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Climate Change and Aggregate Productivity in Sweden

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Abstract: This thesis investigates the effect of climate change on firm-level and aggregate productivity in Sweden. Using a framework by Caggese et al. (2023), the impact of climate change on key microeconomic mechanisms affecting productivity is studied. Specifically, we estimate the impact of temperature fluctuations on the demand firms face, the productivity of their factor inputs, and their allocation of the same. By analyzing comprehensive firm-level data for the period 1996-2023 and combining it with daily temperature observations across the country, we find that the productivity of labor and materials increases at temperatures above 20 degrees Celsius. Through aggregation of the estimates, we conclude that climate change has a positive effect of low magnitude on Swedish aggregate productivity, which under a 2-degree Celsius temperature increase would amount to approximately 0.038 percent. This productivity increase is driven by efficient reallocation of inputs on the firm-level capturing the rise in productivity of labor and materials. Our thesis thereby corroborates research reporting productivity gains in cold countries due to climate change.

Keywords: Firms, Climate Change, Sweden, Temperature, Aggregate Productivity

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1. Introduction

Studies have found conflicting results regarding whether the stage of development of a country impacts how aggregate output responds to climate change. A similar conjecture is evident regarding whether countries with a lower average temperature could see economic gains from increased temperatures. The present paper studies the effect of rising temperatures on Swedish firms and aggregates these results to find an estimate of how aggregate productivity in Sweden will be affected by global warming.

Sweden has since the end of the 19th century seen a higher temperature increase of approximately 1.9 degrees Celsius in mean temperature compared to the global mean increase of around 1 degree Celsius (Schimanke et al., 2021). This figure is in line with the temperature increase in Europe at large during the same period (World Meteorological Organization, 2023). Consequently, studying how Swedish productivity has been impacted by said temperature increase can reveal how a developed country with a cold climate is affected by climate change. This holds considerable importance as previous studies in the area have focused on countries characterized by a warmer climate.

Before continuing, a crucial distinction must be made between climate and weather, with climate referring to the long-term distribution of weather outcomes. This paper exploits daily variations in weather, namely temperature, to find how firm-level and aggregate productivity in Sweden will respond to a warmer climate. Thus, it contributes to literature using granular weather data to assess economic implications, where researchers exploit high-frequency changes in temperature, and other weather variables, in a given geographical area to determine their effect on economic outcomes.

To conduct this study, we apply a framework developed by Caggese et al. (2023) on Swedish firm-level data. This framework allows for an assessment of three different channels through which temperature affects productivity. Namely, the demand firms face, the productivity of their inputs, and their allocative efficiency of the same. By using temperature bins, we account for non-linearities in the relationship between temperature and these firm level outcomes. This has been shown to be an important consideration as a range of economic outcomes on the micro-level have proven to exhibit such a response to temperature (Dell et al. 2014; Deschênes & Greenstone, 2007; Zhang et al. 2018).

The firm-level data used in our analysis is from the Serrano Database (Weidenman, 2016) hosted by the Swedish House of Finance and the climate data is obtained from the Swedish Meteorological and Hydrological Institute (SMHI), through a database called PTHBV (SMHI, n.d.). The climate data used in this paper is more granular than in the study by Caggese et al. (2023), with grid-cells of 4x4 kilometers ($16km^2$) rather than 11x11 km ($121km^2$). Furthermore, the time period covered by the data, spanning from 1996 to 2023, allows for more precise estimates than said study. Our estimates on the effect of temperature on firm-level and aggregate productivity will therefore be more precise.

The findings of this paper indicate that higher temperatures have a slight but positive effect on Swedish aggregate productivity. With a temperature increase of 2 degrees, aggregate productivity would according to our estimates increase by approximately 0.038 percent. This effect is driven by increases in the productivity of labor and materials on the firm level. Additionally, the results indicate that Swedish firms reallocate factor inputs to capture this productivity increase as aggregate allocative efficiency is positive under different warming scenarios. However, the effects of higher temperatures on aggregate and firm-level productivity in Sweden are significantly lower compared to Italy (Caggese et al., 2023).

1.1. Purpose

The purpose of this study is to analyze how productivity in Sweden is affected by higher temperatures through the model developed by Caggese et al. (2023). This is done by initially estimating the effect of temperature on firm-level outcomes, namely through the demand firms face, the productivity of their factor inputs, and the allocative efficiency of the same. Subsequently, we aggregate these results to find an estimate of how aggregate productivity in Sweden will be affected by higher temperatures. Based on the above, the research question addressed in this paper is:

What is the effect of climate change on aggregate and firm-level productivity in Sweden?

1.2. Contribution

The contribution of this paper lies in extending the analysis by Caggese et al. (2023) to other geographies. More specifically, the analysis will be performed on Swedish firms and Swedish aggregate productivity. Because of the chosen method, we provide further insights on through what channels temperature affects firm-level productivity. Considering the current state of research, we also contribute with novel empirical evidence on how the aggregate productivity of a rich country with a colder average temperature is likely to respond to climate change.

2. Previous Research

In the past decades, CO2 emissions from human activity have resulted in climate change. The global average surface temperature in 2011–2020 was around 1.1 degrees Celsius above the average in 1850–1900, with an even higher increase over land of around 1.6 degrees Celsius (IPCC, 2023). The repercussions of this change in climate include rising sea levels, more frequent extreme weather, climate-driven migration, and losses in ecosystems (IPCC, 2023). Mortality and morbidity rates have also risen due to an increase in food-borne, water-borne, and vector-borne diseases (IPCC, 2023). Moreover, in certain countries, higher temperatures have contributed to an increase in political instability (Dell et al., 2008).

There is a vast literature exploring the relationship between economic variables and climate change. Many focus on climate-related incidents such as natural disasters (Kousky, 2014), health-related deaths (Deschênes & Greenstone, 2011), and crop yields (Schlenker & Roberts, 2009). Recent papers have also investigated the impact of climate change on macroeconomic outcomes such as financial stability (Battiston et al., 2021), inflation (Kotz et al., 2023), and the natural interest rate (Mongelli et al., 2022). Although noteworthy in the literature on the economic effects of climate change, these papers are beyond the scope of this study.

Relevant in the context of this paper are studies on aggregate output and economic growth due to how interconnected these outcomes are with aggregate productivity (Syverson, 2011). In the following sections, an overview of the literature in this area will be provided with emphasis on relevant conjectures in reported findings. Following this overview, the microeconomic impacts of climate change will be presented, as well as how researchers have aggregated these effects to connect observations on the micro-level with the macro-level.

2.1. Economic Effects of Climate Change

In 1977, William D. Nordhaus published one of the earliest papers in the field of climate economics, *Economic Growth and Climate: The Carbon Dioxide Problem*, in which he studied the relationship between global warming and aggregate economic output. Nordhaus was a pioneer in the field and his paper predicted significant economic losses from continued CO2 emissions. Several notable contributions have since been made. In these, there have been conflicting reports on whether rich countries and poor countries respond differently to climate change, both in terms of magnitude and the linearity of the relationship. This is based on the notion that poor countries are more dependent on climate-sensitive sectors, such as agriculture, while rich countries are less susceptible to climate change due to their reliance on sectors such as service and technology (Dell et al., 2014).

In a study examining the effect of temperature on aggregate output of 120 countries, Dell et al. (2012) report that higher temperatures not only reduce output but also reduce growth rates in poor countries. According to their estimates, a 1-degree Celsius rise in temperature in a given year would result in reduced economic growth of approximately 1.3 percent in these poor countries. Dell et al. (2012) find that losses in the agricultural sector are part of this negative effect on growth, but that decreased industrial output and aggregate investment are also of importance. The authors did not find evidence of this effect being non-linear. For rich countries, however, the authors find that higher temperatures have no robust, detectable, effect on growth. In contrast, other studies find varying effects on both rich and poor countries (Kahn et al., 2021; Burke et al., 2015).

Burke et al. (2015) analyzed data on aggregate economic output in 166 countries from 1960 to 2010, finding that economic production follows a smooth, non-linear, concave function, where productivity increases until an optimum 13 degrees Celsius and declines thereafter. Furthermore, the paper reports that technological advances and accumulation of wealth have not fundamentally changed the relationship between productivity and temperature. Thus, the authors conclude that how rich a country is has no substantial effect on how it responds to climate change, specifically that there is no observed adaptation effect over time. It is rather its baseline average temperature that affects the response. Based on this, Burke et al. (2015) estimate that regions with a higher average temperature will be harmed by climate change, with the poorest 40 percent of countries experiencing a decline in gross domestic product (GDP) per capita of 75 percent. However, the richest 20 percent experience slight gains, with Europe standing out as a continent that is likely to benefit from higher average temperatures due to the continent's current cold climate.

In a panel study including 174 countries Kahn et al. (2021) investigated the long-term effect of climate change, finding that neither the economic development status of a country nor its average temperature, is of importance to how it responds to higher temperatures. Rather, they conclude that all countries will experience severe economic losses from global warming. Notably, the authors report that the rate at which temperatures increase away from the historical norm is a key determinant for country-level effects. Yet under all warming scenarios, countries will face a significant decrease in GDP. For the case of the US, the economic loss is 10.52 percent in the case of a 6-degree Celsius increase in average temperature, compared to 1.88 percent in the case of a 2-degree increase in average temperature.

2.2. Aggregating Microeconomic Outcomes

Overall, previous studies have focused on labor productivity as a microeconomic channel through which temperature affects economic activity. Macro-level studies, such as the ones outlined in the previous section, typically use value-added, GDP, or income per capita to find estimates on how the productivity of this factor input is impacted by higher temperatures (Dell et al., 2012; Burke et al., 2015; Kahn et al., 2021). However, these measures have limitations, as they are relatively coarse and can be influenced by other factors. A more ideal approach is therefore to aggregate micro-level labor productivity data (Lai et al., 2023). The following section will provide an overview of the effect of temperature on labor productivity, due to its importance in the literature, as well as present studies that have utilized aggregation to find how aggregate productivity is affected by a warmer climate.

Labor productivity in indoor settings has been seen to display an inverted U-shape, increasing up to 21-22 degrees Celsius and decreasing with temperatures above 23-24 degrees Celsius (Seppänen et al., 2006). For outdoor work, the effect on labor productivity appears to be significantly higher, as a study of time allocation in the United States showed that workers in industries with a high exposure to climate decrease their time working with as much as one hour a day in temperatures above approximately 29.4 degrees Celsius (Graff Zivin & Neidell, 2014). For cold outdoor temperatures, labor productivity has also been seen to decrease. In a study on Chinese manufacturing plants, worker productivity dropped by 11 percent when temperatures were around 15.5 degrees Celsius compared to when facing temperatures in the range 21.1-26.6 degrees Celsius (Cai et al., 2018). Yet, the relationship is complex and context-specific. For example, bankers in Japan have displayed lower productivity when it is sunny outside, as this serves as a distraction from their work (Lee et al., 2014). Further emphasizing the need for a holistic approach where microeconomic effects are aggregated.

Somanathan et al. (2021) aggregated the aforementioned effects of temperature on labor productivity using micro data from Indian manufacturing plants, finding that higher outdoor temperatures have a significant impact on the productivity of workers, as well as absenteeism. The authors adopt an approach wherein temperature observations are assigned to bins that encompass different temperature ranges and these bins are then used as an independent variable. This stands against using temperature as a continuous variable, which requires knowledge about the nature of the relationship between temperature and the dependent variable. Temperature bins were first introduced by Deschênes and Greenstone (2007) who used them to account for non-linearities in the effect of temperature and precipitation on economic outcomes in the agricultural sector.

More recent papers have used firm-level data to investigate the effect of temperature fluctuations on total factor productivity (TFP), thereby connecting the reported effects on aggregate output with micro-level observations. Zhang et al. (2018) used year-to-year variations in Chinese manufacturing plants' exposure to the annual distribution of daily temperatures to assess the relationship between firm-level productivity of factor inputs and TFP. Similarly to Somanathan et al. (2021), the authors utilized temperature bins to account for non-linearities on the micro-level. The findings show that temperature affects economic output primarily through losses in TFP. In addition, the authors observed an inverted U-shape between temperature and TFP, displaying that there are significant TFP losses at particularly high and low temperatures. A day with temperatures above 32.22 degrees Celsius the losses in TFP amount to 0.56 percent, relative to a day with temperatures in the range 10-15.55 degrees Celsius.

Caggese et al. (2023) used firm-level data from Italy to investigate how temperature affects the productivity of firm-level inputs and how this influences aggregated productivity. They proposed a model that identifies misallocation effects, which have been proven to have a significant impact on TFP (Restuccio & Rogerson, 2008; Hsieh & Klenow, 2009) and are therefore important to include to accurately assess aggregate productivity. Caggese et al. (2023) find the effect on the revenue-based marginal product of capital to be significant, following an inverted U-shape. In addition, the authors find that extreme temperatures have a significant negative effect on productivity: In a scenario where the average temperature in Italy would increase by 2 degrees Celsius, the aggregate productivity loss would according to their estimates amount to 1.8 percent, corresponding to approximately USD 38 billion in GDP loss in 2021.

3. Theory

This section gives an overview of the theoretical framework developed by Caggese et al. (2023) in *Climate Change, Firms and the Aggregate Productivity*, which provides a closed-form solution to assess the effects of temperature on firm-level and aggregate productivity and disentangles the effect on different channels. The framework centers around quantifying the effect of temperature through wedges, a form of production distortion, for different supply- and demand-side channels. The temperature semielasticities of these wedges are subsequently used to identify the effect of temperature on firm-level outcomes.

As productivity by nature constitutes the residual between factor inputs and output, it cannot be measured directly in the same way as other economic variables. Hence, one must derive it indirectly using absolute values. In the theoretical framework, this is achieved in three steps, which will be presented in further detail below. First, the demand-side effect of temperature is presented. This is followed by an identification of the supply-side effects through firms' inputs. Lastly, the relationship between demand- and supply-side effects enables us to calculate the effect of temperature on productivity. On the aggregate level, the specifications allow us to make a distinction between productivity effects due to improvements in technology and resource reallocation respectively.

To get an understanding of how wedges work and the effects on output, we briefly explain the Constant Elasticity of Substitution (CES) model, as this is the foundation of the theoretical framework developed by Caggese et al. (2023). We continue by exploring wedges as production distortions and present the main steps required to find the effect of temperature on firm-level outcomes and aggregate productivity.

3.1. The CES Model

Caggese et al. (2023) use a standard CES output model with a monopolistic market structure and heterogeneous firms. The CES model has previously been used to study heterogeneity in various contexts, for example, international trade (Melitz, 2003) and misallocation (Hsieh & Klenow., 2009). Furthermore, empirical evidence supports using the CES model for aggregate input-output relationships where the elasticity of substitution between capital and labor is significantly greater than one, as shown by Duffy and Papageorgiou (2000). The model by Caggese et al. (2023) shows how temperature changes drive the wedges that affect the efficiency of different inputs, as well as a firm's overall input mix and demand-adjusted productivity.

The Constant Elasticity of Substitution (CES) model is a neoclassical production function with the general form:

$$Q = F(\alpha K^{c} + (1-\alpha)L^{\rho})^{\varrho}$$

(1)

where Q gives the quantity of output, F represents factor productivity (TFP on aggregate level), α is a share parameter, ρ is a substitution parameter and K and L represent the quantities of the respective production factors (capital and labor). The standard Cobb-Douglas production function represents a special case of the CES model, where the elasticity of substitution is equal to one.

Since the theory relies on a structural framework with more than two production functions, we present the extended version of the CES model (Caggese et al., 2023). With multiple factors of production (labor, capital and materials), the CES model takes on the general function:

$$Q = F\left[\sum_{i=1}^{n} a_i X_i^r\right]^{\frac{1}{r}}$$

(2)

Where Q is the output quantity, F is the factor productivity, a_i is the factor share and X is the factor inputs. Elasticities of substitution in cases with more than two factor inputs require special conditions. As the framework relies on constant elasticities of substitution between varieties, additional specifications are necessary (Caggese et al., 2023). Uzawa (1962) found that one of two conditions must be satisfied in the case of multiple production factors if the elasticities of substitution between every pair of inputs are to be held constant: (i) identical elasticities of substitution between all input pairs or (ii) the elasticity between at least one pair of inputs must equal to -1. Negative elasticity of substation indicates that two inputs act as complements to each other, while identical elasticities imply that input factors can be switched between each other to the same degree. In line with the framework, we apply case (i) with identical elasticities of substitution, so that capital, labor, and materials are interchangeable to the same degree (Caggese et al., 2023). Subsequently, the production function for each firm is a Cobb-Douglas in productivity, capital, materials and labor.

3.2. Wedges

In a CES model, it is possible to substitute the productivity factor with a wedge or production distortion. Wedges and productivity factors are closely related, as they explain the ratio between actual output quantity and theoretical output quantity. A wedge is simply a productivity factor, indicating distorted production. The structural framework introduces *temperature-dependent wedges* for demand, productivity, and input factors (Caggese et al., 2023). As these wedges are central to quantifying the effect of temperature on firm-level variables, they constitute the variables we will be running regressions on. As defined in the framework, the various temperature-related wedges take the following functional forms (Caggese et al., 2023):

$$e^{\sim z_{it}\left(T_{g(i)t}\right)} \equiv e^{\alpha_i^{\sim z}+\gamma_{s(i)t}^{\sim z}+\lambda_{r(i)}^{\sim z}*t+\sim z_{it}+F^{\sim z}(T_{g(i)t})}$$

(3)

$$e^{\tau_{it}^X(T_{g(i)t})} \equiv e^{\alpha_i^X+\gamma_{s(i)t}^X+\lambda_{r(i)}^X*t+z_{it}+F^X(T_{g(i)t})}$$

(4)

Equation 3 defines the *demand-adjusted productivity wedge*, while equation 4 defines the *inputs-specific wedge*, where $\forall X \in \chi$. In the functional forms, i denotes a firm, t denotes a year, $g_{(i)}$ denotes the grid-cell the firm is operating in, $\gamma_{s(i)t}$ reflects sector-time specific trends, α_i represent a time-invariant firm-fixed effect and $\lambda_{r(i)} * t$ denotes region-specific time trends. Despite the functional form including further non-temperature related effects z_{it}/d_{it}, the focus will solely be on the effects attributable to temperature. The function $F(T_{g(i)t})$ provides a flexible effect, as it enables us to account for potentially non-linear effects on the different wedges.

3.3. Firm-level Variables

In the framework, the relationship between observable variables and productivity is derived in three steps (Caggese et al., 2023). First, the generic demand and supply conditions faced by individual firms are presented. Secondly, the profit-maximizing price is derived under the conditions of demand, which is affected by temperature, and with respect to temperature effect on costs through different inputs. With the profit-maximizing sales function, Caggese et al. (2023) illustrate that the *demand-adjusted temperature-dependent wedge* is the only variable explaining the differences between output sales and production. Lastly, the authors rely on relationships derived by Hsieh and Klenow (2009) to show that the firm-level input factors and sales are the only nominal input data needed to compute the impact on productivity.

The demand function faced by each firm is specified to be dependent on a *temperature-dependent demand wedge* $e^{d_{it}T_{g(i)t}}n$, the price P_{it} of the goods sold by a firm relative to the average price P_t and the total output Y_t. This is given by the function:

$$Y_{it} = \left[e^{d_{it}T_{g(i)t}}\right]^{\sigma-1} \left[\frac{P_{it}}{P_t}\right]^{-\sigma} Y_t \tag{5}$$

The normal profit function, which is now subject to the constraint of the demand function presented above, is given as:

$$\pi_i = \max_{C,Y} Y(P_{it})Y_{it} - C(Y_{it})$$

(6)

The profit-maximizing price is derived as the first-order condition of marginal cost $C'(Y_{it})$times a markup M:

$$P_{it} = \mathrm{M} * C'(Y_{it})$$

(7)

The profit-maximizing cost (i.e. the cost minimizing function) is given as the product of total input-specific cost relative to the elasticity of substitution α^{χ}, and aggregate demand Y_{it}. Both are affected by temperature through wedges, the different input prices through the input-specific wedge $e^{\tau_{it}^{X}(T_{g(i)t})}$and the aggregate demand through the productivity wedge $e^{z_{it}(T_{g(i)t})}$. This is given as follows, where $\chi = \{K, L, M\}$:

$$C(Y_t) = \prod_{X\epsilon\chi}\left(\frac{e^{\tau_{it}^{X}(T_{g(i)t})}P_t^{\chi}}{\alpha^{\chi}}\right)^{\alpha^{\chi}} \frac{Y_{it}}{e^{z_{it}(T_{g(i)t})}}$$

(8)

These three equations yield the central sales function for individual firms:

$$P_{it}Y_{it} = \left(e^{\sim z_{it}(T_{g(i)t})}Y_{it}\right)^{\sigma-1}\left(\mathcal{M}\prod_{X\epsilon\chi}\left(\frac{e^{\tau_{it}^{X}(T_{g(i)t})}P_t^{\chi}}{\alpha^{\chi}}\right)^{\alpha^{\chi}}\right)^{-(\sigma-1)} P_t^{\sigma}Y_t$$

(9)

This sales function comprises of three main components: (i) the *temperature-dependent demand-adjusted productivity wedge* $e^{\sim z_{it}(T_{g(i)t})}$, (ii) the cost of inputs and the *input-specific wedge* $e^{\tau_{it}^{X}(T_{g(i)t})}$ times a markup $\mathcal{M}$and (iii) the aggregate output P_tY_t across all firms. Just as a TFP productivity factor, the *temperature-dependent demand-adjusted productivity wedge* $e^{\sim z_{it}(T_{g(i)t})}$ now explains the difference between theoretical sales and observed values. Importantly, one can observe the impact of temperature clearly, as it only affects firm-level sales through input-specific wedges and the demand-adjusted productivity wedge.

Caggese et al. (2023) show that the input-specific wedges $e^{\tau_{it}^{X}(T_{g(i)t})}$can be derived from the revenue-based marginal product of input X (MRPX). Relying on findings by Hsieh and Klenow (2009), the authors conclude that this can be measured by observing firm-level sales $P_{it}Y_{it}$ and firm-level input quantities $X_{it} = \{K_{it}, L_{it}, M_{it}\}$, under the condition that the production function elasticity σ is known. Taking the logarithm of this relationship, the authors go on to show that temperature only affects the revenue-based marginal product (MRPX) of firms through the *input-specific wedges* $e^{\tau_{it}^{X}(T_{g(i)t})}$. Formally the equation is represented by:

$$log\, MRPX_{it} = e^{\tau_{it}^{X}(T_{g(i)t})} + \mu + p_t^X$$

(10)

The *temperature-dependent demand-adjusted productivity wedge* is the product of the demand wedge and the productivity wedge, as introduced above, and is given by:

$$e^{\sim z_{it}(T_{g(i)t})} = e^{d_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}$$

(11)

In summary, under the condition that temperature changes, sales of a firm either change due to (i) changes in demand-adjusted productivity wedge $e^{\sim z_{it}(T_{g(i)t})}$ or (ii) input-specific wedges $e^{\tau_{it}^{X}(T_{g(i)t})}$. We leverage the firm-level sales figures obtained from our data and the ability to measure the effect of temperature on the input factors, using firm-level sales and input quantities. This allows us to calculate the effect of temperature on productivity through the temperature-semielasticities of the demand-adjusted productivity wedge $\frac{\partial \sim z_{it} T_{g(i)t}}{\partial T_{g(i)t}}$.

3.4. Aggregate variables

Following Caggese et al. (2023), changes in aggregate productivity, or aggregate TFP, are proxied with changes in the Solow residual. As described by Kim and Loayza (2019), the Solow residual captures a variety of factors, from natural resources and excess capacity to intangible capital. For example, changes in the Solow residual could be due to technological progress. To calculate the effect of temperature on aggregate productivity using the Solow Residual, Caggese et al. (2023) compare the aggregate TFP in different counterfactual scenarios with the upper bound of aggregate TFP, where the upper bound is named as an "efficient" or "frictionless" state and input-specific specific wedges are set to zero.

3.4.1. Aggregate TFP

Formally, Caggese et al. (2023) define TFP as the share of aggregate output Y_t in relation to the product of the different input factors, following a standard Cobb-Douglas production function:

$$TFP_t = \frac{Y_i}{\prod_{X \epsilon \chi} X_t^{\alpha X}}$$

(12)

We identify the effect of temperature on aggregate TFP by differentiating and taking the logarithm of equation 12 with regards to temperature. This yields a function that is dependent on three factors; i) *temperature-dependent demand adjusted productivity wedge* $e^{\sim z_{it}(T_{g(i)t})}$, ii) *temperature dependent input-specific wedge* $e^{\tau_{it}^X(T_{g(i)t})}$ and iii) changes in grid-cell-level temperatures, that is $\Delta T_{g(i)t}$. Fittingly, the wedges can be calculated using firm level and aggregate economic data as shown by Hsieh and Klenow (2009). The change in grid-cell level temperature $\Delta T_{g(i)t}$ is the variable of interest in this context, as we subject this variable to different scenarios.

By differentiating and taking the logarithm of equation 12, one can achieve the equation linking changes in grid-cell level temperature to changes in aggregate gross output TFP. Since the complete derivation for this is extensive, we refer to Cagesse et al. (2023) and only show the simplified function here. However, we include the full equation in appendix *TFP Functions*.

$$\Delta log\, TFP_t \equiv \left(e^{\sim z_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}, \Delta T_{g(i)t}\right)$$

(13)

Keeping the structural assumptions on the effect of temperature on demand and profit-maximizing supply as presented previously, Caggese et al (2023) present the first component needed, the firm-level *demand-adjusted productivity wedge* $e^{\sim z_{it}(T_{g(i)t})}$ as:

$$e^{\sim z_{it}(T_{g(i)t})} = \left(\frac{(P_t Y_t)^{-\frac{1}{\sigma-1}}}{P_t} \right) \left(\frac{(P_{it} Y_{it})^{\frac{\sigma}{\sigma-1}}}{\prod_{X \epsilon \chi} X_{it}^{\alpha^X}} \right)$$

(14)

As previously described, we recover the variables needed for measuring the firm-level *demand-adjusted productivity wedge* $e^{\sim z_{it}(T_{g(i)t})}$ from the firm-level data, as $P_t Y_t$ represents aggregate output, P_t denotes a price deflator, $P_{it} Y_{it}$ and X_{it} is firm-level sales and inputs, respectively. The measurement is conditional on the assumption about the elasticity between substation of varieties c and production function elasticities α^X. The second component, the *temperature-dependent input-specific wedge*, is defined as follows, were $M = \frac{\sigma}{\sigma-1}$:

$$e^{\tau_{it}^X(T_{g(i)t})} = \left(\frac{\alpha^X}{M} \right) \left(\frac{P_{it} Y_{it}}{P_t^x X_{it}} \right)$$

(15)

3.4.2. Frictionless aggregate TFP

Frictionless aggregate TFP, defined as the upper bound of aggregate gross output TFP and denoted with a *, is calculated by equalizing all input-specific wedges across all firms. In this frictionless state, all firms and all inputs have the same revenue-based marginal product (MRPX). Hence, this term in the production function becomes obsolete and means that aggregate TFP now formally is given by:

$$TFP_t^* = \left(\sum_{i=1}^{N_t} \left(e^{\sim z_{it}(T_{g(i)t})} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

(16)

The effect of changes in grid-cell-level temperatures on efficient aggregate gross output TFP is, again, achieved by differentiating with respect to temperature and taking the logarithm. This yields the function (see appendix *TFP Functions* for the complete formula):

$$\Delta log\ TFP_t^* \equiv \left(e^{\sim z_{it}\left(T_{g(i)t}\right)}, \Delta T_{g(i)t}\right)$$

(17)

3.4.3. Counterfactual Scenario

Caggese et al. (2023) show that, to calculate the *counterfactual* change in efficient aggregate gross output TFP due to changes in grid-cell-level temperatures, we simply need three things: (i) the *demand-adjusted temperature dependent productivity wedges* $e^{\sim z_{it}\left(T_{g(i)t}\right)}$ and their temperature semielasticities (ii) the *temperature dependent input-specific wedge* $e^{\tau_{it}^X\left(T_{g(i)t}\right)}$ and their temperature semielasticities, as well as $\Delta T_{g(i)t}$. In section 3.2 , we presented how to calculate the wedges using firm-level data as equation 3. For the respective semielasticities $\frac{\partial \sim z_{it} T_{g(i)t}}{\partial T_{g(i)t}}$ and $\frac{\partial \tau_{it}^X T_{g(i)t}}{\partial T_{g(i)t}}$, we use the results from equation 9. The final component, the grid-cell-level temperature changes $\Delta T_{g(i)t}$, is the variable of interest in this section, as we are interested in the effect of temperature increase on aggregate productivity under different global warming scenarios.

The final expression, equation 18, disentangles the change in productivity into two terms. The first term, the technology term, shows changes in efficient aggregate TFP due to changes in temperature, as the input-specific wedges $e^{\tau_{it}^X\left(T_{g(i)t}\right)}$ have been equalized. The second term, named allocative efficiency, captures changes in allocation relative to the efficient allocation, as noted by Beqaee and Farhi (2020). This change in allocation of production factors arises by separating the temperature semielasticities of inputs to only be included in aggregate TFP and not the "frictionless" state.

$$\Delta logTFP_t = \Delta logTFP_t^* - (\Delta logTFP_t^* - \Delta logTFP_t)$$

(18)

As we are using the Solow residual as a proxy for aggregate TFP, which is defined on value-added and not aggregate gross output TFP (as used in equation 18), Caggese et al. (2023) derive the adjusted formula and present the equation 19, where Y_t is gross output and GDP_t is value-added output (gross output net of materials).

$$\Delta \; log \; Solow \; \approx \frac{Y_t}{GDP_t}\left(\Delta logTFP_t^* - (\Delta logTFP_t^* - \Delta logTFP_t)\right)$$

(19)

3.5. Limitations of the Theory

The framework by Caggese et al. (2023) has several limitations. For one, it is static and hence does not take dynamic variables, such as capital accumulation, into account. As studies have shown that these variables are important factors to consider when understanding GDP dynamics (Bilal & Rossi-Hansberg., 2023), this limits the interpretation of results. This static nature of the model prevents us from capturing the importance of anticipation and adaptation. However, it is worth noting that static models are significantly more tractable than dynamic ones. Another limitation comes from the framework being focused on only firms' input allocation to assess adaptation to temperature changes (Caggese et al., 2023). This means that it does not capture the effect of firms undertaking adaptation measures to mitigate the effects of temperature on productivity that are not reallocation of inputs. Emitting this factor may bias results from the framework upwards, as such measures have a significant impact in the long run (Caggese et al., 2023). Yet, climate change will expose areas that have previously been cooler to faster increases of temperature rises and hence firms in these areas will not likely be adapted to such shocks. Thus, the framework may bias results downwards.

3.6. Empirical specification

$$Outcome_{it} = \sum_{\lambda} \beta_{\vartheta} T_{g(i)t}^{\vartheta} + \delta \text{Precipitation} + \boldsymbol{\lambda}' \mathbf{X}_{r(i)t} + \gamma_{s(i)t} + \alpha_i + \varepsilon_{it}$$

(20)

Regression 20 is the empirical counterpart of the theoretical equations 7 and 9 after taking the logarithm, as shown by Caggese et al. (2023). We use it to investigate the relationship between days in a temperature bin and an outcome variable. The dependent variable, $Outcome_{it}$, holds for several variables as it constitutes all dependent variables for the theoretical counterparts. Beyond sales, $p_{it}y_{it}$, the variable of interest is the input X (Capital, Labor and Materials) and each associated log revenue-based marginal product, log $MRPX_{it}$. With this regression, one can determine the effect of one extra day in each individual temperature bin ϑ on the outcome variable(s). β_{ϑ} hence represents the variable of interest, as it shows the coefficient indicating the relationship between an extra day in bin ϑ and the percental change in the outcome variable. Following Caggese et al. (2023), we add yearly precipitation as an environmental control variable and employ several fixed effects: $\mathbf{X}_{r(i)t}$ contains dummies at the regional level for five major economic events (Early 2000s recession, Great recession 2007-2008, European debt cris 2012-2015, Covid-19 pandemic 2019-2020) and time trends at the regional NUTS[1] 2 level. $\gamma_{s(i)t}$ is a sector and year fixed effect while α_i is a firm-fixed effect. As specified by Caggese et al. (2023), the firm-fixed effect is incorporated to control for time-invariant unobserved firm-level heterogeneity, while the sector-year interaction removes sectoral fluctuations. Standard errors are clustered at the grid-cell level to account for serial correlation.

4. Data

4.1. Firm-level data

The Swedish firm-level data is obtained from the Serrano Database (Weidenman, 2016), provided by the Swedish House of Finance at the Stockholm School of Economics. The Serrano Database is built on financial statement data collected from the Swedish Companies Registration Office (Bolagsverket), as well as general firm data from Statistics Sweden (SCB) and group-level data from Bisnode's group register. The database provides yearly data on a firm-level basis either in SEK (e.g. revenue) or number format (e.g. number of employees).

The final firm-level dataset includes the variables measuring output (Y) and the input factors capital (K), labor (L) and materials (M). We follow Caggese et al. (2023) and use net sales as output Y, book value of tangible assets for capital (K), personnel costs measuring labor (L) and production costs for materials (M). For a description of each variable, as stated in *Serrano: A Swedish company database for*

[1] The Nomenclature of territorial units for statistics, abbreviated NUTS, is a geographical nomenclature subdividing the economic territory of the European Union (EU) into regions at three different levels (NUTS 1, 2 and 3 respectively, moving from larger to smaller territorial units).

analysis and register based statistics - Variable documentation by Dun & Bradstreet (2023), see appendix *Firm-level data*.

Furthermore, the dataset provides us with the 4-digit sector classification of economic activity according to the Swedish Standard Industrial Classification (Standard för svenskt näringsindelning, SNI). This system is harmonized, and hence comparable, with the standard used in the European Union, called NACE Rev.2. More importantly for this paper, we obtain zip codes for each firm based on the location of the registered headquarters. This crucial information makes it possible to geomatch each firm-level observation with an observation from the climate data.

We perform data cleaning outlined by Caggese et al. (2023), which involves excluding observations missing key variables. These are sales, operating profit, zip-codes, and assets. Furthermore, we remove extreme observations by constructing three ratios[2], observations falling above or below the 99.9 and 0.01 percentile, respectively, are removed. Lastly, observations missing a branch sector classification, falling in the category "Others" or operating in the branch sectors "Finance and Real estate" or "Energy & Environment" are excluded. All monetary values are deflated in line with Caggese et al. (2023), to reflect real values, using the Eurostat two-digit price deflator. Values for capital are deflated with country-specific prices of investment from the World Development indicators.

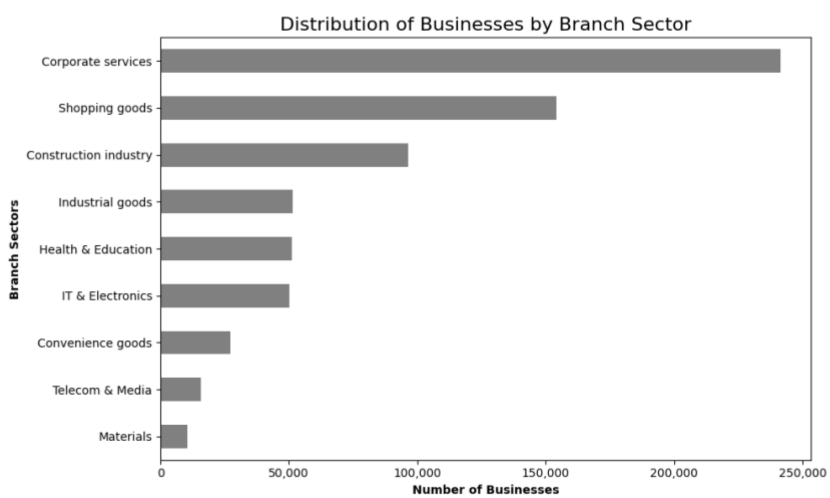

Figure 1: Branch sector distribution of firms in the Serrano Database excluding Finance & Real estate, Others and observations missing sector values (Weidenman, 2016).

[2] Sales to total assets, employment to total assets and employment to sales.

The final dataset of firm-level data contains 5,861,270 observations and spans the period 1996-2023. One major advantage of the Serrano dataset is that, because of its sources, it includes both small and large firms, as well as individual firms and corporate groups. Figure 2 shows the size distribution of firms in the final dataset.

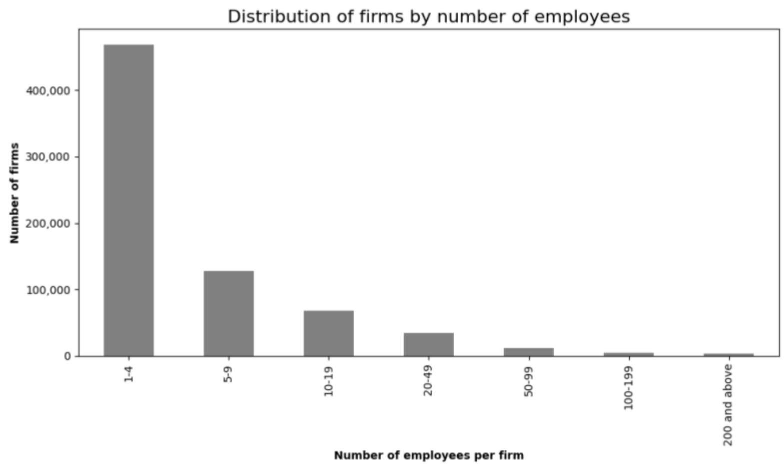

Figure 2: Distribution of firms by number of employees in the Serrano Database after data cleaning (Weidenman, 2016).

4.2. Climate data

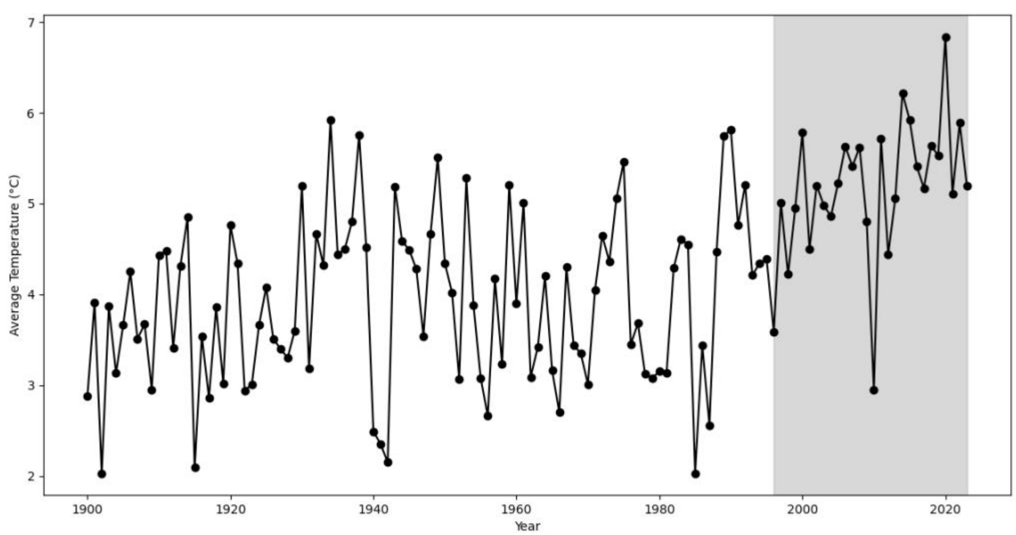

Figure 3: Annual average temperature in Sweden between 1900 and 2023 (SMHI, n.d.). The shaded area is the analyzed time period (1996-2023).

Our climate data is retrieved from the Swedish Meteorological and Hydrological Institute (SMHI), which provides open-source data on daily temperature and annual precipitation levels across Sweden through a database called PTHBV (short for Precipitation Temperature Hydrological Bureau´s water model[3]) (SMHI, n.d.). The PTHBV dataset is built on observations from SMHI's 200 meteorological stations and 100 external meteorological stations. Observations are interpolated in a 4x4 km grid system covering Sweden and provide climate data from 1961 until the present. See appendix *Climate data* for a more detailed description of the dataset as described on the official site of SMHI. For this paper, we obtain daily temperature and annual precipitation levels for the period 1996 to 2023.

Statistic	Value
Mean Temperature (°C)	3.354282
Standard Deviation (°C)	9.351915
Minimum Temperature (°C)	-46.871387
Maximum Temperature (°C)	27.192066

Figure 4: Summary statistics of daily temperatures in Sweden between 1996 and 2023 (SMHI, n.d.).

4.3. Combined data

We construct our final data set by combining the Serrano firm-level financial data with the daily temperature data obtained from PTHBV. The challenge lies in matching the different types of geographical information provided in the two data sets, as well as the different frequencies of the observations (Caggese et al., 2023). The PTHBV data contains longitude and latitude information for each observation, while the Serrano data gives us the zip code of each registered firm's headquarter, as previously mentioned. Moreover, the Serrano Database, based on annual reports, differs from the daily temperature observations in terms of frequency.

The initial discrepancy in the frequency of observations, annually for firm-level data compared to daily for temperature, is addressed by counting the number of days in each temperature bin for each year. This methodology is further elaborated on in section 5.1. We utilize a package in Python called Pgeocode[4] containing zip codes and coordinates, to extract longitude and latitude coordinates based

[3] *Precipitation Temperature Hydrologiska Byråns Vattenmodell* in Swedish

[4] Pgeocode uses the Creative Commons database GeoNames. For Sweden, the database sources are Bebygelseregistret (BeBR) (Data base on Built Heritage), Lantmäteriet (Swedish National Land Survey), Stockholm Stad (Stockholm Municipality), SCB (Statistics Sweden) and valmyndigheten (Swedish Election Authority)

on the zip code from each company. With geographical data in the same measurement, we can match each firm with its closest weather station. This enables us to assign each firm to a distribution of days in each temperature bin for each year and the annual precipitation level.

5. Methodology

Our thesis adopts a method where the effect of temperature on the firm-level inputs of labor, capital, and materials can be separately identified (Caggese et al., 2023) while remaining agnostic about the functional forms of said relationships by using temperature bins (Dell et al., 2014). This allows us to analyze if firms efficiently allocate their resources under global warming. We start by presenting how the daily temperature observations are aggregated into bins on a yearly frequency, before introducing the main regression(s) of this paper.

5.1. Measurement of Temperature

With the climate data obtained from SMHI, we follow Somanathan et al. (2021) and Caggese et al. (2023) when aggregating daily temperatures in degrees Celsius to the annual level. Specifically, this entails counting the number of days in the year falling within different temperature bins. Here, we use the bins {(-∞,-15℃], (-15℃, -5℃], (-5℃, 0℃], (0℃, 15℃],(15℃,+20℃], (20℃,+∞]}. Creating a vector counting the number of days in each of these bins for every grid-cell and each year in creating a vector, we assign any given day to exactly one bin. This makes it possible to match the climate data with yearly financial data, as described in section 4.3.

This temperature vector is the variable of interest and constitutes the main independent variable in subsequent regressions. For the selection of temperature bins, a few conditions need to be considered. Firstly, the distribution of the bins needs to contain one bin (the reference bin) that captures most of the counts of the days in a year. The motive for this follows the hypothesis that extreme temperatures, that is, deviations from the historical mean, have an effect. For example, the hypothesis is that firms in Stockholm will not be significantly affected by an extra day with temperatures falling close to the historical average, but rather from extra days with temperatures deviating from this. Secondly, following mathematical properties and to be able to draw meaningful statistical interpretations, each bin must have a non-zero average value for the number of days falling in that bin. Importantly, the temperature bins chosen satisfies this non-zero average value condition. Furthermore, from the distribution of days in each bin (see figure 5), we can identify (0℃, 15℃] as containing the most days in a year on average. Hence, we will use this bin as the reference bin in our calculations.

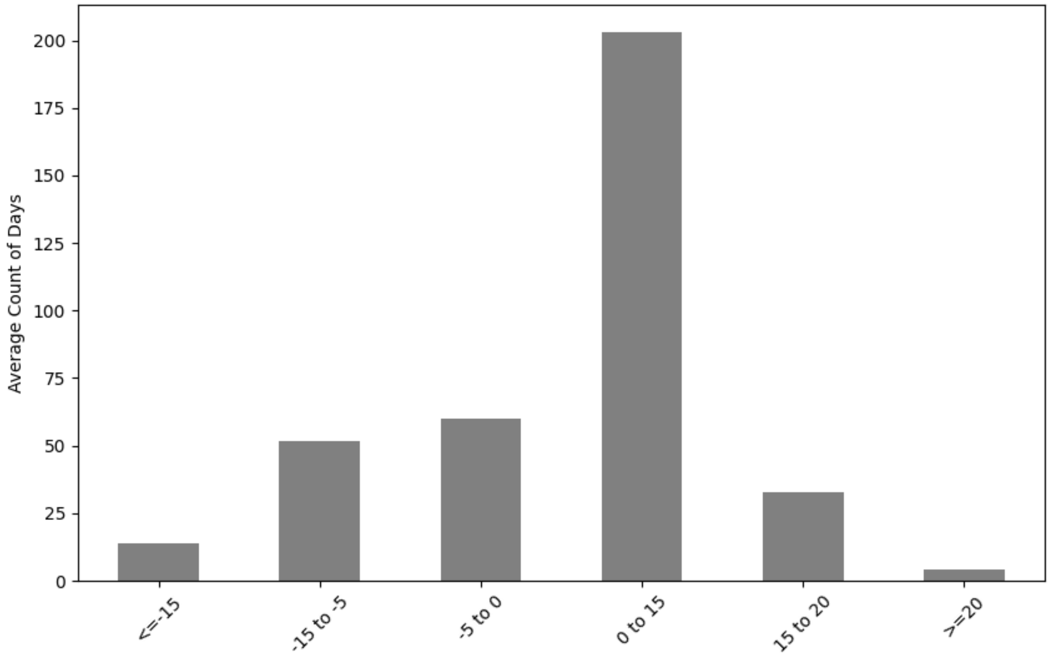

Figure 5: Average number of days within each temperature bin across all grid-cells and years.

5.2. MRPX

To calculate the productivity effect of temperature, we need the temperature semielasticities of the revenue-based marginal product of capital, labor, and materials. Under the Cobb-Douglas production function, we take advantage that $MRPX_{it} = \frac{\partial P_{it}Y_{it}}{\partial X_{it}} = \frac{\alpha^x P_{it}Y_{it}}{X_{it}}$ with $X \epsilon \text{X} = \{K_{it}, L_{it}, M_{it}\}$, where are nominal values are deflated, as described in section 4.1.

As α^x, the elasticity of production factors is the only value not directly found in the data, we need to measure this. Following Caggese et al. (2023), this is done using a cost shares approach as adopted by Foster et al. (2008). This exploits the first-order conditions of firms and relies on two assumptions: (i) constant returns to scale in production and (ii) all inputs are variable in the long-run. With this, the production elasticities can be calculated using the cost shares, which are calculated as following:

$$\alpha^K = 1 - \alpha^L - \alpha^M$$

(21)

$$\alpha^L = med\left(\frac{W_t L_{it}}{W_t L_{it} + r_t K_{it} + P_t^M M_{it}}\right)$$

(22)

$$\alpha^M = med\left(\frac{P_t^M M_{it}}{W_t L_{it} + r_t K_{it} + P_t^M M_{it}}\right)$$

(23)

In the calculations, $W_t L_{it}$ is the wage bill, including social costs, $r_t K_{it}$ is the rental cost of tangible capital[5] and $P_t^M M_{it}$ is the cost of materials. Median firm-level cost shares are taken to account for short-term frictions and measurement errors, as done by De Loecker et al. (2020). For this, we follow Caggese et al. (2023) and assume an elasticity of substitution sigma=4, which is in line with many firm-level estimates and macroeconomic studies (e.g., Bernard et al., 2003; Christiano et al., 2015). The implied cost-weighted markup of 33 percent is also in line with existing literature (De Loeker et al., 2020; Broda & Weinstein, 2006). With these assumptions, we recover the median production function elasticities $\{\alpha^X\}_{X\epsilon\{L,M,K\}}$ equal to $\{0.457, 0.357, 0.186\}$.

As the regression framework includes sector-time-specific effects and firm-fixed effects, the individual production function elasticities are not included in the main regression. However, we use the average production function elasticities for each branch sector when calculating the counterfactual scenario.

[5] To calculate the cost of capital, we multiply the book value of tangible fixed assets with the costs of capital, where cost of capital is calculated with the real interest rate $i_t - \mathbb{E}_t\pi_{t+1}$ following Gopinath, Kalemli-Özcan, Karabarounis, and Villegas-Sanchez (2017). This yields the equation $K_{it} = BV_{it}^K(i_t - \mathbb{E}_t\pi_{t+1} + \delta + RP)$, with δ denoting a depreciation rate of 10% and RP representing a risk premium of 5%, as done by Caballero, Farhi and Gourinchas (2017).

6. Results

6.1. Sales and Inputs

Table 1: Regression Results for Sales and Inputs

	Dependent Variable			
Temperature Bins	**Sales (1)**	**Materials (2)**	**Labor (3)**	**Capital (4)**
$\leq -15°C$	-0.0009	-0.0002	-0.0012	0.0192^{***}
$-15°C$ to $-5°C$	-0.0009^{*}	-0.0002	-0.0004	-0.0001
$-5°C$ to $0°C$	-0.0030^{***}	-0.0030^{***}	-0.0025^{***}	0.0043^{***}
$15°C$ to $20°C$	0.0024^{***}	0.0032^{***}	0.0020^{***}	-0.0074^{***}
$\geq 20°C$	0.0061^{***}	0.0054^{***}	0.0048^{***}	-0.0042^{***}
Fixed Effects	✓	✓	✓	✓
Firm	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Rainfalls	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓
Observations	4,464,020	4,463,672	4,464,020	4,463,672

*Note: All dependent variables are in logs. Standard errors are clustered at the grid-cell level. *, ** and *** denote 10, 5 and 1 percent statistical significance.*

The output above shows how firms' sales and factor inputs are affected by an extra day in each temperature bin relative to the reference bin following regression 20. Although these regression results do not provide any insight regarding inefficiencies of factor inputs, they yield interesting findings regarding the effect of temperature on a firm's input mix relative to the reference bin (0℃, 15℃].

One can observe that firms' annual sales respond positively to warm days, while cold days are associated with lower sales levels. Specifically, additional days with temperatures equal to or above 20 degrees Celsius yield a significant 0.0061 percent increase in sales. An extra day in the bin 0 to negative 5 degrees Celsius reduces sales by 0.003 percent, while the equivalent effects negative 5 to negative 15 degrees results in a reduction of 0.0009 percent. Capital shows a negative effect with increased temperature, as an extra day in the bin 15 to 20 and 20+ decreased capital by -0.0074 percent and -0.0042 percent respectively. Days with colder temperatures than the reference bin have a positive effect of 0.0192 percent and 0.0043 percent for the bins -15 and -15 to -5 degrees Celsius, respectively. Both labor and materials are negatively impacted by additional days with a temperature between 0 and -5 degrees Celsius, relative to the reference bin, while an extra day above the reference bin has positive effects for both variables. Allocation towards Labor and materials increases by 0.0048 and 0.0054 percent with an additional day above 20 degrees Celsius. Notably, the results show a non-linear increase for warmer days.

6.2. MRPX

Regression Results for MRPX

	Dependent Variable		
Temperature Bins	**MRPM**	**MRPK**	**MRPL**
$\leq -15°C$	-0.0138^{***}	-0.0016^{***}	-0.0101^{***}
$-15°C$ to $-5°C$	0.0027^{***}	0.0006^{***}	0.0018^{*}
$-5°C$ to $0°C$	0.0029^{***}	-0.0002^{***}	0.0052^{***}
$15°C$ to $20°C$	-0.0035^{***}	0.0005^{***}	-0.0030^{***}
$\geq 20°C$	0.0047^{***}	-0.0003^{***}	0.0051^{***}
Fixed Effects	✓	✓	✓
Firm	✓	✓	✓
Sector × Year	✓	✓	✓
Economic event × Region	✓	✓	✓
Controls	✓	✓	✓
Rainfalls	✓	✓	✓
Region Trends	✓	✓	✓
Observations	4,032,194	4,032,194	4,032,194

*Note: All dependent variables are in logs. Standard errors are clustered at the grid-cell level. *, ** and *** denote 10, 5 and 1 percent statistical significance.*

We estimate the effects of temperature on revenue-based marginal products using regression 20 presented in section 3.6. The results are reported in the above table and show the effect of one extra day in each temperature bin on firm-level revenue-based marginal product of each input. Overall, the significant effects, although small in magnitude, highlight the importance of a firms' input mix.

The revenue-based marginal product of labor (MRPL) shows a significant negative effect (-0.0101 percent) from one extra day in the bin <=-15. A similar effect can be observed for materials, which is associated with a -0.0138 percent effect for days where the temperature is below -15 degrees Celsius. The results indicate that Swedish firms respond positively to higher temperatures, with labor and materials, increasing with each additional day with temperatures above 20 degrees Celsius. However, this effect is only noticeable for the highest bin. Notably, the negative productivity effect of both inputs is larger at the other extreme, with days where the temperature is below –15 degrees Celsius. The productivity of materials and labor are also positively affected by higher temperatures, as both revenue-based marginal productivities show an increase of 0.047 and 0.051 percent, respectively, by additional days with temperatures above 20 degrees Celsius.

6.3. Demand-adjusted Productivity

With the temperature semielasticities of sales from the table in section 6.1 and the temperature semielasticities of MRPX from the table in section 6.2, we can derive the productivity effect by leveraging the relationship found in equation 9. Using the results from section 6.2, the values for production function elasticities α^X from section 5.2 and the assumption that elasticity between varieties $\sigma = 4$, we compute the temperature semielasticities of demand-adjusted productivity.

Productivity Coefficients for Different Temperature Bins

Variable	$\leq -15°C$	$-15°C$ to $-5°C$	$-5°C$ to $0°C$	$15°C$ to $20°C$	$\geq 20°C$
Unweighted Productivity	0.00358	-0.0003	-0.00241	0.001475	0.005369
Weighted Productivity	-0.007358	0.001455	0.001012	-0.001471	0.004766

Note: Row 1 reports the unweighted average across sectors, while row 2 reports the sales-weighted average across sectors.

The above table presents the effect of an additional day in each bin on demand-adjusted productivity. We present these results both on an unweighted basis, as well as a revenue-based weight for each branch sector. The low magnitude is attributable to the input data we recover from the temperature semielasticities of MRPX and sales, as the demand-adjusted productivity values are a rescaling by nature of equation 9. Nonetheless, we see positive coefficients for higher temperatures and negative for lower temperatures compared to the reference bin in the unweighted case. This results slightly shift when accounting for revenue-based branch sector weights. For the weighted case, the coefficients for demand-adjusted productivity are relatively large in magnitude at the two most extreme bins relative to the reference bin.

6.4. Aggregate Productivity

Using equation 19 we compute the aggregate productivity gain from an increase in temperature according to 4 different scenarios on average temperature increase (1, 2, 4, and 6 degrees Celsius). In the scenario of a 1-degree Celsius average temperature increase, 50 percent of the increase is attributable to firm-level productivity increases, while 50 percent of the increase is attributable to the economy's ability to efficiently reallocate inputs. In the scenario of a 2-degree Celsius increase in average temperature, the aggregate productivity gain is approximately 0.038 percent.

	1 Degree	2 Degrees	4 Degrees	6 Degrees
Allocative	0.00957	0.019143	0.038285	0.057428
Technology	0.00946	0.018921	0.037843	0.056764
Total	0.01903	0.038064	0.076128	0.114192

Note: The above table reports the productivity gains due to increases in temperature under different global warming scenarios. All values are in percent. Columns 1, 2, 3 and 4 report gains under a 1, 2, 4 and 6 degrees increase in average temperature. Row 1 reports the gains due to allocative efficiency and row 2 reports gains from firm-level productivity increases. Row 3 reports the total gains under the different global warming scenarios.

7. Discussion

Our discussion will focus on five areas. Firstly, we will discuss the limitations of utilizing temperature bins, as well as the economic effect of temperature in general. This will be followed by a comparison of our results considering existing literature, most notably Caggese et al. (2023). We shortly outline what effects the results from the model used potentially might have on Swedish productivity and how this is reflected in current literature, before reflecting on future research in the area.

Our findings support that those countries with a lower baseline temperature, such as Sweden, will experience economic gains as a consequence of higher temperatures. In line with Burke et al. (2015) the findings indicate that economic production in Sweden, as a cold country, will increase due to the average temperature not yet having increased to 13 degrees Celsius, where economic activity would peak according to the authors. However, there have been conflicting reports regarding this in the literature as the rate at which temperatures increase have been could potentially result in a significant negative effect on economic activity in Sweden (Kahn et al. 2021).

It is important to note that the temperature bins we have chosen may dampen the measured effect due to the extreme temperatures being averaged away. Based on priorly reported effects of temperature on labor productivity (e.g. Graff Zivin and Neidell, 2014), it is likely the case that additional days with temperatures above our highest bin would negatively affect labor productivity. Nonetheless, as Sweden has not historically faced a substantial number of days with average temperatures in this range, as seen in figure 4 in section 5.1, we conclude that higher temperatures will increase the productivity of labor, and to an extent materials.

The firm-level outcomes and aggregate productivity found in our results do not respond to local temperatures with the same magnitude as in Italy (Caggese et al. 2023). While the results indicate that there is an effect, this effect is lower as no variable responds with a full percentage point to additional days with temperatures in the ranges of our bins. However, in general, the results regarding inputs and sales reflect a similar effect to the findings by Caggese et al. (2023) as sales, labor and materials react positively (negatively) to higher (lower) temperatures. The general absence of the inverted U-shape found by Caggese et al. (2023) is likely due to Sweden having a lower average temperature and is therefore located on the left-hand side of the peak. For the revenue-based marginal product, the negative significant effect of *MRPM* and *MRPL* stand out, as these were not significant in the results presented by Caggese et al. (2023). The negative effect of labor productivity at colder temperatures with a decline in spending on it attributed to temperature, indicating allocation efficiency. In addition, our results indicate that Swedish firms reallocate factor inputs to capture the productivity increase of labor and materials when facing higher temperatures. This means that labor and materials usage is currently suboptimal with regard to efficiency. Higher temperatures, however, will according to our findings result in firms adjusting their input mix to a more efficient state as the revenue-based marginal productivity of these factor inputs rises.

There are several potential biases in addition to the aforementioned risk of temperatures being averaged away. These include omitted variable bias, reverse causation, and the exogeneity of temperature. There are two main omitted variables biases. Firstly, shocks affecting both economic activity and temperature simultaneously and secondly, the possibility that firms relocate to other grid-cells based on temperature predictions to capitalize on productivity gains associated with temperature increases (Caggese et al., 2023). Despite the empirical specification including numerous relevant controls, variables that correlate with grid-cell temperature and the firm-level outcomes may bias our results. In addition, reverse causation may result in biased results, in this case that a specific firm's outcomes influence grid-cell temperature. Given the causal relationship between the release of greenhouse gas emissions by humans and contemporary global warming, temperature may only be considered weakly exogenous instead of strictly exogenous (Kahn et al., 2021). However, in the present paper, this effect is likely not an issue due to the dependent variables being based on data from individual firms in Sweden which are unlikely to significantly impact global temperatures.

While we do find slight positive effects of higher temperatures on productivity, there are several aspects of climate change that will likely reduce overall welfare in Sweden, as well as productivity specifically. For example, reductions in the economic output of countries with a warmer climate (Dell et al., 2012; Burke et al., 2015) will likely have a significant impact on Swedish consumers due to cross-national dependencies. Consequences such as climate-driven migration, increased rates of food-borne, water-borne, and vector-borne diseases (IPCC, 2023) will also potentially influence Swedish welfare. In terms of productivity, higher frequency of extreme weather (IPCC, 2023) is likely a factor that will impact firm-level productivity in a manner not accounted for in this paper. In particular, heat waves would constitute a non-uniform increase in temperature, deviating from this our assumption regarding homogenous increases in temperatures. Thus, several aspects of this paper can be explored further in future studies.

Potential extensions of this study include regional, sectoral, and period-specific sub-sampling. Bilal and Känzig (2024), for example, utilize such sub-sampling in a recent paper on macroeconomic variables. Furthermore, the static nature of the framework used does not account for dynamic variables. Further research on Swedish firms should therefore investigate adaptation mechanisms on the firm-level using multi-period models. For example, Barrage and Nordhaus (2023) use an alternative function to aggregate productivity effects with the Dynamic Integrated Climate-Economy (DICE) model. Additionally, investigating the mechanisms behind the aggregate productivity gains would provide important insights. Lastly, as regional temperatures deviate more from the historical average due to climate change, introducing alternative sets of temperature bins would potentially reveal new relationships between Swedish firms and the climate they are exposed to.

8. Conclusion

This paper has analyzed how firm-level and aggregate productivity in Sweden are affected by climate change. Matching Swedish firm-level data and granular weather data for the period 1996 to 2023, we extend previous research to a developed country with a cooler average temperature, using more detailed data. The empirical strategy and theoretical framework by Caggese et al (2023) enable us to investigate how key microeconomic mechanisms driving productivity and aggregate output are impacted by climate change. Although the measured effects are small in magnitude, our findings offer insights into how Swedish firms reallocate input factors with changes in daily temperature.

Based on our results, Swedish firms appear to reallocate efficiently at temperatures above 20 degrees Celsius. Labor productivity shows an increase of 0.051 percent, while the productivity of materials increases by 0.047 percent with an additional day above 20 degrees Celsius. Following this productivity increase, we observe that Swedish firms opt for more labor-intensive production at higher temperatures, as our results show an increased allocation towards labor and materials above 20 degrees, the factor input-usage of which rise by 0.0048 percent and 0.0054 percent respectively. Aggregating our firm-level results, we show that aggregate productivity, proxied by the Solow residual, increases due to a higher average temperature. This holds in all warming scenarios reviewed. The aggregate effect is driven by firms improving their input mix, reflecting the aforementioned factor input-productivity increases.

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Appendix

Firm-level data

For firm-level data we use the Serrano Database, a database built on financial statement data from the Swedish Companies Registration Office (Bolagsverket). The following is a description of how the Serrano Database is constructed, as reported on the Swedish House of Finance (SHoF) at the Stockholm School of Economics official website.

"The unique principle for the contents in the Serrano Database is that there will be one data entry per calendar year for the respective field in the database for each combination of company (corporate ID no.) and year. In other words, each field in the database comes from the respective source's contents as of December 31 of the respective year. This main principal is what makes it possible to relatively easily follow groups of businesses, describe business trends and analyze the material with statistical methods.

The Serrano Database is built up with the help of an extensive framework that controls how the register data from the Swedish Companies Registration Office, Statistics Sweden, and Bisnodes own register may be compiled. An important part of the framework handles the necessity to, to a certain degree, transform and modify the underlying register data into comparable calendar year values. That primarily applies to the income statement and balance sheet included in financial statements, but other register data is also translated into calendar year values as needed.

The Serrano Database's data is thus adjusted and corrected and manages phenomena such as the following:

- Broken accounting periods.
- Short and long accounting periods.
- Omissions and gaps in a company´s series of submitted financial statements Imputation for the latest year´s calendar values.
- Registration date and deregistration date (SCB) during a calendar year.
- Conversion to calendar year values for stock data (balance sheet) and ow data (income statement).
- Rules for determining whether a business is active or not (AB or other business structures).
- Rules for what a newly started company is.

Bisnodes Serrano Database is thus, contrary to the original and underlying registers with change transactions, a controlled and quality assured history database that has been developed on the basis of a statistician's needs and perspective. The database is updated twice per year, primarily in December, and a small supplement in May."

We employ the overall cleaning methodology laid out by Caggese, Chiavari, Goraya and Villegas-Sanchez (2023). This means that the following steps are taken, as outlined in Section 4.1:

- Removal of observations missing information in the following categories: Sales, operating profit, zip-codes, and assets.
- Removal of extreme observations: we construct three ratios (Sales to total assets, employment to total assets and employment to sales) and remove observations falling above the 99.9 percentile or below the 0.01 percentile.
- Exclusion of specific sectors: we exclude the observations in the branch sectors "Finance and Real estate" or "Energy & Environment", as well as observations missing branch sector classification or falling in the category "Others"

Climate data

Our climate data comes from SMHI, the Swedish Meteorological and Hydrological Institute, which provides open-source data on temperature and precipitation levels across Sweden through a dataset called PTHBV. The following is a description of PTHBV dataset as reported on the official website, translated to English as the only official detailed description available is in Swedish. We hence provide references for both the (short) english description, as well as the detailed Swedish one.

PTHBV is a climate database that was built with a special focus on hydrological model calculations. The database contains daily values for precipitation and temperature, which are mainly used as input data for calculations with hydrological models, for example the S-Hype and HBV models. Climate data from 1961 onwards are available in PTHBV stored in a nationwide grid with a resolution of 4x4 km. PTHBV is an abbreviation of Precipitation Temperature Hydrological Agency's Water Model.

Data from SMHI's meteorological stations have been interpolated to the database's grid squares using a geostatistical interpolation method called optimal interpolation. The method means, among other things, that both the stations' distance from the calculation box and their mutual correlation are taken into account. To describe the spatial variation, information on topography, typical wind direction and wind strength in different parts of the country is used.

In the database, the observed precipitation has also been corrected for measurement losses, which are primarily caused by part of the precipitation blowing past the precipitation gauge. The measurement losses have been calculated according to methods specified by Alexandersson (2003). These methods take into account how wind-exposed the measuring station is and whether the precipitation falls as snow or rain, which is determined based on the temperature.

The PTHBV database is primarily based on observations from the Swedish meteorological stations that are part of SMHI's station network. In the border areas with Norway, a number of stations in the Meteorological Institute's station network in Norway are also used. Once a year, in April, a review is made of changes in the station network. After this review, the database is updated with the recalculated values for the previous year, as well as for the period January to February in the current year. Closing down or restarting stations can in some cases cause homogeneity violations in the database's time series.

TFP functions

The following appendix presents the complete TFP functions, both for aggregate TFP and frictionless TFP.

Aggregate TFP is given by the below, where λ_{it} represents a firm-level weight and ω_t^X represents an aggregate object. For a derivation of the firm-level weight and aggregate object we refer to the appendix of *"Climate Change, Firms and Aggregate Productivity"*.

$$\Delta log\ TFP_t \equiv \left(e^{\sim z_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}, \Delta T_{g(i)t}\right)$$

$$\approx \sum_{i=1}^{N_t} \lambda_{it}\left(e^{\sim z_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right) \sum_{X \varepsilon\, \mathrm{X}} \frac{\alpha^X}{e^{\tau_{it}^X(T_{g(i)t})}}\, \omega_t^X\left(e^{\sim z_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)$$

$$* \left[\left(\sigma - \frac{e^{\tau_{it}^X(T_{g(i)t})}}{\omega_t^X\left(e^{\sim z_{it}(T_{g(i)t})}, e^{\tau_{it}(T_{g(i)t})}\right)} - (\sigma - 1)\right)\left(\frac{\partial \sim z_{it} T_{g(i)t}}{\partial T_{g(i)t}}\right.\right.$$

$$\left.\left.- \sum_{X \varepsilon\, \mathrm{X}} \alpha^X \frac{\partial \tau_{it}^X T_{g(i)t}}{\partial T_{g(i)t}}\right)\right] * \Delta T_g$$

Frictionless TFP is given by:

$$\Delta log\, TFP_t^* \equiv \left(e^{\sim z_{it}\left(T_{g(i)t}\right)}, \Delta T_{g(i)t}\right) \approx \sum_{i=1}^{N_t} \lambda_{it}^* \left(e^{\sim z_{it}\left(T_{g(i)t}\right)}\right) \frac{\partial \sim z_{it} T_{g(i)t}}{\partial T_{g(i)t}} \Delta T_g$$