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The Effects of Temperature on Labor Productivity

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Abstract

This article reviews recent economic studies on the causal effects of temperature on labor productivity. The negative effects of extreme temperatures are widespread, and the magnitudes of the impact differ across social and economic factors. In addition to physical outputs, extreme temperatures also impair mental productivity, including cognition and learning. In utero exposure to extreme temperatures has profound effects on human development. Although the literature has detected various adaptation strategies, the conclusions are mixed. We discuss some limitations of existing studies and propose several directions for future research.

1. INTRODUCTION

Climate change represents one of the most significant challenges of the twenty-first century. Understanding its economic impacts is essential for formulating climate policies and developing adaptation strategies. Existing literature has examined the impact of climate change on various outcomes, including agriculture, human health, total factor productivity, capital accumulation, and institutional quality (Fankhauser & Tol 2005, Dell et al. 2012, Deschenes 2014, Letta & Tol 2019). This literature also highlights the effect of temperature on labor productivity as a crucial element in the mechanisms or consequences explored in the aforementioned studies. As extreme weather events become more intensified, frequent, and widespread under climate change, losses in productivity are expected to worsen in the future.

This article systematically reviews recent economic studies on the impacts of temperature on labor productivity. This body of literature deserves attention for three reasons. First, although the literature has found negative impacts of extreme temperatures on both worker- and plant-level output and per capita output at the regional level using micro- or macro-level data sets, findings on the existence and effectiveness of adaptation are mixed in studies using macro-level data. In addition, most micro-level studies revealing that adaptation can alleviate temperature damage have emphasized external adaptation strategies, including capital and institutional investments. However, recent studies have also highlighted physiological adaptation, which refers to adapting to heat through training one's own mind and body instead of by means of external devices. Because external adaptation strategies may not be feasible in all circumstances, understanding the effectiveness of physiological adaptation in reducing the adverse impacts of extreme temperatures can help to expand the toolkit of adaptation strategies.

Second, many studies examine the average effects of temperature on labor productivity, but less attention has been given to the potential distributional impacts. The distributional effects originate from the nonlinear damage function with regard to different levels of temperature exposure and from various initial socioeconomic attributes at the same level of exposure. Designing efficient environmental policies requires understanding the source of this heterogeneity because these two different drivers for the same observed heterogeneous effects lead to different policy implications (Hsiang et al. 2019). Regarding different causes of the distributional effects, policies should accordingly focus on reducing exposure to heat or concentrate on strengthening socioeconomic factors such as income and education.

Third, although most studies focus on the contemporaneous effects of temperature on labor productivity, extreme temperatures may also have long-term impacts. One example is in utero exposure to extreme temperatures, which can stress mothers and infants, leading to malnutrition and future income losses. Ignoring the long-term effects can underestimate the total costs of climate change. Additionally, it is worth noting that mental productivity, which may also have long-term consequences, is receiving limited but growing attention. Mental productivity includes cognition, learning, and consequential decisions. Empirical evidence shows that outdoor temperature damages the cognitive performance of children and young students, suggesting that society may suffer substantial welfare losses from temperature and climate change.

2. SCIENTIFIC BACKGROUND

In this section, we briefly discuss the scientific evidence of the impact of extreme temperature on productivity. Extreme temperatures trigger thermoregulatory responses and can affect productivity through body and brain functioning. Although both high and low temperatures impact productivity, they have slightly different physiological mechanisms.

High temperatures increase blood flow from the body to the skin by raising the heart rate (Deschenes & Moretti 2009). When heat stress as measured by the wet-bulb temperature (WBT)[1] continuously exceeds 35°C, the human body's ability to dissipate metabolic heat disappears, indicating that autogenous adaptation to temperature has an upper bound (Sherwood & Huber 2010).[2] Long-term exposure to extreme heat has also been found to cause cardiovascular pressure and inflammation (Bouchama et al. 2017). Moreover, the combination of extreme heat and high humidity can lead to asthma symptoms and worsen existing respiratory diseases (Ayres et al. 2009, D'Amato et al. 2014). Exposure to a cold environment causes circulatory and metabolic changes and depresses the immune system (LaVoy et al. 2011). In addition, the performance of tasks requiring finger strength, speed, and dexterity decreases as the temperature falls (Meese et al. 1984).

Fetuses and infants are particularly sensitive to extreme heat because their thermoregulatory and sympathetic nervous systems are not fully developed. Early-life heat exposure can permanently alter sympathoadrenal function by modifying sympathetic innervation of peripheral tissues and sympathetic nerve responsiveness (Young 2002), which can have profound effects on human development, including earnings, cognition, and well-being (Isen et al. 2017).

Ambient temperature can also affect brain function. Heat stress induces changes in brain electrical activity and neural speed, damaging various cognitive processes, including attention, memory, learning, and information processing (Hocking et al. 2001). Exposure to extreme cold changes the concentration of central catecholamines, a neurotransmitter that brain regions rely on for normal functioning, further deteriorating cognitive performance (Taylor et al. 2016). In addition, uncomfortable temperatures can also affect task performance through psychological channels, such as mood and well-being (Noelke et al. 2016).

3. CONCEPTUAL FRAMEWORK

In this section, we develop a concise theoretical model based on that of Deryugina & Hsiang (2014) to depict the role of temperature in economic production. Although the model is in partial equilibrium, it informatively provides insights into the key channels that are the focus of this review.

An economy uses labor L and capital K to produce, with A_L and A_K denoting labor and capital productivity, respectively. Variables A_L and A_K respond to contemporaneous or past temperature T. In addition, the producer can spend an effort $e \in [0, 1]$ to moderate the sensitivity of labor productivity to temperature, such as by installing air conditioners. The cost of effort is $c(e)$, which is a convex function with $\partial c/\partial e > 0$ and $\partial^2 c/\partial e^2 > 0$. Following the Cobb-Douglas production function, the quantity of output is written as

$$q(T) = (A_K(T)K)^{\alpha}(A_L(T, e)L)^{1-\alpha}, \qquad 1.$$

where α and $(1 - \alpha)$ are the output elasticities of capital and labor, respectively. Denote the output price as p, the wage rate as w, and the rent rate of capital as r. The producer faces the standard profit maximization problem:

$$max_{K,L,e}\; p \cdot (A_K(T)K)^{\alpha}(A_L(T, e)L)^{1-\alpha} - wL - rK - c(e). \qquad 2.$$

[1]The WBT is the temperature indicated by a moistened thermometer bulb exposed to air flow. At 100% relative humidity, the WTB is equal to the air temperature.

[2]Autogenous adaptation can be broadly understood as physiological or biological adaptation. We use physiological/autogenous/biological adaptation interchangeably in this review.

In Equation 2, price variables (p, w, r) are endogenously determined by the economy in general equilibrium, and the producer is a price taker. Because the price effects are not the core of this review, they are set to decouple from temperature.

Given T and price variables, the producer chooses labor and capital inputs, as well as the effort level to maximize the profit. Denote the optimal labor and capital under the exogenous temperature T as $L^*(T)$ and $K^*(T)$. We are interested in the total marginal effect of temperature on economic output $q(T)$ and the underlying channels, given in the following equation:

$$\frac{\mathrm{d}\ln q(T)}{\mathrm{d}T} = (1-\alpha)\frac{1}{A_L(T,e^*)}\cdot\frac{\mathrm{d}A_L(T,e^*)}{\mathrm{d}T} + (1-\alpha)\frac{1}{L^*}\cdot\frac{\mathrm{d}L^*(T)}{\mathrm{d}T} + \alpha\frac{1}{A_K(T)}\cdot\frac{\mathrm{d}A_K(T)}{\mathrm{d}T} + \alpha\frac{1}{K^*}\cdot\frac{\mathrm{d}K^*(T)}{\mathrm{d}T}. \qquad 3.$$

The effect of temperature on output is decomposed into four parts, and we focus on the first two components related to labor. The literature finds an inverted U-shaped effect of temperature on economic activities; i.e., after exceeding the threshold, increases in temperature damage economic performance. To simplify our illustration, we restrict T to exceeding the vertex temperature $\bar{T}$ in this section. Then, rises in T represent the monotonic deterioration of ambient temperature.

The first term on the right side of Equation 3 reflects the effect of temperature on aggregate labor productivity. If the temperature crosses the comfortable zone, the partial effect of labor productivity is expected to be negative with $(1-\alpha)\frac{1}{A_L(T,e^*)}\cdot\frac{\mathrm{d}A_L(T,e^*)}{\mathrm{d}T} < 0$. We review the literature on aggregate labor productivity at both macro and micro levels from both physical and mental perspectives in Sections 5.1 and 5.3.

The second term on the right side of Equation 3 presents the impact of temperature on labor demand. When the economy reaches equilibrium, the labor market is cleared, and the labor available in production is equal to the labor supply by workers. That means the impact of temperature on labor supply is implicitly reflected by $\frac{\mathrm{d}L^*}{\mathrm{d}T}$. Because the literature discussing the effect of temperature on firms' labor demand is very limited, we review the empirical literature on temperature-labor supply in Section 5.2 to provide insights into this channel.

The total derivative of labor productivity with respect to temperature in the first term of Equation 3 is a combination of two terms:

$$\frac{\mathrm{d}A_L(T,e)}{\mathrm{d}T} = \frac{\partial A_L(T,e)}{\partial T} + \frac{\partial A_L(T,e)}{\partial e}\cdot\frac{\partial e}{\partial T}, \qquad 4.$$

where the first term $\frac{\partial A_L(T,e)}{\partial T}$ describes the direct effect of temperature on labor productivity, and the second term $\frac{\partial A_L(T,e)}{\partial e}\cdot\frac{\partial e}{\partial T}$ represents the effect of mitigation or adaptation efforts. It is usually difficult to identify these two effects separately, even with exogenous variation in temperature; thus, empirical estimates of $\frac{\mathrm{d}A_L(T,e)}{\mathrm{d}T}$ account for different levels of mitigation and adaptation depending on the context. We provide a review of studies examining whether these efforts exist and how they help to slow down the damage of extreme temperature in Section 5.4.

4. EMPIRICAL METHODOLOGY

In this section, we first briefly review the high-dimensional fixed effects (HDFE) model, a widely used identification strategy in the climate impact literature. Second, we summarize the measurements of labor productivity and temperature used in the literature to trigger more thinking about the strengths and weaknesses of different measures, as well as to improve our understanding of differences across studies. Third, we review how existing literature has investigated adaptation and provide a starting point for subsequent research on the topic.

4.1. Identification

The HDFE model has the advantage of identifying the causal effects of temperature and has been widely used in literature. We focus on introducing the HDFE method here, and for other empirical designs, such as cross-sectional approaches and the long-difference strategy, see Dell et al. (2014) and Hsiang (2016). To estimate the impact of temperature on labor productivity of worker i in location c on date t, the HDFE specification is proposed as follows:

$$Y_{ict} = \beta f(T_{ct}) + \mathbf{W}_{ct}\lambda + \mathbf{X}_{ict}\theta + \mu_i + \delta_c + \theta(t) + \varphi(c,t) + \varepsilon_{ict}, \quad 5.$$

where the explained variable Y_{ict} refers to labor productivity.

T_{ct} represents the temperature exposure, and β measures the response of labor productivity to temperature exposure. However, actual temperature exposure is usually unobserved by researchers, given ex post adaptations, such as air conditioning. Instead, researchers use ambient temperature as a proxy for temperature exposure. Therefore, what β measures is the response of labor productivity to temperature exposure, accounting for potential adaptation behaviors.

$f(T_{ct})$ is a function of temperature. The most straightforward way is to let $f(T_{ct}) = T_{ct}$; then, β describes the effects of average changes in the temperature on labor productivity (see Dell et al. 2012). However, because the temperature effect tends to be asymmetrical on the left and right sides of its distribution, this simple setting may be misleading (Burke et al. 2015). One more flexible specification is using temperature bins, a semiparametric method that allows temperature effects to vary across bins. As this setting is widely used in the literature, we do not introduce details here but provide three noteworthy points.

First, if Y_{ict} is measured at the annual level, a common practice is to calculate the number of days that fall into each degree bin. Thus, β indicates the marginal effect on productivity if one day's temperature moves from the reference bin to a specific bin. Second, the interpretation of temperature bins relies on the choice of the reference bin, which is usually chosen as the temperature bin with the optimal outcome (Graff Zivin et al. 2018). Burke et al. (2015) demonstrate that when the explained variable is the economic output, the optimal temperature point at the macro level (such as countries) is lower than that at the micro level (such as factories). Third, other useful approaches to describing the nonlinear effects of temperature, for example, an inverted U-shape, include piecewise and spline functions (Newell et al. 2021).

$\mathbf{W}_{ct}$ is a vector of weather variables, usually including precipitation, humidity, wind speed, air pressure, and sunshine. Air quality should also be controlled, as it is highly correlated with temperature and has a nontrivial impact on labor productivity, as found in the related literature (Aguilar-Gomez et al. 2022). $\mathbf{X}_{ict}$ is a vector of worker-level time-varying variables, such as gender, age, education, and others. Because the temperature variable is contemporaneously correlated with $\mathbf{W}_{ct}$ and $\mathbf{X}_{ict}$, these control variables should be included in Equation 5. Otherwise, endogeneity due to omitted variables biases the estimation of β. One caveat is that when we aim to estimate the overall effects of temperature on labor productivity, as presented in Equation 4, one should not include adaptation behaviors in $\mathbf{X}_{ict}$. For example, we are interested in the relationship between temperature and productivity. If the equation includes the air conditioner as a control variable, the correlation between temperature and productivity is partially captured by the air conditioner such that the estimates do not represent the overall effects of temperature on productivity.

μ_i represents worker fixed effects, δ_c represents location fixed effects, and $\theta(t)$ refers to flexible time trends. After controlling for these fixed effects, residual shocks in temperature are plausibly random. Some studies include location-by-time fixed effects $\varphi(c,t)$, which absorb location-specific temperature norms and make the temperature residual more exogenous. However, this stricter control may remove too many identifying variations and cause attenuation bias (Fisher et al. 2012, Deryugina & Hsiang 2014). ε_{ict} is the error term, commonly two-way clustered, following Cameron et al. (2011), to simultaneously allow spatial and serial correlation.

4.2. Measurement

In this section, we provide details on how to measure the key variables, including labor productivity, temperature and adaptation, in the literature.

4.2.1. Labor productivity measurement. Macro-level studies usually use value-added, GDP, or income per capita as proxies for country-level labor productivity (Hsiang 2010, Deryugina & Hsiang 2014, Burke et al. 2015). However, these measures are relatively coarse and difficult to distinguish from other economic indicators. An ideal approach is to aggregate detailed micro-level labor productivity data of various activities to the macro level using a reasonable weighting method. Yet, it can be costly to collect broadly representative micro-level data, and it can be challenging to justify the weighting method. Nonetheless, micro-level productivity records with more accurate measurements are increasingly used in developed and developing countries, including worker-level productivity data (Cai et al. 2018, Stevens 2019, Somanathan et al. 2021), athlete performance records in competitive sports (Qiu & Zhao 2022, Sexton et al. 2022), and cognitive performance and decision making in mentally demanding tasks (Graff Zivin et al. 2018, Heyes & Saberian 2019). A similar but coarse data source is firm-level production data from industrial firm surveys (Zhang et al. 2018, Chen & Yang 2019, Somanathan et al. 2021).

4.2.2. Temperature measurement. We provide two key points in using the temperature variable. First, measurement errors can arise during the construction process of the temperature variable. To proxy the temperature experienced by study units, researchers often use a weighting approach to average the values from nearby meteorological monitoring stations or grids (for raster data). However, the resulting temperature may deviate from the actual temperature experienced by study units due to some error. If the error is random, the temperature estimate is biased toward zero. In addition, industrial workers who mostly work indoors experience temperatures different from those outdoors. The direction of bias caused by the measurement error in the outdoor-indoor temperature difference is uncertain and can vary across seasons. Thus, further studies in various contexts are needed to fill this knowledge gap.

Second, the measure of temperature can vary across studies. Most studies use the daily average temperature, which averages the maximum and minimum temperatures of a day (Graff Zivin et al. 2018, 2020; Zhang et al. 2018; Chen & Yang 2019; Stevens 2019; Garg et al. 2020a). A large body of literature also uses daily maximum temperature, which better captures the actual temperature faced by people because jobs are usually done in the daytime (Graff Zivin & Neidell 2014, Cho 2017, Cai et al. 2018, Park et al. 2020, Somanathan et al. 2021). Laboratory studies often examine the effects of the WBT that nonlinearly account for the joint impacts of ambient temperature, humidity, and wind speed (Lemke & Kjellstrom 2012). The heat index is another adjusted heat measure, a nonlinear function of temperature and relative humidity (Qiu & Zhao 2022). While the WBT and heat index measures better capture the heat experienced by individuals, humidity and wind speed data are often unavailable, making studies using these measures difficult to compare with other studies. Overall, the purpose of measuring temperature variables is to capture the temperature stress under specific tasks and reduce measurement errors. One caveat is that temperature effects estimated using different measurements are not directly comparable, which should be taken into account when verifying external validity.

4.3. Adaptation

The existing literature has mostly used two methods to examine the effectiveness of a certain climate adaptation strategy. First, researchers (Isen et al. 2017, Chen & Yang 2019, Adhvaryu et al. 2020, Cook & Heyes 2020, Park et al. 2020, Qiu & Zhao 2022, Sexton et al. 2022) add interaction terms between temperature variables and the possible moderating factor in baseline Equation 5, which gives

$$Y_{ict} = \gamma f(T_{ct}) \times Adapt_{ct} + \beta f(T_{ct}) + \rho Adapt_{ct} + \mathbf{W}_{ct}\lambda + \mathbf{X}_{ict}\theta + \mu_i + \delta_c + \theta(t) + \varphi(c,t) + \varepsilon_{ict}. \quad 6.$$

$Adapt_{ct}$ is an indicator of the existence of external adaptation strategies (e.g., air conditioners) or a proxy for the experience of hot days in the past (e.g., a dummy for the high-temperature region, the number of hot days, or the average temperature in the past) to examine the effect of autogenous adaptation. The key coefficients are γ. Note that some studies have also tried to estimate the heterogeneous effects of temperature by including the interactions between temperature variables and individual demographic characteristics (e.g., gender, income). These results, although not necessarily causal, suggest that some groups of people have better adaptation capabilities.

Second, some studies use subsample analyses (e.g., by gender, race, income, occupation environment, past climate, industry, and climate control) to test the effects of adaptation (Graff Zivin & Neidell 2014, Cho 2017, Park et al. 2020, Somanathan et al. 2021). This method is similar to the interaction method above, with more relaxed assumptions of the functional form of Equation 5 across different subsamples.

In addition, studies have explored whether climate adaptation behavior exists using different analysis methods depending on the data availability. One way is to regress the adaptation behavior variable on temperature. For instance, researchers directly regress the time use indicators within a day to examine intraday time substitution (Graff Zivin & Neidell 2014). In another example, Park (2022) regresses a bunching estimator of the degree of grade manipulation on temperature variables using a fixed effects model similar to Equation 5. In some situations, lagged temperature terms are included. For example, to assess interday time substitution, researchers include lagged and contemporaneous temperature variables and compare the aggregated effect on total time use with effect from a parsimonious model with only contemporaneous temperature (Graff Zivin & Neidell 2014, Garg et al. 2020a). That unpleasant lagged temperatures increase current time use implies interday time substitution. That the total effects from lagged temperatures exceed the contemporaneous temperature effect indicates complementary time use across time.

Finally, researchers have combined the panel data fixed effects model, long-difference model, and cross-sectional model to test the existence of compensatory behavior as an implicit way of adaptation (Graff Zivin et al. 2018). The panel data fixed effects model identifies the short-run effects of temperature, which do not account for adaptation behaviors, whereas the long difference model and the cross-sectional model estimate the long-run effects of climate, which also incorporate the accumulated impacts of weather extremes plus the impacts of ex post compensatory behaviors. Under the assumption that accumulated effects of temperature on the dependent variable are well accounted for in the long-difference model, comparing the estimates from the panel data fixed effects model and the long-difference model would inform the existence of compensatory behavior or lack thereof.

5. EMPIRICAL REVIEW

In this section, we review the temperature effects on labor productivity. First, we summarize the impacts of temperature on labor outputs. Second, we review the temperature effects on mental productivity. Third, we investigate the studies of adaptation in moderating the temperature-productivity relationship. Next, we summarize the distributional effects of temperature and review the issue of in utero exposure. The previous sections focus on studies with causal research designs, mainly the HDFE approach. Finally, we briefly discuss the findings from the studies in a general equilibrium framework.

5.1. Labor Output

We review the effects of temperature on labor output at both macro- and micro-levels. Macro-level evidence refers to findings cross countries or regions, and micro-level studies focus on worker- or plant-level outputs.

5.1.1. Macro-level evidence. We begin our discussion with the study by Hsiang (2010), which examines the impact of surface temperature on the economic output of 28 Caribbean and Central American countries using annual longitudinal data from 1970 to 2006. The study finds that a 1°C increase in surface temperature led to a 2.5% decrease in national output (measured by value added per capita). Notably, the damage caused by higher temperatures to the nonagricultural sector (−2.5% per 1°C) was 20 times greater than that to the agricultural sector (−0.1% per 1°C), indicating that labor productivity losses in labor-intensive nonfarming sectors could be a crucial mechanism behind the result.

Dell et al. (2012) investigate the impact of temperature on aggregate economic outcomes using historical panel data for 125 countries from 1950 to 2005. The study finds that higher temperatures reduce economic growth, but the effect is only significant for poor countries. The negative impact of higher temperatures on economic growth includes both a level effect (reduction in current output level) and a growth effect (negatively affecting innovations, institutions, and other factors that are vital for future economic growth). Moreover, the effects of temperature on agricultural and industrial output are of comparable magnitude. Specifically, a 1°C increase in temperature in poor countries leads to a 2.66% lower growth in agricultural output and a 2.04% decrease in industrial output. In contrast, Deryugina & Hsiang (2014) find that high temperatures also decrease economic output in wealthy places based on panel data of US counties from 1969 to 2011. The income response to temperature is a combination of agricultural and nonagricultural effects. The relationship between temperature and nonagricultural income is consistent with the temperature-labor supply pattern in high-risk heat-exposed industries, as shown by Graff Zivin & Neidell (2014), which suggests that the effect of temperature on labor supply is an important underlying mechanism.

Burke et al. (2015) revisit the relationship between temperature and economic production using panel data of 166 countries from 1960 to 2010. They find a smooth inverted U-shaped response of the annual economic growth rate to the annual average temperature, with a peak at 13°C. Both rich and poor countries respond to temperature nonlinearly, which also applies to agricultural and nonagricultural sectors.

Overall, the abovementioned studies offer two conclusions. First, the adverse effects of heat on economic growth are widespread, affecting both poor and rich countries. Extreme temperatures harm the nonagricultural sector, and the effect can sometimes be greater than that on the agricultural sector because it is more labor intensive. Second, the literature suggests that the decrease in labor productivity may be a potential underlying channel; i.e., the damage first appears as decreased labor productivity in individual workers and then aggregates to the lower outputs at the macro level. However, we still lack a comprehensive understanding of how temperature affects labor productivity across different sectors and countries, as well as the extent to which labor productivity loss explains the effect of temperature on macro-level output.

5.1.2. Micro-level evidence. A strand of studies uses micro-level productivity data, mostly from labor-intensive manufacturing industries, which probably endure more direct effects of extreme temperatures. The literature either focuses on the effects of discrete changes in various temperature measures or the marginal effects of a 1°C temperature increase, which makes the comparison of the estimates less direct. Qiu & Zhao (2022) find that the average labor productivity effects of heat are on the same order of magnitude across studies that use different micro productivity data or study regions, while the heat impact on total factor productivity (TFP) is of a lower order of magnitude compared with that on labor productivity.

Specifically, Cai et al. (2018) use worker-level production records from a paper cup production factory in Xiamen, China, from 2012 to 2014. They find a nearly symmetric inverted-U-shaped relationship between daily maximum temperature and labor productivity (measured by the percentage of overtarget production). Extreme cold (heat) with a daily maximum temperature below 60°F (over 95°F) causes an 11% (8.5%) reduction in productivity compared to the reference bin (75–80°F).

Studies on the impact of temperature on labor productivity in the agricultural sector are relatively sparse. Stevens (2019) uses production data of Californian blueberry pickers from 2014 to 2016 to explore the impact of temperatures on workers' productivity. High-frequency temperature readings near each farm are obtained and combined with the picking period of workers to construct time-weighted temperature measurements, which capture the heat exposure workers face more accurately. Stevens finds an inverted U-shaped relationship between temperature and worker productivity, with both extreme cold and heat having significant negative impacts. Compared to the reference bin of 80–85°F, temperatures below 55°F (over 100°F) lower productivity by 17% (12%).

Zhang et al. (2018) use the annual survey of above-scale industrial firms in China from 1998 to 2007 and find that replacing a day with the mean temperature in the reference bin (50–60°F) with a day over 90°F decreases TFP by 0.56% and output (measured by value added) by 0.45%. The relationship between temperature and output is nearly identical to that of TFP, implying that the effects on TFP instead of labor or capital inputs drive the output response to temperature. However, because TFP is a weighted combination of labor and capital productivity, the role of labor productivity in the temperature effects on firm output is not disentangled separately. Using the same data set, Chen & Yang (2019) estimate the effects of seasonal average temperatures on firm-level labor productivity (value added per worker) and find that a 1°C increase during summer decreases labor productivity by 3.4–4.5%. They also find that firms' investment decreases and inventory levels increase in response to temperature increases. Using automobile assembly data, Cachon et al. (2012) find that six or more days of exposure to over 32.2°C within a week decrease labor productivity by 8%.

Going a step further, Somanathan et al. (2021) combine worker-level productivity, firm-level output, and the subnational industrial GDP of India to explore how the temperature effects on worker productivity can link to the effects on firm-level production and macro-level national output. Using high-frequency worker-level production data in the cloth weaving, garment sewing, and steel production industries, Somanathan et al. (2021) find that high temperatures decrease worker outputs. In a representative context, the output of garment workers decreases by 3% if the temperature every day in a year increases by 1°C. Based on India's Annual Survey of Industries from 1998 to 2012, they find that the annual plant output decreases linearly with higher temperatures once the daily maximum temperature is over 20°C, and a uniform 1°C rise in temperature per day across a year causes a 2.1% reduction in annual plant output.

Under the specification of the Cobb-Douglas production function, Somanathan et al. (2021) confirm that the damage of high temperatures to labor productivity explains the vast majority of the loss of plant output. Based on panel data of manufacturing-sector GDP for 438 districts from 1998 to 2009, they also find that a 1°C increase in average annual maximum temperature is associated with a 3.5% decrease in annual district industrial output. The magnitude of the temperature effect on worker productivity and firm output is close to that of subnational industrial output and comparable to previous studies using cross-country data, highlighting labor productivity as an essential mechanism of the temperature effect on macro-level economic output.

Representativeness of the data set and external validity of the findings are critical challenges for micro-level studies. One way to verify the external validity is to compare the temperature effect in a specific context to the results in other contexts or studies in other disciplines. For instance, studies verify that their estimated productivity effects of temperature are consistent with the temperature-human performance relationship in the ergonomics and physiology literature (Hsiang 2010, Qiu & Zhao 2022). Another solution is to involve data sets of study units at multiple levels to connect the temperature effect on micro-level labor productivity with that on aggregate economic output (Somanathan et al. 2021).

5.2. Labor Supply

Temperatures not only impact labor productivity in terms of reduced work intensity and quality of labor input, but they can also affect labor extensively by increasing work absenteeism or reducing the time allocated to work. Graff Zivin & Neidell (2014) find that workers in high-exposure industries reduce their daily time allocated to labor by one hour when daily maximum temperatures exceed 85°F compared to the reference temperature level at 76–80°F. The decrease in time allocated to labor is concentrated at the end of the day, indicating that fatigue from prolonged exposure to high temperatures is a potential channel. Garg et al. (2020a) examine the relationship between temperature and work time in China using individual-level panel data from the China Health and Nutrition Survey from 1989 to 2011. They find that both extreme heat and extreme cold reduce work time. An additional day with an average temperature above 80°F or below 25°F, compared with the temperature level at 55–60°F, lowers weekly work time by 1.2 h or 1.8 h, respectively.

Some studies adopt administrative record data of worker attendance to explore this issue. Cai et al. (2018) find that neither the attendance decision nor working hours of workers in a manufacturing factory in China are affected by temperature. One explanation is that work attendance and hours are highly related to pay, and the rigidity of the labor market causes labor supply to respond less to ambient temperature. In the context of the Indian industrial factory, Somanathan et al. (2021) find that experiencing high temperatures in the current or preceding week increases workers' absenteeism, and the effect is stronger for paid leave workers. This finding suggests that labor supply is more sensitive to temperature when workers have more flexibility. At a higher level, Zhang et al. (2018) find that the labor inputs of industrial firms in China almost do not respond to temperatures, except when the temperature is extremely high. These results imply that the effect of temperature on labor supply is not as intuitive as imagined but depends on complex factors such as the extent of occupational exposure and labor market conditions.

5.3. Mental Productivity

In some cases, labor productivity is reflected in terms of mental output or mental productivity, such as cognition, learning, and decision making. A growing body of empirical studies demonstrates a causal link between temperature and various outcomes related to mental productivity. Existing studies have examined the impacts of extreme temperatures on cognitive ability test scores in surveys (low stakes) or student exam scores (high stakes) in countries including the United States, China, India, and Canada. Studies are consistent in the magnitudes of the contemporaneous effects of temperatures but differ in the magnitudes of the cumulative temperature effects.

Focusing on a low-stakes test administered in US homes as part of the National Longitudinal Survey of Youth, Graff Zivin et al. (2018) find that children's math (but not reading) performance is sensitive to temperature on the test day. In particular, each degree day above 21°C lowers the math score by 0.219%. The contemporaneous impact of temperature on cognitive performance remains in relatively high-stakes tests in school settings. Graff Zivin et al. (2020) estimate the temperature impact on high school students' performance in the National College Entrance Examination in China, where individual-level adaptation is very limited given the unavailability of air conditioning and the rigidity of the exam location and time. They find that a 1°C increase in temperature during the two exam days decreases the total test score by 0.34%. Park (2022) investigates the relationship between exam-time temperature and student performance in high school exit exams in New York City and finds that a 1°F increase in exam-time temperature reduces performance by 0.9% of a standard deviation.

In addition to the negative impact of high temperatures, Cook & Heyes (2020) provide the first evidence of the detrimental impact of cold outdoor temperatures on cognitive performance in the short run. Leveraging data on exam performance of adult students at the University of Ottawa, they find that a 10°C colder outdoor temperature on exam day reduces performance by 8.09% of a standard deviation. Because the indoor temperature in exam rooms is held almost exactly constant, this result suggests that even with perfect technological protection at the organizational level, the detrimental impact of extreme cold is still substantial.

Some studies evaluate the impact of sustained exposure to temperature on cognitive performance and human capital accumulation, but the results are mixed. Graff Zivin et al. (2018) find limited effects of climate, measured as temperature exposure between successive tests or from birth until the date of the test, on human capital accumulation. They argue that the difference between the short-run and long-run results may be driven by ex post compensatory behaviors, such as the extra time investment of teachers or parents. Similarly, Cook & Heyes (2020) find that cooler temperature during the semester is associated with improved performance, although the contemporaneous impact of the exam day cold temperature is significantly negative. They attribute this to the cold-driven substitution from outdoor leisure to indoor work.

However, leveraging data on the standardized exam PSAT scores of American high school students, Park et al. (2020) demonstrate that cumulative heat exposure reduces the rate of learning in the long run. As the average maximum temperature experienced during school days the year before the test increases by 1°F, students' academic achievement decreases by 0.2% of a standard deviation, mainly because of the disruption of instructional time. Focusing on tests administered in Indian primary and secondary schools, Garg et al. (2020b) find that relative to 1–17°C, one extra day in the previous year with an average daily temperature above 29°C reduces math and reading test scores by 0.3% and 0.2% of a standard deviation, respectively. They provide evidence that the underlying mechanism in this developing country context is reduced agricultural productivity and income driven by growing season heat. Social protection programs designed to offset fluctuations in agricultural income could greatly mitigate the impact.

Graff Zivin et al. (2020) also find a significantly negative effect of extreme heat in the previous year on students' performance in the context of the college entrance exam in China. Cho (2017) studies the medium-term effect of summer heat on the score of the Korean college entrance exam taken in November. The results suggest that relative to 28–30°C, an additional day during the summer with a maximum temperature above 34°C could decrease math and English test scores by 0.42% and 0.64% of a standard deviation, respectively, but has no meaningful impact on reading scores. Over a longer period, summer heat in the previous year also negatively affects the current year's academic performance.

The difference in the cumulative effects of temperature may be attributed to the availability of mitigation and adaptation strategies, e.g., penetration of cooling and heating equipment, which varies significantly across study regions. Besides, temperature-related shocks to cognitive performance and human capital accumulation could generate persistent consequences for educational attainment in the future (Graff Zivin et al. 2020, Park, 2022). However, it is unclear to what extent these effects on children and young adults in school or nonschool settings can be generalized to labor productivity in the workplace. The empirical evidence linking temperature to the workplace cognitive output of mentally demanding tasks is quite scant. A notable exception is Heyes & Saberian (2019), who analyze the short-run impact of outdoor temperature on immigration adjudications made by US professional immigration judges. Even with high-quality climate-control technology available, temperatures can still damage decision consistency and quality. In particular, a 10°F increase in working time temperature on the decision day reduces the probability of a decision favorable to the applicant by 1.075%, equivalent to a 6.55% decrease in the grant rate.

5.4. Mitigation and Adaptation

The extant literature on climate adaptation can be divided into studies that estimate the effectiveness of adaptation strategies and studies that examine whether adaptation behavior exists. On the one hand, the first strand of literature often focuses on the effectiveness of external adaptation strategies. Among the external strategies, some are directly related to protection against extreme weather, while others are not. The former category includes the adoption of climate control devices such as air conditioners (Isen et al. 2017, Park et al. 2020, Somanathan et al. 2021), students taking exams in a new building that is better insulated than older ones, spending more on better winter clothing, and taking taxis on cold days (Cook & Heyes 2020). Examples in the latter category include adopting energy-saving technology (Adhvaryu et al. 2020) and providing a safety net for the poor (Garg et al. 2020b). The literature has also examined the existence and/or effectiveness of physiological/biological/autogenous adaptation strategies (Cook & Heyes 2020, Qiu & Zhao 2022, Sexton et al. 2022). On the other hand, examples of the examination of adaptation behavior include compensatory behavior to counteract the adverse impacts of extreme temperatures on oneself or others and time reallocation of oneself and within the family (Graff Zivin & Neidell 2014, Garg et al. 2020a).

Regarding specific examples of the effectiveness of external adaptation measures, Isen et al. (2017) find that household air conditioning adoption mitigates nearly all of the estimated impacts of early-life exposure to high temperatures on adult earnings for US individuals born between 1969 and 1977. Park et al. (2020) find that school air conditioning decreases the negative impact of hotter school days in the years before the test was taken on standardized PSAT test scores of US high school students. Somanathan et al. (2021) find that climate control in the workplace eliminates productivity declines due to high temperatures but not absenteeism in India. Cook & Heyes (2020) find that taking exams in a new building, spending more on better winter clothing, and taking taxis on cold days could offset some of the adverse impact of cold outdoor temperatures on student test scores in Canada.

In addition, Adhvaryu et al. (2020) find that the replacement of compact fluorescent lamps with light-emitting diode lighting in garment factories attenuates the negative relationship between mean daily outdoor temperature and worker efficiency in India. Garg et al. (2020b) find that the rollout of the world's largest workfare program, the National Rural Employment Guarantee Act, substantially weakens the link between temperature and test scores by providing a safety net for the poor in India.

Although capital and institutional investments such as air conditioning and new technologies have been emphasized in the literature, such investments are still infeasible in many developing countries (Kahn 2016, Qiu & Zhao 2022). As a comparison, autogenous adaptation strategies can complement the adaptation tool kit. The psychology literature has widespread evidence about habituation, i.e., reduced sensitivity of human sensors to heat after repeated exposure (Swim et al. 2009). One kind of autogenous adaptation is acclimatization, which is defined as "the beneficial physiological adaptations that occur during repeated exposure to a hot environment" and can occur within one week and persist amid heat exposure (CDC 2018). Acclimatization can reduce body temperature, improve skin blood flow and thermal tolerance, increase sweat rate, and yield other physiologic responses that improve thermal comfort in hot environments and mitigate the adverse performance impacts of heat (Graff Zivin & Neidell 2014, Périard et al. 2015, Sexton et al. 2022).

Based on archers' performance records in China, Qiu & Zhao (2022) find evidence of autogenous adaptation that the performance of athletes trained in high-temperature regions is much less affected by extreme heat than that of athletes trained in low-temperature regions and that gaining experience and autogenous adaptation together can mitigate 70% of the heat impacts. Sexton et al. (2022) project that acclimatization reduces performance losses from alternative climate change scenarios by more than 50% relative to projections that ignore acclimatization based on the US collegiate track and field performance records. Cook & Heyes (2020) find the biological adaptation of foreign students makes their performance substantially less sensitive to temperature over time.

Other studies have also confirmed the existence of autogenous adaptation. By separately estimating the impact of temperatures in June and August, Graff Zivin & Neidell (2014) find that labor for high-risk workers is less sensitive to temperatures over 100°F in August, which suggests short-run acclimatization to heat that is more common in August. They also estimate heterogeneous time-use responses to temperature across counties with the highest and lowest third of historical July–August temperatures but fail to find significant differences. Researchers also examine autogenous adaptation in the context of individual firms' data by estimating the heterogeneous effects of temperature across hot and cold regions. Chen & Yang (2019) find that higher summer temperatures have larger detrimental effects on industrial output in low-temperature regions than in high-temperature regions, suggesting the existence of adaptation of manufacturing firms to warming in high-temperature regions in China.

Some studies directly examine the existence of adaptation behavior. Compensatory behavior is an ex post adaptive strategy that requires no knowledge of the pernicious effects of extreme temperatures beforehand. Graff Zivin et al. (2018) find that short-run temperature beyond 26°C significantly decreases cognitive performance in math in the panel data fixed effects model, but long-difference and cross-sectional models reveal a significantly much smaller relationship between high temperature and human capital than in the short run, which suggests the existence of compensatory behavior. Another example is Park (2022), who finds compensatory grading manipulation by teachers. A higher exam-time temperature harms high school students' exam performance, and benevolently motivated teachers attempt to manipulate grades upward for exams taken under hot conditions.

Regarding the examination of reallocation of work and leisure hours in response to temperature as a direct way of adaptation, Graff Zivin & Neidell (2014) find a significant intraday substitution of hours worked, a small role for interday substitution in the workplace, and rescheduled outdoor leisure for the nonemployed across days in response to high temperatures. Garg et al. (2020a) include lagged temperature bins for up to three weeks and find that the negative impact of temperature doubles, suggesting that work time in subsequent weeks complements work time in the week experiencing a temperature shock. The authors also explore time substitution across family members by estimating the impact of temperature on the ratio of the husband's work time to the wife's work time but with insignificant results.

To summarize, most studies mentioned above rely on micro-individual-level or firm-level data sets and find that adaptation ameliorates damages of extreme temperatures. A relevant strand of literature examines the relationship between climate change and economic output using macro-level (e.g., country-, state-, or county-level) data sets. Deryugina & Hsiang (2014) estimate the impacts of temperature on income in different decades from 1970 to 2010 in the United States, finding that the negative effects of extreme heat are stable across subsamples. This result suggests limited adaptation in mitigating adverse temperature effects. Dell et al. (2012) use the long-difference approach to examine the effect of temperature changes on the economic growth of 125 countries in two periods: 1970–1985 and 1986–2000. The medium-term result indicates that a 1°C rise in temperature in poor countries is related to a 1.9% reduction in the annual growth rate, which is close to the short-run panel estimates, and implies that poor countries fail to eliminate the negative impacts of temperature increases by adaptation. Using panel data from 166 countries, Burke et al. (2015) find that the dose-response patterns between temperature and national output in 1960–1989 and 1990–2010 are nearly identical, indicating very limited adaptation in the past 50 years. The findings of limited adaptation extents contrast the findings from the micro-level data sets, which implies that more research is needed to reconcile the gap between these two strands of literature.

5.5. In Utero Exposure to Extreme Temperatures

The fetal origins hypothesis suggests that circumstances during fetal development can have significant and long-lasting effects on human development (Almond & Currie 2011, Fishman et al. 2019). Exposure to extreme temperatures in utero may stress both mothers and infants through biological mechanisms discussed in Section 2, such as poor regulation of body temperature in infants. Additionally, such exposure may affect infants' development through impacts on household income and nutrition.

Researchers have investigated the effects of temperature in utero and early childhood on adult earnings and cognitive abilities. Isen et al. (2017) analyze administrative earnings records for over 12 million individuals born in the United States and find that temperatures above 32°C in utero are associated with a 0.1% reduction in adult annual earnings at age 30. Fishman et al. (2019) examine the same question using data from one million formal sector workers above the age of 30 born between 1950 and 1979 in Ecuador and find that a 1°C increase in average monthly temperature in utero leads to a 0.7% decrease in adult earnings and a 0.5% reduction in the probability that females attain higher education. Hu & Li (2019) study the 2010 wave of the China Family Panel Studies, a nationally representative, biannual longitudinal survey of Chinese communities, families, and individuals. They find that exposure to an additional day of high temperature during prenatal periods is associated with a 0.48% decrease in standardized word-test scores, a 0.02-cm reduction in height, 0.02 fewer years of schooling, and a higher risk of illiteracy by 0.18%. Additionally, Hu & Li (2019) validate an income channel by showing that the proportion of heat-tolerant crops (C4 plants) significantly reduces the impacts of high temperatures during pregnancy. These findings suggest that exposure to high temperatures in utero has adverse effects on labor productivity across both developed and developing countries.

However, differences in socioeconomic characteristics and institutional background (e.g., the levels of health care) across sample populations may contribute to different findings regarding temperature impacts during different trimesters and early childhood. Isen et al. (2017) find that temperature impacts are concentrated in the first and third trimesters, while Hu & Li (2019) find that they are concentrated in the first and second trimesters. Isen et al. (2017) also find that temperatures above 32°C in the first year of life are associated with a 0.1% reduction in adult annual earnings at age 30. In contrast, both Fishman et al. (2019) and Hu & Li (2019) find no impact of temperature in the nine months after birth on adult earnings or cognitive abilities. Further research is necessary to address these discrepancies.

Investigating the impacts of exposure to extreme temperatures in utero is important because early interventions in infants can have a significant impact on their future development. Consequently, adapting strategies during pregnancy may lead to substantial welfare gains.

5.6. Distributional Effects

While many studies examine the overall effects of temperature on labor productivity, less attention has been given to the potential distributional impacts. The marginal effects of temperature may vary across social and economic factors, such as income, gender, and race. Understanding the causes of these mixed findings is an important challenge for future research.

Studies on income differences indicate that lower-income individuals may suffer larger marginal damages due to temperature. For example, Park et al. (2020) find that the impact of prior year heat on student scores in lower-income US ZIP codes is twice as large as those from higher-income ZIP codes, likely owing to differences in protective investments. Hsiang & Narita (2012) find that higher spatial concentrations in the capital and rich countries lead to higher defensive investment and lower marginal damages from cyclones. However, there are exceptions in that low-income populations do not have lower vulnerability. Hsiang & Jina (2014) examine the long-run effect of tropical cyclones on GDP growth and show that the relative income losses per unit of exposure for rich and poor countries appear almost identical.

Regarding gender differences, Garg et al. (2020a) find that, among farm workers, the reduction in labor supply in females is approximately twice as large as that in males. Specifically, the marginal effect of an extra day above 80°F on the work time of female farmers is −1.94 hours per week. Moreover, hot days reduce women's time spent on home production. The gender difference in productivity losses is also detected by Park et al. (2021). However, many studies find no gender differences. Park et al. (2020) examine the effects of heat stress on student learning in the United States and find no evidence of heterogeneity by student gender. Additionally, Qiu & Zhao (2022) and Cai et al. (2018) also find no gender differences in professional archery performance and manufacturing worker productivity, respectively.

Studying race differences, Park et al. (2020) find that the impact of prior year heat on learning among Black and Hispanic students is three times as large as that for white students. Park (2022) also finds that approximately 3–4% of average racial achievement gaps in student performance could be attributable to temperature in the United States because more Black and Hispanic students take SAT exams when the temperature is above 90°F. The literature also explores other heterogeneities, including industries, occupations, and family backgrounds. For example, Graff Zivin & Neidell (2014) find that at daily maximum temperatures above 85°F, workers in industries with high exposure to weather extremes reduce the daily time allocated to labor by as much as one hour.

The disparate marginal effects can be decomposed into two sources (Hsiang et al. 2019). The first is the nonlinear damage function owing to different levels of climate exposure. Nonlinearity has been identified in several contexts, including labor supply (Graff Zivin & Neidell 2014) and cognitive performance (Graff Zivin et al. 2018). The levels of exposure vary because people sort to locations according to their preferences. Nordhaus (2006) finds that poor populations tend to live in hotter and drier locations. In addition, Park et al. (2018) find a negative correlation between wealth and warmer temperatures within hot countries but a positive correlation between wealth and warmer temperatures within cold countries. In contrast, Hsiang et al. (2019) show that exposure to tropical cyclones is spread fairly evenly across global income categories. More evidence on exposure heterogeneities is required as the projected distribution of future climate change exposure is even more complex.

The second source of marginal damage is the vulnerability originating from various initial socioeconomic attributes while at the same level of exposure. For example, poorer people tend to exhibit larger marginal damage from temperature shocks. This line of research is particularly difficult because it requires exogenous variations in the source of socioeconomic factors. Garg et al. (2020b) show that high temperatures reduce test scores among school-age children, but the rollout of a workfare program substantially weakens the link between temperature and test scores. Hornbeck & Keskin (2014) show that irrigation techniques can initially reduce the impact of drought on US farmers but that drought sensitivity increases over time as land use is adjusted to water-intensive crops. Although these causal studies are limited, they are growing quickly in number and contributing to our knowledge of the underlying causes of heterogeneity in marginal damages (Fetzer 2014, Hsiang et al. 2013).

5.7. General Equilibrium

Many studies have highlighted the reduced-form impact of temperature on productivity. However, a burgeoning literature has taken a dynamic general equilibrium framework to quantify climate impacts. Such analyses are usually conducted at a global scale, which is rich in the margins of adaptation. Conte et al. (2021) emphasize sectoral specialization and reallocation, finding that rising temperatures increase productivity growth in agriculture but decrease productivity growth in nonagriculture. As a result, warmer temperatures push agriculture to regions such as Central Asia that initially suffered from a large temperature penalty, benefitting these regions from relatively high agricultural productivity. Nath (2022) finds limited gains from the global reallocation of agriculture and highlights the interaction between subsistence needs and sectoral specializations in poor countries.

This line of studies also features trade and migration as adaptation mechanisms. Cruz & Rossi-Hansberg (2021) focus on mechanisms through which individuals can adapt to global warming, including costly trade and migration, local technological innovations, and natality rates. Their results indicate welfare losses as high as 19% in parts of Africa and Latin America but also exhibit high heterogeneity across locations, with northern regions in Siberia, Canada, and Alaska experiencing gains. Burzyński et al. (2022) account for the effects of changing temperatures, sea levels, and the frequency and intensity of natural disasters simultaneously. They find that climate change strongly intensifies global inequality and poverty, reinforces urbanization, and boosts migration from low- to high-latitude areas.

Although these analyses have advantages in distributional effects and adaptation mechanisms, they share critiques in structural modeling, including untestable functional forms, distributional, and other modeling assumptions. The reduced-form approach is suitable for identifying key response parameters causally, but it cannot account for the presence of feedback loops and general equilibrium. As discussed by Timmins & Schlenker (2009), the two approaches can be used in conjunction with one another to provide different perspectives on the same problem. Future research calls for more interactions between the two approaches.

6. CONCLUSIONS

This article provides a review of recent economic studies investigating the effects of temperature on labor productivity. Our review concludes by summarizing the key findings and future research directions. First, the adverse effects of extreme heat on economic growth are ubiquitous, from the poor countries to the rich ones, from individual performance to country-level outputs. Second, the losses from extreme temperatures are also reflected in mental productivity, including cognition, learning, and consequential decisions. Third, the literature has found various adaptation behaviors. These range from external strategies, such as air conditioning, to internal ones, such as autogenous adaptation. Additionally, in utero exposure to extreme temperatures is particularly damaging, with early-life exposure having profound effects on human development. The effects of temperature can also vary across social and economic factors, such as income, gender, and race.

However, research is still required on several aspects of this topic. First, although the adverse productivity impacts of extreme temperatures are substantial at both the micro and macro levels, it is unclear to what extent the temperature impact on micro-level labor productivity explains the impact on macro-level outputs. Second, compared with studies in the agricultural and industrial sectors, studies on the effects of temperature in the service sector are relatively scant. Third, most existing studies have focused on the contemporaneous effects of temperature, whereas the long-term effects (e.g., impacts of early-life exposure to extreme temperatures) warrant more attention because of the potential welfare gains from early interventions. Fourth, while adaptation behaviors have been detected by many studies, the findings are not conclusive, and there is a challenge in attributing a causal relationship between temperature effects and observed adaptive behaviors. Lastly, the current findings on distributional effects are largely limited to income, gender, and race, and the causes of heterogeneous effects are not clear. Understanding the source of heterogeneity is crucial because it leads to different policy solutions.

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