLES	(1)	(2)	(3)	(4)	(5)
Share of Improved Pastures	0.5181*** (0.101)	0.4259*** (0.083)	1.5579*** (0.351)	1.3984*** (0.303)	1.4791*** (0.402)
Log-Area of the farm		-0.2634*** (0.020)	-0.2495*** (0.020)	-0.2515*** (0.020)	-0.2488*** (0.021)
Education of HH (Primary)		0.0791 (0.075)	0.0360 (0.088)	0.0420 (0.085)	0.0315 (0.088)
Education of HH (Secondary)		0.1238 (0.094)	0.0914 (0.110)	0.0959 (0.106)	0.0947 (0.110)
Education of HH (Tertiary)		0.1174 (0.120)	0.0924 (0.126)	0.0959 (0.123)	0.0761 (0.126)
Female HH (1 = Yes)		-0.2817*** (0.081)	-0.2633*** (0.089)	-0.2659*** (0.087)	-0.2807*** (0.096)
Member of Farmers' Association (1 = Yes)		0.1373*** (0.053)	0.1432** (0.058)	0.1424** (0.057)	0.1502** (0.061)
Access to Credit (1 = Yes)		-0.0610 (0.048)	-0.0816 (0.055)	-0.0787 (0.053)	-0.0777 (0.054)
Average precipitation in the past year		0.0116 (0.012)	0.0188 (0.013)	0.0178 (0.013)	0.0075 (0.012)
Average maximum temperature in the past year		-0.0204 (0.014)	-0.0054 (0.015)	-0.0075 (0.015)	-0.0218 (0.015)
Control Function (v)					-1.1435** (0.412)
Observations	974	974	974	974	974
Method	OLS	OLS	2SLS	Opt-IV	CF
Dept Controls	Yes	Yes	Yes	Yes	Yes
Effective F			5.38	44.43	
Montiel-Pflueger: 5% Bias Critical value			25.94	37.42	
Montiel-Pflueger: 10% Bias Critical value			15.11	23.11	
Robust reg. endogeneity Test (<i>p</i> -value)			0.0002	0.0003	
Cluster (village) standard errors in parentheses					
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$					

Notes — Response variable is (log) Kilograms of livestock per hectare. Two-step optimal IV (Opt-IV) and control function (CF) regression estimates report cluster bootstrapped standard errors. (a) Regression included the variable and its square, and the table reports the full average partial effect.

Table 1A.13 Heterogeneous effect of introduced pastures on cattle yield by complementary management practice.

VARIABLES	(1)	(2)
Pasture	0.1590 (0.108)	1.2665*** (0.320)
Pasture + Weed control	0.4305*** (0.111)	1.5464*** (0.308)
Pasture + Fertilization	0.6998** (0.323)	1.8771*** (0.495)
Pasture + Weed control + Fertilization	0.5695* (0.319)	1.6374*** (0.431)
Control function (ν)		-1.2055*** (0.316)
Observations	994	994
Method	OLS	CF
Dept Controls	Yes	Yes
Other Controls	Yes	Yes
Cluster (village) standard errors in parentheses		
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Notes — Response variable is (log) Kilograms of livestock per hectare. Control function (CF) regression estimates report cluster bootstrapped standard errors.

Table 1A.14 Ordered Logit regression and marginal effects on the number of pasture management practices

VARIABLES	(1) Coeff.	(2) Pr($k=0$)	(3) Pr($k=1$)	(4) Pr($k=2$)
Log-Area of the farm	-0.0907 (0.080)	0.0106 (0.009)	-0.0043 (0.004)	-0.0063 (0.006)
Education of HH (Primary)	0.5952* (0.330)	-0.0681* (0.037)	0.0278* (0.016)	0.0403* (0.022)
Education of HH (Secondary)	0.6495* (0.368)	-0.0778* (0.045)	0.0268* (0.015)	0.0510 (0.033)
Education of HH (Tertiary)	1.4901** (0.580)	-0.1667*** (0.060)	0.0167 (0.022)	0.1499* (0.077)
Female HH (1 = Yes)	-0.0114 (0.323)	0.0013 (0.038)	-0.0005 (0.015)	-0.0008 (0.022)
Member of Farmers' Association (1 = Yes)	0.5211*** (0.196)	-0.0582*** (0.022)	0.0172** (0.007)	0.0410** (0.017)
Access to Credit (1 = Yes)	0.3469* (0.198)	-0.0392* (0.021)	0.0130** (0.006)	0.0263 (0.016)
Household Assets Index	0.0559 (0.041)	-0.0066 (0.005)	0.0026 (0.002)	0.0039 (0.003)
Farm Assets Index	0.1078* (0.056)	-0.0126* (0.006)	0.0051* (0.003)	0.0075* (0.004)
λ_1	-1.0937** (0.528)			
λ_2	3.0112*** (0.521)			
Dept Controls	Yes	Yes	Yes	Yes
Observations	947	947	947	947
Cluster (village) standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Notes — The response variable is the number of pasture management practices used on the farm. Column 1 reports the coefficient estimates from Ordered Logit regression. Columns 2-4 report the average marginal effects of covariates on the probability of adopting k pasture management practices. Estimation is restricted to farms with a non-zero level of introduced pasture adoption. Coefficients λ_k are the estimates of cut-off points that partition the predicted values on the extent of adoption.

Table 1A.15 Heterogeneous effect of introduced pastures on livestock-related revenues by complementary management practice.

VARIABLES	(1)	(2)
Pasture	0.0950 (0.182)	2.1057*** (0.715)
Pasture + Weed control	0.6784*** (0.223)	2.6836*** (0.710)
Pasture + Fertilization	0.1532 (0.592)	2.2690** (0.992)
Pasture + Weed control + Fertilization	-0.1944 (0.479)	1.7292** (0.834)
Control function (ν)		-2.1822*** (0.717)
Observations	786	786
Method	OLS	CF
Dept Controls	Yes	Yes
Other Controls	Yes	Yes
Cluster (village) standard errors in parentheses		
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Notes — Response variable is (log) Revenue from livestock-related sales per hectare. Control function (CF) regression estimates report cluster bootstrapped standard errors.

CHAPTER 2

SWEATING BULLETS: HEAT, HIGH-STAKES EVALUATIONS, AND THE ROLE OF INCENTIVES

2.1 Introduction

Although climate change effects are widely studied with a focus on the long run and on monetary measurements of its impacts (Carleton & Hsiang, 2016; Lenton et al., 2023), temperature and environmental changes are becoming increasingly evident in the short run. Hence, analyses that properly measure how harsher weather conditions currently affect diverse social and economic dimensions become of the highest priority (Carleton et al., 2022; Dell, Jones, & Olken, 2014; Hsiang & Kopp, 2018). Human capital accumulation has recently become a central topic in this regard (Garg, Jagnani, & Taraz, 2020; Park, Behrer, & Goodman, 2021; Park, Goodman, Hurwitz, & Smith, 2020). Nevertheless, most of these findings focus on cases of temperate or subtropical weather such as the United States or China, where temperature shocks can be highly seasonal, and thus have a higher relevance if they occur specifically during the period in which students are being evaluated. The case of teenagers and young adults in hot tropical countries, where exposure to increasingly high temperatures throughout the year is becoming the rule instead of a more frequent seasonal event, remains poorly explored.

What are the impacts of long-term exposure to increasing temperatures on students' performance in high-stakes evaluations? How does a hotter environment affect the cost of exerting effort in these high-stakes tests? Using a model of human capital accumulation with temperature stress, we derive three main testable hypotheses: (1) increases in heat exposures negatively affect human capital accumulation, (2) positive shocks to expected income favor the accumulation of human capital, and (3) exerting effort is costly when experiencing hotter temperatures. Combining five years of information from a national semi-annual high school exit exam in Colombia (Saber 11) and daily weather station data on temperature and precipitation, we use fixed-effects estimation to measure the effect of temperature on exam scores. Also, we exploit a large-scale scholarship program (i.e., *Ser Pilo Paga*, henceforth SPP) as a source of exogenous variation in the stakes of the exam,

allowing us to set up a quasi-experimental design to test whether temperature increases make it costly to exert effort in preparation for a high-stakes exam.

We find that temperature increases have significant effects on Saber 11 scores, especially for students in urban areas. Our estimates suggest that a 1°C increase in the average daily maximum temperature experienced in the year before the exam reduces scores by at least 2% of a standard deviation. Relative to days with temperatures between 20-25°C, each additional day of exposure to temperatures between 30-35°C causes a Math score reduction of 0.05% of a standard deviation, while an additional day over 35°C reduces this score by 0.11% of a standard deviation. Slightly lower effects are found for Spanish and total scores. Interestingly, we find that higher temperatures slightly *improve* students' performance in rural areas. Leveraging detailed time-use data, we provide suggestive evidence that higher temperatures lead to an increase in the time spent by youths on activities complementary to studying. We also find that temperature increases lead to a reallocation in the time spent by adults on off-farm labor, an activity that is more human-capital intensive.

Combining variation in temperatures and in the exam stakes resulting from SPP, we find that for each additional percentage point of exposure to the program, average Math scores increase between 3.03% and 6.12% of a standard deviation, with no noticeable effects on Spanish scores. Among students in urban areas, increases in SPP exposure imply lower Math score gains for each additional increase in the average maximum temperature experienced in the year before the exam. Putting these effects into perspective, our results suggest that an interquartile change in the exposure to SPP leads to an 11.9% increase in absolute terms in the impact of temperature on exam performance. Therefore, our findings suggest that the additional effort exerted by students as a response to the program led to a stronger negative effect of temperature on scores.

While this subject is still an emerging literature, and most studies focus on the short-term effects of temperature shocks (e.g., those occurring the day of the exam or the week before it) on score performance, some well-defined patterns are worth highlighting. Graff-Zivin, Hsiang, and Neidell (2018) uses same-day weather variation to measure the effect of temperature in the performance of reading and Math tasks in the National Longitudinal Survey of the Young - 1979

cohort, with evidence suggesting that only “high-complexity” tasks like Math are affected by these shocks. Similar results for low-stakes examinations were found for China in Zhang, Chen, and Zhang (2024).

In the context of high-stakes examinations in Korea, Cho (2017) also finds a significant effect of same-day temperature shock on Math scores but not on reading. Higher temperatures during the day of the exam have also been found to decrease exam scores in China (Graff-Zivin, Song, Tang, & Zhang, 2020), the United States (Park, 2022), and at the world level based on PISA tests (Park et al., 2021). In the context of South America, Li and Patel (2021) find for Brazil that the effects of higher temperatures on high-stakes exam scores may not be substantive. Conversely, Hoffmann, Pulido, and Vera-Cossio (2023) finds that exposure to high temperatures in Colombia during the week before a Saber 11 test day negatively affects scores; on average, an additional hour of exposition to temperatures above 32°C reduces total scores by 0.11% of a standard deviation. To our knowledge, only the works in Park et al. (2020), for the United States, and Garg et al. (2020), for India, exploit the temperature in the year before the exam as potentially affecting final scores, finding that days above 30°C can reduce scores by 0.05% and 0.3% of a standard deviation compared to days with temperatures between 15-17°C, respectively.

Our contribution is, hence, threefold. First, we contribute to the literature on the effects of heat on high-stakes exam performance showing that longer-term exposure to increasing temperatures has negative significant effects, thus suggesting that heat affects not only exam performance but also human capital accumulation (Garg et al., 2020; Graff-Zivin et al., 2018; Park et al., 2021). Second, we study the effect of temperature on students’ scores in a tropical country, where the range of variation of temperature is particularly narrow and, therefore, the adaptation strategies available to students may differ (Helo Sarmiento, 2023). Understanding these dynamics is of the utmost importance for countries for which, as in the case of Colombia, the use of adaptation strategies like air conditioning is severely low (under 5% of buildings (Statista Research Department, 2023)). Third, and more importantly, using an exogenous shock to the stakes of the exam, we provide quasi-experimental evidence revealing that exerting effort becomes increasingly costly as individuals

are exposed to increasing temperature levels and, therefore, provide evidence of an adaptation mechanism elusive so far in the literature (Burke et al., 2016). Moreover, we provide correlational evidence of a mechanism of opportunity costs that supports both the predictions of our theoretical model and our causal analysis.

The remainder of our paper proceeds as follows. In Section 2.2, we set up a theoretical model revealing the structural relationship between exposure to heat and the accumulation of human capital and the role of incentives in this relationship. Then, in Section 2.3, we briefly discuss *Ser Pilo Paga*, its relevance for our analysis, and we summarize our data. Section 2.4 presents our identification strategies in detail. We present and discuss our main results and robustness checks in Section 2.5. We conclude with Section 2.6, where we also provide directions for future research.

2.2 Theoretical Framework

We start by setting a static model where human capital accumulation is sensitive to temperature stress. We have two goals with our model. First, we want to show how changes in the incentives to exert effort may interact with temperature and, as a result, affect the accumulation of human capital. Second, we use the framework to provide an interpretation of the effects being recovered by our empirical analysis and the mechanisms through which they take place¹

We begin by defining a human capital production function h that follows:

$$h = zf(e, t), \tag{2.1}$$

where z is the individual's cognitive skill or ability, e is their effort level, t is the temperature, and f is a function assumed to be increasing in effort ($f_e > 0$), decreasing in temperature ($f_t < 0$), and with negative second and cross derivatives ($f_{ee} < 0$, $f_{tt} < 0$, and $f_{et} < 0$). Individuals take temperature and their cognitive skills as given, with the latter being potentially affected by exogenous parental investments not included in our model. Conversely, their effort is chosen endogenously to solve a maximization problem (described below). In our empirical analysis, we proxy human capital with

¹We closely follow Park (2022), although we have two main differences with his model: (a) we add cognitive skills, which are not only important determinants of academic performance but also useful for interpretations in the presence of heterogeneous effects by socioeconomic status; and (b), given our focus on the incentives to accumulate human capital and their interaction with temperature stress, we derive comparative statics not only for temperature but also for the returns to human capital.

students' performance in the Colombian high-school exit exam to be described below.

Individuals derive instant utility according to $U(c, g(e, t))$, which depends positively on the consumption of a composite good c , whose price we normalize to one, and negatively on the effective effort g . The latter is a function increasing in all of its arguments ($g_e > 0, g_t > 0$), and with positive second and cross derivatives ($g_{ee} > 0, g_{tt} > 0$, and $g_{et} > 0$). This last assumption is consistent with the medical literature suggesting that effort is more physically taxing at higher temperatures (Wendt, Van Loon, & Marken Lichtenbelt, 2007).

Given that there is only one period, individuals consume all their labor income (i.e., there are no savings). Assuming no unemployment and that wages w are determined in a perfectly competitive labor market, we can write the individual's problem as follows:

$$\max_{c,e} U(c, g(e, t)) \quad \text{s.t.} \quad wh = c, \quad (2.2)$$

where the restriction corresponds to the standard budget constraint. The latter means that the agent chooses its consumption and effort levels to maximize utility subject to its labor income. Plugging equation (2.1) in the above problem, we can derive the first-order condition

$$w \frac{\partial U}{\partial h} \frac{\partial h}{\partial e^*} = w z \frac{\partial U}{\partial f} \frac{\partial f}{\partial e^*} = - \frac{\partial U}{\partial g} \frac{\partial g}{\partial e^*},$$

which states that, at the optimum, the agent equalizes the marginal benefit of effort (increase in disposable income) to its marginal cost (increase in disutility).

Setting up our analysis with specific functions f , g , and U , we can derive closed-form solutions for the optimal levels of effort and human capital. In particular, we assume the following:

$$f(e, t) = \frac{e^\alpha}{t^\beta}, \quad 0 < \alpha < 1, \quad \beta > 0;$$

$$g(e, t) = e^\gamma t^\zeta, \quad \gamma > 1, \quad 0 < \zeta < 1;$$

$$U(c, g(e, t)) = c - g(e, t) = wzf(e, t) - g(e, t).$$

All of these functional forms satisfy the assumptions above. The stated restrictions ensure the objective function in (2.2) is well-behaved (first- and second-order conditions hold).² Solving the maximization problem, it is straightforward to show that the optimal level of effort takes the

²One of the key assumptions required for the objective function to be concave in the effort is that $\gamma > \alpha$, this is, the disutility cost of effort increases faster than its effect on human capital (see Appendix 2A).

following form:

$$e^* = \left(\frac{\alpha w z}{\gamma t^{\beta+\zeta}} \right)^{\frac{1}{\gamma-\alpha}}. \quad (2.3)$$

From this expression is clear that effort is increasing in wages and cognitive skills, while it decreases with temperature. The first two results are standard in the economics literature (see, for example, Chadi, De Pinto, and Schultze (2019)). The third one is consistent with recent empirical evidence, including our empirical work with time-use data below, suggesting that temperature affects the time allocated to working and studying (Alberto, Jiao, & Zhang, 2021; Graff-Zivin & Neidell, 2014).

Plugging the expression for the optimal effort in the human capital production function and linearizing, we can get an equation akin to what is usually estimated in the empirical literature, including our analysis below.³ Concretely,

$$\begin{aligned} \hat{h} = & \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \hat{t} + \left[\frac{\alpha}{\gamma - \alpha} \right] \hat{w} + \left[\frac{\gamma}{\gamma - \alpha} \right] \hat{z} \\ & + \frac{1}{2} \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \left[\frac{\alpha}{\gamma - \alpha} \right] \hat{t}\hat{w} + \frac{1}{2} \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \left[\frac{\gamma}{\gamma - \alpha} \right] \hat{t}\hat{z} + R, \end{aligned} \quad (2.4)$$

where $\hat{x}$ is the percent deviation of x with respect to the population (or historical) mean and R is a residual term composed, among others, of the second-order own effects of each of the variables.⁴

As can be seen, a positive deviation in cognitive skills or wages is expected to increase human capital. Conversely, higher-than-average temperatures are expected to decrease it. As in Park (2022), the effect of temperature operates through two channels: a direct effect summarized by the (structural) elasticity of human capital to temperature (β) and an indirect one operating through endogenous changes in effort resulting from temperature increases, namely $\alpha(\beta + \zeta)/(\gamma - \alpha)$. In most empirical setups, individuals' efforts are unobserved or poorly measured. Nevertheless, to identify this effect in (2.4) all we require is a shock to (expected) wages, namely $\hat{w}$, which in our empirical application corresponds to a policy intervention to be explained in the following section.

Given our interest in the interaction between incentives and changes in temperature stress, our expression for optimal human capital includes the cross-effect of wages and temperature. Now,

³The non-linearized expression for human capital and the full mathematical derivation of the optimization problem can be found in Appendix 2A.

⁴By writing the variables in deviations we account for controls such as geography or time fixed-effects, which are usual in empirical work, including ours.

notice that in our model an increase in expected wages incentivizes individuals' efforts, which is expected to increase the accumulation of human capital (first-order effect). However, exerting effort also exposes individuals to the effects of temperature and associated reductions in human capital (interaction effect). This last quantity is precisely what is captured by the fourth term in (2.4), which is indeed negative. As we will show in our empirical analysis, we find evidence in favor of this prediction.

Another effect of interest corresponds to the interaction between cognitive ability and temperature (fifth term in (2.4)). Our framework implies that this interaction should be negative as long as individuals' cognitive skills incentivize the investment in human capital. This is, given that individuals from better socioeconomic backgrounds end up exerting more effort, they are further exposed to temperature stress. We provide suggestive empirical evidence in favor of this implication.

2.3 Background and Data

2.3.1 Policy intervention: Ser Pilo Paga

In 2014, the Colombian Ministry of Education launched the *Ser Pilo Paga* program ("Being a Good Student Pays Off") to promote access to higher education. SPP was a scholarship initiative that provided financial support to high-achieving students from low-income backgrounds, enabling them to attend top universities in the country. The program covered the total cost of tuition to attend a four-year (or five-year) degree-granting program at any high-quality university in Colombia. The program provided individual funding to about 40,000 students, with 10,000 new students chosen each year from Colombia's top decile of the population in the high-school exit exam (Bernal & Penney, 2019; Londoño-Vélez, Rodríguez, & Sánchez, 2020; Londoño-Vélez, Rodríguez, Sánchez, & Álvarez-Arango, 2023; Medina et al., 2018).

Given the program's objectives, applicants had to meet two criteria based on merit and need to be eligible. First, they must score at or above the 90th percentile on the national standardized high-school exit test (Saber 11). Second, they must come from disadvantaged households, defined as those below the median of the wealth distribution in Colombia according to their SISBEN score, the socioeconomic index used by the Colombian Government to target social programs. Finally, to

receive the award, students needed to secure admission to a high-quality accredited university in the country.⁵

There is now abundant literature evaluating the SPP program and its effects on access to higher education, graduation, learning, and wages in the short-and the medium-run (Bernal & Penney, 2019; Laajaj, Moya, & Sánchez, 2022; Londoño-Vélez, 2022; Londoño-Vélez et al., 2020, 2023). For instance, SPP increased the likelihood of immediate access to higher education among eligible students by eliminating the gap in access by socioeconomic strata among the top performers in the Saber 11 (Londoño-Vélez et al., 2020). Relatedly, Bernal and Penney (2019) and Laajaj et al. (2022) argue that SPP increased effort as measured by improvements in the test scores of students with higher exposures to the program. On the negative side, other studies highlight that SPP allowed the concentration of resources in private universities, the financial weakening of public universities, and the reproduction of regional and social inequalities (Mora & Ruiz, 2019).

Instead of evaluating the effects of SPP on students' performance in the Saber 11 test, which others have already done (Bernal & Penney, 2019; Laajaj et al., 2022), we ask the following question: Did the increased effort resulting from SPP lead to a larger effect of temperature on students' test scores? This question speaks to two broad and important topics in the education and climate change literature. First, our results provide evidence of the interaction between environmental factors and education policies, in our case, a large and generous scholarship program. Second, we show that temperature stress increases the cost of effort and, therefore, that further increases in temperature from climate change may end up reducing effort levels in equilibrium. To the best of our knowledge, we are the first to provide causal evidence on this adaptation behavior.

2.3.2 Data

Our outcome of interest is the students' results in the Colombian high school exit exam known as Saber 11. This test has been mandatory since 1980 (compliance rate is around 97%) and is designed to support universities and all other higher education institutions in their admission processes.

⁵As defined by the Operating Regulations of SPP by the Colombian Ministry of Education, in a case in which the number of eligible students exceeds the funds allotted to the program, priority would be given to those with the lowest SISBEN scores.

Saber 11 is administered semiannually on mostly fixed dates⁶ (usually in March and August) by the Colombian Institute for the Evaluation of Education (ICFES). Because of methodological changes in the test that limit the comparability of the scores across time, we use the information from the period between 2014 (August) to 2019 (March), with each calendar year having information on several hundreds of thousands of students. Since Saber 11 serves as a comprehensive evaluation of knowledge and competencies acquired in school, we take it as a proxy variable of human capital accumulation.

For weather, we use station-level data on daily maximum temperatures and total precipitation from the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM)—the national official meteorological data. This information has been available since 1970, but we restrict our analysis to the period 2013-2019. In total, we use temperature data from 143 weather stations located all over the country. Following Auffhammer and Kellogg (2011), we impute missing daily observations with those from the five nearest weather stations with non-missing data. We assign to each Municipality the data for the nearest weather station with information for the full period, which allows us to address endogeneity in the temporal coverage and quality of the data (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). Matching the weather stations to the Municipalities has the additional advantage of making it clear the source of variation of the weather variables in the analysis, something that is less straightforward in reanalysis or gridded data (Dell et al., 2014).⁷ Figure 2B.1 in Appendix 2B shows the location of the weather stations used in our analysis, including those used in the imputation procedure only.⁸

As will be clear below, our empirical results point to important differences between students in urban and rural areas. To explore the mechanisms behind these findings, we use information on

⁶Although the dates of the test change from year to year, each of the two annual tests occurs on a single day, within the same time frame.

⁷In Table 2B.4 in the Appendix 2B, we show that our results are robust to dropping from the sample Municipalities matched to weather stations farther than 25-kilometer or that relied more heavily on the imputation procedure.

⁸The correlation between the temperature variable in our main analysis and the ones obtained using Copernicus' ERA5 is 0.74. We confirmed that our point estimates based on IDEAM data were within the 95% confidence intervals for baseline estimates using ERA5. Nonetheless, estimates using weather-station data revealed higher precision, hence, we chose them as the preferred data source for the entire analysis.

time use from the Colombian Longitudinal Survey (ELCA), available for 2010, 2013, and 2016.⁹ In particular, we employ information for youths between 10 and 16 years of age in urban and rural areas, available in the last two waves of the survey. The question for the youth asks how much time they spent on activities such as watching TV, reading, or doing homework on a typical weekday, with the answer options being categorical (nothing, less than one hour, between 1 and 2 hours, etc.).

To consider potential mechanisms driven by rural non-farm employment, we also consider time-use data on the household heads and their spouses in rural areas from the three waves of ELCA. In this case, the question asks for the exact time (hours and minutes) spent on activities such as working on farms owned by the household, working for other households, or doing household chores, with the reference period being a typical weekday in the week before the survey. In all our analyses, we focus on a repeated cross-sectional approach to keep consistency with our main results using students' scores.¹⁰

Figures 2.1 and 2.2 show the average daily maximum temperature for the period 1981-2010, which is a measure of climate (Dell et al., 2014), and the average standardized Saber 11 score in Math for the exams between 2014-II and 2019-I, respectively. Three results stand out: Firstly, there are high cross-sectional variations in the maximum temperature across counties, with an important number having temperatures as low as 12°C and some as high as 32°C. Secondly, the results for the Math section of the Saber 11 test also show substantial spatial variation. And thirdly, as also evidenced in Figure 2.3, there is a remarkable correlation between temperatures and test scores, with most high-performing counties concentrated in the relatively colder parts of the country.

We present the descriptive statistics of the data for our analysis in Table 2.1.¹¹ Each specific

⁹ELCA data come from a probabilistic, stratified, multistage, and clustered sample, with information on 10,800 households (6,000 in urban areas and 4,800 in rural areas). The urban sample is representative of low- and middle-income households at the national level and for five regions (Bogota, Central, Eastern, Atlantic, and Pacific). The rural sample is representative of small farmers in four micro-regions (Mid-Atlantic, Coffee growing region, *Cundiboyacense* Plateau, and Center-East).

¹⁰The data on time use in the ELCA have been used previously in the economics literature. In particular, Fernández, Ibáñez, and Peña (2014) study how the Colombian armed conflict affects time-use patterns among rural households using the first wave of the ELCA.

¹¹The descriptive statistics for ELCA data are available in Appendix 2B, Table 2B.8.

area evaluated by Saber 11 allows for a score between 0 and 100,¹² while the total score (as defined by ICFES) will be between 0 and 500. On average, students in urban areas consistently outscore those in rural areas by 4.8, 4.4, and 22.9 points in Math, Spanish, and total scores, respectively.¹³ Based on the test theoretical standard deviations for each area (10 points) and the total score (50 points), these amount to a difference roughly equivalent to 50% of a standard deviation. Most of the evaluated students (55%) are female, while 6% are reported as part of an ethnic minority. In terms of the education of the student's mother, 29% have completed only primary education, while 33% and 23% have completed their studies in secondary and postsecondary education, respectively.

Consistent with the climate normal in Figure 2.1, the average daily maximum temperature experienced at the Municipalities in the calendar year before the exam date was 26.6°C, while the median was at 27.8°C. These are close to the measures of maximum temperature on the days when the exam occurred, which have a mean of 26.87 and a median of 28 degrees Celsius. In terms of temperature experienced by weather bins, on average, municipalities experienced 6 days with maximum temperatures of 15°C or below, while the number of days with temperatures over 35°C was 30.7. There is a considerable level of exposition to heat at the Municipality level, with an average of 115.2 days experiencing peak temperatures between 30 and 35°C. In addition, the average daily precipitation during the calendar year before the exam date was 5.52 millimeters per day, while it was 4.66 millimeters during the exam days. Finally, in terms of plausibly exogenous policy shocks, there were between 8 and 9 beneficiaries of the first round of SPP per Municipality, although 50 percent of these Municipalities only experienced up to two beneficiaries.

¹²Saber 11 includes five areas of evaluation: Math, Spanish, natural sciences, social competencies, and English (as a foreign language). We limit our main analysis to Math and Spanish (i.e., reading) since these areas are the most widely studied in the literature, thus allowing for a direct comparison of effects relative to the ones in previous work.

¹³We classify a municipality as urban if the share of the population in the urban area was above the national average for most of the years during 2004-2013.

2.4 Methods

2.4.1 Identification strategy

To study the average effect of heat on students' test scores, we follow a linear unobserved effects model:

$$100 \times y_{ijct} = \beta_T T_{ct} + \beta_P P_{ct} + X_{ijct} \theta + a_j + a_{st} + u_{ijct}, \quad (2.5)$$

where y_{ijct} is the standardized score in Math (or Spanish, or total) in the Saber 11 test for student i in school j and Municipality c at time t (semester in our case). Here X_{ijct} is a vector of student characteristics (e.g., age and gender), while a_j and a_{st} are fixed effects that capture unobserved heterogeneities at the school and State-time levels, and e_{ijct} is a set of idiosyncratic shocks that affect students performance in the test. The variable of interest is T_{ct} , which is the average daily maximum temperature (in °C) experienced during the year before the test date. As an additional control, we include P_{ct} , which measures the precipitation level in the same period as T_{ct} . With this variable, we aim to control for disruptions in learning caused by above-average rain levels. The coefficient of interest is β_T , which measures the effect on the student's scores of experiencing an increase in temperature. Specifically, a 1°C increase from the school average would change scores by $\beta_T\%$ of a standard deviation. We follow a fixed effects framework, thus allowing for arbitrary dependence between the unobserved effects (a_j, a_{st}) and the observed explanatory variables (Wooldridge, 2010). Given that our temperature variable varies at the weather-station level, following the recommendations in Angrist and Pischke (2008), MacKinnon, Nielsen, and Webb (2022), and Abadie, Athey, Imbens, and Wooldridge (2023), we cluster our standard errors at that level to allow for arbitrary correlation between schools (and students) within the area covered by the station.

The identification assumption behind equation (2.5) is that conditional on students' demographic characteristics and school and State-time fixed effects, experiencing a hotter calendar year before the test is not systematically correlated with other determinants of the student's scores (Angrist & Pischke, 2008). In other words, temperatures are as good as random conditional on the controls (Dell et al., 2014). Following Hsiang (2016), we implement a series of measures to rule out several

threats to the identification: First, we control for precipitations to account for other potentially correlated geophysical processes. Second, we compute temperature and precipitation using a constant group of weather stations, which rules out any correlation between our weather data and time-varying socioeconomic conditions. Third, we provide evidence suggesting that temperature does not seem to have any noticeable effects on our sample composition (see next subsection).

Following Hsiang (2016), we also estimate the following flexible specification using our daily weather data:

$$100 \times y_{ijct} = \sum_{k=1}^K \beta_{T,k} DD_{ct}^k + \beta_P P_{ct} + X_{ijct} \theta + a_j + a_{st} + u_{ijct}, \quad (2.6)$$

where DD_{ct}^k is the number of days in the period of interest where the maximum temperature in °C was in the interval k . When estimating this specification, we use the following temperature intervals: [minimum, 15), [15, 20), [20, 25), [25, 30), [30, 35), and [35, maximum). The baseline category throughout the analysis is the number of days between 20 and 25°C; thus, $\beta_{T,k}$ measures the effect of being exposed to one additional day with a maximum temperature in the k th bin with respect to the omitted category.

One of the main goals of this paper is to investigate how changes in the incentives to achieve higher scores in the Saber 11 interact with higher temperatures. For that, we evaluate how the effect of heat varies for students exposed to SPP. In particular, we estimate the following specification

$$100 \times y_{ijct} = \beta_T T_{ct} + \beta_{T,SPP} (T_{ct} \times SPP_c \times Post_t) + \beta_{SPP} (SPP_c \times Post_t) + \beta_P P_{ct} + X_{ijct} \theta + a_j + a_{st} + u_{ijct}, \quad (2.7)$$

where SPP_c is the share of test-takers in Municipality c that were awarded SPP in the first wave of the program, and $Post_t$ corresponds to a dummy for the post-SPP years. Notice then the interaction between SPP_c and $Post_t$ captures the exposure to SPP originated only by the first cohort of winners, which were selected based on pre-determined household characteristics (SISBEN wealth index) and realized performance in the test at the moment of the program's announcement. The coefficient of interest is $\beta_{T,SPP}$, which corresponds to the differential effect of temperature for students with higher exposures to SPP.¹⁴ From our conceptual framework, we expect this coefficient to be negative

¹⁴Notice that any average differences in students' scores associated with SPP_c are already captured by the school

as it maps directly to the fourth term of equation (2.4).

In addition to the identifying assumption for the temperature's effect previously discussed, equation (2.7) requires that the evolution in the students' scores for different levels of exposure to SPP would have been the same in the counterfactual without the program, this is, that there are parallel trends for the groups defined in terms of SPP_c (Angrist & Pischke, 2008). As we already mentioned, we compute this exposure variable using only the first cohort of the program, which ensures we do not capture endogenous responses in the number of winners. Now, to explore the possibility that the SPP's exposure is capturing the impact of other policies or social programs, the next subsection provides evidence on pre-trends for several dimensions arguably relevant to students' performance in the test.

2.4.2 Testing for identification assumptions

In our analysis, we attempt to exploit two sources of exogenous variation, namely the variations in Municipality-level temperature and the exposure to SPP. Thus, we need to evaluate whether (a) the weather correlates with attributes from students,¹⁵ and (b) the shock from SPP has some correlation with pre-intervention attributes at the Municipality level. For the first one, we set up a linear model:

$$X_{ijct} = \eta_T T_{ct} + \eta_P P_{ct} + a_j + a_{st} + u_{ijct},$$

from which we would expect that fixed-effect estimates for η_T and η_P are statistical zeroes. In other words, we are checking if weather shocks are directly connected to attributes of individuals that can also affect their performance in the test. We estimate this specification for six attributes: age, female student, dummies of mother's educational attainment—primary, secondary, or postsecondary-, and whether the student is from an ethnic minority. Our results suggest that there is no evidence of any statistically significant correlation between weather shocks (either from temperature or precipitation) with students' attributes (see Appendix 2B, Table 2B.1). Moreover, the estimated coefficients are very close to zero, further providing support for using these weather shocks as

fixed effects (a_j). Similarly, the post-SPP indicator ($Post_t$) is captured by the State-time fixed effects (a_{st}).

¹⁵A large literature in economics has relied on the assumption that temperature is exogenous conditional of unit and time fixed effects (see Dell et al. (2014) and Hsiang (2016)). For the sake of completeness, we provide evidence in favor of it in our context.

exogenous variations directly affecting students' learning and performance.

We now consider the implicit assumption of parallel trends underlying our empirical strategy of using the announcement of SPP. The assumption of parallel trends is theoretically untestable and the practice of pretesting has recently faced considerable scrutiny (Roth, 2022). Nonetheless, results from pretesting can provide relevant information on potential pre-treatment differences that can be empirically considered to still achieve meaningful difference-in-difference estimates (Bilinski & Hatfield, 2018). Following the literature on the economics of education, we focus on school characteristics that have been thought to be important in explaining students' performance.¹⁶ Given that these variables are also potentially endogenous to policy changes, controlling for them allows us to account for the possibility that SPP assignment rules can turn other social programs into confounders. Therefore, we proceed to analyze any potential differences in pre-trends at the Municipality level based on the exposure to SPP, using pre-treatment information available from the Municipality panel data from the Center of Studies on Economic Development (CEDE) of Universidad de los Andes (Colombia).

With yearly information for the 2010-2019 period on six key variables (i.e., number of schools, population of high-school age, the number of high-school students, total Saber 11 test takers, total educational administrative personnel, and the total number of teachers), we follow an event-study approach. We regress each of these variables on a saturated model where we interact all year dummies (except 2014, the base year of our analysis) with the exposure to SPP in the first round. Figure 2B.2 of Appendix 2B summarizes the point estimates and 95% confidence intervals. We find evidence of a potential violation of the parallel trends assumption at the Municipality level on variables like the total number of teachers and total high-school students. Meanwhile, there is a weakly significant pre-trend correlation between larger exposures to SPP and the number of Saber 11 takers in Municipalities.¹⁷

¹⁶As discussed in Hanushek (2006) and Handel and Hanushek (2022), the effect of school resources on students' test scores seems to be modest at best. However, recent papers have found evidence of positive effects for specific inputs such as teachers (Chetty, Friedman, & Rockoff, 2014a, 2014b) or even school resources when using exogenous variation for identification (Jackson, Johnson, & Persico, 2016).

¹⁷Notice that finding pre-trends in these Municipality characteristics does not necessarily imply that the same is happening with students' scores, the outcome of interest in our empirical analysis. As mentioned earlier, the literature

Pretesting at the student level comes with a challenge in data comparability for Saber 11 scores available before 2014. In order to consolidate Colombia's National Standardized Evaluation System (SNEE by its acronym in Spanish), ICFES introduced a significant adjustment of the Saber 11 test, changing it from a per-subject evaluation to an assessment of generic competencies. For instance, the pre-2014 Math scores reflect a standardized outcome on a math-only set of questions, while the Math scores from 2014 and later years reflect competency in both math and quantitative reasoning questions (ICFES, 2019). Likewise, pre-2014 Spanish scores reflect outcomes on language-only questions, while subsequent years' Spanish scores reflect competency in critical reading (including language and philosophy).¹⁸ This difference is also acknowledged in other studies relying on Saber 11 data, including those of Laajaj et al. (2022), Londoño-Vélez et al. (2020), and Posso, Saravia, and Uribe (2023). In this sense, while score comparability pre- and post-2014 is unfeasible, we can use data from 2010-2013 to evaluate whether there is evidence of potential pre-trends. We find statistically significant deviations in Math and Spanish scores for the case of rural areas, but no systematic patterns or sizable effects in either urban or rural areas that could threaten the validity of our analysis (Appendix 2B, Figure 2B.3).

To further test our identification assumptions, we follow Pei, Pischke, and Schwandt (2019) and take students' comparable attributes to assess whether potential violations of a parallel trends assumption may occur at the individual level, based on exposure to SPP. Our event-study estimates suggest that there are no pre-treatment differences in key variables such as eligibility for SPP by SISBEN category, whether the student is currently working, reported monthly family income, and number of people living at the student's dwelling (Appendix 2B, Figure 2B.4). Moreover, we find that there are no statistically significant changes in the after-treatment period, except for eligibility based on SPP. Therefore, these results provide evidence in favor of our approach, which focuses on exposure to the first (unannounced) wave of SPP, since the following waves of the program may

finds weak effects of school resources on students' performance (Handel & Hanushek, 2022; Hanushek, 2006).

¹⁸This also extends to other areas like physics, chemistry, and biology, which reported separate subject-specific scores before 2014, but were combined into a single competence (and score) in Natural Science afterwards. Furthermore, in addition to the change in the evaluation structure, pre-2014 tests included two additional tests in the same time window: an in-depth test and an interdisciplinary test. Therefore, there is a high likelihood that the time allocation in effort will differ, which will exacerbate the issue of non-comparable scores between periods.

have been influenced by a systematic and strategic behavior of students requesting an evaluation from local authorities to be included in SISBEN (Londoño-Vélez et al., 2020).

Nonetheless, following our findings on Municipality-level variation, we follow an approach in the style of Bilinski and Hatfield (2018), acknowledging the potential differences in pre-trends and setting “one step up” specifications for our main regressions. This is, we further consider specifications that allow for heterogeneous trends based on Municipality-level differences as measured in 2014, and confirm whether there are significant differences between estimates from this more complex specification to those of simple fixed-effects estimates. Controlling for trends along these dimensions, we expect that our estimates will account for other factors or policies that may affect the evolution of students’ scores with different exposures to SPP, thus strengthening our causal interpretation.

2.5 Results and Discussion

2.5.1 Temperature and test scores

We present the results from our baseline regression on weather shocks during the year before the exam date in Figure 2.4 (with all regression summaries’ in Appendix 2B, Table 2B.2). When focusing on the estimates for the total population, evidence points to insignificant correlations between observed scores and increases in the average daily maximum temperature and average precipitation in the year before the Saber 11 exam. The direction of the coefficient estimates is similar in Math, Spanish, or total scores, but there are important differences in estimations when comparing urban and rural areas,¹⁹ despite observing similar levels of exposure to temperature levels between these kinds of Municipalities.²⁰

While exposure to a 1°C increase in the average maximum temperature reduces the average Math score by 2.89% of a standard deviation for urban students, the coefficient estimate is positive for rural students. Similarly, while the same temperature increase has no statistically significant

¹⁹For reference, we further report the estimates of our baseline specification for the remaining subjects that are evaluated in Saber 11, namely Natural Sciences, Social Sciences, and English as a Second Language (Appendix 2B, Figure 2B.5). These estimates align with our main analysis, especially in the stark differences between urban and rural settings.

²⁰See Appendix 2B Figure 2B.6.

effect on Spanish scores for rural students, it reduces urban students' scores by 2.28% of a standard deviation. In terms of total scores, each additional one-degree increase decreases the result of urban students by 2.51% of standard deviation, but it is connected to an *increase* of 1.43% of a standard deviation in rural settings. On the other hand, each additional 1 mm/day in precipitation leads to a reduction of 0.85% and 0.65% of a standard deviation in Math and overall scores, respectively, for urban students. We do not detect any significant effect from precipitation in rural areas.²¹ Based on the projected temperature increases for Colombia over the century, which under RCP 4.5 are 1.5-2.5 °C by mid-century (Alarcón Hincapié & Pabón Caicedo, 2013), the estimated coefficients from this baseline specification are of economic significance.²²

As evidenced by the results Figure 2.5 (Appendix 2B, Table 2B.5), year-long weather effect estimates are robust to the addition of weather exposure during the day of the exam, suggesting that our estimates capture the effects on learning—thus in human capital accumulation—and not only a worsening on performance during the test. Again, we find no significant shocks at the national level, but marked differences persist between urban and rural areas. For urban students, our calculations still suggest a reduction in scores (-2.7%, -2.11%, and -2.58% of a standard deviation, respectively, in Math, Spanish, and total) from a 1°C increase in the average maximum temperature over the previous year, and an additional millimeter of average daily precipitation still points to a statistically significant reduction of scores (-0.89% and -0.63% of a standard deviation in Math and total scores, respectively). Although numerically different, these estimates are statistically equivalent to those of our baseline estimates. Additional specifications including only the effect of test-day weather (Appendix 2B, Table 2B.6) provide estimates of similar magnitudes and directions to those from Figure 2.5 (Appendix 2B, Table 2B.5).²³

Next, we study the effects of exposure (by number of days) across different temperature bins

²¹Our findings are robust to stringent clustering, even when allowing for unrestricted correlation between observations within clusters of weather stations (Appendix 2B, Table 2B.3).

²²Furthermore, our estimates are arguably conservative, given that world-level emissions remain at tracking levels of RCP 8.5 (Field, Barros, & Intergovernmental Panel on Climate Change, 2014).

²³In addition, in Appendix 2B, Figure 2B.7, we test the robustness of the year-long AMT effect but instead using the average maximum temperature during the week before the exam, which does not change our inference or implications about the prevalence of longer-term exposure to increasing temperatures.

over the calendar year before the exam in Figure 2.6 (Appendix 2B, Table 2B.7). For urban areas' students, on average, and relative to maximum temperatures between 20 and 25°C, one additional day exposed to temperatures between 30 and 35°C implies a reduction of 0.055% of a standard deviation in Math, and reductions of 0.066% and 0.047% of a standard deviation in Spanish and overall scores. Likewise, one additional day exposed to temperatures above 35°C negatively affects scores, implying reductions amounting to 0.11%, 0.095%, and 0.099% of standard deviations in Math, Spanish, and total scores, respectively. Interestingly, it turns out that our point estimates for the total score fall between 0.05% of a standard deviation in the United States (Park et al., 2020) and 0.25-0.3% of a standard deviation in India (Garg et al., 2020) for each additional day with temperatures above 30°C.²⁴

Overall, our findings—specifically those for students in urban areas—provide results in line with those in the literature. Nevertheless, these results highlight an important empirical difference between studies in this line depending on the weather variable used in the analysis. For example, studies like Graff-Zivin et al. (2020), Graff-Zivin et al. (2018), and Park (2022) focus their attention on the exposure of test takers to high temperatures during exam days. Meanwhile, our findings are more in line with those like Park et al. (2020) and Garg et al. (2020), who analyze the effects of exposure to high temperatures on test scores focusing on long-run (e.g., past-year) measures of exposure.

In line with the literature, we further consider a specification that allows for differences in the effect of increasing temperatures conditional on the long-run historical average maximum temperature experienced at the Municipality level. We present the key results in Figure 2.7, again revealing a marked difference between urban and rural settings. We find that increasing temperatures have a significant effect on the scores of urban students in Municipalities with long-run temperatures under 28°C. Moreover, our results suggest that the negative effects of increasing temperatures are of larger magnitudes among students in colder Municipalities. Conversely, we do

²⁴In addition, following Helo Sarmiento (2023), we test for the robustness of these effects setting up a narrower variation, with bins increasing by 2°C (Appendix 2B, Figure 2B.8), and pooling exposures to days below 17°C and above 27°. We find quantitatively equivalent results, although weakly significant.

not detect any statistically significant effects for relatively high-heat Municipalities (above 28°C). All these results go in line with recent evidence highlighting the differentiated effect of increasing temperatures on cognitive performance between relatively cold and hot areas (Krebs, 2024), and point to adaptation playing a role in this setting (Barreca, Clay, Deschenes, Greenstone, & Shapiro, 2016; Burke et al., 2016).

Effects of extreme temperature events on the same day of (or week leading to) high-stakes exams are nonetheless relevant to evidence the need for investments in adaptation strategies (e.g., change of exam timing in the season). However, our findings, when taken together with Garg et al. (2020), suggest that developing countries with mostly hot tropical weather are more profoundly affected in an increasingly warming world. Countries like Colombia and India, where the adoption of air conditioning remains under 5% of buildings (Statista Research Department, 2023; Sung, 2022), and that will potentially experience disproportionately harsher climatic conditions (Lenton et al., 2023), are bound to experience considerable losses in human capital unless bold policy interventions take place.

Conversely, our estimates for past-year temperature effects on the performance of students in rural areas suggest that different mechanisms might play a significant role. For instance, there is a high incidence of child labor in rural Colombia, which is estimated up to 20% for children of ages between 15-17 by 2017 (Ramoni-Perazzi, Orlandoni-Merli, Castillo-Paredes, & Peña Guillén, 2021). Hence, increases in average temperatures could be connected to adjustments in time allocations that could—in theory, following Alberto et al. (2021) and Graff-Zivin and Neidell (2014)—lead these rural students to allocate more time to study, since they would likely dedicate more time to indoors activities.²⁵ Below, we provide suggestive evidence in favor of this explanation. While the estimates from Hoffmann et al. (2023) for short-term weather exposure to temperature are qualitatively similar to our estimates of exposure to exam-day weather shocks,²⁶ our findings

²⁵Another related explanation is that as higher temperatures decrease agricultural productivity in Colombia (Melo León et al., 2024), this could potentially lead to a reduction in the opportunity cost of studying (see Shah and Steinberg (2021) for related evidence from India).

²⁶Point estimates from Hoffmann et al. (2023), however, are statistically different from zero for total scores, unlike ours (see Appendix 2B, Table 2B.6), that suggests the presence of an impact from heat only on the performance in Math for urban students. It should be noted, however, that our results are not directly comparable to theirs, given that

support our main hypothesis: increases in heat lead to exposures that negatively affect the learning process and ultimately affect students' performance in high-stakes evaluations.

2.5.1.1 Temperature and time use

From our analysis so far, it follows that the effect of temperature on students' performance in Saber 11 varies markedly between urban and rural areas—negative for the former and slightly positive for the latter. Here we attempt to uncover the mechanisms behind these heterogeneous effects. In particular, we argue that temperature increases may incentivize students in rural areas to spend more time in activities complementary to studying, with the underlying force being a reallocation of labor towards off-farm labor where the returns to human capital are potentially larger (Agrawal & Agrawal, 2019; Jolliffe, 2004). Rural non-farm employment accounts for over 50% of rural households in Asia and Latin America, and it has been identified to work as a response from these households to external shocks on production (Davis, Winters, Reardon, & Stamoulis, 2009; Haggblade, Hazell, & Reardon, 2007; Reardon, Stamoulis, & Pingali, 2007). Hence, increases in temperature would potentially push for a reduction of time allocated to on-farm labor, and instead transitioning into rural non-farm employment. Moreover, evidence from Africa and Asia suggests that as food production and processing tasks become further laborious or comparatively less efficient, there is an additional push on spouses to allocate more time in rural non-farm (or even urban) jobs (Reardon et al., 2019).

To test these hypotheses, we use data from ELCA to estimate specifications that follow:

$$y_{ict} = \beta_T T_{ct} + \beta_P P_{ct} + X_{ict}\theta + a_c + a_m + u_{ict},$$

where y_{ict} is a time-use indicator for individual i in Municipality c at period t , X_{ict} is a vector of individual characteristics (age and gender), a_i and a_m are Municipality and month-by-year fixed-effects, respectively, and e_{ict} is a set of unobservables that affect time-use patterns. We estimate the above expression with two subsamples: First, we employ data for youths 10 to 16 years of age in the last two waves of the ELCA. For them, we know how much time they spend on activities

we focus on the period 2014-2019 to ensure test scores are fully comparable given changes in the test methodology as discussed previously. Meanwhile, Hoffmann et al. (2023) use data for the period 2009-2019 instead.

such as watching TV or reading for fun on a typical weekday.²⁷ Given that these variables are reported in bins, we construct indicators equal to one if the youth spends one hour or more on each of the activities of interest. Second, we use data from the household heads and their spouses for all the years in the survey. In this case, we have information about the time (hours and minutes) spent on activities such as working on farms owned by the household, working on other households' farms in agricultural and non-agricultural activities (off-farm labor), and doing housework. With this information, we can compute the share of time each household member spends on different activities.

As before, we are interested in the effect of temperature on the outcome y_{ict} , which here corresponds to time-use indicators. Given the reference period of the time-use variables (typical weekday in the week before the survey), we recompute our temperature variable (T_{ct}) for each household to be the average daily maximum temperature in the reference week excluding weekends.²⁸ For consistency, we also recompute our precipitation variable (P_{ct}) to match this reference period. Hence, the identification assumption in the current setup is that temperature is as good as random conditional on the controls (Dell et al., 2014), and thus, we include Municipality and month-by-year fixed effects in the specification above. Given that the time-use indicators correspond to flows, we match the timing of our weather variables to that of the time-use variables. In the appendix, however, we show that our results are qualitatively similar when we compute T_{ct} and P_{ct} for the year before the survey (see Appendix 2B, Tables 2B.9 and 2B.10).

Table 2.2 shows the results using information for the youths, reporting separately the cases of rural and urban samples in Panels A and B, respectively. As can be seen, we find that a higher temperature leads to a statistically significant increase in the percentage of individuals in rural areas that spend one hour or more reading. We do not find evidence for changes in any of the other activities, such as watching TV, spending time with parents or siblings, or doing homework. Interestingly, we do not find any statistically significant effects for individuals in the

²⁷None of the options corresponds to on-farm or off-farm labor, which means that we are not able to test for changes in labor supply for this population group.

²⁸Notice that the reference week is potentially household-specific. To simplify the notation, the time index t can be thought to correspond to the reference week instead of the semester as in equations (2.5)-(2.7).

urban areas, including reading. Overall, our results suggest that students in rural and urban areas react differently to temperature stress, with the latter increasing the time spent on an activity potentially complementary to studying.

Even though the results so far point to changes in time use consistent with improvements in students' academic performance in rural areas, it is unclear what mechanisms are behind our findings. One possibility is that temperature stress incentivizes off-farm work, which may have higher returns to education overall. To test for this possibility, we estimate the model above with time-use data for adults in rural areas. We report the results for this exercise in Table 2.3, with panel A having the estimates for the household heads and panel B for their spouses.²⁹ As can be seen, our results suggest that an increase in temperature leads to a reallocation *towards* off-farm labor. In particular, we find that household heads (spouses) decrease (increase) the time spent working on farms owned by the household (other households) when temperatures are higher. The latter goes in line with findings across Africa and Asia, pointing to exogenous shocks in production and productive efficiency, including temperature, as a push for reallocating from on-farm labor out to non-farm activities (Colmer, 2021; Haggblade et al., 2007; Reardon et al., 2019). In summary, we interpret these findings as suggestive of a shift in labor allocation in favor of activities potentially more intensive in human capital for rural settings.³⁰

2.5.2 Incentives and temperature stress

Following our conceptual framework, exerting effort is costly as it exposes individuals to the effects of increasing temperatures. We use the exposure to SPP as an exogenous shock that increases expected wages, thus leading to potential increases in test scores, but with negative interaction effects with temperature.

In table 2.4, we summarize our estimates for equation (2.7). Besides a few small changes in point estimates related to precipitation, estimates of the first-order effects from the average

²⁹We estimate different models for these two groups given the stark differences in the activities each of them seems to engage in, as reported in ELCA data (Appendix 2B Table 2B.8).

³⁰Further disaggregation at quarterly-specific temperature effects aligns with our working hypothesis (Appendix 2B, Table 2B.11). With the largest share of students taking Saber 11 in August of every year, positive and statistically significant effects are found in the first and second quarters (September-February), which are coincidentally those of the main agricultural season of Colombia.

maximum temperature in the year before the exam remain statistically equivalent to those of our baseline specifications (Appendix 2B, Tables 2B.2 and 2B.5). Meanwhile, the first-order effects of SPP are consistently positive across all scores, yet only statistically different from zero for Math (all populations) and total scores (national level and urban students). On average, an additional 1 percentage point increase in the exposure to SPP at the Municipality level led to an increase of 3.03% of a standard deviation in Math scores across all students. We estimate this effect to be 6.12% and 2.12% of a standard deviation for urban and rural students, respectively. For total scores, we detect an average increase of 1.43% and 3.19% of a standard deviation for all students and urban students, respectively, due to an additional 1 percentage point exposure to SPP.³¹ These coefficients are aligned with the evidence in Bernal and Penney (2019) and Laajaj et al. (2022).

All but one of the estimated interaction effects follow the expected sign from our theoretical model, which is a piece of initial evidence in favor of our hypothesis of unobserved costs of exerting effort in a warming climate. Nonetheless, we only find this effect to be statistically significant in the case of Math scores of urban students, which is precisely where SPP had the strongest effect on performance. On average, when a 1 percentage point increase in exposure to SPP takes place along with a 1°C increase in the average maximum temperature over the year before the Saber 11 test, there is a reduction of 0.108% of a standard deviation in the Math section.³² To put these numbers into perspective, our point estimates in column (2) suggest the temperature effect for students in municipalities with exposures in the 25th and 75th percentiles are -2.267 and -2.537, a 11.9% increase when going from the former to the latter (i.e., an interquartile change).³³

Now, we can interpret the previous results in an alternative way. Notice that the negative coefficient for the interaction between temperature and the exposure to SPP implies that heat

³¹We also find similar results for other subjects evaluated in Saber 11 (Appendix 2B, Table 2B.13), showing again that SPP had a seemingly stronger effect in increasing scores among urban students, but mainly for the areas of Social Science and English as a Second Language. Likewise, the interaction between SPP and increasing temperatures is only significant in the case of urban areas but is now centered on Social Science scores.

³²Based on the findings of Graff-Zivin et al. (2018), effects from heat shocks are more likely to be of larger magnitudes in Math tests, as thermal insults primarily affect the performance of brain functions for tasks that are more complex than the average—which is arguably the case of Math vis-à-vis other fields in standardized evaluations.

³³This number can be calculated as $[-0.108 \times (2.5 - 0)] / [-2.267] = 11.9\%$, where 2.5 and 0 are the 75th and 25th percentiles of SPP exposure, respectively.

reduced the effect on test scores of being exposed to the program. Using the descriptive statistics in Table 2.1 and the estimated coefficients in Table 2.4, it follows that increasing the temperature in a Municipality by a standard deviation reduces the effect of being exposed to SPP on Math scores by around 10.9%. Our estimates, then, suggest that the effectiveness of social and educational programs may be compromised by environmental factors such as temperature and, therefore, that climate change can have important consequences for the design and implementation of educational policy.

As discussed in the previous section, our estimation includes interactions of yearly dummies with the Municipality-level dummies of quartiles of (a) the population of high-school age in the municipality, (b) the total administrative personnel, and (c) the total number of teachers, at 2014 values (our available pre-treatment period). We evaluate the robustness of our findings by comparing this “one step up” fixed effects estimation (Bilinski & Hatfield, 2018), with a standard fixed-effects estimation excluding said interactions. Estimates from usual fixed-effects estimation are statistically equivalent, although slightly less precise, under this alternate specification (see Appendix 2B, Table 2B.12), thus providing evidence in favor of our overall empirical strategy.³⁴

2.5.2.1 SPP targeted population as a source of heterogeneity

Based on the results above, and following our discussion about SPP, it is important to explore whether these interaction effects between temperature and incentives on effort vary across specific populations. While the previous findings indicate that SPP had larger direct and second-order (interaction) effects among urban students, we now focus our attention on who among those urban students was more largely impacted by the increased exposure to changes in temperature. Based on the eligibility criteria, we explore two main heterogeneities of interest, namely (a) the students’ mothers’ educational attainment, and (b) the reported strata of the house where a student’s family

³⁴We further explored an alternate specification to that of Equation (2.6), which considers how the SPP policy shock affected the effect of being exposed to bins of temperature. We consider a specification such that the coefficients of interest are interactions between exposure to temperature bins and SPP. These would capture how, on average, the exposure to SPP alters the effect of experiencing an additional day with average maximum temperatures in the k -th bin, relative to days with an AMT between 20 and 25°C. We present the estimates of these interactions in Appendix 2B Figure 2B.9, with results mostly in line with our main findings. In brief, evidence suggests the SPP shock seemingly improves the favorable effect of experiencing additional colder days.

lives.³⁵

Parents' educational attainments are well known to be significant determinants of their offspring's own educational achievements and human capital accumulation (Björklund & Salvanes, 2011). It is such gaps that programs like SPP attempt to potentially address, by providing a window of opportunity to those in less favored backgrounds. In this sense, and in line with our conceptual framework, we would predict two stark differences: (a) exposition to SPP should have a larger effect among exam takers whose mothers have lower levels of education—i.e., a more significant change in incentives; and, as a result of this (b) the interaction effects of temperature and SPP exposure should also be larger (in absolute value) for students whose mothers have lower educational levels. To this purpose, we estimate our model in equation (2.7) on two sub-samples of urban exam-takers: those whose mothers have up to primary education, and those with secondary or post-secondary education.³⁶

We summarize this first heterogeneity analysis in Panel A of Table 2.5. As suggested, we observe that there are larger effects from exposure to SPP for exam-takers with mothers that have lower educational attainment. Ultimately, as this effect is connected to a change in incentives, our finding implies that SPP successfully promoted additional effort among those from less favored backgrounds. Likewise, we see that most interaction effects between temperature and SPP exposure are of the expected sign, although only two of them are statistically significant: for Math and total scores, for students with mothers that have lower levels of education, as hypothesized. In addition, notice that there are some interesting differences in the effect of temperature increases. While all estimates are of the expected sign, they seem larger for those with better household educational backgrounds—again consistent with our framework. We will return to this in the next subsection for our mechanisms analysis.

Since the enforcement of Colombian Law 142 of 1994, the country has followed a system of so-

³⁵Our focus on urban students is also motivated by the fact that the socioeconomic stratum has more variation in urban settings where population density is higher.

³⁶We also do these estimations for both the overall population and for rural students alone (see Appendix 2B, Tables 2B.14 and 2B.15), but here we focus on urban students following our previous discussion on the potentially differentiated mechanisms at play between urban and rural populations.

cioeconomic stratification that assigns a stratum number from 1 to 6 for a residence, which increases with the quality of the residence. The system is widely used as a proxy income, although it has also been found to serve as a potential source of social discrimination (Bogliacino, Jiménez Lozano, & Reyes, 2018). We implement it in our analysis to separate the sample of exam takers between two groups: those coming from households with potentially less-favored backgrounds (strata 1, 2, and 3) and those of potentially more favorable backgrounds (strata 4, 5, and 6). As seen in Panel B of Table 2.5, we find that exposure to SPP had statistically significant effects among exam takers from potentially less-favored backgrounds, which again follows the line of our conceptual framework. Similarly, we find that the interaction between temperature and exposure to SPP is only significant in the case of Math for students from less-favored backgrounds.

Overall, we observe a consistent result among urban exam-takers. For starters, the effects of temperature and exposure to SPP are systematically larger and statistically significant in Saber 11 Math scores than in other sections. On the one hand, these findings are in line with the literature suggesting that heat insults have larger effects on test performance and knowledge accumulation related to high-complexity tasks, which is arguably the case with Math. On the other hand, given that admissions to high-return post-secondary programs (like STEM or STEM-related fields (Kinsler & Pavan, 2015)) usually give a larger weight to Math scores, the shock on incentives from SPP was expected to have a larger impact on Math scores than in others sections, which is what we find. Finally, this combination of shocks leads to important interaction effects again concentrated in Math, mainly changing the behavior of eligible students.

2.5.2.2 Sex-based heterogeneities

Recent literature on climate change impacts reveals that these are sex-differentiated, including dimensions of well-being (Goh, 2012), health (Navas-Martín et al., 2022), and time allocation in labor (Lee, Haile, Seymour, & Azzarri, 2021), specifically among adults. Hence, as evidence related to sex-differentiated impacts among youths is scarce, we further expand our analysis to explore heterogeneities between male and female students. We summarize our results in Table 2.6. Our results indicate that, at the overall level (Panel A), increases in temperature appear to only have

a statistically significant (and negative) effect on male students' scores. Conversely, increasing exposure to SPP seemingly has a positive and significant effect on female students, whereas its interaction with SPP is not statistically significant in any case. Nonetheless, important differences arise when comparing urban and rural settings, as reported in Panels B and C, respectively. Among urban students, we find that increases in temperature negatively affect most scores of both male and female students. In addition, and consistent with our main specification results from Table 2.4, we detect a significant effect from the exposure to SPP on Math and total scores regardless of the student sex, while there is no apparent effect on Spanish scores. However, our results point to a statistically significant interaction between increasing temperatures and SPP exposure only for female students, suggesting that an effort-adjusting mechanism is more prominent among women.

Finally, when focusing on the case of rural students (Panel C), we find substantial differences between male and female students. First, we note that increasing temperatures have no apparent effects on male exam takers, but there is a positive and statistically significant effect on female students' Math, Spanish, and total scores. Thus, the unexpected positive effect from our baseline analysis seems likely driven by behavioral responses to increases in temperature among young females. However, the effect of increasing exposure levels to SPP is only significant for Math scores of female students, while its interaction with increasing temperatures is statistically zero overall. The stark sex-based differences in the effects of increasing temperatures (and incentives to study) on observed scores warrant future research that addresses the institutional and behavioral mechanisms driving these results.

2.5.2.3 Potential mechanism

Up to this point, we exploit the exogenous shock of SPP since, on average, it is tentatively increasing the expected wages or, equivalently, reducing the opportunity costs of accessing tertiary education (Londoño-Vélez et al., 2020). Consistent with this interpretation, we should expect that temperature increases have a larger effect on those who are likely to have lower opportunity costs for exerting effort. Access and completion of higher education are strongly correlated with a student's mother's educational attainment (Guzman Ruiz et al., 2009) and household income

(Londoño-Vélez et al., 2020). Based on our available information, we can test whether temperature increases have increasingly negative effects on students' outcomes as their mother's educational attainment increases or as the reported stratum of the house is higher, which would be consistent with our theoretical model and empirical results so far.

For the first case, we consider a specification that follows

$$100 \times y_{ijct} = \sum_{k=1}^4 \beta_{EM(k),T} (T_{ct} \times EM_k) + \sum_{k=1}^4 \beta_{EM(k)} EM_k + \beta_P P_{ct} + a_j + a_{st} + u_{ijct},$$

where y_{ijct} is the standardized score of interest, and EM_k is an index variable of whether the student's mother has maximum education attainment at level k . Namely, we have that k goes from 1 to 4, following if the mother has no educational attainment, primary education, secondary education, or postsecondary education. We present our fixed-effect estimates in Table 2.7, taking the no educational attainment cases as the base category (for results including coefficients for dummy variables alone, see Appendix 2B, Table 2B.16).

All estimates are consistent with our rationale. To begin with, the first-order coefficient estimates for the effect of temperature increases on test performance and those of our baseline estimates remain in the same ballpark. Also, on average, when mothers' educational attainments are larger, so are their children's test results—up to 51% of a standard deviation when compared to students whose mothers report no educational attainments. Finally, we find that all estimates of the second-order correlations of temperature increase relative to mothers' schooling are of the expected sign (negative), and all are increasingly negative with said education level. Moreover, this correlation is found across all subjects, at the aggregate level, and in urban and rural settings.

Finally, we also estimate an alternative specification following

$$100 \times y_{ijct} = \sum_{l=1}^6 \beta_{HS(l),T} (T_{ct} \times HS_l) + \sum_{l=1}^6 \beta_{HS(l)} HS_l + \beta_P P_{ct} + a_j + a_{st} + u_{ijct},$$

where HS_l is an index variable of whether the exam-taker dwelling is classified as stratum l , according to the Colombian residential strata system. In Table 2.8, we summarize fixed-effects estimates under this alternate specification, with strata 1 (lowest in the scale of dwelling quality) as the base category.³⁷ In line with all our results so far, we observe that temperature increases

³⁷Also see Appendix 2B, Table 2B.17, for a detailed summary table including coefficients for dummies of each stratum.

have a larger impact on the scores of students coming from potentially more favored backgrounds. For instance, take again the case of Math scores of urban exam-takers. While an increase of 1°C in the average maximum temperature during the year leading to the exam day is connected to a reduction of 2.08% of a standard deviation for those living in a stratum 1 residence, the magnitude will increase by up to 1.38 percentage points—i.e., a rough total effect of 3.45% of a standard deviation—for those in a stratum 6 dwelling.

Ultimately, we see that although the direct effects of heat increases may suggest potentially different dynamics between rural and urban settings, the differentiated effects of increased heat suggest a highly consistent mechanism across all individuals in terms of opportunity cost. For those coming from a less favored background (lower mothers' educational attainment or lower dwelling stratum), the opportunity cost of exerting effort in preparation for an exam like Saber 11 is comparatively high since their baseline expectations to access higher education are low. Conversely, those from more favored backgrounds will perceive a lower opportunity cost for exerting additional effort in studying, leading to a larger exposure to the effects of weather on average. It should be stressed that we do not expect the last two specifications to have a causal interpretation. For that, we would need exogenous variation in the mother's education attainments and residence stratum, which is beyond the scope of this paper. However, our estimates of $\beta_{EM(k),T}$ and $\beta_{HS(l)}$ are informative of the mechanisms behind our findings using the variation created by SPP.

2.5.2.4 Additional robustness checks

A final concern about our policy effect of interest arises from potential differences between SPP-exposed and SPP-unexposed Municipalities. For instance, it could be possible that the effect is largely driven by those Municipalities with the largest shares of beneficiaries. Likewise, it could also be the case that the effect is essentially driven by the absolute difference between untreated Municipalities and those in the intensive margin. We extend our analysis to address these critical points.

Based on the positive skew in the distribution of exposure to SPP across Municipalities (Appendix 2B, Figure 2B.10), we recalculate our estimates for equation (2.7) by systematically ex-

cluding those locations with the top one-, five-, and ten- percent levels of exposure to SPP (see Appendix 2B, Tables 2B.18, 2B.19, and 2B.20, respectively). In all three specifications, we find, yet again, that the largest effect of SPP is found among urban students, especially for the subject of Mathematics, where we also find evidence of effort adjustment as temperatures increase with coefficients statistically equivalent. Furthermore, we find that limiting the sample to those Municipalities with non-zero exposure to SPP does not change our inference (Appendix 2B, Table 2B.21). Finally, we estimate a variation of our main specification treating the exposure to SPP as binary—i.e., approaching an average treatment effect on SPP-exposed Municipalities. We find that this approximation would result in qualitatively similar estimates (Appendix 2B, Table 2B.22) but with much larger effects. Following our discussion so far, we believe this further strengthens our preferred approach, as we base our analysis on more conservative estimates that better consider the differentiated levels of exposure experienced across Municipalities.

2.6 Conclusion

We set up a theoretical model for human capital accumulation that is sensible to exogenous weather shocks, which suggests that heat has an overall negative effect on students' academic performance. Also, our model states that increases in effort should improve academic performance, but at the cost of higher exposure to thermal insults that can—as an interaction effect—reduce the performance of students. We use information from a National high-school exit exam in Colombia (Saber 11) between 2014-2019, precipitation and temperature data at the weather station level, and information on a policy intervention of a scholarship program in 2015 that serves as an exogenous shock to test these hypotheses.

Based on linear unobserved effect models and using fixed-effect regression methods, we demonstrate that 1°C increases in the average maximum temperature during the year before taking a high-stakes exam significantly reduce Math, Spanish, and total scores among students in urban settings. Our findings of negative shocks from increases in average temperature are consistent with the theoretical propositions and empirical results in the literature (Garg et al., 2020; Graff-Zivin et al., 2018; Park et al., 2021, 2020). Nevertheless, we highlight that longer-term exposures (e.g., over

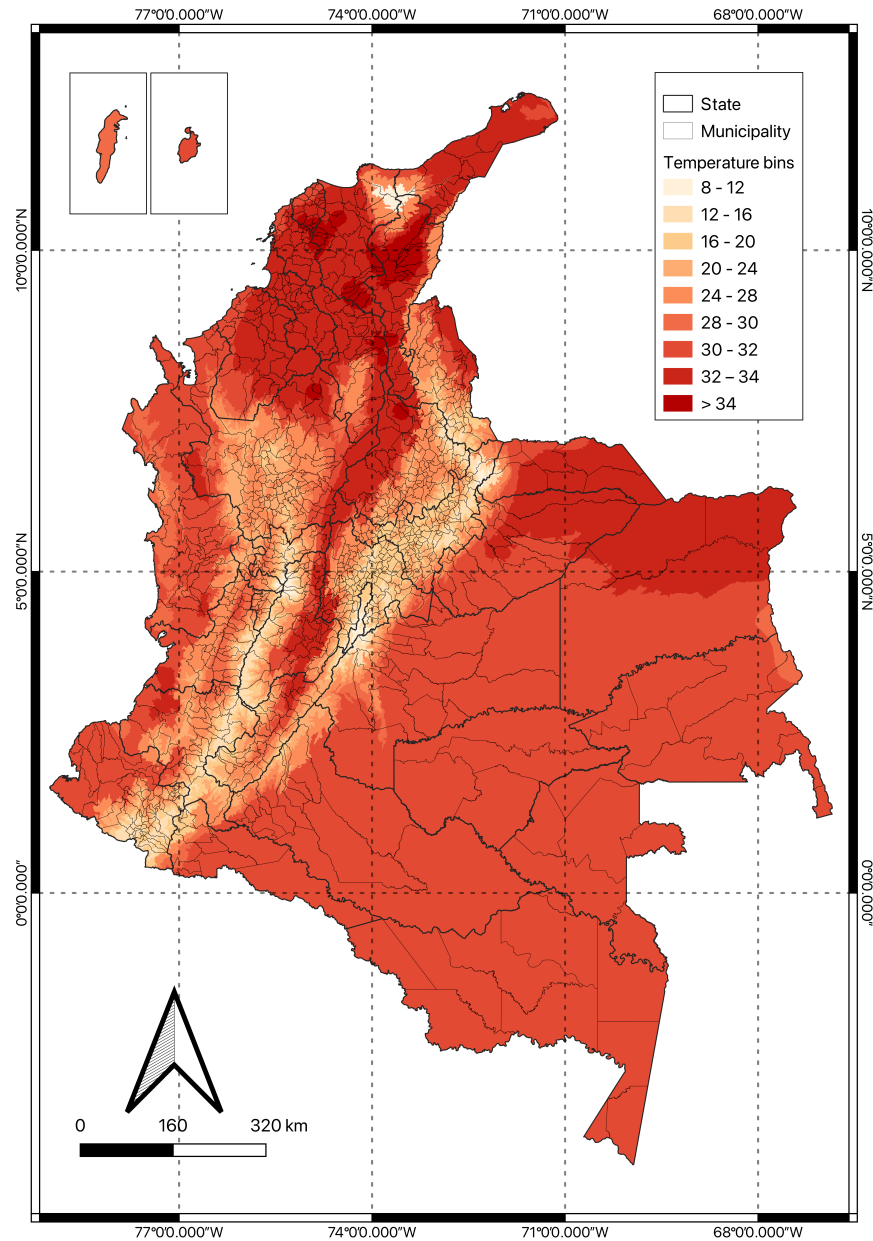
a calendar year) to increasing temperatures, may be of higher relevance than short-term exposures (e.g., exam day or week before the exam) for countries with predominantly tropical weather.

We provide quasi-experimental evidence supporting the hypothesis that exerting effort in high-stakes evaluations is increasingly costly for students as they are further exposed to weather shocks. While government programs like *Ser Pilo Paga* create incentives that increase students' outcomes, the efficacy of these interventions may be compromised under higher temperatures. We also evaluate a potential underlying mechanism supporting these findings, namely from the side of opportunity costs to access tertiary education (and likely expected wages). Students whose mothers achieved greater educational attainments, or who resided in houses of a higher socioeconomic stratum, have better scores in high-stakes exams but exhibit larger negative shocks from exposition to increased temperatures.

Among the limitations of our research, we encounter unexpected results from the effects of increasing temperatures on rural areas—namely, a positive effect in scores. We hypothesize that time reallocation in response to higher temperatures (Alberto et al., 2021; Graff-Zivin & Neidell, 2014) could play an important role in settings where child labor is high. We test this hypothesis with time-use data for youths and their parents in Colombia, finding a reallocation towards activities complementary to study (for youths) and non-farm labor (for household heads and spouses). While these results follow our suggested mechanism, future research should explore these findings in more detail and for other contexts. Furthermore, we encourage research trying to understand the interaction between weather and social policies, which we believe will open the door to a more realistic evaluation of the impacts of climate change.

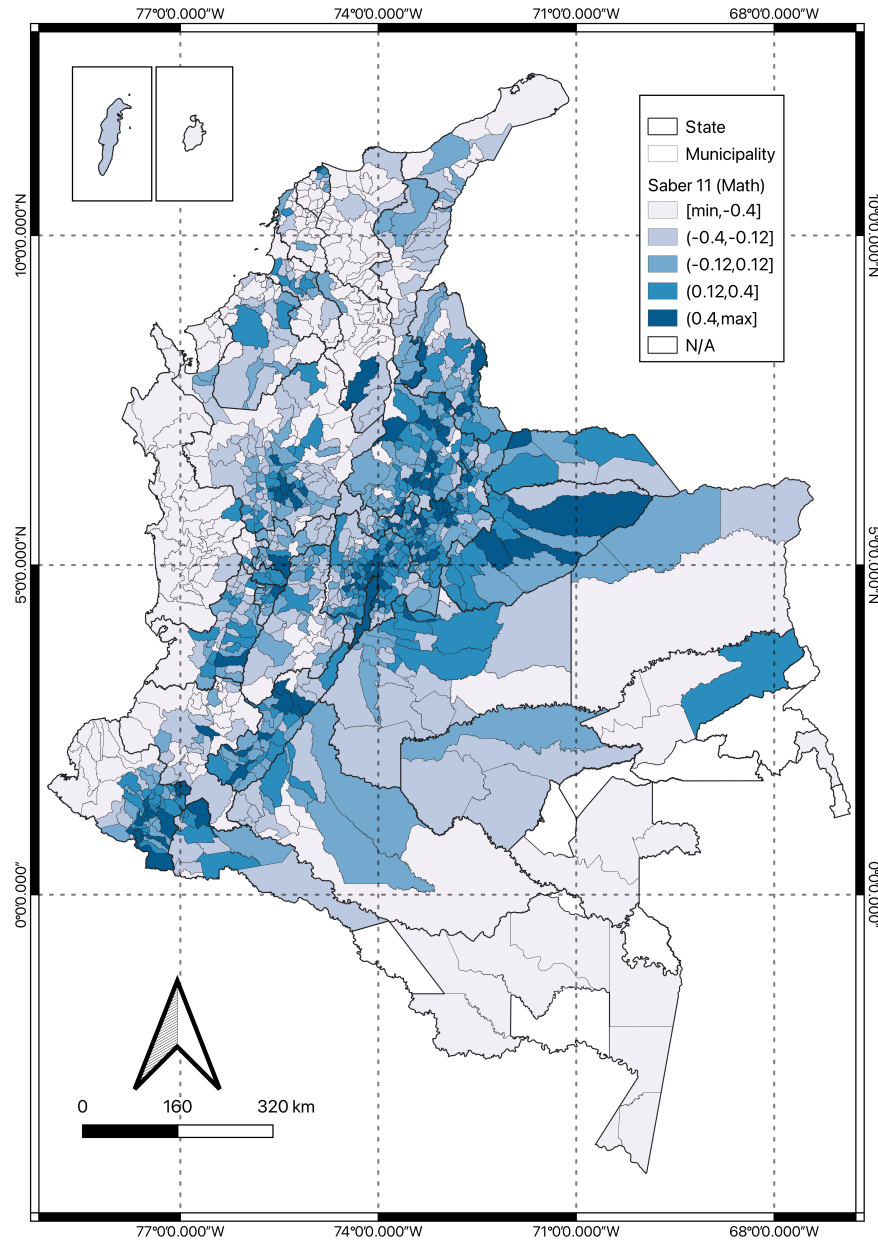
Figures and Tables

Figure 2.1 Municipality-level historical average of daily maximum temperature, 1981–2010.



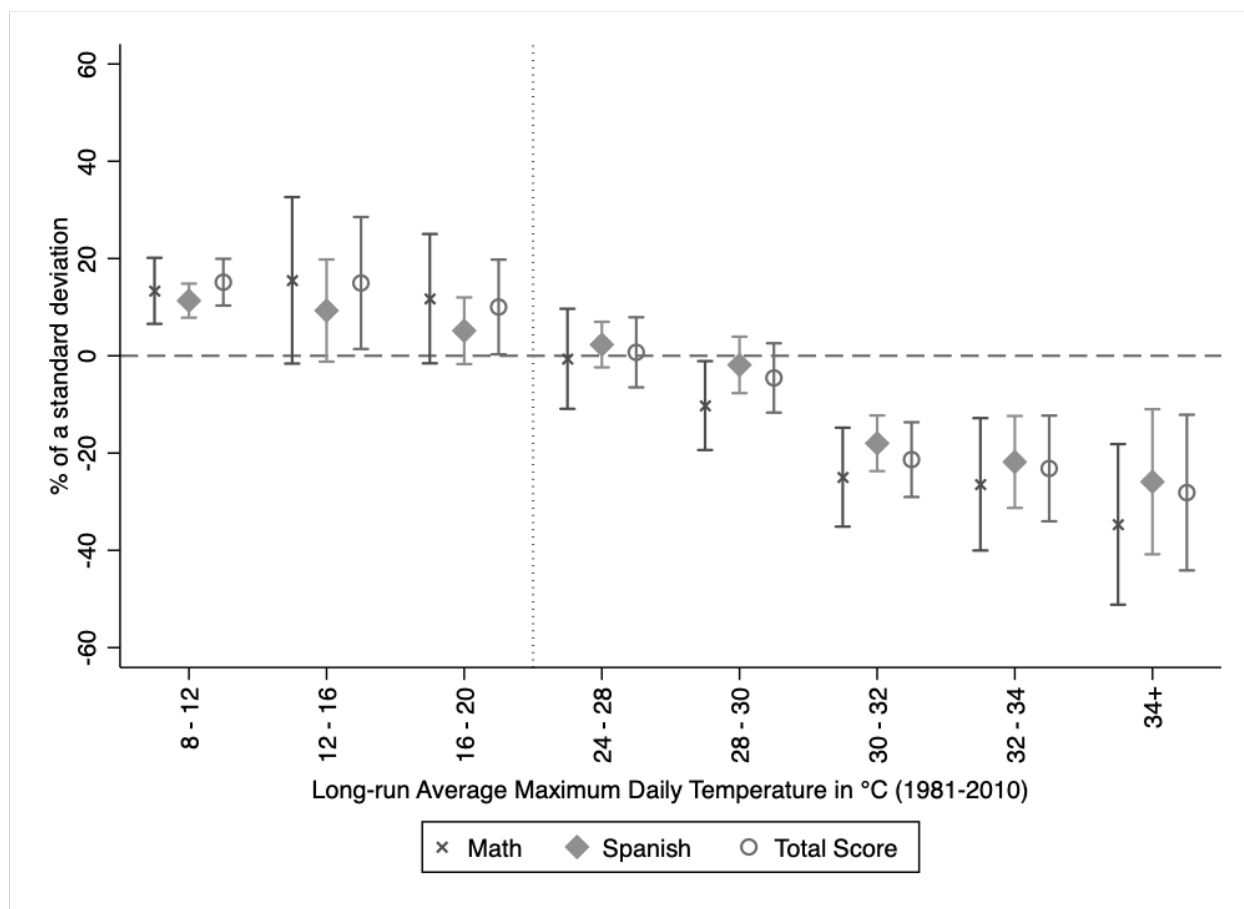
Notes — Figure displays the average of the daily maximum temperature (°C) at the Municipality level for the period 1981–2010 (i.e., climate normal). Raw weather data is publicly available from the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM).

Figure 2.2 Municipality-level average Saber 11 standardized score in Math, 2014-II–2019-I.



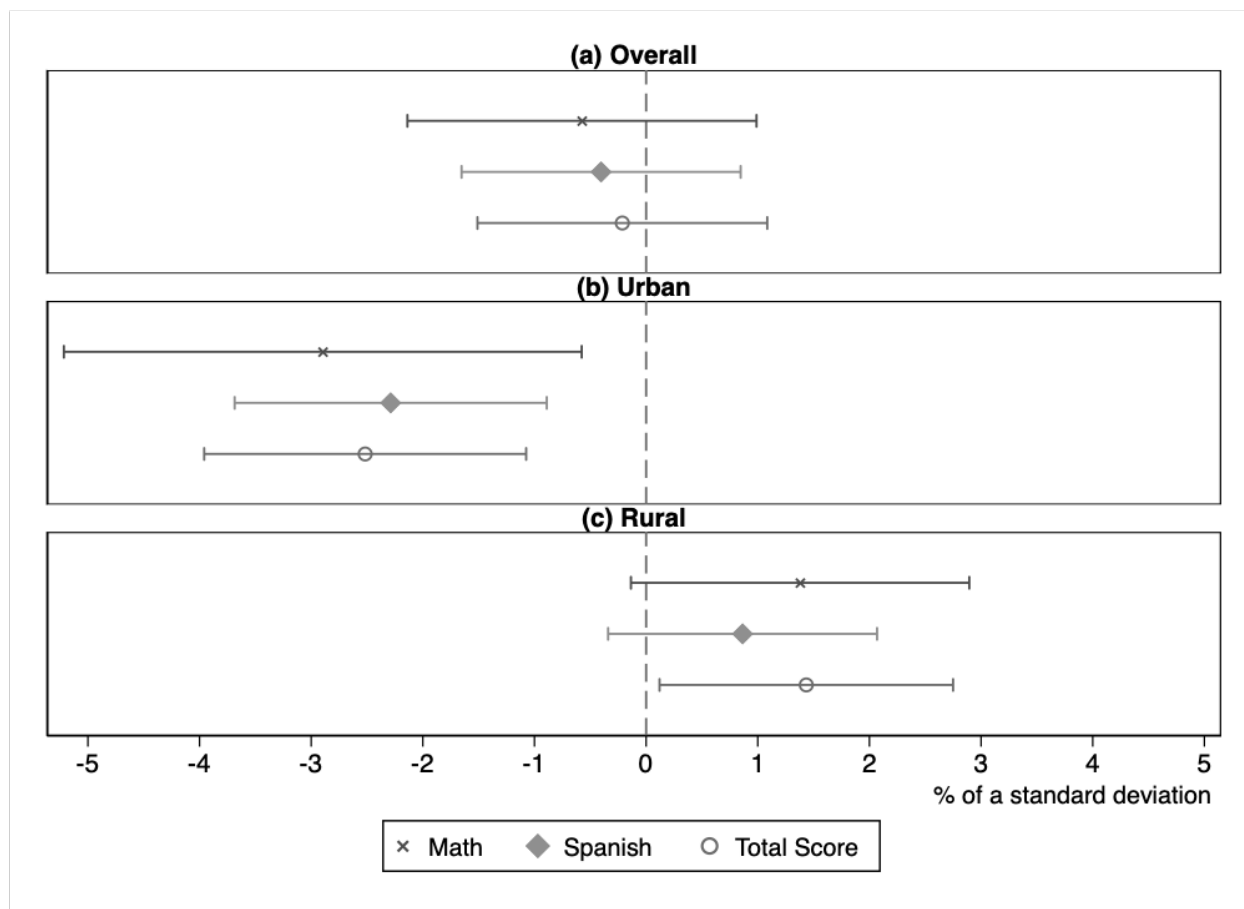
Notes — The figure shows the Municipality-level average standardized Saber 11 score in Math for the tests between 2014-II and 2019-I. Student-level information is publicly available from the Colombian Institute for the Evaluation of Education (ICFES).

Figure 2.3 Correlation of Municipality-level historical average of daily maximum temperature (1981–2010) and Saber 11 standardized scores (2014-II–2019-I).



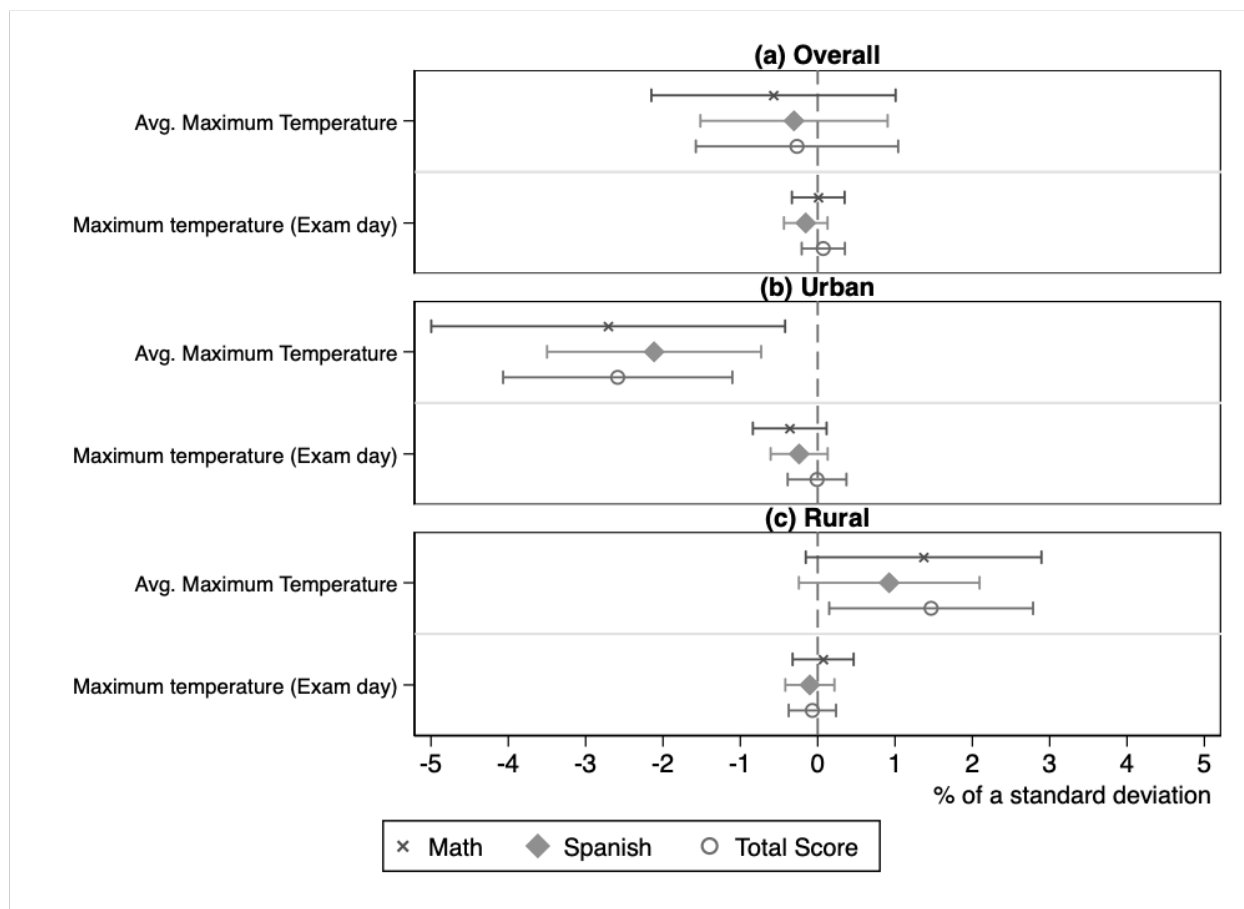
Notes — Reporting Pooled-OLS coefficient estimates (and 95% confidence intervals) for dummy variables of the long-run average maximum temperature (AMT) experienced in the Municipality, captured in temperature bins. The response variable is $100y$, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Estimates capture the difference in scores for Municipalities with a long-run AMT in the bin relative to Municipalities that experienced a long-run AMT between 20 and 24°C. Exam-taker attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2.4 Effect of the past-year average maximum temperature on Saber 11 scores, 2014-II–2019-I.



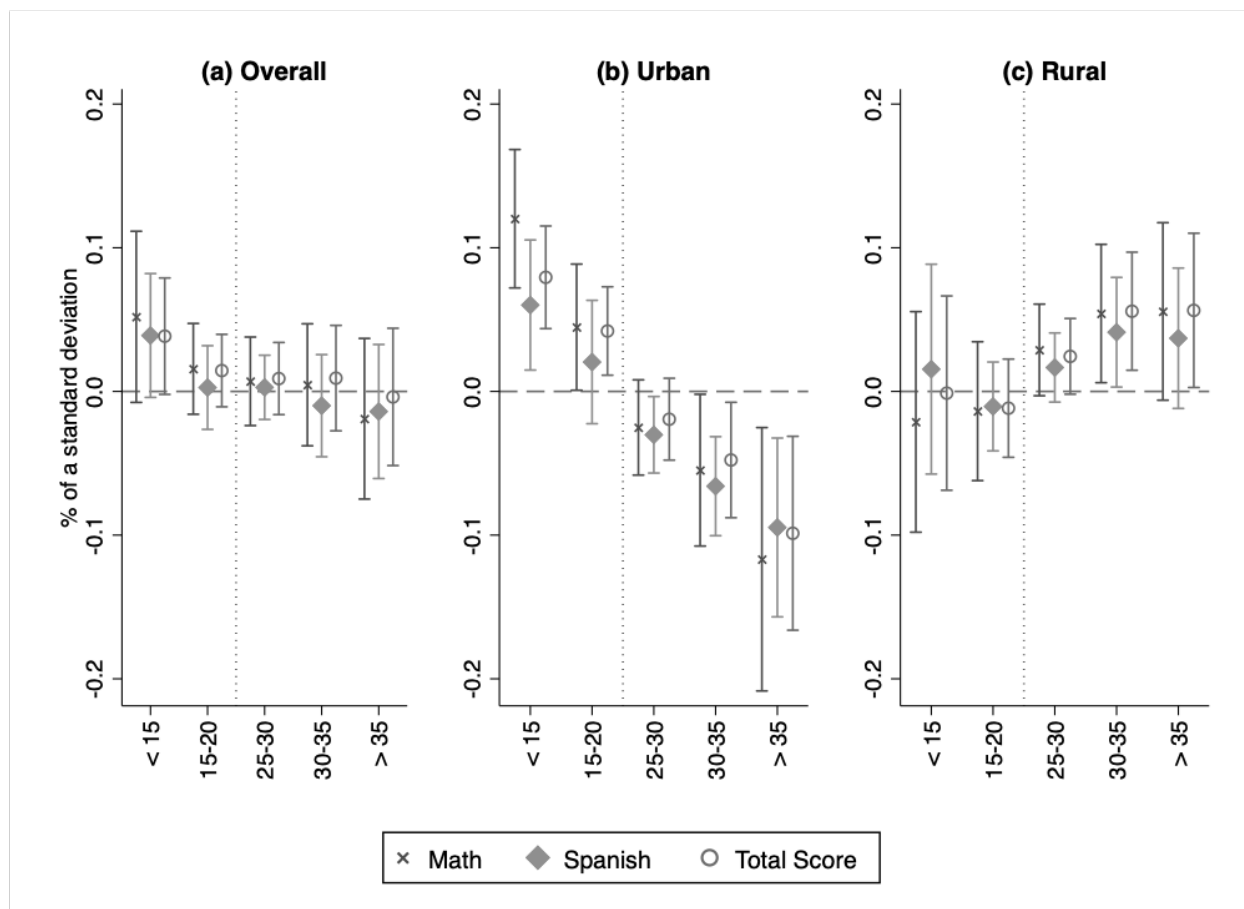
Notes — Reporting Fixed-Effects estimation of the effect (and 95% confidence interval) from a 1°C increase in the average daily maximum temperature at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2.5 Effect of the past-year average maximum and exam date maximum temperatures on Saber 11 scores, 2014-II–2019-I.



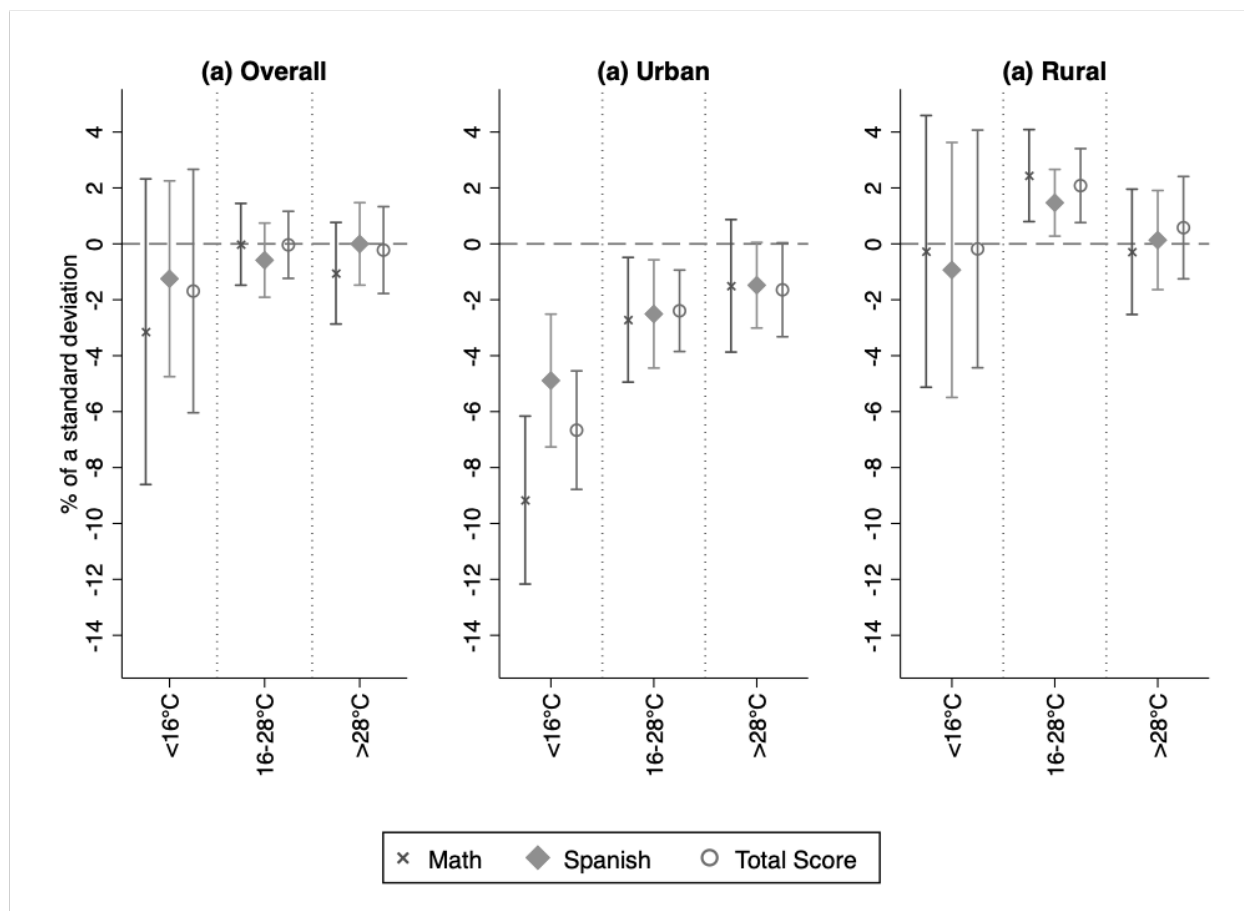
Notes — Reporting Fixed-Effects estimation of the effect (and confidence interval) from 1°C increases in the exam-day maximum temperature and the average daily maximum temperature at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2.6 Effect of the past-year number of days exposure to maximum temperatures on Saber 11 scores, 2014-II–2019-I.



Notes — Reporting Fixed-Effects estimation of the effect (and confidence interval) from 1 additional day exposition to maximum temperatures in the range relative to days with maximum temperatures between 20°C and 25°C at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2.7 Effect of the past-year average maximum temperature on Saber 11 scores by groups of Long-Run Municipality daily maximum temperatures, 2014-II–2019-I.



Notes — Reporting Fixed-Effects estimation of the effect (and confidence interval) from 1°C increases in the average daily maximum temperature at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2.1 Descriptive statistics of the sample and Municipality-level variables.

	Mean	Median	S.D.
STUDENT-LEVEL INFORMATION (N=2,202,917)			
<i>Saber 11 scores</i>			
Mathematics	52.2	52	11.5
<i>Urban</i>	53.7	52	11.6
<i>Rural</i>	48.9	49	10.8
Spanish	53.1	53	9.7
<i>Urban</i>	54.5	54	9.7
<i>Rural</i>	50.1	50	9.1
Total	261.5	258	47.3
<i>Urban</i>	268.7	266	47.6
<i>Rural</i>	245.8	242	42.6
<i>Independent variables</i>			
Age	17.29	17.08	0.99
Female (1=Yes)	0.55	1	0.5
Mother: Complete primary (1=Yes)	0.29	0	0.45
Mother: Complete secondary (1=Yes)	0.33	0	0.47
Mother: Complete postsecondary (1=Yes)	0.23	0	0.42
Ethnic minority (1=Yes)	0.06	0	0.24
Lives and studies in different Municipalities (1=Yes)	0.03	0	0.17
House Strata: Low (1 = Residence stratum is 1, 2, or 3)	0.925	1	0.26
House Strata: High (1 = Residence stratum is 4, 5, or 6)	0.075	0	0.26
MUNICIPALITY-LEVEL INFORMATION (N=1,052)			
<i>Ser Pilo Paga (SPP) 2015</i>			
Number of beneficiaries	8.61	2	59.27
Exposure to SPP	0.017	0.012	0.02
<i>Weather variables</i>			
Average maximum temperature (°C)	26.66	27.81	6.19
Maximum temperature (°C, exam days)	26.87	28.00	6.77
Long-run average maximum temperature above 30°C (1=Yes)	0.34	0	0.47
Mean precipitation (mm/day)	5.52	4.35	3.97
Precipitation (mm, exam days)	4.66	0.30	9.89
<i>Days per temperature bin</i>			
DD < 15	6.0	0.0	20.5
DD 15 – 20	72.2	0.0	124.2
DD 20 – 25	67.1	8.0	104.7
DD 25 – 30	74.8	23.1	96.2
DD 30 – 35	115.2	36.1	122.7
DD ≥ 35	30.7	0.0	58.0

Notes — Student-level information is publicly available from the Colombian Institute for the Evaluation of Education (ICFES). The total number of test takers in urban Municipalities is 1,517,000, while the remaining 685,917 are located in rural Municipalities. Age is calculated as the exact number of years from date of birth to date of exam. Female and Ethnic minority dummies are based on self-identification from test takers. Mothers' education attainment dummies are mutually exclusive and only consider schooling levels fully completed. Anonymized information of beneficiaries of *Ser Pilo Paga* (SPP) was provided by the Colombian Ministry of Education, which can be matched at the school level. The number of beneficiaries relates only to the number of assigned scholarships within the Municipality in the first round of SPP. The variable Exposure to SPP is the ratio of beneficiaries in the Municipality over the total number of test-takers within that first round period of SPP. Raw weather data is publicly available from the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM).

Table 2.2 Effect of the reference-week average maximum temperature on time use for youths (10 to 16 years of age), ELCA (2013 and 2016).

<i>Panel A: Rural</i>								
VARIABLES	(1) TV	(2) Computer	(3) Parents	(4) Play	(5) Chores	(6) Exercise	(7) Read	(8) Homework
Avg. maximum temperature (AMT)	-0.013 (0.012)	0.002 (0.007)	-0.004 (0.013)	-0.014 (0.009)	0.012 (0.011)	0.011 (0.009)	0.018* (0.009)	0.001 (0.009)
Mean precipitation	-0.001 (0.002)	-0.001 (0.001)	0.002 (0.002)	-0.003 (0.002)	-0.004** (0.002)	-0.002 (0.002)	-0.001 (0.001)	0.000 (0.002)
OBSERVATIONS	3,197	3,197	3,197	3,197	3,197	3,197	3,197	3,197
R^2	0.046	0.061	0.063	0.070	0.070	0.081	0.037	0.047
<i>Panel B: Urban</i>								
VARIABLES	(1) TV	(2) Computer	(3) Parents	(4) Play	(5) Chores	(6) Exercise	(7) Read	(8) Homework
Avg. maximum temperature (AMT)	0.006 (0.010)	0.018 (0.014)	-0.002 (0.011)	-0.009 (0.013)	-0.004 (0.011)	0.012 (0.010)	-0.007 (0.007)	0.003 (0.009)
Mean precipitation	0.002 (0.001)	-0.001 (0.002)	0.002 (0.002)	0.001 (0.002)	0.002 (0.002)	0.001 (0.002)	-0.000 (0.001)	0.000 (0.002)
OBSERVATIONS	3,122	3,122	3,122	3,122	3,122	3,122	3,122	3,122
R^2	0.065	0.098	0.060	0.076	0.084	0.109	0.062	0.068
MONTH-BY-YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MUNICIPALITY FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (Municipality level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are dummies equal to one if the respondent spent one hour or more in each of the activities mentioned in the column header. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the week before the survey for each household (the reference period for the time-use variables). Mean precipitation is the average daily precipitation (mm/day) also for the same reference period. Attribute controls added to the regression include age dummies and a dummy variable for whether the individual is female.

Table 2.3 Effect of the reference-week average maximum temperature on time use for household heads and spouses, ELCA (2010, 2013, and 2016).

<i>Panel A: Household Heads</i>					
VARIABLES	(1) Own-farm	(2) Off-farm	(3) Commuting	(4) Chores	(5) Leisure
Avg. maximum temperature (AMT)	-0.620* (0.321)	0.355 (0.397)	0.014 (0.049)	0.253 (0.181)	0.011 (0.261)
Mean precipitation	-0.014 (0.049)	0.018 (0.055)	-0.013 (0.008)	-0.019 (0.026)	0.023 (0.051)
OBSERVATIONS	12,082	12,082	12,082	12,082	12,082
R^2	0.127	0.195	0.065	0.575	0.133
<i>Panel B: Spouses</i>					
VARIABLES	(1) Own-farm	(2) Off-farm	(3) Commuting	(4) Chores	(5) Leisure
Avg. maximum temperature (AMT)	-0.104 (0.111)	0.285** (0.131)	0.033 (0.021)	-0.009 (0.293)	-0.195 (0.352)
Mean precipitation	-0.013 (0.029)	0.057** (0.022)	0.000 (0.005)	-0.006 (0.051)	-0.038 (0.038)
OBSERVATIONS	9,091	9,091	9,091	9,091	9,091
R^2	0.171	0.135	0.067	0.262	0.118
MONTH-BY-YEAR FE	Yes	Yes	Yes	Yes	Yes
MUNICIPALITY FE	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (Municipality level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the percentages of time spent on each activity mentioned in the column header. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the week before the survey for each household (the reference period for the time-use variables). Mean precipitation is the average daily precipitation (mm/day) for the same reference period. Attribute controls added to the regression include age and a dummy variable for whether the individual is female.

Table 2.4 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.511 (0.709)	-2.267*** (0.843)	1.423* (0.774)	-0.553 (0.581)	-2.033*** (0.727)	0.891 (0.626)	-0.268 (0.604)	-2.182*** (0.546)	1.467** (0.684)
Exposure to SPP × Post	3.032*** (0.995)	6.127*** (1.812)	2.126* (1.099)	0.0923 (0.630)	0.376 (1.102)	-0.0699 (0.690)	1.457** (0.722)	3.216** (1.284)	0.785 (0.820)
AMT × Exposure to SPP × Post	-0.0123 (0.0360)	-0.108** (0.0504)	-0.0111 (0.0395)	-0.00647 (0.0232)	0.0231 (0.0379)	-0.0237 (0.0239)	-0.00936 (0.0256)	-0.0356 (0.0393)	-0.0141 (0.0280)
Mean precipitation	-0.354 (0.234)	0.135 (0.381)	-0.0226 (0.203)	-0.536 (0.200)	0.0944 (0.407)	-0.00988 (0.167)	-0.268 (0.172)	0.00478 (0.277)	(0.159)
Mean precipitation × Exposure to SPP × Post	-0.0970 (0.0691)	-0.235 (0.148)	-0.0342 (0.0712)	-0.0173 (0.0428)	0.0525 (0.0978)	-0.0318 (0.0528)	-0.0581 (0.0530)	-0.166 (0.105)	-0.0144 (0.0564)
OBSERVATIONS	2,175,278	1,506,211	669,066	2,175,278	1,506,211	669,066	2,175,278	1,506,211	669,066
R ²	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2.5 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga* in Urban population under specific house strata and mother's educational attainment levels, 2014-II–2019-I.

<i>Panel A: Differences by Mother's Educational Attainment</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature	-1.570** (0.756)	-2.610* (1.337)	-1.170 (1.057)	-2.463** (0.938)	-0.917 (0.724)	-2.855*** (0.878)
Exposure to SPP × Post	7.834*** (2.008)	4.233** (2.000)	2.689* (1.457)	-1.549 (1.602)	5.713*** (1.474)	0.969 (1.671)
AMT × Exposure to SPP × Post	-0.158*** (0.0545)	-0.0602 (0.0604)	-0.0408 (0.0427)	0.0749 (0.0550)	-0.108** (0.0427)	0.0251 (0.0520)
MOTHER'S EDUCATION	Low	High	Low	High	Low	High
OBSERVATIONS	550,045	955,949	550,045	955,949	550,045	955,949
R ²	0.256	0.386	0.205	0.301	0.278	0.427
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes
<i>Panel B: Differences by House Strata</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	-2.319*** (0.789)	0.144 (3.642)	-2.062*** (0.707)	-1.525 (2.112)	-2.102*** (0.529)	-2.234 (2.527)
Exposure to SPP × Post	6.532*** (1.794)	0.566 (4.303)	0.833 (1.050)	-2.911 (3.001)	3.754*** (1.263)	-3.157 (2.878)
AMT × Exposure to SPP × Post	-0.110** (0.0494)	-0.0496 (0.136)	0.0114 (0.0360)	0.136 (0.125)	-0.0489 (0.0386)	0.151 (0.109)
HOUSE STRATA	Low	High	Low	High	Low	High
OBSERVATIONS	1,354,424	150,960	1,354,424	150,960	1,354,424	150,960
R ²	0.320	0.485	0.263	0.370	0.357	0.531
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the calendar year before the exam within each round. All regressions include mean precipitation (not reported), measured as the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2.6 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga* and specific sex of the student, 2014-II–2019-I.

<i>Panel A: Overall</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	-1.664** (0.689)	0.421 (0.835)	-1.128* (0.607)	-0.0116 (0.651)	-1.101* (0.615)	0.450 (0.663)
Exposure to SPP × Post	1.361 (1.165)	4.275*** (0.988)	0.0551 (0.746)	0.0349 (0.769)	0.909 (0.820)	1.835** (0.777)
AMT × Exposure to SPP × Post	0.0419 (0.0406)	-0.0503 (0.0365)	-0.0236 (0.0260)	0.0104 (0.0290)	-0.00164 (0.0278)	-0.0134 (0.0288)
SEX OF THE STUDENT	Male	Female	Male	Female	Male	Female
OBSERVATIONS	986,944	1,188,130	986,944	1,188,130	986,944	1,188,130
R ²	0.383	0.387	0.338	0.341	0.436	0.450
<i>Panel B: Urban</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	-2.881*** (0.961)	-1.558 (0.949)	-2.080** (0.896)	-1.957*** (0.706)	-2.717*** (0.636)	-1.631** (0.619)
Exposure to SPP × Post	5.377*** (1.841)	6.573*** (2.227)	0.665 (1.244)	-0.0927 (1.447)	3.352*** (1.232)	3.028* (1.685)
AMT × Exposure to SPP × Post	-0.0755 (0.0478)	-0.125* (0.0682)	0.00178 (0.0418)	0.0501 (0.0499)	-0.0398 (0.0336)	-0.0287 (0.0555)
SEX OF THE STUDENT	Male	Female	Male	Female	Male	Female
OBSERVATIONS	685,568	820,545	685,568	820,545	685,568	820,545
R ²	0.366	0.384	0.307	0.324	0.414	0.444
<i>Panel C: Rural</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	-0.104 (0.803)	2.557*** (0.920)	-0.0932 (0.703)	1.812** (0.698)	0.308 (0.737)	2.437*** (0.744)
Exposure to SPP × Post	0.417 (1.289)	3.475*** (1.130)	-0.0612 (0.890)	-0.0953 (0.952)	0.124 (1.016)	1.282 (0.858)
AMT × Exposure to SPP × Post	0.0345 (0.0494)	-0.0466 (0.0391)	-0.0497 (0.0334)	-0.00375 (0.0350)	-0.0113 (0.0378)	-0.0159 (0.0301)
SEX OF THE STUDENT	Male	Female	Male	Female	Male	Female
OBSERVATIONS	301,374	367,585	301,374	367,585	301,374	367,585
R ²	0.348	0.320	0.303	0.281	0.387	0.365
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for dwelling stratum classification, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2.7 Heterogeneous effect of past-year average maximum temperature on Saber 11 scores by education of the mother, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.308 (0.782)	-2.563** (1.143)	1.592** (0.766)	-0.145 (0.622)	-1.946*** (0.701)	1.050* (0.611)	0.0722 (0.647)	-2.138*** (0.714)	1.640** (0.665)
AMT × Mother: Complete primary	-0.154*** (0.0542)	-0.166*** (0.0596)	-0.100* (0.0563)	-0.143*** (0.0455)	-0.183*** (0.0477)	-0.0701 (0.0520)	-0.166*** (0.0518)	-0.200*** (0.0570)	-0.0971** (0.0478)
AMT × Mother: Complete secondary	-0.392*** (0.0604)	-0.350*** (0.0594)	-0.498*** (0.0978)	-0.384*** (0.0529)	-0.361*** (0.0551)	-0.460*** (0.0885)	-0.412*** (0.0540)	-0.395*** (0.0611)	-0.471*** (0.0878)
AMT × Mother: Complete tertiary	-0.526*** (0.143)	-0.495*** (0.130)	-0.718*** (0.139)	-0.512*** (0.102)	-0.499*** (0.0737)	-0.671*** (0.124)	-0.575*** (0.117)	-0.560*** (0.109)	-0.730*** (0.125)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R^2	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the calendar year before the exam within each round. All regressions include mean precipitation (not reported), measured as the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2.8 Heterogeneous effect of past-year average maximum temperature on Saber 11 scores by house strata level, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.183 (0.766)	-2.311** (1.146)	1.591** (0.760)	-0.0721 (0.613)	-1.813** (0.691)	1.045* (0.592)	0.149 (0.632)	-1.964*** (0.711)	1.617** (0.651)
AMT × House Strata: Level 2	-0.564*** (0.0571)	-0.554*** (0.0650)	-0.533*** (0.0826)	-0.461*** (0.0571)	-0.441*** (0.0651)	-0.439*** (0.0761)	-0.504*** (0.0598)	-0.512*** (0.0695)	-0.448*** (0.0735)
AMT × House Strata: Level 3	-0.878*** (0.119)	-0.786*** (0.145)	-0.986*** (0.182)	-0.794*** (0.110)	-0.669*** (0.136)	-1.046*** (0.171)	-0.843*** (0.117)	-0.755*** (0.145)	-0.995*** (0.169)
AMT × House Strata: Level 4	-1.392*** (0.200)	-1.165*** (0.203)	-1.559*** (0.347)	-1.165*** (0.163)	-0.913*** (0.157)	-1.454*** (0.399)	-1.339*** (0.180)	-1.124*** (0.178)	-1.442*** (0.351)
AMT × House Strata: Level 5	-1.374*** (0.249)	-1.185*** (0.275)	-0.619** (0.312)	-1.211*** (0.184)	-0.941*** (0.181)	-1.036*** (0.295)	-1.347*** (0.224)	-1.134*** (0.240)	-0.796*** (0.292)
AMT × House Strata: Level 6	-1.619*** (0.279)	-1.376*** (0.263)	-0.990** (0.477)	-1.338*** (0.209)	-1.108*** (0.208)	-0.365 (0.370)	-1.550*** (0.244)	-1.324*** (0.231)	-0.627* (0.327)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R^2	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.372
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the calendar year before the exam within each round. All regressions include mean precipitation (not reported), measured as the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam-taker lives and studies in different Municipalities.

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APPENDIX 2A

OPTIMIZATION PROBLEM

We assume functional forms such that

$$f(e, t) = \frac{e^\alpha}{t^\beta}, \quad 0 < \alpha < 1, \quad \beta > 0;$$

$$g(e, t) = e^\gamma t^\zeta, \quad \gamma > 1, \quad 0 < \zeta < 1;$$

$$U(c, g(e, t)) = c - g(e, t) = wzf(e, t) - g(e, t).$$

Hence, the individual's problem is reduced to

$$\max_e wz \frac{e^\alpha}{t^\beta} - e^\gamma t^\zeta,$$

where the first-order condition (FOC) implies that

$$\alpha wz \frac{e^{\alpha-1}}{t^\beta} - \gamma e^{\gamma-1} t^\zeta = 0,$$

while the second-order condition for maximization

$$\alpha(\alpha - 1) wz \frac{e^{\alpha-2}}{t^\beta} - \gamma(\gamma - 1) e^{\gamma-2} t^\zeta < 0$$

is satisfied when $0 < \alpha \leq 1$ and $\gamma > 1$, and thus $\gamma > \alpha$; hence, we must assume that the marginal cost of effort increases faster than its marginal benefit.

From the FOC we can recover the optimal level of effort, e^* , which follows

$$e^* = \left(\frac{\alpha wz}{\gamma t^{\beta+\zeta}} \right)^{\frac{1}{\gamma-\alpha}}.$$

Therefore, the production of human capital under an optimal effort level is

$$\begin{aligned} h^*(t, w, z) &= z \frac{(e^*)^\alpha}{t^\beta} \\ &= t^{-\beta - \frac{\alpha(\beta+\zeta)}{\gamma-\alpha}} w^{\frac{\alpha}{\gamma-\alpha}} z^{\frac{\gamma}{\gamma-\alpha}} \left(\frac{\alpha}{\gamma} \right)^{\frac{\alpha}{\gamma-\alpha}}. \end{aligned}$$

Finally, linearizing this expression with a second-order Taylor expansion, we have that

$$\begin{aligned} h^*(t, w, z) &= h^*(t', w', z') + \left(\frac{t - t'}{t'} \right) h^*(t', w', z') \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \\ &\quad + \left(\frac{w - w'}{w'} \right) h^*(t', w', z') \left[\frac{\alpha}{\gamma - \alpha} \right] + \left(\frac{z - z'}{z'} \right) h^*(t', w', z') \left[\frac{\gamma}{\gamma - \alpha} \right] \\ &\quad + \frac{1}{2} \left(\frac{t - t'}{t'} \right) \left(\frac{w - w'}{w'} \right) h^*(t', w', z') \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \left[\frac{\alpha}{\gamma - \alpha} \right] \\ &\quad + \frac{1}{2} \left(\frac{t - t'}{t'} \right) \left(\frac{z - z'}{z'} \right) h^*(t', w', z') \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \left[\frac{\gamma}{\gamma - \alpha} \right] + R_2(t, z, w), \end{aligned}$$

where $R_2(t, z, w)$ includes the cross-effect between wages and cognitive abilities and other own- and cross-effects of second and higher orders that are approximate to zero. Then, the percent

deviation of human capital with respect to the mean follows:

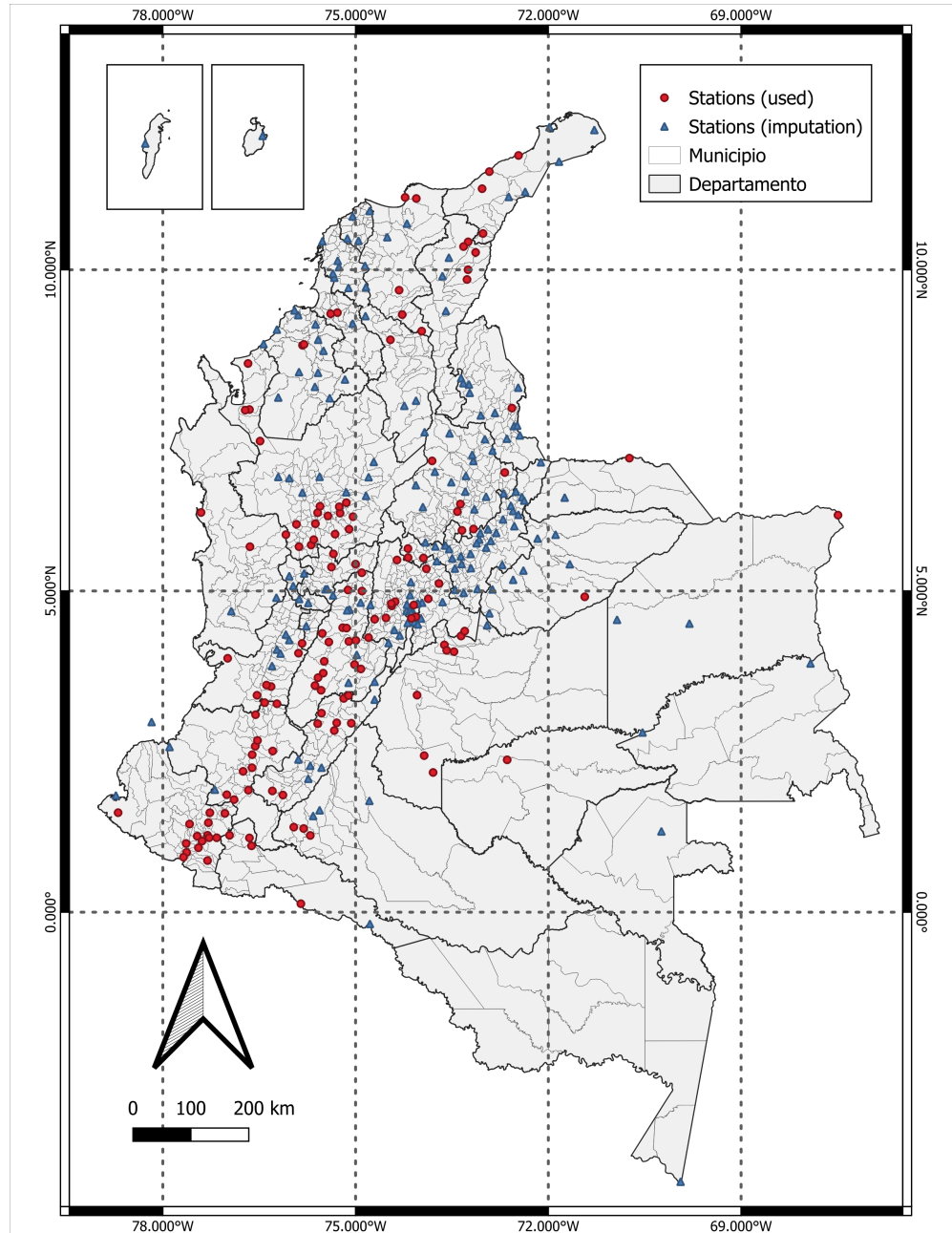
$$\hat{h} = \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \hat{t} + \left[\frac{\alpha}{\gamma - \alpha} \right] \hat{w} + \left[\frac{\gamma}{\gamma - \alpha} \right] \hat{z} + \frac{1}{2} \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \left[\frac{\alpha}{\gamma - \alpha} \right] \hat{t} \hat{w} \\ + \frac{1}{2} \left[-\beta - \frac{\alpha(\beta + \zeta)}{\gamma - \alpha} \right] \left[\frac{\gamma}{\gamma - \alpha} \right] \hat{t} \hat{z} + R,$$

where $\hat{x} = (x - x')/x'$, for $x \in \{h, w, t, z\}$.

APPENDIX 2B

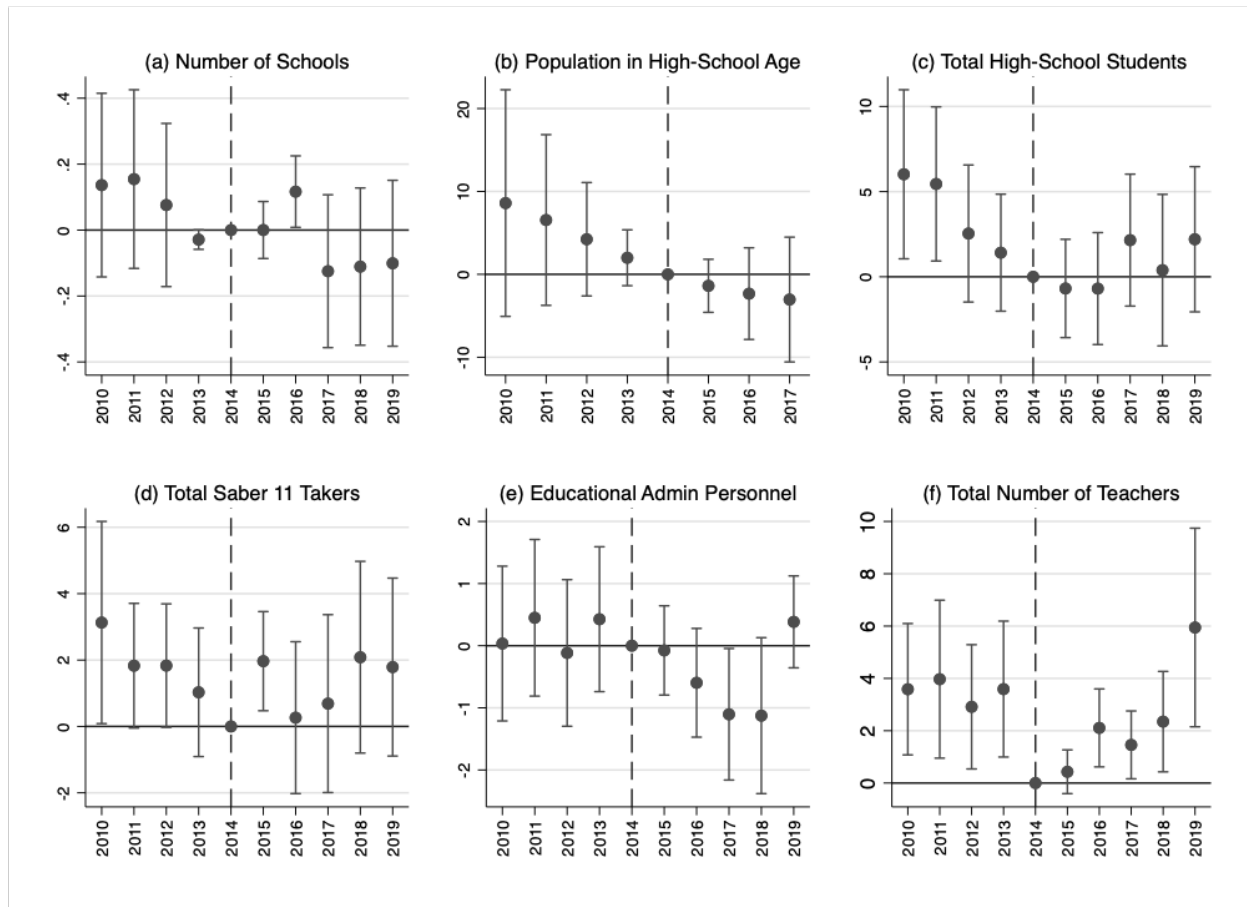
ADDITIONAL FIGURES AND TABLES

Figure 2B.1 Spatial distribution of the weather stations used in the analysis.



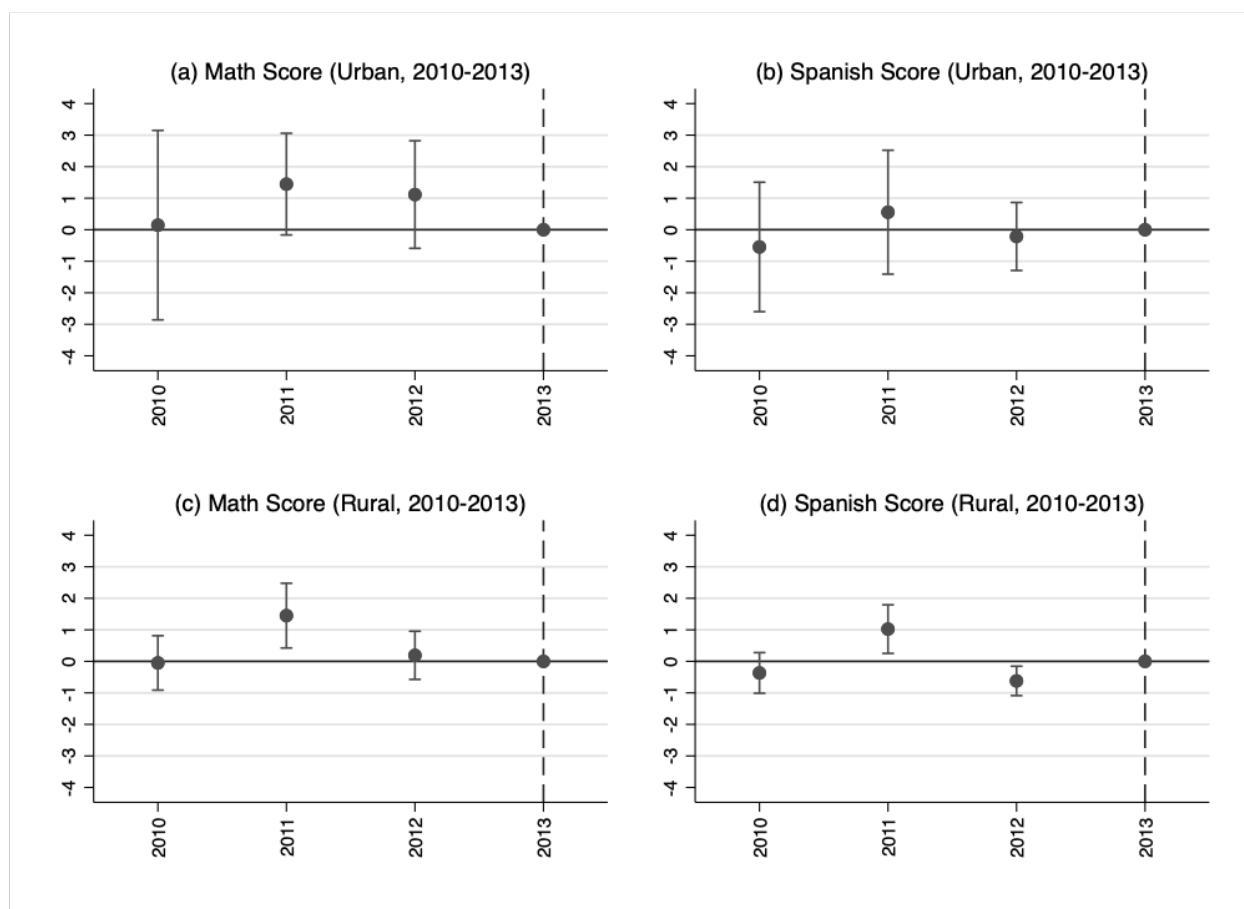
Notes — Figure displays the weather stations used in our analysis (blue) and those included in the imputation procedure. Raw weather data is publicly available from the Colombian Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM).

Figure 2B.2 Pre-trend testing of exposure to *Ser Pilo Paga* on Municipality-level variables, 2010-2019.



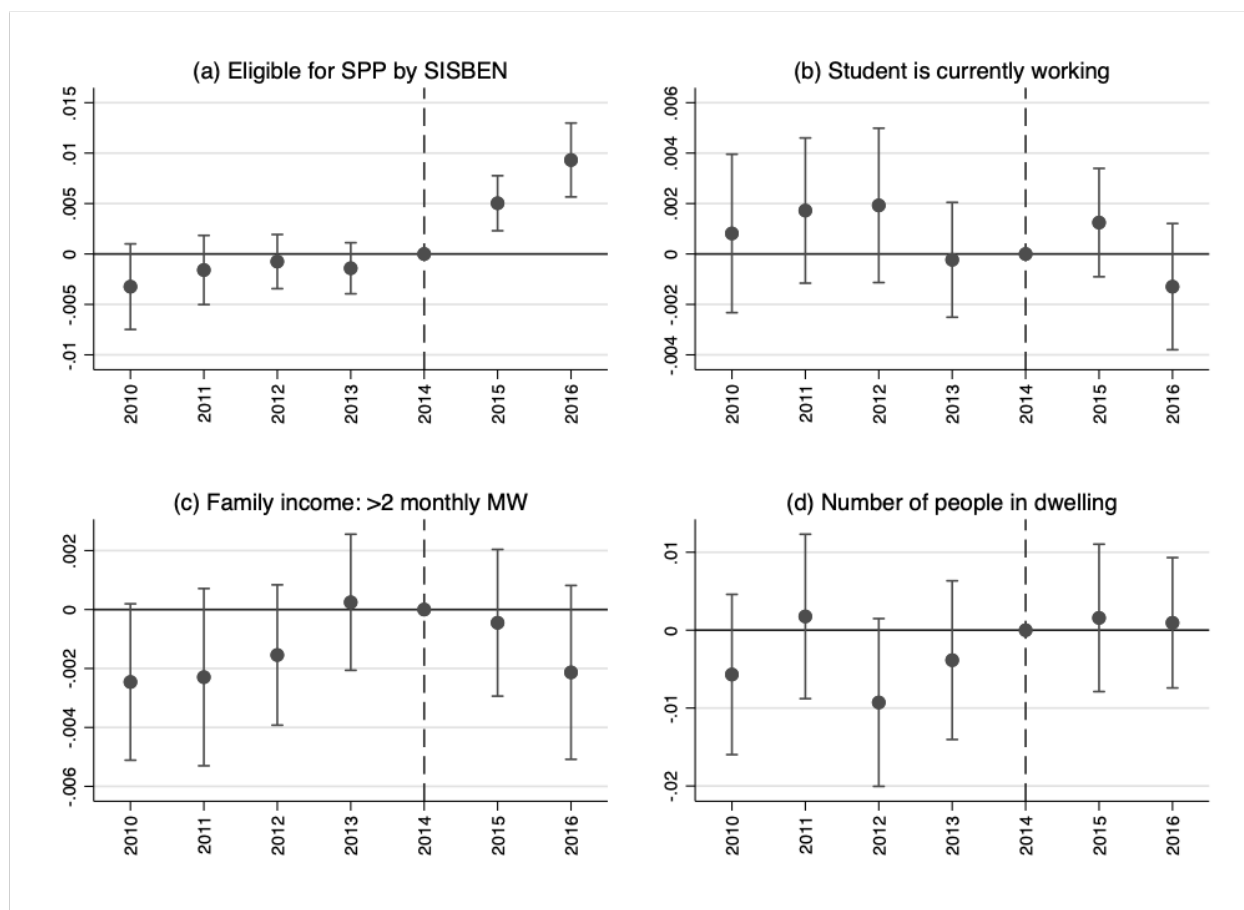
Notes — Municipality-level information is publicly available from the Center for Studies on Economic Development (CEDE) of Universidad de los Andes, Colombia. Graphs report the coefficient estimates (and 95% CI) from the regression of the outcome of interest (e.g., the number of schools in the Municipality) on interactions between the exposure to *Ser Pilo Paga* (SPP) and year dummies. Results are based on linear regression with State-Year and Municipality-level fixed effects. Excluded interaction for the year 2014 (coefficient set at zero) takes into account the baseline of Saber 11 data, for which no Municipality was exposed to SPP.

Figure 2B.3 Pre-trend testing of exposure to *Ser Pilo Paga* on Math and Spanish scores, 2010-2013.



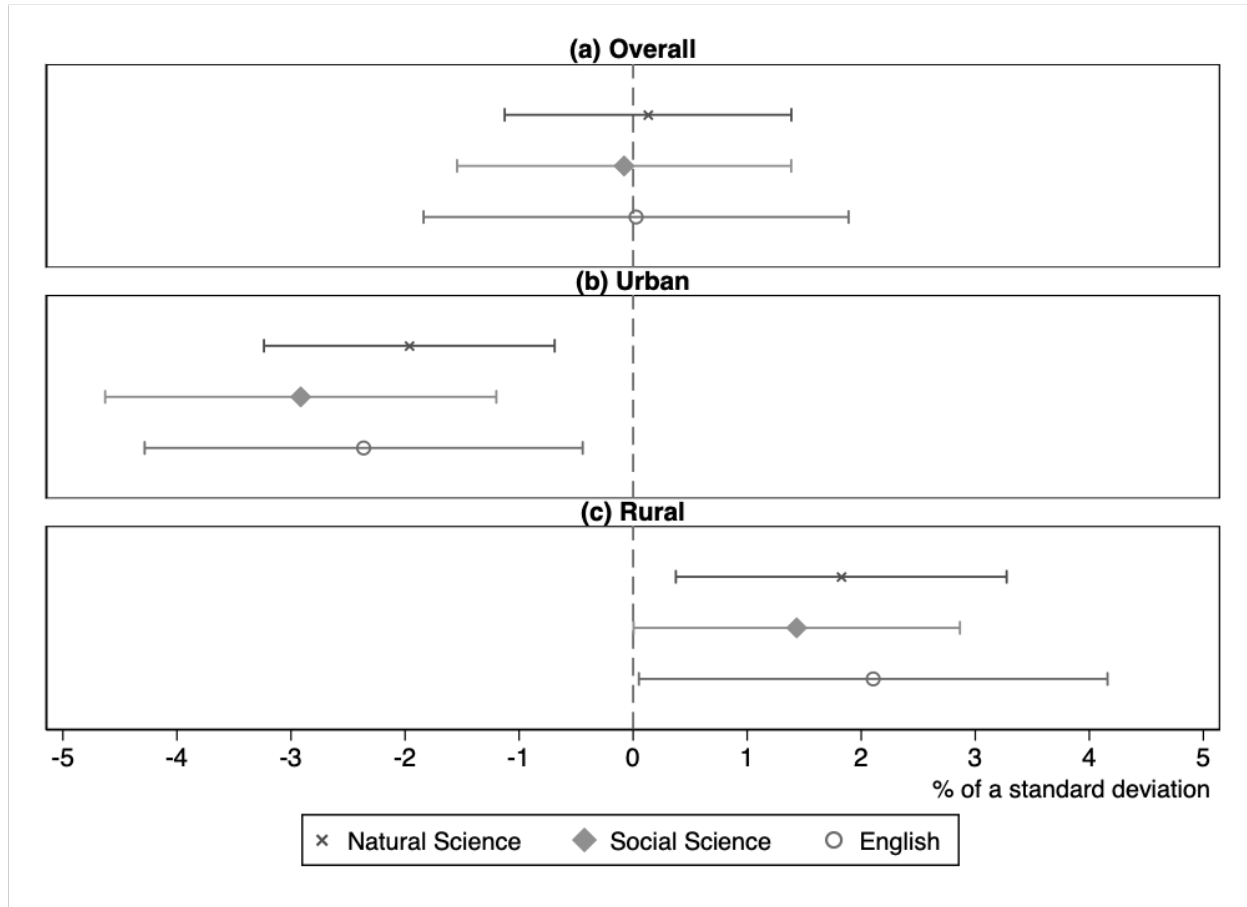
Notes — Student-level scores are publicly available from Instituto Colombiano para la Evaluación de la Educación (ICFES). Graphs report the coefficient estimates (and 95% CI) from the regression of the outcome of interest, namely $100y$ with y the standardized Math or Spanish score, on interactions between the exposure to *Ser Pilo Paga* (SPP) and year dummies. Results are based on linear regression with State-Year and Municipality-level fixed effects. Interaction for the year 2013 is excluded as a base-category comparison. The analysis allowed for trend heterogeneity by adding interactions between period (year) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Figure 2B.4 Pre-trend testing of exposure to *Ser Pilo Paga* on Student-level variables, 2010-2016.



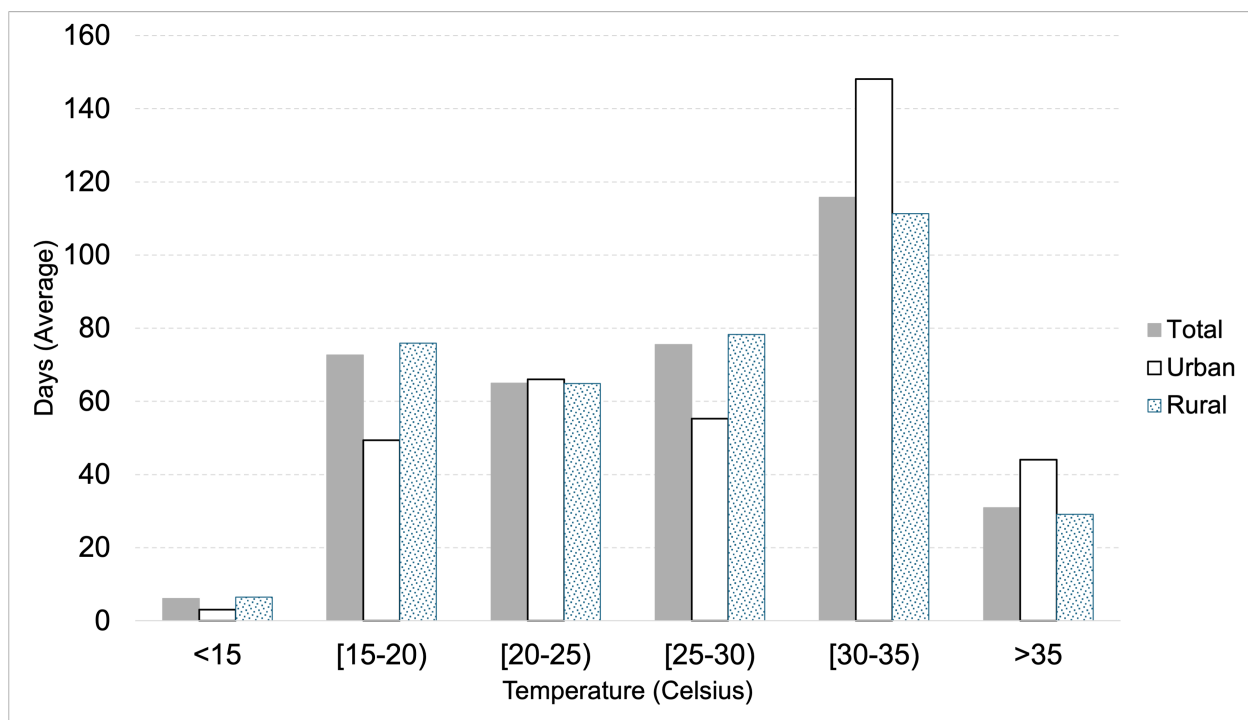
Notes — Student-level information is publicly available from Instituto Colombiano para la Evaluación de la Educación (ICFES). Selected covariates are only available for the years 2010-2016. Graphs report the coefficient estimates (and 95% CI) from the regression of the outcome of interest on interactions between the exposure to *Ser Pilo Paga* (SPP) and year dummies. Eligibility to SPP by SISBEN indicates whether the student reported being in the lower categories (1 and 2) of the SISBEN scores, making a student eligible for the program on a need basis. Family income is a binary variable of whether the student reports a monthly family income above 2 monthly minimum wages (MW). Results are based on linear regression with State-Year and Municipality-level fixed effects. Excluded interaction for the year 2014 (coefficient set at zero) takes into account the baseline of Saber 11 data, for which no Municipality was exposed to SPP.

Figure 2B.5 Effect of the past-year average maximum temperature on Saber 11 scores for additional subjects, 2014-II–2019-I.



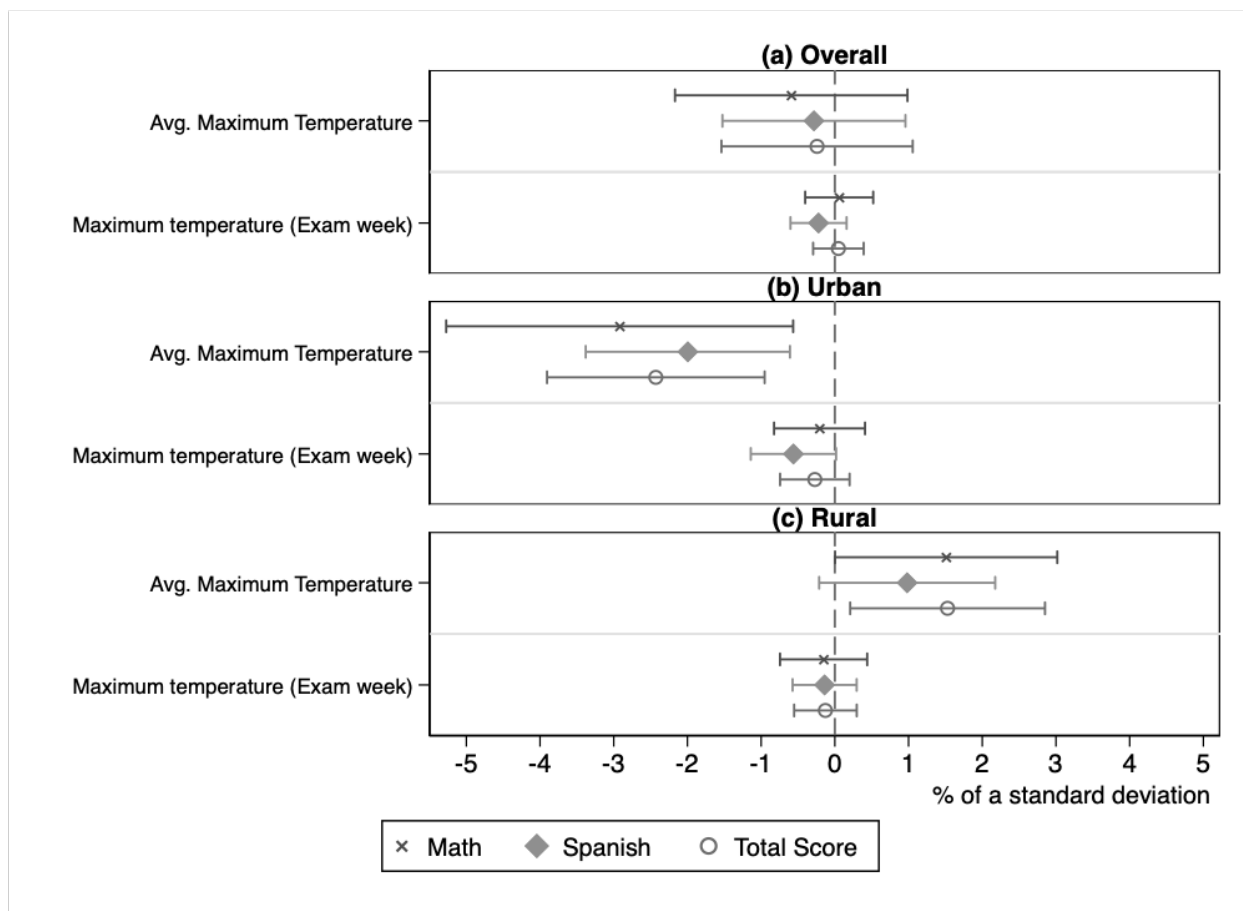
Notes — Reporting Fixed-Effects estimation of the effect (and 95% confidence interval) from a 1°C increase in the average daily maximum temperature at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject, namely Natural Science, Social Science, or English as a Second Language. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2B.6 Average days of exposure to bins of maximum temperature in the year before Saber 11 during the period of analysis across Municipalities, 2014-II–2019-I.



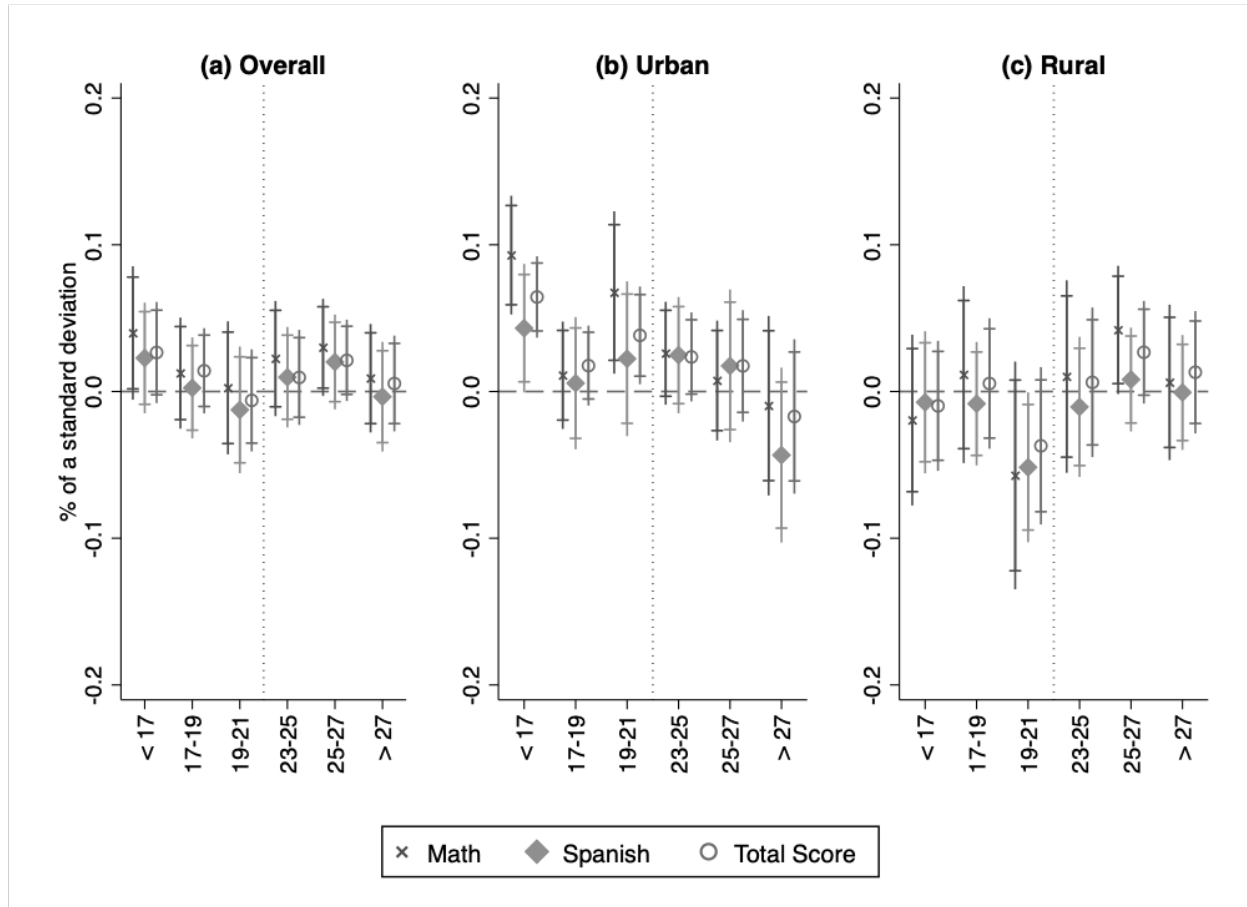
Notes — The figure reports the average number of days a Municipality, during the year before the Saber 11 test, has been exposed to days with maximum temperatures within a given bin between 2014-II and 2019-I.

Figure 2B.7 Effect of the past-year average maximum and exam week maximum temperatures on Saber 11 scores, 2014-II–2019-I.



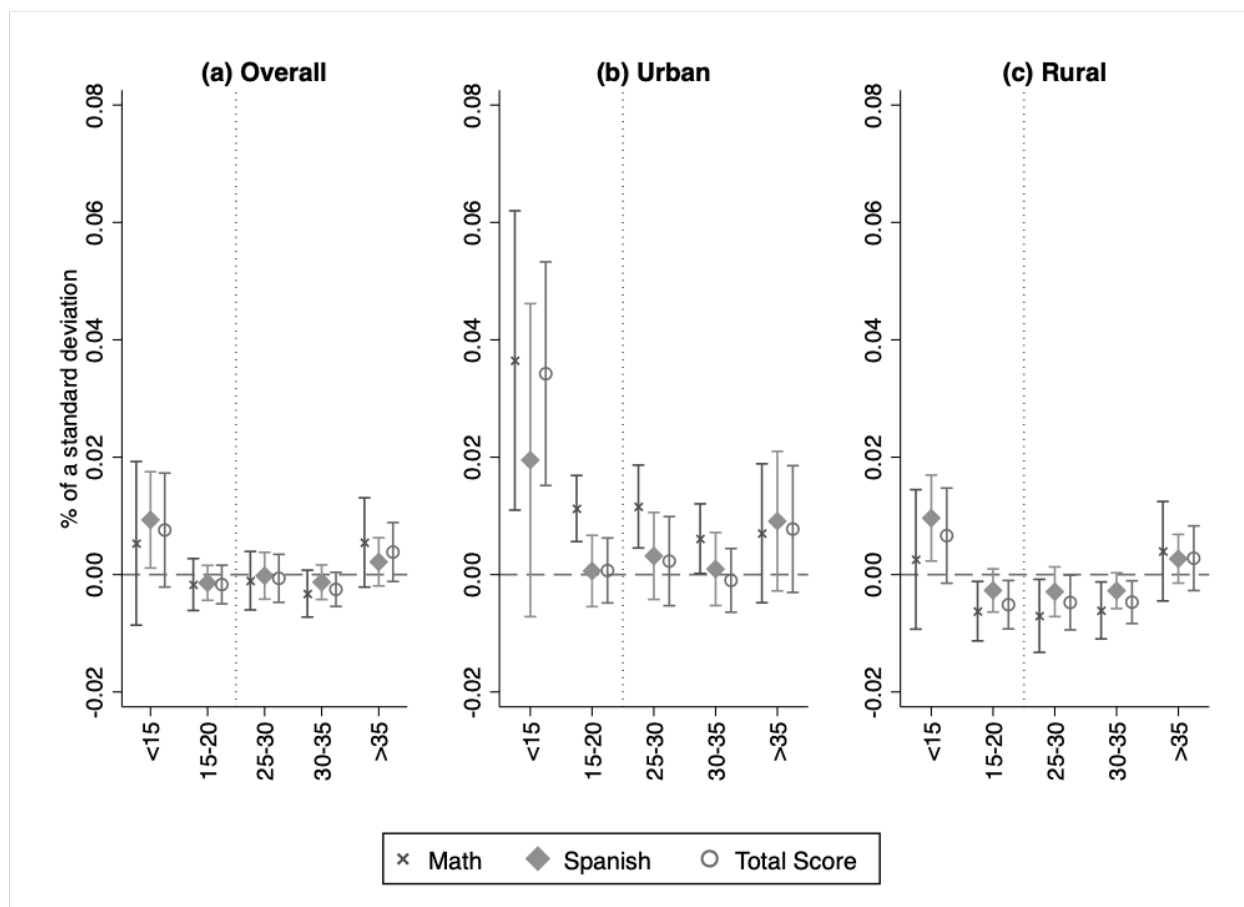
Notes — Reporting Fixed-Effects estimation of the effect (and confidence interval) from 1°C increases in the exam-week maximum temperature and the average daily maximum temperature at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2B.8 Effect of the past-year number of days exposure to maximum temperatures with alternate bins on Saber 11 scores, 2014-II–2019-I.



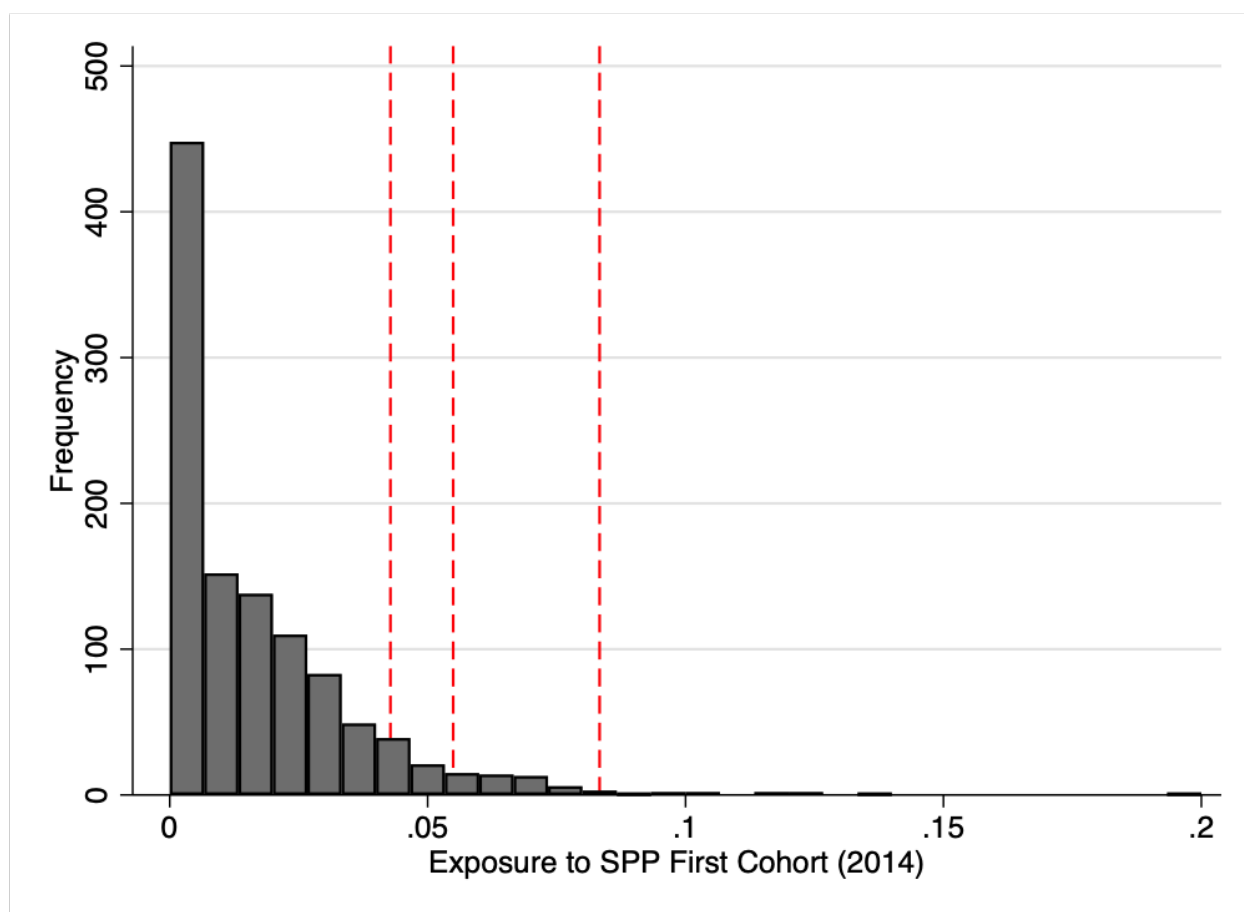
Notes — Reporting Fixed-Effects estimation of the effect (and confidence intervals, 90% and 95%) from 1 additional day exposition to maximum temperatures in the range relative to days with maximum temperatures between 21° and 23°C at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Regressions include controls of precipitation at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Figure 2B.9 Interaction effects of the past-year number of days exposure to maximum temperatures and exposure to *Ser Pilo Paga* on Saber 11 scores, 2014-II–2019-I.



Notes — Reporting Fixed-Effects estimation of the average interaction effect (and confidence intervals, 90% and 95%) from 1 additional day exposition to maximum temperatures in the range and exposure to *Ser Pilo Paga*, relative to days with maximum temperatures between 21° and 23°C at the Municipality level during the calendar before the Saber 11 test on the scores achieved by students between 2014-II and 2019-I. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Regressions include precipitation controls at the Municipality level for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. Estimations allow for trend heterogeneity by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Figure 2B.10 Distribution of the exposure to *Ser Pilo Paga* first round at the Municipality level, 2014.



Notes — Information about SPP scholarship assignment was provided by the Colombian Ministry of Education (MEN). The graph displays the distribution of the exposure measure, as well as the 90th, 95th, and 99th percentiles in red.

Table 2B.1 Correlation of student-level attributes and past-year weather variables: average maximum temperature and average precipitation, 2014-II–2019-I.

VARIABLES	(1) Age	(2) Female	(3) Primary ^(a)	(4) Secondary ^(a)	(5) Tertiary ^(a)	(6) Minority ^(b)
Avg. maximum temperature	0.006 (0.007)	-0.000 (0.002)	0.001 (0.003)	-0.000 (0.003)	-0.001 (0.002)	0.001 (0.004)
Mean precipitation	0.002 (0.002)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
OBSERVATIONS	2,202,869	2,202,869	2,202,869	2,202,869	2,202,869	2,202,869
R^2	0.119	0.077	0.090	0.064	0.263	0.557
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day), also for the calendar year before the exam date. (a) Variables capturing the educational attainment of the test-taker's mother, measured as whether the educational level was completed. (b) Minority is the exam-taker self-identification as part of an ethnic minority.

Table 2B.2 Effect of the past-year average maximum temperature on Saber 11 scores, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature	-0.575 (0.791)	-2.896** (1.158)	1.379* (0.766)	-0.403 (0.632)	-2.288*** (0.698)	0.864 (0.609)	-0.213 (0.656)	-2.516*** (0.720)	1.435** (0.665)
Mean precipitation	-0.161 (0.270)	-0.852** (0.385)	0.0797 (0.191)	-0.0971 (0.190)	-0.519 (0.345)	0.0627 (0.179)	-0.135 (0.189)	-0.631** (0.287)	-0.0201 (0.154)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R ²	0.391	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.3 Effect of the past-year average maximum temperature (alternate clustering) on Saber 11 scores, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature	-0.575 (0.787)	-2.896** (1.122)	1.379* (0.706)	-0.403 (0.690)	-2.288*** (0.600)	0.864 (0.559)	-0.213 (0.677)	-2.516*** (0.665)	1.435** (0.644)
Mean precipitation	-0.161 (0.250)	-0.852** (0.358)	0.0797 (0.212)	-0.0971 (0.175)	-0.519 (0.348)	0.0627 (0.203)	-0.135 (0.177)	-0.631** (0.274)	-0.0201 (0.176)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R^2	0.391	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (groups of weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. As a first stage, we cluster weather stations based on their spatial proximity (k-means clustering), then calculate standard errors at the stations-cluster level. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.4 Quality of weather-station data and the effect of the past-year average maximum temperature on Saber 11 scores, 2014-II–2019-I.

<i>Panel A: Dropping Municipalities matched to weather stations farther than 25 km</i>									
VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.103 (0.973)	-2.517* (1.489)	1.477 (0.928)	-0.434 (0.752)	-2.434*** (0.759)	0.977 (0.767)	-0.0112 (0.787)	-2.404*** (0.892)	1.439* (0.816)
Mean precipitation	-0.182 (0.375)	-0.915* (0.487)	-0.0141 (0.315)	-0.149 (0.280)	-0.900** (0.386)	0.229 (0.239)	-0.112 (0.275)	-0.828** (0.366)	-0.0234 (0.231)
OBSERVATIONS	1,619,952	1,169,658	450,293	1,619,952	1,169,658	450,293	1,619,952	1,169,658	450,293
R ²	0.385	0.376	0.342	0.325	0.300	0.291	0.434	0.420	0.378
<i>Panel B: Dropping weather stations with more than 25% of observations imputed</i>									
VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.178 (0.796)	-2.623** (0.999)	1.739** (0.819)	-0.0983 (0.710)	-2.368** (0.887)	1.049 (0.667)	0.0246 (0.685)	-2.553*** (0.682)	1.655** (0.716)
Mean precipitation	-0.183 (0.287)	-0.909** (0.428)	-0.0106 (0.199)	-0.0361 (0.191)	-0.411 (0.357)	0.0794 (0.189)	-0.0886 (0.193)	-0.542* (0.284)	-0.0287 (0.167)
OBSERVATIONS	1,963,025	1,353,948	609,075	1,963,025	1,353,948	609,075	1,963,025	1,353,948	609,075
R ²	0.395	0.387	0.342	0.338	0.316	0.288	0.446	0.434	0.377
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Age-squared control is demeaned, so the coefficient estimate of age is the partial correlation at the sample mean. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. Panel A drops municipalities matched to weather stations farther than 25 km. Panel B restricts the group of weather stations to those where imputations were used in less than 25% of the days.

Table 2B.5 Effect of the past-year average maximum and exam date maximum temperatures on Saber 11 scores, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. Maximum Temperature	-0.571 (0.798)	-2.709** (1.143)	1.370* (0.770)	-0.306 (0.612)	-2.115*** (0.692)	0.925 (0.591)	-0.267 (0.662)	-2.585*** (0.740)	1.467** (0.666)
Maximum temperature (exam days)	0.00743 (0.172)	-0.362 (0.238)	0.0705 (0.199)	-0.154 (0.143)	-0.240 (0.184)	-0.101 (0.161)	0.0724 (0.141)	-0.00796 (0.190)	-0.0685 (0.155)
Mean precipitation	-0.163 (0.270)	-0.899** (0.390)	0.0793 (0.193)	-0.130 (0.186)	-0.565 (0.338)	0.0337 (0.178)	-0.137 (0.185)	-0.635** (0.285)	-0.0357 (0.154)
Precipitation (exam day)	0.00498 (0.0238)	0.0290 (0.0252)	0.00181 (0.0293)	-0.0327 (0.0205)	-0.0298 (0.0193)	-0.0464* (0.0254)	-0.00948 (0.0185)	0.0114 (0.0197)	-0.0228 (0.0217)
OBSERVATIONS	2,158,356	1,492,021	666,334	2,158,356	1,492,021	666,334	2,158,356	1,492,021	666,334
R ²	0.392	0.385	0.337	0.335	0.313	0.284	0.443	0.431	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date within each round. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.6 Effect of the exam-day maximum temperature on Saber 11 scores, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Maximum temperature (exam day)	-0.0165 (0.174)	-0.511** (0.239)	0.128 (0.203)	-0.165 (0.151)	-0.364 (0.221)	-0.0609 (0.168)	0.0643 (0.145)	-0.163 (0.214)	-0.000979 (0.158)
Precipitation (exam day)	0.00607 (0.0238)	0.0246 (0.0244)	-0.000876 (0.0293)	-0.0318 (0.0205)	-0.0338 (0.0227)	-0.0481* (0.0255)	-0.00860 (0.0185)	0.00637 (0.0193)	-0.0250 (0.0216)
OBSERVATIONS	2,158,356	1,492,021	666,334	2,158,356	1,492,021	666,334	2,158,356	1,492,021	666,334
R^2	0.392	0.385	0.337	0.335	0.313	0.284	0.443	0.431	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Maximum temperature is the highest recorded temperature (in °C) during the exam day within each round. Precipitation is the total precipitation (mm) during the exam day within each round. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.7 Effect of the past-year number of days exposure to maximum temperatures on Saber 11 scores, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
DD < 15	0.0519* (0.0301)	0.120*** (0.0241)	-0.0212 (0.0388)	0.0389* (0.0218)	0.0601** (0.0226)	0.0155 (0.0369)	0.0384* (0.0205)	0.0794*** (0.0178)	-0.00117 (0.0342)
DD 15 – 20	0.0157 (0.0160)	0.0447** (0.0219)	-0.0137 (0.0244)	0.00270 (0.0147)	0.0205 (0.0214)	-0.0105 (0.0156)	0.0145 (0.0127)	0.0420*** (0.0154)	-0.0117 (0.0173)
DD 25 – 30	0.00705 (0.0156)	-0.0251 (0.0166)	0.0289* (0.0161)	0.00283 (0.0113)	-0.0302** (0.0133)	0.0166 (0.0122)	0.00896 (0.0127)	-0.0193 (0.0142)	0.0244* (0.0133)
DD 30 – 35	0.00461 (0.0215)	-0.0548** (0.0264)	0.0542** (0.0243)	-0.00992 (0.0180)	-0.0659*** (0.0172)	0.0412** (0.0193)	0.00926 (0.0186)	-0.0477** (0.0201)	0.0558*** (0.0208)
DD ≥ 35	-0.0190 (0.0283)	-0.117** (0.0458)	0.0557* (0.0312)	-0.0140 (0.0236)	-0.0947*** (0.0311)	0.0370 (0.0247)	-0.00382 (0.0242)	-0.0987*** (0.0337)	0.0564** (0.0271)
Mean precipitation	-0.157 (0.267)	-0.866** (0.384)	0.0804 (0.183)	-0.0851 (0.190)	-0.525 (0.343)	0.0520 (0.180)	-0.132 (0.185)	-0.636** (0.279)	-0.0362 (0.151)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R ²	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. DD counts the number of days during the calendar year before the exam date for which the maximum temperature (in °C) was within the range. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.8 Descriptive statistics of the data from ELCA.

	Mean	Median	S.D.	Mean	Median	S.D.
YOUTHS	Rural (N=3,241)			Urban (N=3,162)		
Time-use variables (1 = One hour or more in a week)						
Watch TV	0.56	1.00	0.50	0.63	1.00	0.48
Use computer	0.13	0.00	0.33	0.36	0.00	0.48
Spend time with parents	0.62	1.00	0.49	0.63	1.00	0.48
Play with siblings or friends	0.59	1.00	0.49	0.58	1.00	0.49
Help with household chores	0.43	0.00	0.49	0.37	0.00	0.48
Do exercise	0.36	0.00	0.48	0.45	0.00	0.50
Read for fun	0.23	0.00	0.42	0.20	0.00	0.40
Do homework	0.63	1.00	0.48	0.67	1.00	0.47
Play videogames	0.06	0.00	0.24	0.17	0.00	0.38
Participate in social groups	0.07	0.00	0.25	0.12	0.00	0.33
Independent variables						
Age	11.99	12.00	1.65	12.06	12.00	1.67
Female (Yes=1)	0.49	0.00	0.50	0.50	0.00	0.50
ADULTS	Household heads (N=12,155)			Spouses (N=9,158)		
Time-use variables (% of reported time)						
Work on household farms	23.17	12.12	26.10	8.09	0.00	15.14
Work on other households' farms	22.02	0.00	27.37	4.46	0.00	13.82
Commuting or looking for jobs	2.66	0.00	5.56	0.70	0.00	3.04
Domestic chores	12.28	0.00	19.43	47.91	50.00	21.69
Leisure and personal care	39.65	36.36	17.39	38.61	36.42	17.45
Other activities	0.23	0.00	2.43	0.23	0.00	2.16
Independent variables						
Age	48.79	48.00	12.59	44.12	43.00	12.88
Female (1=Yes)	0.19	0.00	0.40	0.94	1.00	0.23

Notes — Individual-level information was accessed remotely using the computational infrastructure of the Data Center of the Universidad de los Andes. Age is calculated as the exact number of years from the date of birth to the survey date. Female is a binary variable based on self-identification from the respondents. The time-use variables for the sample of youths are dummies equal to one if the respondent spent one hour or more in a typical day in the reference period in each of the activities mentioned in the row. For the adults, they correspond to the percentage of time spent in the same reference period in each of the activities.

Table 2B.9 Effect of the past-year average maximum temperature on time use for youths (10 to 16 years of age), ELCA (2013 and 2016).

<i>Panel A: Rural</i>								
VARIABLES	(1) TV	(2) Computer	(3) Parents	(4) Play	(5) Chores	(6) Exercise	(7) Read	(8) Homework
Avg. maximum temperature	-0.171** (0.073)	0.100*** (0.026)	0.012 (0.039)	-0.015 (0.052)	0.090* (0.050)	0.173*** (0.032)	0.050* (0.028)	0.094** (0.043)
Mean precipitations	-0.012 (0.028)	0.021** (0.010)	0.014 (0.019)	0.002 (0.029)	0.003 (0.029)	0.059*** (0.015)	-0.002 (0.017)	0.015 (0.025)
OBSERVATIONS	3,197	3,197	3,197	3,197	3,197	3,197	3,197	3,197
R ²	0.048	0.063	0.063	0.069	0.068	0.086	0.036	0.048
<i>Panel B: Urban</i>								
VARIABLES	(1) TV	(2) Computer	(3) Parents	(4) Play	(5) Chores	(6) Exercise	(7) Read	(8) Homework
Avg. maximum temperature	0.033 (0.044)	-0.049 (0.053)	0.012 (0.061)	0.013 (0.037)	0.013 (0.051)	0.074 (0.054)	-0.036 (0.039)	-0.004 (0.054)
Mean precipitations	-0.011 (0.025)	0.020 (0.022)	0.025 (0.031)	0.032 (0.023)	-0.011 (0.026)	0.050* (0.030)	-0.018 (0.021)	-0.013 (0.028)
OBSERVATIONS	3,068	3,068	3,068	3,068	3,068	3,068	3,068	3,068
R ²	0.066	0.100	0.059	0.074	0.083	0.114	0.063	0.070
MONTH-BY-YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MUNICIPALITY FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (Municipality level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are dummies equal to one if the respondent spent one hour or more in each of the activities mentioned in the column header. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the last year relative to the week of the survey. Mean precipitation is the average daily precipitation (mm/day) also for the same reference period. Attribute controls added to the regression include age dummies and a dummy variable for whether the individual is female.

Table 2B.10 Effect of the past-year average maximum temperature on time use for household heads and spouses, ELCA (2010, 2013, and 2016).

<i>Panel A: Household Heads</i>					
VARIABLES	(1) Own-farm	(2) Off-farm	(3) Commuting	(4) Chores	(5) Leisure
Avg. maximum temperature	-4.579* (2.337)	2.376 (3.027)	-0.331 (0.546)	0.334 (1.001)	2.054 (1.430)
Mean precipitations	0.653 (0.574)	-0.376 (0.867)	-0.041 (0.108)	-0.246 (0.360)	-0.038 (0.397)
OBSERVATIONS	12,084	12,084	12,084	12,084	12,084
R ²	0.128	0.195	0.065	0.575	0.133

<i>Panel B: Spouses</i>					
VARIABLES	(1) Own-farm	(2) Off-farm	(3) Commuting	(4) Chores	(5) Leisure
Avg. maximum temperature	0.436 (1.494)	-1.277 (1.210)	0.017 (0.138)	-0.277 (1.285)	1.064 (1.766)
Mean precipitations	-0.177 (0.450)	0.185 (0.211)	-0.021 (0.054)	-0.411 (0.498)	0.371 (0.678)
OBSERVATIONS	9,091	9,091	9,091	9,091	9,091
R-squared	0.171	0.135	0.067	0.262	0.118
MONTH-BY-YEAR FE	Yes	Yes	Yes	Yes	Yes
MUNICIPALITY FE	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (Municipality level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables are the percentages of time spent on each activity mentioned in the column header. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the last year relative to the survey week. Mean precipitation is the average daily precipitation (mm/day) for the same reference period. Attribute controls added to the regression include age and a dummy variable for whether the individual is female.

Table 2B.11 Effect of the past-year average maximum temperature (per quarter) on Saber 11 scores, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
<i>Panel A: Only including AMT from Q1 of previous year</i>									
Avg. maximum temperature Q_1	0.362 (0.446)	-0.709 (0.851)	1.461*** (0.474)	0.110 (0.428)	-1.351** (0.547)	1.062** (0.422)	0.487 (0.415)	-1.044* (0.608)	1.472*** (0.417)
R^2	0.391	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
<i>Panel B: Only including AMT from Q2 of previous year</i>									
Avg. maximum temperature Q_2	0.0398 (0.674)	-1.571 (1.047)	1.460** (0.646)	0.288 (0.480)	-1.188 (0.712)	1.071** (0.459)	0.352 (0.539)	-1.178 (0.764)	1.400*** (0.519)
R^2	0.391	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
<i>Panel C: Only including AMT from Q3 of previous year</i>									
Avg. maximum temperature Q_3	-1.146*** (0.410)	-1.612** (0.647)	-0.195 (0.512)	-0.635* (0.325)	-1.108** (0.417)	-0.244 (0.373)	-0.787** (0.318)	-1.261*** (0.426)	-0.110 (0.410)
R^2	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
<i>Panel D: Only including AMT from Q4 of previous year</i>									
Avg. maximum temperature Q_4	-0.381 (0.608)	-3.019*** (0.767)	0.335 (0.735)	-0.662 (0.502)	-1.560** (0.664)	-0.0161 (0.576)	-0.471 (0.539)	-2.431*** (0.619)	0.437 (0.584)
R^2	0.391	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
REF. QUARTER PRECIPITATION	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. AMT Q(K) captures the average daily maximum temperature (in °C) during the K-th quarter of the calendar year before the Saber 11 exam. Each panel reports coefficients from a regression that includes only the AMT for the K-th quarter of reference as the temperature measure. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.12 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.446 (0.731)	-2.306** (0.936)	1.454* (0.778)	-0.345 (0.625)	-2.142*** (0.729)	0.917 (0.622)	-0.145 (0.628)	-2.293*** (0.585)	1.486** (0.683)
Exposure to SPP × Post	3.484*** (1.103)	6.056*** (1.786)	2.438** (1.140)	0.0940 (0.645)	0.573 (1.170)	0.114 (0.714)	1.761** (0.788)	3.152** (1.250)	1.013 (0.869)
AMT × Exposure to SPP × Post	-0.00485 (0.0416)	-0.0958* (0.0523)	-0.0163 (0.0415)	-0.0195 (0.0242)	0.0134 (0.0397)	-0.0305 (0.0245)	-0.00708 (0.0284)	-0.0297 (0.0398)	-0.0176 (0.0294)
Mean precipitation	0.122 (0.258)	-0.297 (0.413)	0.122 (0.206)	-0.139 (0.197)	-0.552 (0.404)	0.0925 (0.168)	0.0146 (0.180)	-0.266 (0.287)	-0.00126 (0.156)
Mean precipitation × Exposure to SPP × Post	-0.156** (0.0734)	-0.230 (0.148)	-0.0374 (0.0724)	0.0276 (0.0424)	0.0751 (0.0981)	-0.0267 (0.0525)	-0.0876 (0.0532)	-0.152 (0.105)	-0.0159 (0.0557)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R ²	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS	No	No	No	No	No	No	No	No	No
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.13 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, Other subjects, 2014-II–2019-I.

VARIABLES	(1) Nat-Sci	(2) Nat-Sci	(3) Nat-Sci	(4) Soc-Sci	(5) Soc-Sci	(6) Soc-Sci	(7) English SL	(8) English SL	(9) English SL
Avg. maximum temperature (AMT)	-0.163 (0.603)	-2.092*** (0.567)	1.708** (0.738)	0.0142 (0.644)	-2.297*** (0.630)	1.566** (0.753)	0.158 (0.905)	-2.159** (0.960)	2.276** (1.079)
Exposure to SPP × Post	-0.327 (0.746)	-0.244 (1.538)	-0.526 (0.944)	2.874*** (1.017)	6.857*** (1.723)	1.147 (0.955)	1.977** (0.989)	2.534* (1.270)	2.227** (1.110)
AMT × Exposure to SPP × Post	0.0292 (0.0271)	0.0462 (0.0519)	0.0215 (0.0327)	-0.0499 (0.0349)	-0.116** (0.0530)	-0.0323 (0.0315)	-0.00242 (0.0397)	0.00583 (0.0519)	-0.0467 (0.0404)
Mean precipitation	0.0677 (0.172)	-0.390 (0.281)	0.0607 (0.196)	-0.0488 (0.200)	0.156 (0.368)	-0.204 (0.175)	-0.141 (0.255)	-0.0891 (0.592)	-0.196 (0.312)
Mean precipitation × Exposure to SPP × Post	-0.0449 (0.0622)	-0.0805 (0.143)	-0.0381 (0.0655)	-0.104 (0.0655)	-0.368*** (0.120)	0.000701 (0.0632)	0.0256 (0.0613)	-0.276 (0.167)	0.118** (0.0593)
OBSERVATIONS	2,175,278	1,506,211	669,066	2,175,278	1,506,211	669,066	2,175,275	1,506,210	669,064
R ²	0.379	0.373	0.322	0.321	0.312	0.260	0.461	0.458	0.308
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject, namely Natural Sciences, Social Sciences, or English as a Second Language. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.14 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga* under specific mother's educational attainment levels, 2014-II–2019-I.

<i>Panel A: Overall</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature	0.556 (0.729)	-1.429 (0.874)	0.117 (0.633)	-1.080 (0.740)	0.711 (0.602)	-1.135 (0.727)
Exposure to SPP × Post	3.330*** (0.923)	2.729** (1.182)	0.284 (0.569)	-0.239 (1.016)	1.833** (0.711)	0.879 (0.904)
AMT × Exposure to SPP × Post	-0.0387 (0.0327)	-0.00731 (0.0406)	-0.0148 (0.0193)	0.00951 (0.0378)	-0.0334 (0.0239)	0.0105 (0.0323)
MOTHER'S EDUCATION	Low	High	Low	High	Low	High
OBSERVATIONS	965,202	1,209,602	965,202	1,209,602	965,202	1,209,602
R ²	0.281	0.388	0.236	0.313	0.309	0.432
<i>Panel B: Urban</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature	-1.570** (0.756)	-2.610* (1.337)	-1.170 (1.057)	-2.463** (0.938)	-0.917 (0.724)	-2.855*** (0.878)
Exposure to SPP × Post	7.834*** (2.008)	4.233** (2.000)	2.689* (1.457)	-1.549 (1.602)	5.713*** (1.474)	0.969 (1.671)
AMT × Exposure to SPP × Post	-0.158*** (0.0545)	-0.0602 (0.0604)	-0.0408 (0.0427)	0.0749 (0.0550)	-0.108** (0.0427)	0.0251 (0.0520)
MOTHER'S EDUCATION	Low	High	Low	High	Low	High
OBSERVATIONS	550,045	955,949	550,045	955,949	550,045	955,949
R ²	0.256	0.386	0.205	0.301	0.278	0.427
<i>Panel C: Rural</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature	2.081** (0.797)	0.554 (1.085)	1.208* (0.724)	0.612 (0.948)	1.857*** (0.692)	0.988 (0.930)
Exposure to SPP × Post	2.278** (1.100)	1.823 (1.650)	-0.254 (0.666)	0.108 (1.173)	0.856 (0.751)	0.417 (1.227)
AMT × Exposure to SPP × Post	-0.0303 (0.0421)	0.00326 (0.0553)	-0.0192 (0.0244)	-0.0265 (0.0409)	-0.0259 (0.0271)	0.00338 (0.0423)
MOTHER'S EDUCATION	Low	High	Low	High	Low	High
OBSERVATIONS	415,155	253,649	415,155	253,649	415,155	253,649
R ²	0.290	0.343	0.234	0.281	0.314	0.373
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.15 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga* under specific House strata levels, 2014-II–2019-I.

<i>Panel A: Overall</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	-0.376 (0.712)	-0.909 (2.736)	-0.475 (0.565)	-2.416 (1.963)	-0.139 (0.599)	-2.673 (2.048)
Exposure to SPP × Post	3.061*** (0.995)	1.189 (3.222)	0.171 (0.594)	-0.250 (3.042)	1.534** (0.736)	-1.803 (2.776)
AMT × Exposure to SPP × Post	-0.0109 (0.0360)	-0.00880 (0.106)	-0.00679 (0.0218)	0.0414 (0.117)	-0.0108 (0.0262)	0.117 (0.101)
HOUSE STRATA	Low	High	Low	High	Low	High
OBSERVATIONS	2,011,055	162,315	2,011,055	162,315	2,011,055	162,315
R ²	0.337	0.537	0.291	0.438	0.379	0.592
<i>Panel B: Urban</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	-2.319*** (0.789)	0.144 (3.642)	-2.062*** (0.707)	-1.525 (2.112)	-2.102*** (0.529)	-2.234 (2.527)
Exposure to SPP × Post	6.532*** (1.794)	0.566 (4.303)	0.833 (1.050)	-2.911 (3.001)	3.754*** (1.263)	-3.157 (2.878)
AMT × Exposure to SPP × Post	-0.110** (0.0494)	-0.0496 (0.136)	0.0114 (0.0360)	0.136 (0.125)	-0.0489 (0.0386)	0.151 (0.109)
HOUSE STRATA	Low	High	Low	High	Low	High
OBSERVATIONS	1,354,424	150,960	1,354,424	150,960	1,354,424	150,960
R ²	0.320	0.485	0.263	0.370	0.357	0.531
<i>Panel C: Rural</i>						
VARIABLES	Math		Spanish		Total Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Maximum Temperature (AMT)	1.528* (0.779)	-7.397 (4.850)	0.988 (0.624)	-12.65** (5.594)	1.539** (0.690)	-7.106* (4.247)
Exposure to SPP × Post	2.142* (1.102)	21.49* (12.17)	-0.148 (0.687)	17.62* (9.758)	0.757 (0.822)	13.46 (9.851)
AMT × Exposure to SPP × Post	-0.0107 (0.0397)	-0.765* (0.414)	-0.0208 (0.0237)	-0.571* (0.293)	-0.0128 (0.0281)	-0.424 (0.344)
HOUSE STRATA	Low	High	Low	High	Low	High
OBSERVATIONS	656,626	11,335	656,626	11,335	656,626	11,335
R ²	0.326	0.735	0.275	0.674	0.356	0.796
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.16 Heterogeneous effect of past-year average maximum temperature on Saber 11 scores by education of the mother (reporting education-level dummies), 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.308 (0.782)	-2.563** (1.143)	1.592** (0.766)	-0.145 (0.622)	-1.946*** (0.701)	1.050* (0.611)	0.0722 (0.647)	-2.138*** (0.714)	1.640** (0.665)
AMT × Mother: Complete primary	-0.154*** (0.0542)	-0.166*** (0.0596)	-0.100* (0.0563)	-0.143*** (0.0455)	-0.183*** (0.0477)	-0.0701 (0.0520)	-0.166*** (0.0518)	-0.200*** (0.0570)	-0.0971** (0.0478)
AMT × Mother: Complete secondary	-0.392*** (0.0604)	-0.350*** (0.0594)	-0.498*** (0.0978)	-0.384*** (0.0529)	-0.361*** (0.0551)	-0.460*** (0.0885)	-0.412*** (0.0540)	-0.395*** (0.0611)	-0.471*** (0.0878)
AMT × Mother: Complete tertiary	-0.526*** (0.143)	-0.495*** (0.130)	-0.718*** (0.139)	-0.512*** (0.102)	-0.499*** (0.0737)	-0.671*** (0.124)	-0.575*** (0.117)	-0.560*** (0.109)	-0.730*** (0.125)
Mother: Complete primary	9.794*** (1.654)	10.66*** (1.716)	7.375*** (1.659)	8.503*** (1.398)	9.757*** (1.428)	5.936*** (1.535)	8.787*** (1.624)	10.09*** (1.748)	6.257*** (1.418)
Mother: Complete secondary	24.33*** (1.653)	22.66*** (1.606)	28.40*** (2.707)	23.81*** (1.460)	22.61*** (1.480)	26.87*** (2.543)	23.89*** (1.476)	23.03*** (1.665)	26.35*** (2.480)
Mother: Complete tertiary	45.14*** (4.241)	42.96*** (3.498)	54.04*** (3.732)	43.89*** (3.017)	42.17*** (1.861)	51.72*** (3.342)	46.22*** (3.450)	44.69*** (2.903)	53.51*** (3.367)
Mean precipitation	-0.161 (0.269)	-0.855** (0.385)	0.0800 (0.191)	-0.0977 (0.190)	-0.521 (0.345)	0.0628 (0.179)	-0.135 (0.188)	-0.634** (0.286)	-0.0200 (0.154)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R ²	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average of the daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.17 Heterogeneous effect of past-year average maximum temperature on Saber 11 scores by house strata (reporting strata-level dummies), 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.183 (0.766)	-2.311** (1.146)	1.591** (0.760)	-0.0721 (0.613)	-1.813** (0.691)	1.045* (0.592)	0.149 (0.632)	-1.964*** (0.711)	1.617** (0.651)
AMT × House Strata: Level 2	-0.564*** (0.0571)	-0.554*** (0.0650)	-0.533*** (0.0826)	-0.461*** (0.0571)	-0.441*** (0.0651)	-0.439*** (0.0761)	-0.504*** (0.0598)	-0.512*** (0.0695)	-0.448*** (0.0735)
AMT × House Strata: Level 3	-0.878*** (0.119)	-0.786*** (0.145)	-0.986*** (0.182)	-0.794*** (0.110)	-0.669*** (0.136)	-1.046*** (0.171)	-0.843*** (0.117)	-0.755*** (0.145)	-0.995*** (0.169)
AMT × House Strata: Level 4	-1.392*** (0.200)	-1.165*** (0.203)	-1.559*** (0.347)	-1.165*** (0.163)	-0.913*** (0.157)	-1.454*** (0.399)	-1.339*** (0.180)	-1.124*** (0.178)	-1.442*** (0.351)
AMT × House Strata: Level 5	-1.374*** (0.249)	-1.185*** (0.275)	-0.619** (0.312)	-1.211*** (0.184)	-0.941*** (0.181)	-1.036*** (0.295)	-1.347*** (0.224)	-1.134*** (0.240)	-0.796*** (0.292)
AMT × House Strata: Level 6	-1.619*** (0.279)	-1.376*** (0.263)	-0.990** (0.477)	-1.338*** (0.209)	-1.108*** (0.208)	-0.365 (0.370)	-1.550*** (0.244)	-1.324*** (0.231)	-0.627* (0.327)
House Strata: Level 2	15.15*** (1.590)	15.78*** (1.795)	13.83*** (2.240)	14.40*** (1.647)	14.87*** (1.832)	12.95*** (2.173)	14.49*** (1.704)	15.85*** (1.896)	12.10*** (2.037)
House Strata: Level 3	20.01*** (2.949)	19.85*** (3.559)	17.22*** (4.462)	22.68*** (2.779)	21.47*** (3.335)	24.75*** (4.403)	21.85*** (2.898)	21.90*** (3.516)	20.57*** (4.233)
House Strata: Level 4	28.24*** (4.830)	26.59*** (4.889)	12.29 (10.84)	29.09*** (3.982)	26.50*** (3.881)	18.00 (12.49)	30.81*** (4.421)	29.64*** (4.355)	13.18 (11.18)
House Strata: Level 5	23.65*** (6.286)	23.71*** (6.403)	-18.00** (8.730)	27.02*** (4.680)	24.76*** (4.689)	1.163 (8.318)	27.31*** (5.679)	27.07*** (5.812)	-10.36 (8.228)
House Strata: Level 6	26.52*** (7.803)	25.54*** (7.113)	-8.810 (13.86)	26.51*** (5.593)	25.66*** (5.680)	-17.97 (10.98)	28.91*** (6.760)	28.86*** (6.250)	-16.81* (9.802)
Mean precipitation	-0.180 (0.263)	-0.862** (0.380)	0.0635 (0.190)	-0.114 (0.184)	-0.527 (0.337)	0.0477 (0.179)	-0.153 (0.181)	-0.641** (0.276)	-0.0347 (0.153)
OBSERVATIONS	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150	2,175,363	1,506,211	669,150
R ²	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.372
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities.

Table 2B.18 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, excluding Municipalities with top 1% of exposure, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.509 (0.712)	-2.267*** (0.843)	1.436* (0.781)	-0.563 (0.582)	-2.033*** (0.727)	0.886 (0.629)	-0.268 (0.605)	-2.182*** (0.546)	1.476** (0.689)
Exposure to SPP × Post	2.873** (1.147)	6.127*** (1.812)	1.748 (1.370)	-0.110 (0.696)	0.376 (1.102)	-0.516 (0.787)	1.327 (0.811)	3.216** (1.284)	0.455 (0.978)
AMT × Exposure to SPP × Post	-0.00435 (0.0397)	-0.108** (0.0504)	0.00207 (0.0468)	-0.000992 (0.0253)	0.0231 (0.0379)	-0.0125 (0.0272)	-0.00390 (0.0281)	-0.0356 (0.0393)	-0.00454 (0.0325)
Mean precipitation	0.0018 (0.235)	-0.354 (0.381)	0.123 (0.207)	-0.0374 (0.203)	-0.536 (0.407)	0.0910 (0.168)	-0.0244 (0.172)	-0.268 (0.277)	-0.00933 (0.162)
Mean precipitation × Exposure to SPP × Post	-0.0838 (0.0782)	-0.235 (0.148)	-0.0108 (0.0842)	-0.00678 (0.0481)	0.0525 (0.0978)	-0.0245 (0.0636)	-0.0452 (0.0594)	-0.166 (0.105)	0.00480 (0.0666)
OBSERVATIONS	2,171,492	1,506,211	665,280	2,171,492	1,506,211	665,280	2,171,492	1,506,211	665,280
R ²	0.392	0.384	0.336	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.19 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, excluding Municipalities with top 5% of exposure, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.621 (0.727)	-2.359*** (0.865)	1.325 (0.811)	-0.581 (0.600)	-2.167*** (0.730)	0.960 (0.650)	-0.322 (0.617)	-2.270*** (0.552)	1.453** (0.705)
Exposure to SPP × Post	2.547* (1.442)	5.727*** (1.952)	1.194 (1.910)	-0.600 (0.945)	-0.291 (1.204)	-0.782 (1.076)	0.957 (1.026)	2.915** (1.402)	-0.112 (1.321)
AMT × Exposure to SPP × Post	0.0287 (0.0479)	-0.0974* (0.0541)	0.0507 (0.0698)	0.0147 (0.0340)	0.0411 (0.0397)	-0.00571 (0.0385)	0.0236 (0.0351)	-0.0267 (0.0420)	0.0326 (0.0488)
Mean precipitation	0.0495 (0.234)	-0.345 (0.386)	0.187 (0.211)	-0.0436 (0.205)	-0.537 (0.411)	0.0901 (0.168)	0.00847 (0.169)	-0.253 (0.279)	0.0294 (0.162)
Mean precipitation × Exposure to SPP × Post	-0.114 (0.0859)	-0.240 (0.149)	-0.0544 (0.0957)	-8.94e-05 (0.0540)	0.0447 (0.0941)	-0.0271 (0.0732)	-0.0634 (0.0638)	-0.176* (0.103)	-0.0217 (0.0746)
OBSERVATIONS	2,147,373	1,504,785	642,587	2,147,373	1,504,785	642,587	2,147,373	1,504,785	642,587
R ²	0.392	0.384	0.331	0.335	0.312	0.280	0.443	0.430	0.366
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.20 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, excluding Municipalities with top 10% of exposure, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.548 (0.749)	-2.084** (0.914)	1.367* (0.820)	-0.520 (0.619)	-1.878** (0.793)	0.936 (0.659)	-0.237 (0.639)	-1.930*** (0.596)	1.414* (0.716)
Exposure to SPP × Post	3.700** (1.693)	7.331*** (1.581)	3.037 (2.400)	-0.242 (1.116)	0.158 (1.408)	-0.0889 (1.399)	1.634 (1.174)	3.939*** (1.306)	0.818 (1.619)
AMT × Exposure to SPP × Post	0.0228 (0.0562)	-0.136*** (0.0483)	0.0166 (0.0850)	0.0121 (0.0404)	0.00872 (0.0497)	0.00283 (0.0468)	0.0244 (0.0415)	-0.0482 (0.0410)	0.0272 (0.0589)
Mean precipitation	0.148 (0.240)	-0.257 (0.411)	0.277 (0.232)	-0.0576 (0.204)	-0.665 (0.422)	0.161 (0.164)	0.0629 (0.167)	-0.202 (0.302)	0.0969 (0.167)
Mean precipitation × Exposure to SPP × Post	-0.188* (0.107)	-0.340** (0.144)	-0.107 (0.147)	-0.0142 (0.0653)	0.0449 (0.110)	-0.114 (0.102)	-0.113 (0.0793)	-0.242** (0.109)	-0.0812 (0.112)
OBSERVATIONS	2,099,799	1,480,860	618,938	2,099,799	1,480,860	618,938	2,099,799	1,480,860	618,938
R ²	0.394	0.385	0.331	0.337	0.313	0.280	0.445	0.431	0.366
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.21 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, excluding Municipalities with no exposure, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.514 (0.731)	-2.321*** (0.811)	1.730** (0.821)	-0.664 (0.606)	-2.042*** (0.741)	1.058 (0.671)	-0.344 (0.615)	-2.148*** (0.545)	1.641** (0.730)
Exposure to SPP × Post	3.857*** (0.928)	6.124*** (1.809)	2.936** (1.189)	0.437 (0.636)	0.427 (1.105)	0.289 (0.717)	2.116*** (0.660)	3.289** (1.286)	1.406* (0.841)
AMT × Exposure to SPP × Post	-0.0311 (0.0338)	-0.113** (0.0507)	-0.0273 (0.0410)	-0.0126 (0.0239)	0.0194 (0.0390)	-0.0325 (0.0256)	-0.0230 (0.0242)	-0.0410 (0.0393)	-0.0271 (0.0284)
Mean precipitation	0.0702 (0.299)	-0.357 (0.384)	0.232 (0.285)	-0.0212 (0.263)	-0.540 (0.404)	0.189 (0.239)	0.0189 (0.222)	-0.264 (0.274)	0.00609 (0.224)
Mean precipitation × Exposure to SPP × Post	-0.121* (0.0701)	-0.213 (0.149)	-0.0563 (0.0737)	-0.0293 (0.0469)	0.0659 (0.0954)	-0.0525 (0.0561)	-0.0783 (0.0528)	-0.153 (0.103)	-0.0317 (0.0585)
OBSERVATIONS	2,047,351	1,499,740	547,610	2,047,351	1,499,740	547,610	2,047,351	1,499,740	547,610
R ²	0.385	0.383	0.332	0.325	0.311	0.279	0.434	0.429	0.364
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

Table 2B.22 Heterogeneous effect of the past-year average maximum temperature on Saber 11 scores by exposure to *Ser Pilo Paga*, with SPP at the extensive margin, 2014-II–2019-I.

VARIABLES	(1) Math	(2) Math	(3) Math	(4) Spanish	(5) Spanish	(6) Spanish	(7) Total	(8) Total	(9) Total
Avg. maximum temperature (AMT)	-0.285 (0.716)	-2.520** (0.956)	1.831** (0.804)	-0.514 (0.584)	-2.281*** (0.705)	0.955 (0.641)	-0.171 (0.607)	-2.381*** (0.601)	1.655** (0.705)
Exposed to SPP (1=Yes) × Post	15.36*** (3.722)	22.29*** (7.968)	15.60*** (4.733)	0.407 (2.614)	3.168 (6.392)	2.104 (3.046)	6.578** (2.725)	12.21** (5.814)	6.601** (3.222)
AMT × Exposed to SPP (1=Yes) × Post	-0.290** (0.119)	-0.287* (0.170)	-0.420** (0.161)	-0.0431 (0.0860)	0.0604 (0.100)	-0.118 (0.0986)	-0.142 (0.0878)	-0.0959 (0.117)	-0.216* (0.112)
Mean precipitation	0.149 (0.275)	-0.239 (0.431)	0.213 (0.256)	0.0227 (0.187)	-0.425 (0.403)	0.142 (0.168)	0.0938 (0.177)	-0.170 (0.306)	0.0541 (0.178)
Mean precipitation × Exposed to SPP (1=Yes) × Post	-0.456*** (0.163)	-0.610*** (0.129)	-0.203 (0.272)	-0.0849 (0.0999)	-0.111 (0.113)	-0.155 (0.169)	-0.287** (0.140)	-0.447*** (0.110)	-0.118 (0.191)
OBSERVATIONS	2,175,278	1,506,211	669,066	2,175,278	1,506,211	669,150	2,175,363	1,506,211	669,150
R ²	0.392	0.384	0.337	0.334	0.312	0.284	0.442	0.430	0.371
SCHOOL FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME-STATE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ATTRIBUTE CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HETEROGENEOUS TRENDS ^(a)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAMPLE	All	Urban	Rural	All	Urban	Rural	All	Urban	Rural

Notes — Cluster (weather station level) robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The response variable is 100y, where y is the standardized score of the specific subject (Math, Spanish) or total test score. Avg. maximum temperature captures the average daily maximum temperature (in °C) during the calendar year before the exam within each round. Mean precipitation is the average daily precipitation (mm/day) for the calendar year before the exam date. Attribute controls added to the regression include age (and its square), dummy variables for the maximum educational attainment of the mother, dwelling stratum classification, whether the test taker is female, self-identification as part of an ethnic minority, and whether the exam taker lives and studies in different Municipalities. (a) Trend heterogeneity is allowed by adding interactions between period (year-semester) dummies and quartiles of Municipality-level variables (namely Total High-School Students, Total Number of School Teachers, and Total Number of School Administrative Personnel).

CHAPTER 3

HEAT, YIELDS, AND INCIDENTAL TRUNCATION

3.1 Introduction

Global agricultural sustainability is at stake with projected increases in average temperatures, as there are significant concerns about weather and climate impacts on the sector's productivity and its ability to adapt to a changing environment. The literature on the evaluation of the effects of heat on staple crops is vast, highlighting that a warming environment will lead to decreases in the productivity of corn, rice, soybean, sorghum, and wheat (Challinor et al., 2014; Lobell & Asseng, 2017; Miao, Khanna, & Huang, 2016; Miller, Tack, & Bergtold, 2021; Schlenker & Roberts, 2009; Tack, Barkley, & Nalley, 2015), as well as their suitability and production risks (Akpoti, Groen, Dossou-Yovo, Kabo-bah, & Zwart, 2022; Feng, Wang, Ma, Peng, & Shan, 2021; Li, Fleisher, & Barnaby, 2024; Ramirez-Cabral, Kumar, & Shabani, 2017; Yue, Zhang, & Shang, 2019; Zhao et al., 2021), thus meaning a continuous threat to global food security. These shocks further imply a policy challenge as projected negative impacts translate to increasing needs in funding for agricultural research and development in both developed and developing economies (Maredia & Martinez, 2024; Ortiz-Bobea, Chambers, He, & Lobell, 2025). Therefore, properly measuring the effects of warming temperatures remains a significant target of agricultural research.

The increasing availability of large-scale, farm-level data (e.g., yields, input use, timing of production), along with more precise measures of weather conditions (e.g., more granular measures of heat exposure and precipitation), has led to a significant share of recent research being focused on identification issues. For instance, Mérel and Gammans (2021) discusses retrieving short- and long-term climate impacts on yields, using fixed-effects (FE) estimations on large farm-level longitudinal datasets. Moreover, more granular satellite crop data allows for assessing the emergence of adaptation strategies like double-cropping as a response to larger-than-usual productive seasons in traditionally seasonal climates (Gammans, Mérel, & Ortiz-Bobea, 2024). However, especially in the former, most analyses rely on samples displaying considerable variability in farm-observability. Namely, most of these studies leave aside the fact that some farms enter and exit the sample,

presumably considering it a completely random event, which could potentially lead to estimation bias. While studies as Miller et al. (2021) acknowledge that sample selection cannot be completely ruled out, they consider the possibility that the ultimate exit of a farm (i.e., no longer being observed in the sample) resulting from crop failure—argued to be a rare outcome—is the only relevant factor that could bias the estimation of weather-related effects. Nevertheless, this does not fully address why a farm may choose to produce in some (but not all) periods before a total exit from the sample.

Are estimates of heat impact on crop yields sensitive to the inclusion of sample selection corrections? Is there a significant relationship between crop-specific production participation decisions and weather and market variables? Using open-access information by Miller et al. (2021) from the Kansas Farm Management Association (KFMA) for sorghum production during 1978–2015, associated PRISM weather data, and yearly data on farmers’ received prices for sorghum and corn from USDA-NASS during the period, we use (1) a random-effect Probit to estimate how weather variables and prices affect the probability of farmer participation in sorghum production, and (2) a Heckman-style approach in a fixed-effect framework to test (and potentially correct) for sample selection in the estimation of heat impact on sorghum yields.

Under a working assumption of high accuracy in seasonal forecasts, such that farmers correctly predict weather conditions, we find that additional exposure to temperatures favorable for sorghum production (i.e., further degree days between 10 and 33°C) increase the probability of farmer participation. Conversely, increasing exposure to temperatures unfavorable for production (degree days below 10 or above 33°C) decrease the probability of participation. Meanwhile, our results further suggest that increases in expected prices of sorghum increase the probability of participation, while higher expected prices of corn lead to a lower likelihood of producing sorghum. Using contemporary or lagged weather variables yields statistically similar responses in production probability, while using lags of observed prices leads to qualitatively similar (but statistically insignificant) effects on the decision to produce sorghum. Overall, these findings suggest that production decisions are climate-responsive, highlighting that period-specific farm observability in panel data is a potential reflection of adaptation strategies.

Combining the results from various specifications of production participation, we implement a Heckman-style test for sample selection. We find that when contemporary weather variables are present in both participation and yield regressions (i.e., farmers correctly foresee weather conditions), there is evidence of potential estimation bias. Conversely, whenever lags of weather variables are used for the participation equation, I cannot reject the hypothesis that results from fixed-effects estimates are consistent. While this finding is in line with recent literature on sample selection in unbalanced panels (Baltagi, Jiménez-Martín, Labeaga, & Al Sadoon, 2023), I argue that as weather predictions become increasingly precise and more widely available in agricultural settings, the risk of bias in fixed-effects estimation should remain a concern to be addressed.

Our contribution is twofold. First, we contribute to the literature on productive participation, highlighting that choosing to grow a crop of emerging importance is a decision responsive to weather and price expectations. Moreover, we provide correlational evidence suggesting that farmers may be following a forecasting strategy, potentially anticipating (at least partially) severe shocks of heat, and thus adjusting their decision to produce accordingly. Second, we provide a set of methodological recommendations to account for farm-observability in large longitudinal datasets and test for potential sources of bias in estimating weather impacts on crop yields when relying on traditional linear regression approaches. Some of our findings, for instance, indicate that accounting for farm-observability due to productive participation decisions would lead to lower-magnitude estimates—yet still significant—of high heat impacts on crop yields. In aggregate, our findings suggest that in-sample patterns resembling climate adaptation are connected to attenuating impacts from climate change.

The remainder of this chapter proceeds as follows: Section 3.2 briefly addresses our theoretical background and the relevance of our crop of interest—sorghum. Section 3.3 presents our identification strategy, while we present some summary statistics and stylized facts in Section 3.4. Then, we present and discuss our main results and present some robustness checks in Section 3.5. A final section presents a brief conclusion and discusses limitations and recommendations for future work.

3.2 Methods

3.2.1 Theoretical background and crop of interest

I consider a price-taking, profit-maximizing farmer i in a perfectly competitive market, deciding their crop productive allocation in a given agricultural season t , conditional on resource endowments and technology constraints. Without loss of generality, assume that the farmer chooses to allocate production between a crop of interest, S , and a single competing crop (C). Under optimization, the farmer sets production to levels at which the marginal rate of transformation (i.e., their opportunity cost) equals the market price ratio (Nicholson & Snyder, 2012). From a comparative statics perspective, increases in unfavorable weather conditions can impact both specific productive allocations and total output by shifting the production possibility frontiers inward. Likewise, all else equal, an increase in the price of a specific crop would lead to a larger production allocation towards that crop.

The latter implies that in a dynamic setting, a rational farmer uses available information ahead of a productive season to make a decision on productive allocation. For instance, if a farmer expects harsh weather conditions, they would adjust their production allocation accordingly to maximize their expected profits. Likewise, changes in expected prices would drive a decision to the extent of production. Hence, this short-run response reflects an adaptation mechanism by affecting whether a farm produces a given crop in a specific year. Particularly, the possibility that weather shocks affect both the decision to produce a crop (via expectation) and final production outcomes, imply a relevant connection between extensive and intensive margins that warrant further consideration in estimating weather effects.

The relevance of sorghum stems from its (a) nutrient content comparability to that of corn, (b) higher tolerance to heat and lower demand of water resources than other crops, and (c) increasing global demand for biofuel, livestock feed, and processing for human consumption (Hariprasanna & Rakshit, 2016; Wang, Upadhyaya, & Kole, 2014). Although its production has been suggested as a productive alternative in light of harsher climate patterns in the US (Miller et al., 2021), its suitability in global regions where it has been traditionally produced is being challenged by

climate change (Tack, Lingenfelter, & Jagadish, 2017). Moreover, its total acreage in the country has steadily decreased for most of the past two decades, connected with reductions in private investment and political impacts on international trade (Duff, Bice, Hoeffner, & Weinheimer, 2019; Polansek, 2025). Therefore, evaluating how farmers make decisions about producing a crop that could potentially serve as an adaptation to climate change, and whether said decisions could alter the yield impacts of climate change, are questions of economic and policy relevance.

3.2.2 Empirical setting

In general, we are interested in estimating partial effects on the conditional mean of a variable y_1 , namely $E[y_1|\mathbf{x}_1]$. However, we face a case of partial non-response, leading to a scenario in which y_1 is observed if and only if a condition occurs based on another variable y_2 .¹ Therefore, we could only approach the effects of $\mathbf{x}_1$ on $E[y_1|\mathbf{x}_1, 1[\text{Cond}(y_2)]]$, where $1[\text{Cond}(y_2)]$ is an index of whether a specific condition on y_2 is satisfied. In a linear case in which $E[y_1|\mathbf{x}_1, 1[\text{Cond}(y_2)]] = \mathbf{x}_1\boldsymbol{\beta} + f(y_2)$, and $E[\mathbf{x}_1 y_2] \neq \mathbf{0}$, OLS estimates of $\boldsymbol{\beta}$ that wave aside the nature of the relationship between $\mathbf{x}_1$ and y_2 lead to biased and likely inconsistent estimates (Wooldridge, 2010), which is the standard result of sample selection from Heckman (1979).²

As mentioned before, large longitudinal agricultural datasets at the farm level are becoming the standard. If we consider a dataset with yearly information, $t = 1, \dots, T$, on crop yields y_{it} for each farm $i = 1, \dots, n$, during a common season (e.g., summer grains), a case of a perfectly balanced panel, would allow us to observe a yield data point $y_{it} \geq 0$ for all i and all t . Nevertheless, this is not the norm. For most recent applications of yield panel data, we find that a given farm i is observed during a specific period going from $\underline{T}_i$ to $\bar{T}_i$, with $\underline{T}_i \leq \bar{T}_i$ and $\underline{T}_i, \bar{T}_i \in \{1, \dots, T\}$. Moreover, we usually find several cases of missing yield data for some periods—i.e., there exists a farm i such

¹The problem of missing data resulting from non-response is most famously associated with that of consistently estimating effects in wage equations vis-à-vis labor force participation (Gronau, 1974), where one only observes a wage ($w > 0$) whenever an individual is effectively employed ($p = 1$). Otherwise, whenever an individual is not employed ($p = 0$), the wage is not zero and is instead a missing value in the dataset. More specifically, Gronau (1974) defines an individual as participating in the market whenever the wage offer is at least as large as the individual's reservation wage.

²Following the example of wage equations, it is natural to assume that increases in education will raise an individual's reservation wage. At the same time, this affects their decision to participate in the market and whether we will observe a wage offer, thus rendering OLS estimates of the effects of education on a wage equation as potentially inconsistent.

that y_{it} is missing³ for some $t \in [\underline{T}_i, \bar{T}_i]$.

Let p_{it} be a binary variable taking the value of one if farm i produces a crop of interest in period t , and zero otherwise. Hence, we face a scenario where the yield of our crop of interest (intensive margin) follows:⁴

$$\ln y_{it} = \begin{cases} f(\mathbf{x}_{it}; \theta) + u_{it} & \text{if } p_{it} = 1 \\ \text{Unobserved} & \text{if } p_{it} = 0 \end{cases}$$

where $\mathbf{x}_{it}$ includes farm-level, and weather covariates, while θ is a vector of unknown parameters, u_{it} is an error term, and f is defined by the production technology. Meanwhile, the participation in the crop of interest (extensive margin) is defined by a latent participation variable p_{it}^* , such that

$$p_{it} = \begin{cases} 1 & \text{if } p_{it}^* = g(\mathbf{z}_{it}; \psi) + e_{it} \geq G \\ 0 & \text{if } p_{it}^* = g(\mathbf{z}_{it}; \psi) + e_{it} < G \end{cases}$$

where $\mathbf{z}_{it}$ includes farm-level, expected weather, and market (prices) covariates, ψ is a vector of unknown parameters, and e_{it} is an error term. In this context, g captures how weather and price expectations affect the willingness to produce the crop of interest. Hence, there is a threshold of indifference G , which defines whether a farmer chooses to produce.⁵

3.3 Identification strategy

3.3.1 A model of participation in sorghum production

We test whether a farmer's decision to produce sorghum is influenced by weather and price variables by defining our binary variable as $p_{it} = 1[\text{Produces Sorghum}]_{it}$ taking the value of one if farmer i chooses to produce sorghum in year t , and zero otherwise. Specifically, we assume that during a farm's period of presence in the sample (i.e., all periods between $\underline{T}_i$ and $\bar{T}_i$) $1[\text{Produces Sorghum}]_{it} = 0$ if yields are a missing data; otherwise, when yields are observed then

³It is worth noting that crop failure is a different case to that from missing values, as the former implies a yield of zero.

⁴Note that in a case of crop failure (i.e., a significant or complete loss of harvestable yield) it could occur that $y_{it} = 0$, thus leading to an undefined value. However, unless in a case of extremely harsh conditions, this is rather a rare case. In the open-access dataset, only 17 observations are seemingly reflecting a yield of zero (with an apparent imputation of values as $\ln(y_{it} + 1)$ for cases where $y_{it}=0$). Additional testing of our analyses excluding these observations (not included here) does not change our inference.

⁵In a case with more disaggregated data on the cost structure of farms, one could consider the case of g capturing expected profits, in which case a farmer chooses to produce if and only if projected profits exceed a threshold G , which is usually set to $G = 0$ reflecting a decision to at least break even.

$1[\text{Produces Sorghum}]_{it} = 1$. In addition, we assume that the probability of a farmer producing sorghum in a given year follows a process such that:

$$\Pr[p_{it} = 1|\cdot] = \Phi \left[\alpha_0 + \alpha_1 E[\text{Prec}_{it}] + \eta_1 E[\text{DLow}_{it}] + \eta_2 E[\text{DMed}_{it}] + \eta_3 E[\text{DHigh}_{it}] + \mu_1 E[P_t^S] + \mu_2 E[P_t^C] + \zeta t \right], \quad (3.1)$$

where $E[X]$ is the expectation of X for the production period. The use of expectation follows that the decision to produce occurs before the realization of weather or price variables. In this specification, Prec_{it} is total precipitation, while DLow_{it} , DMed_{it} , and DHigh_{it} are, respectively, the number of degree days during the productive period under 10°C , between $10\text{--}33^\circ\text{C}$, and above 33°C . Based on the analysis from Miller et al. (2021), an increasing exposure to degree days in the lower- and upper-temperature bins (DLow_{it} and DHigh_{it}) is detrimental to yields, while added exposure to degree days in the bin DMed_{it} captures a *beneficial* temperature range for the crop. Finally, P_t^S and P_t^C are the prices of sorghum and an on-farm substitute (namely corn) received by farmers in the State, respectively, while t is also included as a trend variable.

From both an agronomic and an economic standpoint, it is a weak assumption having an increasing number of degree days with unfavorable temperatures for the crop leading to a reduction in the probability of producing (i.e., η_1 and η_3 are negative).⁶ Likewise, further exposure to degree days in a range of favorable temperatures would increase the likelihood of producing ($\eta_2 > 0$). On the other hand, higher prices of sorghum (corn) should potentially lead to an increased (decreased) probability of producing sorghum, as it implies a case for likely higher (lower) revenues, and thus $\mu_1 > 0$ ($\mu_2 < 0$). Meanwhile, the effect of precipitation is somewhat ambiguous. While additional rain ultimately favors the vegetative development of the crop, sorghum has a yield gain advantage over corn on lower levels of evapotranspiration and overall precipitation (Assefa et al., 2014). Finally, we expect that the overall trend in participation is negative ($\zeta < 0$), in line with national trends of a reducing number of farms in the US according to the USDA-NASS.⁷

⁶For instance, they may prefer to focus on producing another crop that, while also potentially affected by the projected weather conditions, has a more favorable price and leads to higher profits. Importantly, these ranges of degree days are also close to those found as optimal for modeling climate responsiveness in corn, soybean, and cotton in the US (Schlenker & Roberts, 2009).

⁷<https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=58268>.

We consider various definitions of expected temperatures and prices, with two limiting cases for weather variables. First, we take a case of high-accuracy predictions of weather conditions for the production season, such that $E_t[X] = X_t$. This scenario's direct implication is that farmers have perfect information, and any final exposure to unfavorable temperatures results from unavoidability due to the necessary length of the productive period of sorghum. In our preferred specification, we take contemporary values of weather variables and set up expected prices as the dynamic predictions from a 2-lag vector autoregression.⁸ An alternate specification follows a naive estimation of prices, taking the previous-year prices as reference values. Second, we consider a one-year lag scenario for weather variables, assuming that farmers take the experienced previous year conditions as their reference for making a decision on whether to produce, such that they set $E_t[X] = X_{t-1}$. For this case, we also include specifications based on dynamic price predictions and using the previous year's price information as a reference. Estimation of all specifications is done by maximum likelihood.

3.3.2 Addressing sample selection: *à la* Heckman corrections

We argue that non-observability of yields (i.e., a farmer is not present in the crop yield data for a given year) is potentially linked to climate (and price) responsiveness of production participation. Under this assumption, estimating the unconditional effect of weather variables on yield, namely $\partial E[y_{it}]/\partial w_{jit}$, is unfeasible. Yet, one can try to consistently estimate the effects among those who choose to participate, namely $\partial E[y_{it}|p_{it} = 1]/\partial w_{jit}$ (Wooldridge, 2010). Following the findings of Baltagi et al. (2023), it would be expected that a problem of inconsistency would only arise whenever contemporary weather variables appear in both the participation and yield models (i.e., under a high-precision prediction or perfect information scenario).

We consider an alternative specification of the log-yields equation from Miller et al. (2021), which now follows

$$y_{it} = \beta_0 + \beta_1 \text{Prec}_{it} + \beta_2 \text{Prec}_{it}^2 + \delta_1 \text{DLow}_{it} + \delta_2 \text{DMed}_{it} + \delta_3 \text{DHigh}_{it} + \rho \hat{\lambda}_{it} + \gamma t + c_i + v_{it}, \quad (3.2)$$

⁸Given that using only a current year price to predict a next-year price would leave aside intertemporal adjustments of price expectations (Nerlove, 1956), we define a vector autoregression $Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + U_t$, where $Y_t' = (P_t^S, P_t^C)$. Therefore, the dynamic predictions for sorghum and corn prices for each year, are a function of both their prices in the previous two years.

where y_{it} is the sorghum log-yield for farmer i in year t , the weather variables are defined as in the previous subsection, v_{it} is an idiosyncratic shock to yields, and c_i is an unobserved, time-invariant, individual heterogeneity. Under this specification, $\hat{\lambda}_{it}$ is the inverse Mills ratio derived from the participation model, such that

$$\hat{\lambda}_{it} = \frac{\phi(\mathbf{z}_{it}; \hat{\alpha}, \hat{\eta}, \hat{\mu}, \hat{\xi})}{\Phi(\mathbf{z}_{it}; \hat{\alpha}, \hat{\eta}, \hat{\mu}, \hat{\xi})}, \quad (3.3)$$

where ϕ and Φ are the associated probability density and cumulative density functions from the standard normal distribution, with coefficients retrieved from the participation analysis estimates. Upon cluster-robust estimation, this specification approximates the fully robust test of sample selection by variable addition suggested in Wooldridge (1995). Namely, the null hypothesis $\rho = 0$ means no potential problems due to sample selection. Conversely, a failure to reject implies that FE estimates of (3.2) that wave the role of $\hat{\lambda}_{it}$ are likely inconsistent.⁹

3.4 Data

Our analysis is based on open-access information available in Miller et al. (2021) from the database of the Kansas Farm Management Association (KFMA). The KFMA database is a longitudinal survey maintained by Kansas State University (KSU) and, while not representative of farmers at the state level, it mainly represents large-scale operations (Kuethe, Briggeman, Paulson, & Katchova, 2014). In addition to its application in Miller and coauthors' research, the information is used by Kansas State University researchers to derive production and financial recommendations for farmers in the state. KFMA data has also been used to study the adoption of precision agriculture (Griffin et al., 2017) and farm profitability (Stabel, Griffin, & Ibendahl, 2017).

The publicly available information contains a farm-level unique identifier, sorghum yield data, observed weather variables during the farm- and year-specific production period, an anonymized (yet unique) code that connects a farm to a specific PRISM data grid, and a code linking the farm to a specific agricultural district. Since weather farm-specific data is only available for years in which they produce sorghum, we input the sample-average weather variables¹⁰ from the grid (when

⁹In a case in which one fails to reject, it is necessary to adjust standard errors accordingly. However, in the case of unbalanced panel data, this is no easy feat since the definition of a bootstrap is non-trivial. Hence, we take the one-time estimate to provide some insights on potential problems of bias in usual FE estimations, but take the results with caution since our calculated standard errors are likely inconsistent.

¹⁰Given that different farms choose different times for production, this imputation takes the simple average of degree

available) or the agricultural district for years when the farm does not produce sorghum. While the available data is somewhat limited, as it does not include information about other crops' production, farm acreage, or input use, our setting of a partial equilibrium analysis of the extensive and intensive margins of sorghum production in a competitive market only necessitates data on yields, climate, and prices.

3.4.1 Descriptive statistics and stylized facts

We replicate the main descriptive statistics from Miller et al. (2021) in Table 3.1. The number of farms producing sorghum in a given year varies from 449 to 1,676. The average farm is present in the dataset producing sorghum for roughly 16 years,¹¹ although a given farm may be present on only one occasion or during the entire sample period (1978-2015). Average sorghum yields stand at 63 hundredweight per hectare, with a maximum of 174 cwt/ha. In addition, farms experience an average minimum (maximum) temperature of 16°C (29.8°C), along with an average cumulative precipitation of 382 millimeters.

The KFMA data reveals a significant per-year decrease in the number of farmers producing sorghum. In Figure 3.1, we present the number of farms throughout the 38-year period, along with data on average temperatures experienced in Kansas per year, specifically for the June-September period—the reference time for sorghum production. The average reduction in the number of farmers was slight from 1978 to the late 1990s, but it became sharper in 1998. Given that farms in KFMA usually represent large operations, the reduction is not necessarily trivial and could have important implications at the sector level. Meanwhile, the State-level average temperatures have been slightly increasing overall. Interestingly, there was an apparent downward trend in average temperatures until the mid-1990s, followed by a sharp positive trend thereafter, in line with the global trends reported by World Meteorological Organization (2023), which finds that average temperatures have increased at an accelerated rate since the 1990s.¹² From a pairwise perspective, this could point to

days experienced by farms within the grid.

¹¹It is worth reemphasizing that this differs from the total range in which the farm is present in the sample, which we define in the motivation as the length of $[T_i, \bar{T}_i]$.

¹²I present an alternate version of this figure in Appendix, Figure 3A.1, allowing for a linear fit for the 1978-1990 period, and another for 1990-2015. The marked differences in State-level temperature trends seem potentially connected to farmers' decisions to exit production.

the increases in temperature as a potential mechanism driving farmers out of sorghum production, at least partially.¹³

Meanwhile, prices also reveal a significant trend to be considered. In Figure 3.2, we present again the number of in-sample, KFMA sorghum-producing farms in the reference year, along with farmers' received price (in constant 2015 prices) for sorghum and corn, which are remarkably coupled. Sorghum prices went from roughly 15 dollars per hundredweight (\$/cwt) in the early 1980s to just above \$5/cwt in the 2000s. It is precisely during the mid-2000s, when sorghum prices were steadily at the lowest historic levels, that we observe the sharpest decline in the number of farmers from the KMFA sample. With the price of corn (i.e., a leading competing crop with a much broader market demand) following similar patterns, there are reasons to expect that structural factors potentially affect the decision of farmers to stay out of sorghum production.

In aggregate, this preliminary data analysis hints that farmers' decisions to participate in sorghum production may be related to temperatures and prices in the market.¹⁴ These correlations align with the extended literature on climate change impacts on agriculture, which points to specialization and improvement in productive decisions as factors reducing the costs of a warmer climate (Costinot, Donaldson, & Smith, 2016). Therefore, considering whether usual fixed-effects estimates are potentially biased from a sample selection standpoint would suggest that estimations may want to account for pre-existing adaptation strategies influencing the structure of observed samples.

¹³While increasing temperatures can drive production away from sorghum, price increases could foster compensating effects in observed acreage. For instance, while Kansas' total acreage of sorghum decreased in 1997-2012 (Figure 3A.2)—correlated with increasing average temperatures and decreasing prices—the acreage increased significantly in 2017, likely connected to price increases in 2010-2016. However, the number of sorghum operations in Kansas constantly decreased throughout 1997-2022 (Figure 3A.3), so acreage increases are concentrated across fewer farmers.

¹⁴Moreover, farmers could already be making decisions on their effective production period, potentially pulling forward their planting time to experience more favorable weather. In line with the policy recommendation from Miller et al. (2021), the farmer-observed temperatures display a decreasing trend, which contrasts with trends of increasing average measures of temperature at the State level for the main productive season (Figure 3A.4).

3.5 Results and Discussion

3.5.1 Extensive margin: The case of production participation

We begin our testing of the responsiveness of production participation to weather and price expectations in a case that assumes access to high-accuracy weather predictions, along with variations in definitions of price expectations, and summarize our findings in Table 3.2. Columns one and three report Probit coefficients, while Columns two and four report average partial effects. In line with the literature, we consistently detect a declining production participation rate through time (Duff et al., 2019). Meanwhile, increases in precipitation and degree days in a range favorable for the crop (DMed) are related to an increase in the participation rate. In contrast, additional degree days in ranges detrimental to the crop negatively relate to participation. Coefficients and average partial effects of trend and weather variables are statistically equivalent regardless of the type of price expectation variation. In addition, price expectations operate as expected; using dynamic predictions, we find that an additional dollar per cwt of sorghum (corn) correlated with an increase (decrease) of 2.59 (2.66) percentage points in the participation in sorghum production. These figures are roughly half their magnitude when relying on last-year prices as a reference for expectations.¹⁵

While a scenario of access to high-accuracy forecasting is arguably a strong assumption, this limiting case is informative as it points to a likely connection between farmers' behavior and local weather trends. Moreover, our findings suggest that both prices and expected shocks to production possibilities likely affect the decision to produce a crop like sorghum, which aligns with our theoretical framework. We then estimate the alternative scenario, in which weather predictions are based on weather exposure levels from the past agricultural season, and summarize our findings in Table 3.3. Our estimates for time-trend, precipitation, DLow, and DMed are qualitatively equivalent and of similar magnitudes to those of the case of high-accuracy forecasting. Nevertheless, changes in

¹⁵These findings also indicate that while there are recommendations in switching to sorghum as an adaptation strategy upon harsher climates, farmers still potentially adjust their decision to produce it to avoid yield impacts. However, and perhaps more importantly, market demands (partially captured via price expectations) matter. While sorghum could hypothetically serve as a substitute for a grain like corn, the market size for the latter is significantly larger and could still lead to higher profits for farmers—even after accounting for the shocks of climate change.

price expectations are statistically insignificant regardless of their definition, and additional degree days of high temperatures (DHigh) in the past season only weakly correlate with the decision to participate in sorghum production. These findings could be partially explained by having high-temperature degree days as events that are rarer and thus more difficult to predict, thus reducing the impact of their realization on future behavior.¹⁶

3.5.2 Intensive margin: Yields and incidental truncation

Based on our extensive margin analysis findings, we now evaluate whether a climate-responsive decision to participate can significantly alter (bias) the estimates of weather impacts on yields. Starting again from a case of participation driven by access to high-accuracy weather forecasts, we use a Heckman-style correction approach and summarize our results in Table 3.4. Column one reports the benchmark result from Miller et al. (2021). On the other hand, Columns two and three report the estimates adjusted by the added variable approach (inverse Mills ratio) derived from a participation equation using contemporary weather variables and, respectively, dynamic predictions and one-year lags of prices. We find that a case of high-accuracy weather forecasting, along with price expectations based on dynamic predictions, suggests the presence of bias from FE estimations that omit the role of farmers' productive participation decisions. More specifically, this adjustment leads to now statistically insignificant effects from degree days in low- and medium-temperature bins, as well as to a reduction in the magnitude of the exposure to degree days above 33°C. Conversely, a correction based on a first-step estimation of participation based on price lags suggests no risk of bias.

Next, we consider the alternate case in which the selection adjustment follows weather expectations set as those realized during the previous year. We present these estimates in Table 3.5, presenting again the benchmark estimation in Column one, while Heckman-adjusted regression estimates are in Columns two and three. In this setting, we only detect a weakly significant effect derived from the addition of the inverse Mills ratio. In practical terms, there is only a noticeable

¹⁶For example, in a setting like ours, where we argue that farmers use available information in preparation for the season, past-year trends of cold- and medium-levels of temperature (which occur in the earlier part of the season) may be more informative of the upcoming season.

change in the statistical significance of the trend covariate, thus acknowledging sustained growth in sorghum productivity. Nevertheless, coefficient estimates for weather-related variables are statistically equivalent and are virtually unchanged. Ultimately, this alternate approach provides its expected findings: past-season weather information has a seemingly limited (if any) effect on productive decisions for upcoming productive seasons.

Nevertheless, the first set of results has important economic and policy implications regarding the connection between adaptation strategies and estimating heat impacts on crop yields. For instance, take a comparison between the benchmark and adjusted piecewise linear relationship between temperature and yield (Figure 3.3). Our findings suggest that taking the role of production participation into account as a climate-sensitive response can potentially lead to lower yield responses to increased exposure to detrimentally high temperatures. Therefore, recent institutional and research efforts that have been oriented towards improving seasonal forecasts for agricultural producers respond to stated short-term demands from the sector and further contribute to its long-term sustainability by allowing better adaptation strategies and fostering climate resilience (Klemm & McPherson, 2017; Templeton, Shane Perkins, Aldridge, Bridges, & Lassiter, 2014).

3.5.3 Robustness checks

Our analysis rests on the hypothesis that farmers have access—to some degree—to precise information about seasonal weather forecasts. However, our results so far exploit either previous-year or contemporary weather variations. Thus, it could be argued that long-term trends in weather patterns drive the qualitative similarity in estimated effects from lagged and contemporary weather variables on participation, instead of access to forecasting in elaborating expectations. We provide correlational evidence in favor of our hypothesis in Table 3A.1, where we fit a participation model based on contemporary and lagged weather variables, along with variations in the chosen definition for price expectations. Under this specification, if it were the case that long-term trends lead the results and forecasting played no role, we would expect that only lagged weather variables have a statistically significant effect. Nevertheless, we find qualitatively equivalent and statistically significant average partial effects for most past and contemporary weather variation. If anything,

the results would point to farmers potentially combining both sets of information to make decisions regarding participation.¹⁷

In addition, we have argued that increasing access to high-accuracy forecasting is the most likely driver of participation as an adaptation strategy, which could lead to potential bias in traditional FE estimations. To approximate this, we consider a variation of our analysis that sets weather expectations as a weighted average of past-season and contemporary weather variations. Let $E_t[W]$ be the expectation of a weather variable W for season t , such that

$$E_t[W] = \theta W_t + (1 - \theta)W_{t-1},$$

where $\theta \in [0, 1]$ is a weight factor that reflects the precision of expectations, since whenever $\theta \rightarrow 1$ or $\theta \rightarrow 0$ we get our limiting scenarios. We reassess our analysis of participation in scenarios that reflect increasing values of θ set at 0.25, 0.5, and 0.75 and report the results in Table 3A.2. The coefficients are qualitatively equivalent across all weight scenarios, in line with our previous analyses, which suggest that we would mostly expect an impact from higher accuracy in the intensive margin.

On the other hand, considering the role of participation based on increasingly accurate weather expectations tells a different story. Using the previous results as a first-step analysis, we calculate corresponding inverse Mills ratios based on different values of θ and re-estimate our main intensive margin specification. We summarize these findings in Table 3A.3. Note that as θ increases, the estimated magnitude of ρ also increases—i.e., the odds of bias in traditional FE estimates increase. Therefore, it could be argued that as seasonal weather forecasting increases its precision, farmers' expectations become increasingly and more strongly correlated with effective weather patterns. Thus, the role of production participation (extensive margin) will matter to determine the impacts of weather on yields (intensive margin).

Additionally, we address three additional concerns when studying the case of production participation. Namely, we evaluate whether climate responsiveness is sensitive to (a) considerations of low yields in the immediately previous season, (b) farm-level invariant factors, and (c) alternate

¹⁷Noticeably, these specifications lead to insignificant effects from price variables. However, given that our price data is at the State level, having two years of weather variation takes a significant share of year-to-year price variability.

definitions of production participation due to rotational considerations. We summarize these in Table 3A.4. First, in columns 1-2, we add a binary covariate that takes the value of one if the farm experienced production in the lowest decile of yields in the previous year.¹⁸ Our findings suggest that farmers experiencing sorghum yields in the lowest decile in a year become less likely to produce in the following year. Specifically, experiencing yield in the lowest decile reduces the odds of producing the next year by roughly seven percentage points. Meanwhile, the remaining partial effects align with our main inference. Therefore, farmers' behavior regarding sorghum productive decisions are seemingly responding to (i) weather expectations, (ii) expected prices, and (iii) their assessment of their production efficiency.

Second, we consider the possibility of our random-effects first-stage results being driven by unobserved heterogeneities. Therefore, we follow Wooldridge (1995) and implement a Mundlak approach,¹⁹ by adding the farm-level averages of weather variables²⁰ as control variables (see Columns 3-4 in Table 3A.4). We find that while the magnitude of the average partial effects is somewhat reduced, their statistical significance holds—and so does most of our inference. Interestingly, we find that the between-effect from the Mundlak points to a higher probability of producing sorghum for farms with larger averages in high temperatures. This likely suggests that while weather foresight of high temperatures (short term) can hinder the decision to produce sorghum in a given year, it also happens that farmers in warmer areas are more likely to remain in production.

Finally, we consider the potential sensitivity of estimates to assumptions regarding crop rotation. In particular, we are interested in a case where some of the zeroes in the sorghum production decision index may be misleading, as it is possible that sorghum remains in the farmer's production plan but

¹⁸This addition implies a tradeoff in terms of the number of observations, as this limits the observations to cases in which there exists production in the immediately previous period. Nevertheless, this specification allows us to consider shorter-term dynamic production decisions based on farmers' experienced outcomes.

¹⁹In brief, this approach assumes that individual-level, unobserved heterogeneities are a function of (a) the time averages of time-varying covariates of interest, and (b) purely random individual-level variation. The former can be directly captured as an added variable, leading to the standard Correlated Random Effects estimator.

²⁰Following our framework, we consider the average of weather observed (or approximated) at each farm for each $t \in [\underline{T}_i, \bar{T}_i]$

is not produced in a given year due to a rotation system. We take a simple approach where

$$p_{it} = \begin{cases} 1 & \text{if } (i \text{ produces sorghum in } t) \text{ or } (i \text{ produced sorghum in } t - 1) \\ 0 & \text{if } i \text{ does not produce sorghum in } t \text{ or } t - 1, \end{cases}$$

which assumes a one-year rotation.²¹ Except for price variables, which result in statistically insignificant estimates, we find qualitatively equivalent results to those of our main analysis. Thus, even after accounting for potential strategies of crop rotation, the decision to produce sorghum is climate responsive, which can potentially affect estimates of weather impacts on yields.

3.6 Conclusion

Using longitudinal farm-level data on yields and weather patterns, along with price time series, we assess the potential role of farmers' expectations in shaping productive participation and its effect on yield-related weather impacts. With open-access data of sorghum production in Kansas between 1978 and 2015, we use binary regression and Heckman-style linear regression adjustments, respectively, to (1) evaluate how high-accuracy expectations affect the likelihood of farmers producing sorghum in a given year, and (2) assess whether this behavior warrant a revision of heat impacts on yields.

Our analysis reveals that a farmer's decision to participate in sorghum production in a given year is likely price- and climate-responsive. Moreover, we provide evidence that participation is correlated with past and upcoming season weather variables, suggesting that farmers have some degree of (or access to) high-accuracy forecasting and adapt their behavior accordingly. On the other hand, corrections for potential bias from sample selection (emerging from participation decisions) in yield equations, suggest that only when weather expectations are sufficiently close (or correlated) to realized weather, traditional fixed-effect estimates are likely inconsistent. In particular, accounting for participation as a strategic adaptation choice leads to a lower magnitude in impact estimates from crop exposure to high heat levels. As seasonal forecasting becomes increasingly more precise, our findings signal the possibility of farmers properly using information to adjust their production behavior, likely improving their resilience to climate change.

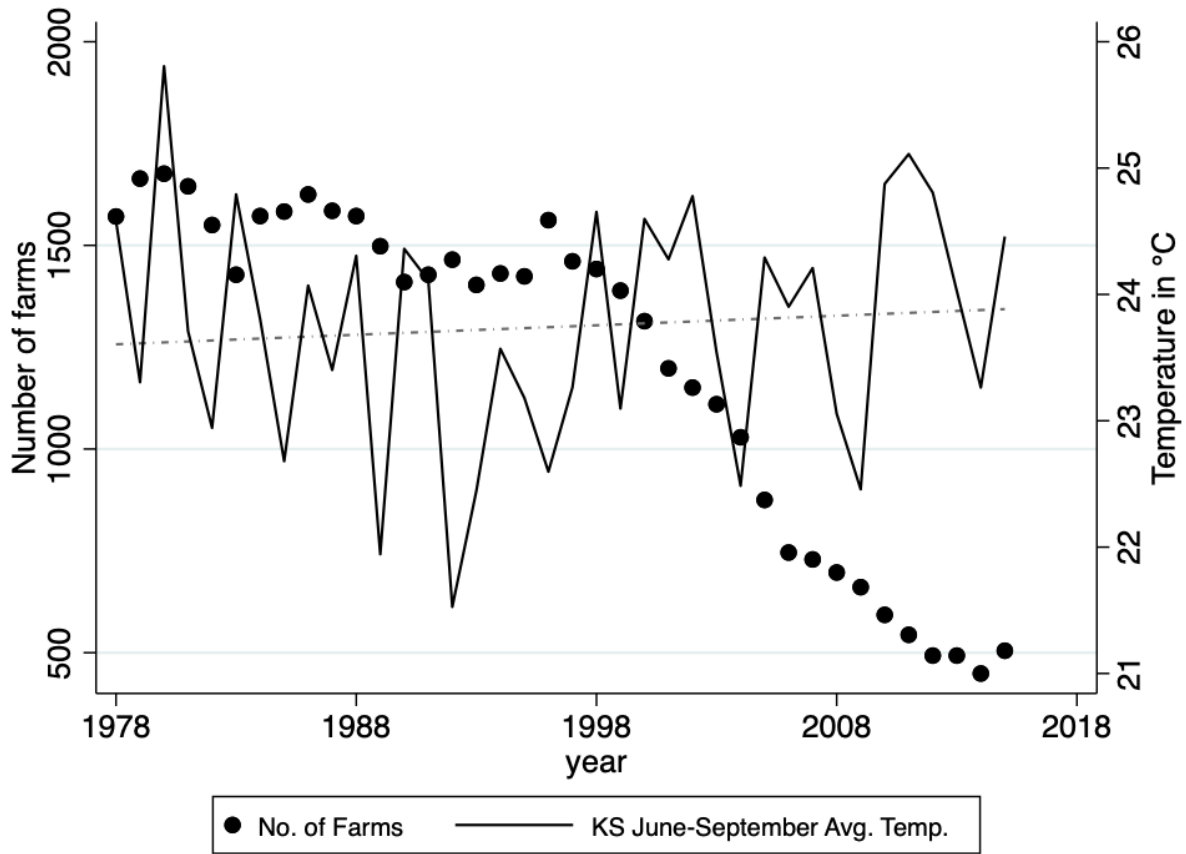
²¹While wheat-sorghum-fallow rotations are common in the region, and would point to longer lags to account for, we do not find cases in our data pointing to potential rotations of more than one year.

Although our results provide relevant insights about the effective use of increasingly granular data to estimate weather impacts on yields, we acknowledge two key limitations. First, future studies could explore the role of expectations in the productive allocation of different crops at the farm level. Our analysis focused on the extensive and intensive margins of sorghum production; yet, it is still possible that farms are producing other in-farm substitute crops like corn, which we cannot observe in the available data. Exploring how crop allocation shares change due to weather and price expectations would provide a more comprehensive assessment of the potential impacts of adaptation strategies on farm-level productive efficiency.

Second, future work could explore the role of farms' and farmers' attributes and financial conditions as drivers of farm observability. Studies that include information about farmers' age, schooling, associativity, family background, and other farmer-level covariates could provide more insights about the prioritization of specific crops in production, and of differentiated mechanisms of adaptation based on changing rates of human and social capital. Likewise, detailed information on the farm's cost structures and financial conditions would allow for isolating the effects of the total exit of agricultural production from those stemming from adaptation. Finally, any details about the presence of contract farming would also allow us to draw important comparisons between a scenario of flexibility towards adaptation vis-à-vis pre-existing commitments.

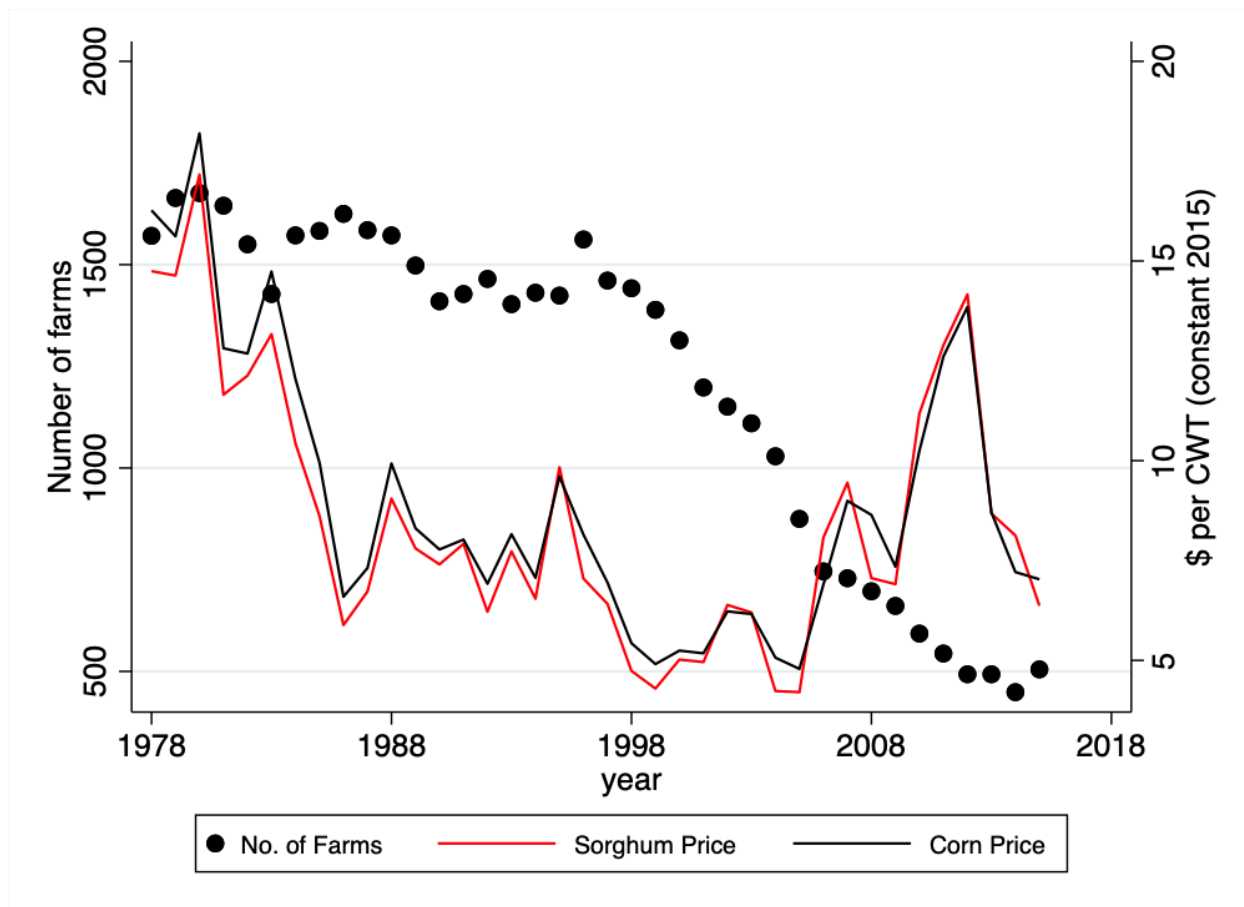
Figures and Tables

Figure 3.1 Number of farms and sorghum season average temperatures in Kansas, 1978-2015.



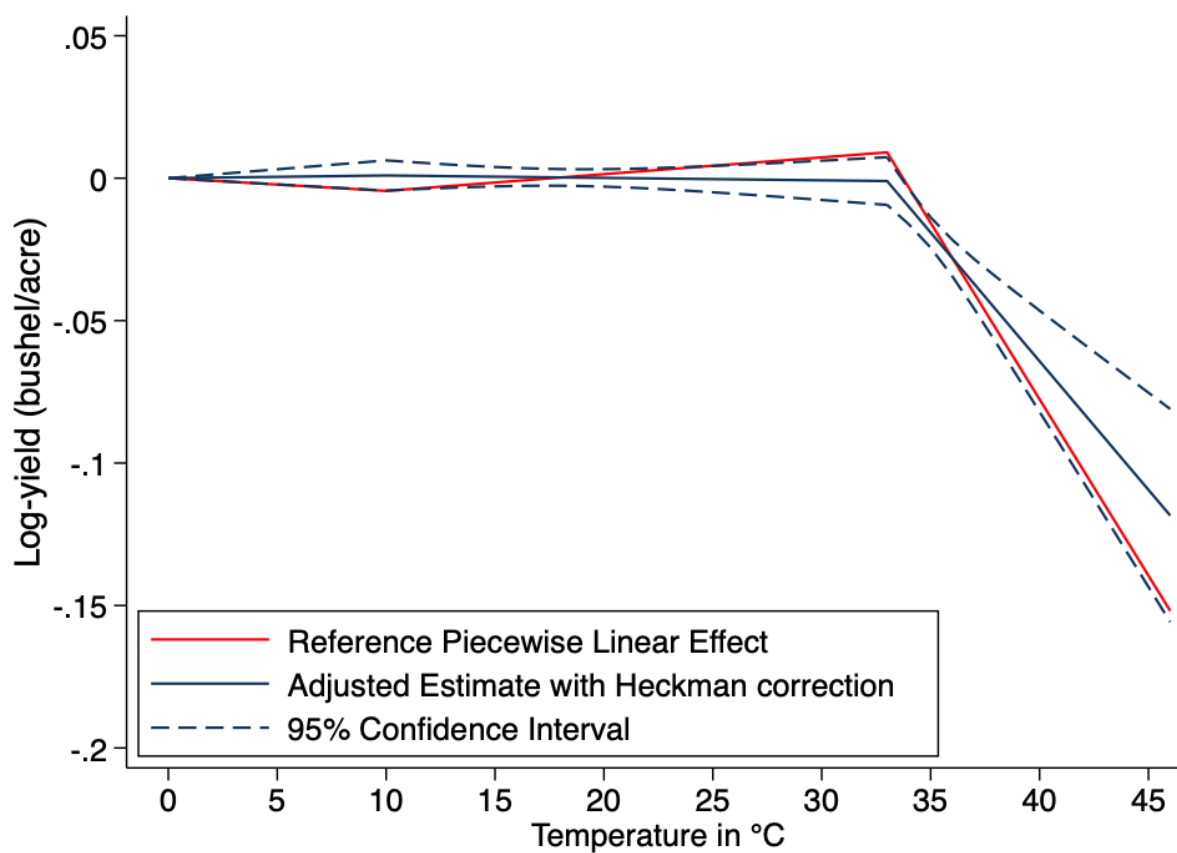
Notes — Figure displays the number of sorghum-producing farms registered in the KMFA (left axis) and the average temperature in Kansas during the June-September period (right axis) for the reference year. Farm information is available from open-access data provided by Miller et al. (2021), while Kansas-level temperature data comes from the National Centers for Environmental Information. The dot-dashed line reports the linear fit of the average temperature as a function of the year variable for the entire period.

Figure 3.2 Number of farms and farmers' received prices for corn and sorghum, 1978-2015.



Notes — Figure displays the number of sorghum-producing farms registered in the KMFA (left axis) and farmers' received prices for sorghum and corn (right axis) for the reference year. Farm information is available from open-access data provided by Miller et al. (2021), while Kansas-level temperature data comes from USDA NASS. Prices are adjusted by CPI from the U.S. Bureau of Labor Statistics.

Figure 3.3 Comparison of marginal effects of degree-days exposure on sorghum yields, with and without Heckman-style sample selection correction.



Notes — Figure displays the marginal effect of exposure to a particular 1°C temperature level on sorghum yields. The red line reflects the baseline estimate from Miller et al. (2021), while the solid blue line reflects the alternate results upon a Heckman-style correction. The dashed lines denote the 95% confidence intervals with standard errors clustered at the agricultural district-year level.

Table 3.1 Descriptive statistics – Adapted from Miller et al. (2021).

VARIABLE	Mean	Std Dev	Min	Max
Number of farms by year	1,348.32	330.54	449	1,676
Number of years by farm	16.13	9.44	1	38
Sorghum yield	63.18	28.50	0	174.55
Cumulative precipitation	382.30	155.17	68.07	988.50
Average daily min temp	16.08	2.11	7.36	20.44
Average daily max temp	29.87	2.14	20.27	36.04
DLow	1,280.07	125.03	989.97	1,844.27
DMed	1,690.30	149.22	1,134.01	2,294.05
DHigh	25.26	21.27	0	140.59

Notes — Total number of observations is 45,971 across 5,541 farms spanning 38 years (1978-2015). DLow is defined as degree days above 0°C minus degree days above 10°C, DMed is defined as degree days above 10°C minus degree days above 33°C, and DHigh is defined as degree days above 33°C.

Table 3.2 Coefficient estimates of sorghum production participation model.

VARIABLES	(1) Probit	(2) APE	(3) Probit	(4) APE
Trend	-0.0102*** (0.000969)	-0.00336*** (0.000318)	-0.0112*** (0.00104)	-0.00369*** (0.000340)
Precipitation	0.000332*** (5.50e-05)	0.000109*** (1.81e-05)	0.000341*** (5.52e-05)	0.000112*** (1.81e-05)
DLow	-0.000314*** (6.80e-05)	-0.000104*** (2.24e-05)	-0.000305*** (6.81e-05)	-0.000100*** (2.24e-05)
DMed	0.000437*** (5.79e-05)	0.000144*** (1.90e-05)	0.000430*** (5.81e-05)	0.000142*** (1.91e-05)
DHigh	-0.00218*** (0.000432)	-0.000716*** (0.000142)	-0.00211*** (0.000432)	-0.000695*** (0.000142)
$\hat{P}_{\text{sorghum}}$	0.0788** (0.0343)	0.0259** (0.0113)		
$\hat{P}_{\text{corn}}$	-0.0807** (0.0324)	-0.0266** (0.0107)		
Lag of P_{sorghum}			0.0337*** (0.0121)	0.0111*** (0.00397)
Lag of P_{corn}			-0.0407*** (0.0122)	-0.0134*** (0.00402)
Constant	0.248*** (0.0830)		0.293*** (0.0848)	
Observations	66,959	66,959	66,959	66,959

Notes — Response variable is a binary index of whether the farm produces sorghum in the reference year. Reporting coefficients and average partial effects (APE) from Random Effects Probit estimation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables $\hat{P}_{\text{sorghum}}$ and $\hat{P}_{\text{corn}}$ are dynamic predictions of farmers' received price from a 2-lag vector autoregression.

Table 3.3 Coefficient estimates of sorghum production participation model: Alternate results using lags of weather variables.

VARIABLES	(1) Probit	(2) APE	(3) Probit	(4) APE
Trend	-0.00657*** (0.000993)	-0.00216*** (0.000326)	-0.00682*** (0.00105)	-0.00225*** (0.000345)
Lag of Precipitation	0.000361*** (5.63e-05)	0.000119*** (1.85e-05)	0.000353*** (5.67e-05)	0.000116*** (1.87e-05)
Lag of DLow	-0.000855*** (6.95e-05)	-0.000282*** (2.28e-05)	-0.000836*** (7.02e-05)	-0.000275*** (2.30e-05)
Lag of DMed	0.000462*** (5.89e-05)	0.000152*** (1.94e-05)	0.000457*** (5.90e-05)	0.000150*** (1.94e-05)
Lag of DHigh	-0.000791* (0.000476)	-0.000261* (0.000157)	-0.000702 (0.000467)	-0.000231 (0.000154)
$\hat{P}_{\text{sorghum}}$	0.0141 (0.0337)	0.00465 (0.0111)		
$\hat{P}_{\text{corn}}$	-0.0194 (0.0323)	-0.00639 (0.0106)		
Lag of P_{sorghum}			-0.00137 (0.0121)	-0.000450 (0.00399)
Lag of P_{corn}			-0.00588 (0.0123)	-0.00194 (0.00403)
Constant	0.786*** (0.0893)		0.786*** (0.0896)	
Observations	64,934	64,934	64,934	64,934

Notes — Response variable is a binary index of whether the farm produces sorghum in the reference year. Reporting coefficients and average partial effects (APE) from Random Effects Probit estimation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables $\hat{P}_{\text{sorghum}}$ and $\hat{P}_{\text{corn}}$ are dynamic predictions of farmers' received price from a 2-lag vector autoregression.

Table 3.4 Coefficient estimates of sorghum yield model: Baseline and Heckman corrections.

VARIABLES	(1) Log-Yield	(2) Log-Yield	(3) Log-Yield
Trend	0.00201 (0.00153)	0.0137*** (0.00459)	0.00572 (0.00385)
Precipitation	0.00340*** (0.000461)	0.00288*** (0.000507)	0.00324*** (0.000499)
Precipitation ²	-3.12e-06*** (4.68e-07)	-3.09e-06*** (4.60e-07)	-3.11e-06*** (4.68e-07)
DLow	-0.000447** (0.000180)	9.46e-05 (0.000270)	-0.000278 (0.000252)
DMed	0.000588*** (0.000140)	-8.49e-05 (0.000272)	0.000377 (0.000241)
DHigh	-0.0124*** (0.00127)	-0.00903*** (0.00171)	-0.0113*** (0.00157)
$\hat{\lambda}_{it}$		-2.742*** (1.045)	-0.867 (0.847)
Constant	3.100*** (0.210)	4.950*** (0.712)	3.685*** (0.590)
Weather Expectation	N/A	Contemporary	Contemporary
Price Expectation	N/A	Dynamic	Price Lag
Observations	45,971	45,971	45,971
R-squared	0.591	0.593	0.591

Notes — Response variable is the log-yield of sorghum in the reference year. Reporting Fixed-Effect (farm-level) estimates, with standard errors clustered at the agricultural district-year level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variable $\hat{\lambda}_{it}$ reflects the inverse Mills ratio derived from the RE Probit estimates of a participation model, including contemporary values of weather variables and either dynamic prediction of farmers' received prices for sorghum and corn or lags of observed prices.

Table 3.5 Coefficient estimates of sorghum yield model: Baseline and Alternate Heckman corrections.

VARIABLES	(1) Log-Yield	(2) Log-Yield	(3) Log-Yield
Trend	0.00201 (0.00153)	0.00441** (0.00200)	0.00415** (0.00201)
Precipitation	0.00340*** (0.000461)	0.00335*** (0.000471)	0.00336*** (0.000473)
Precipitation ²	-3.12e-06*** (4.68e-07)	-3.04e-06*** (4.64e-07)	-3.05e-06*** (4.67e-07)
DLow	-0.000447** (0.000180)	-0.000404** (0.000180)	-0.000402** (0.000182)
DMed	0.000588*** (0.000140)	0.000562*** (0.000137)	0.000560*** (0.000137)
DHigh	-0.0124*** (0.00127)	-0.0121*** (0.00127)	-0.0121*** (0.00127)
$\hat{\lambda}_{it}$		-0.744* (0.400)	-0.661* (0.397)
Constant	3.100*** (0.210)	3.452*** (0.238)	3.413*** (0.239)
Weather Expectation	N/A	Lagged Weather	Lagged Weather
Price Expectation	N/A	Dynamic	Price Lag
Observations	45,971	44,400	44,400
R-squared	0.591	0.587	0.587

Notes — Response variable is the log-yield of sorghum in the reference year. Reporting Fixed-Effect (farm-level) estimates, with standard errors clustered at the agricultural district-year level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variable $\hat{\lambda}_{it}$ reflects the inverse Mills ratio derived from the RE Probit estimates of a participation model, including lagged values of weather variables and either dynamic prediction of farmers' received prices for sorghum and corn or lags of observed prices.

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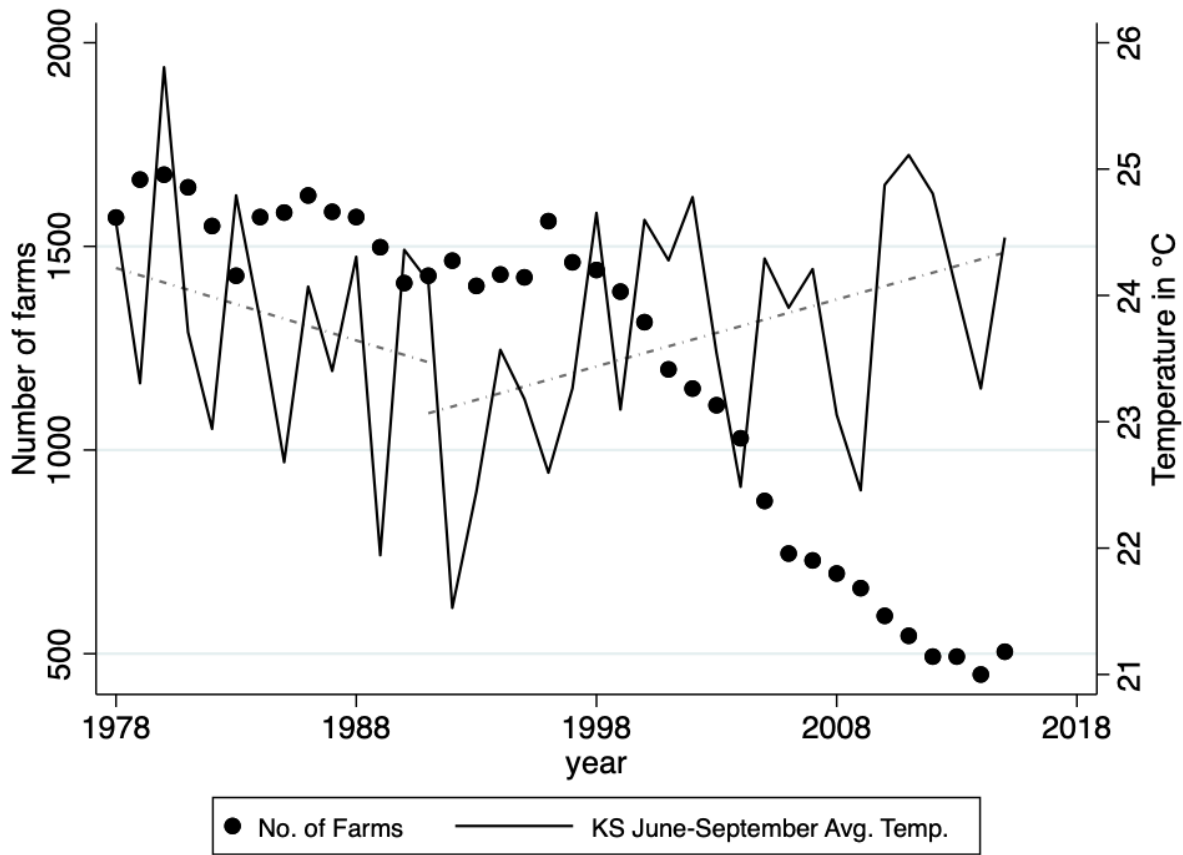
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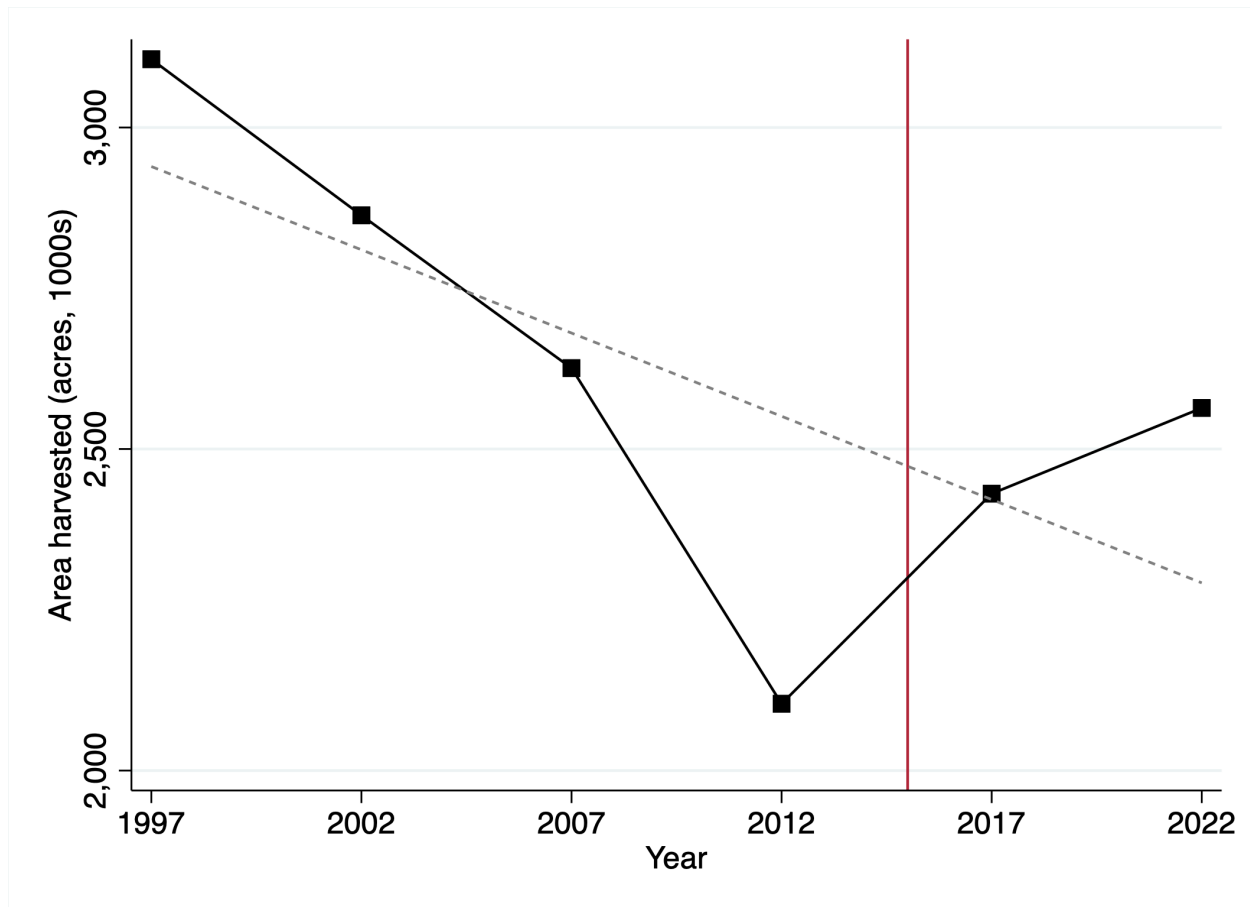
APPENDIX

Figure 3A.1 Number of farms and sorghum season average temperatures in Kansas with varying linear fits, 1978-2015.



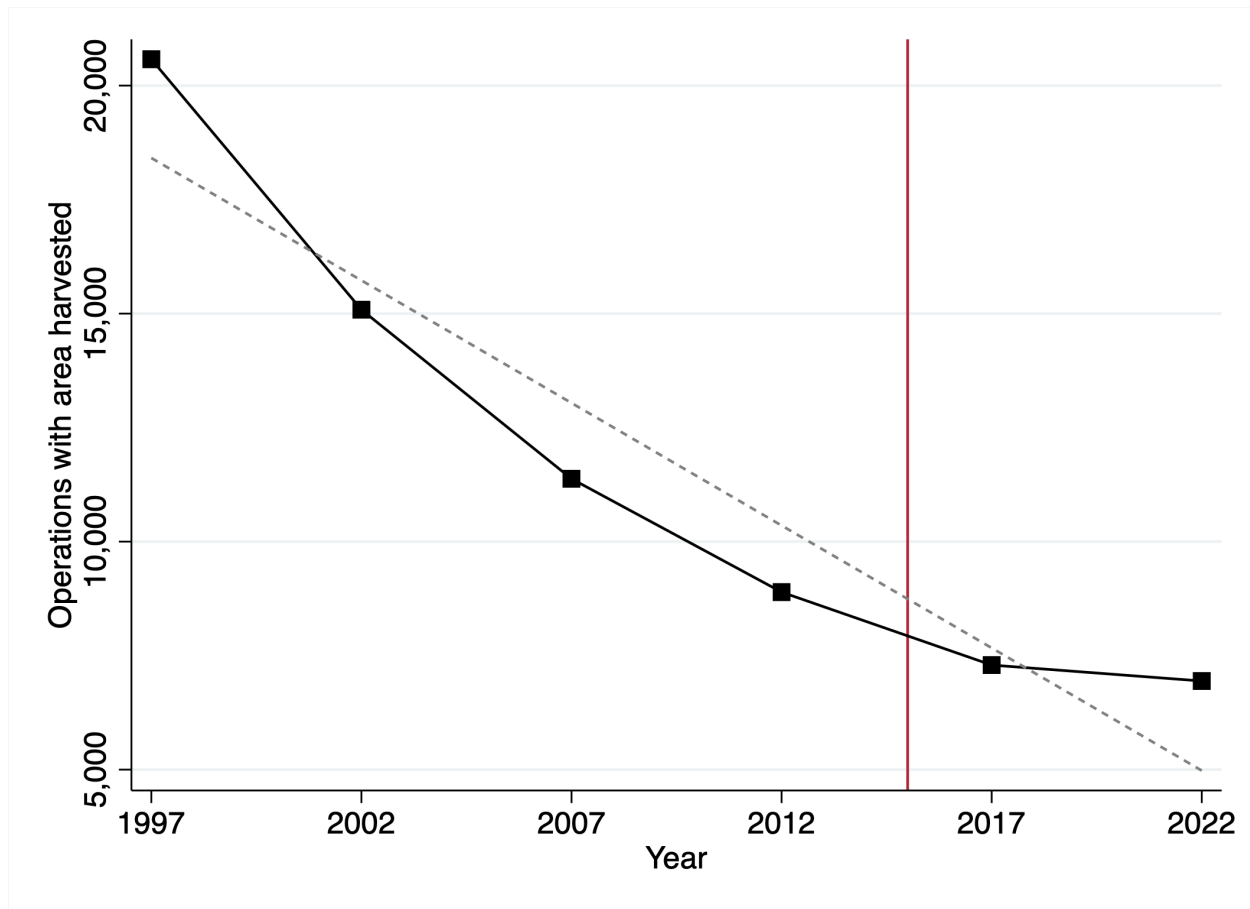
Notes — Figure displays the number of sorghum-producing farms registered in the KMFA (left axis) and the average temperature in Kansas during the June-September period (right axis) for the reference year. Farm information is available from open-access data provided by Miller et al. (2021), while Kansas-level temperature data comes from the National Centers for Environmental Information. The dot-dashed line reports (a) the linear fit of the average temperature as a function of the year for the 1978-1990 period, and (b) a linear fit for the 1990-2015 period.

Figure 3A.2 Total sorghum area (harvested) in Kansas, 1997-2022.



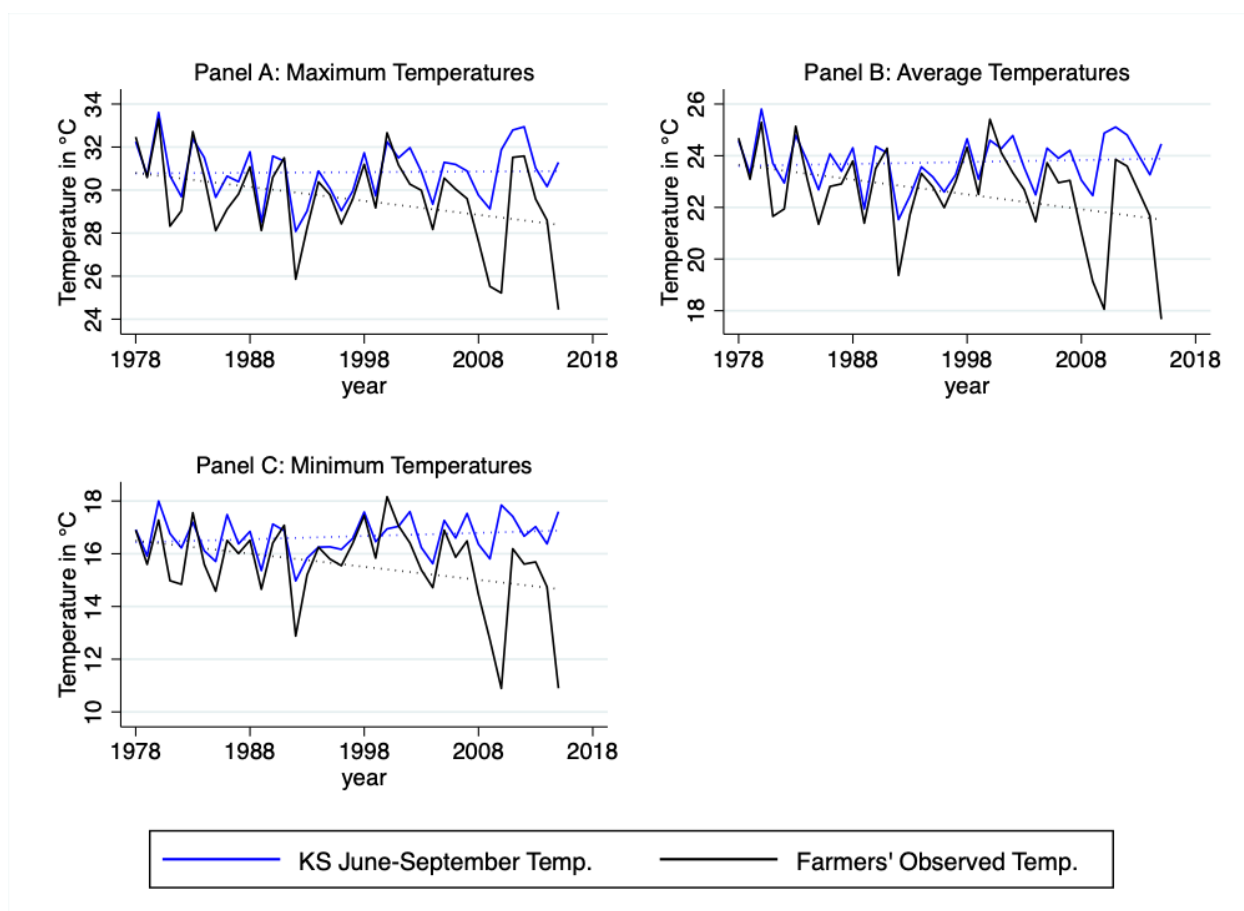
Notes — Figure displays Kansas's total sorghum harvested acreage (in thousands) between 1997 and 2022. The vertical red line marks the final year of available data from KMFA, while the dashed gray line describes the linear fit of acreage and years. Information is available from USDA-NASS Census Aggregates.

Figure 3A.3 Total sorghum operations (with area harvested) in Kansas, 1997-2022.



Notes — Figure displays Kansas's total sorghum operations with harvested acreage between 1997 and 2022. The vertical red line marks the final year of available data from KMFA, while the dashed gray line describes the linear fit of the number of operations and years. Information is available from USDA-NASS Census Aggregates.

Figure 3A.4 Reference temperatures during sorghum season in Kansas and farmers' observed temperatures, 1978-2015.



Notes — Figure displays the average maximum, overall average, and average minimum temperatures for Kansas during the June-September period, and the sorghum farmers' observed values of these variables for the reference year. Kansas-level temperature data comes from the National Centers for Environmental Information, while farm-level information is available from open-access data provided by Miller et al. (2021).

Table 3A.1 Coefficient estimates of sorghum production participation model: Inclusion of both contemporary and lagged values of weather variables.

VARIABLES	(1) Probit	(2) APE	(3) Probit	(4) APE
Trend	-0.00809*** (0.00106)	-0.00266*** (0.000346)	-0.00860*** (0.00111)	-0.00282*** (0.000363)
Precipitation	0.000273*** (5.58e-05)	8.95e-05*** (1.83e-05)	0.000274*** (5.60e-05)	9.01e-05*** (1.84e-05)
DLow	-4.28e-05 (7.29e-05)	-1.41e-05 (2.39e-05)	-3.33e-05 (7.30e-05)	-1.09e-05 (2.40e-05)
DMed	0.000257*** (6.36e-05)	8.45e-05*** (2.09e-05)	0.000249*** (6.37e-05)	8.16e-05*** (2.09e-05)
DHigh	-0.00156*** (0.000465)	-0.000513*** (0.000153)	-0.00150*** (0.000464)	-0.000493*** (0.000152)
Lag of Precipitation	0.000223*** (6.13e-05)	7.33e-05*** (2.01e-05)	0.000226*** (6.15e-05)	7.41e-05*** (2.02e-05)
Lag of DLow	-0.000811*** (7.28e-05)	-0.000266*** (2.38e-05)	-0.000798*** (7.33e-05)	-0.000262*** (2.40e-05)
Lag of DMed	0.000447*** (6.03e-05)	0.000147*** (1.98e-05)	0.000443*** (6.04e-05)	0.000145*** (1.98e-05)
Lag of DHigh	-0.00121** (0.000490)	-0.000398** (0.000161)	-0.00117** (0.000479)	-0.000384** (0.000157)
$\hat{P}_{\text{sorghum}}$	0.0463 (0.0347)	0.0152 (0.0114)		
$\hat{P}_{\text{corn}}$	-0.0497 (0.0330)	-0.0163 (0.0108)		
Lag of P_{sorghum}			0.0145 (0.0124)	0.00476 (0.00406)
Lag of P_{corn}			-0.0211* (0.0125)	-0.00694* (0.00409)
Constant	0.397*** (0.116)		0.414*** (0.118)	
Observations	64,934	64,934	64,934	64,934

Notes — Response variable is a binary index of whether the farm produces sorghum in the reference year. Reporting coefficients and average partial effects (APE) from Random Effects Probit estimation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables $\hat{P}_{\text{sorghum}}$ and $\hat{P}_{\text{corn}}$ are dynamic predictions of farmers' received price from a 2-lag vector autoregression.

Table 3A.2 Coefficient estimates of sorghum production participation model: Weighted average of contemporary and lagged weather variables.

VARIABLES	(1) Probit	(2) APE	(3) Probit	(4) APE	(5) Probit	(6) APE
Trend	-0.00727*** (0.00103)	-0.00239*** (0.000337)	-0.00710*** (0.00103)	-0.00233*** (0.000339)	-0.00811*** (0.00101)	-0.00267*** (0.000331)
Weighted Precipitation	0.000426*** (4.16e-05)	0.000140*** (1.36e-05)	0.000438*** (4.77e-05)	0.000144*** (1.56e-05)	0.000375*** (5.45e-05)	0.000123*** (1.79e-05)
Weighted DLow	-0.000889*** (7.70e-05)	-0.000292*** (2.52e-05)	-0.000879*** (8.58e-05)	-0.000289*** (2.81e-05)	-0.000572*** (8.19e-05)	-0.000188*** (2.69e-05)
Weighted DMed	0.000677*** (7.05e-05)	0.000222*** (2.31e-05)	0.000750*** (7.63e-05)	0.000246*** (2.50e-05)	0.000623*** (7.04e-05)	0.000205*** (2.31e-05)
Weighted DHigh	-0.00298*** (0.000573)	-0.000981*** (0.000188)	-0.00345*** (0.000657)	-0.00113*** (0.000216)	-0.00315*** (0.000574)	-0.00104*** (0.000189)
$\hat{P}_{\text{sorghum}}$	0.0403 (0.0340)	0.0132 (0.0112)	0.0393 (0.0340)	0.0129 (0.0112)	0.0478 (0.0343)	0.0157 (0.0113)
$\hat{P}_{\text{corn}}$	-0.0426 (0.0324)	-0.0140 (0.0107)	-0.0398 (0.0323)	-0.0131 (0.0106)	-0.0490 (0.0324)	-0.0161 (0.0107)
Constant	0.495*** (0.103)		0.347*** (0.112)		0.211** (0.103)	
Weight Factor (θ)	0.25		0.5		0.75	
Observations	64,934	64,934	64,934	64,934	64,934	64,934

Notes — Response variable is a binary index of whether the farm produces sorghum in the reference year. Reporting coefficients and average partial effects (APE) from Random Effects Probit estimation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables $\hat{P}_{\text{sorghum}}$ and $\hat{P}_{\text{corn}}$ are dynamic predictions of farmers' received price from a 2-lag vector autoregression.

Table 3A.3 Coefficient estimates of sorghum yield model: Baseline and Heckman corrections using weighted average of weather variables.

VARIABLES	(1) Log-Yield	(2) Log-Yield	(3) Log-Yield
Trend	0.00423** (0.00208)	0.00508** (0.00252)	0.0105** (0.00421)
Precipitation	0.00321*** (0.000498)	0.00314*** (0.000521)	0.00286*** (0.000561)
Precipitation ²	-3.03e-06*** (4.68e-07)	-3.03e-06*** (4.70e-07)	-3.01e-06*** (4.68e-07)
DLow	-0.000370* (0.000196)	-0.000239 (0.000261)	0.000125 (0.000367)
DMed	0.000547*** (0.000140)	0.000428** (0.000174)	7.47e-06 (0.000306)
DHigh	-0.0122*** (0.00127)	-0.0116*** (0.00132)	-0.00945*** (0.00182)
$\hat{\lambda}_{it}$	-0.611 (0.455)	-0.871 (0.656)	-2.324** (1.174)
Constant	3.421*** (0.273)	3.594*** (0.375)	4.595*** (0.730)
Weight Factor in Participation (θ)	0.25	0.5	0.75
Observations	44,400	44,400	44,400
R-squared	0.586	0.586	0.587

Notes — Response variable is the log-yield of sorghum in the reference year. Reporting Fixed-Effect (farm-level) estimates, with standard errors clustered at the agricultural district-year level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variable $\hat{\lambda}_{it}$ reflects the inverse Mills ratio derived from the RE Probit estimates of a participation model, including a weighted average of contemporary and lagged values of weather variables and dynamic predictions of farmers' received prices for sorghum and corn.

Table 3A.4 Coefficient estimates of sorghum production participation model: Response to low-yields, consideration of correlated random effects, and potential case of productive rotation.

VARIABLES	(1) Probit	(2) APE	(3) Probit	(4) APE	(5) Probit	(6) APE
Trend	-0.0216*** (0.00133)	-0.00649*** (0.000392)	-0.0111*** (0.00100)	-0.00363*** (0.000328)	0.0184*** (0.00138)	0.00212*** (0.000160)
Precipitation	0.000466*** (7.22e-05)	0.000140*** (2.16e-05)	9.88e-05 (6.02e-05)	3.24e-05 (1.98e-05)	0.000400*** (7.45e-05)	4.59e-05*** (8.56e-06)
DLow	-0.000480*** (8.83e-05)	-0.000144*** (2.64e-05)	2.61e-05 (7.92e-05)	8.57e-06 (2.60e-05)	-0.000366*** (8.92e-05)	-4.20e-05*** (1.03e-05)
DMed	0.000459*** (7.56e-05)	0.000138*** (2.26e-05)	0.000186*** (6.64e-05)	6.10e-05*** (2.18e-05)	0.000394*** (7.47e-05)	4.52e-05*** (8.59e-06)
DHigh	-0.00150*** (0.000563)	-0.000451*** (0.000169)	-0.00181*** (0.000454)	-0.000595*** (0.000149)	-0.00207*** (0.000580)	-0.000238*** (6.67e-05)
$\hat{P}_{\text{sorghum}}$	0.0902** (0.0450)	0.0270** (0.0135)	0.0904*** (0.0344)	0.0297*** (0.0113)	-0.0221 (0.0540)	-0.00254 (0.00620)
$\hat{P}_{\text{corn}}$	-0.106** (0.0426)	-0.0318** (0.0128)	-0.0944*** (0.0326)	-0.0310*** (0.0107)	0.00784 (0.0508)	0.000900 (0.00583)
Low yield in $t - 1$	-0.236*** (0.0243)	-0.0707*** (0.00726)				
$\overline{\text{Prec}}$			0.00163*** (0.000235)	0.000536*** (7.70e-05)		
$\overline{\text{DLow}}$			-0.000642*** (0.000181)	-0.000211*** (5.92e-05)		
$\overline{\text{DMed}}$			0.000152 (0.000196)	4.98e-05 (6.43e-05)		
$\overline{\text{DHigh}}$			0.00901*** (0.00192)	0.00296*** (0.000629)		
Constant	0.841*** (0.108)		0.0780 (0.284)		1.138*** (0.118)	
Observations	45,466	45,466	66,959	66,959	66,959	66,959

Notes — Response variable is a binary index of whether the farm produces sorghum in the reference year. Reporting coefficients and average partial effects (APE) from Random Effects Probit estimation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables $\hat{P}_{\text{sorghum}}$ and $\hat{P}_{\text{corn}}$ are dynamic predictions of farmers' received price from a 2-lag vector autoregression.