Temperatures, Productivity, and Firm Competitiveness in Developing Countries: Evidence from Africa

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Abstract

Characterizing the relationship between temperatures and overall economic productivity remains a key challenge in the study of the economic effects of climate change. While some studies have attempted to explain the micro mechanisms behind the established negative effect of temperatures on aggregate output, how such effect takes place and its implications for firms in developing countries need further explanation. This paper examines the relationship between temperatures and firm performance, by using detailed production data from manufacturing, service, and agricultural firms in Côte d'Ivoire. To guide our empirical work, we introduce climate mitigation technology choice into a model of trade with heterogeneous firms. An empirical test of the model shows that increased temperatures leads to lower firm revenues, profits, and survival rate. In addition, our empirical results suggest a negative relationship between daily temperatures and measures of firm performance: total factor productivity, labor and capital productivity. Finally, we find a lower effect of temperatures on firms that can invest in climate mitigation technology. These findings show that higher temperatures in developing countries decrease competitiveness, thus providing the first quantitative estimates of this cost of climate change.

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1 Introduction

As global temperatures rise, it becomes more important to understand the influence of temperature on economic productivity. A growing body of literature has established strong negative relationship between historical fluctuations in levels of temperature and aggregate economic performance (Dell et al., 2012; Burke et al., 2015). However, most of these studies are based on aggregate data and use a cross-country approach. Such an approach does not provide insights on the mechanism behind the observed effects of temperature on economic activity. Further, while these studies suggest that temperatures affect output in sectors other than agriculture, they have been limited in explaining the consequences of the observed effects on firm performance. This paper uses firm-level data across multiple sectors of the economy to analyze the relationship between temperature changes and firm performance. These firm-level effects have important implications for the competitiveness of the economy in the international market.

We answer this question using data from Côte d'Ivoire. Africa is especially vulnerable to rising temperatures due to its low levels of development, making study of the effects of climate change in Africa all the more important. First, we adapt a trade model with heterogeneous firms à la Melitz (2003) to analyze the impact of increased temperatures on firm revenues, profits, and exit productivity cutoff. Second, using a unique, detailed firm-level data set from Côte d'Ivoire coupled with climate data, we estimate total factor productivity (TFP) non-parametrically, using the most recent techniques in the field of industrial organization. Third, we empirically in-

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vestigate whether and how temperatures affect firm productivity. Finally, we test the key prediction from our model that increased temperatures decreases firm's revenues, profits, and market survival rate.

We augment the typical trade model by allowing firms to invest in technologies that mitigate the effects of high temperatures. The seminal work of Melitz (2003) on heterogeneous firms and trade liberalization has stimulated a large empirical literature investigating the links between firm productivity and competitiveness in the global market. Recent studies extend this literature to investigate which types of domestic firms take advantage of trade openness and what factors influence their survival in the export market (Manova, 2013; Minetti and Zhu, 2011). This paper adds a new dimension to current trade theory by examining the effects of temperatures on firm's productivity and market survival. As is standard in the literature, our model predicts that the least productive firms exit the market, the medium productive firms continue producing, but do not invest in climate mitigation technology, and the most productive firms continue producing and invest in climate mitigation technology. Our additional insight is that higher temperatures increase the exit productivity cutoff, because they increase firms' production costs. As a result, some firms make negative profits and stop producing.

In the empirical application we start by using the non-parametric methods developed by Gandhi et al. (2011) to estimate total factor productivity (TFP) across the manufacturing, agriculture, and service sectors. Next, to identify the effects of temperatures on firms' revenues, profits, and TFP, we exploit year-to-year variation in firms' exposure to a daily distribution of temperatures, constructed in a series of temperature bins. We find a strong and statistically significant negative effect between temperatures and firms' revenues, profits, and TFP. In our preferred baseline specification, a one-standard-deviation rise in days with high average temperatures decreases firm's revenues, profits, and TFP, respectively, by 14.83%, 21.71%, and 3.61% relative to the impact of a day with moderate average temperatures. For firms that can invest in climate mitigation technology, the effects of high temperatures on revenues are significantly reduced. To assess the potential mechanisms behind the observed effects of temperatures on TFP, we estimate the effects of temperatures on labor and capital productivity. In various specifications, we find no evidence that the observed effect of temperatures on TFP is solely explained by labor productivity, which suggests high temperatures affect capital productivity as well. The model also predicts that increased temperatures reduces firm market survival rate as a result of higher production costs. To examine the impact of higher temperatures on a firm's exit, we estimate the change in the probability that a firm exits as a function of temperatures. We found that a one-standard-deviation rise in days with high average temperatures increases firm exit rate by 0.04%. This result demonstrates the negative effect of climate change on firms' competitiveness.

The unique and comprehensive data used in this paper helps overcome many of the endogeneity and identification issues in the previous literature. Our data spans a range of manufacturing, agriculture, and service sectors with different levels of mechanization, ability to control for temperatures, and different level of exposure to temperatures. Moreover, by having information about the exact address of the plant, we can identify temperatures at the smallest administrative division where the firm is located. This unique feature of the data enables us to exploit exogenous variation in temperatures at different firms' locations and across time to estimate the impact of increased temperatures on firms. In addition, the richness of our data enables us to perform several robustness checks including different identification strategies, using alternative sub-samples of the data and temperature measures, and controlling for major events in the country. These robustness checks allow us to address potential threats to identification that might come from the concentration of the majority of firms in few localities in the country, sample selection issues due to entry and exit of firm and data requirement to estimate non-parametric firm's productivity. In all specifications, we find strong support for our main results that high temperatures affect firms' revenues, profits, productivity, and market exit rate.

This paper contributes to a number of different strands of the literature on climate, firms, and African development. First, by adding insights from the trade literature on productivity with the climate and productivity literature we make important advances to the climate literature. The trade theory framework we use pays close attention to how temperatures affect competitiveness in contrast to most climate-productivity analyses, which only focus on the effects of temperatures on firm's output.

Secondly, we are the first paper to analyze the effects of temperatures using firm level data in Africa. While this literature has not yet focused on Africa, there are good reasons to believe that African firms are most vulnerable to climate change due to missing market of credit and a high vulnerability of their agriculture sector. Moreover, if non-agricultural sectors are expected to attenuate the effect of climate change by absorbing affected workers in the African agricultural sector, it is important for adequate climate adaptation policies to understand how temperatures might also affect non-agricultural sectors.

Finally, this work also makes important contributions to the broad literature trying to understand factors affecting the competitiveness of African firms. To design a sound industrialization policy, which is often suggested as the path for sustainable growth and poverty reduction in the continent, it is important to understand all the contributing factors that constrain African firms. Our results bolster current evidence on the contributing factors to poor performance of African's firms and in doing so add a new dimension to the analysis of the impact of climate change on economic activities in developing countries.

The reminder of the paper proceeds as follow: in section 2 we review the literature and discuss the mechanisms through which temperature might affect firm productivity. In section 3 we introduce a theoretical model of firm behavior under climate variability. In section 4 we provide the empirical framework and the data. In section 5 we offer the empirical analysis. In the last section we conclude and provide policy implications.

2 Literature Review

While globalization has fostered the expansion of higher productivity sectors in most of East Asia, it seems to have induced an undesirable structural labor movement in Sub-Saharan Africa from the most productive to less productive sectors (McMillan and Rodrik, 2011). Despite a multitude of studies that have looked into potential factors (e.g. weak institutions, political instability, inadequate infrastructures) trailing behind African firms, there are none on the effect of climate on the manufacturing sector in the continent. It is possible that low productivity in African firms is related to climate.

The relationship between temperatures and economic activities has been well established at the aggregate output level. Using historical fluctuations in temperatures within countries and GDP information for about 120 countries, Dell et al. (2012) found that high temperatures reduce agricultural output, manufacturing output, and political stability in poor countries. In a similar exercise, using a non-linear estimation methodology, Burke et al. (2015) showed that increased temperatures affect economic activities not only in developing countries but in developed countries as well. While these studies have resuscitated the debate on the impact of climate on broader economic activities, they are limited in explaining the micro-mechanism behind the observed effects.

Previous studies that used micro-level data have been mainly focused on understanding the influence of temperatures on agricultural yield (Auffhammer et al., 2006; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Lobell et al., 2011). However, despite the economic importance of agriculture in most developing countries, it cannot alone explain GDP losses due to temperature fluctuations observed in macro studies. Few recent studies have investigated the impacts of climate change on labor productivity and absenteeism (Cachon et al., 2012; Zivin and Neidell, 2014; Sudarshan et al., 2015; Park, 2016). Using county level payroll and weather data from 1986 to 2012, Park (2016) estimated the impact of heat days on local labor productivity in the US. He found that an additional day above 32C caused a 0.048% decline in payroll per capita that year, and that the coldest counties suffered more,suggesting that the hottest counties had already invested in long-term adaptation. Using daily worker productivity and attendance from Indian manufacturing firms, Sudarshan et al. (2015) found that intrinsic labor productivity decreases by between 4% - 9% per degree on days above 27C. This is one of the few studies to use firm level data to directly measure the impact of temperatures on firms' productivity. They show that an additional day of high temperature is associated with a 1% - 2% increase in absenteeism of contracted workers. However, they observe no impact on daily (non-contracted) workers for whom the cost of absenteeism is high. In assessing the economic implication of their results, they found that firm output decreases in years of high temperature a little over 3% per degree-day.

While such pioneering micro studies on the impact of extreme weather on firms' productivity (Cachon et al., 2012; Sudarshan et al., 2015) create a basis for firm level evidence of temperatures' effects, they are likely to suffer from external validity issues since the scope of their analysis is usually restricted to specific industries within the manufacturing sector. Moreover, the features of the data (e.g. cross sectional, the lack of information on firm's exact location) used in previous papers raised potential identification concerns about their findings.

2.1 How Does Temperature Affect Economic Activity?

At first glance, the relationship between temperature shocks and secondary or tertiary economic sectors is not obvious. However, there are several ways in which extreme temperatures can affect the production process of firms. One of the primary mechanisms identified in the literature is that higher temperatures cause intrinsic labor productivity loss and a reduction in labor supply (Park, 2016; Sudarshan et al., 2015; Zivin and Neidell, 2014; Cachon et al., 2012; Hsiang, 2010). Hsiang (2010) found that the effect of temperature on economic output in the Caribbean is structurally similar to the effect of intrinsic labor productivity. With the exception of (Zhang et al., 2017), which document the relationship between temperatures and firm output, TFP, labor and capital productivity, most of the previous micro studies have been solely focused on labor productivity channel. Zhang et al. (2017) found that while the effect of temperatures on labor and capital are limited, temperatures affect both labor and capital productivity. Although there are good reasons to believe that temperatures can affect the proper function of machines or divert investment from productive capital, the impact of temperatures on capital productivity has been mostly neglected in the climate-firm literature.

In many developing countries, temperatures can induce higher industrial production cost. In warmer seasons, while there is higher energy demand for cooling purposes from both households and firms, increased temperatures decrease the stream flow of water, which poses potential operating and efficiency problems for hydroelectric plants- the primary source of electricity for many countries in SSA. High demand of energy and downward pressure on electricity and water supply due to hotter seasons lead to poor water supply and intensive power outages, which poses tremendous handicap to firm production. According to (Kaplinsky and Morris, 2008), Kenyan firms facing frequent power interruptions lost significant part of their production despite investing in generators. Most probably because of the strict data requirement, there is no study that has investigated energy interruption as a potential mechanism through which temperatures can affect firm productivity in Africa.

Finally, increases in input prices could also lead to higher production costs for firms. Given the established evidence of the negative impact of temperatures on the efficiency of agricultural production, especially in the tropics, one would expect that higher temperatures would affect both the supply and price of agricultural output. This is particularly of concern for food manufacturing firms or firms that use agricultural output as intermediate inputs.

As shown by Melitz (2003), exposure to globalization induces the most productive firms to enter the export market and the least competitive firms to exit. Hence, if we assume that firms in tropical regions are relatively more exposed to climate change than firms elsewhere, they will be less competitive in the global market if climate change affects firm productivity, ceteris paribus. In other words, in a globalized market where firms in small countries are price takers, climate change can exogenously increases the survival productivity threshold for firms in climate vulnerable countries.

3 Theoretical Model

This section develops a simple model to study the effects of temperatures on the competitiveness of heterogeneous firms by introducing climate mitigation technology choice in Melitz style trade model. This add-on to Melitz model enables us to consider the impact of temperatures on the behavior of firms; an implication of climate on economic activity in developing countries that has been missed in previous studies. To a certain extent, the insights in our model is close to that of Bustos (2011) and Manova (2013). However, while Bustos (2011) and Manova (2013) focuses respectively on the impact of increased trade on firm technology upgrading and the implication of credit constraints for heterogeneous firms in international trade, our model analyses the impact of temperature shocks on firm sorting and exit.

3.1 *Set up of the Model*

We incorporate climate costs and climate mitigation technology choice into a static, partial equilibrium model à la Melitz (2003). Each of J countries is endowed with L units of labor used by heterogeneous firms to produce differentiated products in a single monopolistically competitive industry. Assuming that firms face exogenous constant elasticity of substitution (CES) demand schedule, the demand function for each variety (ω) in country j is determined by $q_j(\omega) = E_j P_j^{\sigma-1} [p_j(\omega)]^{-\sigma}$, where $p_j(\omega)$ is the price of the variety, $\sigma = 1/(1-\rho)$ is the elasticity of substitution between any two goods, $P_j = \left[\int_0^M p_j(\omega)^{1-\sigma} \mathrm{d}\omega\right]^{\frac{1}{1-\sigma}}$ is aggregate price index, M is the number of varieties, and E_j is the aggregate level of spending in the economy. The assumption of symmetry in production technology ensures that wages, the numeraire, and aggregate variables are the same across countries.

Firm entry. - Each economy is populated with a continuum of monopolistically competitive firms, each producing a differentiated product under increasing return to scale technology. Within the industry, firms are heterogeneous in their productivity φ, and they face fixed entry cost of f_e units of labor. Productivity φ, unknown to firms before starting production, is drawn from a known cumulative Pareto distributive function $G(\varphi) = 1 - \varphi^{-k}$ *with* $k > 1$. After observing their productivity, firms decide whether to produce or exit the market.

Temperature Cost. - We assume that temperatures differently affect production technology in different countries, that is, to manufacture 1 unit of a good in country j, firms need to employ $\gamma_j(\theta) > 1$ units of labor that could otherwise be produced with 1 unit of labor in the scenario of no temperature effect ($\gamma_j(\theta = \theta^*) = 1$), where θ and θ^* are respectively the level of current and optimal temperatures. $\gamma_j(\theta)$, which increases in temperature, captures differences in the effects of temperatures on production factors in different countries. Thus the production of each variety involves a fixed cost (f) and a marginal cost $\left(\frac{\gamma_j(\theta)}{\varphi}\right)$, both expressed in terms of units of labor.

A simple interpretation of the climate variable cost would be the decrease in labor productivity due to weather condition. As demonstrated in previous studies (Hsiang, 2010; Sudarshan et al., 2015; Park, 2016), high temperatures reduce intrinsic labor productivity through fatigue or discomfort. To a certain extent, temperatures can affect capital productivity as well (Zhang et al., 2017). Alternatively, climate costs can also be interpreted analogously to environmental regulation requirements. In order to comply with the carbon emission regulation in most countries, firms need to make specific investments in production technology, which might not necessarily increase their productivity.

Henceforth, we will focus on the domestic market, so we will drop the sector j subscript to reduce the intensity of notation.

Production Technology. - Upon staying active, firms produce goods using a technology that features a marginal cost $(\gamma(\theta)/\varphi)$ and a fixed cost (f), both expressed in units of labor. Firms can choose to improve their production technology by reducing their marginal cost of production through an investment in climate mitigation technology at a fixed cost. This can be expressed as the choice between two technologies, low (l), and high (h), where technology h features a higher fixed cost (ηf) and a lower marginal cost $[\gamma(\theta)/\lambda(\theta)\varphi]$, where $\lambda(\theta) > 1$ is increasing in temperatures with $[\lambda(\theta=\theta^*)=1]$, and $\eta > 1$. The total cost functions under each technology are:

$$\mathrm{TC}^l(q,\varphi) = l^l = f + \frac{\mathrm{q}\gamma(\theta)}{\varphi}$$

$$\mathrm{TC}^h(q,\varphi) = l^h = \eta f + \frac{\mathrm{q}\gamma(\theta)}{\lambda(\theta)\varphi}$$

where l^l and l^h are, respectively, labor for firm using low and high technology.

3.2 *Firm behavior*

Profit Maximization

Under CES preferences, the static problem for a monopolistic competitive firm, with productivity φ, is to maximize the following profit function:

$$(1)\max_{\mathrm{l,q}}\ \pi\left(e,\varphi,\theta\right)=pq-\ \frac{\mathrm{q}\gamma\left(\theta\right)}{\varphi}-f+e\left[\left(1-\frac{1}{\lambda\left(\theta\right)}\right)\mathrm{q}\gamma\left(\theta\right)-f(\eta-1)\right]$$

s.t.

$$(1.1)\ \ \mathrm{q}\left(\varphi,\theta\right)=EP^{\sigma-1}\left[p\left(\varphi,\theta\right)\right]^{-\sigma},$$

$$(1.2)\ \ \mathrm{A}\left(\varphi,\theta\right)\equiv\left(1-\frac{1}{\lambda\left(\theta\right)}\right)q\left(\varphi,\theta\right)\gamma\left(\theta\right)-f(\eta-1)\geq 0.$$

where $e=(0,1)$ is an indicator for firm investment status in climate mitigation technology. In the absence of climate mitigation technology choice, the equilibrium production quantities, price of variety, revenues, and profits are the same as in Melitz (2003) scaled by a climate cost shifter $\lambda\left(\theta\right)$:

$$(2)\qquad \mathrm{p}\left(\varphi,\theta\right)=\tfrac{\gamma(\theta)}{\rho\varphi},\qquad q\left(\varphi,\theta\right)=EP^{\sigma-1}\left[\tfrac{\gamma(\theta)}{\rho\varphi}\right]^{-\sigma},$$
$$\mathrm{r}^{l}\left(\varphi\right)=\left[\tfrac{\gamma(\theta)}{\rho\mathrm{P}\phi}\right]^{1-\sigma}E,\qquad \pi^{l}\left(\varphi,\theta\right)=\gamma\left(\theta\right)^{1-\sigma}\tfrac{1}{\sigma}E\left(\mathrm{P}\rho\right)^{\sigma-1}\varphi^{\sigma-1}-f.$$

Climate Mitigation Technology. – Since the benefits of investing in climate mitigation technology increase with productivity and temperature, the investment constraint (1.2) for firms with productivity level above a certain cut-off is not binding. Substituting $A(\varphi,\ \theta) = 0$ into (1), the equilibrium revenues and profits for firms using *high* technology are the following:

$$(3) \qquad r^h(\varphi, \theta) = \left[\frac{\gamma(\theta)}{\rho \mathrm{P} \lambda(\theta)\varphi}\right]^{1-\sigma} E,$$

$$\pi^h(\varphi, \theta) = \gamma(\theta)^{1-\sigma} \frac{1}{\sigma} E (\mathrm{P}\rho)^{\sigma-1} \varphi^{\sigma-1} \lambda(\theta)^{\sigma-1} - \eta f$$

Firms make the decision of whether to invest in climate mitigation technology by comparing the profits in (2) and (3). The decisions to stay active and technology choice are represented in Figure 1, where the two possible profits are depicted as a function of firm productivity. The equilibrium in Figure 1 is obtained when $\varphi^* < \varphi^h$ where φ^* is the productivity cutoff for staying in market and φ^h is the level of productivity above which a firm using *low* technology finds it profitable to invest in climate mitigation technology $\left[\pi^l\left(\varphi^h\right)\right] = \left[\pi^h\left(\varphi^h\right)\right]$. This equilibrium results in the sorting of firms into three different groups: the least productive firms $(\varphi < \varphi^*)$ exit, the low productive firms $\left(\varphi^* < \varphi < \varphi^h\right)$ produce with low technology, and the most productive firms $\varphi^h < \varphi$ produce with *high* technology by investing in climate mitigation technology.

Proposition 1: *An increase in temperatures reduces firm revenues and profits* $\left(\frac{\partial r(\varphi,\theta)}{\partial \theta} < 0,\ \ \frac{\partial \pi(\varphi,\theta)}{\partial \theta} < 0\right)$.

Proof. *See Online Appendix A.*

Proposition 2: *The effect of temperatures on revenues and profits is lower for firms that invest in climate mitigation technology*
$\left(\left|\frac{\partial r^h(\varphi,\theta)}{\partial \theta}\right| < \left|\frac{\partial r^l(\varphi,\theta)}{\partial \theta}\right|, \left|\frac{\partial \pi^h(\varphi,\theta)}{\partial \theta}\right| < \left|\frac{\partial \pi^l(\varphi,\theta)}{\partial \theta}\right|\right)$.

Proof. *See Online Appendix A.*

Intuitively, when there is temperature increases labor productivity reduces and as a result firms produce less and experience higher costs given the same level of production factors. Firm can mitigate the cost of high temperatures by investing in climate mitigation technology (e.g. AC), which will lessen the effects of temperatures on their productivity.

Exit from Market. –The least productive firms maximize profit by using *low* technology. As a result, the exit cutoff productivity φ^*, is defined as:

$$(4) \quad \pi^l(\varphi^*) = 0 \iff \varphi^* = \left(\frac{\sigma \mathrm{f}}{E}\right)^{\frac{1}{\sigma-1}} \frac{\gamma(\theta)}{\mathrm{P}\rho}$$

It is important to note that in a standard Melitz model, a firm's decision to exit is based on its long run profit and, consequently, expectations over future temperatures should be taken into account. However, to make modeling simple and given our context, a developing country with credit constraints, short term cash flow can be critical to firm survival. For this reason, we will assume that short-term profits motivate a firm's decision to exit.

Proposition 3 *(Exit Cut-off) An increase in temperatures reduces firm survival rate* $\left(\frac{\partial \varphi^*}{\partial \theta} > 0\right)$.

Proof. *See Online Appendix A.*

Technology Choice. - The marginal firm using *high* technology is indifferent in using the *low* technology, that is, $\pi^h\left(\varphi^h\right) = \pi^l\left(\varphi^h\right)$. Therefore, the cut-off productivity level requires to invest in climate mitigation technology is defined by:

$$\pi^h\left(\varphi^h\right) = \pi^l\left(\varphi^h\right) = 0 \Leftrightarrow \left(\lambda(\theta)^{\sigma-1} - 1\right)\gamma(\theta)^{1-\sigma}\frac{1}{\sigma}E\left(\mathrm{P}\rho\right)^{\sigma-1}{\varphi_h}^{\sigma-1} = (\eta-1)f$$

combining this condition with equation (4), we can express φ^h as a function of the exit cutoff productivity:

$$(5) \quad \varphi^h = \varphi^* \left(\frac{\eta - 1}{\lambda\left(\theta\right)^{\sigma-1} - 1} \right)^{\frac{1}{\sigma-1}}$$

Note that $\varphi^h > \varphi^*$ as long as $\left(\frac{\eta-1}{\lambda(\theta)^{\sigma-1}-1} \right)^{\frac{1}{\sigma-1}} > 1$. This implies that only the most productive firms invest in climate mitigation technology. Because demand is elastic ($\sigma > 1$), adopting *high* technology will result in higher revenues for firms. Given that the benefit of investing in climate mitigation technology is increasing in productivity and costs are the same for all firms, after certain level of productivity, the dominant strategy for all firms is to adopt *high* technology. From (5), it is also worth mentioning that no firm will invest in climate mitigation technology when there is no temperature effect $[\lambda\left(\theta = \theta^*\right) = 1]$ and an increase in the cost of climate mitigation technology results in a lower share of firms adopting the technology $h \left[\left(\varphi^h / \varphi^* \right)^{-k} \right]$. This implies that firms' decision to invest in adaption technology is motived by both, weather conditions and the cost of technology. For example, if weather conditions have no impact on technology costs, an increase in temperatures will lead to more adoption. On the other hand, if the cost of technology is affected by weather, than the effect of increased temperatures on adoption will depend on the net benefit of investing in the technology.

Discussion. **-** The model outlined above generates testable implications of the effect of temperatures on economic activity that we will evaluate in the empirical section. The key results to our model are that an increase in temperatures decreases firm revenues, profits, and survival rate (Proposition 1 and 3). The model also suggests that firms investing in climate mitigation technology are less affected by temperatures (Proposition 2). Finally, the model predicts that increased temperatures has an ambiguous impact on climate adoption cutoff productivity.

4 Data and Empirical Framework

4.1 *Empirical Framework*

We will first test the assumption in the literature that temperatures affect firm productivity, and then explore the mechanism behind such effects. Second, we will test the prediction of the model that: (1) an increase in temperatures reduces firm revenues, profits, and market survival and (2) temperatures have a lower effect firms that can invest in climate mitigation technology.

Our empirical strategy for studying the impact of temperatures on firms' performance is to regress the variable of interest (TFP, firm revenues, profits, and exit, and labor, capital productivity) on the temperature variables constructed using the bin approach and other control variables. Our key regression is thus specified as:

$$\log\left(Y_{\mathrm{it}}\right) = \alpha_i + \ \theta_d + \ \beta' temp_{\mathrm{it}} + \delta' X_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$$

where Y_{it} denotes firm i TFP, revenues, profits, dummy for exit, labor productivity, or capital productivity in year t. Firm fixed-effect and district fixed-effect are respectively represented by α_i and θ_d. While firm fixed-effect controls for firm specific time invariant characteristics, district fixed-effect controls for shock inherent to each district, such as climate trends, the quality of institution, and policy shocks within the geographical district. The key explanatory variable, $\mathrm{temp}_{\mathrm{it}}$, measures temperature at firm's i location in year t. To capture the non-linear effect of temperatures on economic activities, $\mathrm{temp}_{\mathrm{it}}$ is constructed in series of temperature bins $[\mathrm{bin}_{it1,}\ ,\ \ldots, \mathrm{bin}_{\mathrm{itn}}]$, in which $\mathrm{bin}_{\mathrm{itn}}$ represents the number of days falling into the n^{th} temperature bin for firm i in year t. Other control variables: production factors, firm's characteristics, precipitations, and time trends are included in vector X_{it}. Finally $\varepsilon_{\mathrm{it}}$ is the error term clustered at region-year level, which will allow us to control for spatial correlation across firms within each region. To test whether firms with a specific feature (e.g. investing in climate mitigation technology, labor intensive) are differently affected by temperature, we augment equation (7) with terms that interact the temperature bins and a dummy variable for the feature of the firm.

4.2 *Data and Construction of Variables*

We use two sources of data to analyze the impact of temperatures on firms' outcomes. Firm-level data, covering the universe of registered firms in Côte d'Ivoire from 1998-2013, are collected by the *Registre des Entreprises*, a department of the National Institute of Statistics (INS). Since almost all the establishments have only one branch, we will refer to each establishment as "firm" instead of "plant". The data contains information on sales (domestic, and exported), inputs, employment, ownership status, and operating costs of all formal agricultural, manufacturing, service, and trade establishments in the country. The records distinguish between public enterprises, private domestic firms, and foreign firms.

Given the focus of our analysis, we exclude associations, public administrations, and firms in health, sport, education, and personal beauty industries from the sample. We also exclude firms with zero or missing values of key variables as well as firms with values outside the range of 1 to 99 percentile. Because of permanent firms' exits and possibly the temporary lapses of some firms in filing their balance sheet information, the structure of the data is unbalanced panel.

All monetary variables used in the analysis are converted in real terms using the country GDP deflator from the World Bank. This helps to mitigate the input-quality or markup differences across time that are incorporated in prices. Using firm location information, we merge firm level data with temperature and precipitation data from Surface Meteorology and Solar Energy developed by the Atmospheric Sciences Data Center at the Langley Research of the US National Aeronautics and Space Administration (NASA). The climate dataset contains daily average temperature and precipitation information at a 0.5X0.5 grid degree resolution.

The Capital (K) is measured by the total value of fixed assets in the book values. Labor is represented by the total number of internal permanent and seasonal employees and the total wage bill of all internal workers. Investment (I) is the sum of the value of new investment in machinery and vehicles. Intermediate inputs (M) are defined as the sum of expenditure on raw materials, other goods, and services. While a firm's entry year is directly observed in the data[1], we estimated the firm's exit status. Using the firm's unique account number as an identifier, we are able to distinguish a permanent exit from a temporary lapse in reporting or change in the name of the firm. The ability to detect true exit and entry provide a significant advantage for our data compared to similar data from other countries (Klapper, 2015). Finally, firm revenue (Y) is the value of total sales of all finished goods.

4.3 *Productivity Estimation*

Our measure of productivity is based on the production function estimated by the method of Gandhi, Navarro, and Rivers (Gandhi et al. (2011),GNR henceforth). The Ackerberg-Cave-Frazer (Ackerberg et al. (2006), ACF henceforth) approach is used for robustness check. One of the critical issues in identifying firms' production functions is the possibility that there are factors influencing production that are observed by the firm but not by the econometrician. In such a case, estimating the production function using the ordinary least square method leads to biased and inconsistent estimates of productivity parameters.

Concerned by the potential simultaneity issues, recent empirical studies have used production function estimation based on the "proxy variable" approach (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). The objective of these methods is to get around the identifica-

[1]The dataset is a census of all formal firms in the country therefore, entry of new firms is observed on a yearly basis.

tion issue by inferring the productivity from the observed firm's input choice. However, it has been pointed out by ACF that the early "proxy variable" approaches as well suffer from identification issues. Therefore, they propose an estimation method built on Olley and Pakes (1996) and Levinsohn and Petrin (2003) that does not suffer from the timing and dynamic implications of input choices (Parrotta et al., 2014).

Gandhi et al. (2011) is the first paper to show non-parametric identification of the production function with flexible and quasi-fixed inputs. They argue that the production function is non-parametrically non-identified within the structural model of production in Olley-Pakes, Levinsohn-Petrin, and Ackerberg-Cave-Frazer since there is no exogenous source of variation for a flexible input that comes from outside the production function. GNR provides an improvement over previous "proxy variable" techniques by solving the non-identification issue. They did so, by transforming the firm's first order condition in a gross output specification (see Appendix C for more details on GNR method).

5 Empirical Analysis

5.1 *Descriptive Statistics*

Table 1 provides an overview of the merged firm level and weather data. Information on firms with missing variables, panel length and sub-sector length are reported in appendix Table A5, Table A6, and Table A7. The clean full sample includes 8, 979 unique firms or 34,670 firm-year observations. The skewed distribution of key variables in the sample, as common to firm data from most developing countries, suggests that our economy is mainly composed of small firms and few very large firms. From 1998 to 2013, the median and average value of firm's revenue are and $259, 800 and $1.861 million respectively and the median and average firm size are 9 and 40 employees respectively. Firm entry and exit rate over the 16 years period are respectively 18.6% and 9.9%.

Despite the presence of firms in most of the regions, as is the case in many developing countries, a large proportion of firms are concentrated in the capital. Figure 1 depicts the average number of firms in each region during the period of 1998-2013. Generally, there is a large presence of firms in coastal regions, Abidjan and San-Pedro in the north and in the west. The figure suggests that there is no formal economic activity in the center of the country.

Weather records for 1998-2013 are extrapolated from Surface Meteorology and Solar Energy developed by the Atmospheric Sciences Data Center at the Langley Research of the US National Aeronautics and Space Administration (NASA). This dataset has been extensively validated by ground level measurements. However, larger errors were found in surface temperatures where the site data did not represent the entire grid box, which is likely to be the case in our study country (Whitlock et al., 1995). An alternative source for weather data would be ground level data from local weather stations. However, given a poor spatial and temporal coverage of weather stations that report ground level temperature and rainfall readings, it is less likely that such data would be of higher quality than reanalysis data. Reanalysis data solve the potential bias concerns about ground level data in developing countries due to the lack of coverage and the variation in data quality from different location by combining data from ground stations and satellites using climate models. This type of data has been widely used by economist in both developed and developing countries to analyze the impact of climate on economic activities (Dell et al., 2012; Sudarshan et al., 2015; Burke et al., 2015; Zhang et al., 2017).

Temperature and precipitation are calculated using daily observations. While temperature measure is constructed using daily mean, precipitation is estimated as annual cumulative value using daily observations. To facilitate the comparison of our results with previous works (Hsiang, 2010; Sudarshan et al., 2015), we define our high temperature variable to be the number of days with average temperatures above 27°C. Also this number seems to be a good breakpoint in our case study since the historical average daily temperature for the period 1990-2013 in Côte d'Ivoire is 25.85°C with a standard deviation of roughly 0.65. As such, our temperature shock breakpoint, 27°C, is 1.77 standard deviation above the historical daily average temperatures. Figure 3a and 3b represent respectively the distribution of daily temperatures over years and regions. The regional heterogeneity in the number of hot days is depicted in Figure 4. Hot days are observed in both in the north and the south of the country. For a robustness check to our baseline results we use a different breakpoint. In the sample, the average number of days in that fall into the 3 temperature bins - below 25°C, between 25°C and 27°C, and above 27°C - are respectively 90 days, 226 days, and 49 days.

5.2 *Results*

The empirical analysis proceeds in two steps. The first step tests the hypothesis in the literature that temperatures affect firm productivity and if so, investigates the mechanism behind such effect. The second step then tests the predictions of the model that (1) increased temperatures reduces firms' revenues, profits, and market survival rate, and (2) high temperatures less affect the revenues of firms that invest in climate mitigation technology.

5.2.1 *Effects of Temperatures on TFP*

We start by showing that temperatures indeed affect firm total factor productivity as suggested in the climate and economic activity literature. To this end, we regress (log) TFP on temperature, constructed using the bin approach, following the regression specified in equation (7). The specification includes precipitation, labor, capital, firm age, export status, time trend, district fixed effects, as well as firm fixed effects. Standard errors are clustered at region-year pair to control for spatial correlation between firms within each region. To avoid multicollinearity, we omit the bin with number of days between 25°C and 27°C. Consequently, the coefficients for other bins indicate the effect of temperature relative to the reference bin.

As reported in Table 2, we find economically meaningful and statistically significant negative effects of high temperatures (days with average temperatures above 27°C) on TFP. In the first columns (1) and (3) no other variable except rainfall are controlled for. The second columns (2) and (4) represent the baseline results. They differ from the first in that key firms characteristics including labor, capital, age, and export status are controlled for. Throughout columns (1)-(4), temperatures bins are constructed using daily mean temperature. In columns (1) and (2), the independent variable is TFP estimated using Gandhi-Navarro-Rivers method and in columns (3) and (4), we use TFP estimated using Ackerberg-Caves-Frazer estimator as a robustness check.

The main results confirm the hypothesis in the literature that temperature affects economic activity. Our preferred specification indicates that a one-standard-deviation rise in days with average temperatures above 27°C reduces firm TFP by 3.62% relative to the impact of days with average temperature between 25°C and 27°C[2]. On the other hand, we generally find that days with temperatures below 25°C have no significant effect on economic activity. In general, controlling for firm key characteristics produces different estimates, suggesting that the effect of high temperatures on firms is heterogeneous. The main findings are robust whether we use a different measure of TFP, a different temperature breakpoint, or control for lagged temperatures. Furthermore, the null hypothesis that the effects of all the temperature bins are jointly equal to zero, are rejected in all the specifications.

[2]One standard deviation in days with average temperature above 27°C is 51.7 days.

5.2.2 *Mechanisms of Transmission of the Observed Effects*

Given the importance of the established negative effects of high temperatures on firm TFP, our next focus is to understand the mechanisms through which such effects took place. Unlike previous studies, which have been mainly focused on labor productivity as the mechanism though which temperatures affect economic activities (Sudarshan et al., 2015; Zivin and Neidell, 2014) we also decided to test if capital productivity is a viable channel through which temperatures affect firm activity. Moreover, we also test whether labor intensive and out-door firms are more affected by temperatures.

Effects on labor and capital productivity

Since TFP can be thought of as a weighted average of labor and capital productivity, then it is important to know if the observed effects of temperatures on TFP were through labor, capital productivity, or both. Because of our inability to estimate labor and capital productivity separately in a Cobb-Douglas production function, we use wage per capita and the price of capital - imputed from total value added minus total wage bill, divided by net value of fixed assets as a proxy for labor and capital productivity, respectively. Payroll has been previously used in the literature to estimate the effects of temperature shocks on labor productivity (Park, 2016). This choice is motivated by the fact that changes in wage per capita closely reflect changes in marginal labor product. However, the drawback is that it might also include changes in labor supply.

We could also directly test if the observed effect of temperatures on TFP solely originates from labor productivity by including an interaction of labor-intensive variable (firms with higher labor per sales) and temperature bins in equation (7). However, there are a number of potential issues that can result from such estimation. First, both labor and sales might change because of temperatures. If temperature shock decreases firm value added, then for the same number of employees (e.g. same number of workers, produce less), what is the impact on sales? If price does not change, sales decrease too, and labor intensity will increase. If price moves up due to excess demand, effect on labor intensity is ambiguous. Second, there might be more variability to labor supply of more weather dependent firms or possibly a difference in labor supply between firms that can adjust labor and others that will keep them idle, at the expense of the level of wage. For the above reasons, our preferred estimation approach is to directly test the effect of temperatures on labor and capital productivity using proxy.

Table 3 represents the effect of temperature on labor and capital productivity. Regression models are estimated using equation (7). Results in column (1) and (2) suggest that a one-standard-deviation rise in days with higher temperatures reduces labor and capital productivity by 6.25% and 22.74% respectively. Using average labor and capital elasticity from our GNR and ACF productivity estimation[3], the weighted sum of the affect of temperatures on labor and capital productivity suggest that a one-standard-deviation rise in days with high temperatures reduces firm productivity by 5.97% and 2.16% respectively. These effects are in the range of what we found in our main results as the effects of high temperatures on TFP. These results provide strong support that capital productivity is as well affected by temperatures; a channel that has not been so far well explored in the literature.

Effects of Temperatures on Labor Intensive and Out-door Firms

To test whether labor intensive firms or firms that operate outdoor are differentially affected by temperatures, we regress (log) TFP on temperature bins and their interactions with a dummy for labor intensive firms and outdoor firms, respectively. We classify firms in the agriculture and construction

[3]The average elasticity for labor and capital using GNR method are 0.3 and 0.14, respectively. Using ACF method, the average elasticity for labor and capital are respectively 0.2 and 0.04.

sectors as out-door firms since most of the activities of those firms are implemented outdoor. Given that labor supply might be endogenous to temperatures, we define labor intensity in the initial year, as a number of employees over total sales. However, we are conscious this definition prevents labor intensity status to change of overtime, which is likely to create other bias if firm labor change overtime for reasons that are not related to weather.

In columns (1) and (2) of Table 4, labor intensity is defined as either below or above the mean of raw labor intensity. As such, labor-intensive firms are classified as firms with the ratio of initial labor over initial sales above the mean value. Similarly in columns (3) and (4) labor intensity is defined using the median value of the ratio (initial labor/ initial sales), and consequently firms with value above the median as classified as labor intensive. We found statistically significant negative coefficients on the interaction terms in column (1), (2), and (4) suggesting that labor-intensive firms are more affected by non labor-intensive firms. This result provides an additional support to the claim that labor productivity is a viable channel through which temperature affects economic activity. On the other hand, based on the results in Table 5, we do not have enough evidence to support the argument that firms operating mostly outside are more affected by temperatures.

5.2.3 *Testing the Predictions of the Model*

Effects of Temperature on Firm Revenues and Profits

We next test the hypothesis 1, 2, and 3 from the model, according to which extreme temperatures reduce firm revenues, profits, and survival rate. To do so, we follow the regression specified in equation (7) by regressing (log) revenues and (log) profits on temperature[4]. As the outcome measures for revenues and profits, we use total sales and profits reported by the firms. We

[4]To avoid multicollinearity, we omit the bin with number of days between 25°C and 27°C. Consequently, the coefficients for other bins indicate the effect of temperature relative to the reference bin.

also use our own estimated firm profit as a robustness check to firm reported profits. To assess the impact of temperatures on firm survival rate, we regress exit on lagged temperature bins. The choice of lagged temperatures over current temperatures in the case of firm exit is motivated by three factors. First, firm exit is not reported in the data, therefore, we classified a firm to be exiting when it does not appear in the last two rounds of the panel. Although this definition of exit is a bit more conservative, we believe it is appropriate since it is common in long panels for firms to disappear in one round and reappear in the next round. Second, since output measures are annual instead of monthly, it is possible that a firm starts the process of exiting in a prior year, therefore, current temperatures is less likely to have an impact on the observe exit. Finally, it is very likely that temperatures in previous years have an impact on current output (Dell et al., 2012; Deryugina and Hsiang, 2014). For example, extreme temperatures in a prior year may slow down capital accumulation and reduce short-term cash flows. This outcome may affect firm competitiveness and increase its probability of exiting the market. In all the specifications, we control for precipitation, labor, capital, firm age, export status, time trend, district fixed effects, as well as firm fixed effects. In the regression of firm exit, we also control for firm productivity. Standard errors are clustered at region-year pair to control for spatial correlation between firms within each region.

Table 6 provides a strong empirical support for hypothesis 1, 2, and 3. There is a strong negative and statistically significant relationship between temperatures and the three outcomes of interest: firm revenues, profits, and market survival rate. This result is robust whether we use a different temperature bin's breakpoint, a different measure of profits, or control for lagged temperatures. Also, the null hypothesis that the effects of all the temperature bins are jointly equal to zero, are rejected in all the specifications. Column (1) contains the result of the effect of temperatures on firm revenues, Columns (2) and (3) represent the effect on profits, and columns (4) and (5) report the effect of lagged temperatures on firm exit. The second columns (5) differ from the first column (4) because of the addition of temperature bins lagged by two-year.

A one-standard-deviation rise in days with average high temperatures (above 27°C) respectively reduces firm revenues and profits by 14.83% and 21.71% relative to days with moderate average temperatures (below between 25°C and 27°C). The estimated impact of one-standard-deviation rise using own estimated profits is somewhat smaller, although the two profit measures are strongly correlated. By contrast, while the effects of days with average temperatures below 25°C is not significant using our estimated profits, it has a very large and significant coefficients on firm reported profits. This result suggests that not only high temperatures but also cooler than average temperatures might negatively affect firm profits. On the other hand, a one-standard-deviation rise in one-year lagged days with average high temperatures (above 27°C) increases exit probability by 0.04%. The effect of temperatures on firm survival is an important implication of climate change that has not yet been analyzed in the literature.

From the above results, it is clear that the economic consequence of the extreme temperatures is considerable in developing countries. For example, using the average aggregate revenues in the sample ($4.12 billion), a one-standard-deviation rise in the number of days with average high temperatures reduces total average firm revenues by around $611 million compared to the impact of days with moderate average temperatures. When we extrapolate this estimate using the share of manufacturing and service sectors (33% and 45% of 2016 GDP, respectively), we find the cost to the national economy is around $4.2 billion, or about 8% of the GDP. While appropriate climate adaptation mechanisms can help firms to mitigate the impact of temperatures, widespread use of such mechanisms is likely to be undermined in most developing countries due to firm limited access to credits.

Effects of Temperature on Firms Investing in Technology

To test hypothesis 3 from the model that temperature has a lesser affect on the revenues of firms that invest in climate mitigation, we regress (log) revenues on temperature bins and their interactions with a dummy indicating whether the firms invest in climate technology or not. Except the dummy variable and its interactions with temperature bins, the specification is similar to the one described in the previous section.

This specification requires the use of an empirical proxy to indicate firms that invest in climate mitigation technology. In the absence of direct observation of firm investment choice in climate mitigation technology, we exploit firm level of fixed and financial assets. This choice is motivated by the presumption that firms with more asset, less financially constrained, are more likely to invest in technology that improve the performance of their workers. Consequently, we classify firms that invest in climate technology as those with total fixed and financial asset above the mean or median values. Column (1) and (2) in Table 7 represent the effects where adoption choice is defined as using mean and median total asset values, respectively. In both regressions, we have very strong evidence that firms investing in climate mitigation technology are less affected compared to those that do not. For instance, the effect of one-standard-deviation rise in days with high temperature on revenues is reduced by 8.73.% (more than half of the total effects) for firms investing in climate mitigation technology compared to those that do not. In other word, this result suggests that while temperatures affect economic activity, it has affected economic entities heterogeneously. This is a very important finding and could have important policy implication. In the next section, we discuss potential treats to our results and provide some robustness checks.

5.3 *Robustness Checks*

It is important to assess whether the strong relationship between economic activity and weather established in baseline regressions is causal. Our identification is from plausibly exogenous variations in temperature within firms over time after controlling for firm specific characteristics and shocks common to districts where firms are located. There are, however, a couple of potential issues that can affect our results. First, the concentration of firms in few locations creates potential problems for our identification of the effects. As in many other developing countries, most of the formal economic activity in Côte d'Ivoire is concentrated in the capital, Abidjan. As such, while the level of temperatures changes overtime, the majority of the firms in our sample experience more or less the same level of temperature for a given period. Second, there could be a legitimate concern that our baseline results include effects other than the effects of high temperatures such as time or different political crisis effects on firm revenue and productivity. Third, because of the requirement of productivity estimation, missing data issues, and entry and exit of firms over time, our main specification is estimated using an unbalanced sample of firms. As a result, selection issues could threaten the validity of our baseline findings. Finally, it could be argued that our measure of temperature shock is a not a good enough proxy for the true temperature shocks observed by firms. One could also think that it is not only the level of temperature that affects economic activity but also the variability of temperature, which increases with climate change. We perform several robustness checks, reported in the appendix, to address all the above issues.

Table A1 shows how robust our baseline results are to increasing variation in temperature measures. To introduce more variation in the location of firms, and consequently in our temperature data, we divide Abidjan into two sub-regions North and South. We gather new temperature measures for each sub-region and match them with our firm data. To test whether there is any variation between new temperature measures, South-Abidjan and the former temperature measure of the region of Abidjan, we estimate the correlation between the two measures. As it can be seen in Table A1.2, there are some variations left in the temperatures of South-Abidjan that are not explained by the previous temperature measures of Abidjan. Thus, dividing Abidjan into two sub-regions slightly increases the variability in our temperatures measures for a given period in time. The results when Abidjan is divided in two zones are similar, with slightly larger coefficients, to baseline results. The result of Table 4, 5, and 7 provide an alternative identification strategy by relying on firm vulnerability to temperatures. The effect of temperature on revenue and TFP might differ across firm's types because of the difference in climate exposures, resistance to temperatures, or simply the use of climate adaptation technology such as air conditioning. Given our lack of information on individual firm vulnerability or adaptation strategy to temperature shocks, we assume that labor intensive firms or firms that perform most of their activity outdoor, agriculture and construction, are more vulnerable to temperatures. The results are qualitatively similar to our main results. When the interaction between temperature bins and dummy for labor intensive firms, firms that invest in climate mitigation technology, or firms that perform outdoor activity are including in the regressions, the main coefficients are still significant and the coefficient on the interaction terms have the right sign and significant in most cases.

In the last section of Table A, we control for conflict years. Côte d'Ivoire experienced two major crises over the past 15 years. In September of 2002 a military mutiny led to a rebellion that ended up splitting the north and the south of the country from 2002 to 2007. While the conflict was not intense throughout the whole period of 2002-2007 that many people refer to as "no peace no war period" it has an impact on firm productivity as suggested by Klapper et al. (2015). Also, in 2011 the country experienced a brief post-election crisis. Although the second crisis was very short, it might also have affected economic activity. After controlling for conflict years, we still find similar estimates of the effect of temperatures although the magnitude is somehow slightly smaller than the ones found in the baseline.

Based on results in Table A1, we conclude that our baseline results are robust to alternative identification strategy. Furthermore, the fact that we are able to find statistically significant effects in our baseline results despite the heavy concentration of firms in Abidjan suggests our result would have been even stronger if firms were evenly distributed throughout the country.

Table A2 presents the results from several robustness checks on alternative sub-sample of the data. First, we replace the clean sample of firms from the baseline specification by a larger sample of firms by only dropping firms with missing sales. Since we cannot estimate productivity measures used in the main specification using this sub-sample[5], we proxied TFP by value added per capita, estimated for firms, which reported positive value added. In both estimations, we find similar qualitative results on firm revenues and productivity, with the effects on value added per capita somewhat larger in magnitude than the effects on our TFP measures in baseline regressions. Finally, we dropped firms with gaps appearance in the panel to test the sensitivity of the baseline results the structure of the panel data. As shown by the results, the effect of high temperature on firms' revenues and productivity is similar to the findings in the main regressions. Results in Table A2 provide strong evidence that our baseline results are not driven by the structure of the data. In all the specifications with different sub-samples, we the effect of high temperatures on firms' revenues and productivity remains negative, large, and statistically significant.

In Table A3 we run our baseline specification using alternative measures of temperatures shocks. First, instead of 27°C, we define our extreme temperatures as days with temperatures below and above bottom 10% and top

[5]The estimation of TFP using either GNR or ACF method requires non-missing values for not only firm revenue but also capital, labor, and intermediate inputs. That is the reason why the sample used in the baseline specifications is a smaller sub-sample of the data.

10% of temperature distribution. Even using the new temperature bins, the estimates of the effect of high temperatures on firms are nearly identical to our baseline results when we re-define a different breakpoint for temperature shock. Table A3 also presents results using alternative measures of temperatures. As mentioned above, it could be the case that our measures do not well capture the effect of temperatures on economic activity. To compare our baseline estimates to estimates using other measures of temperature, we re-estimate equation (7) by replacing temperature bins by average temperatures and the coefficient of variation (CV) of daily temperatures respectively. While results of robustness checks using average temperature, qualitatively suggest that an increase in average temperatures negatively affect economic activity, the magnitude of the estimates is way too big and not statistically significant. This could be explained by the fact that yearly average temperature is a very poor indicator of temperatures. Results using the variability in daily average temperatures, CV, also suggest that they poorly capture the effect of temperatures on economic activity when compared to temperature bins used in our main specification. While regression estimates suggest that high coefficient of variation of daily temperatures is negatively corrected with economic activities, the estimates of the effect are often very large and not statistically significant. The weak and inconsistent estimate of the effect of CV suggests that temperature variability is not a major driver of the effects of temperatures on economic activity.

To conclude the results of this section, our baseline results are consistent and robust to different identification strategy, controlling for conflict years, using alternative sub-samples of the data, and different temperature bins and measures. In most cases, we find strong support for our main results that high temperatures affect firm activities.

6 Conclusion

The implementation of optimal climate policy requires better understanding of the mechanisms behind the established negative relationship between temperatures and aggregate outputs. This study provides an inclusive treatment of the relationship between temperatures and key firm competitiveness measures. To this end, we develop a model by introducing climate mitigation technology choice in a standard trade model with cross-country differences in climate costs. Applying our model to a large panel of manufacturing, service, and agricultural firms in Côte d'Ivoire from 1998 to 2013, we found that temperature affects firm productivity as argued in the literature. Consequently, high temperatures reduce firms' revenues, profits, and survival rate. The effect of temperatures on revenues is reduced for firms likely to invest in climate mitigation technology.

We also explore the mechanisms through which temperatures affect firm outcomes and which type of firms are most likely to suffer from the established effects. Our results suggest the effect of temperatures on total factor productivity is through its effect on both labor and capital productivity. While the labor productivity channel has been investigated in the previous literature, there are fewer evidences on capital productivity as a channel through which temperatures affect economic activity. Moreover, while our results provide supportive evidence that labor-intensive firms suffer from high temperatures, we could not find strong evidence that outdoor firms, agriculture and construction firms, are more affected by high temperatures.

The findings in this paper have two important implications. First, regarding the current analysis of the impact of weather on economic activity, our results suggest that we should take into account the role of climate mitigation technology and pay close attention to how temperatures affect the competitiveness of firms. Neglecting these two factors will result in inaccurate measures of the impact of temperatures on economic activity. Second, while temperature affects all firms, labor-intensive and small firms with less capital are the most vulnerable to increased temperatures. Consequently, it is critical for optimal climate policy in developing countries to facilitate the use of adaption technology by paying particular attention to labor-intensive and small firms.

Future research should pay particular attention to the role of technology choice in mitigating the impact of weather conditions on firms' outcomes. While we try to respond this question using a rough proxy for firms' technology choice, we believe that with a more detailed data on firms' technology use, one can provide a better analysis of the role of technology in mitigating the effect of climate on firms. Moreover, it will be important to know which type of firms are likely to adopt climate mitigation technology.

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Figures

Figure 1: Producing and Technology Choices

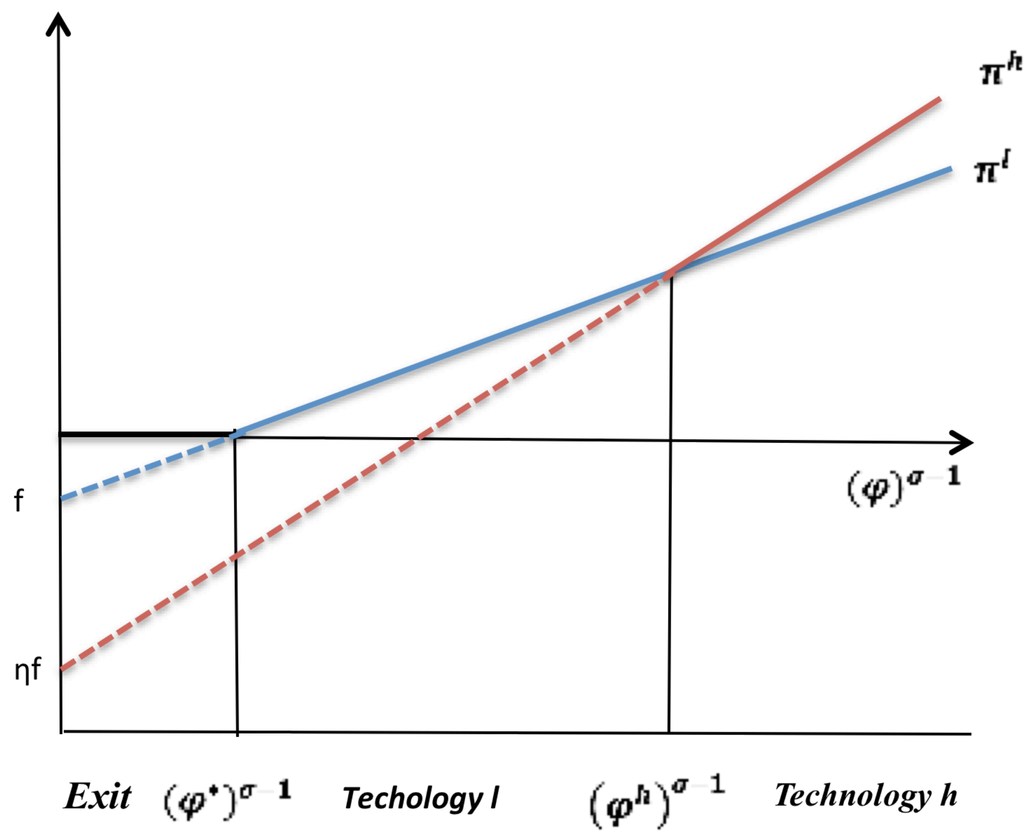
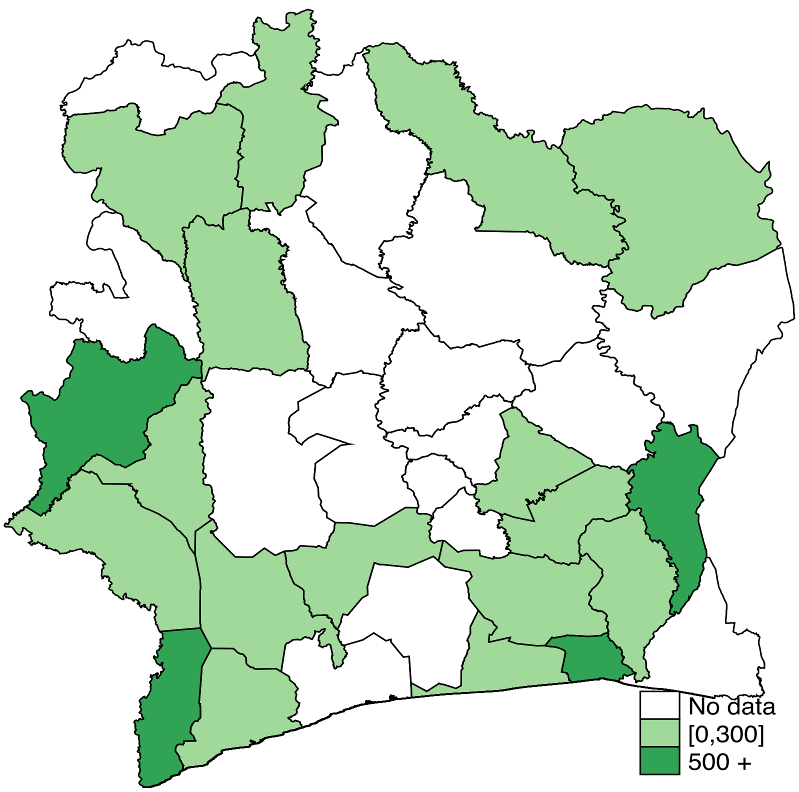
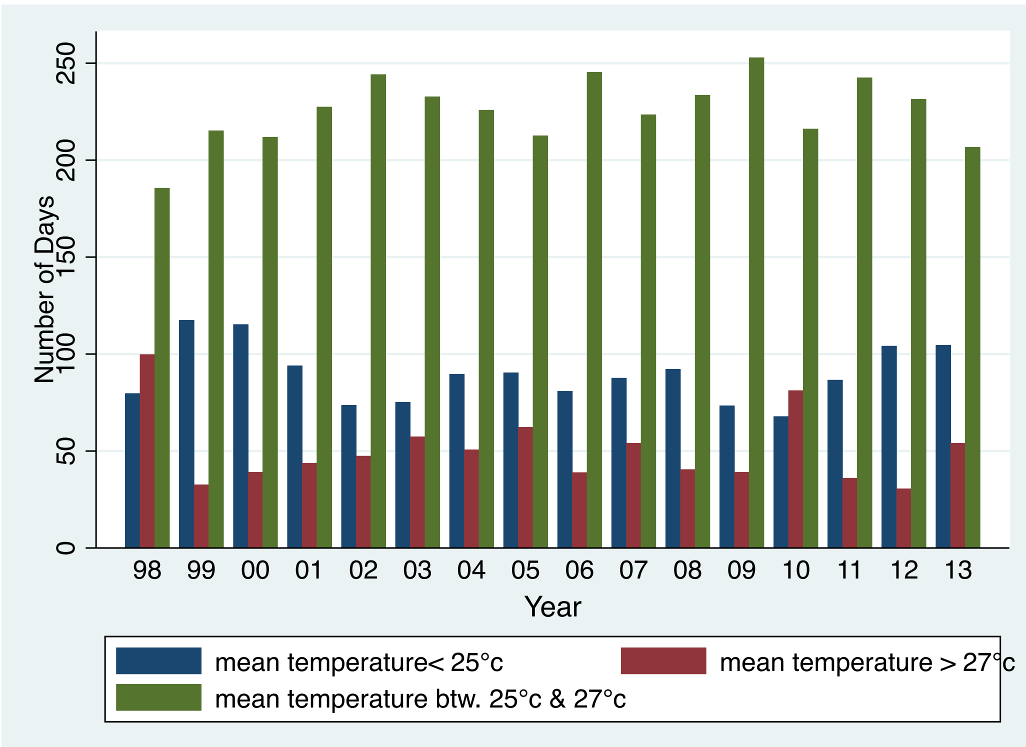
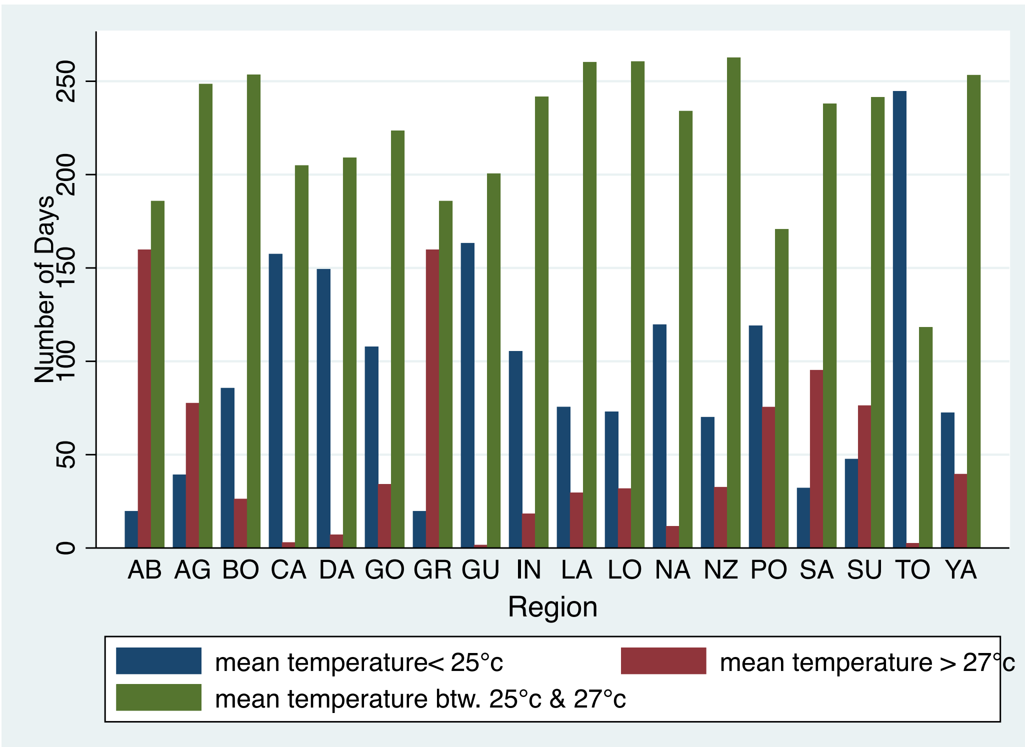


Figure 2: Geographic Distribution of the number of firms



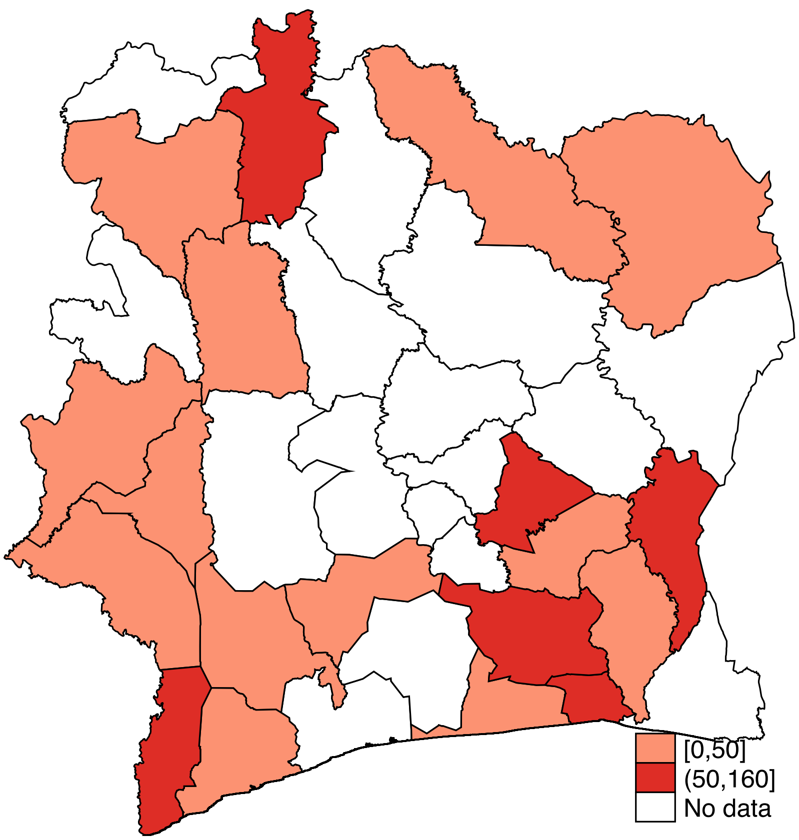
Notes: this figure reports the average number of firms for each region during the period of 1998-2013.


Number of Days
0
50
100
150
200
250
98
99
00
01
02
03
04
05
06
07
08
09
10
11
12
13
Year
mean temperature< 25°c
mean temperature > 27°c
mean temperature btw. 25°c & 27°c



Number of Days
0
50
100
150
200
250
AB AG BO CA DA GO GR GU IN LA LO NA NZ PO SA SU TO YA
Region
mean temperature< 25°c
mean temperature > 27°c
mean temperature btw. 25°c & 27°c

Figure 4: Geographic Distribution of the number of days above 27°C



Notes: this figure represents the average number of days with temperature above 27°C for each region during the period of 1998-2013.

Tables

Table 1: Summary Statistics of Firm and Weather Data

Variables	Obs	Median	Mean	SD	Min	Max
Firm - Year Data						
Revenue (000 USD)	34,670	259.8	1,861	5,754	0.746	77,187
Profit (000 USD)	34,670	4.854	53.38	1,530	-26,716	256,726
Value Added (000 USD)	25,142	78.61	391.6	988.9	0.00346	20,424
Log TFP (GNR)	34,667	8.123	8.209	1.073	4.06	12.95
Log TFP (ACF)	34,667	2.585	2.402	1.016	-6	10.81
Labor (person)	34,670	9	40.07	124.5	1	3,210
Payroll (000 USD)	34,627	30.96	191.5	478	0.348	4,889
Total Asset (000 USD)	34,670	55.37	708.3	2,647	0.254	53,837
Capital (000 USD)	34,670	48.26	638.4	2,411	0.254	40,833
Firm Age (year)	34,670	9	11.65	9.95	1	96
Firm Exit	27,188	-	0.126	-	-	-
Number of Firms	8,979	8,979	8,979	8,979	8,979	8,979
Weather-Year Data						
Temperature (C)	304	25.73	25.76	0.537	24.17	27.02
Days below 25C	304	85	89.99	51.97	4	274
Days above 27C	304	26	48.82	51.68	0	197
Precipitation (mm)	304	2,212	2,203	402.8	1,100	3,305

Notes: the data covers all registered firms in Cote d'Ivoire. Labor is measured by employment and all monetary units are deflated in 1998 CFA and converted in thousand of USD. Precipitation is annual cumulative values in mm. Temperature variables are estimated using daily average temperatures.

Table 2: Effects of Temperature on TFP

	TFP (GNR)		TFP (ACF)	
	(1)	(2)	(3)	(4)
Days below 25C	-0.084*	-0.054	0.047	0.013
	(0.046)	(0.038)	(0.032)	(0.035)
Days above 27C	-0.078***	-0.070***	-0.107***	-0.102***
	(0.026)	(0.024)	(0.033)	(0.030)
Observations	34,644	34,644	34,644	34,644
Control	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES
Time Trend	YES	YES	YES	YES
F-test (All bins=0)	6.825	6.397	5.301	5.840
Prob>F	0.00126	0.00190	0.00546	0.00325

Notes: the dependent variables are logarithms of TFP (multiplied by 100 to reduce the number of decimal point in the coefficients). In columns (1)- (2) and (3)-(4) TFP is measured respectively by Grandhi-Navarro-Rivers estimator and Ackerberg-Caves-Frazer estimator. Bins are constructed using daily average temperature. The comparison bin is the number of days with average temperature between 25°C and 27°C. Control variables include rain, rain square, (log) capital, (log) labor, and dummies for export status, and age above firm median age. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Effect of Temperature on Labor and Capital Productivity

	Labor Productivity	Capital Productivity
	(1)	(2)
Days below 25C	0.046	-0.978**
	(0.064)	(0.455)
Days above 27C	-0.121***	-0.439**
	(0.029)	(0.213)
Observations	20,693	20,693
Control	YES	YES
Firm FE	YES	YES
District FE	YES	YES
Time Trend	YES	YES
F-test (All bins=0)	8.463	4.196
Prob>F	0.000	0.016

Notes: the dependent variables are logarithms of labor and capital productivity (multiplied by 100 to reduce the number of decimal point in the coefficients). Labor productivity is proxied by wage per capita and capital productivity by value added minus payroll divided by total fixed assets. All observations with missing value added have been dropped. The comparison bin is the number of days with average temperature between 25°C and 27°C. Rain, rain square, dummy for export status, age above medium are controlled for in all the regressions. (log) asset and (log) labor are respectively controlled in column (1) and (2). Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of Temperature on Labor Intensive Firms

	TFP (GNR)	TFP (ACF)	TFP (GNR)	TFP (ACF)
	(1)	(2)	(1)	(2)
	Labor Intensity (above mean)		Labor Intensity (above median)	
Days below 25C	-0.057*	-0.006	-0.067**	-0.036
	(0.034)	(0.029)	(0.032)	(0.027)
Days above 27C	-0.061**	-0.058*	-0.064***	-0.044
	(0.024)	(0.032)	(0.022)	(0.043)
25C X Above Mean	0.049	0.279**		
	(0.048)	(0.133)		
27C X Above Mean	-0.066*	-0.321*		
	(0.035)	(0.177)		
25C X Above Med			0.044	0.172**
			(0.029)	(0.072)
27C X Above Med			-0.016	-0.142
			(0.014)	(0.091)
Observations	34,644	34,644	34,644	34,644
Control	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
District FE	YES	YES	YES	YES
Time Trend	YES	YES	YES	YES
F-test (Interactions=0)	3.189	5.181	2.743	5.749
Prob>F	0.0426	0.00613	0.0660	0.00355

Notes: the dependent variables are logarithms of TFP (multiplied by 100 to reduce the number of decimal point in the coefficients). Raw labor intensity is defined as the ratio of employees to sale. In columns (1) and (2), labor intensive firms are classified as those with raw labor intensity above the mean. Similarly, in columns (3) and (4) labor-intensive firms are those with raw labor intensity above the median. The comparison bin is the number of days with average temperature between 25°C and 27°C. Rain, rain square, (log) capital, dummy for export status, age above medium are controlled for in all the regressions. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of Temperature on Outdoor Firms

	TFP (GNR)	TFP (ACF)
	(1)	(2)
Days below 25C	-0.049	0.017
	(0.036)	(0.031)
Days above 27C	-0.070***	-0.088***
	(0.023)	(0.027)
25C X Outdoor Firm	-0.044	-0.032
	(0.048)	(0.106)
27C X Outdoor Firm	-0.002	-0.117**
	(0.047)	(0.052)
Observations	34,644	34,644
Control	YES	YES
Firm FE	YES	YES
District FE	YES	YES
Time Trend	YES	YES
F-test (All interactions=0)	0.463	2.818
Prob>F	0.630	0.0613

Notes: the dependent variables are logarithms of revenues and TFP (multiplied by 100 to reduce the number of decimal point in the coefficients). Outdoor firms are construction and agriculture firms. The comparaison bin is the number of days with average temperature between 25°C and 27°C. Rain, rain square, (log) capital, (log) labor, dummy for export status, age above medium are controlled for in all the regressions. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of Temperature on Firm Revenues, Profits, and Exit Rate

	Revenue	Profit (reported)	Profit (estimated)	Exit	Exit
	(1)	(2)	(3)	(4)	(5)
Days below 25C	-0.148	-0.654***	-0.050		
	(0.001)	(0.237)	(0.167)		
Days above 27C	-0.287***	-0.422***	-0.203**		
	(0.001)	(0.113)	(0.088)		
Lag1 days below 25C				-0.009	0.014
				(0.049)	(0.043)
Lag1 days above 27C				0.086**	0.090***
				(0.036)	(0.030)
Lag2 days below 25C					0.036
					(0.039)
Lag2 days above 27C					0.115**
					(0.048)
Observations	34,647	23,156	21,048	27,177	27,177
Control	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	YES
Time Trend	YES	YES	YES	YES	YES
F-test (All bins=0)	6.397	10.67	2.653	3.796	2.904
Prob>F	0.001	0.000	0.072	0.023	0.022

Notes: the dependent variables are dummy for exit and the logarithms of revenues and profits (multiplied by 100 to reduce the number of decimal point in the coefficients). While reported profits are the profits reported by the firm, estimated profits are the profits we estimated using firm production information. We assume the cost of capital to be 10% of total capital (depreciation rate). The comparison bin is the number of days with average temperature between 25°C and 27°C. Rain, rain square, (log) capital, (log) labor, dummy for export status, age above medium are controlled for in all the regressions. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of Temperature on the Revenue of Firms Investing in Climate Mitigation Technology

	Revenue	
	(1)	(2)
Days below 25C	0.017	0.000
	(0.106)	(0.115)
Days above 27C	-0.292***	-0.330***
	(0.083)	(0.090)
25C X Technology (Mean)	-0.123**	
	(0.049)	
27C X Technology (Mean)	0.169***	
	(0.054)	
25C X Technology (Median)		-0.040
		(0.047)
27C X Technology (Median)		0.126***
		(0.038)
Observations	34,647	34,647
Control	YES	YES
Firm FE	YES	YES
District FE	YES	YES
Time Trend	YES	YES
F-test (Interactions=0)	11.95	10.15
Prob>F	0.000	0.000

Notes: the dependent variable is(log) TFP (multiplied by 100 to reduce the number of decimal point in the coefficients). Technology adaption is proxied by firm total asset. Firm with total assets above either the average or the median total assets in the sample are defined as those likely to invest in climate mitigation technology. The comparison bin is the number of days with average temperature between 25°C and 27°C. Rain, rain square, (log) capital, (log) labor, dummy for export status, age above medium are controlled for in all the regressions. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Online Appendix A

A. Theoretical Model, Comparative Statics

A.1.1 $\frac{\partial \pi(\varphi,\theta)}{\partial \theta} < 0$

$$\pi^{l}(\varphi,\theta) = \gamma(\theta)^{1-\sigma}\frac{1}{\sigma}E(\mathrm{P}\rho)^{\sigma-1}\varphi^{\sigma-1} - f$$

Differentiating the above equation w.r.t. θ

$\frac{\partial \pi^{l}(\varphi,\theta)}{\partial \theta} = \frac{(1-\sigma)}{\sigma\gamma(\theta)^{\sigma}}\mathrm{E}(\mathrm{P}\rho)^{\sigma-1}\varphi^{\sigma-1}\left(\frac{\partial\gamma(\theta)}{\partial\theta}\right) < 0$ because $\sigma > 1$ and $\frac{\partial\gamma(\theta)}{\partial\theta} > 0$

A.1.2 $\frac{\partial r(\varphi,\theta)}{\partial \theta} < 0$

The sign of $\frac{\partial r(\varphi,\theta)}{\partial \theta}$ is the same as the sign of $\frac{\partial \pi(\varphi,\theta)}{\partial \theta}$ in (A.1.1), therefore $\frac{\partial r(\varphi,\theta)}{\partial \theta} < 0$

A.2.1 $\left|\frac{\partial \pi^{h}(\varphi,\theta)}{\partial \theta}\right| < \left|\frac{\partial \pi^{l}(\varphi,\theta)}{\partial \theta}\right|$

$$\pi^{h}(\varphi,\theta) = \gamma(\theta)^{1-\sigma}\frac{1}{\sigma}E(\mathrm{P}\rho)^{\sigma-1}\varphi^{\sigma-1}\lambda(\theta)^{\sigma-1} - \eta f$$

Differentiating the above equations w.r.t. θ

$$\frac{\partial \pi^{h}(\varphi,\theta)}{\partial \theta} = (1-\sigma)\frac{(\rho P\varphi)^{\sigma-1}}{\gamma(\theta)^{\sigma}}\frac{E}{\sigma}\lambda(\theta)^{\sigma}\left[\frac{\frac{\partial\gamma(\theta)\lambda(\theta)}{\partial\theta} - \frac{\partial\lambda(\theta)\gamma(\theta)}{\partial\theta}}{\lambda(\theta)^{2}}\right]$$

Using the derivation in (A.1.1), $\left|\frac{\partial \pi^{h}(\varphi,\theta)}{\partial \theta}\right| < \left|\frac{\partial \pi^{l}(\varphi,\theta)}{\partial \theta}\right|$ implies that:

$$\frac{\partial\gamma(\theta)}{\partial\theta} > \lambda(\theta)^{\sigma}\left[\frac{\frac{\partial\gamma(\theta)\lambda(\theta)}{\partial\theta} - \frac{\partial\lambda(\theta)\gamma(\theta)}{\partial\theta}}{\lambda(\theta)^{2}}\right]$$

From the investment constraint in technology, equation (1.1), firms will only invest in climate mitigation technology if its benefits are positive, therefore, the above inequality has to hold.

A.2.2 $\left|\frac{\partial r^h(\varphi,\theta)}{\partial\theta}\right| < \left|\frac{\partial r^l(\varphi,\theta)}{\partial\theta}\right|$

The condition for this inequality to hold is the same as in (A.2.1), therefore, $\left|\frac{\partial r^h(\varphi,\theta)}{\partial\theta}\right| < \left|\frac{\partial r^l(\varphi,\theta)}{\partial\theta}\right|$.

A.3 $\frac{\partial\varphi^*(\theta)}{\partial\theta} < 0$

$$\varphi^*(\theta) = \left(\frac{\sigma \mathrm{f}}{E}\right)^{\frac{1}{\sigma-1}} \frac{\gamma(\theta)}{\mathrm{P}\rho}$$

Differentiating the above equation w.r.t. θ

$\frac{\partial\varphi^*(\theta)}{\partial\theta} = \frac{1}{\mathrm{P}\rho}\left(\frac{\sigma \mathrm{f}}{E}\right)^{\frac{1}{\sigma-1}}\left(\frac{\partial\gamma(\theta)}{\partial\theta}\right) > 0$ because $\frac{\partial\gamma(\theta)}{\partial\theta} > 0$

Online Appendix B

B. Definition of key variables

Revenue: is measured as the annual total sales, domestic and foreign sales, of the firm.

TFP (GNR): is firm total factor productivity measured using Ghandi-Navarro-Rivers productivity estimator.

TFP (ACF): is firm total factor productivity measured using Ackerberg-Caves-Frazer estimator productivity estimator.

Labor and Wage: labor is the total number of internal permanent and seasonal employees and the total wage bill of all internal works. When there was no internal employee declared, we replace labor by the total number of external worker.

Capital and Asset: capital is measured by the total value of fixed asset in the book values and asset is proxied by the total value of fixed and financial asset in the book values.

Intermediates: are defined as the sum of expenditure on raw materials, other goods, and services.

Firm exit: exiting firms are defined as firms that are not observed in the sample during the last two years of the panel, 2012 and 2013.

Online Appendix C

C. TFP Estimation

C.1 Gandhi, Navarro, and Rivers (GNR) Techniques

The relationship between output and inputs of firm j and time t are of the form:

$$Y_{\mathrm{jt}} = F_t(L_{\mathrm{jt}}, K_{\mathrm{jt}}, M_{\mathrm{jt}})e^{v_{\mathrm{jt}}}$$

where $L,\ K,\ and\ M$ are labor, capital, and intermediate inputs, respectively. Let $v_{\mathrm{jt}} = \omega_{\mathrm{jt}} + \varepsilon_{\mathrm{jt}}$ be the hicks-neutral productivity shock with two elements: persistence productivity shock (ω_{jt}) and ex-post shock ($\varepsilon_{\mathrm{jt}}$). The persistent shock ω_{jt} evolves exogenously following a Markovian process, which implies that the firm's expectation of future productivity depends only on past productivity. Therefore, it can be expressed as: $\omega_{\mathrm{jt}} = h\left(\omega_{jt-1}\right) + \eta_{\mathrm{jt}}$, where η_{jt} is the "innovation" in period t and satisfies $E\left(\eta_{\mathrm{jt}} \middle| \omega_{jt-1}\right) = 0$. Further, $E\left(\varepsilon_{\mathrm{jt}}\right) = 0$. Let's denote $E\left(e^{\varepsilon_{\mathrm{jt}}}\right) = \varepsilon$. Labor and capital are dynamic and their values in period t are determined at or prior to period $t-1$. On the other hand, the intermediate input is flexibly determined at period t. This implies that:

$$E\left(\eta_{jt} + \varepsilon_{jt} \middle| L_{jt}, K_{jt},\ L_{jt-1}, K_{jt-1}, M_{jt-1}, \ldots, L_1, K_1, M_1\right) = 0 \qquad (1)$$

Assuming that intermediate inputs can be written as $M_{jt} = Z_t\left(L_{\mathrm{jt}}, K_{jt}, \omega_{jt}\right)$, where Z_t is a strictly monotone function in ω_{jt}. This implies that we can invert Z_t to obtain $\omega_{jt} = Z_t^{-1}(L_{jt}, K_{jt}, M_{jt})$. Let ρ_t be intermediate inputs price and P_t be the output. The first order condition with respect to intermediate inputs:

$$P_t F_{M,t}\left(L_{jt}, K_{jt}, M_{jt}\right) e^{\omega_{jt}} = \rho_t \tag{2}$$

where $F_{M,t}$ is the partial derivative of the production function with respect to M. The logs of this first order condition and the production function form a system of equations.

$$\ln \rho_t = \ln P_t + \ln F_{M,t}\left(L_{jt}, K_{jt}, M_{jt}\right) + \ln + \omega_{jt}$$

$$\ln Y_{jt} = \ln F_t\left(L_{jt}, K_{jt}, M_{jt}\right) + \omega_{jt} + \varepsilon_{jt}$$

Taking the difference of these two equations to remove the productivity shock, adding M_{jt} to both sides, and re-arranging results in the following equation:

$$s_{jt} = \ln G_t\left(L_{jt}, K_{jt}, M_{jt}\right) + \ln - \varepsilon_{jt} \tag{3}$$

where $G_t\left(L_{\mathrm{jt}}, K_{\mathrm{jt}}, M_{\mathrm{jt}}\right) = \frac{F_{M,t}\left(L_{\mathrm{jt}}, K_{\mathrm{jt}}, M_{\mathrm{jt}}\right) M_{\mathrm{jt}}}{F_t\left(L_{\mathrm{jt}}, K_{\mathrm{jt}}, M_{\mathrm{jt}}\right)}$ is the elasticity of the production function with respect to the intermediate input, and $s_{\mathrm{jt}} = \ln\ (\rho_t M_{\mathrm{jt}})/(P_t Y_{\mathrm{jt}})$ is the log of the share of intermediate inputs to outputs. A non-parametric regression estimation of equation 3 using observable s_{jt} and data on $(L_{\mathrm{jt}}, K_{\mathrm{jt}},\ M_{\mathrm{jt}})$ will identify the ex-post shock and the elasticity. If we divide both sides of the elasticity function by M_{jt}, we will get $\frac{G_t\left(L_{\mathrm{jt}}, K_{\mathrm{jt}}, M_{\mathrm{jt}}\right)}{M_{\mathrm{jt}}} = \frac{\partial \ln F_t\left(L_{\mathrm{jt}}, K_{\mathrm{jt}}, M_{\mathrm{jt}}\right)}{\partial M_{\mathrm{jt}}}$. By the fundamental theorem of calculus:

$$\int \frac{G_t\left(L_{jt}, K_{jt}, M_{jt}\right)}{M_{jt}} dM_{jt} = \ln F_t\left(L_{jt}, K_{jt}, M_{jt}\right) + Q_t\left(L_{jt}, K_{jt}\right) \tag{4}$$

which implies that the share regression in equation (3) can help us non-parametrically identify the production function up to a constant $Q_t(L_{\text{jt}}, K_{\text{jt}})$.

If we subtract equation 4 from the production function, we will get the following:

$$\ln Y_{jt} - \int \frac{G_t\left(L_{jt}, K_{jt}, M_{jt}\right)}{M_{jt}} dM_{jt} - \varepsilon_{jt} = \; -Q_t\left(L_{jt}, K_{jt}\right) + \omega_{jt} \qquad (5)$$

the left hand side of equation 5 is observable/identifiable from the data. Denoting this LHS expression by $\mathcal{R}_{\text{jt}}$, we have then,

$$\omega_{jt} = \mathcal{R}_{jt} + Q_t\left(L_{jt}, K_{jt}\right)$$

We have earlier assumed that $\omega_{\text{jt}} = h\left(\omega_{jt-1}\right) + \eta_{\text{jt}}$.

Thus, we can express equation 5 as:

$$\mathcal{R}_{jt} + Q_t\left(L_{jt}, K_{jt}\right) = h\left(\mathcal{R}_{jt-1} + Q_t\left(L_{jt-1}, K_{jt-1}\right)\right) + \eta_{jt} \qquad (6)$$

the moment restriction we have stated in equation (1) can then help to non-parametrically identify the following regression:

$$\mathcal{R}_{jt} = -Q_t\left(L_{jt}, K_{jt}\right) + \; \tilde{h}\left(\mathcal{R}_{jt-1}, L_{jt-1}, K_{jt-1}\right) + \eta_{jt} \qquad (7)$$

From the above regression, we can recover $Q_t\left(L_{\text{jt}}, K_{\text{jt}}\right)$, which implies that we can recover the production function using equation 4 and also the productivity shock.

C.2 Ackerberg, Cave, and Frazer Estimation Techniques

The ACF estimation procedure draws on aspects of both OP and LP, with the main difference that no coefficients is estimated in the first stage of estimation. However, the first stage is critical to get rid of the transmission bias. To fix ideas, consider the following value added production function,

$$y_{\mathrm{it}} = \beta_L l_{\mathrm{it}} + \beta_K k_{\mathrm{it}} + \ \varphi_{\mathrm{it}} + \epsilon_{\mathrm{it}}$$

where φ_{it} and ϵ_{it} represent respectively productivity and the error term. Labor is chosen by firms at time $t-b$ $(0 < b < 1)$. Then capital is chosen at or before $t-1$. Finally material input is chosen at time t, after both labor and capital. Suppose that φ_{it} evolves according to a first order markov process between these subperiods, $t-1$, $t-b$, and t. In other word:

$$p\left(\varphi_{it} \middle| I_{it-b}\right) = p\left(\varphi_{it} \middle| \varphi_{it-b}\right)$$

and

$$p\left(\varphi_{it-b} \middle| I_{it-1}\right) = p\left(\varphi_{it-b} \middle| \varphi_{it-1}\right)$$

Given the timing assumption (selecting labor, capital, and material input), a firm's material input demand at time t is a function of productivity, capital, and labor, that is:

$$m_{it} = f_t\left(l_{it}, k_{it},\ \varphi_{it}\right)$$

Inverting material input demand function for φ_{it} and replacing it in the production function results in the following first stage equation:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \ f_t^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it}$$

While we cannot identify the coefficients in the first stage, we can exclude the portion of output determined by either the unanticipated shocks at time t or measurement error, that is, $\hat{\Phi}_{\mathrm{it}}$ of the composite term,

$$\Phi_{it} = \beta_L l_{it} + \beta_K k_{it} + \ f_t^{-1}(l_{it}, k_{it}, m_{it})$$

Using this equation we cannot still accurately identify the coefficient on labor and capital since the inverse function is also a function of labor and capital. In order to identify those coefficients, we need two independent moment conditions in the second stage. Given the first-order Markov assumption on productivity, we have:

$$\varphi_{it} = E\left[\varphi_{it} \middle| I_{it-1}\right] + \xi_{it} = E\left[\varphi_{it} \middle| \varphi_{it-1}\right] + \xi_{it}$$

where ξ_{it} is mean independent of all information known at $t-1$. Given the timing assumption, both capital and lagged labor are part of the information set at time $t-1$. this implies:

$$E\left[\xi_{it}.\ \begin{pmatrix} l_{it-1} \\ k_{it} \end{pmatrix}\right] = 0$$

These are the two moments conditions to identify β_{K} and β_{L}. We can recover the implied ξ_{it} for any value fo the parameters (β_L, β_K) as follows. First, given any candidate estimates of (β_L, β_K), compute the implied productivity using this specification:

$$\varphi_{it}\left(\beta_K, \beta_L\right) = \hat{\Phi}_{it} - \beta_L l_{it} - \beta_K k_{it}$$

Second, non-parametrically regress $\varphi_{\text{it}}\left(\beta_K, \beta_L\right)$ on $\varphi_{\text{it-1}}\left(\beta_K, \beta_L\right)$ and a constant term. Given the implied residuals, one can form the sample analogue to the required moment conditions. Now, coefficients on labor and capital can be estimated by minimizing the sample analogue. Finally, using the unbiased coefficients $\left(\hat{\beta}_L, \hat{\beta}_K\right)$, one can estimate the equation of interest:

$$\hat{\varphi}_{it} = y_{it} - \hat{\beta}_L l_{it} - \hat{\beta}_K k_{it}$$

Online Appendix D

D. Robustness Check Tables

Table D1: Increasing Temperature Variation and Controlling for Conflict Years

	Revenue	Profit	TFP (GNR)
	(1)	(2)	(3)
A. Dividing Abidjan into Two Sub-regions			
Days below 25C	-0.128	-0.666***	-0.053
	(0.162)	(0.002)	(0.040)
Days above 27C	-0.308***	-0.453***	-0.080***
	(0.097)	(0.001)	(0.025)
Observations	34,647	23,156	34,644
Control	YES	YES	YES
Firm FE	YES	YES	YES
District FE	YES	YES	YES
Time Trend	YES	YES	YES
F-test (All bins=0)	5.132	9.529	5.487
Prob>F	0.006	0.000	0.004
B. Controlling for Conflict Year			
Days below 25C	-0.105	-0.599***	-0.042
	(0.124)	(0.187)	(0.033)
Days above 27C	-0.178***	-0.280***	-0.040**
	(0.063)	(0.082)	(0.017)
Conflict year dummy	-15.056***	-20.076***	-4.198***
	(3.481)	(5.042)	(0.985)
Observations	34,647	23,156	34,644
Control	YES	YES	YES
Firm FE	YES	YES	YES
District FE	YES	YES	YES
Time Trend	YES	YES	YES
F-test (All bins=0)	4.871	11.85	4.481
Prob>F	0.00828	1.13e-05	0.0121

Notes: the dependent variables are logarithms of revenues, profits, and TFP (multiplied by 100 to reduce the number of decimal point in the coefficients). Profits are the reported profits and TFP is measured by Grandhi-Navarro-Rivers estimator. In panel A, we add more variation to temperatures by dividing Abidjan into two sub-regions. In Panel B, we control for the period of the past two political crises that the country faced. Bins are constructed using daily average temperature. The comparison bin is the number of days with average temperature between 25°C and 27°C. Control variables include rain, rain square, (log) capital, (log) labor, and dummies for export status, and age above firm median age. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table D2: Robustness Checks using Alternative Sub-samples of the Data

	Revenue	Profit	TFP (GNR)	TFP (VA/labor)
	(1)	(2)	(3)	(4)
C. Dropping firms with gap in panels				
Days below 25C	-0.069	-0.524**	-0.027	
	(0.133)	(0.217)	(0.031)	
Days above 27C	-0.270***	-0.380***	-0.059**	
	(0.090)	(0.116)	(0.025)	
Observations	20,641	13,171	20,638	
Control	YES	YES	YES	
Firm FE	YES	YES	YES	
District FE	YES	YES	YES	
Time Trend	YES	YES	YES	
F-test (All bins=0)	4.647	7.413	3.342	
Prob>F	0.010	0.000	0.036	
B. Dropping only firm with missing log VA (N=29,193)				
Days below 25C				-0.143
				(0.167)
Days above 27C				-0.202**
				(0.096)
Observations				25,518
Control				YES
Firm FE				YES
District FE				YES
Time Trend				YES
F-test (All bins=0)				2.588
Prob>F				0.076

Notes: the dependent variables are logarithms of revenues, profits, TFP, and value added per capita (multiplied by 100 to reduce the number of decimal point in the coefficients). Profits are the reported profits and TFP is measured by Grandhi-Navarro-Rivers estimator. In panel A, all firms with gaps in their appearance in the sample are dropped. In panel B, all firms will value-added greater than zero are kept in the sample. Bins are constructed using daily average temperature. The comparison bin is the number of days with average temperature between 25°C and 27°C. Control variables include rain, rain square, (log) capital, (log) labor, and dummies for export status, and age above firm median age. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table D3: Robustness Checks using Alternative Temperature Measures

	Revenue	Profit	TFP (GNR)
	(1)	(2)	(3)
A. Bottom and Top 10% as Bin Cut-off			
Days below bottom 10%	0.310*	-0.030	0.058
	(0.162)	(0.230)	(0.045)
Days above top 10%	-0.136*	-0.234**	-0.037*
	(0.080)	(0.117)	(0.022)
F-test (All bins=0)	2.304	2.020	1.709
Prob>F	0.102	0.135	0.183
B. Using Mean Temperature			
Mean Temperature	-704.929**	-381.688	-167.539*
	(313.141)	(443.827)	(85.207)
Mean Temperature square	12.724**	6.599	3.016*
	(5.917)	(8.464)	(1.608)
B. Using Coefficient of Variation			
Coef. of variation	-4,447.619**	-4,335.110	-1,264.384**
	(1,956.493)	(3,662.014)	(559.408)
Coef. of variation square	43,665.035*	22,244.218	12,130.626
	(25,983.837)	(47,526.537)	(7,355.036)
Observations	34,647	23,156	34,644
Control	YES	YES	YES
Firm FE	YES	YES	YES
District FE	YES	YES	YES
Time Trend	YES	YES	YES

Notes: the dependent variables are logarithms of revenues, profits, and TFP (multiplied by 100 to reduce the number of decimal point in the coefficients). Profits are the reported profits and TFP is measured by Grandhi-Navarro-Rivers estimator. In panel A, we use a new bottom and top 10% of average temperature as temperature bin cut-off. In panel B, replace temperature bins by average temperature and its square and in panel C by the coefficient of variation and its square. Bins are constructed using daily average temperature. Control variables include rain, rain square, (log) capital, (log) labor, and dummies for export status, and age above firm median age. Standard errors are clustered at region-year level. *** p<0.01, ** p<0.05, * p<0.1

Table D4: Panel information

Year	Number of firms with missing: Capital	Labor	Intermediate	Sale	Number of firms with valid values for capital, labor, intermediate input, and sale
1998	560	16	24	130	1945
1999	379	6	6	104	1881
2000	425	12	9	110	1759
2001	440	3	11	114	1743
2002	388	4	3	93	1632
2003	108	5	0	74	2046
2004	149	119	3	109	1920
2005	121	112	7	99	1787
2006	99	91	4	94	1650
2007	110	116	2	80	1608
2008	135	128	4	100	1735
2009	207	152	9	167	2048
2010	349	206	28	278	2713
2011	710	417	66	646	3996
2012	1177	472	85	695	5483
2013	2158	353	40	465	2384
Total	7,515	2,212	301	3,358	36,330

Table D4.1: Number of Firms by Sector

Sector	Number of firms
Agriculture	1073
Commerce	15150
Construction	3287
Extraction	233
Manufacturing	5849
Service	10735

Table D4.2: Panel length

Number of years in data	Number of firms
1	2062
2	3697
3	3905
4	3446
5	1967
6	1564
7	1420
8	1399
9	1261
10	1674
11	1862
12	1797
13	2089
14	2028
15	3291
16	2868