Total factor productivity, markup and the role of climate change

Abstract

We use a detailed establishment-level dataset from Canada to examine how climate shocks influence productivity and market power in the agri-food sector. We estimate firm-level total factor productivity and markups following the approach of De Loecker et al. (2016) combined with a two-step GMM-IV estimator that accounts for input optimization errors and unobserved cost shocks. Our results show that extreme temperature events reduce firm sales and productivity while raising marginal costs. A 10 percent decline in total factor productivity leads to an average 10.1 percent reduction in sales, a 3.3 percent increase in marginal costs, and only a 0.3 percent increase in output prices, resulting in a 1.6 percent contraction in markups. These findings suggest that agri-food firms absorb part of climate-induced cost shocks through lower markups rather than fully passing them to consumers. A vertically integrated two-sector model with a finite set of goods provides theoretical support for these mechanisms. By characterizing the distribution of markups under agricultural demand conditions, we show that large firms possess greater ability to maintain prices above marginal costs, underscoring the role of market structure in shaping resilience to climate risks. The results highlight important implications for competition, price stability, and climate adaptation policies in the agri-food industry.

JEL Classification: L11, D43, D24, F12, Q54

Keywords: Markups, Monopolistic Competition, Productivity, Firm Heterogeneity, Climate Change.

1. Introduction

Over the past few decades, the resilience of the agricultural sector has become increasingly vulnerable to physical climate risks. Adverse weather conditions associated with climate change — such as extreme heat, droughts, and irregular rainfall — have disrupted crop and livestock productions across many regions, leading to lower output (Burke et al., 2015a,b; Hsiang and Jina, 2014), higher input costs, and greater variability in productivity (Rojas-Downing et al., 2017; Nath, 2020). These challenges are further amplified by the interconnected nature of global food systems, where upstream disruptions in one region can reverberate through downstream supply chains.

Recent empirical studies have underscored the growing sensitivity of firm-level productivity to climate change (Burke et al., 2015a; Burke and Emerick, 2016; Deryugina and Hsiang, 2017; Caggese et al., 2024). Emerging evidence also suggests potential interactions between climate risks and industry dynamics such as market concentration (Pankratz and Schiller, 2024; Ponticelli et al., 2023; Conteduca and Panon, 2024). Yet, despite growing attention, the economic consequences of climate change for agrifood firms remain poorly understood and empirically inconclusive. For example, while Burke et al. (2015a) suggest that aggregate productivity might be unresponsive to climate shocks, Addoum et al. (2020) found no causal link between temperature variations and manufacturing firm performance. Conversely, other studies, for e.g., Zhang et al. (2023) show adverse effects on productivity and labor supply.

Only a limited number of studies explore how these climate-induced disruptions translate into changes in market power or pricing behavior. This is a critical gap, as firms may adjust markups in response to cost shocks, thereby affecting consumer prices and profitability (Conteduca and Panon, 2024). Additionally, prior work has documented significant heterogeneity in both productivity (De Loecker and Syverson, 2021; Cunningham et al., 2023) and markups (De Loecker et al., 2020; Gollin and Udry, 2021; Preonas, 2023) across firms and sectors, further motivating the need for firm-level analyses of climate impacts.

This paper contributes to the literature by providing new empirical evidence on how climate shocks affect both productivity and market power, using detailed firm-level data from the Canadian agrifood sector. We develop a framework that captures the interaction between climate-induced input demand shocks, productivity fluctuations, and markup adjustments. Specifically, we aim to: (i) assess how climate shocks influence productivity and markups through their effect on input use, and (ii) estimate firms' downside risk exposure to such shocks.

The analysis unfolds in two stages. First, we build on the production function approach of De Loecker et al. (2016) to estimate firm-level markups and productivity, incorporating climate shocks. We introduce a simple model of cost-minimizing firms with market power in both input and output markets. Following De Loecker et al. (2016) and Dobbelaere and Kiyota (2018), we link markup estimates to input cost shares and output elasticities. This framework allows us to assess how climate shocks shape the dispersion of productivity and market power across firms.

The remainder of the paper is structured as follows. Section 2 offers a brief review of the literature on the sources of productivity dispersion. Section 3 provides a quantitative illustration of recent trends in markup and cost distribution, highlighting the potential role of climate shocks in driving these fluctuations. Section 4 outlines the theoretical framework that underpins the study. Section 5 describes the empirical framework, along with the tools and techniques employed in the analysis. Section 6 discusses the data sources. The following section thoroughly discusses the findings and their welfare implications, while the final section summarizes the main results and highlights how they contribute to the emerging literature on the incidence of climate change on the performance and behavior of agribusiness firms.

2. Evidence-based literature

While there is abundant empirical evidence in the literature regarding the influence of climate change on overall firm output and total factor productivity, there is a noticeable scarcity of research specifically addressing the effect of climate change on productivity dispersion. A central inquiry in the micro-level productivity studies concerns unraveling the reasons behind the substantial productivity variations among firms, even within narrowly defined industries (Cunningham et al., 2023). The notion of productivity dispersion was popularized by the first empirical findings suggesting that factors influencing productivity differ across industries and firms (Keynes, 1937; Lucas Jr, 1975; Mortensen, 2005). Okun (1962) found a higher elasticity of variable inputs for the US economy, in opposition to the standard assumption about the neoclassical production function, which posits that the elasticity of variable inputs is constant and less than 1 for manufacturing firms. Since then, productivity dispersion has become a real phenomenon. Okun and Mortensen both recognized that an economy is not in a neoclassical equilibrium with the marginal products of labor equal across firms and sectors. One of the reasons for this is that the relative demand and productive efficiency of individual firms are continually shocked by events (Mortensen, 2005). Some shocks result from changes in tastes, changes in regulations, and/or changes induced by globalization, among other factors, that might affect productivity in the same way for all firms in the same industry. Other shocks are specific to firms such as equipment failures, employee absenteeism, or labor conflicts, resulting in deviations from anticipated performance.

Early research on productivity dispersion has shown that marginal product dispersion varies across sectors and geographic areas, and over time, due to product substitutability, market structure and competition (Syverson, 2004), dynamic adjustment of inputs within sectors (Asker et al., 2014), or even firm efficiency level on the supply side (Syverson, 2011) or demand shocks (Aoyama et al., 2009). The supply and demand side explanations are often interrelated. A study by Bloom and Van Reenen (2007) finds that intense competition in a firm's market is positively correlated with firm efficiency. For instance, where there are barriers to competition or where products in a market are not easily substitutable, less-productive firms are able to survive and grow (Syverson, 2011).

Aoyama et al. (2009) investigated productivity distribution within and across industries. They identified a Pareto[1] distribution pattern for productivity, with the shape parameter assumed to decrease due to a significant shift in sectoral demand, induced by changes in the external environment, such as variations in temperature. However, they did not establish a link between climate change and productivity dispersion due to data limitation. Instead, they draw on the early work of Gabaix (2011) and a superstatistics framework[2] to demonstrate that higher fluctuation in demand are associated with a skewed distribution of productivity, and vice versa. In simpler terms, they show that, in some cases, productivity dispersion is locally skewed toward the high productivity segments of the economy. This outcome is a common result in statistical physics theory, where conditions related to weather shocks (such as temperature) lead to variations in demand and productivity dispersion. This significant result is also reported by Iyetomi (2012), who showed that an input demand fluctuation due to a change in temperature is associated with productivity dispersion. Iyetomi (2012) argue that non-manufacturing firms face a much larger gap between the desired and actual input quantities, compared with manufacturing

[1]Trade models often use the Pareto distribution to account for differences in productivity across firms to explain so few firms export, but productivity differences are unexplained

[2]Fluctuations induced by climate change may be successfully explained by the Superstatistics framework (Aoyama et al., 2009, 2010) in which the aggregate demand of firms and industries varies because of a changing environment

firms, and that both sectors are always in equilibrium with respect to the demands for inputs. Thus, the input market adjusts through a contraction in the total supply of inputs. Inputs are reallocated both across sectors and among firms within each sector, resulting in an equilibrium characterized by heterogeneous degrees of input rationing across firms and sectors. While the theoretical implications of climate change on input demands have been thoroughly developed with superstatistics theory, some of the results have yet to be validated by empirical evidence.

Several recent papers have empirically investigated the sources of productivity dispersion in the manufacturing sector at the firm level, without considering climate variables. Even though little is known about why firms have different marginal products for key inputs, there is an extensive literature on the decomposition of total factor productivity as the product of different efficiency measures, including allocative efficiencies and resource misallocations (Gorodnichenko et al., 2018). For example, Nishida et al. (2016), Haltiwanger et al. (2018), White et al. (2018), and Bils et al. (2020) all cite resource misallocation as a source of dispersion in productivity. The consequence of firm-level misallocation of resources for aggregate economic outcomes is based on the insight that if there is dispersion across firms, the economy may achieve considerable productivity gains by reallocating capital from firms with low marginal revenue product of capital (MRPK) to firms with high marginal revenue product (Hsieh and Klenow, 2009; Gorodnichenko et al., 2018). Productivity dispersion may also be attributed to sampling and measurement issues. For instance, within narrowly defined industries, the existence of various subcategories of products can make comparisons challenging, mostly in middle- and low-income countries (Gollin and Udry, 2021; Maue et al., 2020). However, Syverson (2011) and Foster et al. (2016) point out that inconclusive empirical evidence of productivity dispersion might indicate distortion or variation in demand shocks, rather than measurement error or misallocation of resources.

A challenge in the productivity dispersion literature is to measure the individual effects of input misallocation, technology shocks, measurement error, and adjustment costs of various kinds. To examine the extent to which productivity dispersion is related to firm characteristics other than resource misallocation, most of the studies incorporate firm characteristics as controls. For instance, Gorodnichenko et al. (2018) perform a Machado-Mata decomposition to construct counterfactual distributions of MRPK and Marginal revenue product of labor (MRPL) for each EU country, using a panel country-year dataset under the assumption that the regression coefficients are estimated from another country. They find that the association between marginal products and firm characteristics is predominantly driven by variables measuring firm demographics, quality of inputs, utilization of resources, and dynamic input adjustments. They document that the cross-country variation in the within-country dispersion of marginal revenue products is largely brought about by differences in firm-level characteristics such as country's business, institutional and policy environment "prices", rather than by differences in the firms' endowments of fixed inputs.

Maue et al. (2020) apply a standard regression-based approach to measure productivity residuals among agricultural firms in four Sub-Saharan African countries (Tanzania, Uganda, Nigeria, and Ethiopia). They isolate productivity that may depend on local factors such as climate, weather and soil characteristics, and find that half of productivity dispersion comes from measurement errors in input and output quantities, questioning the relative importance of potential resource misallocation and heterogeneity in technology and technical efficiency (including production shocks).

Gollin and Udry (2021) investigate the link between the volatility in productivity, resource misallocation, mismeasurement, and heterogeneity with a farming model with heterogeneous land, in which farmers select plots, allocate inputs to individual plots, and subsequently produce output. Through the lens of their model, they find that production shocks, measurement error, and input quality together account for a large fraction (70%) of the variance in measured productivity. However, they did not measure separate effects for each component. Caggese et al. (2024) used data about Italian firms in a general equilibrium structural framework to separate the effects of temperature on firm-level demand, productivity, and input allocative efficiency in their analysis of aggregate productivity losses induced by climate change. They identified a nonlinear relationship between climate change and aggregate productivity, but they did not investigate the impact of climate change on markup dispersion. Given the identified effects of climate change on firm productivity, how does this translate into variations in firm markup?

The mechanism and extent by which climate shocks induce markup adjustments remain grey areas in the literature. The response of markup depends on the nature of the shocks, whether on the supply side or on the demand side. Manufacturing firms can increase markup if extreme weather events lead to higher costs for producers. On the other hand, firms increase their markup holding input prices constant if the price elasticity of demand they face rises. Markup dispersion may also be affected by how we define market. Better dispersion of markup is achieved at higher levels of disaggregation of sales shares, and many studies estimate markups using firm-level datasets.

In this paper, we provide a simple framework to formalize the systematic evidence supporting the effect of climate shocks on productivity and markup dispersion among firms. For instance, productivity and markup dispersions have been found to have similar evolutions in the literature according to Edmond et al. (2023), with more productive firms dominating product market shares in their industries. Campbell et al. (2019) indicate that the decreasing dispersion observed in Australian manufacturing may be due to a lessening of market concentration. However, they find a relatively low market concentration in these industries and no link to productivity dispersion. In a world where a handful of firms control the market, it is important to understand how changes in productivity translate into markup adjustments. We argue that climate shocks negatively affect productivity and markup across agrifood firms.

Our study differs from previous ones in four meaningful ways. First, we identify and estimate production functions using the two-step GMM-IV[3] estimator of Hu et al. (2020), which addresses optimization errors in firms' input choice, unobserved idiosyncratic cost shocks, and measurement errors in proxy variables. Second, we identify variations in productivity caused by climate risks while controlling for demand-side risks that vary by location. Our framework account for iid measurement errors across observations and exploits moment measures of productivity. The method has been widely used in the context of risk management in agriculture (Just and Pope, 1979; Kim and Chavas, 2003; Chavas and Di Falco, 2012). We estimate markup and productivity using material as an instrumental variable, which lets us identify the elasticity of variable inputs for individual firms. By combining tools from the input-output literature, we estimate two equations in an over-identified setting, which imposes more structure on the empirical analysis relative to other papers. Third, we connect to the literature about markups and resource misallocation by measuring the relative dispersion of total factor productivity and markup (Maue et al., 2020; Gollin and Udry, 2021; Gouin-Bonenfant, 2022). Lastly, we assess the degree of production uncertainty when input decisions are made before output prices are known by specifying and estimating cost-minimizing input choices. Our framework is reliable and does not depend on the risk preferences of the firm (Chavas, 2008b; Serra et al., 2014; Chambers et al., 2015).

[3] As described in Hu et al. (2023), a generalized method of moments (GMM) is applied and changes in the material input is used as a proxy for unobservable productivity shocks(Hu et al., 2020; Gupta, 2020). In the first step, we use the proxy variable to control for unobserved productivity shocks. In the second step, a generalized method of moments (GMM) specification is applied with moment conditions that exploit lag inputs as instruments while assuming that the measurement errors in the inputs are independent across time.

3. Micro-evidence

We define the markup as the ratio of price to marginal cost, with each component reflecting how firms adjust their markup to climate shocks. We start with a preliminary analysis of the behavior of markups in the Canadian economy[4] from 2000 to 2022. Let the logarithm of the economy-wide markup in year t ($\log \mu_t$) be given by the weighted average log-markup of all firms at time t:

$$\log \mu_t = \sum_i \omega_{it} \log \mu_{it}, \tag{1}$$

where $\mu_{i,t} = \frac{p_{it}}{C_{it}}$ is the ratio of price over marginal cost for each individual firm i. We derive markup at the firm level using nationally representative census data on Canadian agri-food firms from Statistics Canada. Figure (1) depicts the average markup and average marginal cost across firms[5]. The trend in the markup can be grouped in two phases over the period under consideration. In the first phase, the average markup decreased from approximately 1.66 in 2000 to 1.59 in 2008 (i.e. a reduction of 7%). The last phase saw a significant rise in markup from 1.59 in 2008 to 1.68 in 2022 (i.e. an increase of 9%). To identify a potential driver of this increase, we also present the trend in marginal costs in fig.(1). The figure shows that whenever markups decline, marginal costs rise, and vice versa, indicating that the recent surge in markups may be attributed to decreasing marginal costs. Agricultural commodity prices were high during the so-called 2008 food crisis. This explains the jump in marginal cost and possibly the drop in the average markup which was probably impacted also by the 2009 world-wide recession.

[INSERT Figure 1 ABOUT HERE]

According to the Input-Output literature, the responsiveness of to climate shocks markups may depend on firm size and the expenditure shares in material inputs (Koppenberg and Hirsch, 2022; Edmond et al., 2023). Climate shocks can affect markup through the reallocation of market shares across firms. Some firms may experience an increase in their marginal costs and make downward markup adjustments to tamper the loss in market share. Figure (2) shows that material input expenditure shares are high in the Canadian agri-food sector, with smaller firms reporting a higher share of material input costs compared to larger firms.

[INSERT Figure 2 ABOUT HERE]

[4] By "Canadian economy", we refer specifically to agri-food firms operating in Canada, as captured in the National Accounts Longitudinal Microdata File (NALMF). This database is based on a representative census survey conducted by Statistics Canada, providing firm-level data across industries.

[5] We proxy marginal costs using the ratio of total expenditure in intermediate inputs to physical output. A higher ratio at constant input prices implies greater input use per unit produced —for example, if more milk is needed to produce a liter of yogurt, marginal costs increases.

Table (1) also reports the distribution of markup between agri-food firms. In addition, and interestingly, the distribution in markup is uneven within most of the industries. In all industries, the weighted average log-markup exceeds unity with a higher average value of 1.82 in the animal food manufacturing sector. The dispersion in markup is also large: the 90-10 ratio is 4.76 while the 75-25 ratio is 2.07. These statistics about the empirical distribution of markups raise many questions about market structure and competition in the Canadian agrifood industry. For example, grain and oilseed milling sector exhibits higher variation in markup than the livestock processing sector.

[INSERT Table 1 ABOUT HERE]

Food industries tend to be highly material-intensive but require relatively low capital. Climate shocks (e.g., droughts, floods, extreme temperatures) can disrupt the supply of raw materials, particularly in agriculture and energy-intensive industries, which may incentivize larger firms to adjust their markup.

In the next section, we discuss some of the linkages between climate shocks, productivity, and the adjustments of markups. We draw from a strand of the literature that has theoretically analyzed the welfare cost of markups (Feenstra and Weinstein, 2017; Döpper et al., 2022; Edmond et al., 2023; Santos et al., 2022), and by doing so, we explain why the relationship between climate shocks, productivity and markup is of particular interest for policy analysis.

4. Theoretical foundation

We present a framework to study the effect of climate variability on productivity and markup dispersion, in the tradition of heterogeneous firms models (Bloom et al. (2018); Jaimovich et al. (2023)). Firm optimization is challenging in the agrifood industry context as both upstream and downstream markets must be considered simultaneously. Policies or shocks altering upstream markets may have important implications for the competitiveness of firms downstream. This argument is not new. Bonroy et al. (2007) use a two-stage game between producers and marketers, incorporating production and marketing lags to describe the dynamic nature of most agrifood chains in which production/marketing lags exist. A negative supply shock in the upstream market has the potential to alter the set of goods available to final consumers, coupled with a shift in the aggregate output price (Guerrieri et al., 2022). As a result, climate change can impact productivity and markups through different channels along supply chains.

To motivate our empirical analysis, we present a vertically integrated model with two-sector markets linked through price and quantity in line with the study by Melitz (2003), but with a discrete number of goods, as in Krugman (1980). Our theoretical model is similar to that of Hsieh and Klenow (2009), and establishes a link between the production of a primary good and its processing. In the primary sector (sector ℓ), all firms produce the same unique primary good (e.g. pork, live cattle, poultry) under perfect competition and the same constant returns to scale technology. Processing firms, while behaving as a monopoly, must source a unit of the primary product upstream in order to produce.

We also establish a link between climate shocks and productivity. The overall supply chain is facing climate induced shocks that create productivity and markup dispersion. We assume that input quantities are chosen before consumer demand is known with certainty (Chavas, 2004; Chavas et al., 2022). We also assume that there is input waste which creates a wedge between the quantity of input purchased and the quantity of usable input. Risks factors affecting the output of firms are random variables emanating from *(i)* input demand which we denote by $\theta_1(.)$ and *(ii)* consumer demand for the final output, which we denote by $\theta_2(.)$ – θ being a transformation function of climate variables. $\theta_1(.)$ is a function tied to farmers' productivity, whereas $\theta_2(.)$ influences consumer demand for the final output of firms.

4.1. The representative farmer

As in Gollin and Udry (2021), we make the simple assumption that the production process in the upstream industry employs a set of variable inputs that adjust to the state of the world denoted by s. The state of the world is random and distributed according to a vector $\Delta(s)$ over a support S. Productivity depends on a climate shock, which we denote by $\theta_1(T_{s(\ell)})$. $\theta_1(T_{s(\ell)})$ is embedded in the production process of the upstream industry, and is modeled flexibly to allow for a possible nonlinear relationship between climate and productivity. $T_{s(\ell)}$ indicates climate occurrences, and $s\,(\ell)$ means that climate varies from one farmer to another. We assume that $\theta_1(.)$ is random with a given probability distribution, unknown to farmers at the time of input decisions, and reflects production risk and uncertainty (Chavas, 2004). The representative farmer uses a Leontief production function nesting a Cobb-Douglas input aggregator that combines a raw input M_ℓ and other inputs $X_{\ell,h},\ h \in \mathcal{H}$ such that:

$$g_\ell\,(s) = A_\ell\big(\theta_1(T_{s(\ell)})\big)\ \min\left(\alpha_0\ M_\ell^{\alpha_\ell}\ ,\ \prod_h \big(X_{\ell,h}^{\alpha_{\ell,h}}, h \in \mathcal{H}\big)\right),\ \alpha_0, \alpha_\ell, \alpha_{\ell,h} > 0, \forall h, \qquad (2)$$

where $g_\ell(s)$ is the output produced by farmers under random climate, $A_\ell\left(\theta_1(T_{s(\ell)})\right)$ denotes farmers' productivity, which depends on the random shock $\theta_1(.)$, M_ℓ is the raw input[6], $X_{\ell,h},\ h \in \mathcal{H}$ indicates other inputs and $\alpha_0,\ \alpha_\ell,\ \alpha_{\ell,h}\ > 0$ are constant terms quantifying input variations and their relative importance in production.

$\theta_1(.)$ is a measure of production risk. Gollin and Udry (2021) introduced a similar shock that depends on location and the state of the climate, but in the context of farmers holding a fixed endowment of land. Our assumption is similar to new climate-economy models that imply a shock through which climate change may affect productivity growth but also technological progress (Dietz and Stern, 2015; Letta and Tol, 2019). Here, the climate-induced shock $\theta_1(.)$ is part of the representative farmer productivity. Productivity is a scalar and Hicks-neutral, which implies that inputs are used in the same proportion before and after the shock, with all else, such as input and output prices, held constant. The effect of the representative farmer's input is given by the corresponding output elasticity α_ℓ, keeping all other inputs fixed. The absence of substitution between inputs allows the output per unit input, or total factor productivity, to be expressed as: $\frac{g_\ell}{\alpha_0\ M_\ell^{\alpha_\ell}} = \frac{g_\ell}{\prod_h X_{\ell,h}^{\alpha_{\ell,h}}} = A_\ell\left(\theta_1(T_{s(\ell)})\right),\ \forall h$. With the assumption of constant returns to scale (CRS) and that farmers need one unit of input to produce $A_\ell\left(\theta_1(T_{s(\ell)})\right)$ units of output, the cost of production for a unit of input M can be expressed as (refer to proof in Appendix 1.A and Appendix 1.B):

$$\mathcal{C}(g_\ell, \theta_1) = P_\ell^M + \left(\frac{g_\ell}{A_\ell(.)}\right)^{\frac{\alpha_\ell - 1}{\alpha_\ell}} \left(\frac{1}{\alpha_0}\right)^{\frac{1}{\alpha_\ell}} \prod_h \left(\frac{p_{\ell,h}}{\alpha_{\ell,h}}\right)^{\alpha_{\ell,h}} \quad , \forall h \in \mathcal{H} \tag{3}$$

Farmers profits are therefore given by:

$$\pi_\ell\,(s) = \ p_\ell * g_\ell - \mathcal{C}(g_\ell, \theta_1) \quad , \tag{4}$$

with $\mathcal{C}(g_\ell, \theta_1)$ being a function that varies with productivity, and thus with θ_1. Farmers are price takers under uncertainty, which implies that:

$$E\left(p_\ell(.)\right) = \ E\left(\frac{g_\ell}{\mathcal{C}\,(.)} \middle|\ \theta_1(.)\right) \tag{5}$$

[6]Material inputs tend to play a more prominent role in the production technology of downstream processing firms than in farm-level activities. At the farm level, labor is likely the primary input margin of adjustment when productivity fluctuates, given that harvesting operations are often labor-intensive and manually executed. However, the underlying mechanism remains consistent for farmers, as higher yields typically require greater use of complementary material inputs, such as baskets, containers or other harvesting equipments

4.2. The representative processor

Each processor produces a single variety of a final product, while behaving as a monopoly. The relationship between a firm's i inputs and output in sector k is expressed with a Leontief technology as:

$$q_{i,k}\,(s) = A_{i,k}\ \min\left(\alpha_{0,k}\ g_{i,\ell}^{\alpha_k}\ ,\ \prod_h \left(X_{k,h}^{\alpha_{k,h}}, h \in \mathcal{H}\right)\right) ; \alpha_{0,k},\ \alpha_k,\ \alpha_{i,k,h} > 0,\ \forall h\ , \tag{6}$$

where $q_{i,k}$ is the final output, $0 < \alpha_{0,k}\ ,\ \alpha_k < 1$ are constant terms, $g_{i,\ell}\,(s)$ captures the primary good produced by farmers used in the production of the final output, $X_{i,k,h},\ h \in \mathcal{H}$ indicates other inputs (labor, capital equipments, energy, and packaging materials, etc.) used in the production process. In equation (6), productivity is also hicks-neutral, i denotes the firm operating downstream, α_k the output elasticity of input that measures how changes in the quantity of input affect the level of output for firms, and $A_{i,k}$ indicates the firm-level productivity. Given the Leontief-in-primary good structure of production, cost minimizing firms produce at a "corner" of the isoquant where: $\frac{q_{i,k}}{\alpha_{0,k}\ g_{i,\ell}^{\alpha_k}} = \frac{q_{i,k}}{\prod_h X_{i,k,h}^{\alpha_{k,h}}} = A_{i,k},\ \forall h$.
We denote by $\theta_2(T_{s(\ell)})$ the second disturbance term affecting the demand faced by each firm. We also assume that $\theta_2(.)$ exhibits a nonlinear response between climate change and consumer demand. As in Hsieh and Klenow (2009), the aggregate output in sector k is a CES aggregator of differentiated products $q_{i,k}\,(s)$:

$$Q_k = \left[\sum_{i,s} \omega_i^{\frac{1}{\sigma}}\ \left(\theta_2(T_{s(\ell)})\ q_{i,k}\,(s)\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{7}$$

Here, Q_k is the aggregate output[7] by all processors in sector k, $\sigma > 1$ is the elasticity of substitution between varieties, $q_{i,k}(s)$ is the demand for variety, and ω_i the aggregation weight such that $\sum_{i,s} \omega_i = 1$, with $\omega_i > 0$. The demand function for an individual variety faced by each firm is of the form :

$$q_{i,k} = \omega_i\ \left(\theta_2(T_{s(\ell)})\right)^{\sigma-1} \left(\frac{p_{i,k}}{P_k}\right)^{-\sigma} (\rho_k Q_k), \tag{8}$$

with P_k the price of the aggregate output, $p_{i,k}$ the price of each variety, ρ_k the share of spending on intermediate goods relative to total income. The demand for a given variety may be affected by climatic conditions that influence perceived quality and reliability of supply. Accordingly, θ_2

[7] The model relies on an aggregation function instead of a utility function in order to capture the effects of climate on aggregate output.

captures consumers' valuation adjustments arising from factors such as storage losses or transport disruptions.

The firm's problem

In formal input-output models, firm decisions are frequently depicted using a dual profit or cost function approach, each uniquely representing the underlying technology. The assumption of profit maximization implies that firms adjust their inputs to produce the quantity that maximizes profit at the lowest possible cost. In doing so, they also adjust their level of output accordingly. Cost minimization assumes that inputs are chosen optimally to produce a given output quantity (or given quantities) considering exogenous input prices. The Leontief production function dictates that the primary product is used in fixed proportion with output, but the proportion varies with the scale of production. The processing firm knows all input prices when purchasing its inputs, and only demand is uncertain. Cost minimization implies:

$$[\mathcal{C}_{i,k}] = \min_{g,X} \left(p_{i,\ell}\,(s)\;\; g_{i,\ell}\,(s)\;\; + \sum_{h} p_{i,k,h}\;\; X_{i,k,h}\;\left|\theta_1(.)\right. \right) \tag{9}$$

Note that production costs act as a channel for the risk associated to the shock $\theta_1(.)$ through equations (2) and (5). Each firm encounters risk arising from input demand. Assuming allocative efficiency, the Lagrange function associated with the firm's (conditional) cost minimization is:

$$\mathcal{L} = \;\; p_{i,\ell}\,(s)\;\; g_{i,\ell} + \sum_{h} p_{i,k,h}\;\; X_{i,k,h}\,(s) \mid \theta_1(.) - \lambda_i \left(\; q_{i,k}\,(.) - \overline{q}_{i,k}\right), \tag{10}$$

Under monopolistic competition, each firm behaves as a monopoly in the market of variety of the good produced. The Lagrange multiplier λ_i is therefore a direct measure of the marginal cost (De Loecker et al., 2020), and cost minimization from firms imply:

$$p_{i,\ell}\,(s) - \;\; \lambda_i \frac{\partial\; q_{i,k}\;(s)}{\partial\; g_{i,\ell}\,(s)} = 0 \tag{11}$$

Multiplying all terms by $\frac{g_{i,\ell}(s)}{q_{i,k}\;(.)}$ and rearranging yields an expression of the revenue elasticity of inputs α_k that depends on the firm-level markup $\mu_{i,k}$, and the revenue share of variable inputs:

$$\alpha_k = \frac{\partial\ q_{i,k}}{\partial\ g_{i,\ell}\,(s)} * \frac{g_{i,\ell}\,(s)}{q_{i,k}} \tag{12}$$

$$= \frac{p_{i,k}}{\lambda_i} * \frac{p_{i,\ell}\ g_{i,\ell}}{p_{i,k}\ q_{i,k}} \tag{13}$$

$$= \mu_{i,k} *\ \overline{s}_{i,k}, \tag{14}$$

Where $\mu_{i,k}$ denotes the markup at the firm level, $\overline{s}_{i,k}$ the share of variable input relative to the total revenue under uncertainty, and $p_{i,\ell}$ is the price of the variable input. All variation in input share is due to variations in markups. Equation (14) indicates that one can retrieve markup estimates at the firm level knowing the revenue share of variable input and the output elasticity of inputs, both at the firm level. In a Leontief specification, variations in markups arise not only from changes in input share but also from changes in the revenue elasticity of inputs α_k. As in equation (3), production costs when using a unit of input can be written as:

$$\mathcal{C}(q_{ik}, \theta_1) = p_{i,\ell} + \left(\frac{q_{i,k}}{A_{i,k}}\right)^{\frac{\alpha_k - 1}{\alpha_k}} \left(\frac{1}{\alpha_{0,k}}\right)^{\frac{1}{\alpha_k}} \prod_h \left(\frac{p_{i,k,h}}{\alpha_{k,h}}\right)^{\alpha_{k,h}} \quad, \forall h \tag{15}$$

In addition, the processor aims to maximize its profits while considering its production costs. As a result, the firm's profit when producing $A_{i,k}$ unit of output is given by:

$$\pi_{i,k} = p_{i,k}\ A_{i,k} - \mathcal{C}(q_{ik}, \theta_1) \tag{16}$$

Optimal sales can be achieved at the firm-level by knowing the realized outcomes of the supply shock $\theta_1(.)$. The firm's problem implies making decisions to maximize the value of the sales while facing uncertainty about the values of the intermediate inputs and about the sales of the goods that they produce. Under allocative efficiency, profit maximization implies that:

$$p_{i,k} * A_{ik} = \quad \mu_{i,k} *\ \mathcal{C}(q_{ik}, \theta_1) \tag{17}$$

Combining equations (5), (8), (15) and (17), we can write an expression for sales as:

$$p_{i,k}q_{i,k} = \ \omega_i\ \mathcal{C}(q_{ik}, \theta_1)^{1-\sigma}\ \theta_2(T_{s(\ell)})^{\sigma-1}\ A_{i,k}^{\sigma-1}\mu_{i,k}^{1-\sigma}\rho_k P_k^{\sigma} Q_k \tag{18}$$

Equation (18) indicates a relationship between firm sales and climate shocks. Two key risks can affect firm sales: input-related risk leading to a supply shock $\theta_1(.)$ and demand-side risk affecting consumer preferences $\theta_2(.)$.

4.3. Equilibrium

The equilibrium consists of input and output prices $p_{i,\ell}(s)$ and $p_{i,k}(s)$, such that the representative producer, the representative transformer, and the consumer of the final good are all optimizing. The equilibrium is established by aligning the supply in the primary sector with the demand in the processing sector $S_\ell\left(\,(p_\ell)\right) = D_k\left((p_\ell)\right)$. In addition, the price of the final good must be equal to the inverse demand at the firm level $p_{i,k} = f(q_{i,k}(s))$, where f denotes the inverse demand function.

— ***Implications of the model on sales***

From the model, climate shocks $\theta_1(T_{s,\ell})$ on input demand translate into a price shock p_ℓ. We derive the marginal effect of climate change on firm sales by taking the logarithm of equation (18):

$$\frac{\partial \log\ (p_{i,k}q_{i,k})}{\partial\ T_{s(\ell)}} = (1-\sigma)\ \theta_1'\ \mathcal{C}' + (\sigma-1)\ \theta_2'\ \lesseqgtr 0 \tag{19}$$

With $\theta_1' = \frac{\partial\ \log}{\partial\ T_{s(\ell)}}\theta_1(T_{s(\ell)})$, and $\theta_2' = \frac{\partial\ \log}{\partial\ T_{s(\ell)}}\theta_2(T_{s(\ell)})$. θ_1' and θ_2' indicate the marginal risks incurred in total sales due to climate variabilities. Equation (19) shows that the effect of climate change on sales is a combination of several effects, with significant contribution from climate risks that come from *(1)* the direct effect of climate change on input demand, and *(2)* the effect emanating from consumer demand for the final output. Equation (19) is useful empirically to pinpoint the direct impact resulting from the demand of inputs using multivariate time-series or panel regression models that are purged of heterogeneity at the firm level (for e.g. using fixed effects).

Result 1: *There is a non-linear pattern between climate risks resulting from input demand and firm sales. Two firms facing different baseline levels of climate will experience different marginal impact to their sales.*

— ***Implications of the model on productivity***

Using the F.O.C for capital and labor, we can write the marginal revenue product of input h as:

$$MRP_{i,k,h} = p_{i,k}\ \frac{\partial q_{i,k}}{\partial X_{i,k,h}} = \alpha_{k,h}\ TFPR_{i,k}\ \left(\frac{p_{i,k}q_{i,k}}{X_{i,k,h}}\right) \tag{20}$$

The revenue-based marginal product of input can be measured knowing sales $p_{i,k}q_{i,k}$ and input quantities $X_{i,k,h},\ h \in \{K, L, M\}$ and total factor productivity. We proxy for changes in total factor productivity at the firm level with changes in the Solow residual. Following Hsieh and Klenow (2009) and Foster et al. (2008), and under allocative efficiency, we can derive the Solow measure of total factor productivity, based on the producer's revenue and using equation (13):

$$TFPR_{i,k} = \frac{p_{i,k}\ q_{i,k}}{\prod_h X_{i,k,h}^{\alpha_{k,h}}} \tag{21}$$

where $TFPR_{i,k}$ is a measure of the revenue based total factor productivity. The equilibrium price equations (5), and (17), along with the cost function for a unit of input (15) and the expression for final demand (8) allow to express total factor productivity in terms of climate shocks θ_1 and θ_2 (proof in appendix 1.G).

$$TFPR_{ik} = \left[p_{ik}\ \alpha_{0,k}\ {\alpha_k}^{\alpha_k}\left(\omega_i\ \tilde{\mathcal{C}}(q,\theta_1)^{1-\sigma}\ \theta_2(.)^{\sigma-1}\ \mu_{i,k}^{-\sigma}\ \rho_k P_k^{\sigma} Q_k\right)^{\alpha_k} * \left(\prod_h X_{i,k,h}^{\alpha_{k,h}}\right)^{-1}\right]^{\frac{1}{\alpha_k(1-\sigma)}} \tag{22}$$

where $\tilde{\mathcal{C}}(.)^{1-\sigma} = \frac{1}{p_{i,\ell}} * \mathcal{C}(.)^{1-\sigma}$ and $\alpha_k, \alpha_{0,k}$, and ρ_k are constant terms. Taking the logarithm form of the equation, we draw the following results:

$$\frac{\partial\ \log}{\partial\ T_{s(\ell)}} TFPR_{i,k} = \theta_1' \tilde{\mathcal{C}}' - \theta_2' \quad \lesseqgtr 0 \tag{23}$$

with $\theta_1' = \frac{\partial\ \log}{\partial\ T_{s(\ell)}}\theta_1(T_{s(\ell)})$, and $\theta_2' = \frac{\partial\ \log}{\partial\ T_{s(\ell)}}\theta_2(T_{s(\ell)})$

Result 2: *Equation* (23) *indicates that the effect of climate shocks on productivity follows a nonlinear pattern.*

— ***Implications of the model on Markup***

In the model, θ_2 directly captures shift in consumer demand for the final good, depending on price (a demand shock), and θ_1, a shift based on productive inputs (a supply shock or a productivity shock). We now assume that climate shocks act as supply disruptions, reducing the availability of material inputs (e.g., agricultural commodities). By decomposing the effect of these shocks on price and marginal costs, one can better understand the mechanism of markup adjustment. While sales fluctuations are expected to result from demand and supply shocks, we expect both price and marginal costs to increase in response to a negative productivity shock. Our assumption is based on the fact that when natural disasters cause supply-side disruptions, the market share of impacted firms declines, and a firm faces a larger increase in marginal cost compared to the industry's weighted average (Conteduca and Panon, 2024).

Let us assume that the markup is a function of the firm-sector-specific demand shock θ_2, and the firm-product-specific productivity shock $a(\theta_1)$, both induced by climate change. Each firm will face the inverse demand function: $p = P(q, \theta_2, .)$, when q is the demand for the final product, and $P_q > 0$, $P_{\theta_2} > 0$ [8].

We further assume that the cost function without subscripts at the firm level is given by $c = \mathcal{C}(q, a(\theta_1), .)$, where the marginal cost increases with low output levels initially due to economies of scale $\mathcal{C}_q \geq 0$ and $\mathcal{C}_{a(\theta_1)} > 0$. Our expression for Markup is:

$$\mu = \frac{P(q, \theta_2, .)}{\mathcal{C}(q, a(\theta_1), .)}$$

The total revenue equals price times quantity such that: $y \equiv Y(q, \theta_2, .)$. From the optimality condition $Y_q = c$, we can get the optimal demand such that: $q = Q(\theta_2, a(\theta_1), .)$, where $Q_{a(\theta_1)} < 0$. A negative supply shock on Markup can be summarized by:

$$-\left[\frac{P_q\ Q_{a(\theta_1)}}{c} - \mu\frac{\mathcal{C}_q\ Q_{a(\theta_1)}}{c} \quad - \mu\frac{\mathcal{C}_{a(\theta_1)}}{c}\right] < 0 \tag{24}$$

Result 3: *Climate shocks θ_1 causing supply-side disruptions are expected to (i) increase the marginal cost of firms $\left(\mu\ \mathcal{C}_{a(\theta_1)}/c\right)$, and induce two effects following a decrease in production: (ii) price increase $\left(-P_q\ Q_{a(\theta_1)}/c\right) > 0$ and (iii) cost decrease $\left(\mathcal{C}_q\ Q_{a(\theta_1)}/c\right)$.*

Climate shocks will reduce markup if the price increase only slightly, and if the sales decline is much larger than the marginal cost increase so that:

$$\eta^{\mathcal{C}_{a(\theta_1)}} < \left(\eta^{P_q} - \eta^{\mathcal{C}_q}\right)\ \left(\eta^{Q_{a(\theta_1)}}\right)\ , \tag{25}$$

where η indicates the relative elasticity.

To summarize, the effects of climate shocks on firms are nonlinear and heterogeneous. Climate risks related to input demand affect firm sales differently depending on each firm's baseline climate exposure. Similarly, the impact of climate shocks on productivity also follows a non-

[8] We denote the partial derivative of a function $g = G(x_1, x_2)$ as $G_{x_1} \equiv \frac{\partial G}{\partial x_1}$ and $G_{x_1 x_2} \equiv \frac{\partial^2 G}{\partial x_1\ \partial x_2}$. If $G_{x_1} < 0$, a decrease in x_1 would lead in a increase in G and vise-versa

linear pattern. Furthermore, supply-side disruptions due to climate shocks are expected to increase firms' marginal costs and, as production declines, lead to both price increases and cost reductions. Given the non-linear and heterogeneous effects of climate shocks on firm outcomes—ranging from sales and productivity to cost structures—an empirical investigation is essential to quantify these impacts across different Canadian agri-food industries.

5. Empirical Strategy

In this section, we outline the empirical strategy used to analyze the impact of climate change on three main firm-level outcomes, namely demand and sales (Result 1), productivity (Result 2), and markup (Result 3). We begin by describing the measurement of firm-level productivity. We then outline the approach used to compute firm-level markup. Finally, we explain the identification strategy employed to estimate the effects of climate change.

5.1. Measurement of productivity

5.1.1. Setup

We rely on the production function approach in the study by De Loecker and Warzynski (2012) to estimate productivity. To account for dispersion in the estimation of the production function, we break down the error term into different components. Specifically, the production function that we take to the data and estimate is the log of equation (6), which is assumed to be Leontief in the primary input:

$$q_{it} = f\left(x_{it}, k_{it},\ l_{it}\ ; \beta\right) +\ a^*_{it} + \varepsilon_{it}, \tag{26}$$

Where t is the time subscript, q_{it} is the log-revenue output. k and l are the respective log-labor and log-capital, all of which are observed, x_{it} is a vector of all other inputs and materials, β contains all relevant coefficients, and ε_{it} measures unanticipated shocks to output. Other interpretations for ε_{it} are possible. However, the interpretation itself is not important as long as ε_{it} is unobserved by the firm and the econometrician (see Bond et al. (2021)). We treat climate shocks as unobserved shocks that generate production risks (Chavas, 2008a; Chavas and Zhang, 2025), and a shift of the production function downward due to reduced efficiency of inputs under stress conditions, and the quasi-fixity of inputs in response to climate change (Yang and Shumway, 2016, 2018). Shocks translate into risks and uncertainty by causing productivity to fluctuate within a threshold, $\underline{a}^*$ and $\overline{a}^*$.

To assess production uncertainty and the downside risk exposure to climate change, one must first evaluate the probability distribution and the dispersion of productivity. Following a well-established methodology in the literature (Chavas, 2004; Chavas and Di Falco, 2012; Chavas et al., 2022), we employ a moment-based approach that leverages conditions derived from the first three statistical moments. In line with the study by Chavas and Di Falco (2012), the first, second and third moments (mean, variance and skewness) of the log-output are calculated as:

$$M_j = E[q_{i,k} - E[q_{i,k}]]^j, \quad j = 1, 2, 3 \tag{27}$$

The variance indicates the extent of variability, and the skewness provides information on the asymmetry of the distribution and, therefore, on the downside risk exposure of climate change (Chavas (2004)). We assume that productivity is of the form:

$$a^*_{it} = \ a_{it} + \theta_{it} + \ e_{it} \tag{28}$$

Where a_{it} stands for the stable part of productivity that is unrelated to shocks. The second component θ_{it} denotes variability in productivity over time, stemming from input demand shocks, and e_{it} are independently and identically distributed (i.i.d) error terms encompassing other factors that may contribute to productivity dispersion other than climate (either error measurement or heterogeneity emanating from the demand faced by firms). Plugging (28) into (26) gives:

$$y_{it} = f\left(x_{it}, k_{it},\ l_{it}\ ; \beta\right) + \ a_{it} + \theta_{it} + \ \widetilde{\varepsilon}_{it}, \tag{29}$$

where $\widetilde{\varepsilon}_{it} \ = e_{it} + \varepsilon_{it}$. Building on the work of Chavas and Di Falco (2012), we consider the following functional form for the stochastic components:

$$a_{it} \ + \ \theta_{it} + \ \widetilde{\varepsilon}_{it} \ \equiv \ \left[M_2 - \left(\frac{M_3}{\kappa}\right)^{\frac{2}{3}}\right]^{\frac{1}{2}} v_2(\widetilde{\varepsilon}_{it}) \ + \ \left(\frac{M_3}{\kappa}\right)^{\frac{1}{3}} v_3(\widetilde{\varepsilon}_{it}) \ , \tag{30}$$

where $v_2(\tilde{\varepsilon}_{it})$ and $v_3(\tilde{\varepsilon}_{it})$ are independently distributed error terms satisfying $\mathrm{E}\left[\mathrm{v_i}(\widetilde{\varepsilon}_{it})\right] = 0$, $\mathrm{E}\left[\mathrm{v_i}(\widetilde{\varepsilon}_{it})^2\right] = 1$, $\mathrm{E}\left[\mathrm{v_2}(\widetilde{\varepsilon}_{it})^3\right] = 0$, $\mathrm{E}\left[\mathrm{v_3}(\widetilde{\varepsilon}_{it})^3\right] \equiv \kappa > 0$, and $M_j,\ j = 2,\ 3$, quantifying the second and third moments (variance and skewness) of the distribution of productivity, and therefore dispersion. In line with Chavas and Di Falco (2012), the new error term $\widetilde{\varepsilon}_{it}$ has a variance, a skewness, and a mean zero. Therefore, the stochastic component exhibits heteroscedasticity.

The identification strategy to accommodate dispersion in productivity induced by climate change requires one to estimate the production function. The parameter β in equation (26) can be consistently estimated using proxy methods (Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg et al. (2015)). We apply the control function approach to recover productivity by replacing productivity with the inverted optimal output (investment or intermediate input) demand equation, which yields an estimate of $f\left(x_{it}, k_{it}, l_{it}; \beta\right)$. Collecting terms yields an equation that predicts producer output using inputs and the relevant control variables, productivity, and the estimated error term. Consistent with Chavas and Di Falco (2012), we use the estimated error term in equation (26) to obtain consistent estimates of the second and third moment of productivity.

5.1.2. Estimation procedure

We adopt standard assumptions from the proxy-variable literature, particularly some of those used by Ackerberg et al. (2015), which we discuss below:

— A1: a firm's i information set at time t, *f(·)*, is generated by $\{a^*_{i\tau}\}^t_{\tau=0}$. The random component measuring unanticipated shocks to output in equation (26) is not observed by the firm and satisfies: $\mathbb{E}\left[\varepsilon_{it} \mid f_{it}(.)\right] \equiv \mathbb{E}_t\left(\varepsilon_{it}\right) = 0$.

— A2: the state variables at time t are given by the pair: $(k_{it},\ a_{it})$. The stock of capital accumulates as a function of lagged capital k_{it-1} and investment (in materials) m_{it-1}:

$$k_{it} = \kappa\left(k_{it-1}, m_{it-1}\right) \tag{31}$$

— A3: the industry parameter β is constant and common within an industry group. The gross output production function exhibits constant returns to scale in capital and variable inputs, and productivity evolves according to a first-order Markov process.

— A4: Both productivity and shocks are all unobservable.

— A5: For any flexible input satisfying A4, a firm's input demand function is strictly monotonic in productivity.

Assumptions 1 and 2 are standard in the proxy literature. Because of unobserved productivity, standard regression may bias estimates. Assumption 3 imposes structure via a Markov process on productivity. Assumption 4 is consistent in a context of market power (see Bond et al. (2021)

for a discussion).

Productivity estimation is carried out in two steps. In the first-stage regression, we run:

$$y_{it} = \phi_{it} \left(l_{it}, m_{it}, k_{it}, \mathbf{z}_{it} \right) + \epsilon_{it} \ , \tag{32}$$

We collect firm level characteristics potentially affecting optimal input demand choice in a vector $\mathbf{z}_{it}$ and retrieve a measure $\widehat{\phi}$ of the expected output, with an estimate for ϵ_{it}. The first-stage estimation is meant to remove the error term from the output. The expected output is therefore given by:

$$\phi_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + h_t \left(m_{it}, k_{it}, \mathbf{z}_{it} \right) \tag{33}$$

Where m is the log of materials and energy. One potential concern is that Assumption 4 introduces a bias in estimating $\widehat{\phi}$. We use the proxy variable estimator of Hu et al. (2020), which relaxes the assumption that only productivity is unobserved in input demand. This approach is more robust when there are important unobservable factors in addition to the latent productivity. Following Hu et al. (2020), we are able to compute the firm-level total factor productivity, by relying on GMM techniques and Assumption 3 with the law of motion for productivity:

$$a^*_{it} = g_t \left(a^*_{it-1}, \ \right) + \xi_{it} \ , \tag{34}$$

5.2. Measurement of markup

The markup results from multiple first-order conditions as a function of the revenue elasticity of variable inputs (in this case materials[9]), and the revenue share of the variable input bundle (see De Loecker and Warzynski (2012)). Under constant returns of scale (Hubmer and Restrepo, 2021; Meier and Reinelt, 2022), one can recover output elasticities from revenue elasticities. Based on our firm-level markup equation (14), we can write:

$$\mu_{it} = \alpha^m_t \ \frac{p_{i,t} \ y_{i,t}}{P^m_{i,t} \ m_{i,t}} = \ \alpha^m_t \ (\overline{s}^m_{it})^{-1} \ , \ \alpha^m_t \ = \ \frac{\alpha^{m,r}_t}{\alpha^{m,r}_t \ + \ \alpha^{m,k}_t} \tag{35}$$

Where μ_{it} is the markup at the firm-level, $\overline{s}^m_{it}$ is the share of variable input relative to the total revenue, $p_{i,t} \ y_{it}$ denotes firm sales, $P^v_{i,t} \ m_{i,t}$ is the material-input expenditure in logarithm, $\alpha^{m,r}_t$ and $\alpha^{k,r}_t$ are the revenue elasticities previously estimated, and α^m_{it} is the output elasticity.

[9]We use materials as variable inputs since Materials expenditures typically make a larger share of total costs in industries with high input use.

Assumption 3 of constant return to scale deals with the fact that we do not observe prices in the data and that the production function approach with proxy variable cannot generate an unbiased estimator of market power (Yeh et al., 2022).

In the case of Leontief production functions, elasticity estimates are subject to bias due to the dependence of returns to scale on output levels. In such settings, the cost function provides a more suitable alternative for identifying elasticities (proof in appendix 8 1.C). For this reason, we rely on the cost function approach (De Loecker, 2011; Daglish et al., 2015) to estimate output elasticities and return to scale. Following Diewert (1971), we specify a general Leontief cost function of the form:

$$\begin{aligned}\mathcal{C}(p,q,t) = \sum_{i,j} b_{ij}\ p_i^{1/2} p_j^{1/2} q + \sum_{i=1}^{n} b_i\ p_i + \sum_{i=1}^{n} b_{it}\ p_i\ t\ q + \left(\sum_{i} \alpha_i\ p_i\right) t \\ + \left(\sum_{i=1}^{n} \beta_i\ p_i\right) q^2 + \left(\sum_{i=1}^{n} \gamma_i\ p_i\right) t^2 q\ ,\end{aligned} \tag{36}$$

where $\mathcal{C}$ is the total cost function of production, $p_i, p_j\ , i \neq j$ are the price of inputs, q the total output, t the time period, and $b_{ij}\ , b_{it},\ b_i, \alpha_i,\ \beta_i, \gamma_i$ are parameters. By construction, the generalized Leontief function satisfies homogeneity of degree one in input prices and qualifies as a flexible functional form, and each input component includes an interaction between the input price and a power function of the output y. The SUR system for the generalized Leontief is constructed from the input demand equations derived from the cost function using Shephard's lemma (Diewert and Wales, 1989):

$$x_i = \frac{1}{2}\sum_{i,j} b_{ij} \left(\frac{p_j}{p_i}\right)^{1/2} q + (b_i + \alpha_i\ t) + (1 + b_{it}t + \gamma_i t^2)\ q + \beta_i\ q^2 \tag{37}$$

where $x_i = \frac{\partial C(p,q,t)}{\partial p_i}$ is the i-the input demand.

5.3. Estimating the effects of climate change

The key motivation choices of our modeling come from stylized facts that climate shocks are both supply shocks and demand shocks. In addition to these shocks, firm heterogeneity significantly influences sales performance and productivity. Consistent with the previous work assessing climate extremes (Ortiz-Bobea et al., 2019; Yao, 2021; Schuurman and Ker, 2025), we use extreme heat degree days (HDD) over the entire April–September growing season as climate shock variables, with growing degree days (GDD) and precipitation as as additional control variables.

Growing degree days represent the cumulative time crops spend in an ideal temperature range, with daily temperature exposure added up throughout the season to determine the yearly growing degree days (Burke and Emerick, 2016). This variable is determined for each month within the growing season. With T_ℓ as the lower temperature boundary (10 °C), T_h as the upper boundary (29 °C), and T_d the daily average temperature for day d, the degree days calculation for that specific day is:

$$GDD_{d;T_l:T_h} = \begin{cases} 0 \text{ if } T_d \leq t_l \\ T_d - T_l \text{ if } T_l < T_d \leq T_h \\ T_h - T_l \text{ if } T_h < T_d \end{cases}$$

Following Roberts et al. (2013) and Schuurman and Ker (2025) we determine extreme heat degree days (HDD) as the cumulative growing degree days calculated only for daily mean temperatures exceeding 29°C, with no upper bound. Growing degree days, extreme heat degree days, and precipitations are added together over all the days for each month of the growing season. To provide an overview of the weather distribution across years, we formulated vectors $GDD_{t,m}$, $HDD_{t,m}$, and $P_{t,m}$, where t refers to the year and m indicates each month of the growing season.

Our assessment of climate change effects relies on the theoretical predictions (Results 1, 2, and 3) and the firm-level measures of productivity and markup. Equations of total sales (18), productivity (20), (22) and markup (35) provide a basis for our empirical investigations. We investigate the marginal effect of yearly variation in climate change on outcomes with the following panel specification:

$$y_{it} = \sum_m \zeta^{h,m} HDD_{i,t,m} + \zeta^z Z_{i,t} + \Gamma_i + \delta_t + \tau_t + \varepsilon_{it}, \tag{38}$$

Where i denotes the firm, t the year, and m the month of the growing season, y_{it} is the main dependent variable (either sales revenue, markup or productivity) and $HDD_{i,t,m}$ the extreme heat degree day variables. Z_{it} are additional controls (including the relative size of the firm, Growing degree days GDD, and cumulative precipitations P), Γ_i , δ_t and τ_t are the time-invariant, sector-year, and region-year fixed effects respectively. δ_t and τ_t control for the fluctuation of sectoral and regional variables, Γ_i accounts for unobserved heterogeneity, and ε_{it} are independently distributed error terms.

When y_{ij} expresses total sales, $\zeta^{h,m}$ measures the risk exposure to climate change stemming following a supply shock. Controlling for the time invariant firm characteristics is especially important in order to make sure that our empirical analysis does not confuse unobserved heterogeneity with risk exposure (Chavas and Di Falco, 2012).

6. Data and descriptive statistics

We use data from the National Accounts Longitudinal Micro database (NALMF) of Statistics Canada and for the period 2000-2022. This data set is constructed using annual cross-sectional files. The data include several characteristics of firms over time, such as employment, payroll, income, profits, assets, stock of capital, R&D capital stock, R&D spending, investment, and value added. The data do not include the quantities and prices of inputs and outputs but only report input expenditures and revenues from output sales. We use operating expenses as a direct measure of variable inputs, which include materials, labor, marketing, and management.

To estimate a generalized Leontief cost function and elasticities, firm-specific prices were computed for material input, Labor and Capital. The labor input price is measured by the ratio of total annual payroll to the total number of hours worked. The expression for the price of capital is taken from Singbo et al. (2025), and is represented by the formula $\mathrm{p_{it} = r_t q_{t-1} + d q_t - g_t}$, where p is the price of capital, r the discount rate (or rate of return), q_t the price of fixed assets in period t, d is the average rate of depreciation of the asset, and g is the expected capital gain, represented by the difference between current and previous year prices.
Climate data are from the Canadian Center for Climate Services (CCCS)[10] of Environment and Climate Change Canada. These data reconstruct historical temperature using a combination of observational data and local climate models. The key climate variables includes daily temperatures and precipitation by region. Since we do not have precise coordinates, we assign to each firm the average temperature and rainfall corresponding to the geographic province in which it is situated. These numbers are obtained by spatially averaging temperatures and precipitations over the geographical boundaries of each region. We select agri-food firms belonging to the four-digit North American Industry Classification system (NAICS) codes for classes 3111-3119, with a total number of 9 industries. Table 2 provides summary statistics of these firms.

[10]Official website: https://climatedata.ca/

[INSERT Table 2 ABOUT HERE]

Firms employ on average about 29 workers and there is a large variation across firm-years. This table also show that materials is an important component of the production process, followed by capital and labor. Table 9 in the appendix indicates variations by 4-digit industry code and firm size. The most significant sectors in terms of production are Meat Products, Grain and Oilseed Milling, and Dairy Product Manufacturing, which together account for 56% of total output share.

7. Results and interpretations

7.1. Production and cost function estimates

We display in table 3 the estimated elasticities across industries from the general Leontief specification (36), and the two-step GMM-IV specification used to estimate the production function and productivity.

[INSERT Table 3 ABOUT HERE]

The GMM-IV specification allocates lower elasticities to labor and capital inputs, and higher elasticity to material inputs, compared to the General Leontief specification. Differences in the specifications are most likely due to the restrictive functional form of the production function on the coefficients. Without flexibility to allocate elasticities across inputs dynamically, the GMM-IV specification may under-allocate elasticities to labor and capital and over-allocate to materials, which tend to dominate in industries with high variable input usage (e.g., manufacturing).

Overall, the estimates of both production and cost function specification indicate that the elasticities are accurately estimated and reasonable. These findings are broadly in line with previous results, with positive capital elasticities and returns to scale around one. Material inputs have higher elasticity estimates, which is typical in manufacturing sectors. The return to scale estimates across industries, measured by the sum of the elasticities, indicate that, on average, all sectors appear to have constant return to scale.

In the following sections, we examine the firm-level effects of climate shocks on various key indicators and explore potential adjustment mechanisms for markup.

7.2. Sales, Inputs and Total Factor Productivity

We use equation (38) to estimate the effects of extreme temperature variations on firm outcomes. Although our primary objective is to assess the impact of climate shocks on sales, we also explore in table 4 their effects on the input use of firms, that is, materials, labor and capital, to support the interpretation of marginal income products, productivity, and marginal costs discussed in Table 5.

[INSERT Table 4 ABOUT HERE]

The results indicate that firms reduce their expenditures on inputs in response to climate shocks. In addition, climate shocks tend to reduce sales at the firm level. The response of sales is stronger than the response of inputs, especially in May, June, July, August, and September. For example, a one percent increase in climate extremes in May reduces sales by 0.1%, all else being equal. Sales drop more sharply, which suggests that climate shocks lead to a greater reduction in sales compared to the expenses on inputs.

Next, we investigate the impact of these shocks on firm-level productivity. Table 5 presents the results, indicating that climate shocks reduce total factor productivity (TFP), except toward the end of the growing season. With the exception of labor, both MRPM and MRPK respond to climate shocks due to the sensitivity of these inputs to environmental fluctuations. This suggests that climate shocks decrease the efficiency of inputs in the production process.

We also observe a rise in marginal production costs, except during August and September. Overall, these findings indicate that following a temperature change, labor and materials contribute to reduce firm efficiency and increase the unit production costs — requiring more inputs to produce the same level of output.

[INSERT Table 5 ABOUT HERE]

7.3. Markup and climate change

In this section, we use our empirical strategy to determine if this substantial markup variation within firms can be attributed to climate shocks. Our result indicates heterogeneous impacts, with some industries experiencing significant reductions in market power, while others appear more resilient or even benefit from climate fluctuations.

Overall, climate shocks lead to lower firm-level markups, particularly during the months of May, June, and July. This pattern is consistent with the hypothesis that climate shocks increase production costs and disrupt supply chains, which can limit firms' ability to set higher markups.

Climate shocks in April are associated with a slight reduction in markups in several agri-food sectors, which include Fruit and Vegetable Food Manufacturing, and Bakeries and Tortilla manufacturing. All agri-food firms experience a 0.0142% decrease on average following a one-unit increase in these shocks. However, Seafood Product Preparation and Packaging exhibits a positive and significant effect, indicating a potential demand-driven response in the sector.

The negative impact of climate shocks intensifies in May, with all firms experiencing a significant decline in markups by 0.302% on average. Meat Product Manufacturing and Bakeries also show significant reductions, suggesting a heightened vulnerability to climate fluctuations during this period.

The effect of climate shocks peaks in June and July, with a highly significant and negative impact on markups across nearly all sectors. Unlike previous months, we note a shift in the impact of climate shocks, in August and September, with some sectors exhibiting positive and significant changes in markups.

[INSERT Table 6 ABOUT HERE]

7.4. Response of Markup to shocks

In Section (4), Result 3 and equation (24) suggest that climate shocks can lead to higher marginal costs and reduced markups. In this section, we examine the adjustment dynamics of markups in response to climate shocks by reporting, in table (7), the response of markups, prices and sales to changes in Total Factor Productivity (TFP) and changes in output. To control for potential biases, we also include firm–year fixed effects. Overall, markups exhibit a negative response to a negative supply shock.

[INSERT Table 7 ABOUT HERE]

We then explore some implications of equation (24) and quantify the responses: a negative 10% TFP shock is predicted to increase prices by 0.27% and to reduce sales by 10.1%, while reducing markups by 1.65%. In a nutshell, a negative TFP shock leads to a slight increase in prices, with firms absorbing part of the increase in marginal costs through lower markups, at least in the short run.

However, the price increase is small (0.27%) compared to the cost increase because firms cannot fully pass the cost increase to consumers because of demand elasticity. As firms increase prices (even slightly), demand shrinks, leading to a large drop in sales. The sales drop is much larger than the price increase, indicating that demand is relatively elastic. Thus, a small increase in price leads to a significant reduction in quantity demanded.

The results can also can be interpreted in light of equation (24). A negative supply shock raises firms' marginal costs, exerting greater upward pressure on prices. This is consistent with having $\mu C_{a(\theta_1)}/c > 0$. Markups are negatively correlated with climate shocks if the effect operating through the decrease in production (increase in price and marginal cost) outweighs the effect of a marginal cost variation, i.e., if the price adjustment is relatively small.

7.5. Firm Characteristics and Heterogeneous Responses

—***Does the number of products matter?***

Table 8 contains the results from splitting the sample by the number of products. Consistent with our theoretical predictions (Results 1 and 2), we observe substantial heterogeneity in the estimates, indicating that product diversification shapes the impact of climate shocks. The estimated losses in June are -0.030% for markups and -0.095% for TFP in single-product firms, and -0.051% and -0.046%, respectively, for firms with five or more products. Since single-product firms experience larger declines in TFP, they are more vulnerable to climate shocks in terms of productivity. However, multi-product firms experience a larger decline in markups following a climate shock.

[INSERT Table 8 ABOUT HERE]

— ***Age and firm size***

We perform additional robustness checks to address potential concerns with our baseline results. First, we verify that our results hold when controlling for firm age and size, both of which are widely recognized as key drivers of firm heterogeneity. The outcomes of these additional exercises closely align with our benchmark specification on the impact of climate shocks. Our findings remain unchanged across these robustness tests (See table 10 in the appendix).

Additionally, we test the sensitivity of our results to various sources of firm heterogeneity. Specifically, our specification accounts for (i) multi-establishment firms (firms with more than one operating establishment); (ii) multi-location firms (firms with multiple branches or offices, regardless of their geographic distribution); (iii) multi-province firms (firms operating across multiple provinces or territories); and (iv) multi-activity firms (firms engaged in multiple business activities). Our estimates remain unaffected by the inclusion of these firm types.

8. Conclusion

In this paper we examined the impact of climate shocks on firm-level markups and productivity using a Canadian dataset. We also introduced a framework to explore the adjustment mechanisms of these aggregates in response to climate shocks. The availability of firm-level sales information was central to our study as it allowed us to capture heterogeneity in firm characteristics that aggregate data may obscure. We enhance the empirical analysis by incorporating high-resolution climate data at the sub-national level.

Our findings are robust and consistent: first, markups exhibit a negative response to climate shocks across (nearly) all sectors; second, climate shocks lead to an increase in marginal costs, a decrease in productivity, and a reduction in firm sales. In this typical monopolistic competition scenario, firms encounter downward-sloping demand curves and must balance pricing strategies with market share retention. Our results remain robust even when controlling for firm size and age.

Conflict of Interest

The authors declare that there is no conflict of interest.

Financial Disclosure

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Table and figures

Tables

Table 1: Markup estimates by NAICS groups

Classification	Mean	P10	P25	P50	P75	P90	75-25	90-10	CV
Animal food manufacturing	1.82	0.66	1.22	2.00	2.57	2.76	2.11	4.18	0.45
Grain and oilseed milling	1.63	0.33	1.03	1.66	2.36	2.76	2.29	8.36	0.52
Sugar product manufacturing	1.46	0.69	1.04	1.40	1.91	2.38	1.84	3.45	0.46
Fruit and vegetable food manufacturing	1.56	0.49	1.08	1.56	2.11	2.67	1.95	5.45	0.49
Dairy product manufacturing	1.58	0.20	0.98	1.64	2.30	2.76	2.35	13.80	0.54
Meat product manufacturing	1.76	0.72	1.20	1.81	2.51	2.76	2.09	3.83	0.45
Seafood product preparation and packaging	1.64	0.46	0.90	1.66	2.58	2.76	2.87	6.00	0.55
Bakeries and tortilla manufacturing	1.41	0.74	1.04	1.33	1.81	2.28	1.74	3.08	0.44
Other food manufacturing	1.40	0.28	0.94	1.37	1.90	2.48	2.02	8.86	0.53
All firms	1.53	0.58	1.02	1.47	2.11	2.76	2.07	4.76	0.50

Note: The table summarizes the key statistics, especially the moments of estimated Markup (in logarithm) for various NAICS. 75-25 is the 75-25 ratio, 90-10 is the 90-10 ratio, CV is the coefficient of variation.

Source: Authors' computations based on Statistics Canada data.

Table 2: Summary Statistics

Statistics	**Average Number of Employees**	**Labor (% of Revenue)**	**Capital (% of Revenue)**	**Material (% of Revenue)**	**Revenue ($)**
Mean	29.068	7.746	23.628	70.107	10,400,000
Standard Deviation	268.380	0.2435	0.290	0.574	145,000,000
Coefficient of Variation	9.233	3.142	1.227	0.271	14.001
Skewness	38.053	3.391	1.005	-0.131	45.476
Kurtosis	2,062.417	12.872	2.850	1.542	2,962.691
Percentiles					
25th Percentile	0.000	0.000	0.000	40.000	4,730.632
50th Percentile	3.5	0.000	14.041	73.100	253,010.000
75th Percentile	13.167	1.348	48.526	98.600	1,610,735
Number of Observations	171,430	171,430	171,430	171,430	171,430

Note: Summary statistics of the main variables. The data span the period 2000 to 2022. Revenue is expressed in Canadian dollars. Mean and percentiles are expressed in as share of revenue. Materials include Energy and other expenses.

Table 3: Elasticities by industries

Cost function estimates	Capital	Labor	Material	RTS	Firms
Animal food manufacturing	0.478	0.018	0.564	1.060	1,327
Grain and oilseed milling	0.442	0.025	0.551	1.018	611
Sugar product manufacturing	0.349	0.024	0.687	1.060	1,130
Fruit and vegetable food manufacturing	0.362	0.024	0.642	1.028	1,435
Dairy product manufacturing	0.423	0.017	0.605	1.046	2,049
Meat product manufacturing	0.365	0.019	0.572	0.957	2,263
Seafood product preparation and packaging	0.368	0.018	0.577	0.963	2,094
Bakeries and tortilla manufacturing	0.313	0.018	0.655	0.986	7,291
Other food manufacturing	0.343	0.020	0.645	1.009	5,538
All firms	0.352	0.019	0.729	1.100	23,738
Production function estimates (GMM-IV Estimator)					
All firms	0.075	0.025	0.956	1.056	23,738

Note: Estimation of the General leontief cost function; The last row estimates indicates the two-step GMM-IV estimator of Hu et al. (2020), which address optimization errors in firms' input choice, unobserved idiosyncratic cost shocks, and measurement errors in proxy variables; Materials, as defined, include energy components. RTS indicates returns to scale; Obs. denotes the total number of observations, and Firms the total number of firms;

Table 4: Effect of Climate Shocks on Input and Output

Variables	**Sales**	**Materials**	**Labor**	**Capital**
HDD April	-0.001	-0.0000145	-0.00188	-0.000936**
	(0.001)	(0.000162)	(0.000271)	(0.000238)
HDD May	-0.001**	-0.000334*	-0.000703***	-0.00092*
	(0.001)	(0.000200)	(0.000306)	(0.000282)
HDD June	-0.000*	0.000592***	0.000162	-0.000662*
	(0.001)	(0.000222)	(0.000389)	(0.000323)
HDD July	-0.002***	-0.000970***	-0.00155***	-0.00264***
	(0.001)	(0.000224)	(0.000389)	(0.000325)
HDD August	-0.002***	-0.00236***	-0.00213***	-0.00133***
	(0.001)	(0.000267)	(0.000387)	(0.000376)
HDD September	-0.001*	-0.000394*	-0.00084**	-0.00070*
	(0.001)	(0.000210)	(0.000363)	(0.000293)
Fixed effects	Yes	Yes	Yes	Yes
Controls				
Growing degree days	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Observations	161,973	161,973	161,973	161,973

Notes: Materials include Energy and other expenses. All variables are in logs. climate shocks are constructed as explained in section 5.3. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effect of Climate Shocks on Firm-Level Marginal Costs and Productivity

VARIABLES	**Marginal Cost**	**TFP**	**MRPK**	**MRPL**	**MRPM**
HDD April	7.43E-05	6.57E-05	-7.84e-06	-0.0000658	2.40e-06
	(4.01E-05)	(7.05e-05)	(1.42e-05)	(0.0000548)	(3.40e-06)
HDD May	0.000175 ***	-3.50e-05	-1.49e-06	-0.0000579	1.83e-06
	(4.85E-05)	(8.18e-05)	(8.76e-06)	(0.0000511)	(3.78e-06)
HDD June	0.000379 ***	-0.000862***	-2.92e-05***	0.0000604	-2.60e-05***
	(6.43E-05)	(0.000105)	(1.02e-05)	(0.0000576)	(5.19e-06)
HDD July	0.000410 ***	-0.000265***	-6.58e-06	0.0000674	-8.95e-06**
	(5.93E-05)	(9.03e-05)	(1.80e-05)	(0.0000568)	(4.06e-06)
HDD August	-0.000335 ***	-0.000221**	-4.76e-05	0.0000173	-2.54e-06
	(6.67E-05)	(0.000108)	(4.20e-05)	(0.0000645)	(5.04e-06)
HDD September	-0.000117 ***	0.000682***	3.87e-05***	0.0000383	2.50e-05***
	(5.75E-05)	(8.95e-05)	(1.11e-05)	(0.0000365)	(4.38e-06)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls					
Growing degree days	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes
Observations	124,803	31,896	5,746	3,653	6,327
R squared	0.005	0.017	0.003	0.005	0.032

Notes: Materials include Energy and other expenses; all variables are in logs; MRPK, MRPL and MRPM denote the revenue-based marginal products, with respect to each input; standard errors are reported in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Impact of climate shocks on Markup

VARIABLES	**All firms**	3111	3112	3113	3114	3115	3116	3117	3118	3119
HDD April	-0.000142**	-0.000172	-0.000313	-0.000224	-0.000336**	0.000148	0.000260***	-0.000166	-0.000194***	0.000177**
	(0.0000347)	(0.000126)	(0.000198)	(0.000147)	(0.000141)	(0.000149)	(0.0000880)	(0.000135)	(0.0000604)	(0.0000846)
HDD May	-0.00302***	-0.000418**	-0.000424	-0.0000813	-0.000253	-0.000609***	-0.000325**	0.000305*	0.000359***	-0.000348***
	(0.0000403)	(0.000174)	(0.000270)	(0.000154)	(0.000159)	(0.000179)	(0.000128)	(0.000165)	(0.0000641)	(0.0000931)
HDD June	-0.00705***	-0.000678***	-0.00000457	-0.00114***	-0.000809***	-0.000798***	-0.000510***	-0.000425***	-0.000981***	-0.000788**
	(0.000753)	(0.000196)	(0.000332)	(0.000227)	(0.000199)	(0.000220)	(0.000134)	(0.000162)	(0.0000819)	(0.000124)
HDD July	-0.00641**	-0.000853***	-0.000340	-0.000434**	-0.000479***	-0.000340	-0.000865***	-0.000684***	-0.000852***	-0.000359**
	(0.000615)	(0.000197)	(0.000304)	(0.000203)	(0.000180)	(0.000211)	(0.000135)	(0.000173)	(0.0000789)	(0.000112)
HDD August	-0.00607**	0.00115**	0.000744**	0.000477**	0.000557**	0.00109***	0.000746***	-0.000206	0.000673***	0.000915***
	(0.000703)	(0.000211)	(0.000368)	(0.000224)	(0.000230)	(0.000238)	(0.000165)	(0.000207)	(0.0000932)	(0.000137)
HDD September	-0.00513**	0.000142	-0.000304	0.000334**	-0.000412**	0.000222	0.000208	0.0000574	0.000421***	0.000467***
	(0.000155)	(0.000179)	(0.000277)	(0.000197)	(0.000199)	(0.000192)	(0.000127)	(0.000160)	(0.0000718)	(0.000119)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls										
GDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,880	9,100	3,569	6,244	8,480	7536	15,774	13,317	40,561	25,299
R-squared	2.4	109.2	50.4	86.4	116.9	113.9	165.2	136.9	508.7	456.8

Notes: HDD: Higher Degree Days;GDD: growing Degree Days; 3111: Animal food manufacturing, 3112: Grain manufacturing, 3113: Sugar product manufacturing, 3114: Fruit and vegetable food manufacturing, 3115: Dairy product manufacturing, 3116: Meat product manufacturing, 3117: Seafood product preparation and packaging, 3118: Bakeries and tortilla manufacturing, 3119: Other food manufacturing. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Effects of Negative Productivity Shock and Output Change

	Productivity Shock Effects				**Output Change Effects**	
	$\eta^{Q_{a(\theta_1)}}$	$\eta^{P_{a(\theta_1)}}$	$\eta^{C_{a(\theta_1)}}$	$\eta^{\mu_{a(\theta_1)}}$	η^{P_q}	$\eta^{\mathcal{C}_q}$
Negative productivity shock	-1.010***	0.0273***	0.334***	-0.165***		
	(0.0593)	(0.0021)	(0.0105)	(0.0115)		
Negative change in output					0.00356***	0.535***
					(0.000153)	(0.00861)
Observations	33,387	33,387	28,995	32,453	171,430	130,267
Number of firms	7,758	7,758	6,201	7,420	23,738	17,019
R-squared	0.059	0.017	0.181	0.18	0.015	0.395
Firm-year f.e.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are reported in parentheses. *** denotes statistical significance at the 1% level.

Table 8: Effects of climate shocks by number of products

No. of products	1		2		3		4		5+	
	Markup	TFP	Markup	TFP	Markup	TFP	Markup	TFP	Markup	TFP
HDD April	0.00005	0.00032	0.00020	0.00011	0.00008	-0.00004	0.00023	0.00008	0.00012	0.00013
	(0.00011)	(0.00021)	(0.00013)	(0.00025)	(0.00017)	(0.00038)	(0.00014)	(0.00030)	(0.00017)	(0.00017)
HDD May	-0.00029**	-0.00029	-0.00011	0.00012	0.00003	-0.00043	0.00013	-0.00025	-0.00014	0.00013
	(0.00013)	(0.00027)	(0.00014)	(0.00032)	(0.00019)	(0.00044)	(0.00014)	(0.00035)	(0.00045)	(0.00046)
HDD June	-0.00030*	-0.00095***	-0.00057***	-0.00102**	-0.00068**	-0.00074*	-0.00008	0.00001	-0.00051***	-0.00046*
	(0.00017)	(0.00034)	(0.00019)	(0.00044)	(0.00027)	(0.00041)	(0.00030)	(0.00052)	(0.00013)	(0.00025)
HDD July	-0.00025	-0.00071**	0.00004	0.00029	-0.00080***	0.00012	-0.00036	-0.00027	-0.00041***	-0.00023
	(0.00016)	(0.00031)	(0.00017)	(0.00039)	(0.00024)	(0.00042)	(0.00024)	(0.00048)	(0.00011)	(0.00023)
HDD August	0.00011***	0.00035	0.00098**	0.00003	0.00059**	-0.00024	0.00073**	-0.00076	0.00091**	0.00017
	(0.00019)	(0.00038)	(0.00020)	(0.00046)	(0.00026)	(0.00057)	(0.00033)	(0.00066)	(0.00015)	(0.00032)
HDD September	0.00037**	0.00075**	0.00038**	0.00079*	0.00069***	0.00013	0.00100*	0.00026**	0.00088**	0.00027
	(0.00015)	(0.00033)	(0.00017)	(0.00046)	(0.00022)	(0.00047)	(0.00028)	(0.00059)	(0.00013)	(0.00027)
Controls										
GDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitations	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: regression results of climate shocks on markup and productivity by number of products; HDD: Higher Degree Days; GDD: growing Degree Days; Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Share of output by industry (4-digit NAICS)

Name of category	**NAICS**	**Number of observations**	**Frequencies (%)**	**Output share (%)**
Animal food manufacturing	3111	11126	6.49	7.11
Grain and oilseed milling	3112	4492	2.62	11.58
Sugar and confectionery product man.	3113	7966	4.65	5.05
Food and vegetable preserving and special	3114	10806	6.30	6.98
Dairy product manufacturing	3115	12548	7.32	16.16
Meat products	3116	20326	11.86	28.11
Seafood products	3117	18297	10.67	4.74
Bakeries manufacturing	3118	54401	31.73	9.42
Other products manufacturing	3119	31468	18.36	10.85
Total		171430	100	100

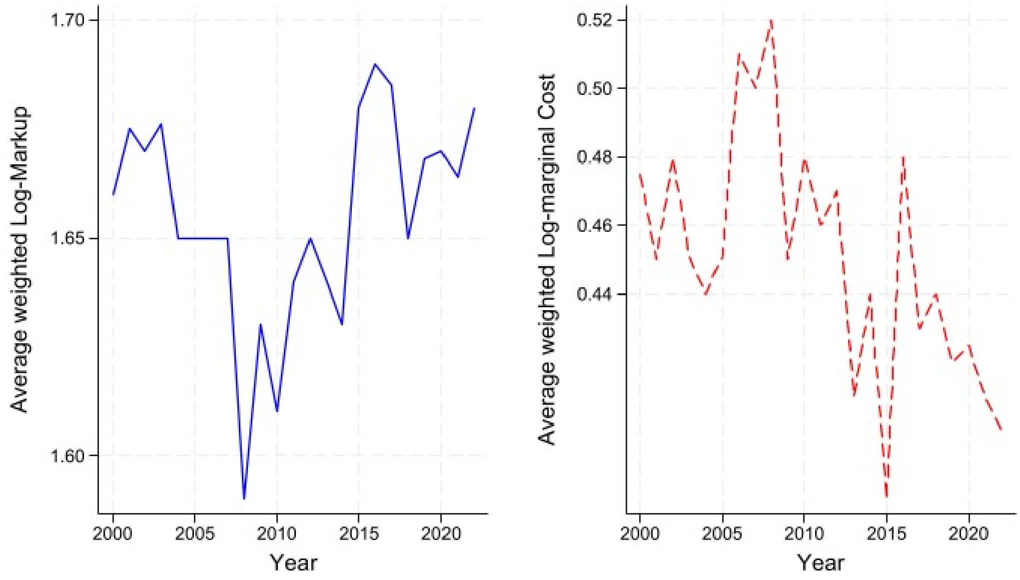
Table 10: Effect of climate shocks on markup and productivity with additional control

Variables	**Markup**	**Productivity**
HDD_April	-0.000136**	6.72e-05
	(3.48e-05)	(7.04e-05)
HDD_May	-0.000301**	-3.34e-05
	(4.03e-05)	(8.19e-05)
HDD_June	-0.000759**	-0.000862***
	(4.03e-05)	(8.19e-05)
HDD_July	-0.000648**	-0.000267***
	(4.69e-05)	(9.03e-05)
HDD_August	0.000697**	-0.000220**
	(5.62e-05)	(0.000108)
HDD_September	0.000308**	-0.000680***
	(4.52e-05)	(8.93e-05)
Controls		
EntMultiLocation (1 = Yes)	0.0479	-0.0909
	(0.0368)	(0.0825)
EntMultiEstablishment (1 = Yes)	0.0466	0.0837
	(0.0469)	(0.0857)
EntMultiProvince (1 = Yes)	-0.0487	-0.00114
	(0.0361)	(0.0594)
EntMultiActivity (1 = Yes)	-0.0322	0.0480
	(0.0434)	(0.0533)
Age	-0.0139***	-0.00379
	(0.00463)	(0.00648)
Age square	8.64e-05**	4.99e-05
	(3.41e-05)	(4.42e-05)
Size	0.0245	0.00518
	(0.00175)	(0.00252)
Constant	0.507***	0.898***
	(0.117)	(0.188)
GDD	Yes	Yes
Precipitations	Yes	Yes
Fixed effects	Yes	Yes
Observations	129,880	31,896

Notes: GDD refers to growing degree days; HDD refers to high degree days. Markup and Productivity are in logarithm. Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

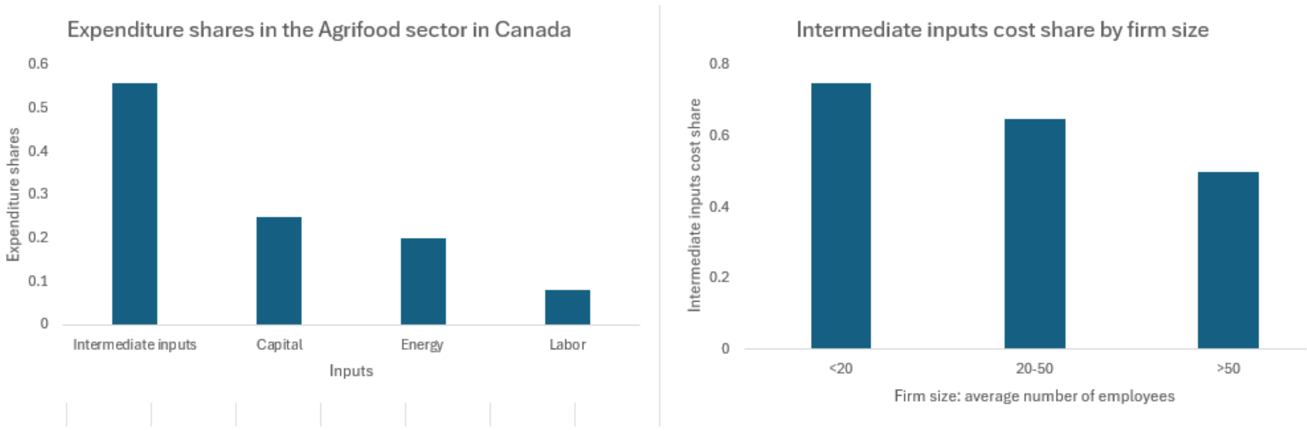
Figures

Figure 1: Evolution of markup and marginal costs



Source: Authors' computations based on Statistics Canada data.

Figure 2: Expenditure shares in the agrifood sector and material input costs by firm size



Source: Authors' computations based on Statistics Canada data.

Appendix

1.A Cobb-Douglas cost function with n inputs to produce an output y

$$\text{Min}\,\mathcal{L} = \sum_{j=1}^{n} w_j \ + \lambda \left(y - A \prod_{j} x_j^{\alpha_j} \right)$$

FOCs for i and $k \Rightarrow x_i = w_i^{-1} \alpha_i \ \alpha_k^{-1} \ w_k \ x_k$

$$\begin{aligned}
x_i^{\alpha_i} &= w_i^{-\alpha_i} \alpha_i^{\alpha_i} \alpha_k^{-\alpha_i} w_k^{\alpha_i} x_k^{\alpha_i} \\
\prod x_i^{\alpha_i} = y/A &= \alpha_k^{\sum_i^n -\alpha_i} w_k^{\sum_i^n \alpha_i} x_k^{\sum_i^n \alpha_i} \prod_i w_i^{-\alpha_i} \alpha_i^{\alpha_i} \\
x_k^{\sum_i^n \alpha_i} &= \left(\frac{y/A}{\prod_i w_i^{-\alpha_i} \alpha_i^{\alpha_i}} \right) \alpha_k^{\sum_i^n \alpha_i} w_k^{-\sum_i^n \alpha_i} \\
x_k &= \left(\frac{y^{1/\delta} A^{-1/\delta}}{\prod_i w_i^{-\alpha_i/\delta} \alpha_i^{\alpha_i/\delta}} \right) \alpha_k w_k^{-1}; \quad \delta \equiv \sum_i^n \alpha_i \\
C[\mathbf{w}, y] = \sum_{j=1}^{n} w_j \ x_j &= \left(\frac{y^{1/\delta} A^{-1/\delta}}{\prod_i w_i^{-\alpha_i/\delta} \alpha_i^{\alpha_i/\delta}} \right) \sum_{j=1}^{n} \alpha_j
\end{aligned}$$

The above cost function is inclusive, as it accounts for both economies of scale and diseconomies of scale. Constant returns to scale (CRS) implies:

$$\sum_{j=1}^{n} \alpha_j = 1, \quad C[\mathbf{w}, y] = \frac{y/A}{\prod_i w_i^{-\alpha_i} \ \alpha_i^{\alpha_i}}$$

.

1.B Leontief cost function with n inputs to produce an output g_ℓ

We posit a Leontief technology $g_\ell\,(s) = A_\ell\big(\theta_1(T_{s(\ell)})\big)\ \min\left(\alpha_0\ M_\ell^{\alpha_\ell}\ ,\ \prod_h X_{\ell,h}^{\alpha_{\ell,h}}\right)$, with a primary input M_ℓ being used in fixed proportions with other inputs such that: $\alpha_0 M_\ell^{\alpha_\ell} = \prod_h X_{\ell,h}^{\alpha_{\ell,h}} = \frac{g_\ell(s)}{A_\ell(.)}$. The demand for the primary input is:

$$M_\ell = \left(\frac{g_\ell(s)}{\alpha_0 A_\ell(.)} \right)^{\frac{1}{\alpha_\ell}}$$

with cost:

$$P_\ell^M M_\ell = P_\ell^M \ \left(\frac{g_\ell(s)}{\alpha_0 A_\ell(.)} \right)^{\frac{1}{\alpha_\ell}}$$

The costs for the other inputs, with CRS, is : $\frac{g_\ell(s)}{A_\ell(.)} \prod_h (\frac{p_{\ell,h}}{\alpha_{\ell,h}})^{\alpha_{\ell,h}}$, and the cost function associated with the Leontief production function is:

$$C_\ell \left(P_\ell^M, p_{\ell,h}, \frac{g_\ell(s)}{A_\ell(.)} \right) = P_\ell^M \left(\frac{g_\ell(s)}{\alpha_0 A_\ell(.)} \right)^{\frac{1}{\alpha_\ell}} + \frac{g_\ell(s)}{A_\ell(.)} \prod_h \left(\frac{p_{\ell,h}}{\alpha_{\ell,h}}\right)^{\alpha_{\ell,h}}.$$

The production cost for a unit of input can also be expressed as:

$$\mathcal{C}(g_\ell, \theta_1) = \frac{\mathcal{C}_\ell(.)}{\left(\frac{g_\ell(s)}{\alpha_0 A_\ell(.)}\right)^{\frac{1}{\alpha_\ell}}} = P_\ell^M + \left[\frac{g_\ell(s)}{A_\ell(.)}\right]^{\frac{\alpha_\ell - 1}{\alpha_\ell}} \left[\frac{1}{\alpha_0}\right]^{\frac{1}{\alpha_\ell}} \prod_h \left(\frac{p_{\ell,h}}{\alpha_{\ell,h}}\right)^{\alpha_{\ell,h}}$$

1.C Cost Functions for Leontief Technologies with variable returns to Scale

Assume the Leontief production function:

$$y = \min \left[\frac{x^{1/\gamma}}{\alpha}, \varphi[k,l] \right] \implies x = (\alpha y)^\gamma, x = \alpha' \left(\varphi[k,l]\right)^\gamma \implies \frac{x}{\varphi} = \alpha' \left(\varphi[k,l]\right)^{\gamma - 1}$$

$$\text{If } \varphi[\cdot] \text{ is homogeneous of degree } p, \quad \varphi[\lambda k, \lambda l] = \lambda^p \varphi[k,l].$$

$$\left(\frac{\lambda x}{\alpha}\right)^{1/\gamma} = \lambda^{1/\gamma} \frac{1}{\alpha}, \quad \text{and } \frac{1}{\gamma} < p.$$

We can see that there is a proportional relationship, but it varies with the level of output. In such a case, scale elasticity does not make much sense. If all inputs are multiplied by λ, the proportionality will not be maintained unless $k = \lambda$. If all inputs are multiplied by λ, the return to scale is λ. If $\lambda > 1$, there is "slacks"in the sense that the same level of production could be achieved with less of the aggregate x. If, alternatively, we assume $\lambda < 1$, part of the input x is then redundant. In studies measuring efficiency by data envelopment analysis (or mathematical programming), this is called "slacks".

For example, if $y = \min(x, k)$, the optimal input quantities for $y = 1$ are $x = 1 = k$, for $y = 4$, $x = 2, k = 4$, and for $y = 9$, $x = 3, k = 9$. As the optimal x/k ratios change, multiplying the inputs by the same multiple does not make sense.

The cost function associated with the production function is of the form:

$$C[w_x, w_k, w_y, y] = w_x(\alpha y)^\gamma + \Gamma[w_k, w_y, y], \quad \Gamma = T \cdot r$$

We can see that the input x enters in a particular way due to the proportionality in the production function. The cost elasticity is:

$$\epsilon_C \equiv \frac{\partial C/\partial y}{C/y} = \frac{\gamma w_x \alpha' y^{\gamma-1} + \partial\Gamma/\partial y}{w_x \alpha' y^{\gamma-1} + \Gamma/y}$$

You have economies of scale if $\epsilon_C \in (0,1)$. The technology has constant costs if $\epsilon_C = 1$, and there are diseconomies of scale if $\epsilon_C > 1$.

1.D Share of output by industry

[INSERT Table 9 ABOUT HERE]

1.F Robustness check

[INSERT Table 10 ABOUT HERE]

1.G Productivity and climate shocks

Following Hsieh and Klenow (2009), total factor productivity (TFP), based on the producer's revenue, can be expressed as:

$$TFPR_{i,k} = \frac{p_{i,k}\ q_{i,k}}{\prod_h X_{i,k,h}^{\alpha_{k,h}}}$$

Since $\frac{q_{i,k}}{\alpha_{0,k}\ g_{i,\ell}^{\alpha_k}} = \frac{q_{i,k}}{\prod_h X_{i,k,h}^{\alpha_{k,h}}} = TFPR_{i,k},\ \forall h$, the following condition must hold under equilibrium:

$$p_{ik}\ *\left(\alpha_{0,k}\ g_{i,\ell}^{\alpha_k}\right)\ *\left(\prod_h X_{i,k,h}^{\alpha_{k,h}}\right)^{-1} = 1$$

With equation (14): $\frac{\alpha_k}{\mu_{ik}} = \frac{p_{i,\ell}\ g_{i,\ell}}{p_{i,k}\ q_{i,k}}$ we have:

$$p_{ik}\ * \alpha_{0,k}\ \left(\frac{\alpha_k}{\mu_{ik}} * \frac{p_{i,k}\ q_{i,k}}{p_{i,\ell}}\right)^{\alpha_k}\ *\left(\prod_h X_{i,k,h}^{\alpha_{k,h}}\right)^{-1} = 1$$

By substituting the sales equation (18) into the previous expression, we obtain:

$$p_{ik} * \alpha_{0,k}\ \left(\frac{\alpha_k}{\mu_{ik}}\right)^{\alpha_k} * \left(\frac{1}{p_{i,\ell}}\ \ \omega_i\ \mathcal{C}(q,\theta_1)^{1-\sigma}\ \theta_2(T_{s(\ell)})^{\sigma-1}\ TFPR_{i,k}^{\sigma-1}\mu_{i,k}^{1-\sigma}\rho_k P_k^{\sigma} Q_k\right)^{\alpha_k} * \left(\prod_h X_{i,k,h}^{\alpha_{k,h}}\right)^{-1} = 1$$

Setting $\frac{1}{p_{i,\ell}} * \mathcal{C}(.)^{1-\sigma} = \tilde{\mathcal{C}}(.)^{1-\sigma}$ yields an expression for total factor productivity that depends on the shocks θ_1 and θ_2.

$$TFPR_{ik} = \left[p_{ik}\ \alpha_{0,k}\ {\alpha_k}^{\alpha_k}\ \left(\omega_i\ \tilde{\mathcal{C}}(q,\theta_1)^{1-\sigma}\ \theta_2(.)^{\sigma-1}\ \mu_{i,k}^{-\sigma}\ \rho_k P_k^{\sigma} Q_k\right)^{\alpha_k}\ * \left(\prod_h X_{i,k,h}^{\alpha_{k,h}}\right)^{-1}\right]^{\frac{1}{\alpha_k(1-\sigma)}}$$