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

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December 8, 2017

Abstract

Are less productive firms in developing countries disproportionately affected by climate change both along the intensive and extensive margin? This paper provides an answer in the context of Indonesia using gridded daily weather data and the Indonesian firm-level survey, the Statistik Industri. In a heterogeneous firm model with capital-biased productivity, I incorporate the thermal stress channel and illustrate how less productive firms decides on production and re-optimize factor intensity as temperature increases. Empirically, I highlight the presence of survival bias intrinsic to firm-level intensive margin analysis. I found that: First, under heat shocks, the initially less productive firms are more likely to exit. Second, on the aggregate, resources reallocate from less to more productive firms within industries. Among surviving firms,, we observe factor substitution from unskilled to skilled workers, and firms switching from domestic to foreign intermediate input when temperature increases. The initially more productive firms that survived also incur output gain under heat shocks possibly due to shifts in market structure and/or selection. These evidence highlight the importance of incorporating the manufacturing sector in the damage functions of traditional Integrated Assessment Models such as DICE/FUND. It also provides a potential explanation as to why poor countries are more affected by temperature shocks from the perspective of firm size distribution.

*I thank my advisors Gordon Hanson and Richard Carson for advice and encouragement, Laura Beaudin, Julie Cullen, Gordon Dahl, David Victor, Roger Gordon, Teevrat Garg, Mark Jacobsen, Jeff Shrader, Josh Graff-Zivin, and many others at the UCSD applied micro seminar and the WEAI for comments. I'm grateful to Sam Bazzi for generously sharing data.

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1 Introduction

Future 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 local economic activities, and in particular, industrial production. Such an assessment is perhaps especially pressing for less-developed countries where the adverse consequences of climate change concentrate (World Economic Outlook, IMF, 2017).

In this paper, I show that there is important within-industry heterogeneity in how manufacturing firms are affected by climate change in the context of Indonesia, and that the initially less productive firms incur significantly more damage. Further, results on differential firm exit highlight the presence of survival bias in firm-level intensive margin analysis. On the combined extensive (firm exit) and intensive margin (firm output), temperature shocks lead to a within-industry resource redistribution from the initially less to more productive firms. I illustrate the intuition for this result building on a heterogeneous firm model with capital-biased technology based on Burstein and Vogel (2016), and incorporate temperature shocks through the labor productivity channel.

Given the ample evidence at the aggregate-level on the disproportional impact of climate change on less-developed countries [1], one important challenge lies in identifying the sources of such heterogeneity in damages (Hsiang, Oliva, and Walker, 2017). In this paper, I show in a simple model that heterogeneity in productivity across firms within sectors give rise to individual damage functions based on initial firm-level attributes, which alone could generate differences in observed damages even without variations in exposure to heat shocks or non-linear effects.

The model (Burstein and Vogel, 2016), incorporating a mechanism of "capital-biased productivity", captures the empirical fact that more productive firms within each sector are also less labor intensive. This approach derives different individual damage functions addressing important within sector firm heterogeneity and the strong correlation between firm-level attributes. Intuitively, the initially less productive firms within each industry, which experience significantly

[1] Dell, Jones and Olken (2012), Burke, Hsiang, and Miguel (2015a), Jones and Olken (2010)

more damage from heat shocks, are also the initially most labor intensive. Regional temperature shocks and associated labor productivity decrease lead to a rise in the zero-profit cutoff productivity level, and push the least productive firms to exit the market. On the aggregate, heat shocks reshuffle industrial output from less productive to more productive firms within sectors.

The firm-level survey in Indonesia offers an opportunity to test predictions on differential firm exit and within industry resource reallocation. Indonesia is an important developing economy which is 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 productivity, capital and labor intensity. This paper exploits the rich variations in kabupaten-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 may be 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 [2] 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. These data point to a relatively low air conditioner penetration rate at the initial period of our analysis in Indonesia, as one may expect in a developing country context.

In terms of mechanisms, a key 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 poorer decision making. Higher temperature is also associated with lower measured and self-reported work performance, as well as substantial change in labor supply [3].

[2] Auffhammer (2011)

[3] Zander et al.(2015), Graff-Zivin and Neidell (2014), Niemela et al.(2002), Seppanen, Fisk, and Lei (2006), Kjellstrom et al.(2009), Park (2017)

Using daily micro-data from selected Indian plants, Somanathan et al., (2014) and Adhvaryu et al., (2016) show labor productivity significantly decreases with temperature in a manufacturing setting. While there are many other channels through which heat shocks could affect manufacturing firms [4], I offer evidence that the direct physiological channel is important for firm-level outcomes in the Indonesian context. When excluding all ISIC sectors which primarily use agricultural input, I found slightly more magnified results on resource reallocation. Consistent with the hypothesis that manual labor are more affected by thermal stress than skilled labor, we also observe that less productive firms which survived substitute unskilled workers with skilled workers.

This paper is also closely related with the recent literature examining the impact of temperature shocks on manufacturing firm-level outcomes. Deschenes et al., (2017) found large negative effects of temperature on Chinese firm-level manufacturing output, mainly driven by decreases in total factor productivity. Somanathan et al., (2014) found a 2.8 % decrease in Indian firm-level manufacturing output per one degree (Celsius) change in average annual temperature. Colmer (2017) found that higher temperature leads to a net increase in manufacturing output in flexible labor markets and have no significant impact in rigid labor markets in India.

Motivated by the salience of within-industry heterogeneity among Indonesian manufacturing firms, I show theoretically that an increase in temperature leads to differential exit across firms within each sector, pushing out the initially less productive firms. On the aggregate, heat shocks also generate resource redistribution from less to more productive firms within industries. However, these predictions do not suggest that temperature increases are welfare enhancing. One degree (Celsius) increase in yearly average temperature away from the kabupaten mean leads to a significant 10.37% decrease in aggregate output for less productive firms, but only a marginally significant gain for more productive firms. Like many other developing countries, Indonesia has a firm size distribution with a heavy left tail, suggesting heat shocks would likely be welfare reducing to the manufacturing sector on the aggregate, despite of its pro-competitive effect.

[4] Such as: the agricultural income and local demand channel (Burke and Emerick, 2016), the agricultural input/output linkage channel (Acemoglue, et al., 2012), the sectoral labor reallocation channel (Colmer, 2017).

Empirically, instead of focusing on firm-level intensive margin changes alone, this paper shows that heat shocks lead to differential firm exit, highlighting the presence of survival bias for intensive margin analysis in the Indonesian context. A positive and significant coefficient of temperature on firm-level output in the unbalanced panel could result from selection and/or shifts in market structure, accompanied by significant losses for firms that exit. Also distinct from existing work on climate change heterogeneity at the firm-level, I focus on heterogeneity across firms *within sectors* consistent with firm-level empirical facts. This approach simultaneously addresses the silence of the strong correlation between firm-level attributes and allows us to examine resource reallocation within sectors.

Findings in this paper 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[5]. A number of studies in the climate change literature estimate an approximate 2 percent industrial output loss per 1°C increase in temperature, but only in poor countries. [6] Accounting for the non-linear effect of temperature could explain this disproportional impact, given the strong negative correlation between baseline income and baseline temperature. (Burke et al., 2015) Results in this paper suggest that less productive firms, which are more prevalent in poor countries, may be more vulnerable due to underlying productivity-specific damage function when temperature increases. The aggregate loss may be larger for countries whose firm size distribution is skewed to the left in the absence of adaptation.

Section 2 introduces data sources and relevant empirical facts. Section 3 outlines a simple heterogeneous firm model with temperature shocks and comparative statics. Section 4 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 survival. Section 5 discusses underlying mechanism. Section 6 concludes.

[5](Hsieh and Olken, 2014) (Poschke, 2017)

[6]Dell, Jones and Olken (2012), Jones and Olken (2010)

2 Data Background and Empirical Facts

2.1 Data Background

This paper relies on four data sources. 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 establishment-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. I explore variables on employment, value-added output, domestic and foreign input, industry category and other firm-level balance sheet information through the period 2001-2012.

Each establishment in the SI is matched with an Indonesian administrative 2-level regency, or *kabupaten*. I then use GIS data from the GADM database of Global Administrative Areas to obtain the coordinates of the centroid of each kabupaten. 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.

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.

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 capital-biased productivity in Section 3. Second, I show descriptive facts on the spatial distribution of regional temperature variations and industrial clusters.

A key contribution of this paper is to show how within-industry firm heterogeneity condition firms' responses to regional temperature shocks. Before diving into formal analysis, I present facts on the salience of heterogeneity across firms within each sector.

Table 1 gives the standardized coefficients from regressions of within-industry firm productivity on a series of firm-level covariates using 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 productivity 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.[7]

Figure 1 illustrates how firm labor intensity, measured by total wage bill over total 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. Firm-level labor intensity decreases as within-industry productivity measure increases. This suggests that within-industry firm heterogeneity gives rise to important sources of variations in labor intensity.

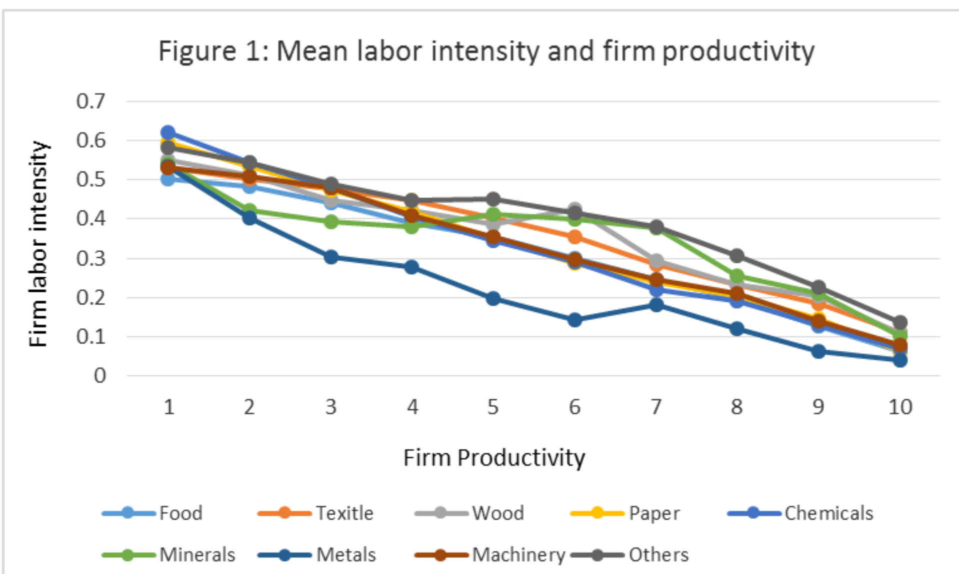
In Section 3, I adopt a heterogeneous firm model developed by Vogel and Burstein (2016) with capital-biased productivity motivated by these facts. Intuitively, heat shocks working through the labor productivity channel would have heterogeneous response from firms with different initial (within-industry) productivity draws, along with other firm-level covariates.

[7] A large body of empirical and theoretical trade literature has highlighted the importance of considering firm heterogeneity in response to changes in trade barriers and product market shocks. (Bernard and Jansen, 1999) (Melitz, 2003) (Chaney, 2008) (Bernard et al., 2012)

Table 1: Standardized coefficients of productivity on firm characteristics

	Productivity (V.A./employee)			Obs
	(1)	**(2)**	**(3)***	
Total V.A.	.3732**	.3659**	.3732**	72,153
	(.1670)	(.1646)	(.1670)	
Total Sales	.3387***	.3276***	.1474***	72,076
	(.1020)	(.0998)	(.0378)	
Exporter status	.1032***	.1276***	.1603***	56,862
	(.0091)	(.0101)	(.0111)	
Capital/Prd employee	0.0271	.0257	.0206**	71,756
	(.0238)	(.0230)	(.0085)	
Nonprd/Prd employees	.0891***	.0764***	.0667***	72,132
	(.0194)	(.0174)	(.0136)	
Labor Intensity (Wage bill/V.A.)	-.2916***	-.2811***	-.2406***	72,153
	(.0099)	(.0095)	(.0060)	
Wages/employee	.4256***	.4123***	.2681***	72,153
	(.0355)	(.0388)	(.0114)	
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



To illustrate the variation 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. Many regencies in the East Java region where manufacturing firms are clustered have a higher average temperature baseline, and experienced warming through the sample period. 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.

Figure 2

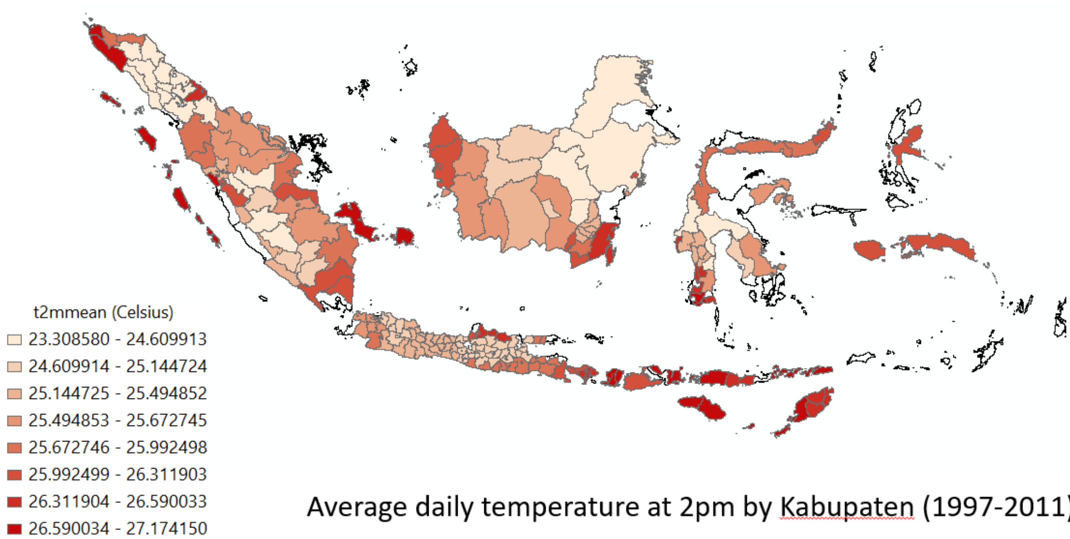


Figure 3: Yearly average temperature difference between 2012 and 1997

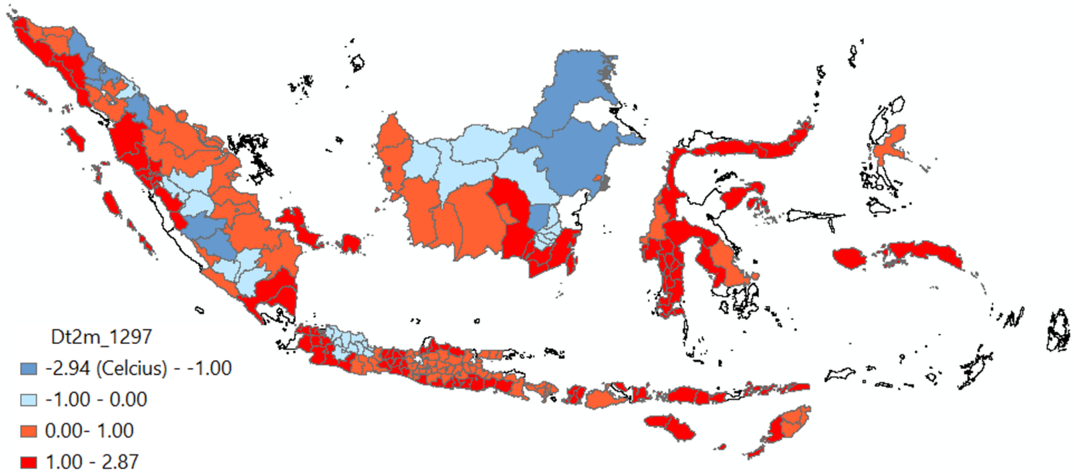
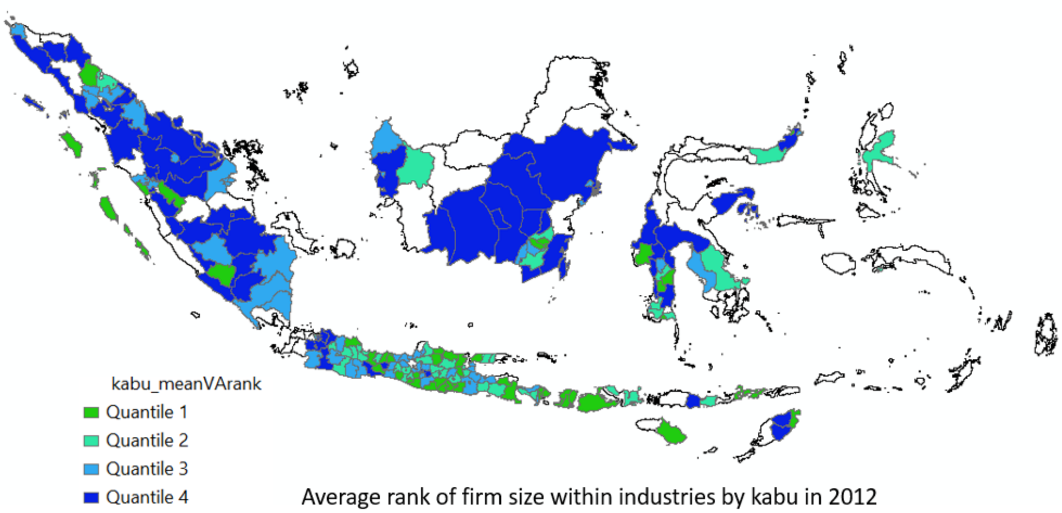


Figure 4: Firm size distribution by quantiles within two-digit ISIC industry



3 The Model

I begin with a model where firms are monopolistically competitive and derive how firms with different productivity draws optimally choose their factor intensity under temperature shocks. To echo the empirical facts on within-industry firm productivity and labor intensity reported in the previous section, I adopt a production function developed by Burstein and Vogel (2016) where more productive firms are also less labor intensive.

To the original production function, I add an element of temperature shocks faced by the firm modeled as a change in labor productivity. This modeling choice is motivated by the empirical literature on thermal stress and labor productivity impact discussed earlier. There are many other channels through which manufacturing firms could be affected by heat shocks. Section 5 offers a brief discussion of mechanisms and offer empirical support that the direct thermal stress channel is important in the Indonesian context. In this section, focusing on the direct physiological channel, I show how within-industry firm heterogeneity in productivity could condition their responses to heat shocks.

3.1 Temperature Shocks

Temperature shocks influence manufacturing production through changes in labor productivity. In this section, I assume that heat exposure negatively impact production (or unskilled) workers more than skilled workers, and labor productivity more than capital productivity.

Specifically, temperature enters the firm's production function through 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 geographic characteristics.

3.2 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.

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

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.

3.3 Production

Firms face monopolistic competition and each produces variety (ω, j) where j is the industry index. There are two factors of production, capital k, and 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 more productive firms are also less labor intensive, I employ a production function with "capital-biased productivity" proposed by Burnstein and Vogel (2016).

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

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 labor-intensity of production.

In addition to the firm's initial productivity draw $z(\omega, j)$, temperature shapes labor productivity through $F(T)$. Beyond the ideal body temperature point, increases in temperature reduces effective labor. The production function given in equation 2 deviates from the classic CES production function by incorporating the "capital-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 capital to labor ratio.

3.4 Price-Setting

The production function given in equation 2 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: $pq(\omega) - cq(\omega) - f = \Gamma p^{1-\sigma} - c(r, w, z)p^{-\sigma} - f$. From the profit function, we can derive the optimal price: $p(\omega)^* = \frac{\sigma}{\sigma-1}c$. As in the Melitz model, we also have that optimal price is a constant mark-up of the constant variable cost.

It is worth noting that 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:

$$q(\omega) = \Gamma(\frac{\sigma}{\sigma - 1}c)^{-\sigma} = Gc^{-\sigma} \tag{3}$$

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

3.5 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:

$$\min_{k,l} e = wl + rk + f, s.t : y = x \tag{4}$$

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

$$\frac{k(\omega,j)}{l(\omega,j)}=(\frac{r}{w})^{-\rho}\frac{\alpha_j}{1-\alpha_j}z(\omega,j)^{\phi(\rho-1)}F(T)^{1-\rho} \tag{5}$$

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 capital to labor ratio in equilibrium, thus productivity is capital-biased. Assuming factors are substitutes, or $\rho>1$, we see that the firm's capital to labor ratio increases as temperature shocks decrease labor productivity. The equilibrium-level of capital to labor ratio 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.

3.6 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 unique 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:

$$c(z^*)=[\frac{f(\sigma-1)}{RP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{-\sigma}}]^{\frac{1}{1-\sigma}}=[\frac{f(\sigma-1)}{G}]^{\frac{1}{1-\sigma}} \tag{6}$$

3.7 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 6 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. Absent of significant adaptation behavior, less productive firms in a region-year which experienced temperature shocks will be more likely to exit through the physiological channel.

Prediction 2: *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 capital to labor, or from unskilled workers to skilled workers*

So far in the model, we have used k to represent capital and l to represent labor. When capital adjustment cost is high, firms may substitute unskilled workers with skilled workers as long as the former is more negatively affected by heat shocks than the later. Empirical observations support this claim in two ways. First, there is evidence that the performance of manual tasks is more impacted than cognitive tasks under thermal stress [8]. Second, skilled workers may operate in environment with better climate control, as suggested by Indian factory-level evidence from Somanathan et al,. (2015).

From Table 1, we know that firms with larger within-sector productivity is associated with higher skilled-to-unskilled worker ratio. We could substitute the "capital-biased mechanism" with a "skill-biased mechanism", where the two factors of production are skilled and unskilled labor. Taking log on both sides of equation (5) and assume that factors are substitutes, or $\rho > 1$, we see that the skilled to unskilled worker ratio will increase as temperature increases.

[8] 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.

4 Empirical Results

4.1 Firm Exit

Are less productive firms more likely to exit under temperature shocks? *Prediction 1* derived from the zero profit condition in section 3.7 suggests that as temperature increases and labor productivity decreases, firms who continue to produce need to have a higher initial productivity draw. This subsection examines the empirical evidence for this prediction in a discrete time hazard framework.

To construct a panel of firm exit 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. 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.

4.1.1 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.

$$P(t_{ij} = \tau + 1 \,|\, t_{ij} > \tau, pdty_i^s * temp_{i,\tau+1}, pdty_i^s * rain_{i,\tau+1}, pdty_i^s * humidity_{i,\tau+1}, pdty_i^s * age_i^{2001}, \theta_{jt})$$
$$= g(\tau, pdty_i^s * temp_{i,\tau+1}, pdty_i^s * rain_{i,\tau+1}, pdty_i^s * humidity_{i,\tau+1}, pdty_i^s * age_i^{2001}, \theta_{jt}) \quad (7)$$

$Exit$ is a binary variable that takes the value of one if the firm exits in the next period and zero otherwise. $pdty_i^s$ 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 temperature faced by firm i in period $\tau + 1$. 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. Because of the inclusion of these fixed effects, the regional variations in temperature I am exploiting are temperature shocks, measured as deviation from the year-by-island, year-by-industry average.

To address the fact that firms with different initial productivity ranks and initial age may have distinct 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.

4.1.2 Results

I begin by presenting the results on exit patterns for firms in different initial productivity bins. Table 2 shows the coefficients on the interaction terms of firm's initial productivity bins with temperature and humidity. The interaction terms with rainfall 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 (main)

	(1) exit b/se	(2) exit b/se	(3) exit b/se
$Pdtybin1^{2001}$*Temperature	1.1586**	1.1687**	1.4018***
	(0.571)	(0.549)	(0.529)
$Pdtybin2^{2001}$*Temperature	0.2891	0.3626	0.5114
	(0.470)	(0.452)	(0.440)
Temperature	2.0434***	2.1497***	1.9731***
	(0.476)	(0.561)	(0.535)
$Pdtybin1^{2001}$*Humidity	0.2311	0.2380	0.2654*
	(0.151)	(0.145)	(0.145)
$Pdtybin2^{2001}$*Humidity	-0.0217	-0.0054	0.0175
	(0.120)	(0.117)	(0.117)
Humidity	0.4088***	0.5833***	0.5305***
	(0.128)	(0.178)	(0.173)
Observations	108187	108187	108187
Year*Industry FE	Yes	Yes	Yes
Year*Island FE		Yes	Yes
Industry*Island FE			Yes
Bin*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) $PdtybinS^{2001} * Temperature$ are the interaction terms of the firm's pre-period within-industry productivity ranks and yearly average temperature (c) Controls for rainfall, $Bin_s X Rain$, $Bin_s X Age2001$ and duration dummies are omitted from the table. (d) All coefficients are multiplied by 100

Column (1) - (3) demonstrates 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 year-by-island, year-by-industry averages. $Pdtybin3^{2001}$ is omitted from the regression, so that the interpretation for the main effect on temperature is for firms with the largest initial productivity. $Pdtybin_1^{2001} * Temperature$ gives the differential exit propensity for firms in smallest initial productivity bin.

We focus on estimates from the preferred specification in column (3), where year*industry, year*island and industry*island fixed effects are all included. We see that an increase in yearly average temperature makes it more likely for all firms to exit. Moreover, exit propensity for firms with the smallest initial productivity is significantly higher under heat shocks, consistent with earlier theory prediction. In particular, one degree Celsius increase in average yearly temperature from the year-by-island, year-industry mean increases the probability of exit for firms in the largest productivity bin by 1.97%, and for firms in the smallest initial productivity bin by 3.37%. This corresponds to a 27.02% increase in exit propensity relative to the baseline average firm exit rates (7.29%) for firms with the largest initial productivity, and 34.35% increase in exit propensity relative to the baseline (9.81%) for the initially least productive firms.

These results suggest that temperature shocks have significant impact on manufacturing firm exit in the context of Indonesia, and that these extensive margin effects are larger for firms with the smallest initial within-industry productivity. Importantly, a 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, downscaling to below 20 employees, or becoming informal.

Intensive margin analysis conducted at the firm-level in the Indonesian context is therefore subject to survival bias. In the following subsection, I present aggregate-level results aiming to mitigate selection concerns.

4.2 Resource Redistribution: Combined Effects

Do temperature shocks redistribute value-added output from less productive to more productive firms? The answer involves a combination of the extensive margin changes (which firms are more likely to exit), and the intensive margin changes (how output changes for each surviving firm).

The extensive margin results in section 4.1 suggest that less productive firms are more likely to exit under regional heat shocks. In this subsection, 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 of the unbalanced panel, 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 entry and exit. 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. Given the results on exit, analysis for the intensive margin at the firm-level would be subject to selection bias. Aggregating to the productivity bin-by-region-by-industry level would lessen this concern. Within each productivity tercile, both firm exit and output reduction will show up as a decrease in the aggregate value-added output.

4.2.1 Empirical Strategy

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

$$\begin{aligned} y_{it} = \alpha_0 &+ \sum_s \alpha_{1s} PdtyBin_{is}^{initial} * Temperature_{it} + \sum_s \alpha_{2s} PdtyBin_{is}^{initial} * Humidity_{it} \\ &+ \sum_s \alpha_{3s} PdtyBin_{is}^{initial} * Rain_{it} + \beta_s PdtyBin_{is}^{initial} * t + \theta_i + \sigma_{jt} + \gamma_{rt} + \epsilon_{it} \end{aligned} \tag{8}$$

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 4.1.1, 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.

4.2.2 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 significant percentage decrease in aggregate value-added output as temperature increases, while firms in the largest productivity tercile experienced a marginally significant 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 loss in aggregate output for firms in the smallest initial productivity tercile. This negative impact results from a combined intensive and extensive margin changes. Firms in the largest productivity bin incur a marginally significant percentage increase of 6.85% in aggregate output per 1°C increase in temperature. Since the SI only include medium and large establishments with employment more than 25, I do not observe the effects on the smallest firms.

Comparing these results with previous studies in the literature [9] 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.

[9] Dell, Jones and Olken (2012), Jones and Olken (2010)

Table 3: Temperature Shocks and Combined Effects on Output

	(1)	(2)	(3)
	ln(vlad)	ln(vlad)	ln(vlad)
	b/se	b/se	b/se
$Pdtybin1^{initial}$*Temperature	-0.1049***	-0.1037***	-0.1037***
	(0.035)	(0.038)	(0.038)
$Pdtybin2^{initial}$*Temperature	-0.0321	-0.0323	-0.0323
	(0.032)	(0.035)	(0.035)
$Pdtybin3^{initial}$*Temperature	0.0666*	0.0685*	0.0685*
	(0.035)	(0.038)	(0.038)
$Pdtybin1^{initial}$*Humidity	-0.0338***	-0.0373***	-0.0373***
	(0.007)	(0.009)	(0.009)
$Pdtybin2^{initial}$*Humidity	-0.0155*	-0.0190*	-0.0190*
	(0.008)	(0.010)	(0.010)
$Pdtybin3^{initial}$*Humidity	0.0142**	0.0108	0.0108
	(0.007)	(0.009)	(0.009)
Observations	31329	31329	31329
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

Given the results on temperature shocks and firm exit, one important motivation for conducting the combined margin analysis on the aggregate level is to mitigate concerns of selection bias, which arises in firm-level intensive margin analysis for the Indonesian context. In the next sub-section, I present firm-level intensive margin results using the original unbalanced panel, and provide suggestive evidence that the ”selected” firms behave differently due to changes in market structure and/or better adaptation behavior.

4.3 Factor Substitution and Intensive Margins

The remaining analysis uses the unbalanced panel and conduct analysis at the firm-level. First, we look at evidence for factor substitution within firms under temperature shocks. Second, I present results on firm-level output and suggest that selection bias is an important consideration when interpreting these estimates.

4.3.1 Factor Substitution

Taking logs on both side, I transform the equilibrium condition in equation 5 to the following equation which directly relates capital to labor ratio with labor productivity $F(T)$:

$$ln[\frac{k}{l}]_{it} = \beta_0 + \theta_1 F(T)_{it} + r_i + \epsilon_{it} \tag{9}$$

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 "capital-biased productivity" mechanism.

Absent of adaptation behavior such as air-conditioner installation, a degree increase in temperature would lead to the same percentage change in the capital to 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.

I take the original unbalanced panel and construct initial productivity bins following the procedure described in section 4.2. 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:

$$\begin{aligned} y_{it} = \alpha_0 &+ \sum_s \alpha_{1s} PdtyBin_{is}^{initial} * Temperature_{it} + \sum_s \alpha_{2s} PdtyBin_{is}^{initial} * Humidity_{it} \\ &+ \sum_s \alpha_{3s} PdtyBin_{is}^{initial} * Rain_{it} + \beta_s PdtyBin_{is}^{initial} * t + \eta_i + \sigma_{jt} + \gamma_{rt} + \epsilon_{it} \end{aligned} \tag{10}$$

This specification is essentially the same as equation (8) 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 capital intensity or alternatively, skill 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.

Here 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, previous research using the SI showed that the average level of education attainment is much higher for nonproduction workers than production workers. [10]

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, possibly because of non-negligible capital adjustment cost.

[10]See for example, Amiti and Cameron (2011)

Figure 5: Factor substitution to skilled labor

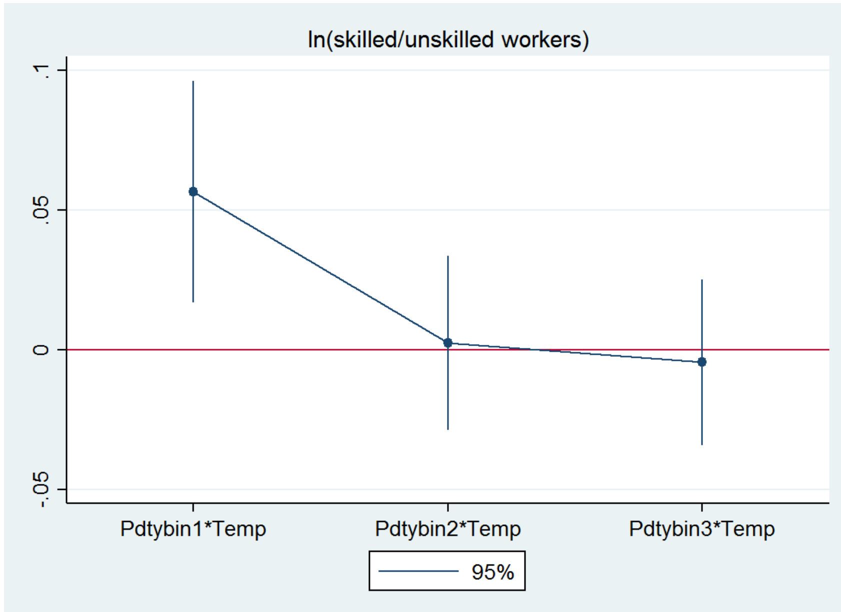


Table 4: Temperature Shocks and Firm-level Factor Substitution

	(1) lmp_ratio b/se	(2) lCaptoProd b/se	(3) lrawimp_ratio b/se
$Pdtybin1^{initial}$*Temperature	0.0565***	0.0124	0.0837**
	(0.020)	(0.024)	(0.041)
$Pdtybin2^{initial}$*Temperature	0.0024	0.0232	0.0560
	(0.016)	(0.023)	(0.035)
$Pdtybin3^{initial}$*Temperature	-0.0045	0.0368	0.0550**
	(0.015)	(0.029)	(0.028)
$Pdtybin1^{initial}$*Humidity	0.0095**	0.0036	0.0120
	(0.004)	(0.005)	(0.008)
$Pdtybin2^{initial}$*Humidity	-0.0017	0.0048	0.0113
	(0.003)	(0.005)	(0.007)
$Pdtybin3^{initial}$*Humidity	-0.0073**	0.0056	0.0026
	(0.003)	(0.006)	(0.006)
Observations	212197	153435	35406
Year*Industry FE	Yes	Yes	Yes
Year*Island FE	Yes	Yes	Yes
Bin*Time	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Clustering	Firm, KabuXYear	Firm, KabuXYear	Firm, KabuXYear

Evidence from the physiological literature suggests that heat exposure may impact the performance of manual tasks more than cognitive tasks. [11] Another possible explanation is that skilled workers may work in conditions with better climate control, as suggested by Indian factory-level evidence from Somanathan et al,. (2015) 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.

A unique feature of the Statistik Industri 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 exploited in 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 8.37% increase in the imported input ratio for the initially least productive firms, and a 5.5% 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.

4.3.2 Intensive Margins

To look at firm-level changes on the intensive margin, I follow the exact same specification in equation (10). 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 increased their value-added output as temperature increases

[11] 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.

while the initially least productive firms incur a smaller, marginally significant loss.

Figure 6: Firm-level value-added output

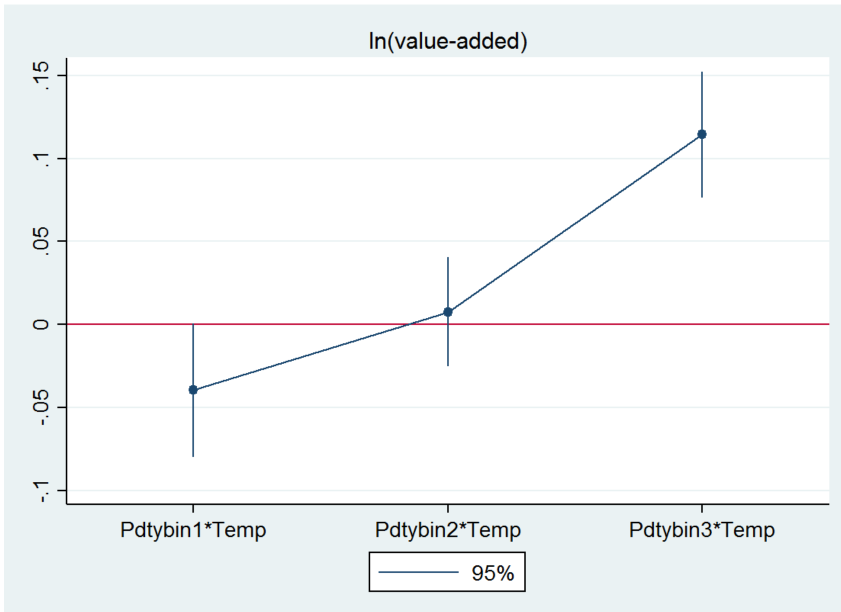


Table 5: Temperature Shocks and Firm-level Output

	(1) ln(vlad) b/se	(2) ln(vlad) b/se	(3) ln(vlad) b/se
$Pdtybin1^{initial}$*Temperature	-0.0234	-0.0363*	-0.0394*
	(0.019)	(0.021)	(0.020)
$Pdtybin2^{initial}$*Temperature	0.0245	0.0083	0.0075
	(0.015)	(0.018)	(0.017)
$Pdtybin3^{initial}$*Temperature	0.1294***	0.1173***	0.1143***
	(0.018)	(0.020)	(0.019)
$Pdtybin1^{initial}$*Humidity	-0.0089**	-0.0162***	-0.0159***
	(0.004)	(0.005)	(0.005)
$Pdtybin2^{initial}$*Humidity	0.0052*	-0.0024	-0.0024
	(0.003)	(0.004)	(0.004)
$Pdtybin3^{initial}$*Humidity	0.0286***	0.0212***	0.0204***
	(0.004)	(0.004)	(0.004)
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

Comparing the previous aggregated combined margin results in Table 3, column (3), with the firm-level intensive margin results in Table 5, column (3), some interesting patterns emerge. The negative impact of a heat shock on the initially least productive firms decreases from 10.37% to a marginally significant 3.94%. The firm-level intensive margin analysis also yields a larger, more significant impact on the initially most productive firms.

One important consideration in interpreting these large, positive impact of heat shocks on firm-level output is the presence of survival bias. In section 4.1, I show that heat shocks lead to firm exit and the attrition is differentially higher 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 what survived. These firms are likely to be better adapted to temperature shocks. Further, as we have seen previously how heat shocks lead to firm exit and shifts in market structure, the positive impact could also occur as the surviving firms gain larger market share.

5 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 (Acemoglue, et al., 2012). Heat shocks could also lead to sectoral labor reallocation through influencing crop yields (Colmer, 2017). In this section, I offer suggestive evidence that the physiological channel is one of the channels at work in driving the main empirical results.

5.1 Agricultural Input Linkages

A large strand of literature found significant negative impact of temperature shocks on agricultural yields in both OECD and developing countries. [12] If higher temperature raises the price 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.

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, except Products of Petroleum and Coal
37 - Basic Metal Industries
38 - Manufacture of Fabricated Metal Products, Machinery and Equipment
39 - Other Manufacturing Industries
Source: http://unstats.un.org/unsd/cr/registry/regcs.asp?Cl=8&Lg=1&Co=3

[12](Fisher et al. 2012) (Guiteras, 2009)(Schlenker and Lobell, 2010)(Lobell, Schlenker, Costa-Roberts, 2011)

In Table 7, I implement the same fixed effects model as in equation (8), excluding the four industries which mainly use agricultural input. These coefficients are comparable to previous results in Table 4. One degree (Celsius) increase in yearly average temperature from the kabupaten, year-industry, year-island average leads to a 12.91% percentage 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.

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
$Pdtybin1^{initial}$*Temperature	-0.0837*	-0.1246**	-0.1291**
	(0.051)	(0.055)	(0.055)
$Pdtybin2^{initial}$*Temperature	0.0131	-0.0360	-0.0395
	(0.053)	(0.056)	(0.056)
$Pdtybin3^{initial}$*Temperature	0.0627	0.0211	0.0129
	(0.055)	(0.059)	(0.059)
$Pdtybin1^{initial}$*Humidity	-0.0300***	-0.0488***	-0.0485***
	(0.011)	(0.013)	(0.013)
$Pdtybin2^{initial}$*Humidity	0.0070	-0.0117	-0.0121
	(0.013)	(0.014)	(0.014)
$Pdtybin3^{initial}$*Humidity	0.0208*	0.0029	0.0009
	(0.011)	(0.012)	(0.013)
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

5.2 Agricultural labor reallocation

Temperature shocks could affect manufacturing firm outcomes through shifting labor supply. Jayachandran (2006) and other papers [13] suggest that negative weather shocks would drive down agriculture wages and lead to outmigration. When inter-sectoral mobility is high and

[13] (Gray and Muller, 2012) (Feng, Oppenheimer, and Schlenker, 2012) (Feng, Krueger and Oppenheinmer, 2010) (Munshi, 2003)

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, 2017)

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 be contributing to the differential exit and combined margin resource reallocation results earlier. In a related project, I exploit the Brazilian employer-employee matched labor records (RAIS) which track formal workers across jobs to directly examine the existence of the labor reallocation channel and its heterogeneous impact on the incumbent manufacturing workforce.

6 Conclusion

There is significant within-industry heterogeneity in climate change impact among manufacturing firms. The initially less productive firms are more likely to exit as temperature increases. Analysis on the combined margins implies that 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. The initially more productive firms that survived also incur output gain under heat shocks possibly due to shifts in market structure or selection.

In developing countries such as Indonesia where electrification capacity and per capita income remain relatively low, air conditioners are not widely installed for manufacturing. Firm size distribution in poorer countries also tends to be more skewed to the left, where less productive firms are dis-proportionally impacted by heat shocks. As a result, these heterogeneous impact of heat shocks are not necessarily welfare-enhancing despite of being pro-competitive.

The significant extensive margin changes under temperature shocks highlights the presence of selection bias intrinsic to the intensive margin analysis at the firm-level in the Indonesian context, which could potentially lead to underestimation of climate change impact if ignored.

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