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Regular Article

Riders on the storm: How do firms navigate production and market conditions amid El Niño?☆

Maria Bas[a,*], Caroline Paunov[b]

[a] University of Paris 1, Centre d'Economie de la Sorbonne (CES), France

[b] OECD, Directorate for Science, Technology and Innovation, 2, rue André Pascal, 75 775, Paris, Cedex 16, France

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ABSTRACT

This paper investigates how heavy rainfalls resulting from the 2002–03 El Niño climate pattern affect Ecuadorian firms' production and market conditions. We show that affected firms' revenue productivity (TFP-R) and markups decrease. This is due to production efficiency losses (TFP-Q) and higher marginal costs of initially less efficient firms. Decreased product output prices in response to lower product demand explain the impact on initially more efficient firms. However, the shock neither affects market shares nor survival rates of initially less efficient firms. Consequently, the productivity distribution of Ecuador's industry is not affected by the shock. We also show a swift recovery of production and market demand in the immediate aftermath of the shock. Impacts in 2002–03 are like those of the 1997–98 rainfall shock. Differentiating firms by their TFP-R rather than their production efficiency indicates firms with better (worse) market positions can mitigate the negative impacts of the shock more (less).

1. Introduction

Once regarded a distant worry, tackling climate change has become an urgent global issue, given its role in escalating the frequency and severity of natural disasters. On average, a disaster related to weather, climate or water hazards occurred every day from 1970 to 2019 – killing 115 people and causing US$ 202 million in losses daily (WMO, 2021). Moreover, climate change has contributed to a surge in natural disasters over the past five decades that disproportionately impact developing countries (ibid.). On top of the loss of human lives and well-being, the destruction of production facilities and infrastructure compromise industrial economic development efforts. Impacts on firms' suppliers add to those production challenges. Additionally, households hit by destruction and job losses likely buy fewer products, especially those whose consumption can be postponed, affecting firms' profitability as prices and sales volumes decrease. This demand shock is also possibly amplified by less demand from firms due to uncertainties about future economic conditions.

If there is a silver lining for economic development in the context of climate shocks, it lies in the potential cleansing effect of climate shocks to the advantage of more productive firms. This would lead to increased aggregate industry productivity. A limited body of literature supports this hypothesis, demonstrating that less productive firms suffer more from these shocks (Pelli et al., 2023; Basker and Miranda, 2018).

The questions that this paper seeks to answer are: How are firms' production costs and productivity (efficiency) affected by climate shocks? What happens to the demand for firms' products and what are its implications for firms' profitability? How are differences in

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* Corresponding author. Maison des Sciences Economiques, 106-112 Bd de l'Hôpital, 75647, Paris, France.
E-mail addresses: maria.bas@univ-paris1.fr (M. Bas), caroline.paunov@oecd.org, caroline.paunov@gmail.com (C. Paunov).

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productivity (efficiency) across firms affecting the impact of climate shocks? Our paper investigates these questions for the heavy rainfall episodes Ecuador experienced because of the El Niño climate pattern in 2002–03. We assess market conditions by tracking firm output prices and the evolution of their markups. We capture production conditions by indicators of firm marginal costs and production efficiency, measured by quantity productivity (TFP-Q).

The El Niño natural weather phenomenon describes the unusual warming of surface waters in the eastern tropical Pacific Ocean that results in unexpected episodes of heavy rainfalls across many countries in different regions of the world. Ecuador is among the countries that experienced a substantive shock in 2002–03. Heavy rainfall resulted in landslides and floods that destroyed transportation and electricity infrastructures and buildings (UN-OCHA, 2002). The UN's EM-DAT database recorded that more than 60,000 individuals were directly affected in their health and livelihoods by the floods that ensued, with estimated direct financial damages in 2002 surpassing 26 million USD (EM-DAT, 2023).

In our empirical specifications, we apply the classical difference-in-difference (DID) estimation technique to the exogeneous climate shock of the 2002–03 El Niño heavy rainfall episode. This climate shock provides for a natural experiment due to the unpredictable nature of this climate shock. The exact timing and location of its future occurrences are unknown (Rosales-Rueda, 2018). We validate our empirical DID strategy, that consists in comparing treated firms' post-shock outcomes with untreated firms, by verifying no differences in pre-crisis trends across treated and untreated firm groups exist. We implement our DID approach by classifying firms in the treatment (comparison) group as those firms located in provinces that experienced an excess of rainfall because of the 2002-03 shock relative to the historical mean higher (lower) than the median.

Moreover, the robustness of our estimation strategy builds on a battery of controls and fixed effects. This includes controls for land management at province-year level (expenditures in the province of construction and new constructions). These ensure differential impacts of the shock are not driven by differences in land management across affected and unaffected provinces. We thank an anonymous referee for the suggestion of controlling for land management and natural hazard indicators. Furthermore, our specification accounts for firm-product fixed effects that control for unobservable time-invariant firm-product characteristics and industry-year fixed effects. These account for potential time-variant differences in industry characteristics. We validate our findings with several sensitivity tests probing our specification and variable choices.

Our analysis builds on a Census panel dataset of formal manufacturing plants (corresponding to ISIC Rev. 3 category D) that is collected by the Ecuadorian Institute of Statistics (INEC) for the period 1997–2000. These data are complemented by two other datasets, which provide respectively information on plants' intermediate inputs and on plants' output products. Our data allow assessing impacts on quantity total factor productivity (TFP-Q) as well as measuring markups, marginal costs and output prices. Our final estimating dataset contains 96% of firms with non-missing information, totaling 35,290 firm-product-year and 5,883 firm-year observations. This corresponds to 5,875 firm-products for 980 firms. Importantly, these data only represent the formal manufacturing firms in Ecuador, leaving out informal manufacturing firms.

We identify seven key findings on the impacts of excess rainfall on firms' production and pricing strategies. First, both firm production and market conditions are affected by the rainfall shock. On average, firms' marginal costs increase by 9.4% compared to the control group, pointing to a substantial impact on production. The cost increase is also driven by value chain linkages with affected domestic input suppliers. Due to the shock, suppliers reduce the quantity of their intermediate inputs and increase prices. We also show that firms decrease their output prices by 5.9% compared to the control group. The combined production and demand shocks lead to an average markup decrease of 15.4% for affected firms compared to unaffected ones.

Second, affected firms' TFP-R decrease of on average 7.5% does not result from a decline in production efficiency (TFP-Q). Instead, it is influenced by alterations in firms' pricing dynamics. TFP-R utilizes an output measure of sales adjusted by industry-level price deflators, unlike TFP-Q, which uses firm-level price deflators. Consequently, TFP-R declines for firms that reduce their output prices in response to the climate shock, even though their production efficiency (TFP-Q) remains unchanged. This underscores the need for caution when interpreting evidence on TFP-R, as widely used by analyses of traditional firm-level datasets that do not capture firm output prices, as indicative of impacts on production efficiency.

Third, we find that average effects mask highly heterogeneous impacts on firms depending on whether they have higher or lower initial production efficiency levels (TFP-Q) when the shock hits. On the production side, only the less efficient firms experience an increase in marginal costs (of 28.4% relative to the control group). They also experience a decrease of 11.2% compared to the control group in their production efficiency (TFP-Q). By contrast, the initially more productive firms experience no such negative production efficiency effects.

Both groups face a decrease in markups – albeit of lower magnitude for the more compared to the less productive (9.3% compared to 27%). The more productive firms lower output prices in response to the demand shock. Thereby, the decrease in TFP-R observed for more efficient affected firms is driven by the reduction in output prices. For less efficient affected firms this contraction of TFP-R is due to a decline in production efficiency (the reduction of TFP-Q).

Splitting the sample by use of TFP-R instead shows lower negative measured impacts on production (both marginal cost and TFP-Q) and markups, suggesting that firms with better market positions can attenuate the shock's impacts, possibly as they have more resources to address production problems caused by the climate shock.

Fourth, our results show that despite the shock's heterogeneous impacts on firms with different production efficiency (TFP-Q), the shock has no impacts on the productivity distribution of Ecuadorian firms. The market shares of initially less productive firms, as measured by TFP-Q, compared to the control group, decrease by a negligible 0.5%. The shock also does not force any of these formal manufacturing firms to exit, while entry rates in affected provinces increased by only 0.7%. Moreover, the negative impacts are short-lived with a recovery immediately after the shock. Production benefits from a decrease in marginal costs. Demand also recovers allowing firms to lower by less, still increasing their markups.

Fifth, an important question common to micro-econometric evaluations of specific shocks regards their external validity. Are results specific to the shock or do they point to a general pattern? We are in position to answer this question by investigating the 1997–98 rainfall shock Ecuadorian firms experienced, which was even more substantive than the 2002–03 crisis. Commonalities across both episodes are that both have negative production effects as marginal costs increase and production efficiency decrease for the less productive firms. These in turn result in reduced markups, also as firms are not in position to pass through higher costs to consumers.

Sixth, the demand shock we identify is not driven by manufacturing employment or wage effects. We find both to be unaffected. This is not surprising since the firms in our survey are formal manufacturing firms, who offer the most protected and highest quality positions as compared to the large number of informal workers mostly in services.

Seventh, evidence from an alternative instrumental variable (IV) estimation, that uses excess rainfall to instrument for floods in 2002–03, shows that floods result in higher marginal costs and reduce markups as firms must reduce prices. Since hurricanes are not prevalent in Ecuador, we know they are not drivers of the impacts of excess rains we identify. This evidence on floods also provides a robustness test of our results.

Our findings have several contributions to the literature on firm performance and shocks itself and policy in response to climate change shocks in developing countries. Ours is the first study to look jointly at production and market dynamic impacts of a climate shock, heavy rainfall resulting from the El Niño shock, by assessing impacts on marginal production costs and their implications on firm markups and consumer prices. Our evidence documents the importance of looking at both production and market dynamic effects of shocks. As is the case for our analysis, revenue productivity (TFP-R) measures do not necessarily point to changes in production efficiency. Rather, demand factors explain climate change shock's impacts on revenue productivity. Studies lacking such data should acknowledge the potential influence of demand factors on revenue productivity outcomes.

Moreover, our evidence adds to the wider evidence that shocks are better handled by more efficient firms, illustrating the importance of micro-level analyses that are masked by aggregate studies. These differences may also be a source of efficiency improvements. We add to the literature by showing that the use of TFP-R to differentiate firms production efficiency results underestimates the heterogeneity of impacts, as less efficient firms with more market power can mitigate the shock's negative impacts.

Furthermore, the impacts of our climate shock are short-lived as production recovers in the immediate aftermath. Our findings are in line with the results of Pelli et al. (2023) who also show that the negative effect of another type of climate shock, cyclones, on firm's fixed assets and sales in India are temporary and lasts just one year. This is interesting from the perspective of policy debates on resilience, since the costs of shocks depend critically on their duration, requiring differentiation across different types of climate and other risks in the field of health or geopolitics. Nonetheless, from a development perspective, frequent short-lived climate shocks are a source of concern as they distract firms from engaging in upgrading efforts, by hindering investments (Verhoogen, 2023).

Our paper contributes to the literature on the impacts of natural catastrophes on the economy that complements analyses of their impacts on people with regards to health, human capital and employment (e.g. Shah and Steinberg, 2017; Caruso, 2017; Carrillo, 2020). Groen et al. (2020) use household data to study the effects of hurricanes Katrina and Rita on the US using individual household data and find important short-term earnings losses due to job separations. The latter also includes a study by Rosales-Rueda (2018) on the impacts of early life exposure to the 1997–98 El Niño phenomenon on human capital formation. This literature initially explored macro-level data to study how these shocks related to economic growth (Cavallo et al., 2013; Strobl, 2011, 2012; Felbermayr and Gröschl, 2014; Hsiang and Jina, 2014; Dell et al., 2014 for a review). An interesting debate in this literature is whether developing countries are more sensitive to natural disasters than developed countries (Dell et al., 2012; Loayza et al., 2012; Kotz et al., 2022). Uncovering the specific impacts on economic development, however, requires more granular analyses.

Finally, our work contributes to the small but growing literature that relates to a few firm-level analyses of episodes of natural catastrophes in developed and developing countries. On developed countries, Okazaki et al. (2019) and Okubo and Strobl (2021) provide a historic perspective on the impacts of the 1923 Great Kanto Earthquake and 1959 Ise Bay Typhoon in Japan on firm survival and on surviving firms' employment, capital, investments and labor productivity. Earlier work by Leiter et al. (2009) analyzes the employment and value-added impacts of floods in 2000 on large firms in France, Italy, Spain and the United Kingdom. Craioveanu and Terrell (2016) and Basker and Miranda (2018) investigate firm survival after Hurricane Katrina in 2005 in the US. Findings show lower (higher) survival rates for smaller (larger) firms and less (more) productive ones.

On developing countries, the literature on the effects of natural disasters on firm performance has focus on the effects of tropical cyclones on domestic and export sales as well as investment. Pelli et al. (2023) investigate the effects of tropical cyclones on firm performance in India during the period 1995–2006. Their findings show that the cyclones have a negative effect on firm's fixed assets and sales and that these results are more pronounced for less productive firms. Relying on cross industry-country data, Pelli and Tschopp (2017) study the effects of hurricanes on exports and show that this effect depends on the comparative advantage of the industry. Elliott et al. (2019) investigate the effect of typhoons on firm performance in China. Their findings show that firms reduce their sales to domestic buyers more than foreign ones and they reduce their purchases of domestic suppliers and increase those of foreign suppliers. Vu and Noy (2018) investigate the effect of natural disasters in Vietnam on firms' sales and investments. They find a negative impact of natural disasters on firm sales and an increase of the same magnitude on investments. We complement the literature by analyzing the implications of excess rainfall and its impacts beyond tropical cyclones on firm markups, marginal cost, price and production efficiency (TFP-Q).

The remainder of the paper is structured as follows. Section 2 offers theoretical motivation for our empirical analysis. Sections 3 describes the data and key variables used in the analysis, while section 4 describes the 2002–03 El Niño catastrophe and the empirical specification and validation tests for our chosen approach. Sections 5 and 6 discuss main results, sensitivity tests and extensions. The final section 7 concludes.

2. Theoretical motivation

2.1. Expected effects of heavy rainfalls on firm production and market conditions

Heavy rainfall episodes may affect firms' production and market dynamics. On the production side, heavy rainfalls may affect firms directly by destroying production facilities and machinery and by altering access to key production inputs, such as labor inputs that may be affected by losses of livelihoods and impacts on transportation, as well as electricity shocks and the access to production inputs (as delivery roads are affected). The shock may also propagate through impacts on suppliers and their production capacities. Shortages of intermediate inputs (reduction of the input supply) will push up prices and increase marginal costs faced by final good producers or reduced production volumes. The effect of lower production volumes the climate shock may result in, affects economies of scale or scope. Seminal models by Krugman (1980) and Devarajan and Rodrik (1989) show how output decreases (increases) reduce (increase) quantity productivity. Moreover, alternative production processes or factors may lead to sub-optimal production processes and consequently reduce productivity. Heavy rainfall may consequently result in an increase in production costs and in reduced production efficiency – i.e. (real) productivity (TFP-Q) - at which firms transform production inputs into outputs.

As regards market dynamics, excessive rainfalls may also affect the income of consumers (due to destruction of houses and infrastructure damages) and their purchasing power (Vos et al., 1999; Groen et al., 2020). In addition, consumer preferences may change as a result of the negative income shock and/or uncertainties resulting in precautionary savings (Bunn et al., 2018; Lugilde et al., 2019). Product demand from other firms may also mostly decrease, particularly those that can be postponed, but also variable inputs where production is affected. From the perspective of manufacturing firms, we consequently expect a decrease in product demand that in turn may result in firms' adjusting their output prices depending on what price maximizes revenues.

The join impacts on firm production costs and market dynamics will determine effects of the climate shock on firm profitability, as reflected in their markups, and on TFP-R. In the standard model of imperfect competition setting, output prices can be decomposed into the logarithm of MC and markups so the logarithm of markups (μ_{it}) of firm i in period t can be expressed as the log-difference between the logarithm of output prices (p_{it}) and marginal costs (mc_{it}): $\mu_{it} = p_{it} - mc_{it}$ (see Hall, 1986, 1988). Consequently, if firms face higher production costs and market conditions that do not allow passing through this increase (by increasing their prices), then we would expect to see a reduction in markups. Worsened market conditions that oblige firms to reduce their output prices alone, would also result in a reduction of markups.

Revenue productivity, a frequently used measure as many firm datasets do not have output price information of firms, is also affected by both production and market conditions. Changes in quantity productivity reflect changes in production efficiency, namely that firms produce fewer or more units of output with the same number of inputs. Changes in TFP-R, however, are affected by firms' prices and market power. Obtained by deflating firm revenues by industry prices, the same sales volume can be obtained for the same quantity produced if firm output prices change. That is, TFP-R may change in response to changes in market conditions, unrelated to changes in production efficiency. More detail on how these and other measures are obtained are provided in the next section.

2.2. Possible productivity-enhancing cleansing from heterogeneous impacts on firms

We expect the impacts of a climate shock to differ across firms, with those of higher production efficiency being more resilient. More efficient firms often have more resources and a more skilled workforce to adjust production to the shock and consequently they can likely reduce the impact of a climate shock. Higher profit margins potentially also provide them with necessary resources to repair damages affecting production. Their reliance on better technologies may also facilitate a recovery.

Some empirical works have documented such heterogeneous impacts of climate shocks, echoing an extensive trade literature on such dynamics in response to trade shocks. Pelli et al. (2023) show that the negative effects of cyclones on firm fixed assets and sales differ. Less productive firms reduce their sales more due to the storms. Climate shocks may consequently follow a similar dynamic to trade shocks (Pavcnik, 2002; Lileeva and Trefler 2010; Bas and Paunov, 2021a).

By hitting less efficient firms more these may see their market shares reduced and even exit the market. If this was the case, the shock would result in positive shedding to the advantage of more productive firms. Evidence from Basker and Miranda (2018) points to such developments with less productive firms in the United States having lower survival rates following Hurricane Katrina in 2005. Moreover, wide evidence of trade liberalization "shocks" prompting positive reallocation dynamics to more productive firms is a complementary source of gains from trade to the traditional comparative advantage (Feenstra, 2018).

3. Overview of the data and key variables

3.1. Panel data on manufacturing plants, their inputs and output products

We use a Census panel dataset that is collected by the Ecuadorian Institute of Statistics (INEC) of formal manufacturing plants (corresponding to ISIC Rev. 3 category D) with 10 or more employees for the period 2000–2005. Our final estimating dataset contains 96% of firms with non-missing information, totaling 35,290 firm-product-year and 5,883 firm-year observations. This corresponds to 5,875 firm-products for 980 firms. Importantly, these data only represent the formal manufacturing firms in Ecuador, leaving out informal manufacturing firms. While informal employment, which represented an estimated 82.4% of total employment for 2001–05 (ILO, 2023) is mostly concentrated in services, of the group of smaller informal manufacturers are unfortunately also excluded from our analysis. As these firms are typically among the least productive, we suspect the omission results in an underestimate of the negative impacts on the less productive firms, including firm survival.

The distinctive feature of our data is that the plant census is complemented by two other datasets, which provide respectively information on plants' intermediate inputs and on plants' output products. The first dataset gives annual plant-level information on primary materials, auxiliary materials, replacements and accessories and packing materials used in production. For each intermediate input, plants provide information on quantities and values separately for national and foreign inputs. The second dataset has information on each plant's final products: quantities and values sold in the market and their quantities as well as the cost of production for each product.

Both input and output products are provided by INEC at detailed 11-digit product code level that is built on the ISIC-Rev. 3 industry classification.[1] We implement several data cleaning procedures and check the quality of our dataset following Bernard et al. (2011), Kugler and Verhoogen (2012) and Goldberg et al. (2010). Details on data cleaning procedures and quality checks are provided in Paunov (2011).

3.2. Obtaining prices, markups and marginal cost

Firm-product output prices are computed as total value of a product over the quantity (unit values). We rely on the measures of firm-product level markups estimated based on the methodology developed by Hall (1986), revisited by De Loecker and Warzynski (2012) and applied at the firm-product level by De Loecker et al. (2016) as described below.

The advantage of this methodology is that it allows measuring markups in the absence of information on demand or market structure. The key assumption is that firms minimize costs. In this setting, firm-product markups (μ_{ipt}) are firm-product prices (P_{ipt}) over marginal costs (MC_{ipt}) and correspond to the deviation between output elasticity relative to variable input $\frac{\partial Q_{ipt}}{\partial V_{ipt}}\frac{V_{ipt}}{Q_{ipt}}$ and that input's share of total revenue. $\frac{P^V_{ipt}}{P_{ipt}}\frac{V_{ipt}}{Q_{ipt}}$:

$$\mu_{ipt} = \frac{P_{ipt}}{MC_{ipt}} = \left[\frac{\partial Q_{ipt}}{\partial V_{ipt}}\frac{V_{ipt}}{Q_{ipt}}\right] \Big/ \left[\frac{P^V_{ipt}}{P_{ipt}}\frac{V_{ipt}}{Q_{ipt}}\right]$$

We use the output elasticity relative to variable input estimated in the production function estimation.

Marginal costs are computed by dividing unit values (prices) by the estimated markups. For single product firms, we use the share of expenditures in materials over total sales as input share to compute the firm-product level markups. For multiproduct firms, we followed the method of Garcia-Marin and Voigtländer (2019) to compute product-specific material inputs for multiproduct firms by using the information provided in our firm-product dataset on cost of production for each product and firm by year.

3.3. Quantity and revenue productivity

We obtain measures of TFP-R and TFP-Q as a residual of the following Cobb-Douglas production function:

$$R_{it} = \omega_{it}\boldsymbol{X}^{\rho}_{it}\boldsymbol{L}^{\beta}_{it}\boldsymbol{K}^{\gamma}_{it} \tag{1.A}$$

$$Q_{it} = A_{it}\boldsymbol{X}^{\rho}_{it}\boldsymbol{L}^{\beta}_{it}\boldsymbol{K}^{\gamma}_{it} \tag{1.B}$$

where R_{it} is the revenues (sales) of firm I in year t and Q_{it} is the physical quantity that firm i produces in year t with a Cobb-Douglas technology: using intermediate inputs X_{it}, labor (L_{it}) and capital goods (K_{it}). ω_{it} is TFP-R, which is composed of both output prices and the physical efficiency, A_{it}. ρ, β and γ are the output elasticities relative to production factors. Log linearizing equation (1.A and 1.B), TFP-R and TFP-Q are the

[1] The dataset provides information on plants and does not have information on which plants are part of one single firm and which plants are single-product firms as several other micro datasets used in the literature such as the data for Colombia in the works of Kugler and Verhoogen (2009, 2012) and for Chile in the works of Pavcnik (2002) and Garcia-Marin and Voigtländer (2019).

residual of this log-linear production function, where the lower-case letters represent the logarithms of variables:

$$r_{it} = \rho \boldsymbol{x_{it}} + \beta\, l_{it} + \gamma k_{it} + (a_{it} + p_{it}) \tag{2.A}$$

$$q_{it} = \rho \boldsymbol{x_{it}} + \beta\, l_{it} + \gamma k_{it} + a_{it} \tag{2.B}$$

The last term in brackets in equation (2.A) is the TFP-R composed by the sum of both the logarithm of physical efficiency (a_{it}, TFP-Q) and output prices (p_{it}). The first term, physical efficiency, is the ability of firms to produce more units of output with the same amount of inputs, obtained as the residual (a_{it}) of a production function estimation using firm sales deflated with firm prices (or physical quantities, q_{it}) from the estimation of equation (2.B). Measured effects of heavy rainfall on TFP-R do not allow distinguishing whether these are due to changes in firms production efficiency or due to changes in firm output market conditions.

We rely on the measure of TFP-Q and TFP-R computed by Bas and Paunov (2021b) following De Loecker et al. (2016) and estimate a Cobb-Douglas production function at the 2-digit industry level as the one presented above in equation (2.A) and (2.B). Our production function estimations rely on the methodology introduced by Ackerberg et al. (2015) that controls for the simultaneity bias in the estimation of production functions with firm-level data. This bias arises since input demand for materials and labor is positively correlated with unobserved productivity. We obtain TFP-Q using total revenues and input expenditures deflated with firm level prices obtained as Tornquist price indices based on a weighted average of the growth in price of firm *i*'s manufactured products *p* (input *k*) between year *t-1* and year *t*.

Since we do not have information on how multi-product firms allocate their inputs across products, we rely on single product firms to estimate the production function. For the single product firms, we know that the inputs used in the production of the single product have been allocated to that good. Bas and Paunov (2021b) show the results of the production function estimates (the elasticity of output with respect to inputs) for TFP-Q at the 2-digit industry level. For multiproduct firms, we then compute TFP-Q using the elasticity of output with respect to inputs of their main products at the 2-digit industry level estimated from single product firms and the amounts of inputs of multiproduct firms.

3.4. Rainfall and other variables

Information on heavy rainfalls in Ecuador comes from monthly precipitation data for the 22 provinces of Ecuador provided by the Climate Change Knowledge Portal of the World Bank (World Bank, 2022).

All our estimations control for differences across provinces in land management, by adding measures of the expenditures in the province of construction and the number of new constructions from Ecuador's annual survey of constructions. We also add information on firm expenditures on building acquisition. Moreover, we include controls for natural hazard indicators at the province-year level such as excess of temperature and surface pollution over area from the AIDDATA (Goodman et al., 2019).

Data Annex Table A.1 presents a detailed description of these and additional variables we use in our analysis.

4. The 2002–03 El Nino shock and empirical specification

4.1. Ecuadors 2002–03 El Nino shock

El Nino is a climate pattern that describes the unusual warming of surface waters in the eastern tropical Pacific Ocean that results in heavy rainfalls, severe flooding and landslides on the west coast of South

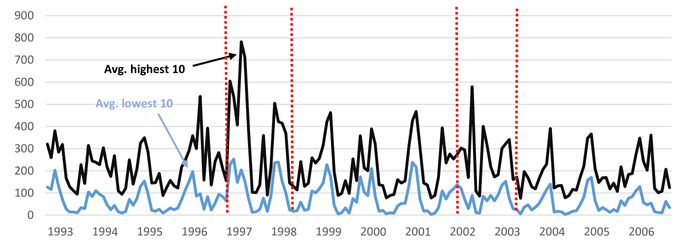

Fig. 1. Monthly rainfall in Ecuadorian provinces, 1993–2006.
Notes: Rainfall is in millimeters (mm). The source of this data is from the Climate Change Knowledge Portal of the World Bank.

America, including Ecuador and its coastal region in particular. Although El Nino is recurrent, the cycle of this climate event is not regular and varies in length. Consequently, the exact timing and intensity are unknown in advance (Kovats et al., 2003).

From the mid-90s to early 2000s, the international disaster database EM-DAT –the most comprehensive record of global disasters available - registered that Ecuador experienced heavy rainfall episodes in 1997–98 and in 2002–03 (EM-DAT, 2023). The intensity of excess rainfalls varied, however, across the most and least rainfall-affected regions, as shown in Fig. 1. While the least affected regions did not experience exceptional rainfall, the most affected experienced very high levels of rainfall. Our indicator of excess rainfall consequently varies substantially across regions as shown in Fig. 1, with pronounced impacts on coastal regions (Fig. 2). We exploit this diversity in our econometric analysis described in section 5.

The 2002–03 El Niño event, though less intense compared to the strong 1997–98 El Niño shock, had significant impacts on patterns of weather variability worldwide and in Ecuador (McPhaden, 2004). For Ecuador, the UN's EM-DAT database registered more than 60,000 individuals were directly affected in their health, including an outbreak of dengue, and livelihoods by the floods (EM-DAT, 2023; Petrova et al., 2019). This impact indicator is close to the estimated count of more than 63,000 for the 1997-98 shock (ECLAC, 1998). Estimated direct financial damages in 2002 surpassing 26 million USD (EM-DAT, 2023). Heavy rainfalls resulted in substantial landslides and floods resulting in destroyed transportation and electricity infrastructures and buildings (UN-OCHA, 2002).

4.2. Baseline difference-in-difference specifications

In our empirical analysis, we employ a quasi-experimental DID specification that compares production and price choices of firms located in provinces with higher increased in precipitation intensity during the 2002–03 period (the treatment group) relative to those firms located in provinces unaffected by the shock (the comparison group).

Using a province-level measure captures not only their own production capital destruction but also the wider destructions, such as damages to transport infrastructures, input suppliers and output distributors. The latter is shared among all firms in provinces no matter the impacts on their own production facilities. Previous works have similarly exploited exogenous regional variations, including Rosales-Rueda (2018) on the 1997–98 El Niño shock, Duflo and Pande (2007), Shah and Steinberg (2017) and Carrillo (2020).

We compare the shock impacts in a non-standard DID approach by comparing the shock period effects with both the pre-period (2000–01) and post-period (2003–05). This approach is valid provided that both pre- and post-shock trends do not differ, which we show to be the case in section 4.3.

Firms in the treatment (control) group are those located in provinces that experienced an excess of rainfall relative to the historical mean

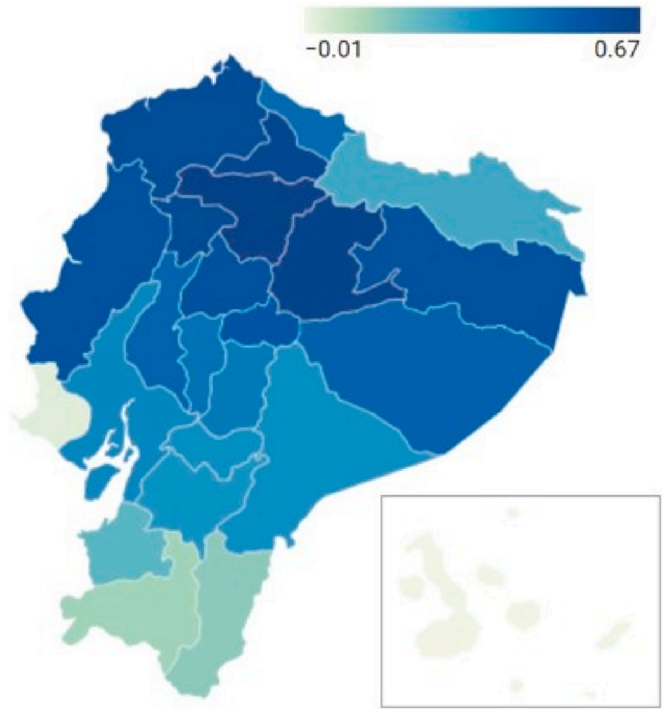

Fig. 2. Average excess rainfall across Ecuadorian provinces in 2002.
Notes: Excess rainfall is computed as described in section 4.2.

higher (lower) than the median during the 2002–2003 period. We measure excess of rainfall using a standard and widely use index in the literature[2]: *Excess Rainfall*$_{mtp}$ $= \frac{(P_{mtp} - \overline{P_{mp}})}{\sigma_{mp}}$, where P_{mtp} is the observed precipitation for a given month m in a year t in province p. $\overline{P_{mp}}$ is the long-term mean of precipitations in each month and province for the years 1950–2005 and σ_{mp} is the standard deviation of monthly rainfalls. This index is expressed in terms of standard deviations to account for the magnitude of the shock by removing the influence of normal dispersion of rainfall. We average the precipitation index at the province-year level as we have annual firm-level data.

The firm-product and firm-level estimation equations are as follows:

$$lnX_{kijpt} = \alpha + \gamma \; Treated_p * shock\ period\ 2002 - 03 + \sum \rho \, I_{pt} + \Pi_{pi} FProdSize_{ki,t0} {}^{*} \eta_t + \pi_{ik} + \eta_{jt} + \varepsilon_{kijpt} \tag{3.A}$$

$$lnY_{ijpt} = \alpha + \gamma \; Treated_p * shock\ period\ 2002 - 03 + \sum \rho \, I_{pt} + \Pi_{pi} FSize_{i,t0} {}^{*} \eta_t + \pi_{ik} + \eta_{jt} + \varepsilon_{ijpt} \tag{3.B}$$

where $ln\ X_{kijpt}$ is respectively the logarithm of firm-product level marginal cost, markups or output prices of product k at 11-digit ISIC Rev.3 level of firm i and $ln\ Y_{ijpt}$ is firm level quantity and revenue productivity of firm i producing in industry j located in province p at time t. $Treated_p$ is a dummy equal to one for firms located in provinces that were exposed to heavy rainfall in the period 2002–2003 as explained above, while *shock period* $2002 - 03$ is a dummy equal to one in the years 2002 and 2003.

I_{pt} is a vector of province-year control variables, which comprises natural hazard indicators - excess of temperature and surface pollution. We also include province size measure by total employment and land management controls, namely expenditures in constructions and number of new constructions at the province level.[3] These controls are important because the way land is managed directly influence whether heavy rainfall leads to floods and the severity of their impact. In sensitivity tests we report in section 6.1. We will apply instrumental variable estimations to delve deeper into the effects of floods.

Respective fixed effects and trends for specifications (3.A) and (3.B) are included. In specification (3.A) at firm-product level, we also control for firm-product-size trends $FProdSize_{kit0} {}^{*} \eta_t$ to control for unobservable diverging trends in demand for firm i's product k. We include firm-product fixed effects (π_{ik}) as well as 3-digit industry-year fixed effects (η_{jt}). In specification (3.B) at firm level, we control for firm-size trends $FSize_{i,t0} {}^{*} \eta_t$ to control for unobservable diverging trends in demand for firms' product basket. We also include firm fixed effects as well as 3-digit industry-year fixed effects (η_{jt}). ε_{kijpt} and ε_{ijpt} are error terms.

4.3. Validation of our specification

The DID approach can only be used if two critical conditions hold. First, there should be no mobility across treatment and control groups. This would be the case in our setting if firms moved their production from affected provinces to unaffected provinces. While a recurrent pattern for individuals, manufacturing firms are less likely to change locations also given the physical production facilities that cannot be easily moved. We confirm this is also the case for our firms and find that only 25 firms change their province location in the period, which we exclude from the estimating sample.

Second, the DID approach requires there are no underlying differences in pre-crisis trends across treated and untreated firms. This is critical as the DID method builds on attributing differences in outcome variables across treated and untreated firms as the shock hits. For the condition to hold, industrial development across the groups of provinces has to follow the same dynamics. Moreover, if firms in treated regions anticipated the shock and changed their behavior, the specification would also be invalid as firms' pre-shock behavior differs. However, anticipatory behavior would require firms could predict the 2002–03 effects prior to the shock, which was not the case. This is because Ecuador experienced very different episodes of El Niño shocks in terms of timing, duration and severity in the years leading up to 2002–03 and afterwards, with short-lived impacts as discussed in section 5.4.[4]

We conducted an event study analysis of the 2002-03 heavy rainfall shock to validate our DID specification by testing for the absence of diverging pre-trends and the duration of the shock. We estimate the following equations for the period 2000–2005:

$$lnX_{kijpt} = \alpha + \sum_t^4 \gamma^t Treated_p * Time_t + \sum \rho \, I_{pt} + \Pi_{pi} FProdSize_{ki,t0} {}^{*} \eta_t + \pi_{ik} + \eta_{jt} + \varepsilon_{kijpt} \tag{4.A}$$

$$lnY_{ijpt} = \alpha + \sum_t^4 \gamma^t Treated_p * Time_t + \sum \rho \, I_{pt} + \Pi_{pi} FSize_{i,t0} {}^{*} \eta_t + \pi_{ik} + \eta_{jt} + \varepsilon_{ijpt} \tag{4.B}$$

[2] See Zeballos (2004) Seiler et al. (2002), Duflo and Pande (2007) Guerreiro et al. (2008), Rosales-Rueda (2018).

[3] All results are robust to including firms' investments in buildings which we omit from these regressions due to the endogeneity concerns the inclusion raises.

[4] Moreover, due to the inaccuracy of predictions and the poor performance of early warning systems, they were disregarded, leaving firms unprepared for the precise timing and locality of future occurrences, with climate change further exacerbating the unpredictability (Rosales-Rueda, 2018; Glantz, 2000; Kovats et al., 2003).

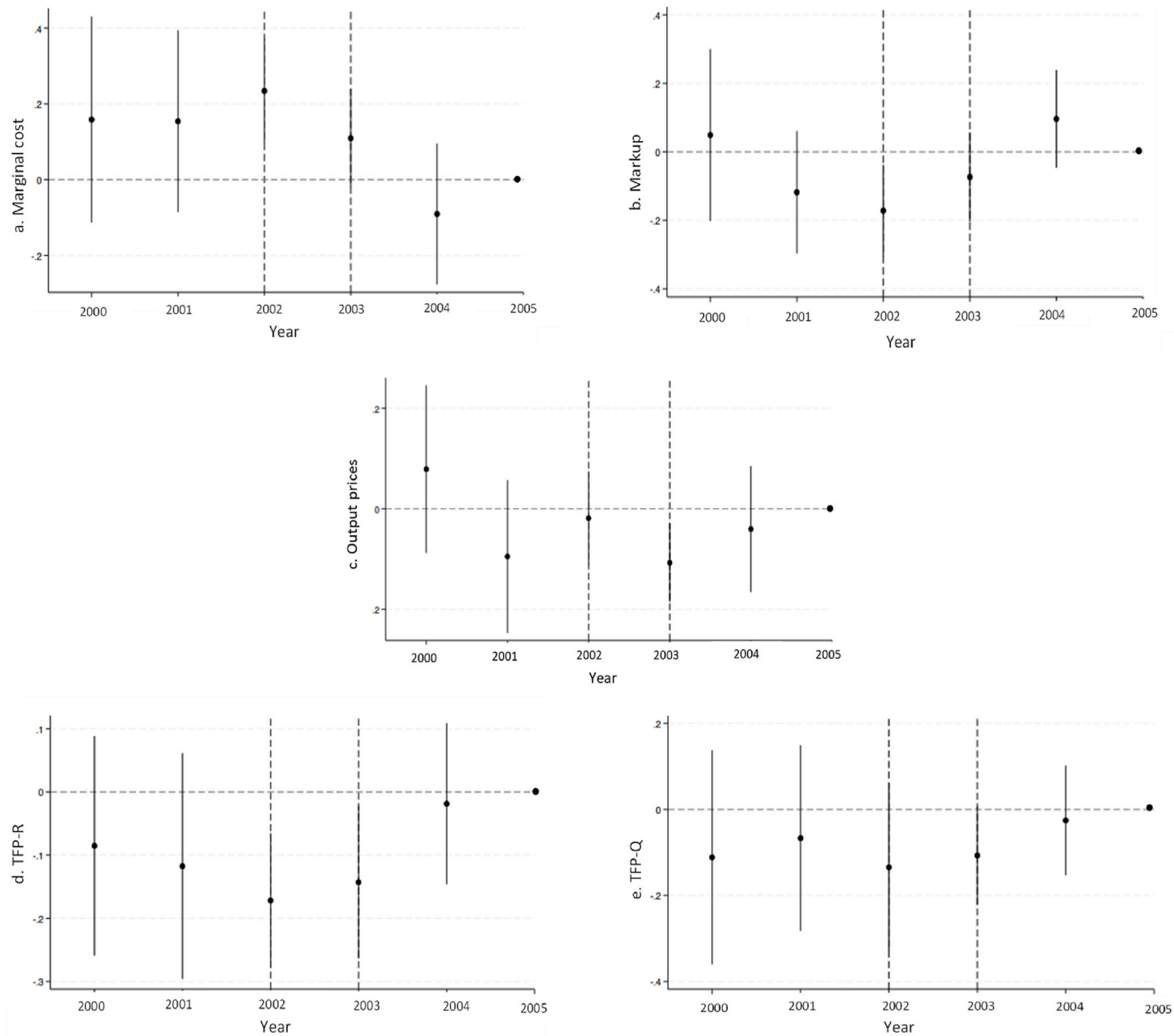

Fig. 3. a–e: Event study results of treated firm outcome variables.
Notes: The figures plot the point estimates of the respective γ corresponding to year t of equation (4) for the sample period 2000–2005 and the 95th percentile confidence levels of robust standard errors. The omitted year is 2005.

where the coefficients of interest, $\sum_t^4 \gamma^t$, are the interaction terms between the treated group and year dummies ($Time_t$). We omit estimating this coefficient for the year 2005. The other variables are identical to those used in equation (3.A) and (3.B), where they are described.

Fig. 3a–e plot the coefficients on the interaction term, showing statistically significant temporary impacts on treated firms in 2002–03 that validate our empirical approach. We find evidence of increased marginal costs, decreased markups and decreased TFP-R but not of TFP-Q in 2002 when the shock started, 2002, and a decrease in output prices and TFP-R in the following year, 2003. Consequently, our results validate our approach of focusing our DID analysis on the effects of the shock in 2002–03 comparing with years before and after the shock.

5. Main results

5.1. Average effects

This section presents the results of the DID estimation of equation (3.A). With regards to the production side, our estimates in columns (1)–(3) of Table 1 show that in exposed provinces faced an increase in marginal costs of 9.4% more than the unaffected firms in the control group (column 3). The inclusion of our battery of controls does not affect the positive impact of the shock on costs, with only excess temperature having an additional positive effect.

On the market dynamics side, columns (4)–(9) show that firms in affected provinces adjust both their markups and output prices due to both the increase in marginal costs and the changes in demand. Column (6) indicate that exposed firms adjust their markups due to the shock by 15% more relative to firms in provinces that were not exposed to the heavy rainfall episode in 2002–2003. This reduction reflects higher production costs but also market constraints that do not allow passing through higher costs to consumers. In consequence, exposed firms reduced their output prices by almost 6% more than firms in the control group (column 9).

Next, we estimate how heavy rainfalls affect firms' quantity and revenue productivity, using specification (3.B). Our findings in columns (1) to (3) of Table 2 show that firms in exposed provinces reduce their revenue productivity. Their TFP-R decreases on average by 7.5% relative to firms in the control group. The decrease in TFP-R is not due to a reduction in production efficiency, as shown in column (6) of Table 2. Quantity productivity is not affected by the shock. Rather the negative TFP-R impact is driven by changes in firms market position that result in reduced output prices. Our results are consequently an example where TFP-R does not reflect changes to production efficiency, illustrating why such results should be interpreted with caution as evidence of changes in output quantities firms produce with the same inputs.

5.2. Heterogeneous effects and their distributional implications

This section explores if firms of heterogeneous initial efficiency levels react differently to the climate shock in 2002–03. To test the unequal effect of the shock across firms, we split our sample into two groups of firms according to their initial level of TFP-Q in the pre-shock period. Firms with an initial TFP-Q level below (above) the median of the sample are classified as less (more) efficient firms. Then we run the same DID estimations as in Tables 1 and 2 for the two different subsamples of firms. Results for initially less and more efficient firms are reported in Table 3.

Our findings show that the heavy rains in 2002–03 only affected the production processes of the initially less efficient firms. The estimates in column 1 of Panel A suggest that initially less efficient firms located in more exposed provinces faced 2.8 % higher marginal costs relative to firms in the control group. Those firms also declined their efficiency measured as TFP-Q by 11% relative to the control group (column 2 of Panel A). By contrast, initially more efficient firms exposed to the shock did not see their marginal costs increase nor quantity productivity decrease (columns 1 and 2 of Panel B). These results indicate that the reduction of TFP-R observed across both groups (column 5 of Panels A and B) is due to the loss of efficiency gains for the initially less efficient firms but not for the initially more efficient firms.

Regarding differences in changes in firms' market conditions, the high increase of marginal costs induce the least efficient firms to reduce their markups by the same amount (column 3). They are, however, not in position to pass through increased costs to consumers by increasing output prices (column 4 of Panel A). By contrast, the initially more efficient firms reduce their output prices, presumably to optimize sales affected by a decline in market demand for their products (column 4 of Panel A). The output price decrease explains these firms' reduction in TFP-R of 6.8% relative to the control group rather than any changes to their production efficiency (column 3 of Panel B).

In view of these heterogeneous effects, we next investigate whether we see any cleansing effect of climate shocks to the advantage of more productive firms. The results presented in Table 4 indicate that the climate shock did not have a distributional impact on Ecuador's formal manufacturing industry. Initially less efficient firms located in provinces more exposed to the heavy rains decreased their market shares only by 0.5% relative to the control group (column 3). Entry rates in affected provinces fall initially by 1.5% and then increase by only 0.7%. There were no significant impacts of the climate shock on firm exit.[5] The low firm exit rate is likely to be an underestimate since our data comprise only formal manufacturing firms, which are group of more established Ecuadorian firms, while many Ecuadorian firms that are more vulnerable to shocks operate informally. Informal employment represented an estimated 82.4% of total employment for 2001–05 (ILO, 2023).

5.3. Heterogeneity using revenue productivity (TFP-R)

When we investigate the heterogeneous effects of the climate shock depending on initial firm performance in the previous sections, we rely on firm TFP-Q since it is a more accurate measure of firm productivity. The existent literature uses firm TFP-R or sales when looking at the differential effect of natural disasters on firms' outcomes. Relying on TFP-R instead of TFP-Q captures not only differences across firms on efficiency but also differences in market power.

This section provides an extension of the previous results by splitting the sample using initial firm productivity measured by TFP-R instead of firm efficiency (TFP-Q). The results are presented in Fig. 4. Our findings suggest that when we rely on TFP-R to measure the differences across the less productive firms, the negative impact of the shock on production (both marginal cost and TFP-Q) and markups is lower than when we rely on firm efficiency (TFP-Q). These findings suggest that firms with better market power were also in position to attenuate the effects of the shock. One reason could be that these firms with higher efficiency and markups had more resources to deal with the shock's production impacts. Interestingly, initially higher TFP-Q firms reduced their output prices more, resulting in higher markup reductions compared to initially higher TFP-Q firms.

5.4. Dynamic effects

This section investigates the effects of the shock in the immediate aftermath. Results shown in Table 5 indicate that the negative impacts of the supply shock identified in the previous estimations are short-lived. We find evidence of a quick recovery after the climate shock. The year after the shock, firms located in more affected provinces benefit from a decrease in marginal costs that allows them to raise their markups (column 1 and 2 of Panel A). The demand also recovers fast allowing them to lower prices (column 4 of Panel A) while still increasing markups. This recovery in terms of reduced marginal costs and higher markups is continued in the following year (columns 1 and 3 of Panel B).

Interestingly, the recovery in marginal costs and the associated reduction in prices is shared across all firms, independently of their initial productivity (columns 1 and 3 of Panels C and D). The reason for this homogeneous impact may be due to the removal of damages to transportation infrastructure and the restoration of access to electricity or water supplies, which all firms in affected areas depend on. These findings may also point to effective support mechanisms for all firms – such as insurance coverage – for repairs of damages caused by floods to their production.

6. Sensitivity tests and extensions

6.1. Sensitivity tests and assessing floods' effects

Next, we conduct several sensitivity tests that validate our findings by implementing falsification test that consists in setting the year of the shock to 2001 and an alternative measure to define our treatment. Annex A.2 describes these tests.

We also test for the role floods played in the impacts of the shock we identify. However, while excess of rainfall is a random natural phenomenon, unexpected and exogenous to firm performance (Rosales-Rueda, 2018; Pelli et al., 2023), floods resulting from excess rainfall can be endogenous to local land management and construction choices. To give an example, forests play a crucial role in mitigating

[5] A limitation of our data is that firms, if they shed employees and fall below 10 employees, would drop out of the dataset even if they had not exited.

Table 1
Average effects on marginal cost, markups and output prices.

Dependent variables:	Marginal cost			Markups			Output prices		
	Firm-product-level regressions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated (p) * 2002-03	0.071**	0.093***	0.094***	−0.134***	−0.145***	−0.154***	−0.063**	−0.051**	−0.059**
	(0.031)	(0.025)	(0.030)	(0.024)	(0.027)	(0.037)	(0.026)	(0.024)	(0.022)
Natural hazard indicators									
Excess temperature (p,t)		0.935***	0.927**		−0.647***	−0.673*		0.288	0.254
		(0.304)	(0.388)		(0.224)	(0.329)		(0.224)	(0.207)
Surface pollution (p,t)		0.018	0.008		−0.007	−0.004		0.011	0.005
		(0.022)	(0.019)		(0.012)	(0.012)		(0.014)	(0.013)
Province size control									
Size (p,t)		−0.267	−0.216		0.122	0.086		−0.145	−0.130
		(0.183)	(0.154)		(0.131)	(0.116)		(0.086)	(0.077)
Land management controls									
Construction value (p,t)			−0.114			0.081			−0.033
			(0.090)			(0.100)			(0.043)
Number of constructions (p,t)			0.032			−0.073			−0.041
			(0.119)			(0.105)			(0.051)
Firm-product-size trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-product fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
Year fixed effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Observations	35,280	35,280	35,280	35,280	35,280	35,280	35,280	35,280	35,280
R-squared	0.80	0.80	0.80	0.61	0.61	0.61	0.86	0.86	0.86

Table 2
Average effects on revenue and quantity productivity.

Dependent variables:	TFP-R			TFP-Q		
	Firm-level regressions					
	(1)	(2)	(3)	(4)	(5)	(6)
Treated (p) * 2002-03	−0.084***	−0.084***	−0.075***	−0.065**	−0.063	−0.062
	(0.015)	(0.016)	(0.021)	(0.024)	(0.039)	(0.049)
Natural hazard indicators						
Excess temperature (p,t)		−0.400*	−0.357*		0.053	0.113
		(0.190)	(0.177)		(0.331)	(0.382)
Surface pollution (p,t)		0.011	0.013*		−0.001	−0.000
		(0.008)	(0.007)		(0.012)	(0.011)
Province size control						
Size (p,t)		0.015	−0.023		−0.005	−0.047
		(0.023)	(0.028)		(0.065)	(0.061)
Land management controls						
Construction value (p,t)			−0.004			0.036
			(0.068)			(0.094)
Number of constructions (p,t)			0.068			0.043
			(0.062)			(0.092)
Firm-size trend	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,877	5,877	5,877	5,877	5,877	5,877
R-squared	0.84	0.85	0.86	0.83	0.85	0.85

floods by absorbing excess rainfall, stabilizing soil, and regulating water flow, thereby helping to minimize the risk of flooding in downstream areas.[6] Consequently, rather than relying on OLS estimates, reported in Panel A of Table 6, we apply an instrumental variable (IV) estimation model.

In the IV estimations, we use excess of rainfall as an exogenous instrument for floods that occurred during the 2002–03 period. We confirm the validity of our IV estimations as we identify a strong correlation between that endogenous variable and the instrument with an R-squared of 0.85–0.87 (depending on the outcome variable). Our specifications do not suffer from weak instrument problems, as reflected by the p-values for the Kleibergen-Paap under-identification test.

Results presented in Panel B of Table 6 show IV results confirm those obtained using an ordinary least squared specification. Firms located in provinces that experienced floods increase their marginal cost (column 1 of Panel B). We also see that floods result in reductions in output prices (column 4 of Panel B). The worsened production and market conditions consequently result in a reduction in markups (column 3 of Panel B). Revenue productivity is affected because of the changes in market conditions but not because of changes to production efficiency. In conclusion, the results indicate that floods contributed to the effects of excess rainfall we identified.

6.2. *Testing for the impacts of heavy rainfalls of the 1997–98 El Niño shock*

A question that applies to rigorous micro-econometric studies such as ours is whether the evidence is unique to the specific shock analyzed or whether it applies more generally, specifically as regards the unexplored market conditions as they have not been addressed in other works.

[6] We thank an anonymous referee for pointing us to this important influencing factor on the impacts of floods.

Table 3
Heterogeneous effects.

Dependent variables:	Marginal cost	TFP-Q	Markups	Output prices	TFP-R
	Firm-product-level reg.	Firm-level reg.	Firm-product-level reg.		Firm-level reg.
	(1)	(2)	(3)	(4)	(5)
Panel A: Initially less efficient firms (TFP-Q)					
Treated (p) * 2002-03	0.283**	−0.110***	−0.267***	0.029	−0.079**
	(0.114)	(0.037)	(0.090)	(0.028)	(0.032)
Observations	13,772	2,843	13,772	13,772	2,843
R-squared	0.77	0.73	0.59	0.87	0.84
Panel B: Initially more efficient firms (TFP-Q)					
Treated(p) * 2002-03	0.009	−0.051	−0.094**	−0.085**	−0.068*
	(0.051)	(0.039)	(0.041)	(0.033)	(0.035)
Observations	21,372	2,953	21,372	21,372	2,953
R-squared	0.82	0.79	0.56	0.86	0.78
Controls of both panels					
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes
Firm-product-size trend	Yes	No	Yes	Yes	No
Firm-size trend	No	Yes	No	No	Yes
Firm-product fixed effects	Yes	No	Yes	Yes	No
Firm fixed effects	No	Yes	No	No	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes

Table 4
Effects on market share, firm exit and entry.

Dependent variables:	Market share			Exit			Entry	
	Firm-level regressions							
	Full sample	High TFP-Q	Low TFP-Q	Full sample	High TFP-Q	Low TFP-Q	t+1	t+2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated (p) * 2002-03	0.000	0.003	−0.005*	−0.002	−0.001	−0.006	−0.015**	0.007*
	(0.002)	(0.003)	(0.003)	(0.009)	(0.023)	(0.016)	(0.007)	(0.004)
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-size trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,859	3,592	3,142	6,919	3,609	3,183	6,919	6,919
R-squared	0.92	0.93	0.94	0.36	0.38	0.40	0.27	0.25

Fortunately, we are in position to extend our analysis to investigate the 1997–98 El Niño shock, during which Ecuador's Meteorology Department recorded precipitations at more than 5 times the normal levels (ECLAC, 1998). Estimated losses of the 1997–98 episode amounted to USD 2.8 billion – which correspond to 13% of Ecuador's GDP in 1996 (ibid.). Annex section A.3 provides more information.

Since Ecuador's firm dataset only start in 1997, we use the following alternative estimation strategy for the 1997-98 shock to the DID we use in our main analysis for 2002–03:

$$lnX_{kijpt} = \alpha + \beta Excess\ Rainfall_{pt} + \sum \rho\ I_{pt} + \Pi_{\boldsymbol{pi}} FProdSize_{ki,t0} {}^{*}\eta_t + \pi_{ik} + \eta_{jt} + \varepsilon_{kijpt} \tag{5.A}$$

$$lnY_{ijpt} = \alpha + \gamma\ Excess\ Rainfall_{pt} + \sum \rho\ I_{pt} + \Pi_{\boldsymbol{pi}} FSize_{i,t0} {}^{*}\eta_t + \pi_{ik} + \eta_{jt} + \varepsilon_{ijpt} \tag{5.B}$$

where $Excess\ Rainfall_{pt}$ captures the difference in the observed precipitation for a given month m in a year y in province p and the long-term mean of precipitations in each month and province for the years 1950–2000.[7] The measure is the same we use to define treatment for our DID specification. It is obtained as described in section 4.2.[8] All other variables are as defined in our main specification described in section 4.2 and in Annex table A.1. As for all other specifications standard errors are clustered at province-year level.

The estimation framework allows for causal interpretation since the sudden onset of the El Niño shock in 1997–98 and its unexpectedly large intensity and long duration meant that Ecuador's population and public authorities were largely unprepared (Glantz, 2000). We validate the estimation approach by confirming checking the exogeneity of rainfall intensity to firm performance in the initial year (1997) [in the absence of pre-1997 data]. We also test for the parallel trends hypothesis by using satellite-based economic development data. Annex A.4 provides all validation tests.

Our findings for 1997-98 shown Table 7 point to the wider validity of our main findings obtained for 2002–03. We find that firms located in provinces with higher excess of rainfall relative to the historical mean during the 1997-98 shock experience an increase of marginal costs that lead to an adjustment of markups (columns 1 and 3 of Panel A). As was the case in 2002–03 we also observe a decrease of firm efficiency measured by TFP-Q. That is, in both heavy rainfall episodes production and market conditions are affected.

[7] We obtain our excess rainfall measure by averaging the indicator described in section 4.1 at the province-year level to match our annual firm-level data.

[8] We use the same measure to identify treatment and control group of our analysis (see section 4).

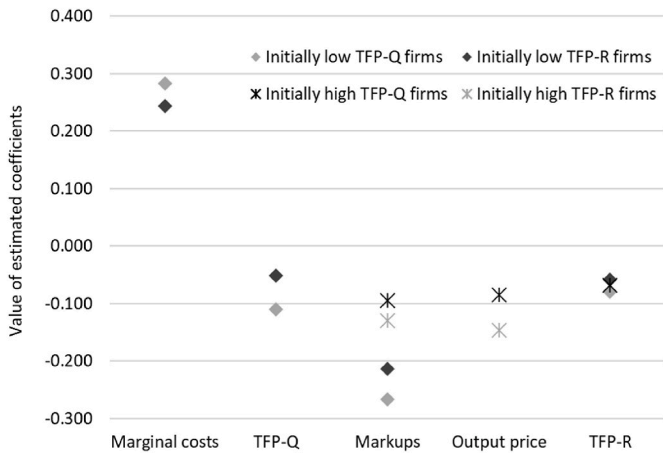

Fig. 4. Heterogeneous effect based on revenue vs quantity productivity.
Notes: Each marker indicates the estimated coefficient of equation (3.A) for marginal cost, markup and output price markers and (3.B) for TFP-Q and TFP-R. Statistically insignificant coefficients are omitted from the figure.

Furthermore, as in 2002–03, we observe heterogeneous impacts across firms of different production efficiency (TFP-Q). Affected initially less efficient firms experience an increase in marginal costs and a reduction in production efficiency (Panel B). Unreported results show no such significant effect on the initially most efficient firms. The main difference between the two heavy rain episodes is that in the 1997-98 shock firms do not adjust their output prices in view of this shock.

6.3. Shock propagation through value chain linkages

In this section we test whether downstream production linkages propagate the shock on firms by investigating impacts of both heavy rainfall episodes on domestic intermediate goods suppliers. We leverage the very detailed input product information to identify the universe of domestic input producers, which are those producing any of the 11-digit ISIC Rev.3 products Ecuador's firms report in the firm-input dataset.

Results presented in columns (1) to (4) of Table 8 show that domestic suppliers of inputs reduce the quantity of supplied of intermediate goods in both the 2002–03 and 1997-98 heavy rainfall periods (columns 1 and 2). These shortages of inputs lead to an increase of input prices (columns 3 and 4) that explain the increase of marginal costs faced by firms located in more exposed provinces to heavy rainfall episodes. This evidence points to the role of input-output linkages in propagating the climate shock. This finding echoes the evidence by Carvalho et al. (2021) on the role of supply chain linkages played in propagating and amplifying the production shock of the Great East Japan Earthquake of 2011. Input linkages were also the driving force of the Earthquake's impacts on Japanese affiliates in the United States (Boehm et al., 2019).

6.4. Impacts on manufacturing workers and their wages

Finally, we explore the effects of the shock on manufacturing firms' total employment and average wages, impacting market dynamics as demand is affected. Among previous works, Groen et al. (2020) used household data to study the effects of hurricanes Katrina and Rita on the US found important short-term earnings losses because of job loss.

Columns (5) to (8) of Table 8 present the results of these estimations for both heavy rain episodes. Our estimates show that firms' employment demand and wages are unaffected by these climate shocks,

Table 5
Dynamic effects.

Dependent variables:	Marginal cost	TFP-Q	Markups	Output prices	TFP-R
	Firm-product-level reg.	Firm-level reg.	Firm-product-level reg.		Firm-level reg.
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effects at t + 1					
Treated (p) * 2002–03 in t+1	−0.154***	0.017	0.055**	−0.099***	0.004
	(0.032)	(0.047)	(0.025)	(0.029)	(0.031)
Observations	35,247	5,240	35,247	35,247	5,240
R-squared	0.80	0.82	0.61	0.86	0.82
Panel B: Average effects at t + 2					
Treated (p) * 2002–03 in t+2	−0.203**	0.080	0.185**	−0.018	0.097**
	(0.094)	(0.066)	(0.065)	(0.055)	(0.040)
Observations	35,247	5,240	35,247	35,247	5,240
R-squared	0.80	0.81	0.61	0.86	0.82
Panel C: Initially less efficient firm effects at t + 1					
Treated(p) * 2002–03 in t+1	−0.163**	−0.038	0.048	−0.115***	−0.065**
	(0.058)	(0.067)	(0.046)	(0.036)	(0.028)
Observations	13,772	2,355	13,772	13,772	2,836
R-squared	0.77	0.78	0.59	0.87	0.85
Panel D: Initially more efficient firm effects at t + 1					
Treated(p) * 2002–03 in t+1	−0.151***	0.008	0.061*	−0.090**	0.065
	(0.037)	(0.043)	(0.035)	(0.035)	(0.046)
Observations	21,372	2,392	21,372	21,372	2,392
R-squared	0.82	0.83	0.56	0.86	0.79
Controls of panels A-D					
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes
Firm-product-size trend	Yes	No	Yes	Yes	No
Firm-size trend	No	Yes	No	No	Yes
Firm-product fixed effects	Yes	No	Yes	Yes	No
Firm fixed effects	No	Yes	No	No	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes

Table 6
Assessing the role of floods.

Dependent variables:	Marginal cost	TFP-Q	Markups	Output prices	TFP-R
	Firm-product-level reg.	Firm-level reg.	Firm-product-level reg.		Firm-level reg.
	(1)	(2)	(3)	(4)	(5)
Panel A: Ordinary least squares regressions					
Floods (p,t)	0.057**	−0.027	−0.115***	−0.063***	−0.046**
	(0.027)	(0.033)	(0.033)	(0.021)	(0.018)
Observations	35,254	5,240	35,254	35,254	5,877
R-squared	0.80	0.81	0.61	0.86	0.84
Panel B: Instrumental variable estimations					
Floods (p,t)	0.114**	−0.081	−0.185***	−0.071**	−0.096***
	(0.045)	(0.063)	(0.050)	(0.026)	(0.028)
R-squared of the first stage regression	0.87	0.85	0.87	0.87	0.85
Kleibergen LM statistic (under-identif. test)	0.07	0.08	0.07	0.07	0.08
Observations	35,254	5,240	35,254	35,254	5,877
Controls of both panels					
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes
Firm-product-size trend	Yes	No	Yes	Yes	No
Firm-size trend	No	Yes	No	No	Yes
Firm-product fixed effects	Yes	No	Yes	Yes	No
Firm fixed effects	No	Yes	No	No	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes

Table 7
Effects of the 1997–98 El Niño shock.

Dependent variables	Marginal cost	TFP-Q (i,t)	Markups	Output prices	TFP-R (i,t)
	Firm-product-level reg.	Firm-level reg.	Firm-product-level reg.		Firm-level reg.
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effects					
Excess rainfall (p,t)	0.143*	−0.184*	−0.136*	0.007	−0.076
	(0.078)	(0.105)	(0.078)	(0.043)	(0.055)
Observations	11,542	2,014	11,542	11,542	2,014
R-squared	0.85	0.93	0.68	0.89	0.90
Panel B: Effects on less efficient firms					
Excess rainfall (p,t)	0.772***	−0.333***	−0.726**	0.046	−0.042
	(0.269)	(0.113)	(0.291)	(0.078)	(0.248)
Observations	4,103	952	4,103	4,103	952
R-squared	0.77	0.89	0.61	0.87	0.90
Controls of both panels					
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes
Firm-product-size trend	Yes	No	Yes	Yes	No
Firm-size trend	No	Yes	No	No	Yes
Firm-product fixed effects	Yes	No	Yes	Yes	No
Firm fixed effects	No	Yes	No	No	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes

suggesting that the demand shock we identify is not driven by manufacturing employment or wage effects. This is not surprising since the manufacturing firms in our dataset are formal larger manufacturing firms, who offer the most protected and highest quality employment positions. As is the case in many developing countries Ecuador has, however, many informal workers. Informal employment represented an estimated 82.4% of total employment for 2001–05 (ILO, 2023). Employed mostly in services and smaller informal manufacturers, these workers were likely also much more exposed to the shock.

7. Conclusion

In conclusion, our study highlights the profound and complex impacts of a natural disaster - excess rainfall caused by the El Niño climate pattern - on both production and market conditions in a developing country. Interestingly, while less efficient firms face rising production cost and production efficiency losses, initially more efficient firms experience only adverse market conditions. The joint production and market shocks prompt reductions in firms' markups, a key firm-internal source for production investments. While firms show remarkable resilience exhibited in response to the natural disaster, the disruptive impacts to long-term development should not be underestimated, especially given the context of accelerated climate change, where such shocks are to occur with greater frequency. Future research exploring the broader implications of firms' responses to climate shocks on economic stability, social equity, and environmental sustainability is relevant to embedding industrial development in growth strategies that address climate-related risks.

From a methodological perspective, our study emphasizes the importance of considering both production and market condition changes when assessing the impacts of any treatment on firms, as both are frequently affected. In our analysis, interpreting negative impacts of our climate shock on revenue productivity as reflecting a reduction in production efficiency would have been wrong. The average effects on revenue productivity resulted from changes in firms' market conditions with marked declines in markups. Caution at the results interpretation

Table 8
Effects on input suppliers, manufacturing employment and wages.

Dependent variables:	Impacts on intermediate good suppliers				Manuf. employment and wage impacts			
	Domestic input quantity		Domestic input prices		Employment		Wages	
	Firm-product level regressions				Firm level regressions			
	2002–03	1997–98	2002–03	1997–98	2002–03	1997–98	2002–03	1997–98
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated (p) * 2002-03	−0.119**		0.038**		0.014		0.007	
	(0.047)		(0.016)		(0.024)		(0.019)	
Excess rainfall (p,t)		−0.305**		0.247***		−0.026		0.070
		(0.116)		(0.068)		(0.055)		(0.066)
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-product-size trend	Yes	Yes	Yes	Yes	No	No	No	No
Firm-size trend	No	No	No	No	Yes	Yes	Yes	Yes
Firm-product fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Firm fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,892	5,069	14,374	4,922	6,919	2,014	6,912	2,014
R-squared	0.82	0.83	0.84	0.88	0.95	0.99	0.95	0.98

stage will also be important based on standard firm data without information on firm output and input prices. The further development and use of alternative methods to account for changes in market conditions for standard firm data, notably markups, are important steps forward in understanding how firms are affected by shocks (see De Loecker and Warzynski, 2012).

CRediT authorship contribution statement

Maria Bas: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Caroline Paunov:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

Annex.

A.1. Variables and their definitions

Table A1

Variable	Description
Main specification	
Marginal cost (i,k,t)	The logarithm of firm-product (i,k) level marginal costs computed by dividing unit values (prices) by the estimated markups. See section 3.2 for detail.
Mark-ups (i,k,t)	The logarithm of firm-product (i,k) level markups computed relying on the methodology developed by De Loecker et al. (2016) as the deviation between output elasticity relative to variable input and input's share of total revenue. See section 3.2 for detail.
Output-product price (i,k,t)	The logarithm of firm-product (i,k) output prices computed as total value of a 11-digit product over the quantity (unit values). See section 3.2 for detail.
TFP-Q (i,t)	Productivity measure obtained following De Loecker et al. (2016) and the methodology outlined by Ackerberg et al. (2015) using total revenues and input expenditures deflated with firm price indices. See section 3.3 for detail.
TFP-R (i,t)	Productivity measure obtained following De Loecker et al. (2016) and the methodology outlined by Ackerberg et al. (2015) using total revenues and input expenditures deflated with industry level price indices. See section 3.3 for detail.
Treated (p)	An indicator variable equal to one for firms that were exposed to heavy rainfall in the period 2002–2003 (excess of rainfall relative to the historical mean higher the median).
Excess temperature (p,t)	Province year measure computed as the annual average of the ratio of the difference of the observed temperature in a given monty year related to the historical mean - average for 1950-2005- over the standard deviation of monthly temperature. Source: Goodman et al. (2019).
Surface pollution (p,t)	Surface pollution over area at the province year level is measured by yearly average monthly estimates of ground level fine particulate matter (PM2.5) produced by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model, and subsequently calibrating to global ground-based observations using a Geographically Weighted Regression (GWR). Source: Goodman et al. (2019).
Province size (p,t)	The logarithm of total number of workers at the province-year level.
Construction value (p,t)	Expenditures in the province-year of construction from Ecuador's annual survey of constructions.
Number of constructions (p,t)	The number of new constructions in the province-year from Ecuador's annual survey of constructions.
Other variables	
Market share (i,t)	Firm market share measured as total sales of firm (i) over total sales of the 3-digit industry in year t
Exit (i,t)	Firm exit dummy is an indicator variable equal to one if the firm(i) is no longer in the dataset in t+1.
Entry (i,t)	Firm entry dummy is an indicator variable equal to one if the firm(i) enters the dataset for the first time at t.
Excess rainfall (p,t)	Province year measure computed as the annual average of the ratio of the difference of the observed precipitation in a given monty year related to the historical mean - average for 1950-2005- over the standard deviation of monthly rainfalls. See Section 4.2 for detail.

(*continued on next page*)

Table A1 (*continued*)

Variable	Description
Domestic input quantity (i, k,t)	The logarithm of firm-product (ig) domestic (imported) input quantity is the quantity at the 11-digit input product produced in Ecuador (in a foreign country) over the quantity (unit values).
Domestic input prices (i,k, t)	The logarithm of firm-product (ik) domestic (imported) input prices which are computed as total value of a 11-digit input product produced in Ecuador (in a foreign country) over the quantity (unit values).

A.2. Additional sensitivity test

We present the results of a falsification test changing the year of the shock to 2001. If our previous estimates were capturing a trend in growth of firm-product level prices (marginal costs and markups) as well as TFP we should observe similar results when changing the year of the treatment to one year prior to the shock. Thereby we run the same estimations using 2001 as the year of the shock. Results presented in Panel A of Table A.2 show that there is no significant effect in any of our outcome variables when we change the year of the treatment. This falsification test is reassuring us that there were no different pre trends between firms located in affected provinces and those in provinces that were not affected by the heavy rainfall of 2002–03.

Moreover, we use just the deviation from the historical mean as an alternative measure of excess of rainfall to then define the treatment group (as firms located in provinces where the difference of rainfall relative to the historical mean is higher than the median). Results presented in Pane B of Table A.2 show that the results are similar to the previous ones and thereby, those results are robust to different measures of the index of excess of rainfall used to define the treatment and control group.

Table A.2
Falsification and alternative treatment test

Dependent variables:	Marginal cost	TFP-Q	Markups	Output prices	TFP-R
	Firm-product-level reg.	Firm-level reg.	Firm-product-level reg.		Firm-level reg.
	(1)	(2)	(3)	(4)	(5)
Panel A: Falsification test					
Treated (p) * 2001	0.103	0.015	−0.048	0.056	0.023
	(0.128)	(0.111)	(0.059)	(0.107)	(0.062)
Observations	35,247	5,240	35,247	35,247	5,877
R-squared	0.80	0.85	0.61	0.86	0.84
Panel B: Alternative treatment					
Alt.Treated (p) * 2002-03	0.099**	−0.044	−0.154***	−0.055*	−0.057**
	(0.039)	(0.051)	(0.044)	(0.026)	(0.024)
Observations	35,247	5,240	35,247	35,247	5,877
R-squared	0.80	0.85	0.61	0.86	0.84
Controls of both panels					
Natural hazard and land management indicators	Yes	Yes	Yes	Yes	Yes
Province size control	Yes	Yes	Yes	Yes	Yes
Firm-product-size trend	Yes	No	Yes	Yes	No
Firm-size trend	No	Yes	No	No	Yes
Firm-product fixed effects	Yes	No	Yes	Yes	No
Firm fixed effects	No	Yes	No	No	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes

A.3. Ecuador's 1997–98 El Niño shock

The 1997–98 El Niño disaster was one of the strongest in terms of magnitude and intensity compared to the previous El Niño climate events of the 20th century. Ecuador's population in affected areas was severely affected. More than 63,000 people were directly touched by major damages to their housing, access to water and electricity and road infrastructures (ECLAC, 1998). Worsened health conditions affected more than 20% of Ecuador's population as diseases such as dengue, malaria and cholera spread while health infrastructures were damaged (Vos et al., 1999). Moreover, by 1998, poverty had increased by as much as ten percentage points in affected areas (ibid.).

Additional critical damages affecting Ecuador's industry included destroyed agricultural and industrial production, transport infrastructure and labor supply due to displacements (Vos et al., 1999). Damages to roads and bridges affected one third of the country's transportation infrastructure, while months-long electricity and water supply disruptions caused an estimated 9.7 million USD (ECLAC, 1998).

A.4. Validation tests of specifications (5.A) and (5.B)

This section describes the validation tests for specifications (5.A) and (5.B) that measures the impacts of the 1997–98 El Niño shock on firm production and market dynamics. First, in the absence of pre-1997 data, we test whether key firm indicators in the initial year of the crisis differ depending on the 1997–2000 change in excess rainfall. Results shown in Panel A of Table A.4 shows there is no correlations for key indicators marginal cost, TFP-Q, markups, output prices and TFP-R, suggesting that the index of excess rainfall is exogenous to the performance of firms.

Second, to check for potentially divergent trends across treated and untreated firms in the absence of firm level data prior to 1997, we use district-year nightlight intensity data as proxies of district-level local GDP. The literature has highlighted that light intensity can be used as a proxy for economic development at the detailed regional level for developing countries when there is no other data available (Henderson et al., 2012; Donaldson and Storeygard, 2016; Pelli et al., 2023). With an F-value of 0.91 and a probability value of 0.34, we have no evidence to reject the notion that the trends are parallel among the groups being compared. Event study results plotted in Figure A.1 show statistically significant impacts on the treatment group of firms only arise as the shock hits.

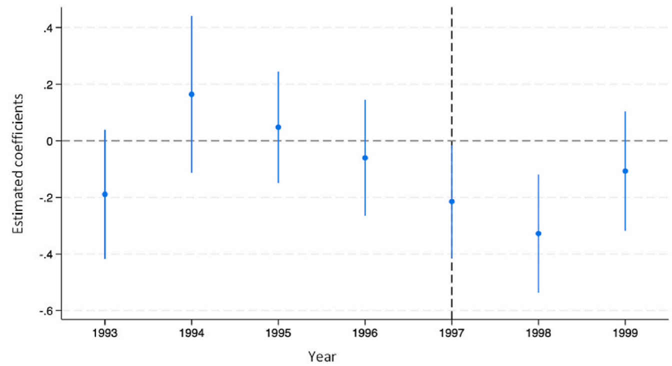

Fig. A.1. Event study results of treated districts' nightlight intensity.

Note: The figure plots the estimated coefficients of the respective γ corresponding to year t of the following equation: $lnY_{dt} = \alpha + \sum_t^4 \gamma^t Treated_d * Time_t + \pi_d + \eta_t + \varepsilon_{dt}$ where lnY_{dt} is light night intensity of distinct d at time t. Data on light night intensity by district level for Ecuador come from the US National Oceanic and Atmospheric Administration's National Geophysical Data Center provided by Goodman et al. (2019).

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