Confounding Adaptation in Perennial Climate Damages: A Unified Statistical Approach for Brazilian Coffee

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Confounding adaptation in perennial climate damages: A unified statistical approach for Brazilian coffee*

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Abstract

Climate change poses significant risks to agricultural production, especially for perennial crops, a crucial form of semi-durable capital in many developing countries. Misreported perennial yields and unobserved crop management decisions can undermine understanding of these risks. In the context of Brazilian coffee production, this study demonstrates that extreme temperatures not only reduce yields, but also shrink reported harvest area due to plant death and farmers' selective harvesting. The marginal damages from extreme temperatures on production are twice their effect on reported yields, as these are calculated using harvested area rather than bearing area. By merging the perennial supply and statistical yield literatures within a structural econometric framework, the effects of management decisions become distinguishable. The analysis reveals both a direct effect of extreme temperatures on biophysical yields and a multi-year plant death effect, and supports a more comprehensive understanding of how prices, weather, and adaptation interact across many perennial crops.

JEL Classification: C32, O13, Q10
Keywords: perennial agriculture, environmental shocks, decision-making

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1 Introduction

Perennial crops account for 13% of global cropland, but produce 35% of the value of agricultural exports (Appendix 1.1, Monfreda et al. 2008). Low income economies are particularly reliant on perennial crops, which constitute an average 56% of the value of their agricultural exports and 10% of their total exports. Despite their economic significance, most agricultural research has focused on annual crops, leaving the understanding of perennials' response to environmental factors, notably climate and weather conditions, comparatively understudied. A critical gap in current research is the accurate measurement of the response of perennial crop production to extreme weather (Devadoss and Luckstead, 2010; Wang and Alonzo, 2013).

Perennial crops possess unique characteristics that demand a nuanced understanding of their responses to environmental shocks and adaptation actions. Perennials are a form of semi-durable capital, requiring long investment horizons and the management of environmental variability.[1] Perennial crop production is deeply influenced by managed factors such as plantings, removals, and age-distributions, for which empirical data are typically unavailable. Many studies rely on recorded harvest areas as proxies when describing investment and yields (Elnagheeb and Florkowski, 1993; Askari and Cummings, 1977; Lobell et al., 2006).

As this paper shows, the use of harvest areas can conflate planting decisions with harvesting decisions, obscuring the true impact of weather shocks on crop production and understating the potential for future adaptation. Poor weather can both reduce yields and kill plants. For both annuals and perennials, farmers can respond to these environmental shocks with both short-term, intensive, and long-term, extensive management decisions. The effects of actions taken after observing a shock but before production outcomes are generally hidden to *ex post* statistical methods.

This paper focuses on two hidden management decisions: selective harvesting and responses to die-off. Farmers can selectively harvest their most productive fields, reducing harvested area relative to planted area and boosting apparent yields. For example, fields that experienced die-off will not be harvested. Selective harvesting applies to both annual and perennial crops. However, die-off for perennials has multi-year consequences and demands new investment. Farmer decisions around new planting, removal of older, less-productive trees, and abandonment are hidden but affect the biophysical yield of an area.

[1] As Brady and Marsh (2013) note, "From a modeling perspective perennial crop planting decisions may have more in common with housing and manufacturing than with annual row crop production".

Underlying this investigation is a pervasive data problem in national agricultural statistics. An accurate accounting of crop yields requires data on area planted, since harvested area hides the effects of selective harvest and die-off. However, a review of all crops reported by the US and Brazilian statistical agencies shows that planted area for perennial crops is universally unavailable in annual surveys (although it is reported in the US Census of Agriculture). While area of mature perennials is reported for many crops, there is strong evidence that it is unreliable in both countries (see appendix 1.2). For annual crops, planted area is unavailable in many countries and there is evidence that reported planted area in Brazil is actually harvested area for many crops and observations. The consequences of calculating yields using this information are elaborated in section 2.3.

Coffee production in Hawaii provides a useful case study of showing both the challenges with perennial crop data and evidence of selective harvesting, for a comparatively well-reported region (see appendix 2.2). Combining data from the USDA's annual survey and the Census of Agriculture, between 1997 and 2022, harvested, planted, and bearing (mature tree) areas are only all available in four years. Mature plant area is reported as equal to harvested area in years when the annual survey reports both (2013 - 2016) but an average of 9.4% higher than harvested area when compared to the available Census years (2002, 2007, and 2012). The portion of planted or bearing area that is harvested declines with high temperatures. That is, even for the US, perennial crop data is sparse and misreported, but shows evidence that damaging temperatures cause selective harvesting.

To investigate these dynamics, I consider coffee in Brazil. Coffee is an important perennial crop for many developing countries, exported by 34 low and lower middle income countries across the tropics and supporting 25 million farmers worldwide (O'Brien and Kinnaird, 2003) and an $81 billion industry (Sharf, 2014), making it one of the most valuable commodities in the world. However, coffee is extremely vulnerable to climate change, perched at high elevations in hot regions. Already changes in climate are increasing the frequency of disease outbreaks and shifting suitable growing regions (Guilford, 2014; Malkin, 2014).

Below, I first show that the effect of extreme temperatures on production is twice the effect on reported yields. This reflects a combination of die-off and selective harvesting. I then develop a unified approach for investigating perennial dynamics in response to weather variation, accounting for management decisions. The next section describes the key features of perennial dynamics and provides a theoretical framework for understanding these hidden management decisions and their empirical consequences in relation to observed production and harvested areas. Section three empirically investigates the evidence of selective harvests and of persistent die-off effects. These exercises also provide the key information needed to calibrate the theoretical model, accounting for both effects and addressing the data issue, in section four.

2 Analytical perennial dynamics

2.1 Literature Review

The complexities of perennials have been studied within the literature on short- and long-run elasticities of supply, often using modifications of the Nerlove model (Nerlove, 1958, 1979).[2] The original Nerlove model describes changes in planted area in response to expected prices and exogenous factors (Nerlove, 1958). Previous studies have modified this model for perennials in a number of ways. Since average yields evolve over the lifespan of a tree, many authors modify the equations to accommodate age classes or vintages (French et al., 1985; Elnagheeb and Florkowski, 1993), although these are rarely estimated empirically (Kalaitzandonakes and Shonkwiler, 1992). Second, authors have distinguished new planting and removals from net area changes (Hartley et al., 1987; Thang, 2011). If new planting replaces existing trees that are past their peak productivity, the total planted area will not expand.[3]

The elasticity literature on perennial supply dynamics falls into three broad camps, in response to the problem of managing the availability of data. Reduced-form approaches are most common, which relate contemporaneous and delayed prices to observed harvest (e.g., Wickens and Greenfield, 1973). A second class captures the distinction between age classes of plants through multiple lags (Bateman, 1965). An alternative approach estimates hidden variables to represent planting and clearing, and this is found to be predictively superior to reduced form methods (Knapp and Konyar, 1991; Kalaitzandonakes and Shonkwiler, 1992; Elnagheeb and Florkowski, 1993). This is the approach used in this paper, combined with the delayed weather and prices used in Wickens and Greenfield (1973). Appendix 2.3 provides a range of supply elasticities for coffee, ranging from 0.11 to 1 for long-run elasticities in Brazil. These wide uncertainties demand a better understanding of the forces at work. Our final estimate will suggest an intermediate value, at 0.57.

[2]The Nerlove model is described further in sections 2.4 and appendix 5.3.

[3]Outside of the Nerlove literature, authors have studied the entry and exit of perennial crop firms (Brady and Marsh, 2013), and provided a sounder micro-foundation to farmer decisions (Devadoss and Luckstead, 2010).

Within this literature, yields are typically modeled as a function of age, occasionally with random shocks (French and Matthews, 1971; Dorfman and Heien, 1989) or random evolution (Price and Wetzstein, 1999). This is in distinct contrast to the statistical yield model literature which relates weather data, such as temperature and precipitation, with observed yields. The most advanced of these use high-resolution weather data and account for varying unobserved characteristics, such as management, elevation, and soil properties (Schlenker and Roberts, 2009; Auffhammer and Schlenker, 2014a; Carleton and Hsiang, 2016). Weather data can be represented as growing degree-days (GDDs) and "extreme degree-days" (EDDs) to capture the non-linear effects of temperature and conform closely to the insights of process-based crop models (Roberts et al., 2012). This approach is well-suited for annual crops when yields are observed and can be approximated as a nonlinear transformation of weather inputs. However, perennial systems, including coffee plantations, involve additional complexities. While yields and die-off for a given age, per unit area, are still a function of weather, that function depends upon past responses to weather, and is difficult to identify. Once those age-specific yields are revealed to farmers, they can adjust their effort by harvesting some areas and not others, and it is only this final harvested production that is ultimately recorded. Coffee has been studied using statistical degree-day models in Colombia (Guzmán Martínez et al., 1999) and Mexico (Gay et al., 2006), however these do not address the challenge of hidden planting or the effects of weather shocks on total supply.

This paper combines insights from the perennial supply elasticity literature with temperature-driven yield shocks. The harvesting decision also plays a central role in this paper, as driven by both prices and weather shocks (Wickens and Greenfield, 1973). At their intersection, I identify important decisions and dynamics missing from both literatures. This connection will ultimately allow us to identify the hidden role of planted areas in data.

2.2 Perennial decision-making

Throughout the paper, the terms production, harvest, and yield will be distinguished as follows. Production is the mass of a crop brought to market in each year, measured in tons (MT) for coffee. Harvest, or harvested area, is the area of trees harvested in a given year, in hectares (Ha). Yield can be computed in different ways, as discussed in section 2.3, but will always be measured in terms of production per unit area ($^{\mathrm{MT}}/_{\mathrm{Ha}}$). Furthermore, it is important to distinguish new planting area, when seeds or grafts are added into a plantation, from planted area, which is the entire area under cultivation irrespective of its planting year. Total planted area often is less important than bearing area, defined as the area of mature plants capable of producing yield. Bearing area can be reduced by plant die-off (due to temperatures extremes and disease), plant removal (the clearing of old trees to be replaced by seedlings), and abandonment (the wholesale reduction of planted land).

As a long-term investment in productive capital, perennial crops differ from annuals in economically significant ways. These investments are made under considerable risks, because of the long delays between planting and first harvests, typically 24 - 36 months for coffee. The production of perennials typically varies by age, where for coffee the full potential of a tree may take 10 years to achieve and declines after 15 years (see appendix 2.5). As a result, farm management requires the carefully timed removal of plants with declining productivity, under the expectation of greater yields a few years later. Other management decisions may also have effects lasting multiple years, such as pruning, capping, and the introduction of similarly long-lived shade crops (Wintgens, 2009). Thang (2011) provides an overview of the literature on optimal investment decisions for perennial crops.

The perennial farmer faces two key types of decisions: how to plant and how to harvest. The extensive margin decisions consist of new planting, removal, and abandonment of farm acres, as studied in the perennial supply elasticity literature.

The farmer's choice of which plants to harvest depends on observed yields, as driven by age, die-off, weather, and disease. The supply elasticity literature has assumed that these harvesting decisions are driven only by plant age. However, it is manifestly also a matter of yield. Brazil production has had a marked biennial cycle, characterized by "on" and "off" years. This is driven by a natural resting period for the plants, where many regions have low yield years after high-yield years. If the entire unabandonded planted area were harvested every year, irrespective of yields, we would not expect to see a similar biennial cycle amongst in harvested hectares. Figure 1 shows production and harvest area as they vary over time, with a correlation of 0.54.

This harvesting adjustment is a form of adaptation. Farmers are changing their behavior to increase their profits even under lower yields. However, the adaptation comes at a cost of foregone revenue left on the trees. The basic economic intuition is shown in figure 2.

Furthermore, the intensive margin behaviors affect the extensive margin decisions. Planting, removal, and abandonment decisions are made in light of the potential for intensive-margin buffering of shocks: the true value of plants that drives these decisions is comprehensive of the ability to buffer possible weather shocks.

2.3 Yield calculations

Since perennial crops are not planted every year, their total area is rarely recorded. Instead, yields are often reported as the quantity of production, divided by the area harvested. However, this represents a distorted perspective on yields. A comprehensive measure of yield would compare production in year t to the potential bearing area for that year, as planned in year $t-s$, with s is the age of the first harvest. In year $t-s$, all of the planted intended to be harvested in t would exist as plants or seeds in the ground. Should any of these die in the intervening s years, these losses should be reflected in decreases in comprehensive yield.

The typically reported measure of yield conflates three sources of yield shocks: decreases in production per plant, decrease in area harvested, and loss of plants. Consider a simple model for log yield as a function of weather, w, and without planned removals. Let production quantity in year t be q_t, harvested area be h_t, and the area of mature plants be b_t. We can define,

$$\log {}^{q_t}/_{b_t} = \log(\bar{y}) + A(w) \qquad \text{instantaneous yield}$$

$$\log {}^{b_t}/_{b_{t-s}} = B(w) < 0 \qquad \text{plant die-off}$$

$$\log {}^{h_t}/_{b_t} = C(w) < 0 \qquad \text{harvest selection}$$

where $A(w)$, $B(w)$, and $C(w)$ describe the various data-generating processes as functions of one or more years of weather.

Instantaneous yield is the aggregate productivity, per unit of potentially harvestable area. This potentially harvestable area can differ from the bearing area s years ago due to die-off in the intervening years. Finally, harvested area can be less than the potentially harvestable area if there is harvest selection.

From these, it follows that the comprehensive yield is the instant yield plus die-off, $\log {}^{q_t}/_{b_{t-s}} = \log {}^{q_t}/_{b_t} + \log {}^{b_t}/_{b_{t-s}} = \log(\bar{y}) + A(w) + B(w)$, where both $A(w)$ and $B(w)$ are negative in an unfavorable year. Furthermore, conventional perennial yield is the instant yield artificially inflated by the harvest selection, $\log {}^{q_t}/_{h_t} = \log {}^{q_t}/_{b_t} - \log {}^{h_t}/_{b_t} = \log(\bar{y}) + A(w) - C(w)$. The total bias in log yields between the comprehensive and conventional yields is $\log {}^{q_t}/_{b_{t-s}} - \log {}^{q_t}/_{h_t} = B(w) + C(w) < 0$.

Annual yield estimates are supported both by better data (recorded planted area, which can be used to estimate comprehensive yield losses), and the absence of multi-year impacts. Since bearing area is generally not available for perennial crops, it must be inferred from harvested area. However, harvested area is affected annually by harvest selection and over multiple years by die-off. In light of this situation, we propose to consider both of these issues simultaneously as affected by exogenous weather, as a method of identifying underlying bearing areas.

2.4 Analytical model

This section presents a simple model of heterogeneous perennial assets. See Appendix 3.1 for a related age-structured model, which includes optimal removals and replanting, of which this is a simplification. The purpose of the model here is to describe how harvests, yields, production, and expansion are related to one another, with sufficient simplicity to be estimated in section 4.

Rather than considering a full distribution of ages, here we only distinguish between young trees, before they produce a crop, and mature trees. The age of a plant at its first yield is s, and b_t is the area of mature plants that are at least s years old.

Year t then produces a weather shock, w_t, which affects both plant die-off and yields in year t (yields will be discussed after area dynamics). Plant die-off is described as a fractional loss of bearing area, $d(w_t)$. At the same time, new plantings in year $t-s$, n_{t-s}, have the potential to join the bearing area. However, these are also exposed to die-off in the prior s years, so that the final bearing area is year t is

$$b_t = b_{t-1}(1 - d(w_t)) + n_{t-s} \prod_{k=0}^{s-1} (1 - d(w_{t-k}))$$

New plantings are related to plant die-off and prices. Appendix 3.1 shows that under ecological-economically suitable conditions (minimally, where the expected planting is > 0), replantings will also equal lost and removed plants. Replacement for lost plants is $d(w_t)b_t$. Removals due to plants that have outgrown their productive lifespan can be described as a portion of area each year, $\rho_a b_t$.

The rational planted area depends upon expected yields, costs, and prices at the extensive margin, as well as the opportunity cost of alternative uses, to maximize expected profits. To avoid introducing several unmeasured variables, we will assume that new land becomes profitable under higher prices according to a linear function of expected prices. The total profitable area is then $a_t = \alpha + \phi \mathbb{E}[p_t]$, dependent upon expected prices. The assumption of 100% replanting killed trees and the expansion relationship here based only on prices implicitly assume a static climate.

A central question in previous literature has been the appropriate model of price expectations. Nerlove models assume adaptive expectations, whereby expected prices vary according to changes in current or recent prices (Wittenberg, 1974). Alternatively, rational expectations of future prices would assume that recent prices incorporate information on future prices, including the response of farmers to shocks and the resulting endogenous equilibrium of future prices (Roberts and Schlenker, 2013).

In the discussion here, we will treat expected prices as a given parameter, $\mathbb{E}[p_t]$, and we will not address endogenous price formation. In the empirical analysis, we will adopt a flexible assumption, that expected prices are a linear model of recent historical prices, p_{t-k}: $\phi\mathbb{E}[p_t] = \sum_{l=1}^{K} \phi_l p_{t-l}$.

The total new plantings are then

$$n_t = \rho_a b_t + d(w_t) b_t + \alpha + \phi\mathbb{E}[p_t] - b_t$$

Suppose that the bearing area in before year $t-s$ is b_{t-s}. Then

$$b_t = b_{t-s} \prod_{k=0}^{s} (1 - d(w_{t-k})) + n_{t-s} \prod_{k=0}^{s-1} (1 - d(w_{t-k}))$$
$$n_{t-s} = \rho_a b_{t-s} + d(w_{t-s}) b_{t-s} + \alpha + \phi\mathbb{E}[p_{t-s}] - b_{t-s}$$

Combined, these produce

$$b_t = b_{t-s} \prod_{k=0}^{s} (1 - d(w_{t-k})) + (\rho_a b_{t-s} + d(w_{t-s}) b_{t-s} + \alpha + \phi\mathbb{E}[p_{t-s}] - b_{t-s}) \prod_{k=0}^{s-1} (1 - d(w_{t-k}))$$

which simplifies to

$$b_t = (\rho_a b_{t-s} + \alpha + \phi\mathbb{E}[p_{t-s}]) \prod_{k=0}^{s-1} (1 - d(w_{t-k})) \tag{1}$$

That is, b_t differs from b_{t-s} due to natural turn-over, profit-induced planting and abandonment, and weather-induced death. Natural turn-over captures natural death and abandonment due to changing conditions, and is represented by a scaling term ρ_a between year $t-s$ and year t. Because planting recovers after s years, only die-off shocks since year $t-s+1$ affect the planting in year t.

To study the intensive margin, we say that a unit area of bearing area produces yields in year t which conform to a distribution $f(y|w_t)$, where y is a random variable for yields conditioned on weather w_t. A single plant is assumed to have a yield drawn from this distribution, while larger areas on the scale of Brazilian municipalities with multiple age vintages have an empirical distribution of realized yields conforming to $f(y|w_t)$.

Let the price of harvested production be p_t, per MT, and the cost of harvesting be c per hectare. Harvesting can be thought of as starting with the most productive plants and proceeding to lower yielding plants until the marginal costs equal marginal revenue. Harvesting will occur for all plants that exceed some threshold level, $\check{y}$, where $p_t\check{y} = c$, with yield in units of MT / Ha.

The harvested area, h_t, and quantity produced, q_t, for a given region in year t is then,

$$h_t = b_t \int_{\check{y}}^{\infty} f(y|w_t) dy$$
$$q_t = b_t \int_{\check{y}}^{\infty} y f(y|w_t) dy$$

for a bearing area b_t. These equations relate latent bearing area to observed variables.

Appendix 3.2 provides conditions for bioeconomic suitability and appendix 3.3 describes the bioeconomic equilibrium and its transient response to weather shocks. Results from these will inform our interpretation of the empirical analyses.

The purpose of the theory above is to provide intuition and testable hypotheses for the next section, and to be estimable in the integrated approach in the last section. It excludes some important features of the farming process, including explicit ages and a full treatment of the effects of uncertainty (Feinerman and Tsur, 2014). It also does not include learning and the updating of priors or other expectations for a changing climate.

3 Empirical tests for Brazilian coffee

3.1 Background information

Coffee in Brazil provides a useful empirical case study for applying the model described above to determine latent biophysical yield sensitivity and the effects of die-off. This section provides a basic information about the sensitivity of coffee production to weather, to inform our empirical and integrated models.

Two species make up the vast majority of commercial coffee. *Coffea canephora* (Robusta coffee) is the hardier of the two in terms of both disease and heat resistance and has a higher caffeine content than Arabica. *Coffea arabica* (Arabica coffee), however, is demanded for its finer taste, and remains the most widely cultivated form of coffee. Brazil produces both varieties.

Coffee plants require particular ranges of temperature, rainfall, and soil conditions to produce a high-quality product. Arabica grows best in regions with mean annual temperatures of 18 to 22°C, while Robusta prefers temperatures between 22 and 30°C. Heavy precipitation (over 1400 mm per year) is important, but too much (over 3000 mm in a year) harms the plant (Wrigley, 1988). Yields of both varietals are most sensitive to the period of flowering and berry development, when weather shocks are most likely to harm the final product. While low temperatures are preferred, to allow the beans to accumulate flavor, frosts damage the plant, so temperatures need to remain moderate (Pendergrast, 1999). Brazil is the only large coffee-producing country prone to frosts.

Elevation is generally considered to be a primary concern, with Arabica commonly grown above 600 m and Robusta below 800 m. Elevation in many countries is used to distinguish coffee quality within varieties as well, with quality broadly considered to increase with elevation. However, this is largely explained by the differences in temperatures: higher elevations in the tropics have a low enough temperature for coffee flavors to develop and benefit from mountain-effect (orographic) rains (Thurston et al., 2013).

Farmers incur costs throughout the life of a coffee tree. While the costs vary according to the practices engaged in by small, medium, and large farmers (see appendix table 3), planting costs per hectare are 50% greater than a typical year's maintenance cost, and maintenance costs can be 85% of the revenue from a peak age yield (Rodriguez and Vasquez, 2009).

3.2 Data

The Brazilian Institute of Geography and Statistics (IBGE) provides municipality-level production for coffee in Brazil since 1985. Nearly 2,700 municipalities produce coffee, with an average municipality size of less than (40 km)^2. This dataset allows for a broad case study of the impacts of weather variation at a high spatial resolution. Appendix figure 8 shows the distribution of coffee production across Brazilian municipalities.

The production data is combined with weather data from ERA5, a global reanalysis weather product constructed by ECMWF (Hersbach et al., 2020). This data product combines station and satellite measurements using weather models to produce reliable weather estimates at a high spatial and temporal resolution. The spatial resolution is 0.25°x0.25°, a grid with boxes that are about 28 km on a side at the equator.[4] The weather described for the grid cell at the centroid of each municipality is used in the analyses.

Growing degree-days are the integral of temperature and time, between upper and lower temperature limits, and have long been used to capture plant growth. We explore a range of minimum and maximum temperatures for GDDs, to identify the limits that provide the greatest predictive capacity under cross-validation. Cross-validated RMSE is minimized with a minimum GDD temperature of 10°C, confirming the proposal in Guzmán Martínez et al. (1999). We also find that above 30°C additional damage is observed. All temperatures above 30°C are combined into the measure of "extreme degree-days" (EDDs). Growing degree-days are calculated as in Schlenker and Roberts (2009), using minimum and maximum daily temperature (Snyder, 1985).

The season limits for computing temperatures are also important, given the perennial nature of the plants. Again using cross-validation, we find that May through August of the year before harvest provides the greatest predictive potential. These months coincide closely with the harvesting months of May through September (Brodie, 2015), and the intervening year may reflect conditions that influence the flowering period.

The preferred specification also includes average minimum temperatures, which has been found to be relevant for coffee and other perennials (Jaramillo et al., 2013). Winter chill is a common requirement for perennial crops, and the increase in winter temperatures with climate change can undermine fruit production (Atkinson et al., 2013). It also includes precipitation, using the total accumulated precipitation during the same period as used for temperature. Precipitation is included as a quadratic, to capture the expectation that both too little precipitation and too much precipitation harmfully impact yields. Appendix figure 10 shows the distributions of these weather predictors.

[4]The high spatial resolution is important for the mountainous areas in which coffee is grown. Where the available resolution is insufficient to capture coffee farm micro-climates, our results will be biased toward zero.

3.3 Baseline reduced-form specification

The first step in our empirical analysis is to estimate the nonlinear relationship between observed yields and weather. This provides a baseline for comparison to subsequent estimates of production, harvests, and biophysical yields. It will also provide a functional form for the modeling of yields in the integrated model.

The approach taken is a yield regression, accounting for growing degree-days and extreme degree-days (Schlenker and Roberts, 2009). This kind of statistical relationship is based on the biological response of coffee to temperature, but encompasses all *ex post* consequences of weather, farmer responses, and ecosystem and pest dynamics. If farmers are providing sufficient irrigation and shade to coffee plants, the effect of high temperatures will be mitigated beyond what biological models suggest on their own.

The form of the statistical model is,

$$\log y_{it} = \gamma g_{it} + \kappa k_{it} + \mu m_{it} + \pi o_{it} + \psi o_{it}^2 + \alpha_i + \theta_t + P_{3,s(i)}(t) + \epsilon_{it} \tag{2}$$

where i indexes municipalities and t the years. Above and in the other models below, the observation variables and their corresponding effect estimating coefficients are:

	Variable	Coefficient
Yield	y_{it}	
Average minimum temperature	m_{it}	μ
Growing degree-days	g_{it}	γ
Extreme degree-days	k_{it}	κ
Total precipitation (linear term)	o_{it}	π
Total precipitation (quadratic term)	o_{it}^2	ψ

Municipality fixed effects, α_i, and year fixed effects, θ_t, absorb unobserved regional and year characteristics, and $P_{3,s(i)}(t)$ is a state-specific cubic trend to capture shifting productive capacity, through technology and management. The biennial cycle of Brazilian yields is not driven by weather, and is captured by year effects (Bernardes et al., 2012). Soil properties are assumed to be time-invariant and captures by the year fixed effects.

The specification assumes that yields in each year reflect the seasonal accumulation of beneficial or damaging effects of temperature. We assume that the effects of temperature are constant throughout the period used to predict yields, May through August. This assumption is motivated by agronomic theory and has previously been validated for annuals (Schlenker and Roberts, 2009). We allow errors to be correlated across space and time using two-way clustering over municipalities and years and Conley spatial heteroskedasticity and autocorrelation consistent standard errors (Conley, 1999; Hsiang, 2010) (see appendix 4.4).

These statistical models can be interpreted as a natural experiment, by comparing observed yields in years with different distributions of weather to estimate the effect of weather in general. In particular, the coefficients are estimated off year-to-year variation in weather within each region, accounting for Brazil-wide shocks and smooth state-wide trends. The identification strategy relies on the randomness of local weather variations, reducing the risk of omitted variable bias. Precipitation is included as a control, to isolate the effects of temperature separately from correlated precipitation (Auffhammer et al., 2013).

We estimate the specification above using conventional $y_{it} = {}^{q_{it}}/_{h_{it}}$. Table 1 displays the results across all municipalities, including a range of standard error corrections to account for spatial and temporal correlation and heteroskedasticity. Our preferred specification uses municipality-year 2-ways clustering. As expected, the effect of extreme temperatures is large and negative. Growing degree-days are also estimated as having a negative impact, which counter-balances the positive effect of average minimum temperature. Across most specifications, rising average minimum temperatures increase yields, either because of their direct biological effect or their interaction with pest species. Precipitation has a concave quadratic form.

Under model (6), an additional extreme degree-day (an average year has 5.6 EDDs and the 95$^{\text{th}}$ percentile from 2010 to 2018 is 46 EDDs) decreases yields by 3.9% (95% confidence interval from 2.2% to 5.6%). These values are estimated using marginal changes, so the average year is the baseline from which these percent changes are applied.

Figure 3 shows a graphical representation of the growing degree-day production model, with 95% confidence intervals. Temperatures below 10°C and above 30°C are damaging, while temperatures between these bounds are produce relatively little effect on the yields. Also included are the production model estimates for regions with 100% Arabica or 100% Robusta coffee. These varieties are grown under different environmental conditions, with Arabica coffee is grown at higher elevations, and are expected to respond differently to weather shocks.

3.4 Production and harvesting

As described in section 2.3, yield calculations can hide multiple effects, particularly if harvested area is also affected by weather because of selective harvesting or die-off. By applying the log specification of yields from the previous section to production and harvested area separately, we show that total losses are indeed greater than observed yield losses.

Table 2 shows the same specification as model (6) of table 1, our preferred specification, but columns 2 and 3 estimate the effects on log production and log harvested areas. The total effect of high temperatures on production is twice the effect estimated on yields. This is driven by the large and statistically significant negative effect on harvested acres due to extreme degree-days. This suggests that in hot years where the crop is damaged, the plants are simply not harvested as fully. As a result, the actual damaging effects of high temperatures on yields are likely to be greater than estimated using $y = q/h$. The yield numbers hide die-off and the selective harvest of under-productive plots in poor years, causing both total production and harvested acres to decrease and produce a counter-balancing effect on the dependent variable.

3.5 Direct hysteresis from weather shocks

Damaging effects from weather on perennial crops are likely to have multi-year consequences. Here, we use a distributed lag model to identify the duration of these effects. Losses that persist for greater 2 years or more are characteristic of die-off effects.

To evaluate persistent effects, we estimate

$$\Delta \log h_{it} = \gamma^H \Delta g_{it} + \sum_{d=-1}^{4} \kappa_d^H \Delta k_{i,t-d} + \mu^H \Delta m_{it} + \pi^H \Delta o_{it} + \psi^H \Delta o_{it}^2 + \theta_t^H + P_{3,s(i)}^H(t) + \epsilon_{it}^H$$

$$\Delta \log q_{it} = \gamma^Q \Delta g_{it} + \sum_{d=-1}^{4} \kappa_d^Q \Delta k_{i,t-d} + \mu^Q \Delta m_{it} + \pi^Q \Delta o_{it} + \psi^Q \Delta o_{it}^2 + \theta_t^Q + P_{3,s(i)}^Q(t) + \epsilon_{it}^Q$$

This is equivalent to the regressions in the two previous sections but estimated in first-differences to remove autocorrelation and trends. As shown in figure 3, weather shocks result in losses to production in the year of the shock, but also produce reductions in harvest in the following two years. Columns 3 and 6 impose the constraint that the effect of the 1-year and 2-year lags are equal, as we would expect for a die-off and replanting dynamic. The estimates are not statistically significantly different from the estimates in columns 2 and 5.

Fields recover 2-4 years after a weather shock. While a contemporaneous effect of EDDs on harvested area is not detected, harvests are depressed for the next two years by an average of 0.11 % per degree-day (column 3, which pools the effect of 1-2 years). This represents multi-year damage caused by extreme temperatures, which we will interpret as die-off. This is consistent with a replanted seedlings recovering the yields of the killed tree after 24-36 months and reaching harvestable age.

Production shows a more pronounced contemporaneous effect of 0.41 % per degree day (column 5). This combines yield losses, physical damage, and reduced harvesting area. Subsequent years do not show a statistically significant decline in production, which may be explained by remaining trees being over-harvested while planted area recovers.

3.6 The extensive margin decision

While the evidence of reduced harvested areas suggests selective harvesting or die-off, the decision to plant new area is conflated in the harvest area data. To disentangle these, we need both a model of yields, driven by weather, and a model of planting, driven by prices.

Farmers are expected to expand planted areas in response to expected profits, where higher prices both expand the range of profitable land and relax budget/credit constraints to purchase land or invest in new plants. The specific processes that relate expected prices to planted areas are less important for our analysis than the identification of a reduced-form empirical relationship.

Neither planted areas nor expected prices are directly observed. However, harvested areas can provide information about planted areas, after accounting for growing delays and the variation in yields and harvests driven by weather. Recent observed prices are also expected to contain information about expected prices. By regressing logged harvest areas on past prices and current weather, we can isolate the extensive marginal elasticity to prices.

We use the international price for coffee, according to the World Bank's Commodity Price dataset (The Pink Sheet). This price indicator averages ex-dock market prices from New York and Bremen/Hamburg for Arabica and ex-dock market prices from New York and La Havre/Marseilles for Robusta, reported in real 2010 USD. These values correspond closely both with prices paid to growers, according to the International Coffee Organization (Pearson correlation = 0.93 for Arabica and 0.82 for Robusta) and with futures contracts prices (Pearson correlations 0.94 and 0.95, respectively, see appendix figure 16). Of interest here, they also extend before the ICO, futures, and production data, allowing multiple lags of price to inform changes in harvested area.

We estimate the effect of lagged prices on harvest, as follows:

$$\Delta \log h_{it} = \sum_{l=1}^{4} \phi_l \Delta \log p_{t-l} + \gamma \Delta g_{it} + \kappa \Delta k_{it} + \mu \Delta m_{it} + \pi \Delta o_{it} + \psi \Delta o_{it}^2 + \theta_t + P_{3,s(i)}(t) + \epsilon_{it}$$

We again calculate the estimate in first-differences, to remove autocorrelation. The regression above treats changes in prices as exogenous to changes in harvest area. About 70% of Brazil's coffee production is from an estimated 273 800 small-holder farmers (Enveritas, 2018), which we can assume are price-takers. However, correlated weather shocks and trends have the potential to influence the global price. To account for potential endogeneity, we are only interested in lagged prices. While p_{t-1} may be a function of h_{t-1}, there is no endogeneity ($\mathbb{E}\left[p_{t-1}\epsilon_t\right] = 0$), so long as there is no autocorrelation in the error term. We show that this is the case for lags of more than 1 year (see appendix 5.2).

The price results are shown in table 4. Current prices ($\Delta \log p_t$) are included as a falsification test, since new planting cannot be harvested immediately. The largest effect from prices is from two years prior, consistent with the delay between planting and harvesting. A 1% increase in price results in a 0.25 - 0.29% increase in harvested area, two years later. This provides a reference point for the elasticity in the final model.

Studying the effect of a single recent price or a linear combination of prices is consistent with rational price expectations. Nerlove adaptive price expectations apply an autoregressive relationship (see appendix section 5.3). We evaluate the empirical predictiveness of Nerlove expected prices and find these to be almost indistinguishable from rational expectations. The most predictive adaptive price uses an autoregressive process with $\rho_p = 0.3$, close to the fitted value of the integrated model in the next section adaptive prices are used ($\rho_p = 0.39$).

4 An integrated model

The empirical findings support our theoretical model above: weather affects yields, but it also affects harvested area. In addition, harvested area is affected by lagged weather, which we interpret as a die-off effect, and lagged prices, which we interpret as driving an expansion of planted area.

We now estimate a model for coffee that explicitly describes latent bearing area. We will use the expressions from section 2.4, with the age of maturity, $s = 2$. This conforms to the three-year delay in the recovery of harvested areas shown in table 3 and is within the range of reported years to maturity (1.5 - 4 years). This results in the bearing area relationship,

$$\mathbb{E}[b_t] = (\rho_a b_{t-2} + \alpha + \phi \mathbb{E}[p_{t-2}]) \prod_{k=0}^{1} (1 - d(w_{t-k}))$$

This is a latent variable, since it depends upon past values of b_t, which are themselves unobserved. There may also be a deviation between the theoretical bearing area, $\mathbb{E}[b_t]$, and actual bearing area b_t. We assume that actual bearing area is drawn from a distribution centered on expected bearing area:

$$\log b_t \sim \mathcal{N}(\log \mathbb{E}[b_t], \sigma_b)$$

This Gaussian form here is common in hidden continuous state variable models, such as hidden Markov chain models, and provides an important degree of freedom in relating latent variables to the observed data. The Bayesian fitting process used below will simultaneously estimate the parameters that determine $\mathbb{E}[b_t]$ as well as an annual timeseries of $\log b_t$.

Each municipality is fit separately, and the municipality index is suppressed in the expressions below. This allows municipalities to take exhibit different parameter values, which is also useful for understanding how regions have adapted to their different existing climates. After estimating each individual region, we perform a Bayesian hierarchical meta-analysis, to construct global parameters accounting for the region-specific estimates, their uncertainties, and their variation. The Bayesian hierarchical modeling approach offers a data-driven way to choose the pooling level, reflecting of the extent to which parameter values are consistent with a common distribution. Results under alternative pooling are shown in appendix 6.2.

We also make a series of assumptions, to make the analytical model concrete and estimable, as described below.

First, we fit the model under two forms of price expectations. Under rational expectations, future prices are linearly related to current prices. Since an affine transformation relates expected prices to desired planted area ($\alpha + \phi\mathbb{E}[p_{t-s}]$), we can assume without loss of generality that

$$\mathbb{E}[p_t] = p_{t-1}$$

Under Nerlove adaptive price expectations, an autoregressive expression describes expected prices (see appendix 5.3):

$$\mathbb{E}[p_t] = \rho_p p_{t-1} + (1 - \rho_p)\mathbb{E}[p_{t-1}]$$

The empirical analysis in section 3.6 does not provide guidance between these, so we report both.

Second, we specify the distribution over unobserved biophysical yields. While any distribution with a mean and a dispersion could serve, we use a uniform distribution because it produces a closed-form expression for the harvest fraction. The graphical representation of the harvest fraction under a uniform distribution of yields matches figure 2. We parameterize the uniform distribution with an expected value, $\bar{y}(w_t)$ and a width 2Δ, so that yields are uniformly distributed between $100(1-\Delta)\%$ of the estimated mean and $100(1+\Delta)\%$ of it:

$$f(y|\bar{y}(w_t)) = \text{Uniform}(y|\bar{y}(w_t)(1-\Delta), \bar{y}(w_t)(1+\Delta))$$

The harvest fraction, λ, is the integral of this function above the minimum profitable yield, from ${}^{c}/_{p_{t-1}}$ to ∞:

$$\lambda = \begin{cases} 0 & \text{if } \bar{y}(w_t)(1+\Delta) < {}^{c}/_{p_{t-1}} \\ 1 & \text{if } \bar{y}(w_t)(1-\Delta) > {}^{c}/_{p_{t-1}} \\ \frac{{}^{c}/_{p_{t-1}} - \bar{y}(w_t)(1+\Delta)}{2\bar{y}(w_t)\Delta} & \text{otherwise} \end{cases}$$

Third, we use the expression in equation 2 to model yields:

$$\log \bar{y}(w_t) = \upsilon + \gamma g_t + \kappa k_t + \mu m_t + \pi o_t + \psi o_t^2$$

Previously, we estimated this expression with observed yields (q_t/h_t). Here, we model the mean of unobserved biophysical yields, from which observed yields are derived given harvest selection and die-off.

Fourth, we assume that die-off is driven only by extreme temperatures (EDDs), as

$$\log d_t = \delta k_t$$

While other weather variables, such as frost, can also cause die-off, these will be captured by the time-invariant autoregressive parameter on bearing area. Our goal in modeling the role of high temperatures is to distinguish between the multiple effects of EDDs, our main variable of interest.

We will assume that $\delta < 0$. The remaining weather parameters are unconstrained and given no priors (or equivalently, a uniform prior).

Finally, we also assume constraints on some parameters to maintain their physical or economic meaning. Autoregressive factors are constrained between 0 and 1: $\rho_b \in [0, 1]$ and $\rho_p \in [0, 1]$; no portion of the biophysical yield distribution can be negative: $\Delta \in [0, 1]$; harvest costs are positive: $c > 0$; and higher prices induce an increase in desired planted area: $\phi > 0$.

To relate the model to observed data, we assume that observations of harvest and production are made with geometric errors, as done in the regression models:

$$\begin{aligned} \log \hat{h}_t &\sim \mathcal{N}(\log \lambda b_t, \sigma_h) \\ \log \hat{q}_t &\sim \mathcal{N}(\log v b_t + \theta t, \sigma_q) \end{aligned} \tag{3}$$

where v is the biophysical yield of the harvested portion, $v = \int_{c/p_{t-1}}^{\infty} y f(y|\bar{y}(w_t))dy$, and θt allows production to increase according to exogenous factors, e.g., technology.

4.1 Integrated model results

The Bayesian integrated model presented in the previous section brings together multiple structural assumptions at once. Here we build up these assumptions one at a time. Table 5 includes three models to validate the Bayesian approach, and the results for integrated models that progressively include die-off and selective harvesting, under rational and adaptive (Nerlove) price expectations.

Results are reported under both rational and adaptive price expectations. In many cases, differences between these are a recognizable consequence of the assumptions themselves. Importantly, they also provide a useful range of plausible values for each parameter and outcome, which is more robust than the confidence interval under either assumption individually.

First, we apply the OLS model to each region independently (column 2, OLS x Muni.), to validate the region-by-region estimation approach. Under this usage, the effect of average minimum temperatures and GDDs are both reduced. These predictors show considerable colinearity, which is not well-distinguished in the small sample-size estimates. The EDD effect is not significantly changed. The Bayesian regression estimate (column 3, Bayes Reg.), which using Bayesian hierarchical modeling to perform partial pooling, is similar to OLS results. The coefficient values for precipitation vary considerably between these models and across models and are poorly estimated.

When the dynamic effects of die-off are included, but harvest selection is left out (columns 4 & 7, No Sel (1 & 2)), the estimated EDD effect is smaller (-2.19 under rational expectations and -2.06 under adaptive expectations, compared to -3.92 for OLS and -4.01 for the Bayesian Regression). Under these models, lower production levels are shifted to the extensive margin. The die-off effect is large, suggesting that the average municipality loses 19% (rational) or 13% (adaptive) of its trees in an average year.

The addition of harvest selection results in an increased EDD effect for both the rational and adaptive expectation models (columns 5 & 6). A direct comparison with the corresponding models that do not account for selective harvest (columns 4 & 7) shows a tripling (rational) or doubling (adaptive) of the EDD coefficient. Compared to the original OLS model, the EDD coefficient is 61% (rational) to 21% (adaptive) greater.

Models that assume rational expectations produce larger extreme temperature effects: the die-off coefficient is -44 under rational expectations, compared to -24 under adaptive expectations, and the EDD yield coefficient is -6.3 compared to -4.8. This is driven by changes in the response of desired bearing area to prices. Desired bearing area is the productive area targeted by planting, but it will differ from realized bearing area when there is die-off. Under adaptive expectations, the response to price shocks is delayed and the immediate response is muted. For a similarly muted response to price changes to be captured by the rational expectations model, it can be explained by (1) a large autoregressive term in desired bearing area (ρ_a), (2) a small price response in desired bearing area (ϕ), or (3) a large desired bearing area level. The results show all three of these effects, with most regions showing larger ρ_a, smaller ϕ, and larger desired bearing areas under rational expectations than under adaptive expectations. Average realized bearing area is similar under the two assumptions however, since this is constrained by observed harvest areas. The difference in desired bearing area and realized bearing area is explained by die-off, which is then predicted to be greater under the rational expectation assumption.

Several other parameters are of interest. Of the factors affecting planting, autoregressivity is surprisingly low: an autoregressive factor of 0.56 (rational) or 0.46 (adaptive) suggests that only 44 % or 54 % of planting, respectively, is explained by the previous year's planted area. The low value in the adaptive model is partly explained by a high rate of updating (low ρ_p), suggesting rapid abandonment and re-colonization of fields.

The Δ parameter, describing the range of yields under selective harvesting, is 0.53 (rational) to 0.50 (adaptive), implying that the range of yields observed on plots across harvestable plants varies from 50 % to 150 % of the mean yield.

An elasticity for planting can be derived from the price response estimate. The region-specific price response ϕ describes the marginal effect of expected prices on bearing area. For combining these results across regions, the region-specific values are divided by average harvested area, producing the global estimate of 0.11 (rational) or 0.19 (adaptive). To calculate the elasticity, we multiply by the average applied price, \$3.26 / kg, and the average harvest ratio, 0.91. The elasticity of planting to prices correspondingly varies by price expectation assumptions. Under rational expectations, our estimate is 0.33 [95% credible interval 0.20 - 0.45], comparable to short-run elasticities from the literature for Brazil (see appendix 2.3). Under adaptive expectations, we get an elasticity of 0.57 [0.35 - 0.78], close to the median of long run elasticity from the same source.

On average, a year in the data has 5.6 extreme degree-days, with 23% of municipality-year years having 0 extreme degree-days. The 95$^{\text{th}}$ percentile observation has 29 degree-days. Under the econometric model, this mean and 95$^{\text{th}}$ percentile observation experiences a 2.2% loss in yield and a 11% loss in yield, respectively. According to the integrated model under rational expectations, corresponding losses to biophysical yield are 3.5% and 17%, respectively. Under adaptive expectations, the losses are 2.6% and 13%, respectively. The die-off effect, in comparison, is a loss of 22% and 72% of the area (rational) or 12% and 50% of the area (adaptive), for the same 5.6 and 29 extreme degree-days. These may be overestimates, however, given the high turnover rates predicted through the planting autoregression parameter.

As extreme degree-days increase, the portion of fields left unharvested increases. Under a price of \$3.26/kg for harvested beans (the mean across included years), the minimum yield that will be harvested under our model is 0.17 MT/Ha (rational) or 0.11 MT/Ha (adaptive). According to the fitted model, regions with an average yield of 0.35 MT/Ha (rational) or 0.22 MT/Ha will display yields of this level, and under the average conditions from the sample, this average yield is achieved under 55 EDDs (rational) or 171 EDDs (adaptive). These relationships are shown in figure 4 for the median price and the 10^{th} percentile price. Biophysical yields fall with EDDs, but observed yields drop at about half the rate of biophysical yields when harvest selection is used.

Using the limited information on production varieties, we perform the Bayesian meta-analysis separately for municipalities that have produced only a single variety in observed years. From this, Arabica is estimated to have a sharper impact from extreme degree-days than Robusta: -6.92 (rational) or -5.20 (adaptive) compared to -4.91 (rational) or -1.53 (adaptive). Similarly, Arabica has a higher die-off sensitivity than Robusta: -36.42 (rational) or -25.23 (adaptive) compared to -16.82 (rational) or -9.11 (adaptive). This supports the idea that Arabica plants are more sensitive than Robustas and conforms to the subsampled econometric result.

The choice of Arabica or Robusta varieties is a form of adaptation, with warmer areas growing varieties less susceptible to high temperatures. This transition is shown in figure 5 across all the individual municipalities. Yields in cooler regions are slightly less affected by extreme temperatures, but the die-off effect is about half as strong. This is partly driven by the Arabica vs. Robusta choice, but not fully explained by it: Arabica grown in hotter regions also shows this benefit.

The average yield across years for municipalities that grow Robusta is 0.75, as estimated using production divided by harvested areas. For Arabica growing regions, the average recorded yield is 0.82 MT/Ha. With the integrated model, we estimate that the biophysical yield averages are 0.68 MT/Ha for Robusta and 0.76 MT/Ha for Arabica, for similar harvest selection ratios of about 10%. However, despite the lower die-off effect for Robusta, its greater exposure to high temperatures results in more turn-over. About 7% of Arabica is estimated to die in an average year, while 15% of Robusta experiences die-off.

4.2 Simulation results

Finally, we simulate the contributing effects of the key model assumptions, applying the estimate derived above. For explanatory purposes, the stochastic outcomes of a single tree plot are represented, as it gets planted, replanted or killed, and selectively harvested. As a measure of the significance of the different assumptions, the net present value (NPV) of the stream of yields from the perspective of year 1 is calculated for each simulation, for a single Hectare and a 5% discount rate. Yield-for-age estimates are from Arak (1967), and are used instead of weather-driven yields to study expectations. The other parameters are from the model and data for Arabica under adaptive price expectations, with a sale price of \$3.48 / kg, harvesting cost of \$0.36 per Ha, and the spread of the yield distribution (Δ) at 0.49. Die-off is set to the average experienced by Arabica in the data, 7% per year. The adaptive expectation results are more conservative than the results under rational expectations, which have higher effects of extreme temperatures, higher costs, and a wider range of yields, all of which will drive more selective harvesting.

A series of simulations, layering the effects of age-based yields, management, shocks, die-off, and selctive harvest are shown in figure 6. Relative to constant average yields, accounting for age-based yields increases NPV (panel B), since the highest years are for fairly young trees. Following the optimal removal policy (replanting every 33 years) further increases NPV (panel C). To this point, the yields graphs and NPV reflect theoretical age-structured management. In panel D, the calibrated range of yields is simulated. As expected, the NPV does not change without the additional effect of selective harvesting.

Panel E models die-off and associated replanting. An important result of this is that stochastic yields rapidly stabilize, overshadowing the age-based structure of the simulation. This supports our use of a single age class for mature plants. Die-off reduces NPV by 20%, from \$21,900 to \$17,500.

Selective harvesting is able to reverse half of this effect, bringing NPV to \$19,200 (10% gain). Harvest levels stabilize around 80% of the area in expectation, or the tree being harvested 80% of the time under stochastic yields and die-off.

As a sensitivity test, we consider a range across possible values of the simulated die-off rate parameter, which exposes the relationship between selective harvesting and the maintenance of plant value, as shown in figure 7. The net present value of a plot gradually decreases as die-off increases. If the entire planted area is forced to be harvested, incurring the full harvest cost, the NPV of a unit area becomes negative around a die-off rate of 30% per year. Under selective harvests, the area harvested gradually decreases, and NPV with harvest selection goes only to 0 as die-off increases.

A number of robustness checks are provided in the appendix: comparison to heuristically estimated bearing area is shown in appendix 7.1, estimates based only on top-producing counties are shown in appendix 7.2; an alternative specification is estimated in appendix 7.3; sensitivity on the extreme degree-day threshold is shown in appendix 7.4; the effect of variation in costs is discussed in appendix 7.6; and an alternative calibration of the model is integrated model is considered in appendix 7.7.

5 Conclusion

Estimates of the total economic impacts of climate change vary widely, from a loss of over 4% of global GDP to a gain of over 2% under 2.5°C warming (Tol, 2010). Much of this range is attributable to the considerable uncertainty about the potential for adaptation (Pindyck, 2013; Hertel and Lobell, 2014). However, few empirical estimates of the potential for regional adaptation exist (Auffhammer and Schlenker, 2014b; Deschenes, 2014). The impacts of climate change on agriculture are a particular concern due to their large potential size (Moore et al., 2016) and the uncertainty about adaptation behaviors (Houser et al., 2015, ch. 22).

Adaptation to climate change requires both the adoption of new practices and the intensification of existing adaptive behaviors to extreme temperatures. The current effects and further capacity of existing adaptive behaviors can generally not be distinguished in *ex post* empirical methods. This paper considers a distinct form of adaptation which has not been addressed in the observational literature: within-period selective behaviors. When properly accounted for, I show that the full biophysical impacts of extreme temperatures are greater than linear estimates suggest. Fortunately, these damaging effects can be mitigated through instantaneous adaptation, using selective harvesting. Unfortunately, the capacity of this adaptation is limited, and the marginal costs of high temperatures increase as within-period adaptive practices reach their limit. Within agriculture, perennial crops provide a fertile context for understanding this form of adaptation.

This paper starts with a seemingly simple task: to estimate a yield relationship for a perennial crop. However, for perennial crops, accurate estimates of yields are typically unobserved, as are other key dynamics including die-off, age distributions, and harvest decisions. Average yields can be computed for annuals by dividing observed production by planted area at regional scales. For perennials, planted area is rarely tracked, even by the USDA for the United States. Instead, harvest areas are recorded. Relating this data to underlying yields is an important challenge. Accounting for anything less than the combined effects of the direct shock, the short-term response to the shock, and the long-term evolution of the system distorts our understanding of its dynamics. Resolving these issues requires new models and robust empirical techniques.

I find that temperatures drive changes in yields, harvested areas, and planted areas. These three effects are connected by farmer decisions at the intensive and extensive margins. For perennials, decisions at the intensive margin are cheap but limited and at the extensive margin require years of foresight. Extreme weather affects the profitability of perennials, causing producers to reduce harvest areas. I also show that plant die-off has a large, multi-year effect on production. By combining a reduced-form yield expression with a structural model, the results describe realistic relationships between weather and yields with existing behaviors, rather than theoretical responses of the crops in an experimental setting.

Many aspects of the coffee system are not explicitly represented in the models estimated here. Farmers are likely to perform activities during the season to support high yields, such as the application of irrigation, fertilizer, and pesticides. It is a strength of empirical yield approaches that our results are inclusive of the benefits of these behaviors, but more work is needed to understand the limits to these adaptation practices, similar to the selective harvesting shown here. Other factors which drive coffee yields are not explicitly included in this model: consumption drivers, evolving technology, changing varieties, and the governance and politics which frequently affect the coffee sector. These are all important, but do not affect the estimation of the variables captured here. By limiting our analysis to the study of weather variation, we can better understand their effects. International prices and municipality-level weather act as proxies for local farm-gate prices and on-the-ground weather for shade-grown coffee, allowing for empirical tractability but hiding important drivers of heterogeneity.

Furthermore, their application to climate change requires additional work. The forward-looking perspective embedded in the analytical model here assumes a static climate, despite the long-term horizon perennial farmers need to consider. The use of weather variation to understand the impacts of long-term climate typically depends upon myopic decision-making and the absence of multi-year decisions (Lemoine, 2018), and these assumptions may be inappropriate for perennial crops. Moreover, because they cannot distinguish the social and natural causes, they make an implicit assumption that yields will continue to respond the same way to increasing temperatures over time. The model also does not attempt to describe the labor substitution farmers are making when they choose not to harvest coffee, which limits this model's ability to inform welfare outcomes for farmers.

All perennials share these problems of missing data, which these models address. They all include intensive and extensive margin decisions, which the approach discussed here can distinguish. And all of them are integrated agricultural systems, with long-term impacts of both weather and farmer decision-making. Previous studies of the effects of extreme temperatures on agriculture consider mainly decreases in yields. However, for perennials, the loss of full plants and the effects these have on farmer liquidity is also a threat. Farmer activities can mask the direct effects of yield losses through selective harvesting, but they are still impacted by their reduced revenue in extreme years.

These methods may be appropriate for informing the study of natural-human systems more broadly. Similar adaptive responses through selective curtailing of productive behaviors apply to lumber, fisheries, water resources, and air quality. When environmental shocks occur, the response that we observe is mediated by internal responses: more selective trees are cut, regions are fished, water users are prioritized, and outdoor activities are engaged in. A better understanding how farmers make decisions around perennial crops, and how the farmer-crop system is impacted by the environment, can inform studies of international development, climate change, and food security.

References

Arak, Marcelle V. 1967. The supply of Brazilian coffee. Ph.D. thesis, MIT.

Askari, Hossein, and John Thomas Cummings. 1977. Estimating agricultural supply response with the Nerlove model: a survey. *International Economic Review* : 257–292.

Atkinson, CJ, RM Brennan, and HG Jones. 2013. Declining chilling and its impact on temperate perennial crops. *Environmental and Experimental Botany* 91: 48–62.

Auffhammer, Maximilian, Solomon M Hsiang, Wolfram Schlenker, and Adam Sobel. 2013. Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy* .

Auffhammer, Maximilian, and Wolfram Schlenker. 2014a. Empirical studies on agricultural impacts and adaptation. *Energy Economics* 46: 555–561.

———. 2014b. Empirical studies on agricultural impacts and adaptation. *Energy Economics* 46: 555 – 561.

Bateman, Merrill J. 1965. Aggregate and regional supply functions for Ghanaian cocoa, 1946–1962. *Journal of Farm Economics* 47 (2): 384–401.

Bernardes, Tiago, Maurício Alves Moreira, Marcos Adami, Angélica Giarolla, and Bernardo Friedrich Theodor Rudorff. 2012. Monitoring biennial bearing effect on coffee yield using MODIS remote sensing imagery. *Remote Sensing* 4 (9): 2492–2509.

Brady, Michael P, and Thomas L Marsh. 2013. Do changes in orchard supply occur at the intensive or extensive margin of the landowner? In *2013 Annual Meeting, August 4-6, 2013, Washington, DC*. 150452, Agricultural and Applied Economics Association.

Brodie, Scott M. 2015. When is coffee harvested?

Carleton, Tamma A, and Solomon M Hsiang. 2016. Social and economic impacts of climate. *Science* 353 (6304).

Conley, Timothy G. 1999. GMM estimation with cross sectional dependence. *Journal of econometrics* 92 (1): 1–45.

Deschenes, Olivier. 2014. Temperature, human health, and adaptation: A review of the empirical literature. *Energy Economics* 46: 606 – 619.

Devadoss, Stephen, and Jeff Luckstead. 2010. An analysis of apple supply response. *International Journal of Production Economics* 124 (1): 265–271.

Dorfman, Jeffrey H, and Dale Heien. 1989. The effects of uncertainty and adjustment costs on investment in the almond industry. *The Review of Economics and Statistics* : 263–274.

Elnagheeb, Abdelmoneim H, and Wojciech J Florkowski. 1993. Modeling perennial crop supply: an illustration from the pecan industry. *Journal of Agricultural and Applied Economics* 25 (01): 187–196.

Enveritas. 2018. How many coffee farmers are there? Global coffee farm study.

Feinerman, Eli, and Yacov Tsur. 2014. Perennial crops under stochastic water supply. *Agricultural Economics* 45 (6): 757–766.

French, Ben C, Gordon A King, and Dwight D Minami. 1985. Planting and removal relationships for perennial crops: an application to cling peaches. *American Journal of Agricultural Economics* 67 (2): 215–223.

French, Ben C, and Jim L Matthews. 1971. A supply response model for perennial crops. *American Journal of Agricultural Economics* 53 (3): 478–490.

Gay, C, F Estrada, C Conde, H Eakin, and L Villers. 2006. Potential impacts of climate change on agriculture: A case of study of coffee production in Veracruz, Mexico. *Climatic Change* 79 (3-4): 259–288.

Guilford, G. 2014. How climate change and a deadly fungus are threatening the world's coffee supply. Retrieved from `http://www.citylab.com/weather/2014/06/how-climate-change-and-a-deadly-fungus-are-threatening-the-worlds-coffee-supply/371994/`.

Guzmán Martínez, Orlando, Alvaro Jaramillo Robledo, and José Vicente Baldión Rincón. 1999. Anuario meteorologico cafetero, 1998. .

Hartley, Michael J, Marc Nerlove, and R Kyle Peters. 1987. An analysis of rubber supply in Sri Lanka. *American Journal of Agricultural Economics* 69 (4): 755–761.

Hersbach, Hans, Bill Bell, Paul Berrisford, Shoji Hirahara, András Horányi, Joaquín Muñoz-Sabater, Julien Nicolas, et al. 2020. The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society* 146 (730): 1999–2049.

Hertel, Thomas W., and David B. Lobell. 2014. Agricultural adaptation to climate change in rich and poor countries: Current modeling practice and potential for empirical contributions. *Energy Economics* 46: 562 – 575.

Houser, Trevor, Solomon Hsiang, Robert Kopp, and Kate Larsen. 2015. *Economic risks of climate change: an American prospectus*. Columbia University Press.

Hsiang, Solomon M. 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of sciences* 107 (35): 15367–15372.

Jaramillo, Juliana, Mamoudou Setamou, Eric Muchugu, Adenirin Chabi-Olaye, Alvaro Jaramillo, Joseph Mukabana, Johnson Maina, et al. 2013. Climate change or urbanization? Impacts on a traditional coffee production system in East Africa over the last 80 years. *PloS one* 8 (1): e51815.

Kalaitzandonakes, Nicholas G, and JS Shonkwiler. 1992. A state-space approach to perennial crop supply analysis. *American Journal of Agricultural Economics* 74 (2): 343–352.

Knapp, Keith C, and Kazim Konyar. 1991. Perennial crop supply response: a Kalman filter approach. *American Journal of Agricultural Economics* 73 (3): 841–849.

Lemoine, Derek. 2018. Estimating the consequences of climate change from variation in weather. Technical report, National Bureau of Economic Research.

Lobell, David B, Christopher B Field, Kimberly Nicholas Cahill, and Celine Bonfils. 2006. Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. *Agricultural and Forest Meteorology* 141 (2): 208–218.

Malkin, E. 2014. A coffee crop withers. Retrieved from `http://www.nytimes.com/2014/05/06/business/international/fungus-cripples-coffee-production-across-central-america.html`.

Monfreda, Chad, Navin Ramankutty, and Jonathan A Foley. 2008. Farming the planet: 2. geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global biogeochemical cycles* 22 (1).

Moore, Frances, Uris Lantz Baldos, Thomas Hertel, and Delavane Diaz. 2016. Welfare changes from climate change impacts on the agricultural sector: New damage functions from over 1000 yield studies. Presented at the 19th Annual Conference on Global Economic Analysis, Washington DC, USA, Global Trade Analysis Project (GTAP), Department of Agricultural Economics, Purdue University, West Lafayette, IN.

Nerlove, Marc. 1958. *The dynamics of supply; estimation of farmer's response to price*. Baltimore: John Hopkins University Press.

———. 1979. The dynamics of supply: retrospect and prospect. *American journal of agricultural economics* 61 (5): 874–888.

O'Brien, Timothy G, and Margaret F Kinnaird. 2003. Caffeine and conservation. *Science* 300 (5619): 587–587.

Pendergrast, Mark. 1999. *Uncommon grounds: The history of coffee and how it transformed our world*. Basic Books.

Pindyck, Robert S. 2013. Climate change policy: What do the models tell us? *Journal of Economic Literature* 51 (3): 860–872.

Price, T Jeffrey, and Michael E Wetzstein. 1999. Irreversible investment decisions in perennial crops with yield and price uncertainty. *Journal of Agricultural and Resource Economics* : 173–185.

Roberts, Michael J, and Wolfram Schlenker. 2013. Identifying supply and demand elasticities of agricultural commodities: Implications for the us ethanol mandate. *American Economic Review* 103 (6): 2265–95.

Roberts, Michael J, Wolfram Schlenker, and Jonathan Eyer. 2012. Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics* : aas047.

Rodriguez, B, and M Vasquez. 2009. Economic aspects of coffee production. In *Coffee: growing, processing, sustainable production. A guidebook for growers, processors, traders and researchers*, ed. Jean Nicolas Wintgens. Wiley-Vch.

Schlenker, Wolfram, and Michael J Roberts. 2009. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences* 106 (37): 15594–15598.

Sharf, S. 2014. Mondelez To Take Bigger Sip Of $81B Global Coffee Industry With DE Master Joint Venture. Retrieved from `http://www.forbes.com/sites/samanthasharf/2014/05/07/mondelez-to-take-bigger-sip-of-81b-global-coffee-industry-with-de-master-joint-venture/`.

Snyder, RL. 1985. Hand calculating degree days. *Agricultural and forest meteorology* 35 (1): 353–358.

Thang, Tran Cong. 2011. Optimal investment decisions of coffee farmers in Vietnam. Ph.D. thesis, The University of Western Australia.

Thurston, Robert W, Jonathan Morris, and Shawn Steiman. 2013. *Coffee: A Comprehensive Guide to the Bean, the Beverage, and the Industry.* Rowman & Littlefield Publishers.

Tol, Richard SJ. 2010. The economic impact of climate change. *Perspektiven der Wirtschaftspolitik* 11 (s1): 13–37.

Wang, Ren, and Giuseppe Alonzo. 2013. Foreward to the proceedings. *Perennial crops for food security: Proceedings of the FAO expert workshop* .

Wickens, Michael R, and JN Greenfield. 1973. The econometrics of agricultural supply: an application to the world coffee market. *The Review of Economics and Statistics* : 433–440.

Wintgens, Jean Nicolas. 2009. Coffee: growing, processing, sustainable production. a guidebook for growers, processors, traders and researchers. Wiley-Vch.

Wittenberg, John. 1974. Nerlove's theory of adaptive expectations: some problems of application. *Journal of Agricultural Economics* 25 (3): 331–334.

Wrigley, G. 1988. Coffee. tropical agricultural series. *Long man Scientific and Technical publishing: New York* : 639.

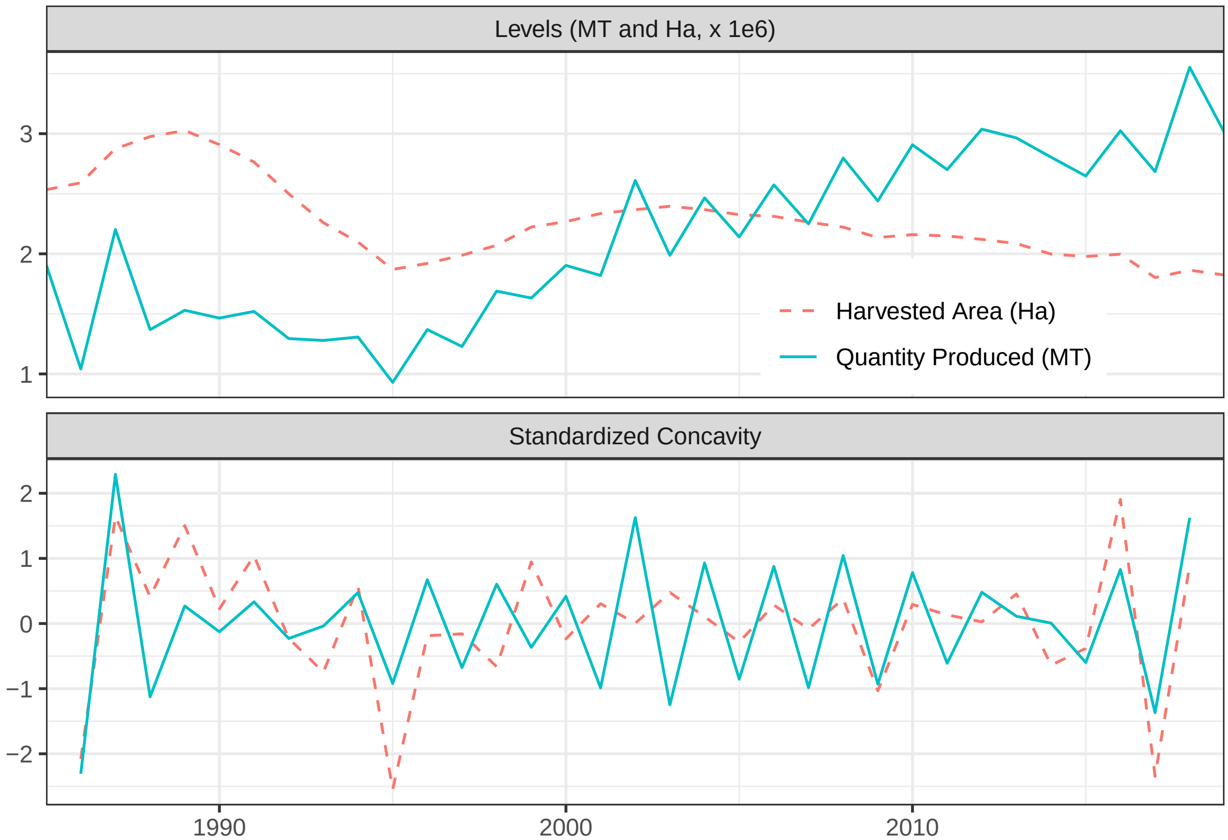

Figure 1: **Top Panel**: Absolute levels of total Brazil production (in million MT) and harvested area (in million Ha), by year. **Bottom Panel**: The point-wise concavity of the functions $(-v_{t-1} + 2v_t - v_{t+1})$, normalized by dividing by its standard deviation. Production and harvest concavity have a correlation of 0.55.

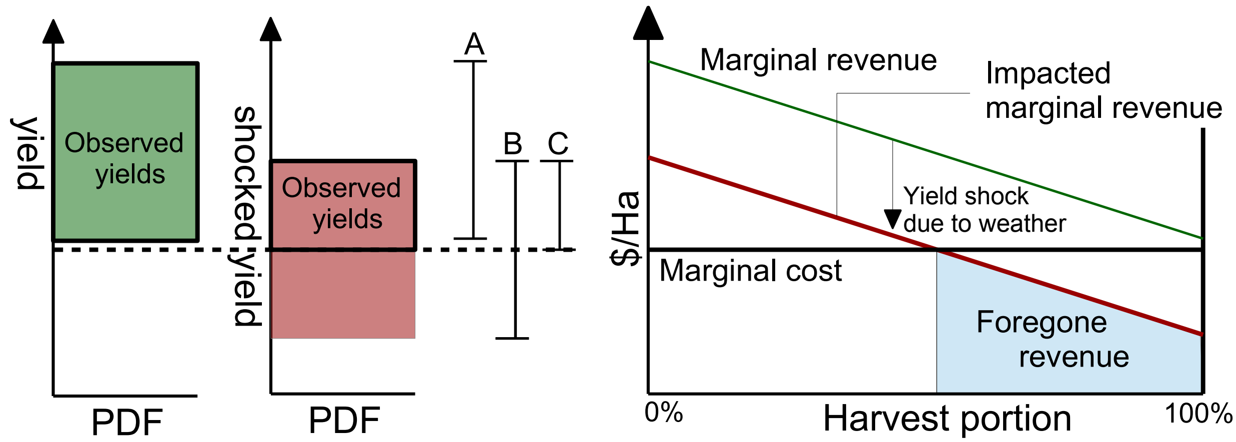

Figure 2: The profit-maximization harvesting decision of a perennial farmer, equating marginal costs with marginal revenue. When yields drop from an initial distribution A to an impacted distribution B, a portion of marginal revenues fall below the marginal cost of harvesting. Partial harvesting produces observed yields drawn from the top portion of the yield distribution, C. However, this adaptation leaves regions unharvested, a kind of foregone revenue which is the main cost of this adaptation.

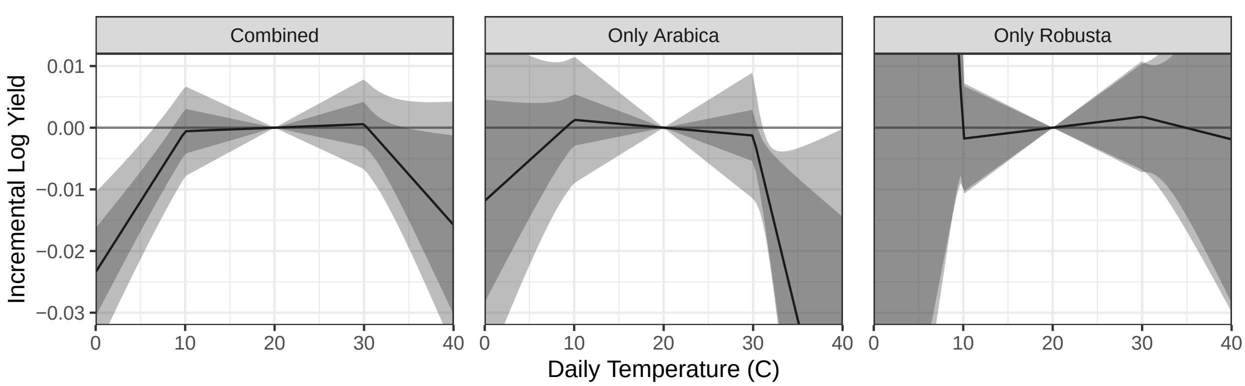

Figure 3: Marginal impact on log yields for an additional day at a given temperature, combining minimum temperatures, growing degree-days, and extreme degree-days. Temperatures between 10°C and 30°C have minor effects, with temperatures outside this range resulting in significant yield losses. The inner grey band shows the 95% confidence interval for errors clustered using Conley spatial HAC standard errors, and the outer grey band shows the 95% confidence interval for two-way clustering over municipalities and years. The poor estimate of the effect of temperatures below 10°C on Robusta coffee is due to lack of data.

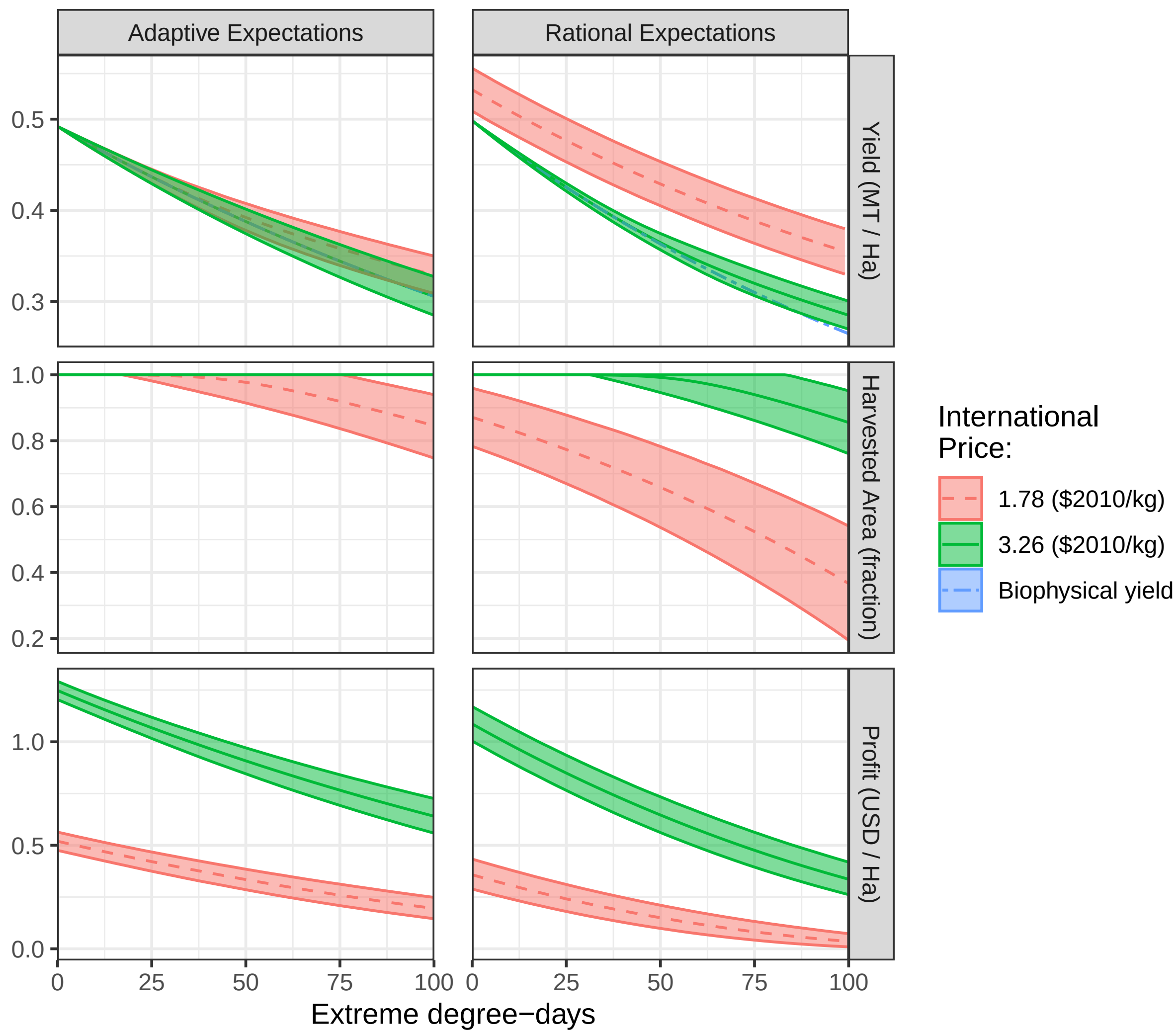

Figure 4: The relationship between yields, harvested area fraction, and total profits across a range of extreme degree-days, under the parameters fit in the integrated model with adaptive (left column) and rational price expectations (right column). The responses are shown for median prices as used in the estimation (1985 - 2017, averaged between Arabica and Robusta based on observed growing portion), shown in green, and 10$^{\text{th}}$ percentile prices, shown in red. Other weather predictors are held constant at their mean value. The lowest, dash-dotted line in the yield graph is observed yields, computed as quantity divided by harvested area. Die-off is ignored, so that this only shows selective harvest for a parcel that has not experienced die-off. Harvested areas are calculated as in the model; profits are calculated as $pq - ch$. 95% confidence intervals shown.

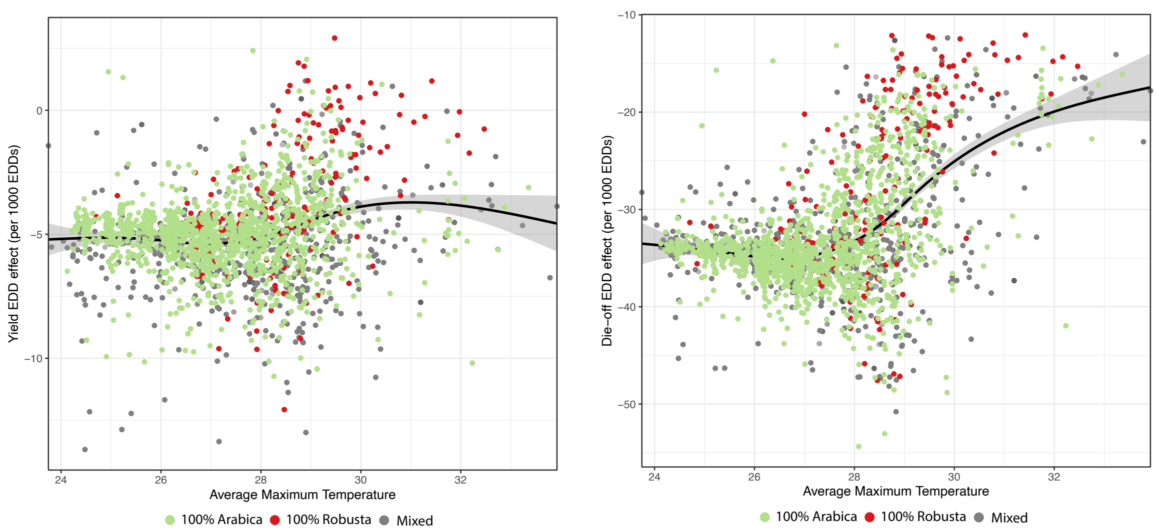

Figure 5: Estimates by municipality of the effects of extreme degree-days on yield vs. average maximum temperature (left), and extreme degree-days on die-off vs. average maximum temperature (right), under adaptive price expectations. Regions are colored by their share of Arabica and Robusta (grey for unknown shares). LOESS curve shown in black. Additional municipality-level scatter plots in appendix section 6.1.

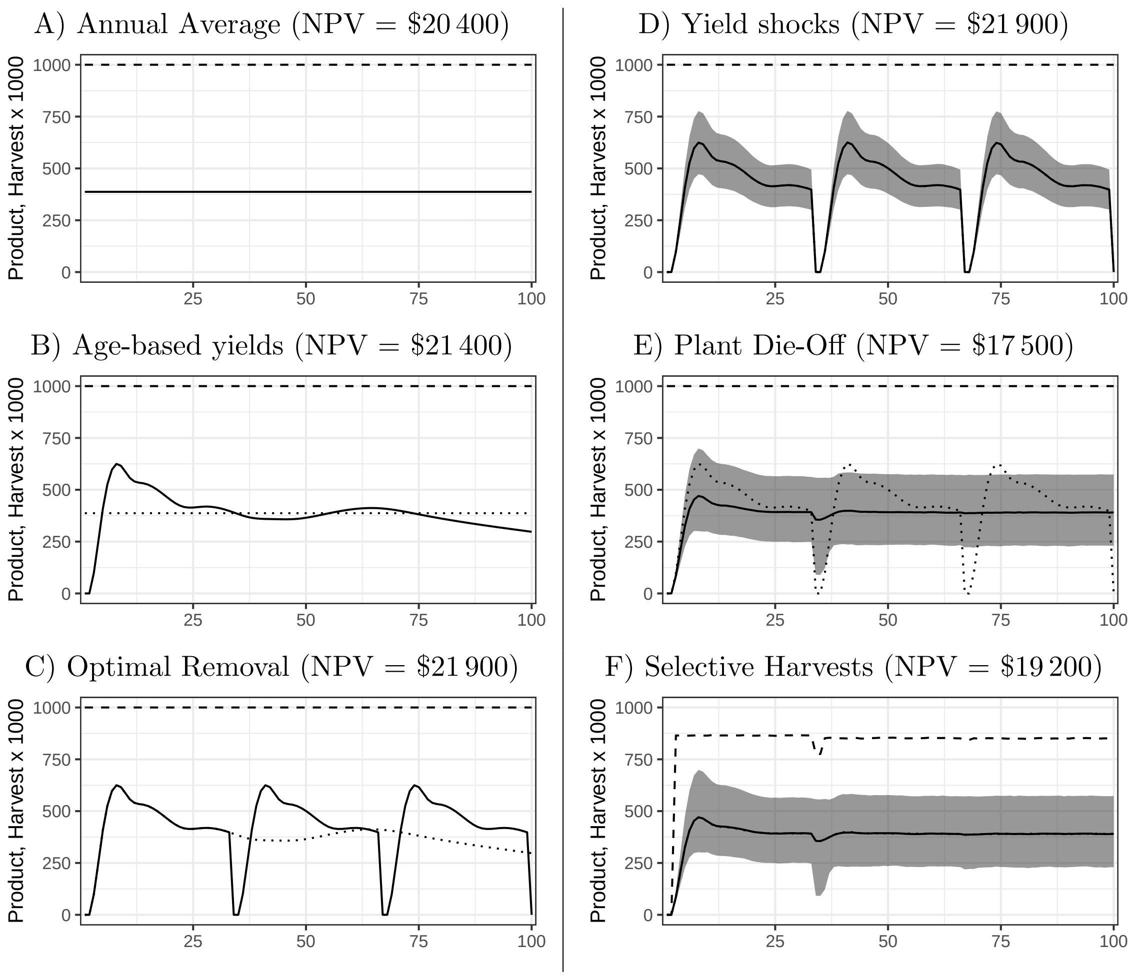

Figure 6: The incremental effects of model elements for a single tree plot, over 100 years of planting. Each figure shows yields (solid line), harvest portion (dashed line, with 1000 = 100%), and the previous graph's yield (dotted line). Titles show net present value (NPV) in USD per Hectare from the perspective of year 1, under 5% discounting. The interquartile range is shown in grey, over Monte Carlo outcomes of yield shocks, die-off, and replanting. **(A)** An annual with the 100-year average yield of coffee from Arak (1967). **(B)** Non-stochastic yields based on ages, from Arak (1967). **(C)** Removal and replanting after the optimal number of years (33 years). **(D)** Stochastic yields, uniformly distributed between $(1-\Delta)$ and $(1+\Delta)$ of the average yield. **(E)** Random die-off of the plant, of 7% per year. **(F)** Selective harvesting, for yields $> {}^{c}/_{p}$.

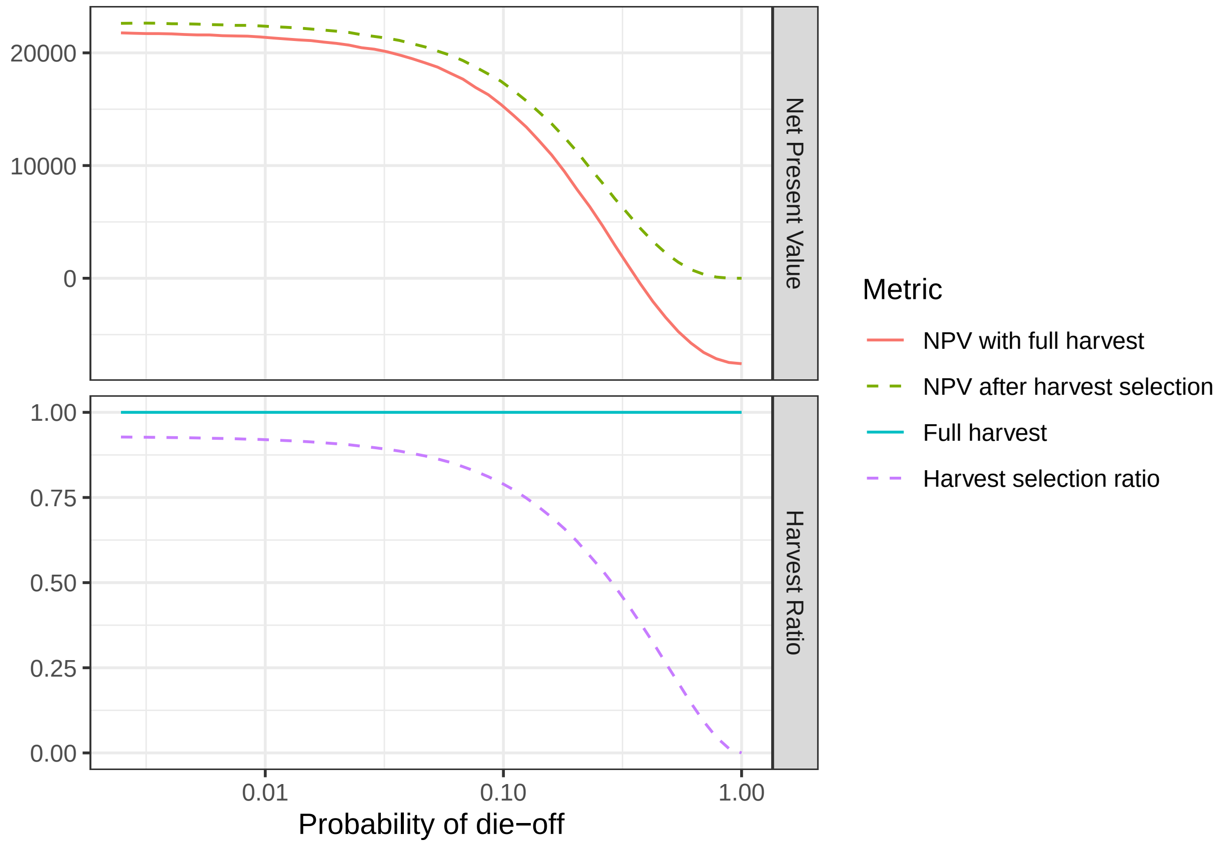

Figure 7: The shifting net present value and average harvest ratio of a single tree plot simulation across a range of probabilities of yearly die-off. The upper panel shows the net present value (NPV) with and without harvest selection. Under harvest selection, the NPV under harvest selection gradually diverges from the NPV under the requirement that all land must be harvested. The lower panel shows harvest ratio under full and selective harvests. The harvest selection ratio shows the average portion of the unit area harvested as die-off increases.

	Dependent variable:					
	Log Yields					
	(1)	(2)	(3)	(4)	(5)	(6)
Average Min.	−0.161	0.343	0.262	0.326	0.273	0.281
(M & Y Cl.)	(0.011)***	(0.054)***	(0.090)***	(0.053)***	(0.078)***	(0.059)***
(Conley)	(0.065)***	(0.037)***	(0.051)***	(0.036)***	(0.044)***	(0.036)***
GDDs / 1000	3.788	−2.658	−1.409	−2.627	−1.801	−2.228
(M & Y Cl.)	(0.111)***	(0.494)***	(0.766)*	(0.507)***	(0.737)**	(0.550)***
(Conley)	(0.521)***	(0.340)***	(0.422)***	(0.331)***	(0.392)***	(0.327)***
EDDs / 1000	−1.422	−5.740	−4.179	−4.103	−4.766	−3.918
(M & Y Cl.)	(0.445)***	(0.905)***	(1.364)***	(0.815)***	(1.085)***	(0.881)***
(Conley)	(1.128)	(0.733)***	(0.978)***	(0.803)***	(0.836)***	(0.722)***
Precip. (m)	0.703	−0.011	0.233	0.031	0.153	0.099
(M & Y Cl.)	(0.036)***	(0.184)	(0.277)	(0.191)	(0.285)	(0.213)
(Conley)	(0.255)***	(0.103)	(0.175)	(0.104)	(0.161)	(0.107)
Precip.^{2}	−0.167	−0.059	−0.147	−0.068	−0.110	−0.064
(M & Y Cl.)	(0.019)***	(0.079)	(0.115)	(0.082)	(0.122)	(0.086)
(Conley)	(0.107)	(0.045)	(0.075)	(0.045)	(0.070)	(0.045)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes
State Trends	None	None	Linear	Linear	Cubic	Cubic
Observations	71,569	71,569	71,569	71,569	71,569	71,569
R^2	0.364	0.575	0.529	0.583	0.565	0.592
Adjusted R^2	0.339	0.558	0.510	0.566	0.547	0.576
Residual Std. Error	0.566	0.463	0.487	0.459	0.468	0.453
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 1: Estimates for statistical models relating average minimum temperature, growing degree-days, extreme degree-days, and precipitation to the logarithm of yields, for all coffee-growing Brazilian municipalities. Models differ by the form of their time controls. For each parameter, two standard error estimates are provided: (M & Y Cl.) Municipality and year two-way clustered errors; and (Conley) Conley standard errors with cut-offs at 400 km and 1 lag.

	Dependent variable:		
	Log Yields	Log Production	Log Harvests
	(1)	(2)	(3)
Average Min.	0.281	0.288	0.007
	(0.059)***	(0.116)**	(0.071)
	(0.036)***	(0.073)***	(0.060)
GDDs / 1000	−2.228	−2.192	0.036
	(0.550)***	(0.983)**	(0.584)
	(0.327)***	(0.647)***	(0.526)
EDDs / 1000	−3.918	−8.102	−4.184
	(0.881)***	(2.108)***	(2.138)*
	(0.722)***	(1.523)***	(1.317)***
Precip. (m)	0.099	−0.089	−0.188
	(0.213)	(0.365)	(0.283)
	(0.107)	(0.211)	(0.164)
Precip.^2	−0.064	−0.092	−0.028
	(0.086)	(0.159)	(0.114)
	(0.045)	(0.087)	(0.066)
Municipality FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State Trends	Cubic	Cubic	Cubic
Observations	71,569	71,569	71,569
R^2	0.592	0.856	0.877
Adjusted R^2	0.576	0.850	0.872
Residual Std. Error	0.453	0.958	0.828
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: The effect of weather on log yields (computed as the ratio of production and harvested areas) and on log production and log harvests (columns 2 and 3). All three outcome variables are reduced by extreme weather shocks. Standard errors are reported two-way clustered at the municipality and year levels (top) and under Conley standard errors with cut-offs at 400 km and 1 lag (bottom).

	Dependent variable:					
	$\Delta \log h_t$			$\Delta \log q_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔEDDs / 1000_{t+1}	1.066	1.129		−1.779	−0.783	
	(1.308)	(1.387)		(2.263)	(2.386)	
	(0.838)	(0.872)		(1.637)	(1.680)	
ΔEDDs / 1000_{t}	−0.050	0.145	−0.513	−5.503	−4.068	−1.953
	(1.271)	(1.316)	(0.687)	(3.029)*	(2.717)	(1.506)
	(0.957)	(0.941)	(0.646)	(1.811)***	(1.736)**	(1.166)*
ΔEDDs / 1000_{t-1}	−0.715	−0.720		−0.744	−0.794	
	(1.333)	(1.278)		(3.565)	(3.354)	
	(1.104)	(1.120)		(2.015)	(1.967)	
ΔEDDs / 1000_{t-2}	−0.822	−0.891		0.565	0.254	
	(1.114)	(1.137)		(2.931)	(2.822)	
	(1.152)	(1.175)		(2.058)	(2.058)	
ΔEDDs / 1000_{t-3}	−0.337	−0.444		0.501	0.443	
	(1.386)	(1.376)		(2.223)	(1.918)	
	(1.218)	(1.223)		(1.962)	(1.921)	
ΔEDDs / 1000_{t-4}	−0.604	−0.690		0.579	0.661	
	(1.137)	(1.152)		(1.541)	(1.635)	
	(1.044)	(1.053)		(1.741)	(1.753)	
ΔEDDs / 1000_{t-5}	0.265	0.283		1.364	1.527	
	(0.842)	(0.886)		(1.600)	(1.650)	
	(0.764)	(0.759)		(1.467)	(1.458)	
ΔEDDs / $1000_{t-1,2}$			−1.089			−0.282
			(0.894)			(1.889)
			(0.658)*			(1.196)
Weather controls	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Trends	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Observations	32,346	32,346	36,160	32,346	32,346	36,160
R^2	0.033	0.034	0.039	0.103	0.112	0.117
Adjusted R^2	0.031	0.031	0.036	0.100	0.109	0.115
Residual Std. Error	0.479	0.479	0.474	0.689	0.686	0.685
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 3: Distributed lags model of extreme weather (extreme degree-day predictors). Except for columns 1 and 4, regressions include average minimum temperatures, GDDs, and quadratic precipitation controls. One lead of EDDs is included as a falsification test. The regression is estimated in first-differences, to reduce autocorrelation in the error terms. Standard errors are reported two-way clustered at the municipality and year levels (top) and under Conley standard errors with cut-offs at 400 km and 1 lag (bottom).

	Dependent variable:						
	$\Delta \log h_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta \log p_t$		0.125	-0.008				
		(0.089)	(0.102)				
		(0.090)	(0.089)				
$\Delta \log p_{t-1}$		0.188		0.136			
		(0.100)*		(0.099)			
		(0.087)**		(0.081)*			
$\Delta \log p_{t-2}$		0.253			0.191		
		(0.105)**			(0.095)*		
		(0.091)***			(0.082)**		
$\Delta \log p_{t-3}$		0.098				-0.017	
		(0.089)				(0.064)	
		(0.088)				(0.072)	
$\Delta \log f(p_{t-2}, 0.3)$							0.263
							(0.135)*
							(0.111)**
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trends	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic	Cubic
Observations	38,139	38,139	38,139	38,139	38,139	38,139	38,139
R^2	0.045	0.045	0.045	0.045	0.045	0.045	0.071
Adjusted R^2	0.042	0.042	0.042	0.042	0.042	0.042	0.030
Residual Std. Error	0.478	0.478	0.478	0.478	0.478	0.478	0.481
Note:				*p<0.1; **p<0.05; ***p<0.01			

Table 4: The effects lagged prices on log harvested areas. The estimate is computed in first-differences, using annual changes in predictors and change in harvests, $\Delta \log h_t$. All regressions include average minimum temperatures, GDDs, EDDs, and quadratic precipitation controls. In addition to current and past prices, the two-period delayed Nerlove price with autoregression set to 0.3 is included ($\Delta \log f(p_{t-2}, 0.3)$), discussion in text). Prices differ between counties depending on the share of Arabica and Robusta production. Standard errors are reported two-way clustered at the municipality and year levels (top) and under Conley standard errors with cut-offs at 400 km and 1 lag (bottom).

Description		OLS	OLS x Muni	Bayes. Reg.	No Sel. (1)	Rational	Adaptive	No Sel. (2)
Average Min.	μ	0.281	0.119	0.072	0.278	0.339	0.303	0.290
		(0.0586)	(0.0103)	(0.0066)	(0.0123)	(0.0100)	(0.0129)	(0.0149)
GDDs / 1000	γ	-2.228	-0.573	-0.413	-0.124	-2.413	-0.437	-0.152
		(0.5496)	(0.0941)	(0.0234)	(0.0604)	(0.0486)	(0.0736)	(0.0706)
EDDs / 1000	κ	-3.918	-3.880	-4.007	-2.191	-6.324	-4.764	-2.055
		(0.8810)	(0.4610)	(0.0963)	(0.4353)	(0.2086)	(0.3545)	(0.4775)
Precip. (m)	π	0.099	0.370	-0.143	0.023	-0.211	-0.115	-0.006
		(0.2132)	(0.0790)	(0.0216)	(0.0639)	(0.0492)	(0.0617)	(0.0739)
Precip.^{2}	ψ	-0.064	0.014	0.036	-0.243	-0.006	-0.145	-0.196
		(0.0862)	(0.0002)	(0.0317)	(0.0659)	(0.0534)	(0.0635)	(0.0725)
Die-off EDD effect	δ				-37.432	-44.382	-23.914	-25.302
					(1.2134)	(1.3996)	(0.8520)	(0.7562)
Planting autoreg.	ρ_a				0.479	0.585	0.464	0.443
					(0.0107)	(0.0097)	(0.0114)	(0.0116)
Nerlove autoreg.	ρ_p						0.387	0.403
							(0.0103)	(0.0106)
Cost of harvest	c					0.538	0.356	
						(0.0424)	(0.0230)	
Planting price resp.	ϕ				0.138	0.110	0.190	0.197
					(0.0284)	(0.0211)	(0.0370)	(0.0308)
Exogenous trend	θ		0.029	0.027	-0.016	0.031	-0.025	-0.026
			(0.0002)	(0.0045)	(0.0057)	(0.0067)	(0.0063)	(0.0079)
Range of yields	Δ					0.530	0.498	
						(0.0082)	(0.0095)	
Bearing std. dev.	σ_b				0.581	0.678	0.501	0.489
					(0.2200)	(0.1922)	(0.1942)	(0.2538)
Harvest std. dev.	σ_h				0.187	0.193	0.205	0.184
					(0.0080)	(0.0087)	(0.0111)	(0.0100)
Production std. dev.	σ_q				0.496	0.395	0.509	0.507
					(0.0100)	(0.0110)	(0.0133)	(0.0126)

Table 5: Comparison between yield models. Column shading is used to group columns into method validation (dark grey), extensive-margin-only estimates (light grey), and full model estimates (white). **OLS** is the preferred regression model of log yields; **OLS x Muni** regresses the same predictors and a linear trend for each region and pools the results; **Bayes Reg.** fits the same parameters in a Bayesian framework and applies hierarchical pooling; **No Sel. (1)** uses the full model assuming rational price expectations but excluding the harvest selection process; **Rational** shows the full model using rational price expectations. **Adaptive** is the full model using Nerlove price expectations. **No Sel. (2)** uses the full model with Nerlove price expectations but excluding the harvest selection process. Standard errors are given below the mean parameter estimates.

		Arabica		Robusta	
Description		(Rational)	(Nerlove)	(Rational)	(Nerlove)
Average Min.	μ	0.33	0.26	0.30	0.32
GDDs / 1000	γ	-2.21	0.14	-2.88	-0.54
EDDs / 1000	κ	-6.92	-5.20	-4.91	-1.53
Precip. (m)	π	-0.20	0.01	-0.24	-0.06
Precip.^{2}	ψ	0.07	-0.32	-0.03	-0.02
Die-off EDD effect	δ	-36.42	-25.23	-16.82	-9.11
Planting autoreg.	ρ_a	0.63	0.47	0.53	0.45
Nerlove autoreg.	ρ_p		0.36		0.41
Cost of harvest	c	0.54	0.36	0.53	0.38
Planting price resp.	ϕ	0.08	0.12	0.20	0.20
Exogenous trend	θ	0.03	-0.03	0.04	-0.03
Range of yields	Δ	0.52	0.49	0.56	0.54
Bearing std. dev.	σ_b	0.63	0.51	0.85	0.65
Harvest std. dev.	σ_h	0.19	0.20	0.17	0.18
Production std. dev.	σ_q	0.43	0.54	0.30	0.42

Table 6: Point estimates of each parameter in the integrated model, under rational and Nerlove price expectations, for municipalities that only grow Arabica (left) or Robusta (right).