Heterogeneous firms under regional temperature shocks: exit and reallocation, with evidence from Indonesia*

Victoria Wenxin Xie†

Santa Clara University

Abstract

Are less productive firms in developing countries disproportionately affected by climate change? Using firm-level data from Indonesia, I find less productive firms are more likely to exit the surveys when temperature rises. Second, there is relative output redistribution to the initially more productive firms. The results are consistent with a heterogeneous firm model with skill-biased production function, where heat disproportionately affects unskilled labor productivity. Finally, surviving firms switched to using more skilled labor and more imported inputs. These results illustrate how climate change affects firms of different initial productivity and how various margins of firm-level adjustment could mitigate such effects.

JEL codes: Q54, O13, J24, Q56

*I thank Richard Carson and Gordon Hanson for advice and encouragement. I thank Marcel Fafchamps and an associate editor for their comments and guidance. I thank two anonymous referees whose comments helped me improve the paper. I'm indebted to Sam Bazzi for providing valuable support and feedback. I am also grateful to Laura Beaudin, Julie Cullen, Gordon Dahl, David Victor, Roger Gordon, Teevrat Garg, Mark Jacobsen, Kyle Meng, Jeff Shrader, Brigitte Roth Tran, Josh Graff Zivin, and many others at the the ASSA meetings in Philadelphia and UCSD environmental and applied seminar for comments. Data are provided through Dataverse at https://doi.org/10.7910/DVN/GMRUHC

†Xie: Santa Clara University, 500 El Camino Real, CA, 95053, wxie@scu.edu.

1 Introduction

Climate change shifts the annual distribution of daily weather outcomes and increases the frequency of extreme heat waves. To assess climate change damages and devise policies for adaptation, there is considerable interest in understanding how temperature shocks affect industrial production. Such an assessment is perhaps especially pressing for less-developed countries where the adverse consequences of climate change concentrate and adaptation is relatively costly (Acevedo et al. 2017). Recent evidence suggests heat has negative impact on aggregate output and labor productivity (Dell et al. 2012, Graff Zivin and Neidell 2014). Yet how climate change affects firms of different initial productivity through various margins of adjustment remains poorly understood.

In this paper, I show how within-industry firm heterogeneity matters for firm output redistribution when temperature increases. Using a firm-level panel data from Indonesia, I apply a discrete time hazard model as well as a fixed-effect approach exploiting rich temperature variations across kabupatens (a second-level administrative division in Indonesia) and years for identification. Measuring initial firm productivity using a control function approach, I show that less productive firms are more likely to exit the surveys when temperature rises. This illustrates the selection bias intrinsic to intensive margin analysis. Second, I demonstrate that on the combined margin at the kabupaten-by-industry level, there is relative output redistribution to the initially more productive firms. These empirical results are consistent with a heterogeneous firm model with skill-biased production function. Theoretically, I build on a simplified version of Burstein and Vogel (2017) and incorporate a thermal stress channel where heat lowers labor productivity, and disproportionately affects unskilled labor. Exploiting distinctive features of the Indonesian firm-level data, I show that the initially less productive firms that survived switched from unskilled to skilled labor.

Indonesia is an important developing economy vulnerable to extreme weather conditions. As is the case for many developing countries heavily integrated into the world market, manufacturing production is an important part of national income for Indonesia. According to the World Bank National Accounts data, manufacturing value-added takes up 21% of annual GDP for Indonesia in 2014. Firm production technologies are widely different in terms of total factor productivity and skilled labor intensity. Regions in Indonesia also differ drastically in temperature and humidity due to changes in latitude, elevation, and proximity to coast.

This paper exploits the rich variations in local level exposure to heat shocks and within industry firm productivity differences to examine heterogeneous dose-responses to temperature shocks across Indonesian manufacturing firms. Unlike more advanced economies, the manufacturing sector in Indonesia is less adapted to temperature shocks due to low air conditioner penetration. Using data from the World Bank's Living Standards Measurement Surveys (LSMS), an EPA report (Auffhammer 2011) estimates a 2.7% residential air conditioner saturation rate in 1997 for Indonesia, whereas the saturation rate was 72% for the U.S in 2001 and 85% for South Korea in 2000.

How geographic conditions and climate variables affect economic growth and output has been a question of long debate. The climate-economy literature exploits heat shocks using panel estimates and finds large negative effect of heat exposure on aggregate output (Dell et al. 2014, Hsiang 2010), recent firm-level level evidence shows that high temperature days affect manufacturing output and productivity (Adhvaryu et al. 2020). Zhang et al. (2018) find large negative effects of temperature on Chinese firm-level manufacturing output, driven by decreases in total factor productivity. Somanathan et al. (2021) find a 2.8 % decrease in Indian firm-level manufacturing output per one degree increase in annual temperature. Colmer (2021) shows that higher temperature leads to a net increase in manufacturing output for flexible labor markets in India. These contributions have focused on firm-level intensive margin analysis. In this paper, I show that the initially less productive Indonesian firms are more likely to exit the surveys when temperature increases. This suggests, in the context of Indonesia, analysis focusing on the intensive margins would be subject to survival bias and understate aggregate impact. The only other paper discussing firm survival rates is Traore and Foltz (2018) using evidence from Ivory Coast, but they do not consider heterogeneous impact across firms with different productivity nor firm factor switching. I demonstrate that output redistribute to the initially most productive firms, and that the surviving firms switched to using more skilled labor.

The main motivation for this paper comes from recent empirical evidence suggesting a significant negative relationship between temperature and labor productivity. Heat leads to fatigue, lower performance in physical tasks, and poor decision making. Higher temperature is also associated with lower measured and self-reported work performance [1]. While there

[1] Zander et al. (2015), Graff Zivin and Neidell (2014), Niemelä et al. (2002), Seppanen et al. (2006), Kjellstrom et al. (2009), Park (2017)

are many other channels through which heat shocks could affect manufacturing firms [2], I conduct robustness checks excluding sectors with primary agricultural linkages and show that the direct labor productivity channel is important in the Indonesian context. Previous studies also suggest high temperature days may impact unskilled workers more than skilled workers, due to both physiology [3] and differential adaptation. Collecting daily Indian factory-level data, Somanathan et al. (2021) find that skilled workers operate in environment with better climate control, consistent with a larger productivity drop for low value-added unskilled workers. Motivated by these facts, I show how various margins of firm-level adjustment can mitigate the effects of heat.

These empirical results are consistent with a simplified heterogeneous firm model with skill-biased production function Burstein and Vogel (2017), incorporating a thermal stress channel where high temperature leads to larger productivity drop for unskilled labor relative to skilled labor (Ramsey 1995, Somanathan et al. 2021). The trade literature focusing on firm heterogeneity demonstrates strong correlations between firm-level attributes such as productivity, firm size, skilled labor intensity, etc (Bernard et al. 2007). These established facts featured in the model guide me to empirically examine the heterogeneous impact of heat using firm productivity as sufficient statistics for other firm-level attributes. Intuitively, the initially less productive firms are also more intensive in unskilled labor, experiencing larger productivity drop from heat shocks. Regional temperature shocks and the associated drop in labor productivity lead to a rise in the zero-profit cutoff productivity level, and push the least productive firms to exit. Less productive firms also experience more output contraction on the combined margin. One advantage of the Indonesian industrial surveys is that they report skilled versus unskilled employment separately (Amiti and Cameron 2012). Exploiting this data feature, I empirically show that less productive firms that survived switched from unskilled to skilled workers, consistent with the model mechanism. I also find that less productive survivors switched to using more imported intermediate input.

Findings in this paper also contribute to a literature focusing on the aggregate disproportionate impact of climate change in less-developed countries. A number of studies estimate

[2] Such as: the agricultural income and local demand channel (Burke and Emerick 2016), the agricultural input/output linkage channel (Acemoglu et al. 2012), the sectoral labor reallocation channel (Colmer 2021).

[3] Using matadata from the physiological literature, Ramsey (1995) finds that for perceptual motor tasks, performance is significantly lowered with high temperature exposure, although less dominant effect was found for mental tasks.

an approximate 2 percent industrial output loss per 1°C increase in temperature, but only in poor countries (Dell et al. 2012, Jones and Olken 2010). One important challenge lies in identifying the sources of such heterogeneity in damages (Hsiang et al. 2020). Accounting for the non-linear effect of temperature could explain this disproportionate impact, given the strong negative correlation between baseline income and baseline temperature (Burke et al. 2015). Alternatively, I show in a simple model that heterogeneity in productivity and skilled labor intensity across firms gives rise to firm-specific damage functions, which alone could generate differences in observed damages even without variations in exposure to heat shocks or non-linear effects. This offers a potential explanation for why poor countries are more affected by climate change from the perspective of firm size distribution. The development literature documented the prevalence of small firms in less developed countries using cross-country micro data (Hsieh and Olken 2014, Poschke 2018). Results in this paper suggest that less productive firms, prevalent in poor countries, are also more vulnerable to heat due to underlying firm-specific damage function. The aggregate loss may be larger for countries whose firm size distribution is skewed to the left in the absence of adaptation.

The paper proceeds in five sections. Section 2 introduces data and empirical facts. Section 3 presents the main empirical strategies and results on differential firm exit and within-industry resource reallocation. I also present descriptive results on factor substitution and intensive margin changes conditional on remaining in the surveys. Section 4 discusses underlying mechanism. Section 5 concludes. In the Theory Appendix, I outline a simple heterogeneous firm model with skill-biased production function incorporating a thermal stress channel.

2 Data and Empirical Facts

2.1 Data

The main data on firm-level outcomes come from the Indonesian Large and Medium-scale Manufacturing Survey, or the Statistik Industri (SI). This is a firm-level survey conducted by the Indonesian BPS and answered yearly by all manufacturing firms with more than 20 employees, which allows for the construction of a firm-level panel. Main variables include value-added output, domestic and foreign input, skilled and unskilled employment, industry category and other firm-level balance sheet information through the period 2001-2012.

Each firm in the SI is matched with an Indonesian administrative 2-level regency, or *kabupaten*, similar to the concept of a county in the US. I then use GIS data from the Global Administrative Areas to obtain the coordinates of the centroid of each kabupaten.

Daily weather variables from 2001-2012 are obtained from NASA's Prediction of Worldwide Energy Resource (POWER) database, which provides global coverage on a 1° latitude by 1° longitude grid. I calculate the yearly average temperature based on the daily average air temperature for each kabupaten. I also obtain daily weather outcomes on relative humidity, and cumulative precipitation to add as controls. The matched panel gives variations at the kabupaten-by-year level for both weather and firm outcomes, which I exploit later in the empirical section. Finally, to transform the yearly nominal value-added output reported in the SI to real output values, I use the GDP deflator from the World Bank National Accounts data.

2.2 Empirical Facts

In this section, I first describe data patterns in the Statistik Industri which motivates the heterogeneous firm model with skill-biased productivity in the Theory Appendix. The model is static and therefore only offers a highly stylized conceptual framework. Second, I show descriptive facts on the spatial distribution of regional temperature variations and industrial clusters.

First, I present facts using data from the Indonesian firm surveys on the correlations between firm-level attributes such as productivity, sales, skilled labor intensity, etc. These patterns echo previous papers in the trade literature (Bernard et al. 2007, 2012) on firm heterogeneity and guide me to empirically examine the heterogeneous impact of heat using firm productivity as sufficient statistics for other firm-level attributes. Table 1 gives the standardized coefficients from regressions of within-industry firm productivity on a series of firm-level covariates in the SI. Each cell represents a single regression, where standard errors are clustered at the firm-level. Firm productivity is measured as value-added per employee, ranked in terciles within each firm's two-digit ISIC industry code. Focusing on column 3, which uses pre-period productivity in 2001, we see that more productive firms have higher output, measured by both value-added and total sales, are less labor intensive, have higher skilled to unskilled labor ratio, and pay higher average wages. They are also more likely to be exporters. These strong correlations between firm-level attributes are highlighted in a large body of trade literature considering the importance of firm heterogeneity in response to changes in trade barriers and product market shocks (Bernard and Jensen 1999, Melitz 2003).

In the Indonesian context, within-industry firm heterogeneity matters more than variations across sectors. As an example, Figure 1 illustrates how firm-level labor intensity, measured by wage bill over value-added output, varies within and across industries. On the x-axis, firms in each industry were put into ten productivity bins using their value-added per employee in 2001 ranked within respective two-digit ISIC industry codes. We observe strong negative correlation between firm productivity and labor intensity similar to Table 1, and more variations within industries than across industries. In the Theory Appendix, I incorporate a thermal stress channel in a simplified heterogeneous firms with skill biased production function, building on Burstein and Vogel (2017). These baseline facts also guide the following empirical analysis which uses within-industry firm productivity as sufficient statistics for firm heterogeneity.

Next, to illustrate the variations in temperature by kabupaten, Figure 2 plots the daily mean temperature averaged from 1997-2011. Figure 3 plots the difference in yearly average temperature between 2012 and 1997. In the empirical analysis, I explore year-to-year temperature shocks by kabupaten, defined as deviations from the kabupaten, and year-by-island mean temperature. Finally, Figure 4 shows geographic firm size distribution. Firms are categorized into quantiles within their respective two-digit ISIC industry according to their average value-added output through the sample period. There is a cluster of small firms in the East Java region. In the empirical analysis, I include region or firm fixed effects to exclude initial spatial sorting.

Table 1: Standardized coefficients of productivity on firm characteristics

	Productivity (V.A./employee)			**Obs**
	(1)	**(2)**	**(3)***	
Total V.A.	0.3132**	0.3081**	0.0755**	150,181
	(0.131)	(0.128)	(0.031)	
Total Sales	0.3275***	0.3192***	0.1025***	150,181
	(0.070)	(0.069)	(0.023)	
Exporter status	0.0972***	0.1206***	0.1511***	117,580
	(0.007)	(0.008)	(0.007)	
Capital/Prd employee	0.0339	0.0321	0.0196**	148,347
	(0.022)	(0.021)	(0.007)	
Nonprd/Prd employees	0.0577**	0.0463**	0.0453**	150,120
	(0.023)	(0.019)	(0.02)	
Labor Intensity (Wage bill/V.A.)	-0.2532**	-0.2480**	-0.2312**	150,181
	(0.007)	(0.006)	(0.004)	
Wages/employee	0.4083***	0.3981***	0.2789***	150,181
	(0.020)	(0.022)	(0.008)	
2-digit industry F.E.	No	Yes	No	

(a)This table shows standardized coefficients from a regression of firm productivity (measured by V.A. per employee) on firm characteristics. (b)The first 2 columns use current period productivity (c)*Column 3 uses pre-period productivity, ranked within 2-digit ISIC codes. (d)Errors are clustered at the firm-level (e)*p<0.10, **p<0.05, ***p<0.01

Figure 1: Mean Labor Intensity and firm productivity

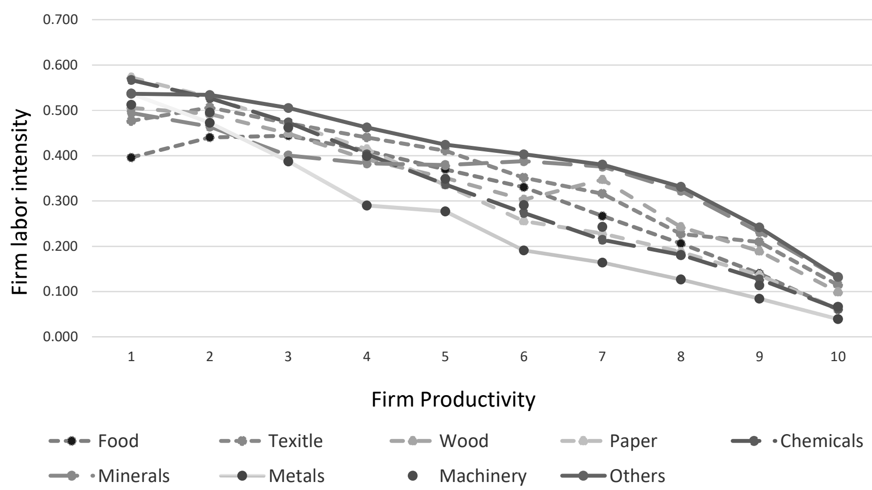


Figure 2: Average daily temperature at 2pm

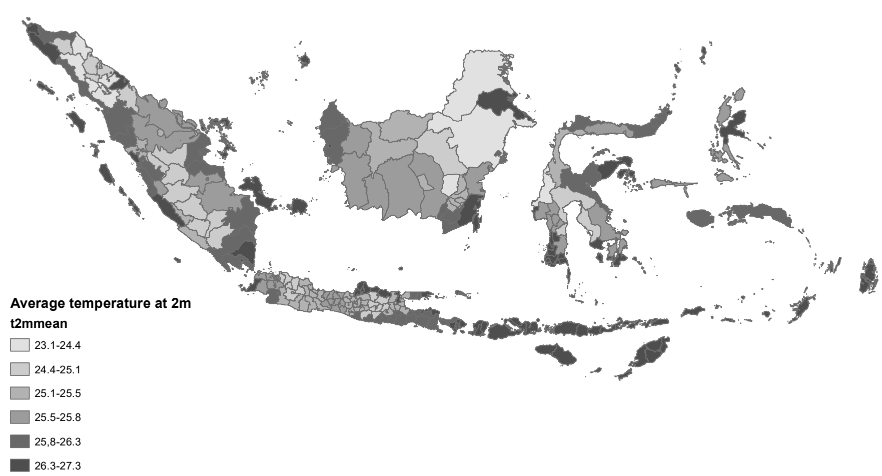


Figure 3: Yearly average temperature difference between 2012 and 1997

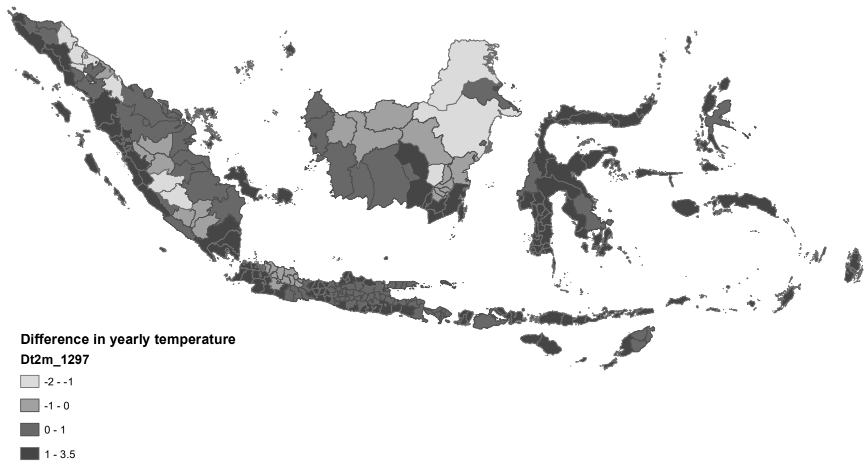
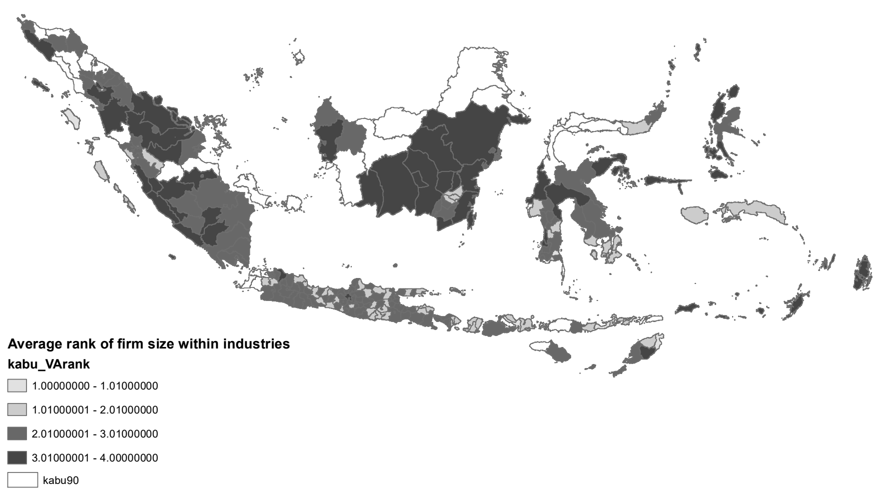


Figure 4: Firm size distribution by quantiles within two-digit ISIC industry



3 Empirical Results

3.1 Extensive Margins

How does increasing temperature affect extensive margin adjustment in the Indonesian firm surveys? This subsection examines the empirical evidence in a discrete time hazard framework. To construct a panel typical for hazard analysis, I treat the first year that a firm is in the survey as its entry year and last year in the survey as the exit year. Note that firm exit in this paper is defined as the firm exiting the survey, as the Statistik Industri only contains firms with more than 20 employees. More details are discussed in Section 3.1.2. The sample period of analysis is from 2001-2012. I start with all firms that are present in the initial year, 2001, and look at exit outcomes thereafter. The binary variable on exit takes a value of zero if a firm does not exit in the next period, and one otherwise.

Firms were put into three bins according to their initial within-sector productivity. Initial productivity bins were obtained by ranking each firm's value-added per worker in the year 2001 within their respective two-digit ISIC industry codes. This is therefore a measure which reflects within-industry productivity. I define the year 2001 as the pre-period and examine the effects of subsequent regional temperature shocks on firm exit. Exit behavior exhibits duration dependence, so that the likelihood of exit depends on the elapsed time that the firm has been in the sample.

3.1.1 Empirical Strategy

The empirical framework I use is a discrete time hazard model. The probability of firm exit in any period is a function of the elapsed duration of the firm's survival τ, the initial productivity bin that the firm belongs to, $pdty_i^s$, and the temperature facing the firm in the current period, $temp_{i,\tau+1}$. Each spell is represented as a sequence of (0, 1) observations.

$$\begin{aligned} P(t_{ij} = \tau + 1 \,|\, t_{ij} > \tau, pdty_i^s * temp_{i,\tau+1}, pdty_i^s * rain_{i,\tau+1}, pdty_i^s * humidity_{i,\tau+1}, pdty_i^s * age_i^{2001}, \\ \theta_{jt}) = g(\tau, pdty_i^s * temp_{i,\tau+1}, pdty_i^s * rain_{i,\tau+1}, pdty_i^s * humidity_{i,\tau+1}, pdty_i^s * age_i^{2001}, \theta_{jt}) \end{aligned} \tag{1}$$

$Exit$ is a binary variable that takes the value of one if the firm exits in the next period and zero otherwise. Throughout this paper exit is defined as "permanent exit" where the firm is not reentering in a later year. I prefer linear probability model as the main specification instead of nonlinear models to avoid incidental parameter problems. $pdty_i^s$ are dummies for whether firm i's initial productivity rank is in the sth tercile within their industry, with $s = 1, 2, 3$. $temp_{i,\tau+1}$ measures the annual average temperature faced by firm i in year $\tau + 1$. Duration dummies τ are included to nonparametrically model duration dependence. This yields a cross-section regression where I look at how current period temperature influences firm exit across time-invariant productivity bins, controlling for other covariates.

To the baseline hazard model, I add in a set of fixed effects to control for other variations in the data possibly correlated with regional average temperature. Year*Industry fixed effects control for product demand shocks. Year*Island fixed effects control for island-specific business cycles. Industry*Island fixed effects control for island-specific industry specializations. Fourth, kabupaten fixed effects are included to control for any time-invariant characteristics that correlate with temperature at the kabupaten level. Because of the inclusion of these fixed effects, the regional variations in temperature I am exploiting are temperature shocks, measured as deviation from the kabupaten, year-by-island, year-by-industry average.

To address the fact that firms with different initial productivity ranks and initial age may have varying exit probability, I include a firm's initial productivity by age-in-2001 bins, $pdty_i^s * age_i^{2001}$, to control for the main effects on exit. Finally, I control for productivity-bin-specific relative humidity and rainfall. Standard errors are clustered two-way, at the firm-level and kabupaten*year level.

3.1.2 Results

I begin by presenting the extensive margin results for firms in different initial productivity bins. Table 2 shows the coefficients on the interaction terms of firm's initial productivity bins with temperature. The interaction terms with cumulative rainfall and humidity are controlled for but omitted from the reported table. All coefficients are multiplied by 100. $Pdtybin1^{2001}$ corresponds to firms with the smallest initial productivity tercile ranking, measured by value-added per worker in 2001 within their respective two digit ISIC industry codes.

Table 2: Differential firm exit under heat shocks

	(1) exit b/se	(2) exit b/se	(3) exit b/se
$Pdtybin1^{2001}$*Temperature	2.0220***	1.7523**	1.8104**
	(0.783)	(0.845)	(0.846)
$Pdtybin2^{2001}$*Temperature	0.6029	0.4017	0.4236
	(0.751)	(0.832)	(0.831)
$Pdtybin3^{2001}$*Temperature	0.1595	0.0233	-0.0461
	(0.728)	(0.808)	(0.807)
Observations	108187	108187	108187
Year*Industry FE	Yes	Yes	Yes
Year*Island FE		Yes	Yes
Industry*Island FE			Yes
Kabupaten FE	Yes	Yes	Yes
$Pdtybin$*Age^{2001}	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear
Y(mean): pdtybin1	9.81	9.81	9.81
Y(mean): pdtybin2	8.11	8.11	8.11
Y(mean): pdtybin3	7.29	7.29	7.29

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome is a binary variable on exit. (c) $PdtybinS^{2001} * Temperature$ are the interaction terms of the firm's pre-period within-industry productivity ranks and yearly average temperature (d) Controls for $PdtybinS^{2001} * Rain$, $PdtybinS^{2001} * Humidity$ and duration dummies are omitted from the table. (e) All coefficients are multiplied by 100

Column (1) - (3) demonstrate a cascade of specifications with increasingly more restrictive fixed effects. The temperature variation exploited here are deviations of the annual average kabupaten temperature from the kabupaten, year-by-island, year-by-industry averages.

We focus on estimates from the preferred specification in column (3), where year*industry, year*island, industry*island and kabupaten fixed effects are all included. Indonesia has a high baseline temperature (an average of 25.6 degree Celsius during the period of 2001-2012), so here we assume that increases in temperature are above the ideal body temperature and thus adopt a linear specification. An increase in yearly average temperature makes it more likely for firms in the smallest initial productivity bin to exit from the surveys. Point estimates for firms in the second productivity bin is also positive, although statistically imprecise. In particular, one degree Celsius increase in average yearly temperature from the year-by-island, year-industry, kabupaten mean increases the probability of exit for firms in the smallest initial productivity bin by 1.81 percentage points. This corresponds to a 24.8% increase in exit propensity relative to the baseline (9.81 percentage points) for the initially least productive firms.

I conduct several robustness checks. First, as an alternative measure of productivity, I adopt the control function approach which corrects for selection and simultaneous bias (Olley and Pakes 1996, Rovigatti and Mollisi 2018, Wooldridge 2009). Similar estimation has been done in Kassem (2018) also using Indonesian data. I estimate the productivity measures within each 2-digit sector and take the firm-level average across the years to proxy for the non-transitory component of firm-level productivity [4]. The results are robust with similar magnitude as before, presented in Table A1. Second, the results hold when not including productivity-bin-by-age fixed effects, as shown in Table A2. Although in the most restrictive specification with year-by-island fixed effects and kabupaten fixed effects among others, the point estimate in column 3 became marginally significant. Third, I run alternative specifications where lead temperature shocks one year-ahead are also included in the regressions. Despite serial correlation in yearly temperature, reassuringly, we see current year temperature shocks significantly increase exit rates, whereas future shocks do not. Results are in Table A4.

[4]One caveat for the Indonesia data is that firm-level capital is zero for around 30% of the sample. This means that Wooldridge (2009) which involve log transformation could only be implemented for a subsample of the data.

Finally, Firm exit in this paper is defined as the firm exiting the survey. Given that the Statistik Industri only contains firms with more than 20 employees, this could mean the firm is either going out of business, downsizing to below 20 employees, or becoming informal. To examine this issue, I conduct robustness checks restricting to firms with more than 40, 50 or 60 workers, the results are presented in Table A3. In the most restrictive specifications with industry*year and island*year FEs among others, the coefficients on exit for the least productive firms are still positive, though not statistically significant (columns 4-6). Since this robustness check requires dropping around half of the firms in the sample, I also include alternative specifications with industry time trends and island time trends (columns 1-3), where the estimates are positive and significant. Given the sensitivity of the results under employee size cutoffs, it is likely results are driven by firms dropping below the firm-size thresholds of the surveys. The extensive margin results should be interpreted as firms exiting the survey instead of firm closure. I note this important distinction when interpreting the extensive margin results.

These results illustrates that firm-level intensive margin analysis using the Indonesian firms surveys would be subject to selection bias. In the next subsection, we examine output redistribution at an more aggregate level by looking at the combined margins.

3.2 Resource Redistribution: Combined Effects

Do temperature shocks redistribute value-added output from less productive to more productive firms? The answer involves a combination of extensive margin changes and intensive margin changes. I aggregate firms within each productivity bin, industry and kabupaten to examine the differential net effect of heat shocks on firms' combined margins, and within-industry resource reallocation.

I start with the full sample, covering the years 2001-2012. Contrary to the regressions on exit propensity, I include not only firms that were in the sample in 2001 but also firms that entered later into the survey. This means the extensive margin changes will now account for both firm entering and exiting the surveys. Value-added output for each year measured in the Indonesian rupiah is adjusted using the GDP deflator from the World Bank National Account Database.

To construct the time-invariant productivity tercile cutoffs for each two-digit ISIC industry, I first rank the annual productivity for each firm within their industry, and take the average of tercile cutoffs across all years for each industry. Each firm is then placed in a productivity tercile based on its productivity in the first available year since 2001. This gives us the firm-specific, time-invariant initial productivity ranking within the industry a firm belongs to. In order to account for both the intensive and extensive margin changes for firms in each productivity tercile, I aggregate the value-added output for firms in each productivity bin, region, industry and year so that the new unit of analysis is at the productivity bin*region*industry level.

3.2.1 Empirical Strategy

The combined effect of temperature shocks on firms in each productivity tercile is estimated with the following fixed effects model:

$$\begin{aligned} y_{it} = \alpha_0 + \sum_s \alpha_{1s} PdtyBin_{is}^{initial} * Temperature_{it} + \sum_s \alpha_{2s} PdtyBin_{is}^{initial} * Humidity_{it} \\ + \sum_s \alpha_{3s} PdtyBin_{is}^{initial} * Rain_{it} + \beta_s PdtyBin_{is}^{initial} * t + \theta_i + \sigma_{jt} + \gamma_{rt} + \epsilon_{it} \end{aligned} \tag{2}$$

Here we are interested in how the aggregate value-added output at the region-industry level for firms in each productivity tercile is impacted by temperature shocks. I control for bin*region*industry fixed effects, and focus on the changes across years for the within estimator. The outcome of interest, y_{it}, measures the log of value-added output, or percentage changes in output. $PdtyBin_{is}^{initial}$ are dummies for whether the aggregate-level observation i's initial productivity rank is in the sth tercile within their industry, with $s = 1, 2, 3$. $Temperature_{it}$ measures the average annual temperature for observation i in year t.

Similar to the specification in seciton 3.1, I also include a rich set of fixed effects to control for concurrent shocks which may be correlated with the observed weather variations. I add Year*Industry fixed effects, to control for year-specific unobserved heterogeneity related to industry demand or factor prices. Year*Island fixed effects control for year-specific regional business cycles. The identification of α_{1s} comes from the differential impact of temperature on the aggregate output of firms in different productivity bins.

To exclude the possibility that the differential impact on the combined margin is driven by weather variables other than temperature, I control for productivity-bin-specific annual cumulative rainfall, and annual average relative humidity. Finally, I allow for differential time trends for each productivity bin. Standard errors are clustered at the bin*kabupaten*industry level.

3.2.2 Results

Table 3 presents the combined effects of temperature shocks on aggregate value-added output. The three specifications with increasingly restrictive fixed effects yield numerically similar estimates. We focus on the preferred specification in column 3, where shocks are defined as temperature deviation from the year-industry, year-island, and kabupaten average. Firms in the smallest productivity tercile experienced a relative percentage decrease in aggregate value-added output as temperature increases, while firms in the largest productivity tercile experienced a marginally significant relative percentage increase.

Across specifications in columns 1-3, we observe that heat shocks redistribute value-added output on the aggregate, from the least productive firms, to the most productive firms in each industry. In particular, one degree Celsius increase in yearly average temperature from the kabupaten, year-industry, year-island average leads to a 10.37 percentage point loss in aggregate output for firms in the smallest initial productivity tercile. Firms in the largest productivity bin incur a marginally significant relative increase of 6.85 percentage points in aggregate output per 1°C increase in temperature. Since the SI only include medium and large establishments with employment more than 20, I do not observe the effects on the smallest firms.

Comparing these results with previous studies in the literature [5] which consistently find a 2.5 percent decrease in aggregate industrial output per 1 degree Celsius increase in yearly temperature, we see that the magnitude of impact from temperature shocks on the least productive firms may be much larger than the industry aggregate. Changes in aggregate output and per capital income under temperature shocks could be accompanied with substantial resource reshuffling within each industry.

[5] Dell et al. (2012), Jones and Olken (2010)

Table 3: Temperature shocks and relative combined effects on output

	(1) ln(vlad) b/se	(2) ln(vlad) b/se	(3) ln(vlad) b/se
$Pdtybin1^{2001}$*Temperature	-0.1049***	-0.0972***	-0.1037***
	(0.035)	(0.038)	(0.038)
$Pdtybin2^{2001}$*Temperature	-0.0321	-0.0294	-0.0323
	(0.032)	(0.036)	(0.035)
$Pdtybin3^{2001}$*Temperature	0.0666*	0.0745*	0.0685*
	(0.035)	(0.039)	(0.038)
Observations	31329	31329	31329
Year*Industry FE	Yes		Yes
Year*Island FE		Yes	Yes
Kabu**Pdtybin**Industry FE	Yes	Yes	Yes
*Pdtybin**time	Yes	Yes	Yes
Clustering	bin*kabu*year	bin*kabu*year	bin*kabu*year

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome is log(value added output) (c) $PdtybinS^{2001} * Temperature$ are the interaction terms of the firm's pre-period within-industry productivity ranks and yearly average temperature (d) Controls for $PdtybinS^{2001} * Rain$ and $PdtybinS^{2001} * Humidity$ are omitted from the table.

On the combined margins, we observe aggregate output redistribution towards the most productive firms, illustrating a "pro-competitive" effect. In the next subsection, I present firm-level intensive margin results using the original panel, and provide suggestive evidence that the survival firms behave differently, possibly due to factor switching and other adaptation behavior.

3.3 Factor Substitution and Intensive Margins

Analysis in this subsection focuses on firms remaining in the surveys. First, we look at evidence for factor substitution. Second, I present firm-level intensive margin results and suggest that selection bias is an important consideration when interpreting these estimates.

3.3.1 Factor Substitution

Taking logs on both side, I transform the equilibrium condition in equation 9 in the Theory Appendix to the following equation which directly relates skilled to unskilled labor ratio with the thermal stress function $F(T)$:

$$ln[\frac{k}{l}]_{it} = \beta_0 + \theta_1 F(T)_{it} + r_i + \epsilon_{it} \tag{3}$$

Both the industry-specific input elasticity α_j and the firm-specific productivity draw $z(\omega, j)$ are absorbed in the firm-fixed effect term r_i. As discussed previously, $\theta_1 = \sigma(\rho - 1)$ is assumed to be larger than zero under the "skill-biased productivity" mechanism.

Assuming unskilled worker are more affected by heat as suggested in the physiological literature (Ramsey 1995), a degree increase in temperature would lead to the same percentage change in the skilled to unskilled labor ratio for all firms. In other words, firm-level heterogeneity does not necessarily lead to different factor substitution behavior under temperature shocks. However, if the initially more productive firms have higher air-conditioner penetration rate, the same temperature shock would lead to a smaller decrease in labor productivity $F(T)$ for these firms. As a result, we would observe less factor substitution for more productive firms as temperature increases. Alternatively, if factor adjustment is costly, we may only observe less productive firms switching to skilled workers in order to survive.

I take the original panel and construct initial productivity bins following the procedure in subsection 3.2. To test whether firms adjust factor inputs under temperature shocks, and whether these adjustment responses differ across firm productivity bins, I estimate the following firm fixed-effect model:

$$\begin{aligned} y_{it} = \alpha_0 + \sum_s \alpha_{1s} PdtyBin_{is}^{initial} * Temperature_{it} + \sum_s \alpha_{2s} PdtyBin_{is}^{initial} * Humidity_{it} \\ + \sum_s \alpha_{3s} PdtyBin_{is}^{initial} * Rain_{it} + \beta_s PdtyBin_{is}^{initial} * t + \eta_i + \sigma_{jt} + \gamma_{rt} + \epsilon_{it} \end{aligned} \tag{4}$$

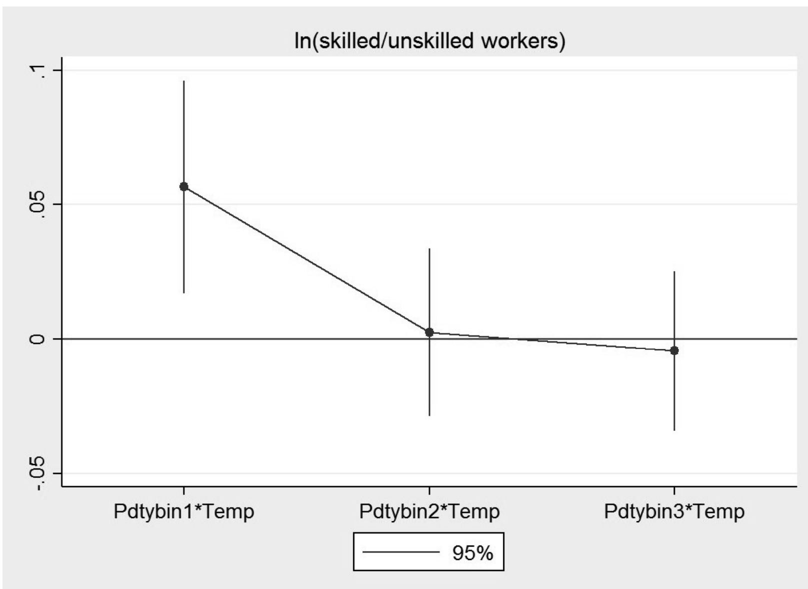
This specification is essentially the same as equation 2 for the combined margins, but without aggregating to the bin*kabupaten*industry level. The fixed effect η_i is therefore at the firm level. Standard errors are clustered two-way, at the firm and kabupaten-by-year level. The outcome of interest, y_{it}, measures the log of skill intensity or alternatively, capital intensity. Capital intensity is defined as the firm's estimated capital over the number of production workers. Capital each year is adjusted using the GDP deflator from the World Bank. Skill intensity is measured as the firm's number of skilled (non-production) workers over the number of unskilled (production) workers.

A valuable feature of the Indonesian industrial surveys is that they report the employment numbers for skilled versus unskilled workers separately. This has been used to study the effect of trade liberalization on wage skill premium (Amiti and Cameron 2012). Following the literature, I use the the terms skilled workers/non-production workers, and unskilled workers/production workers inter-changeably. Although the production/nonproduction division does not map perfectly into skill levels, using the SI, Amiti and Cameron (2012) show that the average level of education attainment is much higher for nonproduction workers than production workers.

In addition to firm fixed effects, I include year*island, year*industry, industry*island fixed effects, and productivity bin specific rainfall, humidity and time trends as before. Column (1) and (2) in Table 4 show results on two kinds of factor substitution within firms: switching from unskilled workers to skilled workers, and switching from unskilled workers to capital. Figure 5 plots the coefficients on the interaction terms of a firm's initial productivity and temperature, corresponding to the specification in column 1. We observe significant factor switching from unskilled to skilled workers, but only for firms with the smallest initial productivity. There is no evidence for factor substitution from unskilled labor to capital. Since the heat shocks defined in this paper are short-run unexpected deviations from regional and industry averages, we do not expect capital adjustment given likely significant capital adjustment costs.

Evidence from the physiological literature suggests that heat exposure may impact the performance of manual tasks more than cognitive tasks[6]. Skilled workers may also work in conditions with better climate control because they engage in higher value-added tasks, as suggested by Indian factory-level evidence from Somanathan et al. (2021). To the extent that the negative labor productivity shock is larger for manual task workers than for cognitive task workers, firms would adapt to heat shocks by switching to skilled workers.

Figure 5: Factor substitution to skilled labor



[6] In a study using matadata, Ramsey (1995) found that for perceptual motor tasks, performance is lowered with high temperature exposure, although no dominant effect of thermal level was found on mental/cognitive tasks.

Table 4: Temperature Shocks and Firm-level Factor Substitution

	(1) lunskilledtoskilled b/se	(2) lcapitaltolabor b/se	(3) lrawimp_ratio b/se
$Pdtybin1^{2001}$*Temperature	0.0565***	0.0124	0.0837**
	(0.020)	(0.024)	(0.041)
$Pdtybin2^{2001}$*Temperature	0.0024	0.0232	0.0560
	(0.016)	(0.023)	(0.035)
$Pdtybin3^{2001}$*Temperature	-0.0045	0.0368	0.0550**
	(0.015)	(0.029)	(0.028)
Observations	212197	153435	35406
Year*Industry FE	Yes	Yes	Yes
Year*Island FE	Yes	Yes	Yes
$Pdtybin$*Time	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome variables are log(unskilled to skilled labor ratio), log(capital to labor ratio), and log(imported to total raw material ratio). (c) $PdtybinS^{2001} * Temperature$ are the interaction terms of the firm's pre-period within-industry productivity ranks and yearly average temperature. (d) Controls for $PdtybinS^{2001} * Rain$ and $Pdtybin1^{2001} * Humidity$ are omitted from the table.

Another feature of the SI is that it includes variables on imported raw materials and total raw materials, which allows us to look at firm switching from domestic to imported intermediate inputs. These measures have been previously used by Amiti and Konings (2007) to examine the effects of input tariff reduction on firm productivity. Column (3) in Table 4 shows the differential impact of temperature shocks on log(imported input/total input). One degree Celsius increase in yearly average temperature relative to the year*industry, year*island, kabupaten mean leads to a 8.4 percentage points increase in the imported input ratio for the initially least productive firms, and a 5.5 percentage points increase for the initially most productive firms. This evidence suggests that temperature shocks may also operate through an agricultural channel and influence domestic input prices, in addition to the physiological channel this paper focuses on.

3.3.2 Intensive Margins

To look at firm-level changes on the intensive margin, I follow the same specification in equation 4. The outcome of interest y_{it} is log(value-added output), or the percentage change in output. This estimator is identified through within-firm output changes for firms in different productivity bins under temperature shocks, conditional on being observed in the SI (survival).

Figure 6 illustrates how value-added output changes as temperature increases for firms in different productivity bins. This corresponds to column (3) in Table 5, where firm fixed effects, year-industry fixed effects and year-island fixed effects are all present. We see the surviving firms with the largest initial productivity have a relative increase in value-added output as temperature increases, while the initially least productive firms incur a marginally significant relative loss in output. Results are similar using alternative measures of productivity based on the control function approach (Olley and Pakes 1996, Rovigatti and Mollisi 2018, Wooldridge 2009), presented in Table A5.

Figure 6: Firm-level value-added output

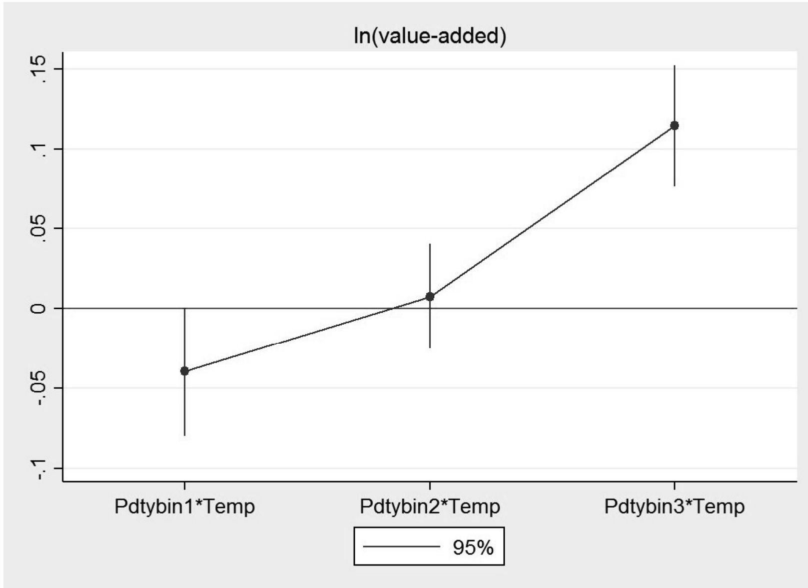


Table 5: Temperature Shocks and Firm-level Output

	(1) ln(vlad) b/se	(2) ln(vlad) b/se	(3) ln(vlad) b/se
$Pdtybin1^{2001}$*Temperature	-0.0234	-0.0363*	-0.0394*
	(0.019)	(0.021)	(0.020)
$Pdtybin2^{2001}$*Temperature	0.0245	0.0083	0.0075
	(0.015)	(0.018)	(0.017)
$Pdtybin3^{2001}$*Temperature	0.1294***	0.1173***	0.1143***
	(0.018)	(0.020)	(0.019)
Observations	238889	238889	238889
Year*Industry FE	Yes		Yes
Year*Island FE		Yes	Yes
Bin*Time	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome variable is log(value added output). (c) $PdtybinS^{2001} * Temperature$ are the interaction terms of the firm's pre-period within-industry productivity ranks and yearly average temperature. (d) Controls for $PdtybinS^{2001} * Rain$ and $Pdtybin1^{2001} * Humidity$ are omitted from the table.

We can compare the previous aggregated combined margin results in Table 3, column (3), with the firm-level intensive margin results in Table 5, column (3). The relative output loss resulting from one degree increase in annual temperature on the initially least productive firms decreases from 10.37 percentage point to a marginally significant 3.9 percentage point. The firm-level intensive margin analysis also yields a larger, more significant relative impact on the initially most productive firms.

One important consideration in interpreting these positive relative impact of heat shocks on firm-level output is the presence of selection bias. In section 3.1, I show that heat shocks lead to firms exiting the survey for the initially less productive firms. In other words, looking at the intensive margin changes at the firm-level would only give us the treatment effect on firms that remained in the surveys. These firms are likely to be better adapted to temperature shocks. The positive impact could also occur as the surviving firms gain larger market share.

4 Mechanisms

Main results in this paper are motivated by micro-level evidence of the physiological channel, that is, the negative labor productivity impact of temperature shocks on manufacturing workers. However, there are many other potential mechanisms through which variations in temperature could affect manufacturing firms. For example, heat shocks could lead to changes in agricultural income and generate local demand shocks (Burke and Emerick 2016). Higher temperature may affect manufacturing firms through input/output linkages with agriculture (Acemoglu et al. 2012). Heat shocks could also lead to sectoral labor reallocation through influencing crop yields (Colmer 2021). In this section, I offer suggestive evidence that the direct labor productivity channel is one of the channels at work in driving the main empirical results.

4.1 Agricultural Input Linkages

A large strand of literature find significant negative impact of temperature shocks on agricultural yields in both OECD and developing countries[7]. If higher temperature raises the price

[7] Fisher et al. (2012), Guiteras (2009), Schlenker and Lobell (2010), Lobell et al. (2011)

of agricultural raw materials, upstream manufacturing firms could face higher cost, reduce their output or exit. To make sure that previous results are not solely driven by changes in raw material prices, I exclude two-digit ISIC sectors which primarily use agricultural input.

Table 6 gives a breakdown of the 2-digit industry codes for all manufacturing firms in the SI. As a robustness check, I exclude firms that are in industries 31, 32, 33 and 34, producing food, textile, wood and paper products. The remaining sectors mainly use raw materials from the metals and minerals sector, which is less affected by temperature shocks.

In Table 7, I implement the same fixed effects model as in equation 2, excluding the four industries which mainly use agricultural input. These coefficients are comparable to previous results in Table 3. One degree Celsius increase in yearly average temperature from the kabupaten, year-industry, year-island average leads to a 12.91 percentage point relative loss in aggregate output for firms in the smallest initial productivity tercile. Effects on firms with the largest initial productivity is statistically insignificant. These results show that the resource reallocation on the aggregate combined margins does not solely operate through linkages with agriculture.

4.2 Agricultural labor reallocation

Temperature shocks could affect manufacturing firm outcomes through shifting labor supply. Jayachandran (2006) and other papers[8] suggest that negative weather shocks would drive down agriculture wages and lead to outmigration. When inter-sectoral mobility is high and inter-regional mobility is low, if temperature shocks push workers out of agriculture, it could potentially lead to an increase in manufacturing labor supply. As a result, manufacturing firms could experience positive impact from temperature shocks due to lower factor prices Colmer (2021). Since the inter-sectoral labor reallocation mechanism is beneficial to the manufacturing sector through the provision of lower wage agricultural labor, it is unlikely to explain differential firm exit and negative results on the combined margins.

[8] Gray and Mueller (2012), Feng et al. (2010, 2012), Munshi (2003)

Table 6: Excluding Sectors Using Agricultural Input

Two-digit Industry code: ISIC Rev.2 code 3
31 - Manufacture of Food, Beverages and Tobacco
32 - Textile, Wearing Apparel and Leather Industries
33 - Manufacture of Wood and Wood Products, Including Furniture
34 - Manufacture of Paper and Paper Products, Printing and Publishing
35 - Manufacture of Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products
36 - Manufacture of Non-Metallic Mineral Products, exctp Products of Petroleum and Coal
37- Basic Metal Industries
38 - Manufacture of Fabricated Metal Products, Machinery and Equipment
39 - Other Manufacturing Industries

Table 7: Temperature Shocks and Combined Effects on Output (Robustness)

	(1) ln(vlad) b/se	(2) ln(vlad) b/se	(3) ln(vlad) b/se
$Pdtybin1^{2001}$*Temperature	-0.0837*	-0.1246**	-0.1291**
	(0.051)	(0.055)	(0.055)
$Pdtybin2^{2001}$*Temperature	0.0131	-0.0360	-0.0395
	(0.053)	(0.056)	(0.056)
$Pdtybin3^{2001}$*Temperature	0.0627	0.0211	0.0129
	(0.055)	(0.059)	(0.059)
Observations	12849	12849	12849
Year*Industry FE	Yes		Yes
Year*Island FE		Yes	Yes
Kabu*Bin*Industry FE	Yes	Yes	Yes
Bin*Time	Yes	Yes	Yes
Clustering	bin*kabu*year	bin*kabu*year	bin*kabu*year

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome variable is log(value added output). (c) $PdtybinS^{2001} * Temperature$ are the interaction terms of the firm's pre-period within-industry productivity ranks and yearly average temperature. (d) Controls for $PdtybinS^{2001} * Rain$ and $Pdtybin1^{2001} * Humidity$ are omitted from the table.

5 Conclusion

Climate change has significant consequences for industrial activities in developing countries. Yet how increasing temperature affects firms of different productivity through various margins of adjustment remains poorly understood. In this paper, I show how within-industry firm heterogeneity matters for extensive margin adjustment and output redistribution as temperature increases.

Exploiting rich variations in local level exposure to heat shocks and within industry productivity differences across a panel of Indonesian manufacturing firms, I show that the initially less productive firms are more likely to exit the surveys as temperature increases. These extensive margin changes highlight the presence of selection bias. In the Indonesian context, focusing on intensive margin analysis at the firm-level alone could lead to underestimation of aggregate impact. On the combined margins, value-added output reallocate from the initially less to more productive firms within each industry. Among surviving firms, we observe factor substitution from unskilled to skilled workers, and firms switching from domestic to foreign intermediate input. Finally, I show that these results are consistent with a simplified heterogeneous firm model with skill-biased production function based on Burstein and Vogel (2017), incorporating a direct labor productivity channel. This paper also offers a basis for firm-specific damage functions potentially explaining observed aggregate heterogeneity in climate change impact.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A. and Tahbaz-Salehi, A. (2012), 'The network origins of aggregate fluctuations', Econometrica **80**(5), 1977–2016.

Acevedo, S., Mrkaic, M., Novta, N., Poplawski-Ribeiro, M., Pugacheva, E., Topalova, P. and IMF (2017), 'The effects of weather shocks on economic activity: How can low-income countries cope', World Economic Outlook .

Adhvaryu, A., Kala, N. and Nyshadham, A. (2020), 'The light and the heat: Productivity co-benefits of energy-saving technology', Review of Economics and Statistics **102**(4), 779–792.

Amiti, M. and Cameron, L. (2012), 'Trade liberalization and the wage skill premium: Evidence from indonesia', Journal of International Economics **87**(2), 277–287.

Amiti, M. and Konings, J. (2007), 'Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia', American Economic Review **97**(5), 1611–1638.

Auffhammer, M. (2011), 'The relationship between air conditioning adoption and temperature', unpublished, UC Berkeley, Department of Agriculture and Resource Economics .

Bernard, A. B. and Jensen, J. B. (1999), 'Exceptional exporter performance: cause, effect, or both?', Journal of international economics **47**(1), 1–25.

Bernard, A. B., Jensen, J. B., Redding, S. J. and Schott, P. K. (2007), 'Firms in international trade', Journal of Economic perspectives **21**(3), 105–130.

Bernard, A. B., Jensen, J. B., Redding, S. J. and Schott, P. K. (2012), 'The empirics of firm heterogeneity and international trade', Annu. Rev. Econ. **4**(1), 283–313.

Burke, M. and Emerick, K. (2016), 'Adaptation to climate change: Evidence from us agriculture', American Economic Journal: Economic Policy **8**(3), 106–40.

Burke, M., Hsiang, S. M. and Miguel, E. (2015), 'Global non-linear effect of temperature on economic production', Nature **527**(7577), 235–239.

Burstein, A. and Vogel, J. (2017), 'International trade, technology, and the skill premium', Journal of Political Economy **125**(5), 1356–1412.

Colmer, J. (2021), 'Temperature, labor reallocation, and industrial production: Evidence from india', American Economic Journal: Applied Economics **13**(4), 101–24.

Dell, M., Jones, B. F. and Olken, B. A. (2012), 'Temperature shocks and economic growth: Evidence from the last half century', American Economic Journal: Macroeconomics **4**(3), 66–95.

Dell, M., Jones, B. F. and Olken, B. A. (2014), 'What do we learn from the weather? the new climate-economy literature', Journal of Economic Literature **52**(3), 740–98.

Feng, S., Krueger, A. B. and Oppenheimer, M. (2010), 'Linkages among climate change, crop yields and mexico–us cross-border migration', Proceedings of the national academy of sciences **107**(32), 14257–14262.

Feng, S., Oppenheimer, M. and Schlenker, W. (2012), Climate change, crop yields, and internal migration in the united states, Technical report, National Bureau of Economic Research.

Fisher, A. C., Hanemann, W. M., Roberts, M. J. and Schlenker, W. (2012), 'The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment', American Economic Review **102**(7), 3749–60.

Graff Zivin, J. and Neidell, M. (2014), 'Temperature and the allocation of time: Implications for climate change', Journal of Labor Economics **32**(1), 1–26.

Gray, C. L. and Mueller, V. (2012), 'Natural disasters and population mobility in bangladesh', Proceedings of the National Academy of Sciences **109**(16), 6000–6005.

Guiteras, R. (2009), 'The impact of climate change on indian agriculture', Manuscript, Department of Economics, University of Maryland, College Park, Maryland .

Hsiang, S. M. (2010), 'Temperatures and cyclones strongly associated with economic production in the caribbean and central america', Proceedings of the National Academy of sciences **107**(35), 15367–15372.

Hsiang, S., Oliva, P. and Walker, R. (2020), 'The distribution of environmental damages', Review of Environmental Economics and Policy .

Hsieh, C.-T. and Olken, B. A. (2014), 'The missing" missing middle"', Journal of Economic Perspectives **28**(3), 89–108.

Jayachandran, S. (2006), 'Selling labor low: Wage responses to productivity shocks in developing countries', Journal of political Economy **114**(3), 538–575.

Jones, B. F. and Olken, B. A. (2010), 'Climate shocks and exports', American Economic Review **100**(2), 454–59.

Kassem, D. (2018), 'Does electrification cause industrial development', Grid Expansion and Firm Turnover in Indonesia (052).

Kjellstrom, T., Holmer, I. and Lemke, B. (2009), 'Workplace heat stress, health and productivity–an increasing challenge for low and middle-income countries during climate change', Global health action **2**(1), 2047.

Lobell, D. B., Schlenker, W. and Costa-Roberts, J. (2011), 'Climate trends and global crop production since 1980', Science **333**(6042), 616–620.

Melitz, M. J. (2003), 'The impact of trade on intra-industry reallocations and aggregate industry productivity', econometrica **71**(6), 1695–1725.

Munshi, K. (2003), 'Networks in the modern economy: Mexican migrants in the us labor market', The Quarterly Journal of Economics **118**(2), 549–599.

Niemelä, R., Hannula, M., Rautio, S., Reijula, K. and Railio, J. (2002), 'The effect of air temperature on labour productivity in call centres—a case study', Energy and buildings **34**(8), 759–764.

Olley, G. S. and Pakes, A. (1996), 'The dynamics of productivity in the telecommunications equipment', Econometrica **64**(6), 1263–1297.

Park, J. (2017), 'Heat stress and human capital production', Unpublished, Harvard University, Cambridge, MA .

Poschke, M. (2018), 'The firm size distribution across countries and skill-biased change in entrepreneurial technology', American Economic Journal: Macroeconomics **10**(3), 1–41.

Ramsey, J. D. (1995), 'Task performance in heat: a review', Ergonomics **38**(1), 154–165.

Rovigatti, G. and Mollisi, V. (2018), 'Theory and practice of total-factor productivity estimation: The control function approach using stata', The Stata Journal **18**(3), 618–662.

Schlenker, W. and Lobell, D. B. (2010), 'Robust negative impacts of climate change on african agriculture', Environmental Research Letters **5**(1), 014010.

Seppanen, O., Fisk, W. J. and Lei, Q. (2006), 'Effect of temperature on task performance in office environment'.

Somanathan, E., Somanathan, R., Sudarshan, A. and Tewari, M. (2021), 'The impact of temperature on productivity and labor supply: Evidence from indian manufacturing', Journal of Political Economy **129**(6), 1797–1827.

Traore, N. and Foltz, J. (2018), 'Temperatures, productivity, and firm competitiveness in developing countries: Evidence from africa', University of Wisconsin Madison .

Wooldridge, J. M. (2009), 'On estimating firm-level production functions using proxy variables to control for unobservables', Economics letters **104**(3), 112–114.

Zander, K. K., Botzen, W. J., Oppermann, E., Kjellstrom, T. and Garnett, S. T. (2015), 'Heat stress causes substantial labour productivity loss in australia', Nature climate change **5**(7), 647–651.

Zhang, P., Deschenes, O., Meng, K. and Zhang, J. (2018), 'Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants', Journal of Environmental Economics and Management **88**, 1–17.

Theory Appendix

I begin with a model where firms are monopolistic competitive and derive how firms with different productivity draws optimally choose their factors of production under temperature shocks. To capture correlations between within-industry firm productivity and skilled labor intensity found in Section 2, I adopt a production function developed by Burstein and Vogel (2017) where less productive firms are also less skilled labor intensive.

To the original production function, I incorporate temperature shocks faced by the firm modeled as a drop in labor productivity of unskilled workers. This modeling choice is motivated by the empirical literature on thermal stress and labor productivity. Heat leads to fatigue, lower performance in physical tasks, and poor decision making (Zander et al. 2015, Graff Zivin and Neidell 2014, Niemelä et al. 2002). Previous studies also suggest high temperature days may impact unskilled workers more than skilled workers, due to both physiology [9] and differential adaptation. Collecting daily Indian factory-level data, Somanathan et al. (2021) find that skilled workers operate in environment with better climate control, consistent with a larger productivity drop for low value-added assembly line workers. There are many other channels through which manufacturing firms could be affected by heat shocks, which I discuss in Section 5. In this stylized model, focusing on the direct labor productivity channel, I show how within-industry firm heterogeneity in productivity could condition firm responses to heat shocks.

Temperature Shocks

There are two factors of production, skilled and unskilled labor. Temperature shocks influence manufacturing production through affecting unskilled labor productivity. In the stylized model, I assume only unskilled workers are affected by heat shocks due to physiological reasons and worse climate control. Specifically, temperature enters the firm's production function through affecting unskilled labor productivity, $F(T)$, which is modeled flexibly to allow for possible nonlinear relationship between temperature and labor productivity. Numerous empirical studies suggest that $F(T)$ is single-peaked, with a global maximum at the ideal body temperature point t_0, although the value of t_0 could differ by population and

[9] Using matadata from the physiological literature, Ramsey (1995) found that for perceptual motor tasks, performance is significantly lowered with high temperature exposure, although less dominant effect was found for mental tasks.

geographic characteristics.

Demand

As in Melitz (2003), the representative consumer has CES utility over a continuum of goods, each produce by a single firm, indexed by ω.

$$U = [\int_{\omega \in \Omega} q(\omega)^{\sigma} d\omega]^{1/\sigma} \tag{5}$$

Consumption varieties has the elasticity of substitution σ. Here I assume that consumption goods are substitutes, i.e. $\sigma > 1$. Solving the consumer's utility maximization problem, we can derive the demand function for an individual variety ω, given by $q(\omega) = p(\omega)^{-\sigma} R P^{\sigma-1} = \Gamma p(\omega)^{-\sigma}$.

R is the national income, and P is the national price index. For now in the partial equilibrium analysis, both are assumed to be fixed and taken as exogenous under regional temperature shocks. In addition, I assume that there's a numeraire good in an outside agricultural sector which fixes wage.

Production

Firms are monopolistic competitive and each produces variety (ω, j) where j is the industry index. There are two factors of production, skilled labor k, and unskilled labor l. Let ρ denote the elasticity of substitution between factors. I assume for now that factors are substitutes with the elasticity $\rho > 1$. Each industry j faces a sector total factor productivity $A(j)$.

In order to produce, firms have to incur a fixed cost f. Upon entry, each firm has a productivity draw, from an i.i.d. distribution of random variables $z(\omega, j) = u^{-\theta}$, where u is exponentially distributed with mean and variance 1.

To capture the empirical fact that less productive firms are also less skilled labor intensive, I adopt a production function with "skill-biased productivity" in Burstein and Vogel (2017).

$$y = A(j) z(\omega, j) * [\alpha_j^{\frac{1}{\rho}} (z(\omega, j)^{\frac{\phi}{2}} k)^{\frac{\rho-1}{\rho}} + (1-\alpha_j)^{\frac{1}{\rho}} (z(\omega, j)^{\frac{-\phi}{2}} F(T) l)^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}} \tag{6}$$

α_j is the industry input elasticity. $z(\omega, j)$ represents within industry productivity. Both $\alpha_j \in (0,1)$ and $\phi \in [-2,2]$ shape the skill-intensity of production.

In addition to the firm's initial productivity draw $z(\omega, j)$, temperature shapes unskilled labor productivity through $F(T)$. Beyond the ideal body temperature point, increases in temperature reduces effective unskilled labor. The production function given in equation 6 deviates from the classic CES production function by incorporating the "skill-biased productivity" mechanism, assuming $\phi(\rho - 1) > 0$. This is reflected in the equilibrium condition that firms with a higher productivity draw $z(\omega, j)$ also has a higher skilled to unskilled labor ratio.

Price-Setting

The production function given in equation 6 has constant returns to scale and a constant variable cost $c(r, w, z)$. The firm therefore sets its price p, maximizing profit according to: $pq(\omega) - cq(\omega) - f = \Gamma p^{1-\sigma} - c(r, w, z)\Gamma p^{-\sigma} - f$. From the profit function, we can derive the optimal price: $p(\omega)^* = \frac{\sigma}{\sigma-1}c$. As in Melitz (2003), we also have that optimal price is a constant mark-up of the constant variable cost.

In the monopolistic competition setting with CES preferences, the price of a variety (ω, j) does not depend on the number of competing firms in the market. The price elasticity of demand for any variety also does not respond to changes in the number or prices of competing varieties.

For now, I continue the baseline model with the settings in Melitz (2003), the optimal quantity produced is:

$$q(\omega) = \Gamma(\frac{\sigma}{\sigma - 1}c)^{-\sigma} = Gc^{-\sigma} \tag{7}$$

where $G = \Gamma(\frac{\sigma}{\sigma-1})^{-\sigma} = RP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{-\sigma}$ and the firm's profit is $\pi(\omega)^* = \frac{1}{\sigma-1}Gc^{1-\sigma} - f$.

Expenditure Minimization

To derive the firm's optimal factor choices, I solve the following expenditure minimization problem. A firm in industry j, producing variety ω, faces the following cost minimization problem upon entry:

$$\min_{k,l} e = wl + rk + f, s.t : y = x \tag{8}$$

From the equilibrium condition of the cost minimization problem, I derive the skilled-to-unskilled labor ratio equation which illustrates the "skill-biased productivity" mechanism in the production function.

$$\frac{k(\omega, j)}{l(\omega, j)} = (\frac{r}{w})^{-\rho} \frac{\alpha_j}{1-\alpha_j} z(\omega, j)^{\phi(\rho-1)} F(T)^{1-\rho} \tag{9}$$

Here we see that when $\phi(\rho-1) > 0$ as assumed before, firms with a higher productivity draw $z(\omega, j)$ will have a higher skilled-to-unskilled labor ratio in equilibrium, thus productivity is skill-biased. Assuming factors are substitutes, or $\rho > 1$, we see that the firm switch from unskilled to skilled labor as temperature rises. The equilibrium-level of skilled labor intensity is shaped by both industry parameters, ϕ and ρ, as well as the within industry firm-specific productivity, $z(\omega, j)$, which is the key parameter for comparative statics and empirical analysis.

The Zero Profit Cutoff Condition

Next, I look at how temperature shocks impact firm exit and regional productivity cutoffs. From optimal price-setting, we know that each firm has the maximized profit $\pi(z) = \frac{1}{\sigma-1} Gc(z, T)^{1-\sigma} - f$. We can show that $c(z, T)$ is monotonically decreasing in z, and monotonically increasing in T.

For any fixed temperature T, there exist a productivity cutoff z^* such that $\pi(z^*) = 0$, so that any firm with a productivity draw $z < z^*$ will immediately exit and never produce. The zero cutoff productivity z^* is given by the condition:

$$c(z^*) = [\frac{f(\sigma-1)}{RP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{-\sigma}}]^{\frac{1}{1-\sigma}} = [\frac{f(\sigma-1)}{G}]^{\frac{1}{1-\sigma}} \tag{10}$$

5.1 Comparative Statics

Prediction 1: *Less productive firms are more likely to exit under heat shocks.*

Intuitively, as temperature increases in a region and everything else staying the same, unit cost of production also increases. From equation 10 we see that the marginal firm which satisfies the zero profit cutoff condition has a fixed unit cost $c(z^*)$. Since unit cost as a function of the productivity cutoff $c(z^*)$ is pinned down by deep parameters in the model and has to remain the same, the productivity cutoff z^* must increase. Thus less productive firms in a region-year which experienced temperature shocks will be more likely to exit through the labor productivity channel.

Prediction 2: *Conditional on remaining in produciton, less productive firms will have larger percentage output loss from heat shocks.*

Prediction 3: *As temperature increases, firms will re-optimize factors by switching from unskilled workers to skilled workers*

Appendix A: Additional Tables

Table A1: Differential firm exit: alternative productivity measures

	(1) exit b/se	(2) exit b/se	(3) exit b/se
$Pdtybin1$*Temperature	2.0744***	1.8537**	1.8945**
	(0.749)	(0.818)	(0.819)
$Pdtybin2$*Temperature	0.8264	0.6740	0.6827
	(0.741)	(0.807)	(0.807)
$Pdtybin3$*Temperature	0.6043	0.5023	0.4287
	(0.716)	(0.776)	(0.775)
Observations	96173	96173	96173
Year*Industry FE	Yes	Yes	Yes
Year*Island FE		Yes	Yes
Industry*Island FE			Yes
Kabupaten FE	Yes	Yes	Yes
$Pdtybin*Age^{2001}$	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome is a binary variable on exit. (c) $PdtybinS * Temperature$ are the interaction terms of the firm's within-industry productivity ranks and yearly average temperature, where productivity is estimated following the control function approach (Wooldridge, 2009) (Rovigatti and Mollisi, 2016) (d) Controls for $PdtybinS * Rain$ and $PdtybinS * Humidity$ and duration dummies are omitted from the table. (e) All coefficients are multiplied by 100

Table A2: Differential firm exit: without $Pdtybin{*}Age^{2001}$ FEs

	(1)	(2)	(3)
	exit	exit	exit
	b/se	b/se	b/se
$Pdtybin1$*Temperature	1.3880**	1.4503**	1.2632*
	(0.672)	(0.674)	(0.741)
$Pdtybin2$*Temperature	0.9072	0.9677	0.7814
	(0.676)	(0.679)	(0.749)
$Pdtybin3$*Temperature	0.6755	0.7035	0.5440
	(0.658)	(0.659)	(0.738)
Observations	96173	96173	96173
Year*Industry FE	Yes	Yes	Yes
Industry*Island FE		Yes	Yes
Year*Island FE			Yes
Kabupaten FE	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome is a binary variable on exit. (c) $PdtybinS * Temperature$ are the interaction terms of the firm's within-industry productivity ranks and yearly average temperature, where productivity is estimated following the control function approach (Wooldridge, 2009) (Rovigatti and Mollisi, 2016) (d) Controls for $PdtybinS * Rain$ and $PdtybinS * Humidity$ and duration dummies are omitted from the table(e) All coefficients are multiplied by 100

Table A3: Differential firm exit: alternative cutoff

	(1) exit b/se	(2) exit b/se	(3) exit b/se	(4) exit4 b/se	(5) exit5 b/se	(6) exit6 b/se
$Pdtybin1$*Temperature	2.0355***	1.8777***	2.1981***	0.4574	0.3664	0.8161
	(0.544)	(0.578)	(0.609)	(0.685)	(0.709)	(0.703)
$Pdtybin2$*Temperature	1.4580**	1.5742***	1.5560**	0.0575	0.1618	0.3039
	(0.575)	(0.602)	(0.609)	(0.725)	(0.736)	(0.714)
$Pdtybin3$*Temperature	0.9596*	0.9252	0.9673	-0.3303	-0.3714	-0.1694
	(0.563)	(0.576)	(0.591)	(0.665)	(0.666)	(0.638)
Observations	50789	43509	38475	50789	43509	38475
Employee Cutoff	40	50	60	40	50	60
Industry*Year Time Trends	Yes	Yes	Yes			
Island*Year Time Trends	Yes	Yes	Yes			
Year*industry FE				Yes	Yes	Yes
Year*Island FE				Yes	Yes	Yes
Industry*IslandFE	Yes	Yes	Yes	Yes	Yes	Yes
Kabupaten FE	Yes	Yes	Yes	Yes	Yes	Yes
$Pdtybin*Age^{2001}$	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear
ymean	5.231	5.066	5.006	5.231	5.066	5.006

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome is a binary variable on exit. (c) $PdtybinS*Temperature$ are the interaction terms of the firm's within-industry productivity ranks and yearly average temperature, where productivity is estimated following the control function approach (Wooldridge, 2009) (Rovigatti and Mollisi, 2016) (d) Controls for $PdtybinS*Rain$ and $PdtybinS*Humidity$ and duration dummies are omitted from the table (e) All coefficients are multiplied by 100

Table A4: Differential firm exit: lead shocks

	(1) exit b/se	(2) exit b/se	(3) exit b/se
$Pdtybin1$*Temperature	2.6877***	2.3122**	2.3328**
	(1.004)	(1.147)	(1.146)
$Pdtybin2$*Temperature	0.8112	0.6026	0.6039
	(0.973)	(1.124)	(1.124)
$Pdtybin3$*Temperature	0.7364	0.7674	0.7118
	(0.993)	(1.173)	(1.172)
$Pdtybin1$*F.Temperature	-0.7279	-0.5162	-0.4933
	(0.707)	(0.790)	(0.789)
$Pdtybin2$*F.Temperature	0.0032	0.0977	0.1060
	(0.690)	(0.795)	(0.797)
$Pdtybin3$*F.Temperature	-0.1701	-0.2859	-0.3059
	(0.792)	(0.890)	(0.890)
Observations	96173	96173	96173
Year*Industry FE	Yes	Yes	Yes
Year*Island FE		Yes	Yes
Industry*Island FE			Yes
Kabupaten FE	Yes	Yes	Yes
$Pdtybin*Age^{2001}$	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear
ymean	8.123	8.123	8.123

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome is a binary variable on exit. (c) $PdtybinS * Temperature$ are the interaction terms of the firm's within-industry productivity ranks and yearly average temperature, where productivity is estimated following the control function approach (Wooldridge, 2009) (Rovigatti and Mollisi, 2016) (d) Controls for $PdtybinS * Rain$ and $PdtybinS * Humidity$ and duration dummies are omitted from the table(e) All coefficients are multiplied by 100

Table A5: Firm-level output: alternative productivity measures

	(1) exit b/se	(2) exit b/se	(3) exit b/se
*Pdtybin*1*Temperature	0.0130	0.0074	0.0035
	(0.017)	(0.019)	(0.018)
*Pdtybin*2*Temperature	0.0213	0.0172	0.0120
	(0.017)	(0.019)	(0.018)
*Pdtybin*3*Temperature	0.0566***	0.0521***	0.0474**
	(0.018)	(0.020)	(0.020)
Observations	204604	204604	204604
Year*Industry FE	Yes		Yes
Year*Island FE		Yes	Yes
Bin*Time	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear

(a) *p<0.10, **p<0.05, ***p<0.01 (b) The outcome variable is log(value added output). (c) $PdtybinS * Temperature$ are the interaction terms of the firm's within-industry productivity ranks and yearly average temperature, where productivity is estimated following the control function approach (Wooldridge, 2009) (Rovigatti and Mollisi, 2016) (d) Controls for $PdtybinS * Rain$ and $PdtybinS * Humidity$ and duration dummies are omitted from the table