The Effects of Temperature on Labor Productivity[1]

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Abstract: This article reviews recent economic findings on the causal effects of temperature on labor productivity. The impact of temperature shocks on micro-level worker and plant productivity is a core channel in explaining temperature effects on aggregate economic output at the macro-level. Besides physiological effects revealed in scientific studies, economic studies also find negative effects of temperature on mental productivity, including cognition performance, learning, and consequential decisions. The effectiveness of adaptation is inconsistent in macro and micro findings. Adaptation is found to be almost futile at the regional scale, but indeed alleviates temperature damage in various micro-level contexts. We highlight the distributional effects of temperature, and early-life exposure to extreme temperatures causes long-standing effects in adulthood. We propose some limitations of existing studies and provide several key points for future work.

Keywords: temperature, labor productivity, mental productivity, adaptation, early-life exposure, distributional effects
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1. Introduction

Climate change is one of the biggest challenges in the 21st century worldwide. Understanding its economic impacts is essential for formulating climate policies and adopting adaptation behaviors. The existing literature has examined the impact of climate change on economic growth through channels including capital accumulation, human health, TFP growth, and institutional quality (Fankhauser et al., 2005; Dell et al., 2012; Deschenes, 2014; Letta & Tol, 2019). Notably, burgeoning literature highlights the effect of temperature on labor productivity, a key element of the mechanisms or consequences in aforecited studies. As the laboratory experiments have confirmed the sensitivity of labor performance to temperature (Pilcher et al., 2002), future productivity losses from global warming are expected to be more deteriorating. In this paper, we systematically review the recent economic studies on the impacts of temperature on labor productivity, which deserves attention for three reasons.

First, the effects of temperature on productivity are well documented, but the findings on the effectiveness of adaptation are inconsistent. At the national or regional scale, extreme temperatures decrease per capita output. This negative relationship is also detected using the worker and plant output records, which clarifies the role of the temperature shock at the micro level in causing aggregate output loss. Both the micro- and macro-level patterns coincide with the temperature-productivity relationship in the laboratory. However, macro-level studies find a limited extent of adaptation globally, but micro-level studies reveal that adaptation indeed alleviates temperature damages. Additionally, while the literature has emphasized external adaptation measures, including capital and institutional investments, recent studies also find evidence of physiological adaptation in different contexts.

Second, while many studies examine the overall effects of temperature on labor productivity, less attention has been given to the potential distributional impacts. The distributional effects originate from the nonlinear damage function regarding different levels of temperature exposure as well as from various initial socioeconomic attributes while at the same level of exposure. Designing efficient environmental policy requires understanding the source of this heterogeneity because these two different explanations for the same observed heterogeneous effects lead to different policy implications (Hsiang et al., 2019). If it is the former case, policies may focus on reducing exposure to heat. If it is the latter case, policies may focus on strengthening socioeconomic factors such as income and education.

Third, most studies focus on the contemporaneous effects, but extreme temperatures may also have long-term effects on labor productivity. Ignoring the long-term effects will underestimate the total costs of climate change. One example that receives more attention is in-utero exposure to extreme temperatures, which stresses mothers or infants, leading to malnutrition and losses of future income. Additionally, it is worth mentioning that mental productivity, which may also have long-term consequences, receives growing but limited attention. Mental productivity includes cognition, learning, and consequential decisions. Empirical evidence shows that outdoor temperature damages the cognitive performance of children and young students as well as the decisions of experienced decision-makers. These findings shed light on the long-term impacts, suggesting substantial and wider welfare implications of temperature and climate change.

2. Scientific Background

In this section, we provide brief scientific evidence on the impact of temperature exposure on physical and brain functioning. Physically speaking, exposure to extreme temperatures triggers the thermoregulatory response, such as promoting blood flow from the body to the skin by increasing heart rate to cope with heat stress (Deschenes & Moretti, 2009). Therefore, long-term exposure causes cardiovascular pressure and inflammation (Bouchama et al., 2017). The combination of extreme heat and high humidity leads to asthma symptoms and aggravates workers' existing respiratory diseases (Ayres et al., 2009; D'Amato et al., 2014). The immediate damage of extreme temperatures on physical health manifested as increased absenteeism and decreased productivity of workers. When the heat stress measured by the wet-bulb temperature continues to exceed 35°C, the human body's metabolic heat dissipation becomes impossible, indicating autogenous adaptation to temperature has an upper bound (Sherwood & Huber, 2010). In addition to causing serious disease, even a moderate deviation from the optimal temperature zone can reduce task performance. For example, Meese et al. (1984) find the performance of tasks that need finger strength, speed, and dexterity decreases with the temperature falling.

Mentally speaking, scientific evidence shows that brain function can be affected by ambient temperature. Heat stress induces brain electrical activity and neural speed changes, which damages 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 function, further deteriorating cognitive performance (Taylor et al., 2016). Besides physiological effects, uncomfortable temperatures are also found to affect task performance through psychological channels, such as mood and well-being (Noelke et al., 2016).

Particularly, early-life exposure has profound effects on human development, such as earning, cognition, and well-being (Isen et al., 2017). The biological mechanism is that fetuses and infants are especially sensitive to extreme heat since their thermoregulatory and sympathetic nervous systems are not fully developed. For instance, the sympathetic innervation of peripheral tissues and sympathetic nerve responsiveness can be modified by early-life heat exposure and alter sympathoadrenal function permanently (Young, 2002).

3. Conceptual Framework

In this section, we build a concise theoretical model based on 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 this paper focuses on.

An economy uses labor L and capital K to produce. A_L and A_K denote labor and capital productivity, respectively. The production function follows the Cobb-Douglas form. L, K, A_L, and A_K respond to contemporaneous or past temperature T. The quantity of output is:

$$q(T) = \left(A_K(T)K(T)\right)^{\alpha}\left(A_L(T)L(T)\right)^{1-\alpha} \quad (1),$$

where α and $(1-\alpha)$ are the output elasticities of capital and labor. Denote the price of goods as p, the wage rate as w, and the rent rate of capital as r. The producer can spend an effort $e \in [0,1]$ to mitigate (or adapt) the impact of temperature on production, such as installing air-conditioners and autogenous adaptation. The cost of effort is $c(e)$, which is a convex function with $\partial c/\partial e > 0$ and $\partial^2 c/\partial e^2 > 0$. The effort moderates the sensitivity of labor productivity to temperature, thus $A_L(T)$ is extended to $A_L(T, e)$.[2] We will describe the role of e in detail later. The producer faces the standard profit maximization problem:

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

In equation (2), price variables (p, w, r) are endogenously determined by the economy in general equilibrium and the producer is a price taker. Since the price effects are not the core of the paper, 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 are $L^*(T)$ 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:

$$\frac{d\ln q(T)}{dT} = (1-\alpha)\frac{1}{A_L(T,e)} \cdot \frac{dA_L(T,e)}{dT} + (1-\alpha)\frac{1}{L^*} \cdot \frac{dL(T)}{dT} + \alpha\frac{1}{A_K(T)} \cdot \frac{dA_K(T)}{dT} + \alpha\frac{1}{K^*} \cdot \frac{dK(T)}{dT} \quad (3).$$

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 monotonical deterioration of ambient temperature.

Labor productivity. The first term 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 $(1-\alpha)\frac{1}{A_L(T,e)} \cdot \frac{dA_L(T,e)}{dT} < 0$. We review the literature on aggregate labor productivity at both macro and micro levels from both physical and mental perspectives in Section 5.1 and Section 5.3.

Labor supply. The second term of equation (3) presents the impact of temperature on labor at the extensive margin. Labor supply is one channel explaining the temperature effects on aggregate output. Extreme temperature is likely to reduce labor supply, thus $\frac{dL(T)}{dT} < 0$. We provide empirical reviews on labor supply in Section 5.2.

Mitigation and adaptation. The total derivative of labor productivity with respect to temperature in the first term of equation (3) is actually a combination of two terms:

$$\frac{dA_L(T,e)}{dT} = \frac{\partial A_L(T,e)}{\partial T} + \frac{\partial A_L(T,e)}{\partial e} \cdot \frac{\partial e}{\partial T} \qquad (4),$$

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,

[2] In the literature, e can affect the sensitivity of productivity to temperature for any factor, not limited to labor. Since this paper focuses on labor productivity, we reasonably ignore the link between effort and capital productivity.

thus empirical estimates of $\frac{dA_L(T,e)}{dT}$ 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

4.1 Identification

In this section, we provide a brief introduction to the high-dimensional fixed effects (HDFE) approach because this method is essential in causally identifying temperature effects. For other methods, readers can seek Dell et al.(2014) and Hsiang (2016) for detailed reviews. To estimate the impact of temperature on labor productivity of worker i in location c on date t, the HDFE specification is proposed as:

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

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

$\boldsymbol{T}_{ct}$ represents the temperature exposure. $\boldsymbol{\beta}$ measures the response of labor productivity to temperature exposure. However, actual temperature exposure is usually unobserved by researchers, given ex-post adaptations have been adopted, such as air conditioning. Instead, researchers use ambient temperature as a proxy of temperature exposure. Therefore, what $\boldsymbol{\beta}$ measures is the response of labor productivity to temperature exposure, accounting for the adaptation behaviors.

$f(\boldsymbol{T}_{ct})$ is a function of temperature. The most straightforward way is to let $f(\boldsymbol{T}_{ct}) = \boldsymbol{T}_{ct}$, then $\boldsymbol{\beta}$ describes the effects of *average* changes in the temperature on labor productivity (such as Dell et al., 2012). However, once the temperature effect is symmetrical 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 semi-parametric method that allows temperature effects to vary across bins. Since 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 $\boldsymbol{\beta}$ 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 less flexible but useful approaches to describing the nonlinear effects include piecewise and spline functions.

$\boldsymbol{W}_{ct}$ is a vector of weather variables, usually including precipitation, humidity, wind speed, air pressure, and sunshine. Air quality should also be controlled, since 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). $\boldsymbol{X}_{ict}$ is a vector of worker-level time-varying variables, such as gender, age, education, and others. One caveat is when estimating the ambient temperature-labor productivity relationship, adaptation behaviors should not be included in $\boldsymbol{X}_{ict}$, otherwise causes bad control problems.

μ_i represents worker fixed effects, δ_c represents location fixed effects, and $\theta(t)$ refers to flexible time trends. After controlling these fixed effects, residual shocks in temperature are plausibly random. Some studies include location-by-time fixed effects $\varphi(c,t)$, which absorbs location-specific temperature norms and makes 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

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). These measurements are relatively coarse and hard to distinguish from other economic indicators. An ideal way is to aggregate detailed micro-level labor productivity data of various activities to the macro level in a reasonable weighting method. However, this method is too costly and almost infeasible.

Micro-level productivity records have more accurate measurements and are increasingly used in developed and developing countries. These include worker-level production data (Cai et al., 2018; Stevens, 2019; Somanathan et al., 2021), athlete performance records in competitive sports (Qiu & Zhao, 2022; Sexton et al. 2022), cognitive performance and decision choices in mentally demanding tasks (Graff Zivin et al., 2018; Heyes & Saberian, 2019). A similar but coarser data source is firm-level production data in surveys of industrial firms (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, measure errors arise in the construction process of the temperature variable. Researchers usually use a weighting approach to average the values from nearby meteorological monitoring stations or grids (for raster data) to their study units. The resulting temperature deviates from the actual temperature experienced by study units by 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 outdoor ones. The direction of bias caused by the measurement error in the outdoor-indoor temperature difference is uncertain and can vary across seasons. We need further studies in various contexts to fill this knowledge gap.

Second, the measure of temperature depends on the specific task. Most studies use the daily average temperature, which averages maximum and minimum temperatures within a day (Graff Zivin et al., 2018, Zhang et al., 2018, Chen & Yang, 2019, Stevens, 2019, Garg et al., 2020a, Graff Zivin et al., 2020). However, a large body of literature also uses daily maximum temperature, considering that works are always carried out at the warmest times of the day (Graff Zivin & Neidell, 2014, Cho, 2017, Cai et al., 2018, Park et al., 2020, Somanathan et al., 2021). Qiu & Zhao (2022) use the heat index, a nonlinear function of temperature and relative humidity, to capture the heat felt by professional archers. 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

Existing literature has examined adaptation in four different ways. First, researchers add interaction terms between temperature variables and the possible moderating factor in baseline equation (5), which gives (Isen et al., 2017; Adhvaryu et al., 2020; Park et al., 2020; Qiu & Zhao, 2022; Sexton et al., 2022; Chen & Yang, 2020; Cook & Heyes, 2020):

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

$Adapt_{ct}$ is an indicator of the existence of external adaptation strategies (e.g., A.C.) 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). The key coefficients are $\boldsymbol{\gamma}$. Notice that some studies have also tried estimating 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, imply subgroups of people with better adaptation capabilities.

Second, some studies use subsample analyses 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.

Third, studies on the impacts of temperature on time allocation have included lags of temperature variables to examine the existence of temporal substitution as a way of adaptation (Graff Zivin & Neidell, 2014; Garg et al., 2020a).

Fourth, as an implicit way of adaptation, compensatory behavior is people's spontaneous action to counteract the outcome's deterioration without knowing the temperature is the reason. Park (2022) uses the fixed effects model similar to equation (5) to estimate the impacts of temperature on a bunching estimator that proxies the degree of grade manipulation. Graff Zivin et al. (2018) find suggestive evidence of compensatory behavior by comparing the results from short-run estimations of the temperature effects on cognitive abilities using the individual fixed effects model to long-run estimations using the long difference model and the cross-sectional model.[3]

5. Empirical Review

In this section, we review the empirical findings of the temperature effects on labor productivity. First, we summarize the impacts of temperature on extensive and intensive margins of labor. Second, we review the temperature effects on mental productivity. Third, we investigate the studies on the effectiveness of adaptation in moderating the temperature-productivity relationship. We then summarize the distributional effects of temperature, and review the effects of in-utero exposure to temperature extremes. We focus on studies using causal identification designs, mainly the HDFE approach described above. Finally, we introduce studies that discuss the role of

[3] We refer readers to Hsiang (2016) for detailed explanation of the two models.

temperature in the general equilibrium framework, which suggests that combining causal estimations from the reduced-form approach with the general equilibrium modeling is a direction for future research.

5.1 Labor Productivity

5.1.1 Macro-level evidence

As described in Section 2, extreme temperatures can cause non-negligible physical or mental damage to the human body. The damage first appears as decreased labor productivity at the worker level and then aggregates to lower outputs at the regional or national level. Hsiang (2010) examines the effect of surface temperature on the economic output of 28 Caribbean and Central American countries by using Annual longitudinal data from 1970-2006. They find that a 1°C increase in surface temperature caused a 2.5% decrease in national output (measured by value added per capita). The temperature damage to the non-agricultural sector is 20-fold larger than the agricultural sector, suggesting that labor productivity damages in labor-intensive nonfarming sectors can be a crucial mechanism of the result.

Dell et al. (2012) investigate the impact of temperature on aggregate economic outcomes using historical panel data for 125 countries from 1950-2005. Higher temperatures reduce economic growth, but this effect is only significant for poor countries. The negative effect of higher temperatures consists of not only the level effect (reduction in current output level) but also the growth effect (negatively affecting innovations, institutions, and other factors that are profound for future economic growth). Moreover, the effects of temperature on agricultural and industrial output are comparable in magnitude. In contrast, Deryugina & Hsiang (2014) find that high temperatures also decrease economic output in wealthy places using the panel data of U.S. counties from 1969-2011. The income response to temperature is a combination of agricultural and non-agricultural effects. However, due to data limitation, the labor productivity channel is not well examined in the paper, although the relationship between temperature and non-agricultural income is consistent with the labor supply response to temperature in high-risk heat-exposed industries in Garff Zivin & Neidell (2014). Burke et al. (2015) revisit the relationship between temperature and economic production using panel data of 166 countries from 1960-2010. They find a smooth inverted U-shaped response of annual economic growth rate to annual average temperature, with the peak at 13°C. Both rich and poor countries respond to temperature nonlinearly, which also applies to agricultural and non-agricultural sectors.

Overall, the existing macro-level studies provide two important conclusions. First, the pernicious effects of heat on economic growth are ubiquitous, applying to both poor and rich countries. Extreme temperatures adversely influence the output of the non-agricultural sector, with an effect possibly greater than that on the agricultural sector. Second, the literature suggests that the decrease in labor productivity is a possible influencing channel, especially for the non-agricultural sector, by comparing the temperature-aggregate output relationship to the temperature-labor performance pattern in the ergonomics and labor economics literature (Hsiang 2010). However, we still do not fully understand how temperature affects labor productivity across sectors and countries from the micro perspective and to what extent labor productivity explains the effect of temperature on macro-level economic output.

5.1.2 Micro-level evidence

A strand of literature explores the impact of temperature on labor productivity at a microscopic individual or firm level, providing detailed insights to understand the temperature effects on aggregate economic output. Most micro-level studies use data from labor-intensive manufacturing industries, which probably endure more direct effects of extreme temperatures. Cai et al. (2018) use the worker-level production records of a paper cup production factory from 2012-2014 in Xiamen, China. The daily maximum temperature and labor productivity (measured by the percentage of over-target production) have a nearly symmetric inverted-U-shaped relationship. 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. Using production data of Californian blueberry pickers from 2014-2016, Stevens (2019) find an inverted U-shaped relationship between temperature and worker productivity, and both extreme coldness and heat have significant negative impacts. Compared to the reference bin of 80-85°F, temperatures below 55°F (over 100°F) lower productivity by 17% (12%). Competitive sports provide an advantageous setting to study the effects of temperature on individual worker performance because of the limited measurement errors in the input and output variables and standard capital equipment (Qiu & Zhao, 2022).

Using the annual survey of above-scale industrial firms in China from 1998 to 2007, Zhang et al. (2018) find that replacing a day with the mean temperature in the reference bin (50-60°F) by 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, since 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 dataset, Chen & Yang (2019) estimate the effects of seasonal average temperatures on firm-level labor productivity (value added per worker). They also find that firms' investment decrease and inventory levels increase in response to temperature increases.

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 waving, garment sewing, and steel products industries, Somanathan et al. (2021) find high temperatures decrease worker outputs. In a representative context, the output of garment workers decreases by 3% if every day in a year increases by 1°C. Based on India's Annual Survey of Industries (ASI) from 1998-2012, 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, the authors verify that the negative effect of high temperatures on labor productivity dominates the plant output losses rather than capital productivity. Based on panel data of manufacturing-sector GDP for 438 districts from 1998-2009, 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 on 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 dataset 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 datasets 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

In addition to the intensive impact on labor productivity in terms of reduced work intensity and quality of labor input conditional on working, temperatures can also affect labor productivity extensively by increasing work absenteeism or reducing the time allocated to work. Using individual-level data from the 2003-2006 American Time Use Surveys (ATUS) and daily weather information, Graff Zivin & Neidell (2014) find that when daily maximum temperatures exceed 85°F, workers in high-exposure industries reduce their daily time allocated to labor by one hour compared with the reference temperature level at 76-80°F. The decrease in the time allocated to labor is concentrated at the end of the day, indicating that fatigue from prolonged exposure to high temperatures is likely to be a potential channel. Furthermore, by exploring the intra-day and inter-day substitution effects, they find a limited adaptation of labor time. 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 (CHNS) from 1989-2011. They find that both extreme heat and extreme cold reduce work time. Compared with the temperature level at 55–60°F, an additional day with an average temperature above 80°F or below 25°F lower weekly work time by 1.2 hours or 1.8 hours, respectively.

Some studies adopt administrative record data of worker attendance to explore this issue. Cai et al. (2018) find that both the attendance decision and working hours of workers in a manufacturing factory in China are not affected by temperature. One explanation is that work attendance and hours are highly related to pay, and the rigidity 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 labor inputs of industrial firms in China almost do not respond to temperatures, except the temperature is extremely high. The above 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. Since the pattern between temperature and labor supply varies across occupation types and regions, existing studies are still insufficient to clarify the issue.

5.3 Mental Productivity

In some situations, labor productivity is reflected in terms of "mental output" or "mental productivity", such as cognition, learning, and consequential decisions. A growing body of empirical studies provides a causal link between temperature and various outcomes related to mental productivity.

Cognitive performance, measured as scores on various academic and non-academic tests, could be reduced by high temperatures in the short run. Focusing on a low-stakes test administered in U.S. 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. Besides damages generated by high temperatures, Cook & Heyes (2020) provide the first evidence of the detrimental impact of outdoor cold 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.

In addition to short-run impact, some of the above-mentioned papers and several additional papers evaluate the impact of sustained exposure to temperature during a period of time on cognitive performance and human capital accumulation, but the results are not unanimous. 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 extra time investment of teachers or parents. Similarly, Cook and Heyes (2020) find that cooler temperature during the semester is associated with improved performance, though the contemporaneous impact of the exam day cold is significantly negative. They attribute the reason 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 does reduce 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 reduces 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 the 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.

Temperature-related shocks on cognitive performance and human capital accumulation could generate persistent consequences on 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 non-school settings can be generalized to labor productivity in the workplace. The empirical evidence linking temperature to 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 U.S. professional immigration judges. Even with high-quality climate-control technology available, the temperature can still damage decision consistency and quality. Particularly, 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

Macro-level studies provide an aggregated perspective to understand the role of adaptation in moderating the relationship between climate change and economic output. Deryugina & Hsiang (2014) estimate the impacts of temperature on income in different decades from 1970-2010 in the U.S., finding that the negative effects of extreme heat are stable across subsamples. This result suggests limited adaptation in mitigating the 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 annual growth rate, which is close to the short-run panel estimates and implies poor countries fail to eliminate the negative impacts of temperature increases by adaptation. Using panel data of 166 countries, Burke et al. (2015) find that the does-response patterns between temperature and national output in 1960–1989 and 1990–2010 are nearly identical, informing very limited adaptation in the past fifty years.

However, micro-level studies show that adaptation measures on a smaller scale do help to weaken the temperature damage. 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 U.S. individuals born between 1969 and 1977. Adhvaryu et al. (2020) find that the replacement of compact fluorescent lamps (CFLs) with light-emitting-diode (LED) lighting in garment factories attenuates the negative relationship between mean daily outdoor temperature and worker efficiency in India. Somanathan et al. (2021) find that climate control in the workplace eliminates productivity declines due to high temperatures but not absenteeism in India. Garg et al.

(2020b) find that the roll-out of a workfare program, by providing a safety net for the poor, substantially weakens the link between temperature and test scores in India. 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 U.S. high school students. Cook & Heyes (2020) find that writing 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.

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, physiological/biological/autogenous adaptation strategies– adapting to heat through training one's own mind and body instead of devices that are "external" to one's body – 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 adaptation is acclimatization, which is defined as "the beneficial physiological adaptations that occur during repeated exposure to a hot environment" by the U.S. Centers for Disease Control and Prevention (CDC), and can occur within one week and persist amid heat exposure. 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 (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 those 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 U.S. collegiate track and field performance records. Cook & Heyes (2020) find that foreign students' performance becomes substantially less sensitive to temperature over time, suggesting that biological adaptation exists.

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 since heat 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 and fail to find significant differences. Similarly, Chen & Yang (2020) finds 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 to warming in high-temperature regions in China.

The ex-post adaptive strategy is a compensatory behavior 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, 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. 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. Garg et al. (2020a) 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.

Finally, reallocation of work and leisure hours in response to temperature is a direct way of adaptation. In the U.S. background, 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 the negative impact of temperature doubles, suggesting work time in subsequent weeks complements work time in the week experienced a temperature shock.

5.5 In-Utero Exposure to Extreme Temperatures

The fetal origins hypothesis posits that in-utero circumstances can have substantial long-term impacts on human development (Almond & Currie, 2011; Fishman et al., 2019). Earning is a proxy for labor productivity, and cognitive function is one aspect of human capital. Extreme temperatures can influence adult development not only through biological channels mentioned in Section 2, but also through economic channels, as in-utero exposure to extreme temperatures may stress mothers or infants by influencing household income and nutrition status.

Isen et al. (2017) estimate the effects of temperature in utero and early childhood on adult annual earnings using administrative earnings records for over 12 million individuals born in the United States. They find that temperature above 32°C in utero is associated with a 0.1% reduction in adult annual earnings at age 30. Fishman et al. (2019) examine the same question using the data set of the 2010 earnings of all one million formal sector workers above the age of 30 born between 1950 and 1979 in Ecuador. They 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) explore the 2010 wave of the China Family Panel Studies (CFPS), a nationally representative, biannual longitudinal survey of Chinese communities, families, and individuals. They find that adults who experienced an additional day of high temperature during their prenatal periods show a 0.48% decrease in standardized word-test scores, are shorter by 0.02 cm, attain 0.02 fewer years of schooling, and have a higher risk of illiteracy by 0.18%. Hu & Li (2019) also validate an income channel by finding that the proportion of heat-tolerant crops (C4 plants) significantly reduces the impacts of high temperatures during pregnancy. The above findings indicate a strong external validity in the adverse impacts of in-utero exposure to high temperatures on labor productivity across developed and developing countries.

On the other hand, the differences in socioeconomic characteristics of the sample people, and institutional background differences of the sample countries (e.g., the levels of health care), may contribute to disagreements in temperature impacts in different trimesters and early childhood. The temperature impacts appear to be concentrated in the first and third trimesters in Isen et al. (2017) and the first and second trimesters in Hu & Li (2019). In addition, Isen et al. (2017) find that temperature above 32°C in the first year of life is associated with a 0.1% reduction in adult annual earnings at age 30. Both Fishman et al. (2019) and Hu & Li (2019) find that the temperature in the 9 months after birth shows no impact on adult earnings or cognitive abilities.

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 can vary across social and economic factors, such as gender and income.

Regarding gender differences, Garg et al. (2020a) find that male farmers are more affected by extreme temperatures than male non-farmers in China. Moving a day from the reference bin 55-60°F to bins below 30°F reduces work for male farmers by more than two hours per week relative to other male workers. Among farm workers, the reduction in labor supply is larger in females than in males. 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 U.S. They 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 performances and manufacturing worker productivity, respectively.

Regarding income differences, most studies find that lower-income people suffer larger marginal damages. For example, Park et al. (2020) find that the impact of prior year heat on students in lower-income zip codes is twice as large as on those from higher-income zip codes, likely due to differences in protective investments. As evidence, 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 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. Understanding the causes of these mixed findings is an important challenge for future research.

Regarding other heterogeneities, differences in industries, occupations, and family backgrounds receive more attention. Graff Zivin & Neidell (2014) find that at daily maximum temperatures above 85°F, workers in industries with high exposure to climate reduce the daily time allocated to labor by as much as one hour. Park et al. (2020) find the impact of prior year heat on black and Hispanic students is three times larger than the impact on white students. Hu & Li (2019) find that the effects of hot days on years of schooling, risk of illiteracy, and height are mainly driven by rural-born individuals but not those born in urban China. Overall, all these analyses of heterogeneous effects have implications for inequality, and other heterogeneities, such as education, require more attention in the future.

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 the exposure heterogeneities is required as the projected distribution of future climate change exposure is even more complex.

The second 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 damages from temperature shock. This line of research is particularly difficult because it requires exogenous variations on the source of socioeconomic factors. Garg et al. (2020b) show that high temperatures reduce test scores among school-age children but the roll-out 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 U.S. farmers but that drought sensitivity increases over time as land use is adjusted to water-intensive crops. While these causal studies are limited, they are growing quickly 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 highlight the reduced-form impacts of temperature on productivity. However, burgeoning literature quantifies the climate impacts in a dynamic general equilibrium framework. Such analyses are usually conducted on a global scale. Global analyses are rich in heterogeneities, providing us with both average and distributional effects. Conte et al. (2021) quantitatively assess the impacts of global warming on sectoral specialization and economic geography by a two-sector dynamic spatial growth model, and find that rising temperatures increase productivity growth in agriculture and decrease productivity growth in non-agriculture. Warmer temperatures push agriculture to regions, such as Central Asia, that initially suffered from a large temperature penalty. With global warming, these regions benefit from relatively high agricultural productivity. By contrast, Nath (2021) 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 and other 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 show welfare losses as large as 19% in parts of Africa and Latin America but also high heterogeneity across locations, with northern regions in Siberia, Canada, and Alaska experiencing gains. Burzyński et al. (2022) model the impact of climate change on productivity and utility in a dynamic general equilibrium framework. They simultaneously account for the effects of changing temperatures, sea levels, and the frequency and intensity of natural disasters. They find that climate change strongly intensifies global inequality and poverty, reinforces urbanization, and boosts migration from low- to high-latitude areas.

While these analyses have advantages in distributional effects and adaptation mechanisms, they share the critiques in structural modeling, including untestable functional form, distributional, and other modeling assumptions. While the reduced form approach is suitable for identifying key response parameters casually, 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

Scientific research has revealed the negative impacts of temperature shocks on physical and mental health, which further led to responses of labor productivity, as economic findings reviewed in the paper. Benefiting from the increase in the availability of high-frequency microdata, increasingly studies have established causal links between temperature and labor productivity. However, there are still several limitations that call for future research.

First, existing studies focus on the impact of temperature on labor productivity in the industrial and agricultural sectors, and study on the service sector is still limited. One possible explanation is that high-frequency production data in the service sector is hard to obtain, especially in developing countries. More importantly, both supply and demand in the service sector can be affected by immediate temperature changes, causing challenges in identifying the impact of temperature on labor productivity alone. Since they are intertwined and synchronously affected by temperature, the naïve HDFE setting still produces biased estimates for the labor productivity effect. It is important to rule out demand factors when estimating the impact of temperature on labor productivity in the service sector from the supply side in empirical exercises.

Second, evidence from empirical studies reveals temperature-related impairments in both physical and mental productivity separately, but with less understanding of the interaction between them. In domains like mental productivity, where most studies focus on the cognitive performance of children and young adults, a plausible extrapolation from school settings to a general workplace requires more work. Moreover, the long-run impact of sustained temperature exposure on mental productivity and behavioral responses is much less clear and would be an area of future work. In addition, studies on the mechanisms underlying in-utero extreme temperature exposure impacts are scant. Future studies should explore mechanisms underlying the impact of in-utero extreme temperature exposure on productivity.

Third, future studies should reconcile the inconsistency between the macro-level and micro-level evidence of the effectiveness of adaptation. Researchers should also explore data on adaptation behavior and policies in different countries and compare the effectiveness of adaptation in various contexts.

Lastly, the general equilibrium effect of temperature on productivity is another area that remains unclear. On the one hand, areas that today have ideal temperatures for agricultural production will become too hot for agriculture in the future. Some sectors, such as agriculture, are more sensitive to rising temperatures, than other sectors, such as manufacturing and services. Therefore, global warming will change the comparative advantage across regions and industries. It is essential to consider the interactions among regions and linkages across industries. On the other hand, while climate change affects productivity, the reverse is true. It contributes to our knowledge by explicitly introducing the feedback from the productivity shock in the economy to the climate.

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