Total factor productivity, markup and the role of climate change

Abstract

We use establishment-level data from Canada to examine how climate shocks affect productivity and markup in the agri-food sector. Our empirical strategy separates productivity measurement from markup recovery. We estimate total factor productivity using a two-step estimator that is robust to optimization errors in input choices, unobserved cost shocks, and measurement errors in proxy variables. Firm-level markups are recovered under cost minimization as the ratio of the output elasticity of materials to their revenue share, with the required elasticities obtained from a Generalized Leontief cost system. Extreme temperature events reduce firm sales and productivity while raising marginal costs. Climate shocks compress markups, while price responses remain small, suggesting that agri-food firms absorb climate-induced cost increases through lower markups rather than passing them to consumers. Single-product firms experience significant declines in both productivity and markups. Responses also vary across multi-product firms, underscoring the role of firm characteristics in shaping vulnerability to climate shocks.

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

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

1. Introduction

Over the past few decades, 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 production across many regions, leading to lower output (Burke et al., 2015a,b; Hsiang and Jina, 2014), higher input costs, and greater variability in farm productivity (Rojas-Downing et al., 2017; Nath, 2020). A large body of empirical work documents the sensitivity of farm productivity to climate extremes, as well as the extent of farmers' adaptation (Burke and Emerick, 2016; Deryugina and Hsiang, 2017).

The evidence on how climate shocks affect downstream food processing firms specifically remains limited and mixed. While localized climate shocks are known to disrupt agricultural input availability, raise input costs, and reduce production efficiency along the food supply chain (Conte et al., 2021; Lee, 2025; Yim and Dall'erba, 2025; Schuurman and Ker, 2025), their firm-level consequences for agri-food processors remain poorly understood. The few existing studies either focus on aggregate productivity (Caggese et al., 2024), or find no effect in broader manufacturing samples, suggesting that impacts may be sector-specific (Addoum et al., 2020).

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 (Panon and Conteduca, 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 agri-food sector. We develop an empirical framework that links climate-induced disruptions in agricultural input markets to productivity fluctuations and markup adjustments. Specifically, we examine whether climate shocks affect productivity and markups through changes in input use, and whether these effects differ by product scope, firm size, and factor-input adjustment margins. Thus, our analysis contributes to the emerging literature on the direct and indirect effects of climate extremes on the productivity of food processing firms and to the literature on the linkages between firms' productivity and markups.

The core of our dataset is an establishment-level file from Statistics Canada, which reports detailed information on revenues, payroll, assets, and R&D expenditures for agri-food firms filing corporate tax statements. The data span the period 2000–2022 and follow the North American Industry Classification System (NAICS), allowing for consistent comparisons across sectors,

regions, and time. We combine these records with high-frequency climate information and measure climate shocks as extreme heat degree days accumulated over the growing season.

Empirically, we examine how climate shocks affect firm performance through two related margins: productive efficiency and market power. Under cost minimization, firm-level markups are measured as the ratio of the output elasticity of materials to the share of material expenditures in firm revenue. The revenue share is directly observed from firms' reported expenditures and sales, whereas the output elasticity must be estimated. We use materials as the variable input because they account for a substantial share of production costs in Canadian agri-food processing and are treated as flexible inputs in the empirical framework. However, because our data contain revenues and input expenditures rather than physical quantities and firm-level prices, output elasticities cannot be reliably recovered from a revenue-based production function (Bond et al., 2021). We therefore adopt a cost-side approach and estimate a Generalized Leontief cost system to recover the material output elasticities used in the markup calculation. Total factor productivity is estimated separately using the two-step GMM-IV estimator of Hu et al. (2020). This separation allows us to examine whether climate shocks affect food processors through productivity losses, changes in marginal costs, and adjustments in markups.

Our results document a transmission mechanism from climate shocks to firm performance and markups. First, climate shocks reduce firm activity and productive efficiency, while increasing marginal costs. These effects are consistent with recent evidence that temperature shocks can affect firm performance and productivity (Caggese et al., 2024), and with evidence from food processors showing that input-cost shocks can induce markup adjustment (Kang and Lee, 2026). We contribute to this literature by documenting, at the establishment level, how climate shocks affect productivity in Canadian agri-food processing and how these productivity effects translate into markup adjustments.

Second, we show that lower productivity compresses markups. Climate-induced productivity declines are associated with lower sales and higher marginal costs, while the measured price responses remain comparatively weak. This pattern points to incomplete cost pass-through: firms adjust prices in response to climate-induced cost pressures, but not enough to fully offset the increase in marginal costs. As a result, agri-food processors absorb part of the shock through lower markups.

Third, these effects are unevenly distributed across firms. Single-product firms experience larger productivity losses and stronger markup compression, suggesting that firms have limited scope to reallocate inputs and sales across product lines. By contrast, larger and more diversified firms display greater resilience. This heterogeneity indicates that the incidence of climate shocks depends not only on exposure to extreme weather, but also on input flexibility and the ability to adjust production across products.

Fourth, we extend our framework beyond the historical sample by projecting markups, productivity, prices, and marginal costs through 2100 under two emissions scenarios, SSP2-4.5 and SSP3-7.0. These projections combine our estimated productivity-climate elasticities with climate projection data to illustrate how the historical transmission mechanism would extend under future warming trajectories. The results show that marginal costs rise faster than prices in both scenarios, with the gap widening under high emissions.

We complement the empirical analysis by developing a theoretical framework that provides an economic interpretation of the mechanisms identified in the data. Rather than serving as the basis for the empirical specification, the model is intended to clarify the channels through which climate shocks propagate from agricultural production to agri-food processing firms. Within this framework, heterogeneous processors rely on agricultural inputs supplied by farmers, while extreme weather events affect the availability, quality, and cost of these inputs.

The remainder of the paper is structured as follows: section 2 reviews the literature related to climate change, productivity and markup dispersion. Section 3 discusses the data sources and definitions of climate shocks. In Section 4, we present the empirical strategy. Section 5 provides a quantitative analysis of recent developments in the markup distribution and discusses the estimation results, highlighting the contribution of climate shocks to observed fluctuations. Section 6 presents an interpretive theoretical framework that rationalizes the empirical patterns documented in the paper. Section 7 concludes.

2. Productivity, climate and markups: a selective review

While numerous studies document the effects of climate change on firm output and total factor productivity, little attention has been given to its impact on productivity dispersion. A long-standing puzzle in industrial economics is why firms exhibit large and persistent productivity differences, even within narrowly defined industries (Cunningham et al., 2023). Early work on firm and plant-level productivity showed that producers operating in the same industry often differ in efficiency, input use, and performance, challenging representative-firm descriptions of production. This evidence established productivity dispersion as a persistent feature of firm dynamics rather than a transitory deviation from equilibrium.

Building on this evidence, a large literature has examined the sources of productivity dispersion across firms, sectors, and geographic areas. One strand emphasizes market structure and competition: product substitutability, entry barriers, and competitive pressure shape the extent to which less productive firms can survive and expand (Syverson, 2004, 2011). Another strand highlights firm-level capabilities and adjustment frictions, including management practices, input quality, and dynamic input adjustment within sectors (Bloom and Van Reenen, 2007; Asker et al., 2014). A related literature attributes dispersion to resource misallocation, showing that reallocating capital and labor from firms with low marginal revenue products to

firms with high marginal revenue products could generate large aggregate productivity gains (Hsieh and Klenow, 2009; Gorodnichenko et al., 2018). Finally, observed dispersion may also reflect demand shocks, product heterogeneity, or measurement issues rather than pure technical inefficiency (Foster et al., 2016; Gollin and Udry, 2021). Together, these studies suggest that productivity dispersion reflects a combination of firm efficiency, demand conditions, adjustment frictions, and distortions.

Yet this literature has paid little attention to the role of climate factors. A partial exception is Aoyama et al. (2009), who analyze productivity distributions within and across industries. They identify a Pareto pattern, where the shape parameter decreases following major shifts in sectoral demand induced by external factors such as temperature variation. Drawing on Gabaix (2011) and the superstatistics framework,[1] they show that greater demand fluctuations are associated with more skewed productivity distributions, often favoring highly productive firms. This result is consistent with the superstatistics framework of Aoyama et al. (2009), which treats fluctuations in aggregate demand as a source of variation in productivity distributions. While they invoke temperature variation as one illustrative source of such external demand shocks, they stop short of establishing a direct empirical link between climate change and productivity dispersion, citing data limitations. Similarly, Iyetomi (2012) find that temperature-induced input demand fluctuations contribute to productivity dispersion: non-manufacturing firms experience larger gaps between desired and actual input quantities than manufacturing firms, and input reallocation across firms and sectors leads to an equilibrium characterized by heterogeneous input rationing. Yet their analysis remains largely theoretical, and empirical validation of the climate-dispersion mechanism is limited.

A separate but closely related literature studies how productivity differences, input costs, and market exposure shape firm performance and markup behavior in food and agricultural markets. Chevassus-Lozza et al. (2013) show that lower input tariffs can reallocate export market shares toward more productive downstream agri-food firms, highlighting the role of agricultural input-cost channels in shaping firm outcomes. Curzi et al. (2021) show that import competition affects firm-level markups in the food industry, with final goods competition exerting pro-competitive pressure and imported intermediates operating through input-cost channels. Jafari et al. (2023) document that markups are closely related to export behavior among French food-processing firms, suggesting that more productive and internationally exposed firms differ in their pricing power. Recent evidence also shows that markups have increased in U.S. food manufacturing when productivity is modeled flexibly (Jaumandreu and Lopez, 2024). Closely related to our mechanism, Kang and Lee (2026) study food inflation pass-through from agricultural imports and show that markup adjustments depend on firms' reliance on imported inputs and demand conditions. Together, these studies suggest that markup dispersion in food markets reflects differences in productivity, input costs, market exposure, and pass-through conditions. Yet none of these studies examine whether climate shocks systematically alter this dispersion and how.

[1] Superstatistics explains how fluctuations induced by environmental changes affect aggregate demand and productivity across firms (Aoyama et al., 2009, 2010).

Recent evidence indicates that climate shocks captured by indicators such as heatwaves (Lee, 2025) or cumulative high-temperature exposure (Yim and Dall'erba, 2025) can generate unexpected declines in agricultural output. These shocks may also affect downstream agri-food firms by disrupting input availability, raising input costs, and reducing production efficiency. Such supply disruptions may increase commodity-price pressures and affect downstream firms through input-cost channels, a mechanism closely related to the pass-through evidence documented by Kang and Lee (2026). Because climate shocks are highly localized, their effects propagate unevenly across space: firms more exposed to climate-induced input disruptions may face higher input costs and lower input availability, while firms less exposed may be relatively insulated (Conte et al., 2021). This spatial heterogeneity suggests that climate shocks can generate uneven productivity losses and cost pressures across firms within the same industry, creating the conditions for markup dispersion.

Yet the markup implications of climate-induced productivity and cost shocks remain largely unexplored. Caggese et al. (2024) analyze Italian firms within a general equilibrium framework to separate the effects of temperature on demand, productivity, and input efficiency. They find a nonlinear link between climate change and aggregate productivity, but do not examine its implications on markup. In principle, if climate shocks reduce productivity and raise input costs, markups may decline when firms cannot increase output prices in proportion to rising marginal costs. However, if these shocks affect firms unevenly or weaken competitive pressure for less-exposed firms, some firms may sustain or even increase their markups. The net effect is therefore ambiguous and must be examined empirically.

In this paper, we argue that climate shocks reduce productivity and compress markups among agri-food firms through incomplete cost pass-through. Our study addresses this gap and differs from previous work in three key ways. First, we provide establishment-level evidence on how extreme heat affects downstream agri-food processors, a segment of the food supply chain that has received less attention than farms and primary agricultural production. This focus allows us to examine how climate shocks transmit through input availability, input costs, and production efficiency in food manufacturing.

Second, we examine whether climate-induced productivity losses translate into markup adjustment. While existing studies document substantial productivity dispersion across firms (Gollin and Udry, 2021; Gouin-Bonenfant, 2022), less is known about whether climate shocks contribute to this dispersion among downstream food processors and how these shocks affect markups. We show that extreme heat reduces productivity and raises marginal costs, while output prices adjust only partially. This incomplete pass-through compresses markups and generates heterogeneous effects across firms, especially between single-product and multi-product producers. In doing so, the paper connects the climate-productivity literature with work on markups and firm heterogeneity.

Third, our empirical approach separates the estimation of productivity from the measurement of markups. Firm-level productivity is recovered by estimating the production function using the proxy-variable approach of Hu et al. (2020), which extends the control-function literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015) by allowing for errors in proxy variables and other unobserved disturbances affecting firms' input choices. This provides a robust framework for addressing the simultaneity between input choices and latent productivity. Markups are recovered through a separate procedure. Because our data contain revenues and input expenditures rather than physical quantities and firm-level output prices, we do not recover markups from the estimated production function. Instead, we combine observed material expenditure shares in revenue with output elasticities recovered from a Generalized Leontief cost system.

3. Data

This section describes the firm and climate data used in the empirical analysis. We first present the administrative data and the construction of the output and input variables. We then describe the historical climate data and how climate shocks are constructed and used in the regressions. Finally, we introduce the climate projection data used to extend the analysis under alternative future emissions scenarios.

3.1. Firm data

We use data from the National Accounts Longitudinal Micro database (NALMF) of Statistics Canada for the period 2000–2022. This data set is constructed using annual cross-sectional files. We select agri-food firms belonging to the four-digit NAICS codes for classes 3111-3119, with a total number of 9 industries. 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. Quantities and prices of inputs and outputs are not observed; only input expenditures and output revenues are reported. We use operating expenses as a direct measure of variable inputs, which include materials, labor, marketing, and management. Table (1) provides summary statistics of the dataset.

[INSERT Table 1 ABOUT HERE]

Firms employ on average about 29 workers and there is a large variation across firm-years. This table also shows that materials is an important component of the production process, followed by capital and labor. Table A.1 in Appendix 1.D 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.

The variables used in the empirical analysis are constructed as follows. Since the NALMF reports output revenues and input expenditures rather than firm-level physical quantities and prices, we work with deflated revenue and expenditure aggregates, following the standard firm-level productivity literature; see Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015) and De Loecker and Syverson (2021). Real composite output is measured as total operating revenue, augmented by farm revenue when reported, and deflated by the annual industry-level Industrial Product Price Index. Material input is proxied by total expenses net of the establishment's annual payroll and capital cost allowance, and is deflated using a fixed-weight material-input price index that varies by province, industry, and year. Labour costs are measured using the annual payroll, while the labour price is defined as average labour cost per worker. Capital is proxied by the establishment's tangible-asset stock, and its price is measured using a user-cost-of-capital approach. Appendix A.8 provides the detailed construction of the real composite output, material-input, labour, and capital price measures.

3.2. Climate data and climate shocks

Historical climate data are drawn from the Climate Prediction Center (CPC) database, developed by the National Oceanic and Atmospheric Administration (NOAA). The CPC provides daily gridded observations of maximum and minimum temperature and precipitation at a spatial resolution of $0.5^\circ \times 0.5^\circ$, constructed by interpolating ground-based weather station records into a spatially consistent observational product. Daily mean temperature is computed as the average of daily maximum and minimum values. We then spatially aggregate to the provincial level using cropland area shares from Mehrabi et al. (2024) as weights, ensuring that the resulting climate measures reflect conditions in agriculturally productive areas rather than the administrative unit as a whole.

[INSERT Figure 1 ABOUT HERE]

To document the spatial and temporal variations of the exposure to temperature, Figure 1 presents two complementary views of growing-season temperature over our sample period. Panel (a) shows the evolution of the average temperature across Canadian provinces from 2000 to 2022. A positive trend is visible over the period, consistent with broader warming patterns documented in the Canadian climate literature. Panel (b) displays the cross-sectional distribution of average temperature at the grid-cell level, illustrating the substantial spatial heterogeneity across the country: southern agricultural regions face significantly warmer temperatures than northern areas.

[INSERT Table 2 ABOUT HERE]

This spatial and temporal variation is further summarized in Table 2. We report two temperature measures. The first is the grid-cell growing-season temperature, computed at the finest spatial

resolution available. It covers 1,675,761 grid-cell-day observations and averages 13.81°C over the April–September growing season, with a standard deviation of 1.67°C and values ranging from −47.73°C to 43.61°C. The second measure is the province-year cropland-weighted average temperature, constructed by aggregating grid-cell temperatures using cropland shares as weights. This province-year measure spans 299 observations, with a mean of 14.950°C, a standard deviation of 8.978°C, and values ranging from −0.990°C to 27.355°C.

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 additional control variables. 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. This approach is motivated by evidence that crop yields decline sharply when temperatures exceed approximately 29–32°C (Roberts and Schlenker, 2009; Lobell et al., 2011; D'Agostino and Schlenker, 2016). We adopt $29°C$ as the baseline threshold, as temperatures above this level have been shown to be particularly harmful for major crops (Roberts and Schlenker, 2009; Parent and Tardieu, 2012).

$$HDD_{d;T_l:T_h} = \begin{cases} 0 \text{ if } T_d \leq 29°C \\ T_d - 29°C \text{ if } T_d > 29°C \end{cases}, \quad \text{HDD} = \sum_{d \in \mathcal{S}} \text{HDD}_{d;\, T_\ell:T_h} \tag{1}$$

where T_d is the daily average temperature for day d. The seasonal HDD variable entering the empirical specification is obtained by summing daily values over all days d in the April–September growing season $\mathcal{S}$.

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). With T_d the daily average temperature for day d, a lower boundary of 10°C, and an upper boundary of 29°C, GDD is constructed such that:

$$GDD_{d;10:29} = \begin{cases} 0 \text{ if } T_d \leq 10°C \\ T_d - 10°C \text{ if } 10°C < T_d \leq 29°C \\ 29°C - 10°C \text{ if } 29°C < T_d \end{cases}, \quad \text{GDD} = \sum_{d \in \mathcal{S}} \text{GDD}_{d;\, 10:29} \tag{2}$$

Growing degree days, extreme heat degree days, and precipitation are added together over all days of the April–September growing season.

3.3. Climate Projection Data

We complement the historical data with climate projections sourced from the Global Downscaled Projections for Climate Impacts Research (GDPCIR) dataset (Gergel et al., 2024), yielding a combined climate series spanning 1950 to 2100. The dataset provides bias-corrected, spatially downscaled daily projections of maximum temperature, minimum temperature, and precipitation over the 2015–2100 period. Projections are examined under two emission scenarios: SSP2-4.5, a moderate mitigation pathway associated with 2.7–3.0°C of warming by 2100, and SSP3-7.0, a high-emission pathway associated with 3.8–4.5°C of warming by 2100. Rather than relying on a single model, we follow Wen et al. (2026) and Schuurman and Ker (2025) and construct climate indicators as the median across 8 models from the Coupled Model Intercomparison Project Phase 6 (CMIP6) available in the GDPCIR dataset, which mitigates sensitivity to any individual model's projections. Gridded outputs are spatially aggregated to the provincial level following the same procedure applied to the historical data, and identical GDD, HDD, and precipitation indicators are constructed for each province-year cell over the April-September growing season.

4. Empirical Strategy

This section describes the empirical strategy. Because the data report firm revenues and expenditures rather than firm-level quantities and prices, productivity is estimated separately from markups. We estimate firm-level productivity using the two-step GMM-IV estimator of Hu et al. (2020). Markups are recovered as the ratio of the output elasticity of materials to the share of material expenditures in firm revenue. Since revenue-based production-function estimates do not directly deliver the output elasticities required for markup measurement when firm-level prices are unobserved (Bond et al., 2021), the relevant elasticities are instead recovered from a Generalized Leontief cost system. Finally, we estimate the effects of climate shocks on productivity and markups using panel regressions with firm and sector-year fixed effects.

4.1. Measurement of productivity

We recover firm-level productivity by relying on the proxy methods developed by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015). This approach uses observed input choices to control for productivity while allowing for imperfect proxy variables. The production function separates observed output into a deterministic production component, latent productivity, and a transitory output disturbance. Our specification is

$$q_{it} = f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) + a_{it} + \varepsilon_{it}, \tag{3}$$

where q_{it} denotes log output, while k_{it}, l_{it}, and m_{it} denote log capital, labor, and material inputs, respectively. The parameter vector is $\boldsymbol{\beta} = (\beta_k, \beta_l, \beta_m)$. For estimation, the deterministic compo-

nent is specified as $f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it}$. The term a_{it} denotes log productivity, whereas ε_{it} captures transitory output shocks that are not observed by the firm when variable inputs are chosen. At the time of input choice, capital is predetermined, whereas materials are flexible inputs chosen after the firm observes its productivity state a_{it} but before the realization of ε_{it}. Let $\mathcal{I}_{it}$ denote the firm's information set at that time. We assume that $\mathbb{E}[\varepsilon_{it} \mid \mathcal{I}_{it}] = 0$, so that the conditional expectation of output is $\Phi_{it} \equiv \mathbb{E}[q_{it} \mid \mathcal{I}_{it}] = f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) + a_{it}$.

A central challenge in estimating productivity is that firms observe their productivity when choosing inputs. Input choices are therefore endogenous, and standard production-function estimates may be biased. Proxy-variable methods address this simultaneity problem by using observed input choices to control for latent productivity (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). However, standard proxy methods typically require the proxy input to reveal productivity through a monotonic input-demand relationship. This restriction may fail when observed materials are affected by measurement error, optimization errors, unobserved cost shocks, or firm-specific input-price variation.

We therefore estimate productivity using the robust proxy-variable approach of Hu et al. (2020). This approach treats proxy variables as imperfect signals of latent productivity and uses the information contained in multiple proxies, together with the productivity process, to recover production-function parameters and firm-level productivity under weaker conditions than standard proxy-variable methods. The detailed timing assumptions, identification conditions, and estimation procedure are reported in Appendix A.9. Productivity is assumed to follow a first-order Markov process:

$$a_{it} = g_t(a_{i,t-1}) + \theta_{it}, \tag{4}$$

where $g_t(\cdot)$ captures the persistent component of productivity and θ_{it} is a firm-specific productivity innovation. Climate-related disruptions may constitute one source of these innovations by affecting the availability, timing, quality, and reliability of intermediate inputs, thereby reducing production efficiency (Chavas, 2008; Chavas and Zhang, 2025).

4.2. Measurement of markups

The markup results from the cost minimization and the first-order condition as a function of the revenue elasticity of variable inputs (in this case materials[2]), and the revenue share of the variable input bundle (see Hall (1988); De Loecker and Warzynski (2012); De Loecker et al. (2016); Jafari et al. (2023)). The expression for the firm-level markup μ_{it} is:

$$\mu_{it} = \frac{P_{it}}{\mathcal{C}_Q} = \beta_{it}^M \left(s_{it}^M\right)^{-1} \tag{5}$$

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

Where P the price of the output, $\mathcal{C}_Q$ the marginal cost of production, β_{it}^M the revenue elasticity of the variable input, and s_{it}^M the share of variable input relative to the total revenue. s_{it}^M is directly measured using the available data.

A natural implementation of (5), and the one followed by most applications of the production approach, is to recover elasticities from the production function estimation using proxy-variable methods. This approach is problematic in our setting because the data report revenues and input expenditures rather than physical quantities and firm-level prices. Using industry-level price deflators to convert firm revenues into real output may not fully remove firm-specific price variation. As a result, measured output may still reflect differences in output prices, product quality, or demand conditions, generating measurement error in real output (Yeh et al., 2022). Similarly, deflated input expenditures may reflect firm-specific input prices rather than only physical input use. This measurement concern is particularly important for markup measurement. As emphasized by Bond et al. (2021), when output prices are unobserved and revenue is used as the dependent variable, production-function estimates recover revenue elasticities rather than the physical output elasticities required in the markup identity.

For these reasons, we rely on the cost approach (Diewert, 1971; De Loecker, 2011; Daglish et al., 2015) to estimate the elasticity entering equation (5), by specifying a general Leontief cost function of the form:

$$\mathcal{C}(P,Q) = \left[a_M P_M + a_{LL} P_L + 2a_{LK}(P_L P_K)^{1/2} + a_{KK} P_K\right] Q^d \tag{6}$$

with $(a_M, a_{LL}, a_{LK}, a_{KK})$ a vector of parameters and d the inverse the cost elasticity with respect to output. In equation (6), materials enter as a separable linear component, while labor and capital enter through a Generalized Leontief price aggregator. This structure is useful for food manufacturing because materials are the dominant variable input, while flexible substitution is allowed within the labor-capital block. The function is homogeneous of degree one in input prices. The parameter d governs the relationship between costs and output scale and therefore determine the cost elasticity with respect to output. We do not impose constant returns to scale, but estimate d from the data. The estimated system yields revenue-based elasticities, denoted by $\beta_{it,r}^M$, $\beta_{it,r}^L$, and $\beta_{it,r}^K$, which summarize the relative contribution of materials, labor, and capital in the cost-side system. To convert these revenue-based elasticities into output elasticities, we account for the scale elasticity implied by the estimated cost function. The output elasticities used in the markup calculation are then recovered as (see Appendix A.3 for details):

$$\beta_{it}^M = \frac{1}{d} \frac{\beta_{it,r}^M}{\beta_{it,r}^M + \beta_{it,r}^L + \beta_{it,r}^K}. \tag{7}$$

The output elasticities of labor and capital are recovered analogously. Combining the material output elasticity from equation (7) with the observed revenue share of materials delivers the firm-level markup. The aggregate markup in year t is computed as the sales-weighted average

of firm-level log markups:

$$\log \mu_t = \sum_i \omega_{it} \log \mu_{it}, \qquad \omega_{it} = Y_{it} \Big/ \sum_i Y_{it} \ , \tag{8}$$

where Y_{it} denotes firm sales, w_{it} is firm i's share of total sales in year t, and μ_{it} is the estimated firm markup.

4.3. Estimating the effects of climate shocks

We investigate the effect of climate shocks on firm outcomes using the following panel specification:

$$y_{it} \ = \zeta^h HDD_{i,t} + \zeta^z Z_{i,t} + \Gamma_i + \delta_{s,t} + \varepsilon_{it}, \tag{9}$$

Where i denotes the firm, and t the year. The dependent variable y_{it} corresponds to either firm-level markups or productivity. $HDD_{i,t}$ captures extreme heat degree days. The vector Z_{it} includes additional controls, such as growing degree days (GDD) and cumulative precipitation (Pr).

Firm fixed effects Γ_i absorb all time-invariant heterogeneity across firms, including technology and management practices. Sector-year fixed effects $\delta_{s,t}$ control for sector-specific shocks such as changes in global demand or price. Standard errors are clustered at the regional level to account for spatial correlation in weather shocks and potential serial correlation within regions over time. The coefficients $\zeta^{h,m}$ measure the marginal effect of an additional extreme heat degree day in month m on firm outcomes.

The identification of causal effects relies on the assumption that within-firm, within-sector variation in extreme heat exposure is plausibly exogenous to firm-level decisions. This assumption is supported by the nature of climate shocks, which are determined by large-scale atmospheric processes outside the control of individual firms. The inclusion of firm fixed effects removes all time-invariant confounders, while sector-year fixed effects absorb common demand and supply shocks at the sector level. Remaining threats to identification would require unobserved firm-level shocks that are simultaneously correlated with local temperature extremes and firm markups, a scenario we consider unlikely given the inclusion of firm and sector-year fixed effects alongside growing degree days and precipitation as additional climate controls, which together absorb the bulk of confounding seasonal and sectoral variation.

4.4. Productivity, markup and climate shocks

To provide intuition about how climate shocks affect firm-markups, we consider a monopolistic model with endogenous markups following Melitz and Ottaviano (2008). Firm productivity

A_{it} affects both marginal costs and perceived demand elasticity, implying that climate-induced productivity shocks translate directly into markup fluctuations. This mechanism is consistent with empirical evidence linking productivity and markups (De Loecker and Warzynski, 2012; De Loecker et al., 2020). Identification does not rely on the exogenous nature of productivity, but on the exogenous nature of climate shocks that generate variation in productivity.

Using the first-order conditions specified in equation (5) for output, and under the assumption that the output is determined endogenously within the model, price–cost markup can be expressed as:

$$\mu_{it} = \frac{P(Q(\theta_{it}), .)}{C_Q(Q(\theta_{it}), .)} \quad , \tag{10}$$

Where C_Q is the marginal cost of production, P is the price of the output Q, and θ_{it} indicates variations in productivity. Climate shocks affect markups indirectly through their impact on prices, quantities, and marginal costs. To investigate these transmission channels, we construct the climate-induced productivity component:

$$\theta_{it} = \zeta^h \ \mathrm{HDD}_{it} + \zeta^g \ \mathrm{GDD}_{it} + \zeta^{pr} \ \mathrm{Pr}_{it} \quad , \tag{11}$$

where $\zeta^h, \zeta^g, \zeta^{pr}$ are the estimated coefficients for productivity from equation (9). Our next step is to examine possible Total Factor Productivity (TFP) paths over future climate scenarios, and the implications on markup fluctuations:

$$\widetilde{\theta} = \widehat{\zeta^h} \ \widetilde{\mathrm{HDD}} + \widehat{\zeta^g} \ \widetilde{\mathrm{GDD}} + \widehat{\zeta^{pr}} \ \widetilde{\mathrm{Pr}} \ , \tag{12}$$

with $\widetilde{\mathrm{HDD}}$, $\widetilde{\mathrm{GDD}}$ and $\widetilde{\mathrm{Pr}}$ constructed using future scenarios of climate data. We then estimate the reduced-form regressions of the following form:

$$\widetilde{\mathrm{Outcome}}_{it} = \eta \ \widetilde{\theta}_{it} + \phi_i + \phi_t + \varepsilon_{it} \ , \tag{13}$$

Where $\widetilde{\mathrm{Outcome}}_{it}$ corresponds to firm-level price, quantity, or marginal cost. ϕ_i and ϕ_t denote firm and time fixed effects, respectively, and ε_{it} is a random error term. η captures the firm response of each outcome to changes in climate shocks over time, after controlling for firm and time fixed effects. $\widetilde{\theta}_{it}$ is computed from the estimated coefficients following equation (11).

5. Results

This section presents the main empirical results. We first report the output elasticities recovered from the Generalized Leontief cost system and describe the distribution of markups. We then estimate the effects of climate shocks on productivity, marginal costs, and markups, before

examining the transmission channels and the heterogeneity of these effects across firms.

5.1. Elasticities

Table 3 reports the output elasticities recovered from the Generalized Leontief cost system for the full sample and for each of the nine four-digit NAICS food-manufacturing subsectors. At the aggregate level, the estimated elasticities are 0.72 for materials, 0.22 for labour, and 0.09 for capital. Materials therefore represent the dominant input in the production process. The corresponding returns-to-scale estimate is 1.03, indicating mild increasing returns to scale that remain close to constant returns.

[INSERT Table 3 ABOUT HERE]

The predominance of materials is consistent with the central role of upstream inputs in food processing. Using U.S. input–output data, Wahdat and Lusk (2023) show that food-manufacturing industries are highly exposed to upstream suppliers, including agricultural industries, and that this exposure varies substantially across food subsectors. Our estimates complement this evidence by showing that intermediate materials represent the dominant production margin in Canadian food manufacturing.

The estimates also reveal meaningful heterogeneity across subsectors. Material elasticities range from 0.57 in bakeries and tortilla manufacturing to 0.84 in animal food manufacturing. Labour elasticities display the opposite pattern, ranging from 0.11 in animal food manufacturing to 0.37 in bakeries and tortilla manufacturing. This variation is consistent with differences in production processes and input composition across food-manufacturing activities. Returns to scale remain close to unity in all subsectors, ranging from 1.00 in animal food manufacturing to 1.05 in sugar and confectionery product manufacturing and bakeries and tortilla manufacturing.

Our findings are also consistent with Canadian evidence by Gervais et al. (2008), who estimate flexible cost functions for the meat, dairy, and bakery industries and show that substitution patterns and scale economies vary across food-processing activities and provinces.

5.2. Markup

We use equation (5) to estimate firm-level markups and examine their evolution over time. We begin by analyzing the aggregate markup dynamics for Canadian agri-food firms over the period 2000–2022.

Figure 2 depicts the average markup and average marginal cost across firms. The trend can be grouped into two phases. In the first phase, the average markup decreased from approximately 1.66 in 2000 to 1.59 in 2008 (a reduction of 7%), coinciding with the 2007–2008 food crisis, during which rising commodity prices compressed margins across agri-food processors. The second phase saw a significant rise from 1.59 in 2008 to 1.68 in 2022 (an increase of 9%), likely reflecting easing input cost pressures in the post-crisis period. This upward trajectory

is consistent with Jaumandreu and Lopez (2024), who document a secular increase in markups among U.S. food manufacturers over a comparable period when productivity is modeled flexibly. The inverse co-movement between markups and marginal costs visible in Figure 2 supports the interpretation that agri-food firms adjust their pricing behavior in response to cost conditions, a pattern consistent with De Loecker et al. (2020).

[INSERT Figure 2 ABOUT HERE]

Table 4 reports the distribution of markups across industries. The distribution is uneven within most industries: the weighted average log-markup exceeds unity in all sectors, with the highest mean in animal food manufacturing (1.82) and the lowest in bakeries and other food manufacturing (1.40–1.41). The dispersion is substantial: the 90–10 ratio is 4.76 and the 75–25 ratio is 2.07, indicating that market power is highly concentrated among a subset of firms even within narrowly defined industries. Grain and oilseed milling exhibits notably higher markup variation than meat processing, pointing to structural differences in the degree of competition across sub-sectors. While our data do not allow us to directly identify the sources of this differential, one plausible channel is exposure to import competition: Curzi et al. (2021) show that import competition exerts pro-competitive pressure on firm-level markups in food manufacturing, compressing pricing power in more open segments. Variation in such exposure across subsectors may thus partly account for the observed differences in markup dispersion.

[INSERT Table 4 ABOUT HERE]

Figure 3 helps explain part of this dispersion. Material input expenditure shares are high throughout the Canadian agri-food sector, and smaller firms report systematically higher input cost shares than larger firms. Since markups are mechanically decreasing in input cost shares (as shown in equation (5)), size-related differences in input intensity translate directly into markup heterogeneity across firms. This also implies that climate shocks, by disrupting the supply and raising the cost of raw materials, will affect markups unevenly: smaller, higher-cost firms have less room to absorb cost increases without compressing their margins (Koppenberg and Hirsch, 2022; Edmond et al., 2023).

[INSERT Figure 3 ABOUT HERE]

Estimated markup distribution is consistent with recent evidence in the agri-food sector. Kang and Lee (2026), using Korean firm-level financial statements and a similar methodological framework building on De Loecker et al. (2016) and a Leontief production technology, report a mean markup of approximately 1.2, with values ranging from 0.77 to 3.69. While their mean is somewhat below our estimate of 1.53, the distributional range overlaps substantially with ours, and the pattern of firm-level heterogeneity is consistent across both settings.

A noteworthy feature of Table 4 is the prevalence of markups below unity in the lower tail of the distribution, most strikingly in dairy (P10 = 0.20), grain and oilseed milling (P10 = 0.33),

and other food manufacturing (P10 = 0.28). The presence of markups below unity in the lower tail of the distribution is consistent with incomplete cost pass-through among constrained or climate-exposed firms, a hypothesis we test formally in Section 5.3.

5.3. Effect of climate shocks on firm performance

The results in the previous section suggest there is considerable heterogeneity in markups within the Canadian agri-food sector, with a subset of firms operating at markups below unity. We now examine whether climate shocks help explain this heterogeneity. We examine the firm-level effects of climate shocks on key outcomes and explore the adjustment mechanisms underlying markup responses.

5.3.1. Input productivity and total factor productivity

We use equation (9) to estimate the effects of extreme temperature variations on firm productivity. We also explore the effect on the use of inputs, that is, materials, labor and capital, and discuss the results in Table 5.

[INSERT Table 5 ABOUT HERE]

Estimates indicate that climate shocks reduce TFP and increase unit production costs. This implies that firms require more input to generate a given level of output. A one-unit increase in HDD raises marginal costs by 0.011% and reduces productivity by 0.012%. At the input level, the marginal revenue product of materials (MRPM) declines significantly in response to climate shocks. The marginal revenue product of capital (MRPK) is negative but not statistically significant, while the marginal revenue product of labor (MRPL) does not show a significant response, suggesting that labor is less sensitive to temperature extremes than material inputs. Our findings suggest that material inputs constitute the primary margin of adjustment in the short-run, in response to climate-induced productivity shocks, as firms can more rapidly scale their material use than capital or labor (Asker et al., 2014).

Precipitation follows a similar pattern to HDD: higher seasonal rainfall is associated with increased marginal costs, reduced TFP, and a decline in MRPM. These effects may reflect disruptions to harvesting, transportation, and storage of agricultural inputs caused by excess moisture, particularly during the growing season. The effects on MRPK and MRPL are not statistically significant. Growing degree days are associated with lower marginal costs and higher productivity. Favorable temperature conditions improve input efficiency and reduce the cost of producing a given level of output. The marginal revenue product of materials also responds positively to growing degree days, though the effects on capital and labor productivity are small and statistically non-significant.

Taken together, the results suggest that climate shocks operating through extreme heat reduce input efficiency and raise unit production costs. Among the inputs considered, material inputs bear the greatest burden of climate-induced productivity losses, while labor productivity remains comparatively resilient.

5.3.2. Markup

Having documented the effects of climate shocks on productivity and input efficiency, we next assess whether these shocks translate into changes in markups. Following equation (9), Table 6 reports the panel estimates of the impact of climate aggregates on firm-level markups, controlling for firm and sector-year fixed effects, for all firms and by four-digit NAICS industry group.

The results reveal that extreme heat degree days and precipitation exert both negative and statistically significant effects at 1% on markups at the aggregate level, with coefficients of -0.00019 and -0.00025 respectively. Extreme weather conditions increase marginal costs and disrupt supply chains, limiting firms' ability to maintain prices above marginal costs. The negative markup response to HDD is broadly consistent across industries, with all sectors reporting significant negative estimates except for Other food manufacturing (3119). The effects of precipitation are similarly pervasive, with particularly large responses in Grain and oilseed milling (-0.00035), Fruit and vegetable food manufacturing (-0.00035), and Dairy product manufacturing (-0.00034), sectors that rely heavily on raw material inputs.

Growing degree days are positively and significantly associated with higher markups (0.00090). This result is consistent with the productivity-enhancing role of favorable temperatures documented in Section 5.3.1: as input efficiency improves, firms face lower marginal costs and are better positioned to sustain or expand their price-cost margins. The positive effect of GDD on markups is consistent across all nine industry groups, with coefficients ranging from 0.00058 (Grain and oilseed milling, 3112) to 0.00117 (Bakeries and tortilla manufacturing, 3118).

[INSERT Table 6 ABOUT HERE]

5.3.3. Total factor productivity and markup

We use equations (11)-(13) to examine how climate-induced productivity shocks translate into markups, prices, sales, and marginal costs. Drawing on the estimated TFP coefficients reported in Table 5 and using historical climate data, we construct the climate-induced productivity component. We then estimate the elasticity coefficients linking this component to firm outcomes.

[INSERT Table 7 ABOUT HERE]

Table 7 reports the estimated elasticity coefficients. The results point to two related transmission channels. First, a one-percent climate-induced decline in total factor productivity is associated with a 0.0194% reduction in firm sales and a 0.0028% decline in markups. At the same time, output prices increase by only 0.000049%, while marginal costs rise by 0.0007%. The marginal-cost response is approximately fourteen times larger than the price response, indicating incomplete cost pass-through. Firms therefore absorb part of the cost increase through lower markups rather than passing it fully through to consumers.

The second transmission mechanism is the output channel. Climate-induced productivity losses also reduce output, and this output contraction affects both prices and marginal costs. The estimated price elasticity with respect to the output contraction is $\eta_q^P = 0.00356$, while the estimated marginal-cost elasticity with respect to output is $\eta_q^{MC} = 0.535$. Again, the marginal-cost elasticity is larger than the price elasticity, suggesting that output contractions raise per-unit production costs more than prices, consistent with short-run input rigidities. When output contracts, firms cannot immediately adjust all inputs, so per-unit costs rise even under constant returns to scale.

In both channels, marginal costs respond more strongly than prices. Next, we use these estimated elasticity coefficients to project the implied paths of productivity, markups, prices, and marginal costs under alternative climate scenarios. This projection exercise extends the historical mechanism to future climate conditions and illustrates how the magnitude of the adjustment depends on the emissions pathway.

[INSERT Figure 4 ABOUT HERE]

Figure 4 reports projected paths for markups, total factor productivity, prices, and marginal costs through 2100 under two emission scenarios: SSP2-4.5 and SSP3-7.0. All series are expressed as a level index with base year 2014 equal to one. The projections show that productivity declines under both scenarios, with stronger losses under the high-emission pathway. Under SSP2-4.5, TFP remains close to 0.90-0.92 by the end of the century. Under SSP3-7.0, the decline is larger, with TFP falling to roughly 0.85-0.90 by 2100. Markups follow a similar downward trajectory. Under SSP2-4.5, the markup index declines gradually and remains around 0.93 by 2100. Under SSP3-7.0, markup compression is stronger, with the index falling to approximately 0.88–0.90 by the end of the century. This pattern is consistent with the historical estimates: climate-induced productivity losses raise marginal costs and reduce firms' ability to maintain markup.

The price and marginal-cost panels provide further evidence of incomplete pass-through. Prices increase under both scenarios, reaching approximately 1.03 under SSP2-4.5 and about 1.05–1.06 under SSP3-7.0 by 2100. Marginal costs rise more strongly, reaching approximately 1.06 under SSP2-4.5 and about 1.10–1.11 under SSP3-7.0. The fact that marginal costs rise more than prices explains the projected decline in markups. Firms increase prices in response to climate-induced cost pressures, but the price adjustment remains smaller than the increase in marginal costs.

The divergence between SSP2-4.5 and SSP3-7.0 becomes more visible after mid-century. Under the moderate mitigation pathway, productivity and markups decline gradually, while prices and marginal costs rise moderately. Under the high-emission pathway, the deterioration is stronger, reflecting the cumulative effect of greater exposure to extreme heat.

Additional evidence on the cost-price adjustment mechanism is reported in Figure A.1 in Appendix A.7. The figure shows the dispersion of prices and marginal costs under extreme heat exposure, both constructed from the climate-induced productivity component. Marginal-cost dispersion remains above price dispersion throughout the historical period and under both climate scenarios, with a larger gap under SSP3-7.0 after mid-century.

Overall, the results indicate that climate shocks compress firm markups through two related channels. First, adverse productivity shocks increase marginal costs, while prices adjust only partially. Second, the associated output contraction raises per-unit costs through short-run input rigidities. In both cases, marginal costs rise more than prices, which reduces price-cost margins. The historical estimates document this mechanism over the observed period, while the scenario analysis shows that it may intensify under a high-emission pathway.

5.3.4. Heterogeneous effects

We investigate whether the effects documented above vary across firms by examining heterogeneity along three dimensions: product scope, firm age, and firm size.

—Does the number of products matter?

Table 8 contains the results from splitting the sample by the number of products. We observe substantial heterogeneity in the estimates across product groups. The HDD coefficient is negative and statistically significant at the 1% level for both markup and TFP in single-product firms (-0.00019 and -0.00014, respectively), indicating that climate shocks compress both price-cost margins and productive efficiency for the most specialized firms. The effect on markup remains negative and significant for firms producing three or more products, though the magnitude declines modestly as product diversification increases. In particular, the markup effect loses statistical significance for firms with two or four products, which may reflect sample size constraints given the smaller number of observations in those groups.

The TFP results reveal a complementary pattern: the adverse productivity effect of heat stress is largest and most precisely estimated for single-product firms, while it becomes statistically indistinguishable from zero for firms with four or more products.This suggests that multi-product firms appear better able to absorb climate shocks, possibly by redirecting inputs toward less affected product lines.

Overall, these results indicate that product diversification shapes the transmission of climate shocks: single-product firms bear a disproportionately larger burden in terms of both productiv-

ity losses and markup compression, while larger multi-product firms exhibit greater resilience, particularly on the productivity margin.

[INSERT Table 8 ABOUT HERE]

— ***Age and firm size***

Appendix A.5 (Table A.2) reports the results of augmenting the baseline specification with firm age, its square term, and four binary indicators capturing multi-location, multi-establishment, multi-province, and multi-activity firms. The HDD coefficient remains negative and statistically significant at the 1% level for both markup (-0.00019) and TFP (-0.00012), with magnitudes identical to the baseline estimates, confirming that the adverse effect of climate shocks is not driven by differences across firms of different ages or organizational complexity.

Firm age enters negatively and significantly in the markup equation, suggesting that older firms operate with somewhat lower price-cost margins. The quadratic term is positive and marginally significant, pointing to a mild U-shaped age-markup profile. Neither age nor its square is significant in the TFP equation, indicating that productivity is orthogonal to firm age once climate and fixed effects are controlled for. Across both outcomes, firm organizational controls are statistically insignificant, supporting the robustness of the baseline results.

6. Conceptual framework

This section provides an economic interpretation of the empirical patterns documented in the previous sections. We develop a vertically linked two-sector framework in which climate shocks propagate from upstream agricultural production to downstream food processors. The economy consists of an upstream agricultural sector, denoted by ℓ, and a downstream processing sector, denoted by k. The upstream sector supplies a homogeneous agricultural input, such as livestock, grain, milk, or other raw food materials. Downstream processors transform this input into differentiated final products.

We define θ as a transformation function of T, such that $\theta = \theta(T)$ serves as our measure of climate shocks. We assume that climate shocks are random variables emanating from *(i)* input demand which we denote by $\theta_1(T)$ and *(ii)* consumer demand for the final output, which we denote by $\theta_2(T)$. $\theta_1(T)$ affects farmers' productivity, whereas $\theta_2(T)$ influences consumer demand for the final output of firms. We assume that $\theta_1(T)$ is random with a given probability distribution, unknown to farmers at the time of input decisions. We assume that more severe extreme weather exposure increases both shocks:

$$\theta_1'(T_s) > 0, \qquad \theta_2'(T_s) > 0.$$

For simplicity, we suppress the state index s in quantities and prices whenever there is no ambiguity.

6.1. The upstream agricultural sector

The representative upstream producer combines a material input M_ℓ and a bundle of other inputs $\mathbf{X}_\ell$ according to a Leontief technology:

$$g_\ell = A_\ell\left(\theta_1\right) \min\left\{ \frac{M_\ell}{a_{\ell M}},\ H_\ell\left(\mathbf{X}_\ell\right) \right\}, \tag{14}$$

where g_ℓ is agricultural output, $A_\ell(\theta_1)$ is upstream productivity, $a_{\ell M} > 0$ is the material requirement, and $H_\ell(\cdot)$ is an aggregate of the remaining agricultural inputs. We assume that adverse climate shocks reduce agricultural productivity:

$$\frac{\partial A_\ell(\theta_1)}{\partial \theta_1} < 0.$$

Because the material input and the bundle of other inputs are strict complements, cost minimization requires both terms in the minimum operator to be equal. Let P_ℓ^M denote the price of M_ℓ and let $\mathbf{P}_\ell^X$ denote the prices of the inputs included in $\mathbf{X}_\ell$. The conditional cost function is therefore

$$C_\ell(g_\ell, \theta_1) = P_\ell^M a_{\ell M} \frac{g_\ell}{A_\ell(\theta_1)} + c_\ell^H\left(\frac{g_\ell}{A_\ell(\theta_1)}, \mathbf{P}_\ell^X\right), \tag{15}$$

where $c_\ell^H(\cdot)$ is the minimum cost of producing one unit of the input bundle $H_\ell(\mathbf{X}_\ell)$. Upstream producers are perfectly competitive. Hence, the equilibrium price of the agricultural input equals marginal cost:

$$p_\ell = MC_\ell = \frac{\partial C_\ell(g_\ell, \theta_1)}{\partial g_\ell}. \tag{16}$$

Because a negative supply shock lowers $A_\ell(\theta_1)$, it increases the effective input requirement needed to produce a given quantity of agricultural output. Therefore, climate shocks raise the upstream marginal cost and the equilibrium price p_ℓ paid by downstream processors.

6.2. The downstream processing sector

Each processor i produces a differentiated final product using an agricultural input $g_{i\ell}$ and a capital-labour bundle. We impose complementarity between agricultural materials and the capital-labour bundle:

$$q_i = A_i(\theta_1) \min\left\{ \frac{\tau_i(\theta_1) g_{i\ell}}{a_{iG}},\ F_i(K_i, L_i) \right\}, \tag{17}$$

where q_i denotes output, $A_i(\theta_1)$ is firm-specific production efficiency, $a_{iG} > 0$ is the technical requirement for agricultural materials, and $F_i(K_i, L_i)$ is a general capital-labour aggregator. The parameter $\tau_i(\theta_1)$ captures the usable share of agricultural materials after losses due to lower quality, delayed delivery, storage losses, or supply-chain disruptions.

We assume that adverse supply-side climate shocks weakly reduce firm efficiency and strictly reduce the usable share of agricultural materials:

$$\frac{\partial A_i(\theta_1)}{\partial \theta_1} \leq 0, \qquad \frac{\partial \tau_i(\theta_1)}{\partial \theta_1} < 0.$$

The fixed-proportions technology implies the following cost-minimizing input condition:

$$\frac{\tau_i(\theta_1) g_{i\ell}}{a_{iG}} = F_i(K_i, L_i) = \frac{q_i}{A_i(\theta_1)}. \tag{18}$$

In particular, the material requirement is

$$g_{i\ell} = \frac{a_{iG} q_i}{A_i(\theta_1)\tau_i(\theta_1)}.$$

Let P_i^K and P_i^L denote the prices of capital and labour. Let $c_i^{KL}(x, P_i^K, P_i^L)$ denote the minimum cost of producing x units of the capital-labour bundle $F_i(K_i, L_i)$. The processor's cost function is

$$C_i(q_i, \theta_1) = p_\ell(\theta_1) \frac{a_{iG} q_i}{A_i(\theta_1)\tau_i(\theta_1)} + c_i^{KL}\left(\frac{q_i}{A_i(\theta_1)}, P_i^K, K_i^L\right). \tag{19}$$

The marginal cost of production is

$$MC_i(q_i, \theta_1) = \frac{p_\ell(\theta_1) a_{iG}}{A_i(\theta_1)\tau_i(\theta_1)} + \frac{1}{A_i(\theta_1)} \frac{\partial c_i^{KL}}{\partial x}\left(\frac{q_i}{A_i(\theta_1)}, P_i^K, P_i^L\right). \tag{20}$$

Equation (20) shows the three channels through which a supply-side climate shock increases downstream marginal costs. First, it raises the price of agricultural inputs, $p_\ell(\theta_1)$. Second, it lowers the share of purchased materials, $\tau_i(\theta_1)$. Third, it may reduce firm-level production efficiency, $A_i(\theta_1)$. Under these conditions,

$$\frac{\partial MC_i(q_i, \theta_1)}{\partial \theta_1} > 0.$$

6.3. Product market and vertical equilibrium

Each processor faces a downward-sloping inverse demand curve, $p_i = P_i(q_i, \theta_2)$, with $P_{iq} < 0$. The variable $\theta_2(T_s)$ captures climate-related demand conditions, including changes in consumers'

valuation of product quality, delivery reliability, or local market conditions.

Processor i chooses output to maximize $\pi_i = P_i(q_i, \theta_2)q_i - C_i(q_i, \theta_1)$, and the optimal output choice satisfies

$$P_i(q_i, \theta_2) + q_i P_{iq}(q_i, \theta_2) = MC_i(q_i, \theta_1). \tag{21}$$

For a given climatic state, vertical equilibrium requires that upstream producers and downstream processors optimize, and that the agricultural-input market clears:

$$S_\ell\left(p_\ell, \theta_1\right) = D_\ell^k\left(p_\ell, \theta_1, \theta_2\right) = \sum_i g_{i\ell}. \tag{22}$$

The supply function $S_\ell(\cdot)$ is generated by competitive upstream producers, whereas $D_\ell^k(\cdot)$ is the aggregate demand for the agricultural input from processors. An adverse supply-side climate shock reduces upstream productivity and shifts the supply of agricultural materials inward. Holding downstream demand constant, this raises the equilibrium input price p_ℓ and, through the processor cost function, increases downstream marginal costs.

6.4. Implications of the model for sales

We isolate the supply-side transmission channel by holding downstream demand conditions, θ_2, constant. This comparative static focuses on the mechanism through which climate shocks affect processors through agricultural input markets. Let the processor's optimal output be implicitly defined by equation (21).[3] With θ_2 held constant, differentiation with respect to the supply-side shock θ_1 gives

$$\frac{\partial q_i}{\partial \theta_1} = -\frac{MC_{i\theta_1}}{MC_{iq} - 2P_{iq} - q_i P_{iqq}}. \tag{23}$$

The denominator is positive under the second-order condition for profit maximization. Moreover, equation (20) indicates that $MC_{i\theta_1} > 0$: an adverse climate shock raises the equilibrium price of agricultural inputs, reduces their usable share, and may lower firm-level production efficiency. It follows that

$$\frac{\partial q_i}{\partial \theta_1} < 0.$$

Since $\theta_1'(T_s) > 0$, the chain rule implies that

$$\frac{dq_i}{dT_s} = \frac{\partial q_i}{\partial \theta_1}\theta_1'(T_s) < 0.$$

[3] The total differential of equation (21) with respect to T_s is $[2P_{iq} + q_i P_{iqq} - MC_{iq}]\,\frac{dq_i}{dT_s} + [P_{i\theta_2} + q_i P_{iq\theta_2}]\,\frac{d\theta_2}{dT_s} - MC_{i\theta_1}\theta_1'(T_s) = 0$. Holding demand conditions fixed implies $d\theta_2/dT_s = 0$.

Let firm sales be $Y_i = p_i q_i$. Holding θ_2 constant and using the optimality condition in equation (21), the effect on sales is

$$\frac{dY_i}{dT_s} = (P_i + q_i P_{iq}) \frac{dq_i}{dT_s} = MC_i \frac{dq_i}{dT_s} < 0. \tag{24}$$

Result 1. *Holding demand conditions constant, adverse climate shocks reduce firm sales by raising the marginal cost of agricultural materials and reducing the optimal output of downstream processors. The magnitude of this effect may differ across firms according to their exposure to climate shocks and their dependence on material inputs.*

6.5. Implications of the model for productivity

The complementarity condition in equation (18) implies that the effective productivity of agricultural materials for processor i can be summarized by

$$\Omega_i(\theta_1) \equiv A_i(\theta_1)\tau_i(\theta_1), \qquad \frac{d \ln \Omega_i(\theta_1(T_s))}{dT_s} = \left[\frac{\partial \ln A_i}{\partial \theta_1} + \frac{\partial \ln \tau_i}{\partial \theta_1} \right] \theta_1'(T_s) < 0. \tag{25}$$

Climate shocks therefore reduce the effective contribution of purchased agricultural materials to production. They can lower productivity either by directly reducing firm efficiency, $A_i(\theta_1)$, or by reducing the usable quantity and quality of materials, $\tau_i(\theta_1)$.

Result 2. *Climate shocks reduce effective productivity by lowering firm efficiency and by reducing the usable quantity or quality of agricultural materials. The productivity effect may be nonlinear and differ across firms according to their baseline climate exposure and dependence on agricultural inputs.*

The productivity object $\Omega_i(\theta_1)$ is a theoretical mechanism rather than an exact counterpart of the empirical TFP index. In the empirical analysis, the productivity index recovered using the two-step GMM-IV approach of Hu et al. (2020) may capture both direct changes in firm efficiency and climate-induced disruptions in the availability, timing, and quality of material inputs.

6.6. Implications of the model for markups

The firm-level markup is defined as

$$\mu_i = \frac{p_i}{MC_i}. \tag{26}$$

Under a Leontief technology, the primal output derivative with respect to agricultural materials is not defined at the kink. The markup identity can nevertheless be expressed using the dual cost representation. Define the revenue share and the cost-side contribution of materials as

$$s_{iG}^{R} = \frac{p_\ell g_{i\ell}}{p_i q_i}, \qquad \vartheta_{iG} = \frac{p_\ell g_{i\ell}}{MC_i q_i}.$$

It follows directly that

$$\mu_i = \frac{\vartheta_{iG}}{s_{iG}^{R}}.$$

This cost-side expression provides the theoretical counterpart to the markup identity used in the empirical analysis. Taking logarithms of equation (26) and differentiating with respect to T_s yields

$$\frac{d\ln \mu_i}{dT_s} = \left(\frac{P_{iq}}{p_i} - \frac{MC_{iq}}{MC_i}\right)\frac{dq_i}{dT_s} + \frac{P_{i\theta_2}}{p_i}\theta_2'(T_s) - \frac{MC_{i\theta_1}}{MC_i}\theta_1'(T_s). \tag{27}$$

The first term captures the output-adjustment channel. The second term captures the direct effect of climate-related demand conditions on prices. The final term is the direct marginal-cost effect associated with higher agricultural input prices, lower material quality, and lower production efficiency. A lower output tends to raise the output price along the demand curve, which partly offsets the direct increase in marginal cost. However, when processors face input rigidities, a reduction in output may itself raise marginal costs. In that case, the output contraction reinforces the direct cost effect and further compresses markups. Markup compression occurs whenever the response of output prices is smaller than the response of marginal costs:

$$\frac{d\ln p_i}{dT_s} < \frac{d\ln MC_i}{dT_s} \quad \Longrightarrow \quad \frac{d\ln \mu_i}{dT_s} < 0.$$

Result 3. *Adverse climate shocks compress markups when their direct effect on marginal costs exceeds the adjustment in output prices. The markup decline is amplified when the induced contraction in output raises marginal costs through input rigidities. Conversely, if lower output reduces marginal costs, the output adjustment partly offsets markup compression.*

7. Conclusion

This paper examines the impact of climate shocks on firm-level markups and productivity in the Canadian agri-food sector. Using establishment-level data from Statistics Canada combined with high-resolution climate information, we estimate firm-level productivity using the two-step GMM-IV approach of Hu et al. (2020). Markups are recovered separately by combining observed material expenditure shares in firm revenue with material output elasticities obtained from a Generalized Leontief cost system. Our findings are robust across specifications: climate shocks compress markups and reduce productivity across nearly all agri-food subsectors, while raising marginal costs. A one-percent climate-induced decline in total factor productivity is associated with a 0.0194% reduction in firm sales and a 0.0028% decline in markups, with firms absorbing

a share of cost increases rather than passing them through to consumers. These results contribute to a growing literature linking climate change to firm performance and market structure, and provide some of the first firm-level evidence on markup responses to climate shocks in food processing.

Several limitations should be noted. Our analysis is confined to Canadian agri-food firms over 2000–2022, and it remains an open question whether these results generalize to other institutional and climatic contexts. In addition, our elasticity estimates are revenue-based, a standard limitation when firm-level price and quantity data are unavailable. Future work with product-level price and quantity data could build on the decomposition framework developed to further refine the separate identification of price and output responses to climate shocks.

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Table and figures

Tables

Table 1: Summary Statistics

	Avg. Employees	**Labor (% Rev.)**	**Capital (% Rev.)**	**Material (% Rev.)**	**Revenue (CAD $)**
Mean	29.068	7.746	23.628	70.107	10,400,000
Std. Dev.	268.380	24.4	29.0	57.4	145,000,000
Coeff. of Variation	9.233	3.142	1.227	0.819	14.001
Skewness	38.053	3.391	1.005	-0.131	45.476
Kurtosis	2,062.4	12.872	2.850	1.542	2,962.691
Percentiles					
25th	0.000	0.000	0.000	40.000	4,730.6
50th	3.500	0.000	14.041	73.100	253,010.0
75th	13.167	1.348	48.526	98.600	1,610,735.0
Observations	171,430	171,430	171,430	171,430	171,430

Notes: Data span 2000–2022 (NALMF, Statistics Canada). Revenue in Canadian dollars. Labor, capital, and material inputs are reported as percentages of revenue. Materials include energy and other operating expenses.

Table 2: Weather Statistics during the Growing Season

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Precipitation (Pr)	299	89.459	77.084	0.000	304.320
Extreme Heat Degree Days (HDD)	299	21.427	16.605	0.000	61.531
Growing Degree Days (GDD)	299	46.313	29.967	0.000	95.045
Cropland-weighted mean temperature $\bar{T}$	299	14.950	8.978	-0.990	27.355
Average temperature $\bar{T}^{gc}$ (Grid-cell)	1,675,761	13.812	1.674	−47.726	43.614

Notes: Statistics computed over the April–September growing season for the period 2000-2022. HDD: cumulative degree days above 29°C. GDD: cumulative degree days in the 10–29°C range. Precipitation (Pr) in millimeters. $\bar{T}^{gc}$: daily mean temperature at the grid-cell level (°C). $\bar{T}$: average temperature aggregated at the province level (°C). Data from the Climate Prediction Center(CPC)/NOAA.

Table 3: Elasticities by Four-Digit NAICS Food-Manufacturing Industry

Industry	**Capital**	**Labor**	**Material**	**RTS**	**Firms**
Animal food manufacturing	0.05	0.11	0.84	1.00	1,327
Grain and oilseed milling	0.08	0.13	0.81	1.02	611
Sugar product manufacturing	0.12	0.30	0.63	1.05	1,130
Fruit and vegetable food manufacturing	0.10	0.21	0.72	1.03	1,435
Dairy product manufacturing	0.10	0.19	0.74	1.03	2,049
Meat product manufacturing	0.08	0.17	0.77	1.02	2,263
Seafood product preparation and packaging	0.08	0.17	0.76	1.01	2,094
Bakeries and tortilla manufacturing	0.11	0.37	0.57	1.05	7,291
Other food manufacturing	0.09	0.22	0.73	1.04	5,538
All firms	0.09	0.22	0.72	1.03	23,738

Notes: Estimation of the Generalized Leontief cost function. Materials include energy components. RTS denotes returns to scale. Firms indicates the total number of firms.

Table 4: 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

Notes: The table reports moments of estimated markups by NAICS group. 75–25 and 90–10 denote interquartile and interdecile ratios, respectively. CV is the coefficient of variation. Source: Authors' computations based on Statistics Canada data.

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

Variables	**Marginal Cost**	**TFP**	**MRPK**	**MRPL**	**MRPM**
HDD	0.00011***	−0.00012***	−0.00002	0.00004	−0.00001***
	(0.00002)	(0.00003)	(0.00001)	(0.00002)	(0.00000)
Controls					
GDD	−0.00053***	0.00027***	0.00001	−0.00002	0.00001***
	(0.00005)	(0.00009)	(0.00001)	(0.00004)	(0.00000)
Pr	0.00008***	−0.00042***	−0.00006	−0.00002	−0.00001***
	(0.00003)	(0.00005)	(0.00004)	(0.00003)	(0.00000)
Constant	1.22700***	1.00001***	0.03501***	0.10764	0.02760***
	(0.07680)	(0.12100)	(0.01270)	(0.10764)	(0.00356)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	124,806	31,896	23,698	15,212	31,131
R-squared	0.002	0.006	0.001	0.000	0.008
Number of firms	16,533	7,447	5,199	4,133	7,136

Notes: HDD, GDD, and *Pr* denote seasonal aggregates (April–September) of extreme heat degree days, growing degree days, and precipitation, respectively. Dependent variables are expressed in logarithms. MRPK, MRPL, and MRPM denote revenue-based marginal products of capital, labor, and materials. Materials include energy and other expenses. Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Impact of Climate Shocks on Markup

VARIABLES	**All firms**	**3111**	**3112**	**3113**	**3114**	**3115**	**3116**	**3117**	**3118**	**3119**
HDD	-0.00019***	-0.00021***	-0.00022**	-0.00025***	-0.00018***	-0.00018***	-0.00020***	-0.00016***	-0.00028***	-0.00003
	(0.00002)	(0.00006)	(0.00009)	(0.00006)	(0.00006)	(0.00006)	(0.00004)	(0.00005)	(0.00002)	(0.00004)
Controls										
GDD	0.00090***	0.00112***	0.00058**	0.00101***	0.00083***	0.00074***	0.00077***	0.00060***	0.00117***	0.00071***
	(0.00005)	(0.00019)	(0.00026)	(0.00021)	(0.00019)	(0.00022)	(0.00014)	(0.00014)	(0.00009)	(0.00012)
Pr	-0.00025***	-0.00025**	-0.00035**	-0.00031**	-0.00035***	-0.00034***	-0.00033***	-0.00021***	-0.00022***	-0.00014**
	(0.00003)	(0.00010)	(0.00015)	(0.00013)	(0.00012)	(0.00012)	(0.00009)	(0.00007)	(0.00005)	(0.00007)
Constant	0.41200***	0.43500	0.81100**	0.18400	0.58700**	0.69300**	0.78300***	0.84900***	-0.13400	0.69300***
	(0.06950)	(0.27400)	(0.39200)	(0.29700)	(0.26400)	(0.30300)	(0.20500)	(0.18700)	(0.12400)	(0.16900)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,883	9,100	3,569	6,244	8,480	7,536	15,774	13,317	40,563	25,300
R-squared	0.011	0.015	0.008	0.016	0.010	0.008	0.009	0.004	0.018	0.007
Number of firms	16,976	1,092	504	864	1,169	1,139	1,652	1,369	5,087	4,568

Notes: HDD, GDD, and Pr denote seasonal aggregates (sum over April–September) of extreme heat degree days, growing degree days, and precipitation, respectively. 3111: Animal food manufacturing; 3112: Grain and oilseed milling; 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: In-Sample Estimates of Responses to the Climate-Induced Productivity shock

	Productivity shock				**Output change**	
	Sales	**Price**	**Marg. cost**	**Markup**	**Price**	**Marg. cost**
Estimated coeff. ($\hat{\eta}$)	-0.0194^{***}	0.000049^{***}	0.0007^{***}	-0.0028^{***}	0.00356^{***}	0.535^{***}
	(0.0002)	(0.000012)	(0.0001)	(0.0001)	(0.0002)	(0.0057)
Observations	171,430	171,430	171,430	171,430	171,430	171,430
Number of firms	23,738	23,738	23,738	23,738	23,738	23,738
R^2	0.253	0.017	0.181	0.196	0.015	0.395
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

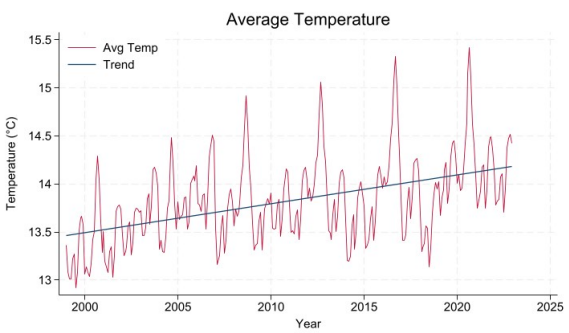
Notes: The table reports estimates from equation (13): $Outcome_{it} = \eta\,\theta_{it} + \phi_i + \phi_t + \varepsilon_{it}$, where θ_{it} is the climate-induced productivity component constructed following equation (11) using estimated coefficients from Table 5, and historical climate data. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effects of Climate Shocks by Number of Products

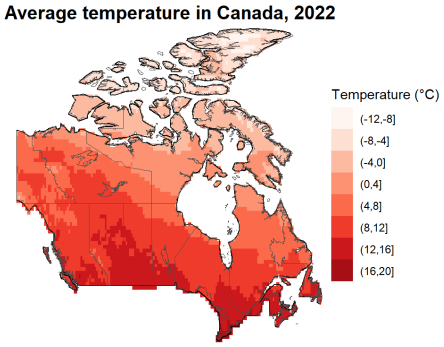
	1		2		3		4		5+	
Variables	**Markup**	**TFP**	**Markup**	**TFP**	**Markup**	**TFP**	**Markup**	**TFP**	**Markup**	**TFP**
HDD	−0.00019***	−0.00014***	−0.00002	−0.00023*	−0.00011***	−0.00013***	−0.00012	−0.00026	−0.00014***	0.00007
	(0.00005)	(0.00003)	(0.00006)	(0.00013)	(0.00003)	(0.00003)	(0.00010)	(0.00021)	(0.00004)	(0.00007)
Controls										
GDD	0.00086***	0.00023**	0.00064***	0.00070*	0.00073***	0.00025***	0.00067**	0.00052	0.00064***	0.00034
	(0.00016)	(0.00010)	(0.00022)	(0.00040)	(0.00008)	(0.00009)	(0.00029)	(0.00069)	(0.00011)	(0.00023)
Pr	−0.00016*	−0.00046***	−0.00014	−0.00027	−0.00020***	−0.00040***	−0.00010	−0.00054	−0.00030***	0.00002
	(0.00009)	(0.00006)	(0.00012)	(0.00027)	(0.00005)	(0.00005)	(0.00017)	(0.00038)	(0.00007)	(0.00013)
Constant	0.77400***	0.97100***	1.36300***	0.49700	1.22300***	1.00000***	1.30400***	0.80500	1.46600***	1.30000***
	(0.21900)	(0.14400)	(0.30400)	(0.52900)	(0.11800)	(0.12100)	(0.42800)	(0.91100)	(0.16500)	(0.30600)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113,540	25,646	4,064	1,351	2,660	1,025	1,886	760	7,733	3,114
R-squared	0.017	0.006	0.013	0.012	0.015	0.006	0.010	0.014	0.017	0.003
Number of firms	11,955	6,778	1,581	638	1,212	535	901	422	1,327	698

Notes: HDD, GDD, and Pr denote aggregates (from April to September) of extreme heat degree days, growing degree days, and precipitation, respectively. Markup and TFP are in logarithm. Columns are split by the number of products manufactured by the firm. Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figures



(a) 2000–2022 Trend



(b) 2022 Cross Section

Figure 1: Growing-season temperatures in Canada, 2000–2022

Notes: Panel 1a shows the evolution of average growing-season temperature in Canada from 2000 to 2022. The dashed line represents the linear time trend. Panel 1b shows the spatial distribution of average temperature across Canadian grid cells during the 2022 growing season. Growing-season temperature is measured over the April-September period. Provincial boundaries are shown in grey

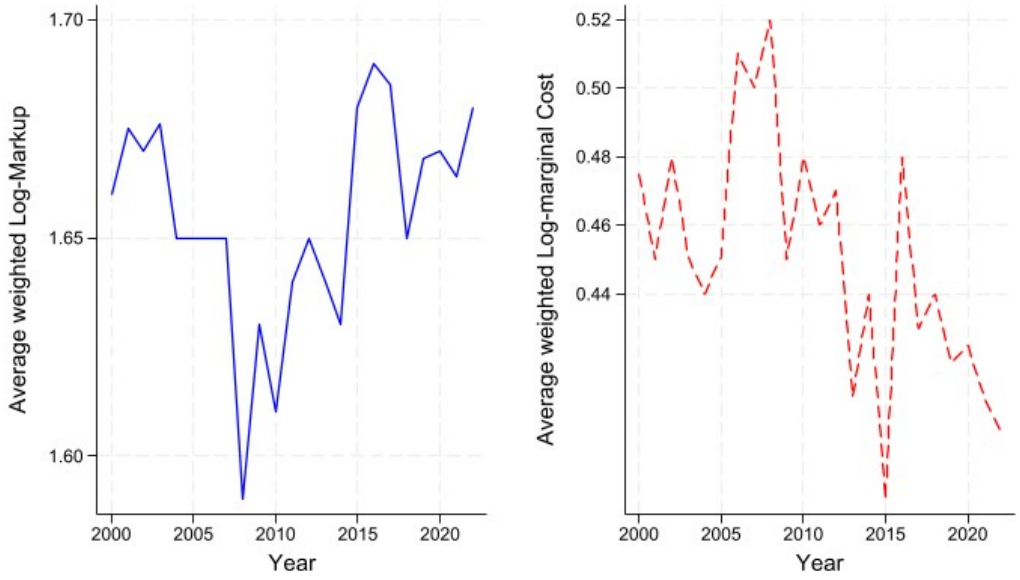
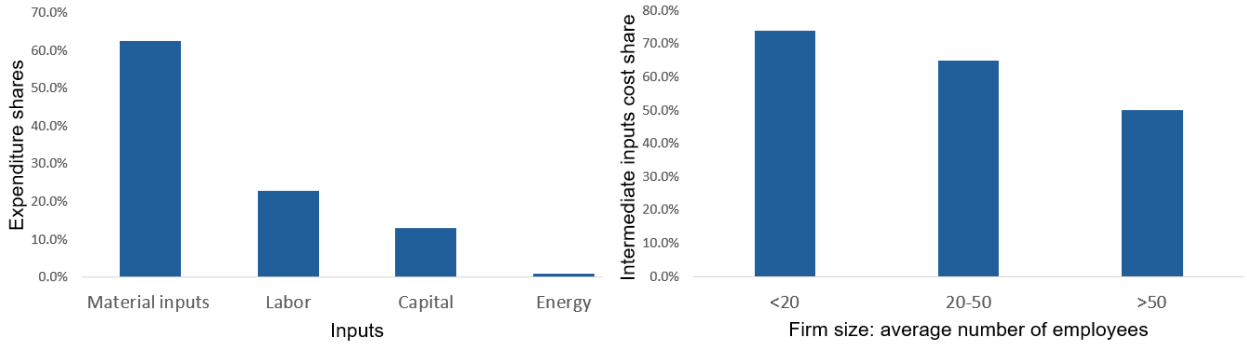


Figure 2: Sales-weighted average markups and marginal costs, 2000–2022

Notes: The figure reports the annual sales-weighted average firm-level markup and the corresponding annual sales-weighted average marginal cost. The sample includes Canadian agri-food establishments observed between 2000 and 2022. Authors' calculations based on Statistics Canada data



(a) Input expenditure shares

(b) Material expenditure share by firm size

Figure 3: Input expenditure shares and material intensity by firm size

Notes: Panel 3a reports the average shares of material inputs, labor, capital, and energy in total expenditure among Canadian agri-food establishments. Panel 3b reports the average share of material expenditures by firm-size category. Firm size is measured using the average number of employees. The categories correspond to firms with fewer than 20 employees, 20–50 employees, and more than 50 employees. Authors' calculations based on Statistics Canada data

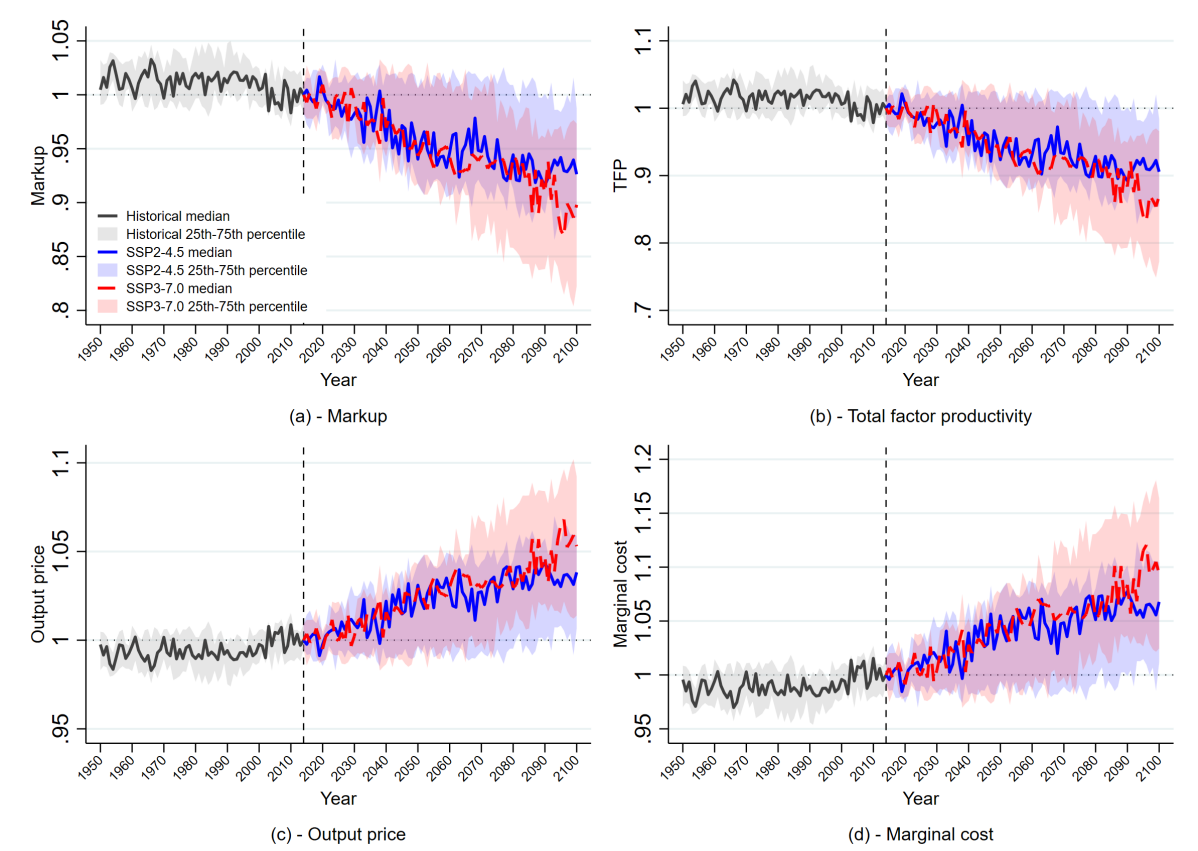


Figure 4: Projected paths of markup, productivity, prices, and marginal costs under alternative climate scenarios

Notes: Panels (a)-(d) show the historical and projected paths of markups, total factor productivity, output prices, and marginal costs. The grey line reports the historical provincial median constructed using historical climate data (1950–2014); blue and red lines report projections under SSP2-4.5 and SSP3-7.0, respectively (2015–2100). Shaded areas indicate the 25th-75th percentile ranges across provinces. All series are normalized to one in 2014. The pre-2000 series are climate-implied historical reconstructions. Authors' calculations based on NALMF and GDPCIR data

Appendix

This appendix provides supplementary derivations, robustness analyses, data-construction details, and additional information on the estimation procedure.

A.1. Leontief technology and dual cost representation

We consider a production technology in which materials and a capital-labor composite enter as complementary input blocks. The output is given by

$$Q_{it} = A_{it} \min \left\{ \alpha_0 M_{it}^{\beta_m}, F\left(K_{it}, L_{it}; \beta_k, \beta_l\right) \right\}, \tag{A.1}$$

where Q_{it} denotes output, A_{it} is firm-level productivity, M_{it} denotes materials, and K_{it} and L_{it} denote capital and labor, respectively. The parameter $\alpha_0 > 0$ scales the efficiency of materials, while β_m governs the curvature of the materials block. The function $F(\cdot)$ represents a capital–labor composite indexed by the parameters β_k and β_l. At this stage, no specific functional form is imposed on $F(\cdot)$.

Let

$$X_{it} \equiv \frac{Q_{it}}{A_{it}} \tag{A.2}$$

denote the level of effective input services required to produce Q_{it}. Given the Leontief structure in equation (A.1), producing Q_{it} requires both input blocks to satisfy

$$\alpha_0 M_{it}^{\beta_m} \geq X_{it}, \qquad F\left(K_{it}, L_{it}; \beta_k, \beta_l\right) \geq X_{it}. \tag{A.3}$$

Thus, productivity A_{it} reduces the amount of effective input services required for a given level of output. The associated cost-minimization problem is

$$C\left(Q_{it}, P_{it}^M, P_{it}^K, P_{it}^L; A_{it}\right) = \min_{M_{it}, K_{it}, L_{it}} \left\{ P_{it}^M M_{it} + P_{it}^K K_{it} + P_{it}^L L_{it} \right\} \tag{A.4}$$

subject to the production requirement in equation (A.3). Since materials and the capital–labor composite are combined in fixed proportions, the dual cost function can be written as the sum of the cost of the materials block and the cost of the capital–labor block:

$$C_{it} = P_{it}^M \left(\frac{Q_{it}}{A_{it}\alpha_0} \right)^{1/\beta_m} + C_{KL}\left(\frac{Q_{it}}{A_{it}}, P_{it}^K, P_{it}^L; \beta_k, \beta_l \right), \tag{A.5}$$

where the dual cost of the capital–labor composite is defined implicitly as

$$C_{KL}\left(X_{it}, P_{it}^K, P_{it}^L; \beta_k, \beta_l\right) = \min_{K_{it}, L_{it}} \left\{ P_{it}^K K_{it} + P_{it}^L L_{it} : F\left(K_{it}, L_{it}; \beta_k, \beta_l\right) \geq X_{it} \right\}. \tag{A.6}$$

If the cost function is differentiable, marginal cost is given by

$$\mathcal{C}_{Q,it} = \frac{\partial C_{it}}{\partial Q_{it}} = \frac{P_{it}^{M}}{\beta_m} \left(A_{it}\alpha_0\right)^{-1/\beta_m} Q_{it}^{1/\beta_m - 1} + \frac{1}{A_{it}} \frac{\partial C_{KL}}{\partial X} \left(\frac{Q_{it}}{A_{it}}, P_{it}^{K}, P_{it}^{L}; \beta_k, \beta_l\right). \tag{A.7}$$

A.2. Cost functions for Leontief technologies and returns to scale

Technology. We consider the Leontief production technology

$$Q_{it} = A_{it} \min\left\{\alpha_0 M_{it}^{\beta_m}, F\left(K_{it}, L_{it}; \beta_k, \beta_l\right)\right\}, \tag{A.8}$$

where Q_{it} denotes output, A_{it} is productivity, M_{it} denotes materials, and K_{it} and L_{it} denote capital and labor. The function $F(\cdot)$ is a capital–labor composite. We impose no specific form on this composite. Let $X_{it} \equiv Q_{it}/A_{it}$ denote the effective input requirement. The Leontief structure implies that both input blocks must be able to produce X_{it}:

$$\alpha_0 M_{it}^{\beta_m} \geq X_{it}, \qquad F\left(K_{it}, L_{it}; \beta_k, \beta_l\right) \geq X_{it}. \tag{A.9}$$

With strictly positive input prices, both constraints bind at the cost-minimizing allocation. Therefore, the conditional demand for materials is

$$M_{it}^{*} = \left(\frac{X_{it}}{\alpha_0}\right)^{1/\beta_m}. \tag{A.10}$$

Production function and returns to scale. To assess returns to scale from the production function, suppose that the capital–labor composite is homogeneous of degree ρ:

$$F\left(\lambda K, \lambda L; \beta_k, \beta_l\right) = \lambda^{\rho} F\left(K, L; \beta_k, \beta_l\right), \qquad \lambda > 0. \tag{A.11}$$

At the efficient allocation, we have:

$$\alpha_0 M_{it}^{\beta_m} = F\left(K_{it}, L_{it}; \beta_k, \beta_l\right) = X_{it}.$$

If all inputs are multiplied by the same factor λ, the output becomes

$$\begin{aligned} Q_{it}\left(\lambda M_{it}, \lambda K_{it}, \lambda L_{it}\right) &= A_{it} \min\left\{\alpha_0 (\lambda M_{it})^{\beta_m}, F\left(\lambda K_{it}, \lambda L_{it}; \beta_k, \beta_l\right)\right\} \\ &= A_{it} X_{it} \min\left\{\lambda^{\beta_m}, \lambda^{\rho}\right\} \\ &= Q_{it} \min\left\{\lambda^{\beta_m}, \lambda^{\rho}\right\}. \end{aligned} \tag{A.12}$$

Equation (A.12) highlights a key feature of the Leontief technology. At the efficient allocation, the materials and the capital-labor composite must be exactly balanced. However, when $\beta_m \neq \rho$, this balance is not preserved by multiplying materials, capital, and labor by the same factor. If $\beta_m < \rho$ and $\lambda > 1$, output expands at the rate λ^{β_m}, materials remain binding, and the

capital-labor composite becomes excessive relative to the attainable output level. Conversely, if $\beta_m > \rho$ and $\lambda > 1$, the capital–labor composite is binding and materials become excessive. The direction of the imbalance is reversed when $0 < \lambda < 1$.

Thus, although the technology is Leontief across the two input blocks, the cost-minimizing relationship between materials and the capital–labor composite generally changes with the scale of production. Only when $\beta_m = \rho$ does proportional scaling preserve the efficient input mix and yield a single degree of homogeneity. For this reason, we characterize scale economies using the dual cost function and the local elasticity of minimized cost with respect to output. The cost function is preferable because it evaluates scale economies along the cost-minimizing input path.

Cost function. The dual cost function associated with equation (A.8) can then be written as

$$C_{it} = C_{it}^{M} + C_{it}^{KL}, \tag{A.13}$$

where

$$C_{it}^{M} = P_{it}^{M} \left(\frac{X_{it}}{\alpha_0} \right)^{1/\beta_m} \tag{A.14}$$

is the cost of the materials, and

$$C_{it}^{KL} = C_{KL}\left(X_{it}, P_{it}^{K}, P_{it}^{L}; \beta_k, \beta_l\right) \tag{A.15}$$

is the minimum cost of producing the capital–labor composite:

$$C_{KL}\left(X_{it}, P_{it}^{K}, P_{it}^{L}; \beta_k, \beta_l\right) = \min_{K_{it}, L_{it}} \left\{ P_{it}^{K} K_{it} + P_{it}^{L} L_{it} : F\left(K_{it}, L_{it}; \beta_k, \beta_l\right) \geq X_{it} \right\}. \tag{A.16}$$

This representation is useful because the cost elasticity can be written in terms of the cost elasticities of the two blocks. Since $X_{it} = Q_{it}/A_{it}$, and A_{it} is fixed when differentiating with respect to output, the elasticity of cost with respect to Q_{it} is the same as the elasticity of cost with respect to X_{it}. Thus, using equation (A.13), we can write:

$$\varepsilon_{it}^{C} \equiv \frac{\partial \ln C_{it}}{\partial \ln Q_{it}} = \frac{\partial \ln C_{it}}{\partial \ln X_{it}} = \frac{X_{it}}{C_{it}} \left[\frac{\partial C_{it}^{M}}{\partial X_{it}} + \frac{\partial C_{it}^{KL}}{\partial X_{it}} \right], \tag{A.17}$$

Rearranging equation (A.17) yields a cost-share-weighted average of elasticities:

$$\varepsilon_{it}^{C} = \frac{C_{it}^{M}}{C_{it}} \left[\frac{X_{it}}{C_{it}^{M}} \frac{\partial C_{it}^{M}}{\partial X_{it}} \right] + \frac{C_{it}^{KL}}{C_{it}} \left[\frac{X_{it}}{C_{it}^{KL}} \frac{\partial C_{it}^{KL}}{\partial X_{it}} \right] = s_{it}^{M} \frac{1}{\beta_m} + s_{it}^{KL} \varepsilon_{it}^{KL} \tag{A.18}$$

where

$$s_{it}^{M} = \frac{C_{it}^{M}}{C_{it}}, \qquad s_{it}^{KL} = \frac{C_{it}^{KL}}{C_{it}}, \tag{A.19}$$

and

$$\varepsilon_{it}^{KL} \equiv \frac{\partial \ln C_{KL}\left(X_{it}, P_{it}^{K}, P_{it}^{L}; \beta_k, \beta_l\right)}{\partial \ln X_{it}} \tag{A.20}$$

is the cost elasticity of the capital–labor composite. The measure of returns to scale is therefore

$$RTS_{it} = \frac{1}{\varepsilon_{it}^{C}}. \tag{A.21}$$

Economies of scale correspond to $\varepsilon_{it}^{C} < 1$, constant returns to scale to $\varepsilon_{it}^{C} = 1$, and diseconomies of scale to $\varepsilon_{it}^{C} > 1$. To illustrate the source of variable returns to scale, suppose that the capital–labor composite is homogeneous of degree ρ. Then the dual cost of the capital–labor block is homogeneous in X_{it} of degree $1/\rho$, so that

$$\varepsilon_{it}^{KL} = \frac{1}{\rho}. \tag{A.22}$$

In this case, the total cost elasticity becomes

$$\varepsilon_{it}^{C} = s_{it}^{M} \frac{1}{\beta_m} + s_{it}^{KL} \frac{1}{\rho}. \tag{A.23}$$

Equation (A.23) shows that returns to scale depend on the curvature of the materials block and of the capital–labor composite. If $\beta_m = \rho$, the two blocks have the same degree of homogeneity and the cost elasticity is constant. In that case,

$$\varepsilon_{it}^{C} = \frac{1}{\beta_m} = \frac{1}{\rho}, \qquad RTS_{it} = \beta_m = \rho. \tag{A.24}$$

The special case $\beta_m = \rho = 1$ corresponds to constant returns to scale. If $\beta_m \neq \rho$, however, the cost elasticity is a weighted average of two different elasticities. Since the cost shares s_{it}^{M} and s_{it}^{KL} may vary with the level of output, returns to scale may also vary with output.

A.3. Production function to markup

A.3.1. Setup

Consider a firm i that, in each period t, minimizes the cost of producing output Q_{it} with technology $Q_{it} = A_{it}\ F(K_{it}, L_{it}, M_{it})$, where K, L, and M denote capital, labor, and materials, and A_{it} is Hicks-neutral productivity. For any input X_{it} that is free of adjustment costs, the first-order condition of the cost-minimization problem reads

$$P_{it}^{X} \ = \ \lambda_{it} \frac{\partial Q_{it}}{\partial X_{it}}, \tag{A.25}$$

where P_{it}^{X} is the input price and the Lagrange multiplier λ_{it} is the marginal cost of production. Multiplying both sides of (A.25) by X_{it}/Q_{it}, dividing by the output price P_{it}, and defining the markup as $\mu_{it} \equiv P_{it}/\lambda_{it}$ yields

$$\mu_{it} \ = \ \frac{\beta_{it}^{X}}{s_{it}^{X}}, \tag{A.26}$$

where $\beta_{it}^X \equiv \partial Q_{it}/\partial X_{it} \cdot X_{it}/Q_{it}$ is the output elasticity of input X and $s_{it}^X \equiv P_{it}^X X_{it}/(P_{it}Q_{it})$ is the share of expenditure on input X in revenue. Equation (A.26) is the markup expression. Its appeal lies in its generality: it requires only cost-minimizing behavior with respect to a flexible input. It involves no specification of consumer preferences or demand, no assumption on the mode of competition, and it accommodates heterogeneous firms charging markups that differ across firms and vary over time.[4] We apply (A.26) to materials, which constitute the largest and most flexible component of variable costs in the agri-food sector.[5] The revenue share s_{it}^M is directly observed in our data; the empirical content of the approach therefore lies entirely in the recovery of the output elasticity β_{it}^M, to which we now turn.

A.3.2. Why the production function cannot deliver the elasticities

A natural implementation of (A.26), and the one followed by most applications of the production approach, is to estimate β_{it}^M from the production function using proxy-variable methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). This route is not available to us. Our data report input expenditures and output revenues, not physical quantities and firm-level prices. As shown by Bond et al. (2021), when output prices are unobserved and revenue is used as the dependent variable, proxy-variable estimators recover the *revenue* elasticity rather than the output elasticity. Under cost minimization, the revenue elasticity of a flexible input equals its output elasticity divided by the markup, $\beta_{it}^{M,R} = \beta_{it}^M/\mu_{it}$, but so does the revenue share, $s_{it}^M = \beta_{it}^M/\mu_{it}$. The ratio of the two is therefore identically equal to one:

$$\frac{\beta_{it}^{M,R}}{s_{it}^M} = \frac{\beta_{it}^M/\mu_{it}}{\beta_{it}^M/\mu_{it}} \equiv 1, \tag{A.27}$$

so that markups are not identified from revenue-based production function estimates, regardless of the estimator used (see also Yeh et al., 2022). This is a problem of identification, not of bias.

A.3.3. Recovering the elasticities from the cost side

The information needed to recover the output elasticity of materials, β_{it}^M, can be obtained from the cost side. Rather than identifying the required elasticity from a revenue-based production function, we use a dual cost representation of the underlying technology. This approach exploits variation in observed costs, input prices, and output to recover input demand responses and the corresponding output elasticities. The Generalized Leontief cost function used to recover elasticities is given by

$$C(P,Q) = \left[a_M P_M + a_{LL} P_L + 2a_{LK}(P_L P_K)^{1/2} + a_{KK} P_K\right] Q^d. \tag{A.28}$$

In equation (A.28), materials enter as a separable linear component, while labor and capital enter

[4] Whether firms operate under monopolistic competition with heterogeneous productivities or under oligopoly with differentiated products, cost-minimizing firms satisfy condition (A.25), so the markup expression (A.26) holds across these market structures.

[5] Materials expenditures typically make up the largest share of total costs in industries with high input use.

through a Generalized Leontief price aggregator. This structure is useful for food manufacturing because materials are the dominant variable input, while flexible substitution is allowed within the labor-capital block. The function is homogeneous of degree one in input prices. The parameter d governs the relationship between costs and output scale and therefore determine the cost elasticity with respect to output. We do not impose constant returns to scale, but estimate d from the data. Using Shephard's lemma, the conditional demand for materials implied by equation (A.28) is

$$M_{it} = \frac{\partial C(P,Q)}{\partial P_M} = a_M Q_{it}^d. \tag{A.29}$$

The conditional demand for labor is

$$L_{it} = \frac{\partial C(P,Q)}{\partial P_L} = \left[a_{LL} + a_{LK} \left(\frac{P_{K,it}}{P_{L,it}} \right)^{1/2} \right] Q_{it}^d. \tag{A.30}$$

The conditional demand for capital is

$$K_{it} = \frac{\partial C(P,Q)}{\partial P_K} = \left[a_{KK} + a_{LK} \left(\frac{P_{L,it}}{P_{K,it}} \right)^{1/2} \right] Q_{it}^d. \tag{A.31}$$

Because the common output exponent d is estimated, the system is nonlinear in the parameters. We therefore estimate equations (A.29)–(A.31) as a nonlinear system of input demand equations, allowing the disturbances to be correlated across inputs. The estimated system yields revenue-based elasticities, denoted by $\beta_{it,r}^M$, $\beta_{it,r}^L$, and $\beta_{it,r}^K$, which summarize the relative contribution of materials, labor, and capital in the cost-side system.

To convert these revenue-based elasticities into output elasticities, we account for the scale elasticity implied by the estimated cost function. Let

$$\varepsilon_{it}^C = \frac{\partial \ln C(P_{it}, Q_{it})}{\partial \ln Q_{it}} \tag{A.32}$$

denote the cost elasticity with respect to output. The implied returns to scale are

$$RTS_{it} = \frac{1}{\varepsilon_{it}^C} = \frac{1}{d}\ . \tag{A.33}$$

Since d is estimated rather than imposed, returns to scale are not restricted to be constant. The cost-side relative elasticities are therefore:

$$\beta_{M,r} = \frac{a_M P_M}{C(P,Q)/Q^d}, \tag{A.34}$$

$$\beta_{L,r} = \frac{a_{LL} P_L + a_{LK} (P_L P_K)^{1/2}}{C(P,Q)/Q^d}, \tag{A.35}$$

$$\beta_{K,r} = \frac{a_{KK} P_K + a_{LK} (P_L P_K)^{1/2}}{C(P,Q)/Q^d}\ , \tag{A.36}$$

where each term summarize the relative contribution of each input to variable cost. The output elasticities used in the markup calculation are then recovered as :

$$\beta_{it}^{M} = \frac{1}{d} \frac{\beta_{it,r}^{M}}{\beta_{it,r}^{M} + \beta_{it,r}^{L} + \beta_{it,r}^{K}}. \tag{A.37}$$

The output elasticities of labor and capital are recovered analogously. Combining the material output elasticity from equation (A.37) with the observed revenue share of materials delivers the firm-level markup:

$$\mu_{it} = \beta_{it}^{M} \left(s_{it}^{M,R} \right)^{-1}, \tag{A.38}$$

where $s_{it}^{M,R}$ denotes the revenue share of materials.

A.4. Share of output by industry

Table A.1: Output Shares by Four-Digit NAICS Food-Manufacturing Industry

Industry	**NAICS**	**Obs.**	**Freq (%)**	**Output share (%)**
Animal food manufacturing	3111	11,126	6.49	7.11
Grain and oilseed milling	3112	4,492	2.62	11.58
Sugar and confectionery products	3113	7,966	4.65	5.05
Fruit and vegetable preserving	3114	10,806	6.30	6.98
Dairy product manufacturing	3115	12,548	7.32	16.16
Meat products	3116	20,326	11.86	28.11
Seafood products	3117	18,297	10.67	4.74
Bakeries manufacturing	3118	54,401	31.73	9.42
Other products manufacturing	3119	31,468	18.36	10.85
Total		**171,430**	**100**	**100**

Notes: Sample covers Canadian agri-food processing firms over the period 2000–2022. NAICS denotes the North American Industry Classification System at the 4-digit level. Frequencies and output shares are expressed as percentages of the full sample.

A.5. Robustness check

Table A.2: Effect of Climate Shocks on Markup and TFP with Additional Controls

Variables	**Markup**	**TFP**
HDD	−0.00019***	−0.00012***
	(0.00002)	(0.00003)
Controls		
GDD	0.00088***	0.00027***
	(0.00005)	(0.00009)
Pr	−0.00025***	−0.00041***
	(0.00003)	(0.00005)
EntMultiLocation	0.05950	−0.08580
	(0.03710)	(0.08310)
EntMultiEstablishment	0.04950	0.08410
	(0.04730)	(0.08730)
EntMultiProvince	−0.05030	0.00195
	(0.03610)	(0.05920)
EntMultiActivity	−0.03010	0.03870
	(0.04350)	(0.05340)
Age	−0.00981**	−0.00406
	(0.00463)	(0.00654)
Age^2	0.00006*	0.00006
	(0.00003)	(0.00004)
Constant	0.62600***	1.06600***
	(0.11300)	(0.18400)
Fixed effects	Yes	Yes
Observations	129,883	31,896
R-squared	0.011	0.006
Number of firms	16,976	7,447

Notes: HDD, GDD, and *Pr* denote seasonal aggregates (April–September) of extreme heat degree days, growing degree days, and precipitation, respectively. Markup and TFP are in logarithm. EntMultiLocation, EntMultiEstablishment, EntMultiProvince, and EntMultiActivity are binary indicators equal to one if the firm operates across multiple locations, establishments, provinces, or activities, respectively. Age is measured in years; Age^2 is its square term. Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

A.6. Effect of climate shocks on sales and inputs

Table A.3: Effect of Climate Shocks on Input and sales

Variables	**Sales**	**Capital**	**Labor**	**Materials**
HDD	−0.00067***	−0.00045**	−0.00064***	−0.00029***
	(0.00009)	(0.00022)	(0.00011)	(0.00007)
Controls				
GDD	0.00072**	−0.00045**	0.00104***	0.00193***
	(0.00028)	(0.00022)	(0.00032)	(0.00034)
Pr	−0.00035**	−0.00001	−0.00084***	−0.00045**
	(0.00015)	(0.00012)	(0.00021)	(0.00018)
Constant	8.86400***	10.05000***	1.58500***	4.18200***
	(0.40900)	(0.32500)	(0.46800)	(0.49700)
Fixed effects	Yes	Yes	Yes	Yes
Observations	161,978	161,978	161,978	161,978
R-squared	0.001	0.000	0.000	0.001
Number of firms	22,627	22,627	22,627	22,627

Notes: HDD, GDD, and *Pr* denote seasonal aggregates (April–September) of extreme heat degree days, growing degree days, and precipitation, respectively. Dependent variables are expressed in logarithms. Materials include energy and other expenses. Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

A.7. Predicted prices and marginal costs dispersion

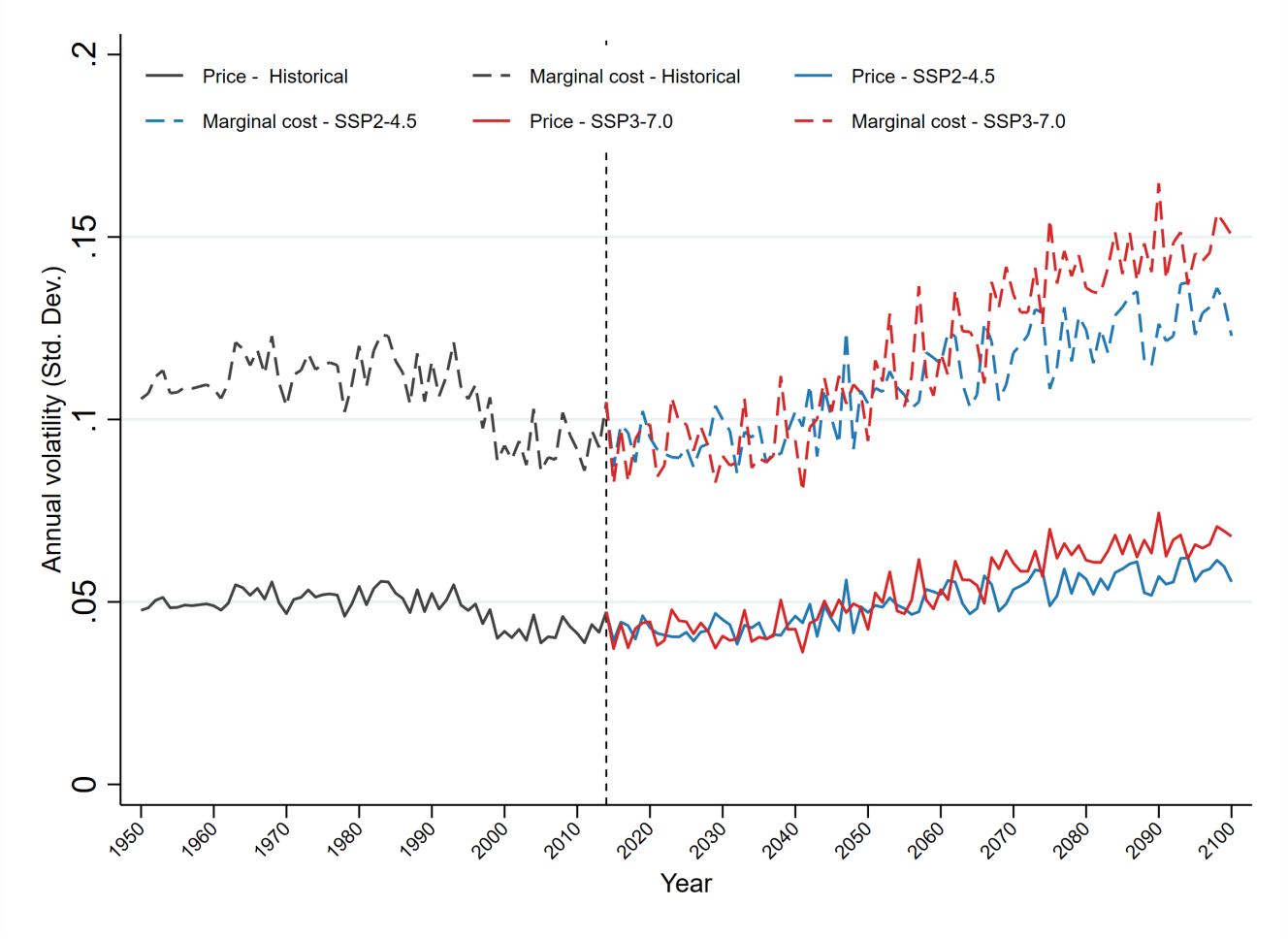


Figure A.1: Dispersion of predicted output prices and marginal costs under alternative climate scenarios

Notes: The figure reports the dispersion of price and marginal cost under climate shocks by year and scenario. Dispersion is measured as the standard deviation across provinces. Predicted outcomes are constructed from the climate-induced productivity component. Solid lines denote prices and dashed lines denote marginal costs. Authors' calculations based on NALMF and GDPCIR data

A.8. Data and Price Measurement

A.8.1. Firm-level data and nominal variables

We use establishment-level information from the National Accounts Longitudinal Microdata File (NALMF) for Canadian food manufacturing firms over the period 2000–2022. The empirical analysis focuses on four-digit NAICS industries. The data provide annual information on sales, operating expenses, payroll, capital cost allowance, employment, and establishment location. All monetary variables are observed in current Canadian dollars.

Output. The data report nominal sales rather than firm-level physical quantities. For each firm, we construct gross sales as total operating revenue, augmented by farm revenue when reported. This is appropriate for food-manufacturing establishments that may combine processing activity with farm-related operations. We therefore construct real composite output as

$$Q_{it} = \frac{Y_{it}}{P} \tag{A.39}$$

where Y_{it} is firm-level sales revenue and P is an output price index at the sector-year (s,t) level. We use a common industry price movements to deflate nominal sales in the absence of firm-level prices. The resulting object is a composite-output measure, not a direct measure of physical output

Material input expenditure. We first construct nominal materials as a broad intermediate-input aggregate.

$$X_{it} = \text{Total Expenses}_{it} - \text{T4 Payroll}_{it} - \text{Capital Cost Allowance}_{it}. \tag{A.40}$$

The resulting measure includes purchased agricultural commodities, processed inputs, energy, packaging, transportation, and other market services. T4 Payroll$_{it}$ denotes annual employee remuneration reported through T4 slips, including wages and salaries paid by the establishment. Capital Cost Allowance$_{it}$ is the tax-based deduction for the depreciation of capital assets claimed by the establishment. Capital cost allowance is excluded because it is a tax-depreciation measure rather than a current purchase of intermediate inputs. A limitation of the available accounting aggregates is that total expenses may contain small components, such as interest expenses or book depreciation, that cannot be separately identified in all records. Thus, we interpret M_{it} as the closest observable approximation to purchased intermediate expenditure, rather than as a perfectly measured accounting concept. The real material input quantity used in the analysis is:

$$M_{it} = \frac{X_{it}}{P^M} \ , \tag{A.41}$$

with P^M the price index of material inputs at the province-industry-year level (p,s,t).

Labour, capital, and total cost. Wages and salaries paid by the establishment are used to proxy total Labour costs:

$$L_{it} = \text{T4 Payroll}_{it}. \tag{A.42}$$

Capital cost is approximated by a user-cost expression based on tangible assets, which is available in the data:

$$K_{it} = \bar{K}_{it} \ , \tag{A.43}$$

where $\bar{K}_{it}$ is the nominal value of tangible-asset stock. The total cost proxy is therefore:

$$\text{Total Cost}_{it} = M_{it} + K_{it} + L_{it}. \tag{A.44}$$

For the cost-system estimation, total cost is expressed in units of the intermediate-input price index:

$$C_{it} = \frac{\text{Total Cost}_{it}}{P^M}. \tag{A.45}$$

Because the cost function is linearly homogeneous in input prices, this normalization allows the model to be expressed in relative prices, with the intermediate-input price as the numeraire. The labour price and the capital price therefore enter the system relative to material input price.

A.8.2. Inputs price Measurement

Output price. We deflate sales using the Industrial Product Price Index (IPPI) by industry from Statistics Canada Table 18-10-0267-01. The table provides monthly industry-level producer price indexes for Canada. We match each four-digit food manufacturing industry to its corresponding IPPI series, and convert monthly observations into annual averages, for the reference year 2017. Our final output price deflator varies by industry and year, but not by province, because the published IPPI-by-industry series are available at the national level.

Capital and Labour price. We construct establishment-year labour and capital prices as average factor costs. Labour price is measured as average labour cost per worker. In addition, let P^K_{it} denote the user cost of one unit of capital:

$$P^K_{it} = r_t q_{t-1} + \delta_{it} q_t - g_t, \tag{A.46}$$

where q_t is the price of fixed assets in year t , r_t is the assumed real required return, δ_{it} is an establishment-specific effective depreciation rate constructed as a weighted average of the depreciation rates for machinery and equipment and for buildings, with weights based on the composition of the establishment asset. g_t denotes expected capital gains. Following the empirical approximation in Singbo et al. (2025), expected capital gains are measured as the observed annual change in the fixed-asset price index.

Material input price deflator. We construct a fixed-weight intermediate-input price index for each province, industry, and year, by following the logic of input-output-based deflation used in the productivity literature (Orazem and Vodopivec, 2009; Brandt et al., 2017). The main innovation is to exploit the provincial detail available in Canadian supply-use tables and price

statistics.

For each province–industry cell, the base-year expenditure weight assigned to product group h is:

$$\omega_{psh}^{2017} = \frac{E_{psh}^{2017}}{\sum_{h \in \mathcal{H}} E_{psk}^{2017}}, \tag{A.47}$$

where E_{psh}^{2017} is the value of product group h purchased by industry s in province p in 2017, and $\mathcal{H}$ denotes the set of purchased intermediate-input products in province–industry cell (p, s).

The denominator includes market purchases of agricultural products, energy, manufactured goods, and services. We exclude accounting aggregates and non-market imputations that do not correspond to purchased intermediate inputs: total products, taxes on products, subsidies on products, gross value added at basic prices, imputed head-office services, imputed holding-company services, and financial intermediation services indirectly measured. Market services are retained because they are part of the intermediate expenditure aggregate used in the firm-level analysis. The province–industry intermediate-input price index is then defined at the province-industry-year level (p, s, t) as:

$$P^{M} = \sum_{h \in \mathcal{H}} \omega_{psh}^{2017} P_{pht}, \tag{A.48}$$

where P_{pht} is the price index assigned to product group h in province p and year t.

Table A.4 summarizes the data sources used to construct P_{pht}. All monthly indexes are converted to annual averages and rebased to 2017 equal to 100 before aggregation.

Primary agricultural products are matched to Farm Product Price Index (FPPI) commodity groups, including grains, oilseeds, specialty crops, fresh fruit, vegetables, potatoes, cattle, hogs, poultry, eggs, and milk. Electricity is matched to the provincial Electric Power Selling Price Index (EPSPI). Processed food products, beverages, petroleum products, packaging materials, and other manufactured inputs are matched to broad IPPI product groups. The CPI "Services" series provides a transparent provincial proxy for the price of purchased market services.

A national industry-level intermediate-input deflator would impose both a common input composition and common input-price movements across provinces. In contrast, equation (A.48) allows the price index to vary across provinces for two reasons. First, input baskets differ across province–industry cells. For example, food processors in different provinces may rely on different combinations of local agricultural inputs, electricity, transportation, packaging, and market services. Second, several important price components are directly province-specific, notably farm-product prices, electricity prices, and the services proxy.

The provincial variation in material input price is methodologically important. In specifications

Table A.4: Price Sources Used in the Intermediate-Input Deflator

Input category	Price source	Geographic variation
Primary agricultural products	Farm Product Price Index, Statistics Canada Table 32-10-0098-01	Province–commodity–year
Electricity	Electric Power Selling Price Index, Statistics Canada Table 18-10-0204-01	Province–year
Processed food, beverages, fuels, packaging, and manufactured inputs	Industrial Product Price Index by product, Statistics Canada Table 18-10-0266-01	Canada–product–year
Market services	Consumer Price Index, Services aggregate, Statistics Canada Table 18-10-0004-01	Province–year

Notes: Product categories are linked to the corresponding Statistics Canada price series using the North American Product Classification System codes in the supply-use tables. Where a detailed provincial farm-price series is unavailable, we use the Canada-level index for the same commodity group. For a small number of remaining missing farm-price observations, we use the mean index across available geographies for the same commodity group and year. Where a detailed IPPI product aggregate is unavailable in early years, we use the aggregate all-industrial IPPI as a fallback. These substitutions are recorded in the construction file and affect only the relevant product-year cells.

with sector-year fixed effects, any index that varies only at the sector-year level is absorbed by those fixed effects. Since material input price also varies across provinces, the relative input prices retain within-sector-year variation and remain identified in the estimation.

A.9. Productivity estimation

A.9.1. Setup

We adopt a control function approach (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015), and estimate productivity using proxy methods. The central idea is that firms observe their productivity when choosing inputs, so input choices contain information about the latent productivity state. By using flexible inputs such as materials as proxies, these methods control for unobserved productivity and address the simultaneity between input choices and output. The empirical specification separates the output into a deterministic production component, latent productivity, and a transitory error term. Our specification is of the form:

$$q_{it} = f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) + a_{it} + \varepsilon_{it}, \tag{A.49}$$

where $\boldsymbol{\beta} = (\beta_m, \beta_k, \beta_l)$ is the vector of parameters. Here, q_{it} denotes log output, while k_{it}, l_{it}, and m_{it} denote log capital, labor, and material inputs, respectively. The term a_{it} denotes the log-productivity. We assume that productivity evolves according to a first-order Markov process:

$$a_{it} = g_t\left(a_{i,t-1}\right) + \theta_{it}, \qquad a_{it} \in [\underline{a}, \overline{a}], \tag{A.50}$$

where $g_t(\cdot)$ captures the persistent component of productivity and θ_{it} is a firm-specific productivity innovation, reflecting climate-related disruptions to the adjustment and effective use of material inputs. Such disruptions may affect the availability, timing, quality, or reliability of intermediate inputs, thereby reducing production efficiency and shifting the production frontier downward (Chavas, 2008; Chavas and Zhang, 2025). We define the deterministic component of the log output as

$$\phi\left(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}\right) \equiv f(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}) = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} \tag{A.51}$$

Substituting equations (A.51) and (A.50) into equation (A.49) yields

$$q_{it} = \phi\left(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}\right) + g_t\left(a_{i,t-1}\right) + \theta_{it} + \varepsilon_{it}. \tag{A.52}$$

Thus, climate-related shocks affect output through their effect on productivity. By contrast, ε_{it} is a transitory disturbance that is separate from the productivity process. Let $\mathcal{I}_{it}$ denote the firm's information set at the time of its input choices. We assume that the firm observes its productivity state a_{it}, including the realization of θ_{it}, whereas ε_{it} is not observed when inputs are chosen such that: $\mathbb{E}\left[\varepsilon_{it} \mid \mathcal{I}_{it}\right] = 0$. The conditional expected log output is therefore:

$$\Phi_{it} \equiv \mathbb{E}\left[q_{it} \mid \mathcal{I}_{it}\right] = \phi\left(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta}\right) + a_{it}, \quad \text{such that} \quad q_{it} = \Phi_{it} + \varepsilon_{it}. \tag{A.53}$$

A.9.2. Estimation procedure

We rely on the 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, $f(\cdot)$, is generated by $\{a_{i\tau}\}_{\tau=0}^{t}$. The random component measuring unanticipated shocks to output in equation (A.49) 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: At time t, the firm's state variables are capital and productivity, denoted by (K_{it}, A_{it}). Capital is predetermined and evolves according to the standard law of motion, $K_{it} = (1 - \delta)K_{it-1} + I_{it-1}$, where I_{it-1} denotes investment undertaken in period $t-1$. By contrast, materials are flexible inputs: firms choose them after observing their productivity state A_{it}, but before the realization of the transitory output shock ε_{it}.

— A3: the industry parameter vector $\beta = (\beta_k, \beta_l, \beta_m)$ is constant and common within an industry group, and productivity evolves according to a first-order Markov process.

— A4: Productivity A_{it} and cost shocks are observed by the firm when input decisions are made but are unobserved by the econometrician. Unexpected output shocks ε_{it} are observed neither

by the firm nor by the econometrician at the time input choices are made.

— A5: For any flexible input satisfying A4, a firm's input demand function is strictly monotonic in productivity. These assumptions allow material input demand to serve as a proxy for latent productivity while allowing additional unobserved cost shocks.

This baseline control-function approach implicitly treats the observed proxy as a noiseless function of productivity, i.e., $m_{it} = m_t(k_{it}, a_{it})$, so that the inverse $a_{it} = m_t^{-1}(k_{it}, m_{it})$ recovers productivity exactly. In practice, however, observed material use may reflect measurement error, optimization frictions, or cost shocks that are distinct from productivity itself. We therefore rely on the two-step GMM-IV estimator of Hu et al. (2020), which uses lagged input choices as instruments to recover productivity. Let $\mathbf{z}_{it}$ denote observed firm characteristics and input-demand shifters. In the first step, we estimate the conditional expectation of output:

$$q_{it} = \Phi_t \left(m_{it}^{obs}, k_{it}, l_{it}, \mathbf{z}_{it} \right) + \varepsilon_{it}. \tag{A.54}$$

Following Hu et al. (2020), we allow the observed proxy to satisfy

$$m_{it}^{obs} = m_t \left(k_{it}, a_{it} \right) + \nu_{it}, \tag{A.55}$$

where ν_{it} captures error in the proxy that is unrelated to the production technology itself. Under strict monotonicity of $m_t(\cdot)$ in a_{it}, the standard inversion no longer recovers a_{it} alone but a combination of a_{it} and ν_{it}, biasing both the technology parameters and firm-level productivity.

— A6: Identification does not rely on directly inverting equation (A.55). Materials serve as the proxy variable, reflecting their larger share of variable costs in input-intensive industries, while labor is the other flexible input whose reduced-form demand equation, together with the polynomial structure of $g_t(\cdot)$ in equation (A.50), identifies $\boldsymbol{\beta}$ and separates a_{it} from ν_{it}, following Hu et al. (2020).

Under Assumption A6, the control function $h_t(\cdot)$ absorbs both productivity and the proxy error rather than productivity alone, so Φ_{it} is now indexed on the observed proxy:

$$\Phi_{it} \left(m_{it}^{obs}, k_{it}, l_{it}, \mathbf{z}_{it} \right) = \phi \left(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta} \right) + h_t \left(m_{it}^{obs}, k_{it}, l_{it}, \mathbf{z}_{it} \right), \tag{A.56}$$

where $\phi(\cdot)$ is unchanged, but $h_t(\cdot)$ is now estimated using the robust procedure of Hu et al. (2020), which separately identifies the component of $h_t(\cdot)$ attributable to a_{it} from the component attributable to ν_{it}, as detailed in Assumption A6. For any candidate parameter vector $\boldsymbol{\beta}$, firm-level productivity is recovered as

$$\widehat{a}_{it} \left(\boldsymbol{\beta} \right) = \widehat{\Phi}_{it} - \phi \left(k_{it}, l_{it}, m_{it}; \boldsymbol{\beta} \right). \tag{A.57}$$

Because $h_t(\cdot)$ in equation (A.56) is estimated under A6, $\widehat{a}_{it}(\boldsymbol{\beta})$ in equation (A.57) already nets

out the proxy error ν_{it}, rather than combining it with productivity as in the standard inversion procedure of the control function.

The associated productivity innovation is then recovered from the productivity process:

$$\widehat{\theta}_{it}\left(\boldsymbol{\beta}\right) = \widehat{a}_{it}\left(\boldsymbol{\beta}\right) - g_t\left[\widehat{a}_{i,t-1}\left(\boldsymbol{\beta}\right)\right]. \tag{A.58}$$

In a second step, the technology parameters are identified using moment conditions that require productivity innovations to be mean-independent of information available before their realization:

$$\mathbb{E}\left[\widehat{\theta}_{it}(\boldsymbol{\beta}) \mid \mathcal{I}_{i,t-1}\right] = 0. \tag{A.59}$$

In implementation, this conditional moment restriction is converted into unconditional moment conditions using functions of predetermined firm characteristics and lagged state variables. Once $\widehat{\boldsymbol{\beta}}$ is obtained, the estimated transitory output disturbance is

$$\widehat{\varepsilon}_{it} = q_{it} - \widehat{\Phi}_{it}. \tag{A.60}$$

To measure productivity dispersion, we rely on a moment-based approach that exploits the first three moments, mean, variance, and skewness following Chavas and Di Falco (2012):

$$\mathcal{M}_{j,it} = \mathbb{E}\left[\theta_{it}^{j} \mid \mathcal{I}_{i,t-1}\right], \qquad j = 2, 3. \tag{A.61}$$

The second moment, $\mathcal{M}_{2,it}$, measures the conditional variance of production innovations, while the third moment, $\mathcal{M}_{3,it}$, captures conditional skewness and exposure to downside production risk.