Title
Essays in Environmental Economics and International Trade

Author
Xie, Wenxin

Publication Date
2019

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA SAN DIEGO

Essays in Environmental Economics and International Trade

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Economics

by

Wenxin Xie

Committee in charge:

Professor Richard T. Carson, Co-Chair
Professor Gordon H. Hanson, Co-Chair
Professor Julianne Berry Cullen
Professor Teevrat Garg
Professor Natalia Ramondo

2019

The dissertation of Wenxin Xie is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Co-Chair

Co-Chair

University of California San Diego

2019

DEDICATION

To my grandpa, *Laoye*.

EPIGRAPH

But the work of man is only just beginning, and it remains to conquer all the violence entrenched in the recesses of our passion... and no race, possesses the monopoly of beauty, of intelligence, of force, and there's a place for all, at the rendezvous, of victory.

—Aime Cesaire, Notebook of a Return to the Native Land

TABLE OF CONTENTS

Signature Page iii

Dedication iv

Epigraph v

Table of Contents vi

List of Figures ix

List of Tables xi

Acknowledgements xii

Vita xiv

Abstract of the Dissertation xv

Chapter 1 Labor-market adjustment under extreme heat shocks: Evidence from Brazil 1
- 1.1 Introduction 1
- 1.2 Data and Empirical Facts 6
  - 1.2.1 Data 6
  - 1.2.2 Empirical Facts 8
- 1.3 Baseline: Immediate Impact 13
  - 1.3.1 Empirical Strategy 14
  - 1.3.2 Results 15
- 1.4 Transmission Mechanism 19
  - 1.4.1 Identifying the Physiological Channel 20
  - 1.4.2 Manufacturing Layoff and Hiring: Nongrowing vs. Growing Seasons 24
- 1.5 Labor Reallocation 30
  - 1.5.1 Empirical Strategy 30
  - 1.5.2 Results: Reallocation for Manufacturing Workers 32
- 1.6 Heterogeneity 38
  - 1.6.1 Empirical Strategy 38
  - 1.6.2 Results 40
- 1.7 Additional Evidence 41
  - 1.7.1 The Role of Nominal Wage Rigidity 42
  - 1.7.2 Bartik Shocks in Output 45
- 1.8 Conclusion 48
- 1.9 Acknowledgements 49
- 1.10 Additional Figures and Tables 50

1.11 Agricultural Layoff and Hiring: Nongrowing seasons vs. Growing seasons . . . 53
1.12 Reallocation for Agricultural Workers . . . 57

Chapter 2 Heterogeneous firms under regional temperature shocks: exit and reallocation, with evidence from Indonesia . . . 59
2.1 Introduction . . . 59
2.2 Data Background and Empirical Facts . . . 64
2.2.1 Data Background . . . 64
2.2.2 Empirical Facts . . . 65
2.3 The Model . . . 70
2.3.1 Temperature Shocks . . . 71
2.3.2 Demand . . . 71
2.3.3 Production . . . 72
2.3.4 Price-Setting . . . 73
2.3.5 Expenditure Minimization . . . 73
2.3.6 The Zero Profit Cutoff Condition . . . 74
2.3.7 Comparative Statics . . . 75
2.4 Empirical Results . . . 77
2.4.1 Firm Exit . . . 77
2.4.2 Resource Redistribution: Combined Effects . . . 81
2.4.3 Factor Substitution and Intensive Margins . . . 85
2.5 Mechanisms . . . 93
2.5.1 Agricultural Input Linkages . . . 94
2.5.2 Agricultural labor reallocation . . . 97
2.6 Conclusion . . . 97
2.7 Acknowledgements . . . 98

Chapter 3 Mining Activity and Spatio-Temporal Dynamics of Forest Cover Loss . . . 99
3.1 Introduction . . . 99
3.2 Data and Empirical Facts . . . 104
3.2.1 Data . . . 104
3.2.2 Empirical Facts . . . 106
3.3 Elasticity of Forest Cover Loss . . . 114
3.3.1 Baseline: Empirical Strategy . . . 114
3.3.2 Baseline: Results . . . 114
3.4 Country and Firm-Level Determinants of Deforestation . . . 117
3.4.1 Double Interaction . . . 117
3.4.2 Triple Interaction . . . 120
3.5 Mining Activities and Night Lights . . . 123
3.6 Conclusion . . . 127
3.7 Acknowledgements . . . 129
3.8 Additional Figures . . . 130

3.8.1 Average Forest Cover Loss at 20 km 130
3.8.2 Google Earth Images of Open Pit Mines 132

Bibliography 136

LIST OF FIGURES

Figure 1.1: Distribution of daily average temperature 11
Figure 1.2: Spatial distribution of daily mean temperature from 1990 to 2000 11
Figure 1.3: Spatial distribution of extreme heat shocks (daily mean temp > 31°C) . . . 12
Figure 1.4: Prediction of future extreme heat days: CMIP5, RCP8.5, access1_0 13
Figure 1.5: Quarterly heat shocks and manufacturing layoff: Net impact 17
Figure 1.6: Quarterly heat shocks and agricultural layoff: Net impact 18
Figure 1.7: Agricultural vs. manufacturing hiring: Net impact 19
Figure 1.8: Main crop of municipality by production value 22
Figure 1.9: Main-crop nongrowing season by production value 23
Figure 1.10: Manufacturing worker layoff: nongrowing seasons, with interacting specification 25
Figure 1.11: Quarterly heat shocks and manufacturing layoff: Growing seasons 29
Figure 1.12: Quarterly heat shocks and manufacturing workers layoff, with reallocation to manufacturing within 36 months 35
Figure 1.13: Quarterly heat shocks and manufacturing workers layoff, with reallocation to agriculture within 36 months 35
Figure 1.14: Quarterly heat shocks and manufacturing workers layoff, with reallocation to Services/Primary within 36 months 36
Figure 1.15: Quarterly heat shocks and manufacturing workers layoff: failure to reallocate within 36 months 36
Figure 1.16: Quarterly Brazilian inflation index 43
Figure 1.17: Manufacturing worker layoff: nongrowing seasons, with worker fixed effects and lagged weather shocks 50
Figure 1.18: Manufacturing worker layoff: nongrowing seasons, excluding outliers (cooksd) 51
Figure 1.19: Quarterly heat shocks and agricultural layoff 54
Figure 1.20: Quarterly heat shocks and agricultural hiring 55
Figure 1.21: Sugarcane worker layoff: growing versus nongrowing seasons 56

Figure 2.1: Mean Labor Intensity and firm productivity 68
Figure 2.2: Average daily temperature at 2pm 68
Figure 2.3: Yearly average temperature difference between 2012 and 1997 69
Figure 2.4: Firm size distribution by quantiles within two-digit ISIC industry 70
Figure 2.5: Factor substitution to skilled labor 88
Figure 2.6: Firm-level value-added output 91

Figure 3.1: Standardized Prices of Major Commodities 108
Figure 3.2: Standardized Prices of Minor Commodities 108
Figure 3.3: Average Forest Cover Loss around Mines by Radius, 2000-14 109
Figure 3.4: Average Forest Cover Loss at 5km by Country, 2000-14 109
Figure 3.5: Average Forest Cover Loss at 5km by Country, IFC>25%, 2000-14 110
Figure 3.6: Average Forest Cover Loss at 5km by Country, IFC>40%, 2000-14 110

Figure 3.7: Mina Cerro Vanguardia: gold and silver mine, Argentina 111
Figure 3.8: Cadia: gold mine, Australia 111
Figure 3.9: Triple Interaction: MineGDP*OwnerGDP*Price 122
Figure 3.10: Triple Interaction on Night Lights: MineGDP*OwnerGDP*Price 126
Figure 3.11: Average Forest Cover Loss at 20km by Country, 2000-14 130
Figure 3.12: Average Forest Cover Loss at 20km by Country, IFC>25%, 2000-14 131
Figure 3.13: Average Forest Cover Loss at 20km by Country, IFC>40%, 2000-14 131
Figure 3.14: Batu Hijau: copper and gold mine, Indonesia 132
Figure 3.15: Belchatow: coal mine, Poland 133
Figure 3.16: Tagebau Hambach: lignite mine, Germany 133
Figure 3.17: Lavender Pit: Arizona 134
Figure 3.18: Berkeley Pit: copper mine/superfund site, Montana 134
Figure 3.19: Huckleberry Mine: copper/molybdenum/gold/silver, Canada 135

LIST OF TABLES

Table 1.1: Quarterly heat shocks and manuf. worker reallocation, all seasons 34
Table 1.2: Examples of occupations by RMTI 39
Table 1.3: Manufacturing layoffs: Worker-level heterogeneity 41
Table 1.4: Heat shocks and nominal wage rigidity: Growing vs. nongrowing seasons . 44
Table 1.5: Manufacturing layoff and yearly Bartik shock in output 47
Table 1.6: Quarterly heat shocks and manuf. worker reallocation, nongrowing seasons 52
Table 1.7: Quarterly Heat Shocks and Agr. Worker Reallocation, GS 57
Table 1.8: Quarterly Heat Shocks and Sugarcane Worker Reallocation, GS 58

Table 2.1: Standardized coefficients of productivity on firm characteristics 67
Table 2.2: Differential firm exit under heat shocks (main) 80
Table 2.3: Temperature Shocks and Combined Effects on Output 85
Table 2.4: Temperature Shocks and Firm-level Factor Substitution 89
Table 2.5: Temperature Shocks and Firm-level Output 92
Table 2.6: Excluding Sectors Using Agricultural Input 95
Table 2.7: Temperature Shocks and Combined Effects on Output (Robustness) 96

Table 3.1: Average Mine Characteristics 112
Table 3.2: Share of Primary Commodity 113
Table 3.3: Percentage of Forest Cover Loss, Initial Forest Cover>40% 116
Table 3.4: Interaction with Mine Country GDPPC 118
Table 3.5: Interaction with Owner Firm SOE Status 119
Table 3.6: Triple Interaction: MineGDP*OwnerGDP*Price 121
Table 3.7: Triple Interaction: OwnerSOE*MineGDP*Price 124
Table 3.8: Triple Interaction: MineGDP*OwnerGDP*Price 125

ACKNOWLEDGEMENTS

I'm deeply grateful to my advisors, Richard Carson and Gordon Hanson, for their invaluable intellectual insight, patience, and continuous support over the years. They guided me to think rigorously and to pursue research questions with passion. I would also like to thank my other committee members, Julie Cullen, Teevrat Garg and Natalia Ramondo, who always made time for me and provided crucial comments. Marc Muendler deserves special credit for many helpful conversations about my projects, and generously providing access to the crucial data source that got me started on my job market paper. I'm indebted to Sam Bazzi, who was generous with feedback and encouragement on multiple occasions and shared with me the data which helped me start my first project. Throughout the past six years, I have also received a lot of helpful advice from Judson Boomhower, Gordon Dahl, Josh Graff-Zivin, Roger Gordon, Ruixue Jia, Mark Jacobsen, Gordon McCord, Crag McIntosh, Paul Niehaus and Jeff Shrader. The incredibly honest and vibrant intellectual community at UCSD has filled my graduate school years with challenges, inspiration and joy.

I would also like to acknowledge my coauthors, Ran Goldblatt, Amit Khandelwal and my advisor, Gordon Hanson. I've really enjoyed and learned so much from working with you. My closest firends, Yaein Baek, Ying Feng, Onyi Lam, Penny Liao, Xueying Lv, Yifei Lv, Xiao Ma, Fanglin Sun, Shihan Xie, Alex Yu, Xu Zhang are a constant source of comfort and happiness. Thank you for the laughter, stimulating conversations, understanding and unconditional support.

Finally, I'm incredibly blessed to have a family who is always there for me. I thank my Mom and Dad for always encouraging me to explore the world and to pursue what truly interests me. To Jongmyun, thank you for always believing in me, making me laugh, and loving me for all my imperfections. Wherever you are is my home.

Chapter 1 is being prepared for publication. Xie, Wenxin, ”Labor market adjustment under extreme heat shocks: evidence from Brazil”. The dissertation author is the principle researcher on this chapter.

Chapter 2 is being prepared for publication. Xie, Wenxin, ”Heterogeneous firms under regional temperature shocks: exit and reallocation, with evidence from Indonesia”. The dissertation author is the principle researcher on this chapter.

Chapter 3 is coauthored with Ran Goldblatt, Gordon Hanson and Amit Khandelwal and is being prepared for publication. Goldblatt, Ran; Hanson, Gordon; Khandelwal Amit; Xie, Wenxin, ”Mining Activity and Spatio-Temporal Dynamics of Forest Cover Loss”. The dissertation author is the principle researcher on this chapter.

VITA

2011	BBA, Global Business and Economics (Minor Math), Hong Kong University of Science and Technology
2013	Mphil, Economics, University of Oxford
2019	PhD, Economics, University of California, San Diego

ABSTRACT OF THE DISSERTATION

Essays in Environmental Economics and International Trade

by

Wenxin Xie

Doctor of Philosophy in Economics

University of California San Diego, 2019

Professor Richard T. Carson, Co-Chair
Professor Gordon H. Hanson, Co-Chair

The first two chapters of this dissertation seek to understand how climate change affect labor market outcomes and manufacturing firms in developing country contexts. Chapter One provides worker-level evidence in Brazil on different labor-market adjustment margins with respect to extreme heat shocks and the underlying transmission mechanism. Exploiting rich employer-employee matched data, I find that quarterly heat shocks lead to significant increases in the propensity of manufacturing-worker layoff through the direct labor productivity channel. A significant proportion of manufacturing workers who experienced heat-related layoffs fail to find any formal employment within 36 months. These results show that heat shocks lead to

persistent negative employment effect in the formal manufacturing labor market due to failure in job transitions over the medium run.

In Chapter Two, I turn the focus to manufacturing firms in Indonesia. In a heterogeneous firm model with capital-biased productivity, I incorporate temperature shocks through the direct labor productivity channel and illustrate how less productive firms decide on production and re-optimize factor intensity as temperature increases. Empirically, I match gridded daily weather data with the Indonesian firm-level industrial surveys. I find that under heat shocks, the initially less productive firms are more likely to exit, highlighting the presence of survival bias intrinsic to firm-level intensive margin analysis. 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 using domestic to foreign intermediate inputs.

Chapter Three investigates how global commodity price booms affect land use and forest management, and the factors that influence sustainable environmental practices of mining firms. We employ a spatial and temporal lens, by collecting proprietary data on more than 30,000 mines located around the world and matching the location of these mines to high-resolution satellite imagery. This allows a granular study of the relationship between commodity prices and loss of forest cover worldwide, as well as the spatial distribution of global mines in relation to changes in land use patterns and local economic activities as measured by nighttime luminosity. We find a positive elasticity of forest cover loss. Mine owners from rich countries display larger disparity in the elasticity of forest cover loss when operating in low versus high income countries. Our estimates suggest that the early 2000s ”commodity super-cycle” contributes to roughly 8%-20% of the observed total deforestation around mining sites, and that mining-induced deforestation is not limited to the immediate surroundings of mining pits.

Chapter 1

Labor-market adjustment under extreme heat shocks: Evidence from Brazil

1.1 Introduction

Many developing countries located in tropical and subtropical zones are vulnerable to climate change due to limited adaptation capacity and high baseline temperatures. Climate change is associated with an expected increase in the frequency of extreme heat days. These drastic environmental shocks could potentially bring about significant changes for the workforce in developing economies. Despite rich micro-level evidence on the contemporaneous labor-productivity impact of extreme heat (Adhvaryu et al., 2016; Hancock et al., 2007), little work has been done to examine the worker-level employment implications of temperature shocks over time. Answers to these questions provide a missing perspective on how climate change affects worker welfare. Assessing the costs of climate change within developing country institutions is also crucial for calibrating country-specific calculation for the social cost of carbon.

In this paper, I provide worker-level evidence on different labor-market adjustment margins with respect to extreme heat shocks and the underlying transmission mechanism. First, using employer–employee-matched data, I find that heat shocks lead to a significant increase in the propensity of immediate manufacturing layoff. I further isolate the direct labor-productivity channel by focusing on heat shocks during the local nongrowing seasons, exploiting rich municipality-level agricultural census and crop calendars. Second, I examine medium-run adjustment margins. Tracking workers across employment spells, I find limited intersectoral and interregional worker reallocation. A significant proportion of manufacturing workers fail to reallocate to another formal-sector job within 36 months. Third, heat shocks during the nongrowing seasons have more pronounced impact on workers in more routine manual-task-intensive occupations.

Heat leads to worker fatigue, lower task performance, and poorer decision making.[1] Given the abundant evidence on the direct labor-productivity impact of heat shocks, one natural question is how much it contributes to economy-wide labor-market adjustment. Contract theory suggests firms cannot fully insure workers against random shocks if efforts are not fully observed (Holstrom and Milgrom, 1987). The magnitude of impact then is an empirical question, depending on the degree of firm-level adaptation and such specific labor-market features as de facto firing costs, downward wage rigidity and interaction with the informal economy. The presence (or absence) of a direct labor-productivity channel also has important implications for climate-change-adaptation policies.[2] To separately identify the direct labor-productivity channel among many potential mechanisms through which weather shocks could affect industrial workers,[3] I exploit unique features of Brazilian employer–employee linked administrative data (RAIS) and rich municipality-level agricultural census. With information on individual workers'

[1] Using microdata from assembly lines, Somananthan et al. (2014) and Adhvaryu et al. (2016) show that daily manufacturing labor productivity significantly decreases with temperature. See also Zander et al. (2015), Graff Zivin and Neidell (2014), Niemela et al. (2002), Seppanen et al. (2006), Kjellstrom et al. (2009), and Park (2017).

[2]For example, installing air conditioners in factories versus adopting heat-resistant crops.

[3] Direct labor-productivity channel: Adhvaryu et al. (2016), Somanathan et al. (2014), Heal and Park (2014); interindustry linkages: input–output linkages: Acemoglu et al. (2012), agricultural local-demand channel: Santangelo (2015), Henderson et al. (2017), agricultural labor reallocation: Colmer (2016), agricultural income and nutrition channel: Garg et al. (2017)

month of accession and separation from his/her employer, I am able to match temperature shocks with individual employment outcomes on a quarterly basis to isolate heat shocks during local nongrowing seasons. The underlying assumption is that weather shocks during nongrowing seasons do not operate through agricultural channels (Burgess et al., 2018; Carleton, 2017).

Assessing the labor-market impact of heat shocks from the perspective of worker welfare also requires data on gross instead of net employment flows. Aggregate employment at the firm level provided in industrial surveys only gives net flows and could not inform us of worker displacement if it is accompanied by worker inflow. This issue is particularly important given the multiple, and potentially opposing, channels through which extreme heat could affect the industrial labor market. For example, if temperature increase causes agricultural outmigration into manufacturing due to lower crop yields, we may observe an increase in net firm-level employment. In reality, this increase could be accompanied by agricultural workers substituting existing manufacturing workers, and/or existing workers being laid off due to lower manufacturing labor productivity. Observing worker-level job accession and separation allows me to directly address incumbent worker welfare, whereas the previous literature mostly focused on firm welfare (Colmer, 2017; Santangelo, 2015)

For developing countries, labor-market transitional costs could interact with environmental shocks to further exacerbate the cost of climate change. In particular, if significant cost exists in job transitions, only accounting for the immediate adjustment margins would lead to an underestimation of total worker welfare losses. To understand medium-run adjustment margins, I exploit the employer–employee linkage feature of RAIS and provide evidence on worker reallocation. Tracking each worker across job spells, I decompose postlayoff transition outcomes into seven collectively exhaustive, mutually exclusive channels by the industry and region of the worker's next job. This helps us better understand the medium-run labor adjustment margins through an examination of worker reallocation between sectors and across municipalities.

First, I find quarterly heat shocks lead to significant manufacturing-labor-market churn. Isolating the direct labor-productivity channel, I show that extreme heat days[4] during nongrowing seasons lead to a higher propensity for manufacturing layoff but has no significant impact on manufacturing hiring. In terms of magnitude, swapping a day with daily mean temperature below 17°C for one with daily mean temperature beyond 31°C during the nongrowing seasons increases the probability of layoff by 0.8 percentage points, equivalent to a 11% increase in the baseline layoff propensity. These results are robust to including a rich set of fixed effects controlling for state- and industry-specific seasonality, state and industry growth trends, time-invariant municipality characteristics, and lagged weather shocks.

Second, in terms of medium-run adjustment margins and worker reallocation, I find limited intersectoral and interregional reallocation for manufacturing workers and a significant failure rate to reallocate. 59% of manufacturing workers find another job in the same industry either locally or in a different municipality. However, 24.3% of all formal manufacturing workers laid off due to heat shocks fail to find any formal sector job within 36 months. This suggests over the medium run, environmental shocks interact with labor-market transitional costs to trigger prolonged unemployment or switching to the informal economy.

Third, consistent with the direct labor-productivity channel, the impact of heat shocks is heterogeneous by occupational task intensity and by gender. Matching worker occupational codes with measures from the Dictionary of Occupational Titles (DOT), I find that manufacturing workers engaging in more routine-manual-intensive tasks are more likely to be laid off during the nongrowing seasons, pointing to a potential source of distributional impact of climate change.

[4] Defined as daily mean temperatures above 31°C.

This paper provides a missing perspective on the aggregate employment implications of extreme temperature shocks associated with climate change and establishes an underlying mechanism using rich microdata. On the aggregate level, temperature shocks have been shown to negatively affect GDP per capita, labor income, economic growth, and exports (Dell et al., 2012; Jones and Olken, 2010; Park, 2017). Manufacturing output changes due to heat shocks are also observed with firm-level evidence from China, India and Indonesia (Colmer, 2017; Deschenes et al., 2018; Somanathan et al., 2014). On the micro-level, evidence from labs, call centers and selected factory assembly lines points to a large negative labor-productivity impact of heat shocks (Adhvaryu et al., 2016; Zander et al., 2015; Graff Zivin and Neidell, 2014; Niemela et al., 2002; Seppanen et al., 2006; Kjellstrom et al., 2009). In contrast, we know surprisingly little about the employment impact of extreme heat shocks [5], the associated worker displacement and welfare losses, and the importance of the direct labor-productivity channel as a transmission mechanism. Findings in this paper suggest the direct impact of thermal stress on manufacturing workers leads to significantly higher layoff propensity. Identifying the worker-displacement effect is uniquely achieved by examining administrative individual-level data, uncovering a previously ignored source of worker welfare loss from climate change.

Second, this paper offers broader labor-market implications of environmental shocks through various adjustment margins. In addition to the immediate employment effects, labor-reallocation results suggest high worker adjustment costs to extreme heat shocks during worker–firm rematching. I provide first evidence that heat shocks lead to persist negative employment effect in the formal manufacturing labor market due to failure in job transitions over the medium run. To study worker reallocation, I follow empirical methodology recently used in the trade literature to examine the regional labor-market consequence of tariff reductions (Dix-Carneiro

[5] One exception is Wilson (2017) which studies short run aggregate impact. Instead my paper focuses on worker-level employment outcomes over time and the underlying mechanism.

and Kovak, 2017a; Menezes-Filho and Muendler, 2011; Autor et al., 2014). Compared with more permanent shocks from trade liberalization, I show that even less persistent temperature shocks lead to significant failure to reallocate, contributing to prolonged individual-worker welfare losses.

Next, I begin by describing the data and presenting relevant empirical facts. Section 1.3 presents the baseline empirical specification and net impact. Section 1.4 introduces my methodology to identify the direct labor-productivity channel and main results on transmission mechanisms. Section 1.5 focuses on medium-run adjustment margins in job reallocation. Section 1.6 discusses the heterogeneous impact. Section 1.7 offers further discussions and robustness checks. Section 1.8 concludes.

1.2 Data and Empirical Facts

1.2.1 Data

Worker-level data comes from the Brazilian administrative records Relao Anual de Informaes Sociais (RAIS), covering the years from 1990 to 2000. This employer–employee matched contract-level data includes more than 90% of all formally employed workers in Brazil (Menezes-Filho and Muendler, 2011). The records are created to provide information for the federal wage-supplement program (Abono Salarial) and the employer-contribution program (FGTS).

RAIS provides data on worker-level contracts with the firm–plant registration number and the worker ID. Since workers are identified by a unique ID number, which is fixed over time, I am able to track each worker across employers. The finest geographic unit of identification is a Brazilian municipality, which I use to match the administrative records with gridded weather variables. For each worker, there is information on education, tenure, gender, monthly wage, occupation, and month of accession into and separation from each contract. I also have plant-level information on sector, ownership, and plant size.

To construct the worker sample, I take the list of all worker IDs ever to have appeared in RAIS, draw a 10% random sample, and track the selected worker IDs through the years across multiple job spells. In the case of multiple jobs, only the highest paying, last formal employment of the quarter is kept for each worker (Menezes-Filho and Muendler, 2011). For layoffs, I examine job spells conditional on the worker being employed at the beginning of the quarter. Cases of quitting, transfers, retirement, and death are excluded from the analysis. Since we do not observe the worker during unemployment, hiring is defined at the region–industry level.

One important caveat is that RAIS only covers formal sector employment, defined as working with a signed work card. Informal jobs are a significant portion of the Brazilian labor market. According to the 1991 Demographic Census for workers aged 18–64, 28% of manufacturing and 55% of nontradable sector employment is informal (Dix-Carneiro and Kovak, 2017a). Additionally, 89% of agricultural employment is informal. As a robustness check for results on the agricultural sector, I restrict analysis to sugarcane workers only, where workers are predominantly formal and unionized. Comparing with the household survey PNAD, Davis (2017) documents that roughly 60% of sugarcane employment is captured in RAIS. Layoffs are defined in this paper as layoff from the formal sector, which means the worker can be either unemployed or employed informally. Formal sector layoff is meaningful for individual welfare because workers need the signed work card to claim employment-related benefits and labor protections.

Data on weather outcomes are from the ERA-Interim reanalysis archive. I obtain measures of daily mean temperature, dew point temperature, and cumulative rainfall on a $0.125^\circ \times 0.125^\circ$ grid. Relative humidity is calculated from dry bulb and dew point temperature based on Lawrence (2005). Weather variables are then linked to each municipality using GIS data from the Global

Administrative Borders.

Regional crop production data are from the Municipal Agricultural Production Survey (PAM), maintained through the data portal (SIDRA) by the Brazilian Institute of Geography and Statistics (IBGE). This survey provides the annual production value, area, and average yield of all temporary and permanent crops in Brazil by municipality. I use the municipality crop specific production value from the PAM to determine the main crop of each municipality. To identify the nongrowing seasons of each municipality, I use the Brazilian crop calendars collected by the USDA World Agricultural Outlook Board. These calendars provide regional crop-growing cycles in Brazil by sowing, growing, and harvest stages and allow me to distinguish between growing and nongrowing seasons of major crops in Brazil. Finally, for heterogeneity analysis, I use the occupational-task intensity measures from the Dictionary of Occupational Titles constructed by Autor, Levy, and Murnane (2003).[6] An underlying assumption here is that the relative ranking of occupational task intensity is preserved across U.S. and Brazilian occupations.

1.2.2 Empirical Facts

In this section, I first briefly review the literature on thermal stress and labor productivity. Next, I show the raw distribution of daily average temperature during the sample period of analysis in Brazil. Third, I present the spatial distribution of extreme heat shocks to illustrate from where the temperature variations exploited in later sections come.

One focus of this paper is to identify the direct labor-productivity channel as a transmission mechanism through which heat affects manufacturing employment. To put the extreme heat shocks in Brazil into context, I briefly review key evidence on thermal stress and labor

[6] Concordance from the US Census occupational codes to the ISCO-88, and to the Brazilian occupational codes CBO are from Autor and Dorn (2013), the Center for Longitudinal Studies in UCL, and Muendler et al. (2004).

performance. A large body of literature has documented a highly nonlinear relationship between temperature and individual labor productivity. Recent evidence from selected Indian garment factories documents 29.5°C as the physiological threshold above which temperature strongly impedes human functioning (Adhvaryu et al., 2016). Meta-analysis in ergonomics (Pilcher et al., 2002; Hancock et al., 2007) summarizing multiple experimental studies reveals that task performance losses start to occur with the Wetbulb Global Temperature (WBGT) equivalent of 28°C, at 80% relative humidity and normal sea level air pressures. Sharp performance losses are observed with the WBGT equivalent of 32°C. On the aggregate level, Hsiang (2010) estimates that economic production losses begin at 29°C.

As an important emerging economy, Brazil spans several climate zones and provides rich regional temperature variations. Figure 1.1 plots the probability density distribution of daily average temperature of all municipalities in Brazil, from 1990 to 2000. The mean is 22.82°C, with 3.43% of the observations above 29°C, and 0.24% of observations above 31°C. Throughout this paper, I define an *extreme-heat day* as having daily mean temperature above 31°C. With climate change, this graph is expected to develop a fatter right tail. Because of the nonlinear relationship between labor productivity and temperature, one expects to observe a strong impact of days in the extreme-heat category.

Figure 1.2 plots the spatial distribution of daily mean temperature, averaged over the period from 1990 to 2000. Figure 1.3 illustrates the spatial distribution of extreme-heat days. For each municipality, I aggregate the number of days with daily mean temperature above 31°C from 1990 to 2000. The white regions did not experience an extreme-heat day during the sample period, such as the Amazons. The colored municipalities had from 1 to 471 days of extreme heat. The municipality in the 95th percentile experienced 46 days of extreme heat cumulatively during the sample period. Since extreme-heat shocks display spatial clustering, I include municipality fixed effects in all subsequent analysis to control for any region-specific time-invariant characteristics that correlate with temperature.

Although extreme heat days are rare in Brazil during the period of my analysis (1990–2000), climate projections indicate these days will drastically increase based on our current emission trajectory (Sanford et al., 2014). Figure 1.4 plots the projected change (compared to the baseline period 1986–2005) in annual extreme-heat days, defined as daily mean heat index above 35°C, equivalent to daily mean temperature above 31°C with relative humidity at 60%. Predictions are made assuming the Representative Concentration Pathway 8.5 scenario, which we would surpass without sharp downward transitions. The underlying data comes from the Coupled Model Intercomparison Project (CMIP5) used in the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report, and the World Bank Group's Climate Knowledge Portal.

Figure 1.4 shows large regional disparity in predicted increase of extreme-heat days. For the period 2040–2059, the predicted change in annual extreme-heat days is 0.95 for a southern municipality like Sao Paulo, 69.75 days for a central municipality such as Palmas, and 34.5 days for a northeastern municipality such as Teresina. Later in my analysis, I discuss how these differences in predicted heat exposure could lead to large variations in regional manufacturing employment outcomes.

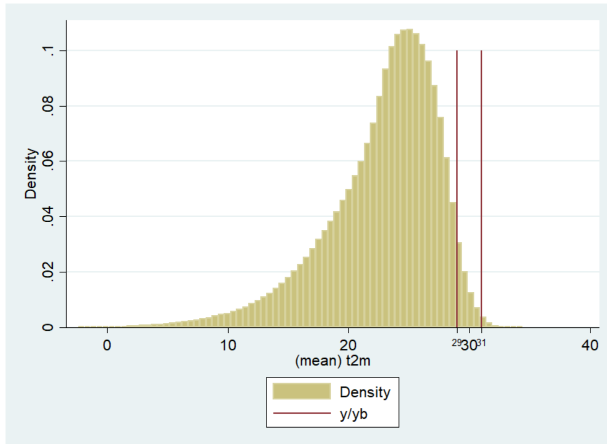


Figure 1.1: Distribution of daily average temperature

This figure plots the probability density distribution of daily mean temperature for all municipalities in Brazil, from 1990 to 2000. Daily mean temperature (t2m) on the X-axis is measured in terms of degrees Celsius. The two red vertical lines represent the 29°C and 31°C thresholds.

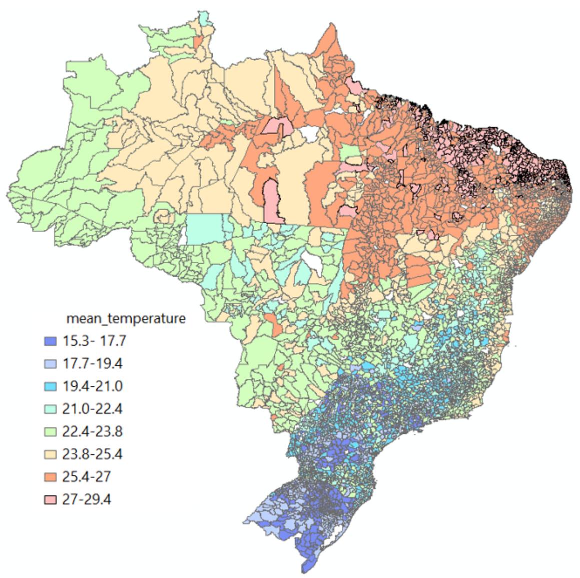


Figure 1.2: Spatial distribution of daily mean temperature from 1990 to 2000

This map plots the spatial distribution of daily mean temperature, averaged over the period from 1990 to 2000. The finest geographic unit is a Brazilian municipality. Ranges in the legend are in terms of degrees Celsius.

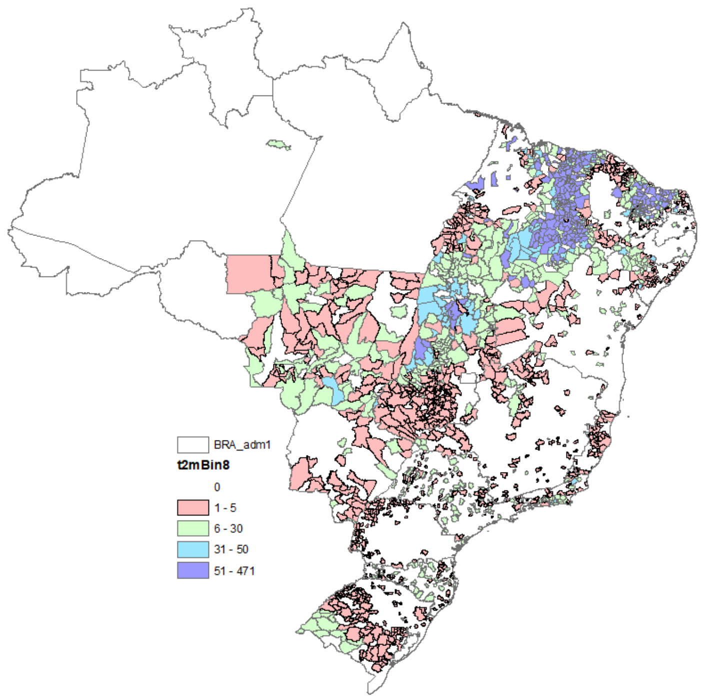
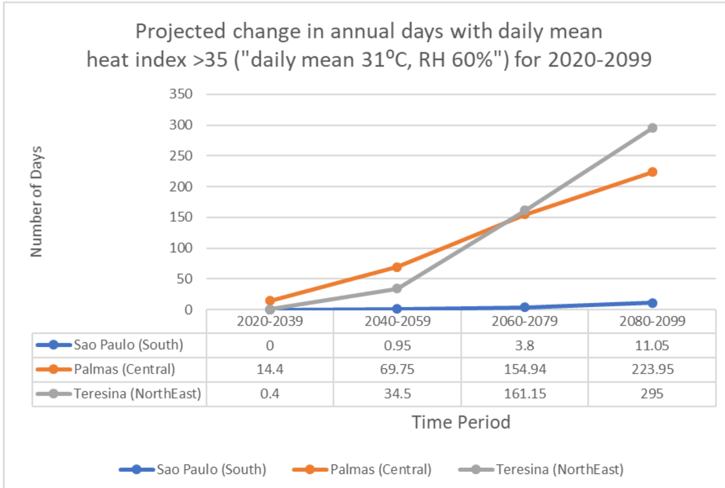


Figure 1.3: Spatial distribution of extreme heat shocks (daily mean temp > 31°C)

This map illustrates the spatial distribution of cumulative extreme-heat days. For each municipality, "t2mBin8" represents the total number of days with daily mean temperature above 31°C from 1990 to 2000. The finest geographic unit is a Brazilian municipality.



	2020-2039	2040-2059	2060-2079	2080-2099
Sao Paulo (South)	0	0.95	3.8	11.05
Palmas (Central)	14.4	69.75	154.94	223.95
Teresina (NorthEast)	0.4	34.5	161.15	295

Figure 1.4: Prediction of future extreme heat days: CMIP5, RCP8.5, access1_0

This chart shows the predicted change in annual count of extreme-heat days, defined as daily mean heat index above 35°C, relative to the reference period (1986–2005). These days represent extremely uncomfortable conditions and are equivalent to daily mean temperature of 31°C, at relative humidity 60%. The point estimates are given for three randomly selected cities: Sao Paulo, Palmas. and Teresina, located in the south, central, and northeast regions in Brazil. Projections are given by the Coupled Model Intercomparison Project (CMIP5) under the "access1_0" model, assuming the Representative Concentration Pathway 8.5 (RCP 8.5) scenario. These data are available through the World Bank Group's Climate Knowledge Portal, and covers periods 2020–2039, 2040–2059, 2060–2079, and 2080–2099.

1.3 Baseline: Immediate Impact

Do quarterly temperature shocks lead to changes in the propensity of manufacturing worker layoff and hiring? Existing literature provides ample evidence on the labor-productivity impact of heat shocks. Whether these productivity shocks cause changes in employment outcomes, however, is largely unexplored. A rather complex array of institutional, firm- and worker-specific factors matter for the employment implications of heat-related productivity shocks. These include, but are not limited to, the labor-market institutions on hiring and firing costs, the presence of nominal wage rigidity, the degree of firm-level adaptation, heterogeneity in workers' sensitivity to heat, and firm managers' attitudes towards ambiguity of quality signals (Ilut et al., 2018). Section 1.7 of this paper provides suggestive evidence on how some of these factors matter in the

Brazilian context.

Other than the direct labor-productivity channel, there are multiple potential mechanisms through which heat shocks could affect the manufacturing labor market. Given what we know about temperature and crop yields (Lobell et al., 2011), heat shocks could influence manufacturing through various interindustry linkages with agriculture, including agricultural outmigration, changes in farmer income and local demand, and changes in raw material prices. Section 1.4 discusses this issue in greater detail and addresses the identification challenge of transmission channels by isolating heat shocks during the local nongrowing seasons. Before diving into the mechanisms, I start with a baseline empirical specification and examine the net impact of heat shocks through all combined channels.

1.3.1 Empirical Strategy

The baseline empirical framework is a fixed-effect model

$$\begin{aligned} Y_{ijmt} = \sum \beta_k Tempbin^k_{m,t} + f(Rain_{m,t}, Humidity_{m,t}) + \alpha_1 X_{it} \\ + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \varepsilon_{ijmt}, \quad (1.1) \end{aligned}$$

where Y_{ijmt} is the binary outcome of worker layoff, for worker i, employed in industry j, residing in municipality m, at time t. Allowing for nonlinear effects, $Tempbin^k_{m,t}$ is the number of days in a quarter with daily mean temperature within the specified range k.[7] $f(Rain_{m,t}, Humidity_{m,t})$ controls for the cumulative rainfall and relative humidity. X_{it} is a vector of worker and plant-level controls including worker education, occupation categories, tenure, potential labor-force experience, plant size, and plant skill composition.

[7] Tempbin1, where $t < 17°$C, is omitted.

To causally identify the effect of heat shocks on worker layoff, a rich set of fixed effects are included to control for confounders that could be correlated with temperature and to rule out spurious relationships. First, since we are examining individual layoff decisions at the quarterly frequency, it is crucial to include controls for seasonality which may correlate within-year employment cycles with temperature fluctuations. To control for state-specific employment seasonality, I include Quarter $\times$ State fixed effects, and, for industry-specific seasonality, I include Industry $\times$ Quarter fixed effects.

One may also imagine that a general warming trend in temperature might be correlated with national business cycles during this period. I address this concern by including Quarter $\times$ Year fixed effects. Further, warmer regions may have different institutions or other geographic features that lead to different employment patterns. To control for any time-invariant municipal characteristics, I include Municipality fixed effects. Finally, I include State $\times$ Year and Industry $\times$ Year fixed effects to control for state and industry growth trends, and State $\times$ Industry fixed effects for regional industrial patterns. This also means the temperature variations I exploit are deviations from averages, instead of variations in raw temperature. Standard errors are clustered at the mesoregion level to allow for serial and spatial correlation.

1.3.2 Results

We first examine the baseline immediate impact of heat shocks on individual layoff and hiring, separately for manufacturing and agricultural workers. These results show that, after pooling together all seasons and several potential mechanisms, temperature shocks significantly influence individual labor-market outcomes.

We start with individual outcomes on layoff. Figure 1.5 illustrates that the probability of manufacturing-worker layoff increases in a nonlinear manner as temperature increases.[8] Specifically, this figure plots the regression coefficients associated with each daily mean temperature bin, where the $<17°C$ bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity for worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. We start to see a significant effect with an additional day where daily mean temperature goes beyond 27°C. The point estimate indicates that swapping a day with daily mean temperature below 17°C for one with daily mean temperature beyond 31°C increases the probability of layoff by 0.236 percentage point, or a 3% increase in the baseline propensity (7.867 percentage points). Similarly for agricultural workers, in Figure 1.6, we see that all estimates associated with daily mean temperature beyond 27°C are positively significant at the 5% level.

Next, we look at changes in baseline hiring rates. Since we do not observe the worker if he or she is unemployed, I construct region–industry hiring shares by aggregating the total number of individual accessions in each quarter at the municipality–industry level, normalized by each municipality's population in 1999. The empirical framework follows Equation 1.1, except that we do not include worker- or plant-level controls. Figure 1.7 shows that heat shocks lead to a lower propensity for hiring agricultural workers but has no significant impact on manufacturing hiring.

[8]Coefficients are multiplied by 100.

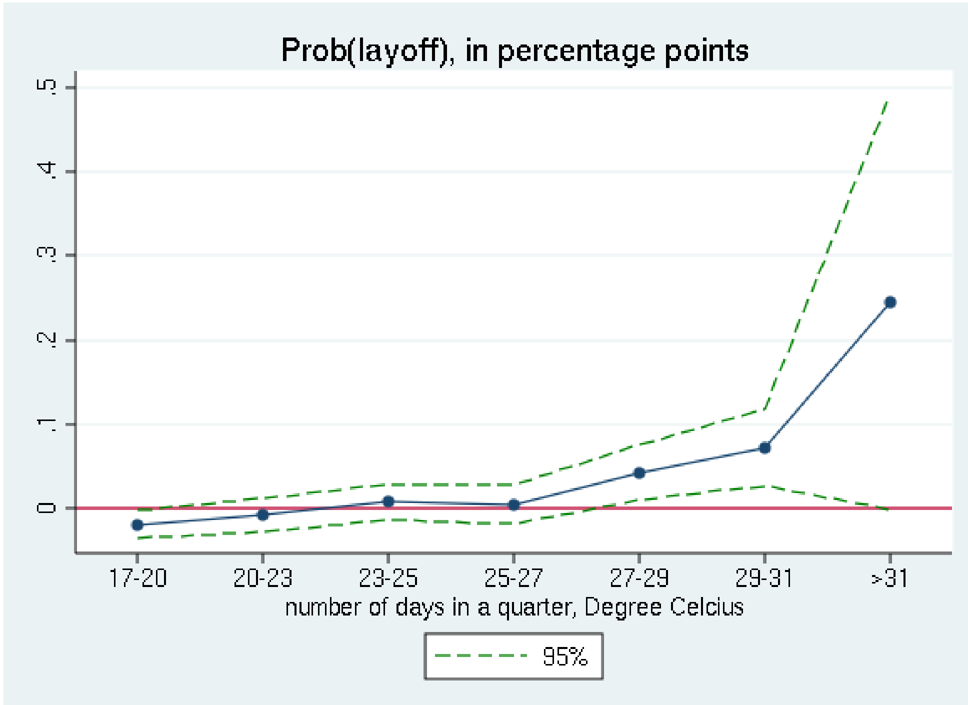


Figure 1.5: Quarterly heat shocks and manufacturing layoff: Net impact

Manufacturing Labor Market—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity for worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry and municipality fixed effects, along with other weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

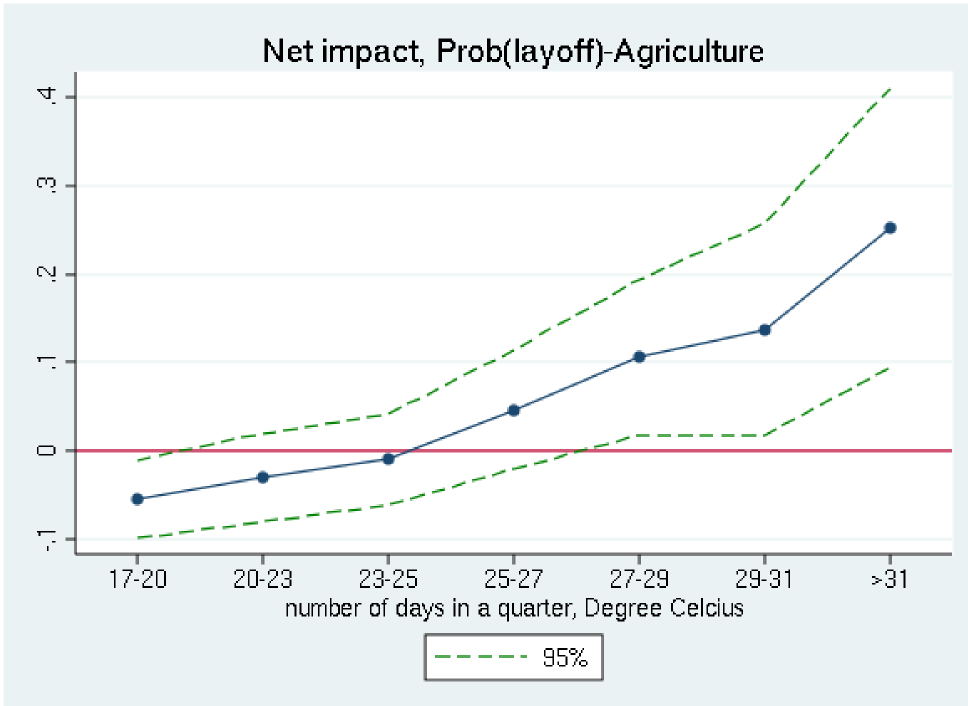


Figure 1.6: Quarterly heat shocks and agricultural layoff: Net impact

Agricultural Labor Market—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity for worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry and municipality fixed effects, along with other weather covariates and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

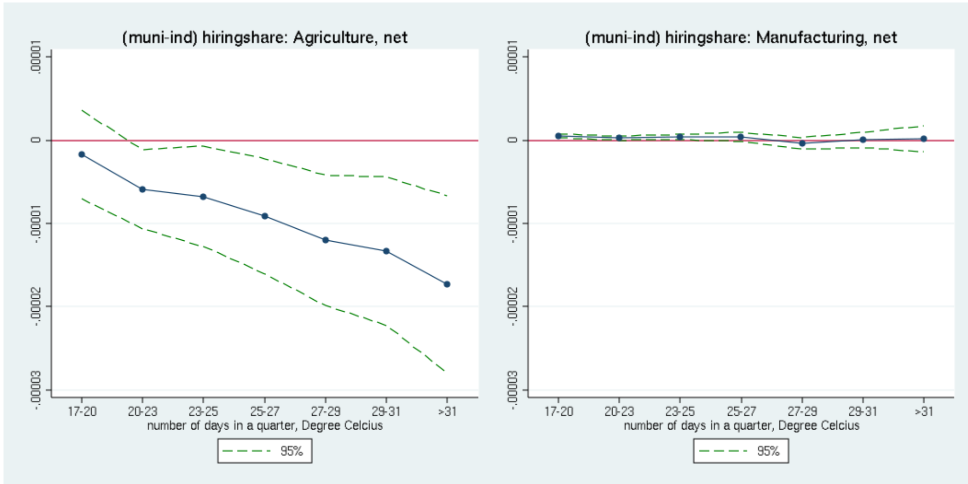


Figure 1.7: Agricultural vs. manufacturing hiring: Net impact

Agricultural and Manufacturing Labor Market—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1. The dependent variable is region–industry hiring share, constructed by aggregating the total number of individual accessions in each quarter at the municipality–industry level, normalized by each municipality's population in 1999. The independent variables are the numbers of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the hiring share, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, municipality fixed effects, along with other weather covariates (see text for details). Standard errors are clustered at the mesoregion level.

1.4 Transmission Mechanism

In Section 1.3, I show that quarterly heat shocks lead to immediate manufacturing and agricultural labor-market churn. These meaningful changes in employment outcomes could be driven by a wide range of underlying mechanisms, possibly operating in opposing directions. We need to rely on additional research design to identify the presence of any specific mechanisms.

Motivated by recent evidence on thermal stress and labor productivity (Adhvaryu et al., 2016), I now focus on identifying the importance of the direct labor-productivity channel in driving heat-related manufacturing layoff and hiring. I first introduce a methodology to isolate the direct labor-productivity channel from other transmission mechanisms, using the Brazilian agricultural surveys and regional crop calendars. Next, I present main results on manufacturing-worker layoff and hiring during growing versus nongrowing seasons. In Appendix C, to verify the underlying identifying assumption, I look at the formal agricultural labor market during growing versus nongrowing seasons.

1.4.1 Identifying the Physiological Channel

Recent evidence from both the climate–economy and ergonomics literature points to a significant labor-productivity drop as temperature increases.[9] However, we know little about whether this direct labor-productivity impact leads to changes in worker employment outcomes in an economy-wide setting. Establishing this crucial link helps us understand how firms and workers share the cost of climate change, and how to better design social-welfare programs in the presence of such environmental shocks.

Numerous factors are relevant when we assess how heat-related productivity shocks matter for market outcomes such as employment. For example, if individuals are heterogeneous in their sensitivity to heat, firms may lay off workers who experience the most productivity drop during heat shocks, or those who are less likely to exert effort when exposed to heat. Transitory heat shocks may also lead to layoff in the presence of downward nominal wage rigidity. The individual employment impact of heat shocks also depends on the degree of firm adaptation either through installing air conditioners or adaptive managerial practices.[10] Overall, the employment implications of the direct labor productivity channel is a rather complex empirical question rooted in labor-market institutions and firm- and worker-specific factors.

[9] Evidence from assembly lines, laboratories, meta-analysis, and self-reported surveys: Somananthan et al. (2014), Adhvaryu et al. (2016), Zander et al. (2015), Graff Zivin and Neidell (2014), Niemela et al. (2002), Seppanen et el. (2006), Kjellstrom et al. (2009), Park (2017)

[10] Adhvaryu, Kala and Nyshadham (2014) show that good managers adapt to air pollution shocks through worker task reassignment.

Identifying the transmission mechanism through which heat affects the manufacturing labor market also has crucial policy implications for targeting efficient climate-change adaptation strategies. If the direct labor-productivity channel is important in contributing to the labor-market impact of extreme heat shocks, we may think about installing more air conditioners in factories to mitigate the negative labor-productivity effect. On the other hand, if manufacturing workers are laid off due to indirect agricultural channels, the policy implications would be quite different. For example, if heat shocks reduce crop yield and raise agricultural input prices, input tariff liberalization may be an effective response. Similarly, establishing farmer-income stabilization programs would be helpful if the local demand channel is present.

The strategy I adopt in this paper to investigate the importance of the direct labor-productivity channel is by isolating heat shocks during the nongrowing seasons of each municipality. The underlying assumption is that heat shocks during local nongrowing seasons do not influence agricultural outcomes, allowing me to shut off various indirect agricultural channels through which temperature shocks affect the manufacturing labor market. A similar methodology has been recently adopted (Carleton, 2017; Burgess et al., 2018) to study the mechanism of how heat affects mortality. In Appendix C, I verify this identifying assumption by comparing outcomes during growing versus nongrowing seasons in the agricultural labor market.

Discerning the regional nongrowing seasons in Brazil involves two steps. Exploiting the Municipal Agricultural Production Surveys (PAM), I first determine the main crop of each municipality based on crop-production shares. Figure 1.8 shows the main crop of each municipality in Brazil ranked by production values. Major seasonal crops in Brazil include corn, cotton, rice, soybean, and sugarcane. The white areas represent municipalities whose main crop has year-round growing seasons. Next, I use the Brazil crop calendars from the USDA World

Agricultural Outlook Board to determine the nongrowing seasons of each crop.[11] A quarter for a municipality is categorized as the nongrowing season if it is the regional nongrowing season of the main crop of that municipality.

Figure 1.9 presents the resulting map showing the nongrowing seasons of each municipality. Excluding the municipalities with year-round growing seasons, quarter three, from July to September, is the main nongrowing season for most central and southern regions in Brazil. In the northeast, nongrowing seasons arrive later in quarter four, from October to December. This categorization corresponds approximately to three months before the arrival of the rain season, which is the approach adopted in Burgess et al. (2018) and Garg et al. (2017) to identify Indian nongrowing seasons.

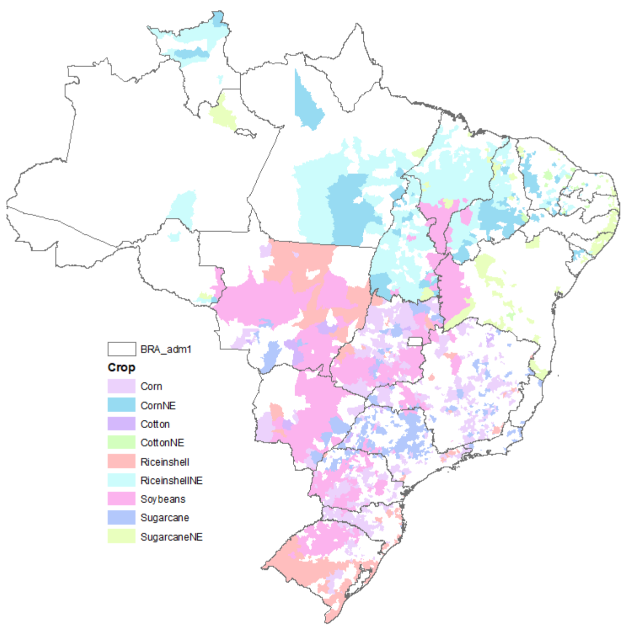


Figure 1.8: Main crop of municipality by production value

This map represents the main crop of each municipality in Brazil ranked by crop production values (see text for details). Major seasonal crops in Brazil include corn, cotton, rice, soybean, and sugarcane. The white areas represent municipalities whose main crop has year-round growing seasons (see text for details).

[11] These nongrowing seasons also correspond to those in the crop calendars by Sacks et al. (2010), which result from digitizing and georeferencing existing observations of crop planting and harvesting dates.

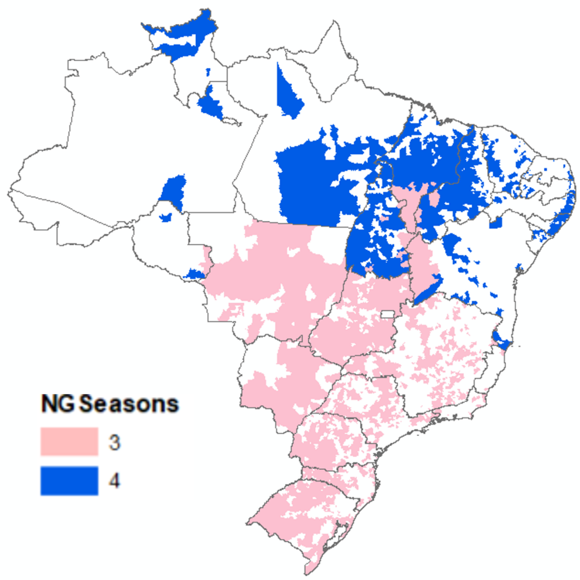


Figure 1.9: Main-crop nongrowing season by production value

This map shows the nongrowing seasons in Brazil. A quarter for a municipality is categorized as the nongrowing season if it is the regional nongrowing season of the main crop of that municipality.

1.4.2 Manufacturing Layoff and Hiring: Nongrowing vs. Growing Seasons

Having identified the regional nongrowing seasons, we are now ready to examine how important the direct labor-productivity channel is for manufacturing layoff. Intuitively, heat shocks during the nongrowing seasons do not affect agricultural outcomes, therefore allowing me to shut off multiple indirect agricultural channels and identify the direct labor-productivity channel. We proceed by comparing regression results during the growing versus nongrowing seasons, and then testing sensitivity in a series of alternative specifications.

Nongrowing Seasons

We first estimate the effect of heat shocks on manufacturing worker layoff in the nongrowing seasons. Under the assumption that nongrowing-season shocks have no effect on agricultural outcomes, I isolate the impact of the direct labor-productivity channel by focusing on nongrowing season shocks. The empirical framework follows Equation 1.2, which is a modification of Equation 1.1, where the dummy for growing seasons, $D^{GS}_{m,q}$, is interacted with temperature bins and other weather covariates.

$$\begin{aligned} Y_{ijmt} = &\sum \beta_k Tempbin^k_{m,t} + \sum \beta_s D^{GS}_{m,q} * TempBin^s_{m,t} + \beta_1 D^{GS}_{m,q} + f(Rain_{m,t}, Humidity_{m,t}) \\ &+ D^{GS}_{m,q} * f(Rain_{m,t}, Humidity_{m,t}) + \alpha_1 X_{it} + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \varepsilon_{ijmt} \end{aligned} \tag{1.2}$$

Figure 1.10 shows how the propensity for manufacturing-worker layoff varies with temperature during nongrowing seasons. We see a significant, highly nonlinear relationship, with extreme-heat days having a pronounced impact, starting with daily mean temperature above 29°C. In particular, the point estimate indicates that replacing a day with daily mean temperature below

17°C with one with daily mean temperature beyond 31°C increases the probability of layoff by 0.8 percentage points, a 11% increase from the baseline layoff propensity (7.2 percentage points). This highly nonlinear relationship is consistent with the thermal-stress literature on heat and individual labor productivity. Meta-analysis in ergonomics (Hancock et al., 2007) documents that task performance losses start to occur at 28°C and 80% relative humidity. Sharp performance losses occur at 32°C. Evidence from Indian garment factories documents 29.5°C as the physiological threshold above which temperature strongly impedes of human functioning (Adhvaryu et al., 2016).

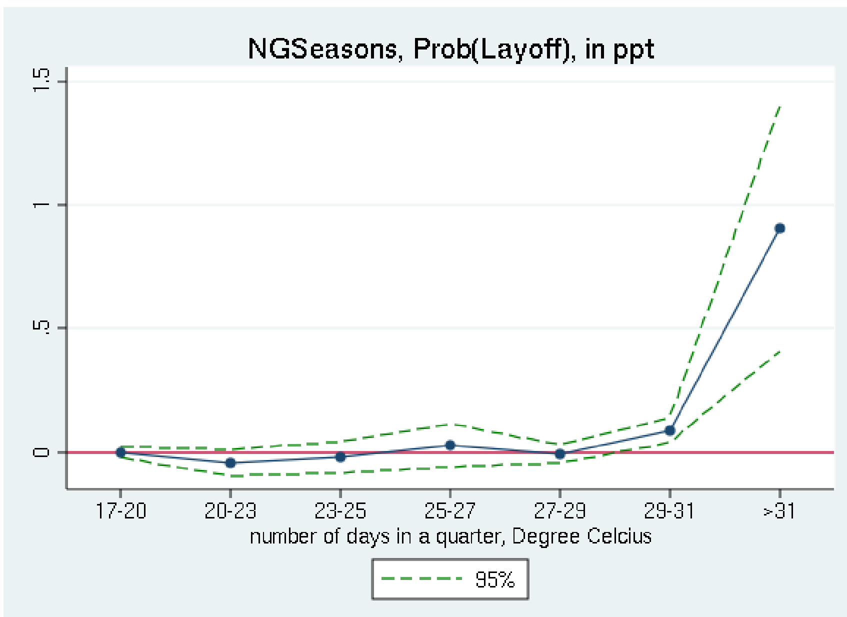


Figure 1.10: Manufacturing worker layoff: nongrowing seasons, with interacting specification

Manufacturing Labor Market, Nongrowing Seasons, Interaction Specification - Each point estimate reflects an individual regression coefficient, β_k, where the dependent variable is the binary outcome on worker layoff. Following Equation 1.2, we estimate the specification where $D^{GS}_{m,q}$ is a dummy for growing seasons. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the nongrowing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

The nongrowing season results in Figure 1.10 show that through the direct labor-productivity channel, thermal stress starts to significantly affect manufacturing layoff decisions only when daily average temperature goes beyond 29°C. This is consistent with the existence of firing and hiring costs in the formal sectors. Intuitively, moderate productivity losses do not justify firing costs, but large productivity losses under extreme heat increase the probability of worker layoff.

Taking the point estimate for the extreme-heat temperature bin (daily mean >31°C), we could compare the difference in layoff propensity for manufacturing workers in different regions. Since my identifying variations in the fixed-effects framework come from quarterly average temperature deviation, I first regress the raw number of days in the extreme-heat temperature bin on the fixed effects in Equation 1.1. Then I examine the distribution of the residuals. A municipality in a quarter with a "residual heat shock" in the 99th percentile experiences, on average, three extreme-heat days relative to the fixed-effect averages. Compared with a municipality that does not experience any extreme-heat days relative to the averages, the difference in the propensity of manufacturing worker layoff is 2.4 percentage points, equivalent to 33.3% of the average baseline layoff propensity (7.2 percentage points). This number should be interpreted with caution. Since the temperature bin setup assumes equal effect of each additional extreme heat day, my point estimate does not take into account possible harvesting effects.

Given these point estimates, future climate predictions also imply large disparities across regional local labor markets in Brazil. Recall from Figure 1.4 that during 2040–2059, under the RCP8.5 scenario, the central city of Palmas is projected to have 69.75 more days annually, or 17.4 more days quarterly of extreme heat. In contrast, the southern city of Sao Paulo incurs only 0.2 more extreme-heat days per quarter. These striking variations in the predicted number of extreme-heat days indicate large labor productivity gap across regions, and likely large second-moment differences in the frequency of productivity shocks from extreme heat. While this paper focuses only on increases in the second moment, absent adaptive capital and perfect labor mobility, both changes have important implications for disparity in regional employment outcomes.

These results on the direct labor-productivity channel are robust to a number of alternative specifications. First, to rule out worker sorting according to heat shocks based on unobserved time-invariant ability, I test sensitivity to including worker fixed effects. Second, lagged response to heat shocks during the growing seasons could influence layoff decisions during the nongrowing seasons if temperature shocks are serially correlated, so I control for lagged weather shocks. Third, to ensure the results are not driven by a few influential outliers, I run a robustness check implementing Cook's distance regression diagnostics. The main results hold under all these alternative specifications (Figures 1.17, 1.18).

Why might quarterly heat shocks lead to manufacturing layoff? In a simple setting, heat shocks during the nongrowing seasons lower marginal labor productivity. Incentive providing firms could adjust by either lowering wages or laying off workers, particularly those with low labor force attachment.[12] This is especially plausible given that the Brazilian labor market during this period is characterized by high turnover rate. Messina and Sanz-De-Galdeano (2014) show that wages in Brazil during the 1990s were subject to substantial downward rigidity due to indexation policies, and that wage adjustment was largely achieved through labor market turnover.

Many other relevant factors could also be at play. For example, the workers laid off could be of lower quality. Recent papers show that workers are heterogeneous in their sensitivity to heat or willingness to exert effort under adverse work conditions (Graff Zivin and Neidell, 2014). Learning a worker's type could be informative of how she/he responds to other types of shocks

[12]By law, manufacturing firms in Brazil pay a moderate penalty for firing workers without cause. The cost amounts to about 8%–19% of the expected UI benefits paid to workers (van Doornik et al., 2017). De facto cost of firing may be lower for firms further from enforcement offices (Almeida and Carneiro, 2012).

to workplace conditions. This worker-specific information could be unknown to the employer ex-ante, but revealed after extreme heat days, leading to layoff of those who experience a larger productivity drop. Firms may also face cash flow constraints (Chodorow-Reich, 2013). Yet another possibility is that workers are transitioning into the informal sector. In Section 1.7, I offer further evidence with respect to some of these factors.

Growing Seasons

Unlike the nongrowing season impact, which is only driven by the direct labor-productivity channel, heat shocks during growing seasons could influence manufacturing hiring and layoff via a complex array of transmission mechanisms, both directly and through interindustry linkages. As we see in Figure 1.11, manufacturing layoff propensity during growing seasons also increases with temperature, but the magnitude is much smaller at extreme temperature ranges. Replacing a day with daily mean temperature below 17°C with one with daily mean temperature beyond 31°C increases the probability of layoff by 0.12 percentage point, or a 1.5% increase from the baseline layoff propensity (7.9 percentage points).

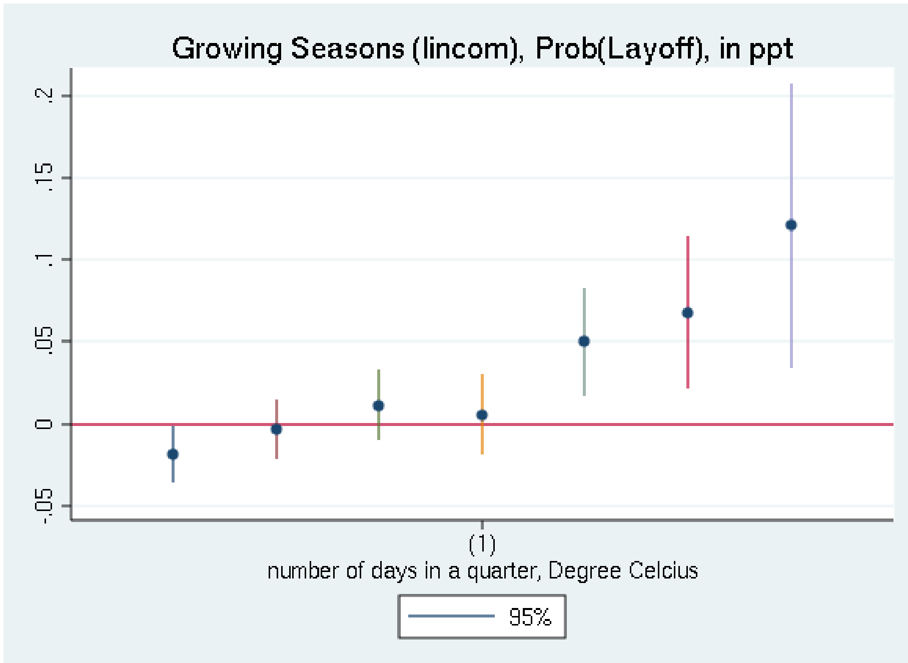


Figure 1.11: Quarterly heat shocks and manufacturing layoff: Growing seasons

Manufacturing Labor Market, Growing Seasons, Interaction Specification - Each point estimate reflects an individual regression coefficient, β_k, where the dependent variable is the binary outcome on worker layoff. Following Equation 1.2, we estimate the specification where $D^{GS}_{m,q}$ is a dummy for growing seasons. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The linear combination of coefficient β_k + β_s is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the growing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

The point estimates in Figure 1.11 can be interpreted as the combined impact of the direct labor-productivity channel and indirect agricultural channels through interindustry linkages. Given the fixed-effects framework and controls on state- and industry-specific seasonality, I am not able to directly compare the magnitude of estimates in Figure 1.10 and Figure 1.11 and infer the direction of impact through agricultural channels. This is because the identified magnitude through the direct labor-productivity channel could be different in growing versus nongrowing seasons due to different baseline temperatures across seasons.

The existing literature suggests that the indirect agricultural channels could be working in an opposing direction as the direct labor-productivity channel at extreme temperature ranges. Colmer (2017) finds that as temperature increases, the manufacturing sector absorbs displaced agricultural workers during growing seasons. If the incoming workers complement incumbent manufacturing workers, existing workers might benefit from this agricultural outmigration channel. If on the other hand, incoming workers substitute, then incumbent manufacturing workers may experience displacement. In Section 1.5, I offer direct evidence on intersectoral labor reallocation by directly tracking workers across job spells and decomposing postlayoff channels.

1.5 Labor Reallocation

In the presence of significant costs in the job reallocation process, only accounting for the immediate adjustment margins would lead to underestimation of total worker welfare losses. The unique employer-employee linkage feature of RAIS allows me to examine individual job reallocation and better understand the medium-run adjustment margins for heat-related layoffs. In this section, I present an empirical strategy and provide evidence on manufacturing worker reallocation between sectors and across municipalities.

1.5.1 Empirical Strategy

To understand heat-related worker reallocation, I construct dummies for seven mutually exclusive, collectively exhaustive categories for postlayoff transition outcomes. Conditional on layoff, I assign the worker to be in one of the following seven categories according to reallocated sector and region: (1) Move to the manufacturing sector in the same municipality within 36 months, (2) Move to the manufacturing sector in a different municipality within 36 months, (3) Move to the agricultural sector in the same municipality within 36 months, (4) Move to the agricultural sector in a different municipality within 36 months, (5) Move to the service/primary sector in the same municipality within 36 months, (6) Move to the service/primary sector in a different municipality within 36 months, or (7) Fail to move to any formal employer within 36 months.

The data requirement for studying worker reallocation is high. Using RAIS, I am able to track each worker across job spells over time, identifying employers by sector and municipality.[13] The empirical specification follows the fixed-effect model in Equation 1.3:

$$Y^{p}_{ijmt} = \sum \beta_k Tempbin^{k}_{m,t} + f(Rain_{m,t}, Humidity_{m,t}) + \alpha_1 X_{it} + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \varepsilon_{ijmt} \tag{1.3}$$

where Y^{p}_{ijmt} is the binary variable for whether the worker i, employed in industry j, residing in municipality m, at time t, belongs to a particular postlayoff category p.[14] For example, Y^{1}_{ijmt} takes the value of one if a worker experiences a layoff at time t, and subsequently moves to a manufacturing employer in the same municipality within 36 months, and zero otherwise. Because Y^{p}_{ijmt}s are conditional on layoff, a worker who has never experienced a layoff during the sample period will have a value of zero for all the postlayoff transition outcomes.

The rest of this fixed-effect specification is the same as in Equation 1.1. Allowing for nonlinear effects, $Tempbin^{k}_{m,t}$ is the number of days in a quarter with daily mean temperature in the specified range k.[15] $f(Rain_{m,t}, Humidity_{m,t})$ controls for the cumulative rainfall and relative

[13]To study worker reallocation 3 years postlayoff, I do not consider layoffs that occur during the last 3 years of my sample period.

[14]To fully decompose the reallocation channels, we run eight regressions in total.

[15]Tempbin1, where $t < 17°$C, is omitted.

humidity. X_{it} is a vector of worker and plant-level controls including worker education, occupation categories, tenure, potential labor force experience, plant size, and plant-skill composition.

I include Quarter*Sate, State*Year, and Quarter*Year fixed effects to control for state-specific seasonality in employment, state growth trends, and national business cycles. Industry*Year and Industry*Quarter fixed effects control for industry-growth trends and industry-specific seasonality. State*Industry fixed effects control for regional industrial patterns of specialization. Municipality fixed effects control for any time-invariant municipality characteristics. Standard errors are clustered at the mesoregion-level to allow for spatial and serial correlation.

1.5.2 Results: Reallocation for Manufacturing Workers

I examine medium-run worker-level adjustment margins of heat shocks by looking at individual job reallocation channels after heat-related layoff. If heat shocks cause contemporaneous layoff but workers quickly transit to another formal employer in a short period of time, the associated medium-run individual welfare loss could be small. However, as I show, a significant portion of workers who experience layoff due to heat shocks fail to find any formal employer within 36 months, leading to prolonged individual labor-market impact. In this subsection, I focus on decomposing manufacturing reallocation outcomes following heat shocks in all seasons. Appendix B offers further evidence for nongrowing seasons.

As illustrated in Table 1.1, the impact of heat shocks on postlayoff transition outcomes in columns 1-7 sum to the impact on total layoffs, given in column 2. Swapping a day with daily mean temperature below 17°C for one with daily mean temperature beyond 31°C increases the total probability of manufacturing layoff by 0.25 percentage points. Note this point estimate is slightly different from the magnitude in Figure 1.5 because I do not look at layoffs during the last

3 years to analyze reallocation over the 3-year horizon.

Decomposing the reallocation channels associated with daily mean temperature beyond 31°C, column 1 shows that 54% (0.14 percentage points) of manufacturing workers laid off due to extreme heat find a formal-sector manufacturing employer in the same municipality within 36 months. Limited intersectoral and interregional reallocation exists for manufacturing workers laid off due to heat shocks. Reallocation to the formal agricultural sector in the same municipality is statistically significant though economically smaller (8%). Based on columns 2, 4, 5, 6, other reallocation channels are economically small and not statistically significant at the 5% level. Figures 1.12, 1.13 and 1.14 present visualizations of these results, where the left panels show transitions within the same municipalities across sectors, and the right panels show interregional worker reallocation.

Figure 1.15 and column 7 in Table 1.1 illustrate the salience of failure to reallocate for manufacturing workers laid off due to heat shocks. A significant 24.3% of all manufacturing workers who experienced heat-related layoffs fail to find any formal sector employment within 36 months. Swapping a day with daily mean temperatures below 17°C for one with daily mean temperatures beyond 31°C increases the propensity of manufacturing layoff followed by failure to reallocate within 3 years by 0.06 percentage points. This is equivalent to 0.8% of the baseline layoff propensity.

Table 1.1: Quarterly heat shocks and manuf. worker reallocation, all seasons

	(1) Manu-s b/se	(2) Manu-d b/se	(3) Agr-s b/se	(4) Agr-d b/se	(5) Serv-s b/se	(6) Serv-d b/se	(7) Failure b/se	(8) Tot. layoff b/se
Temp(17-20)	-0.00946*	-0.00220**	-0.00194**	-0.00190**	-0.00107	-0.00226*	-0.00180	-0.02064**
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
Temp(20-23)	-0.00526	-0.00154	-0.00089	-0.00143	0.00010	-0.00240	-0.00101	-0.01243
	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.011)
Temp(20-25)	0.00799	-0.00022	-0.00052	0.00081	0.00245*	-0.00245	-0.00014	0.00793
	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)
Temp(25-27)	0.00198	-0.00118	-0.00081	0.00015	0.00146	0.00039	0.00253	0.00451
	(0.007)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.013)
Temp(27-29)	0.02413**	0.00166	0.00117	0.00336**	0.00320	0.00628***	0.00380	0.04359**
	(0.010)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.017)
Temp(29-31)	0.03784***	0.00106	0.00420**	0.00454*	0.00478	0.00855***	0.01252**	0.07350***
	(0.014)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.024)
Temp(>31)	0.13816*	0.01057	0.02177***	0.00536	0.00705	0.00818	0.06142*	0.25250**
	(0.075)	(0.009)	(0.007)	(0.003)	(0.006)	(0.008)	(0.032)	(0.127)
N	16322039	16322039	16322039	16322039	16322039	16322039	16322039	16322039
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter × State, State × Year, Quarter × Year, Prod × Quarter, Prod × Year, Prod × State**							

Manufacturing Reallocation, All Seasons—Following Equation 1.3, the dependent variable Y^{p}_{ijmt} is the binary variable for whether the worker belongs to a particular postlayoff category, p. The independent variables are the numbers of days in a quarter with daily mean temperature within a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The outcomes for Columns 1–8 are (1)failure to reallocate to any formal employer, within 36 months. (2)probability of total layoffs (3)reallocate to the manufacturing sector, in the same municipality, within 36 months; (4) reallocate to the manufacturing sector, in a different municipality, within 36 months; (5) reallocate to the agricultural sector, in the same municipality, within 36 months; (6) reallocate to the agricultural sector, in a different municipality, within 36 months; (7) reallocate to the service/primary sector, in the same municipality, within 36 months; (8) reallocate to the service/primary sector, in a different municipality, within 36 months. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with other weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

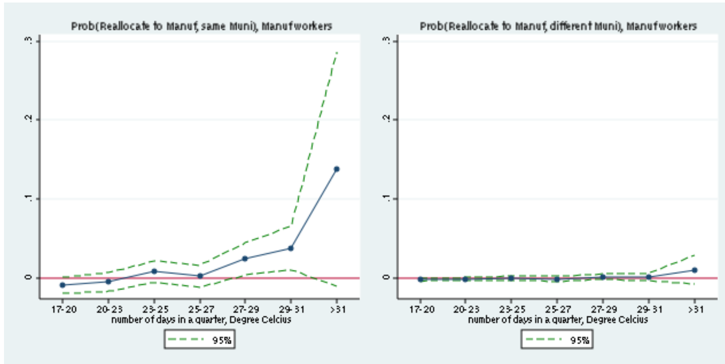


Figure 1.12: Quarterly heat shocks and manufacturing workers layoff, with reallocation to manufacturing within 36 months

Manufacturing Reallocation, All Seasons—Following Equation 1.3, the dependent variable Y_{ijmt}^{p} is the binary variable for whether a worker belongs to a particular postlayoff category p. The independent variables are the number of days in a quarter with daily mean temperature in a specific range, $Tempbin_{m,t}^{k}$. The "<17°C" bin is the omitted category. The outcomes are (Left Panel) Reallocate to the manufacturing sector in the same municipality, within 36 months and (Right Panel) Reallocate to the manufacturing sector in a different municipality within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

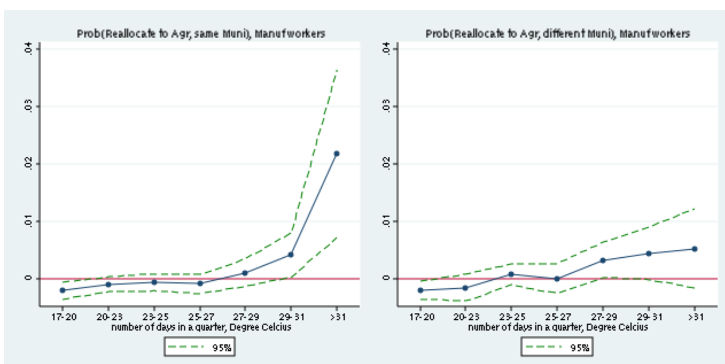


Figure 1.13: Quarterly heat shocks and manufacturing workers layoff, with reallocation to agriculture within 36 months

Manufacturing Reallocation, All Seasons—Following Equation 1.3, the dependent variable Y_{ijmt}^{p} is the binary variable for whether the worker belongs to a particular postlayoff category p. The independent variables are the number of days in a quarter with daily mean temperatures in a specific range, $Tempbin_{m,t}^{k}$. The "<17°C" bin is the omitted category. The outcomes are (Left Panel) Reallocate to the agricultural sector in the same municipality within 36 months and (Right Panel) Reallocate to the agricultural sector in a different municipality within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

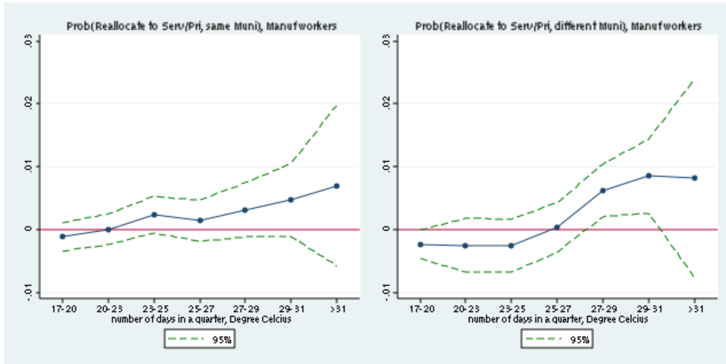


Figure 1.14: Quarterly heat shocks and manufacturing workers layoff, with reallocation to Services/Primary within 36 months

Manufacturing Reallocation, All Seasons—Following Equation 1.3, the dependent variable Y^{p}_{ijmt} is the binary variable for whether a worker belongs to a particular postlayoff category p. The independent variables are the number of days in a quarter with daily mean temperatures in a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The outcomes are (Left Panel) Reallocate to the services sector in the same municipality within 36 months and (Right Panel) Reallocate to the services sector in a different municipality within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

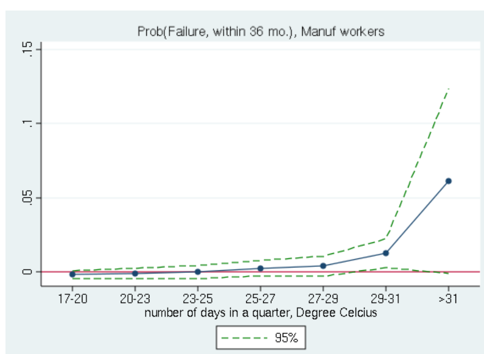


Figure 1.15: Quarterly heat shocks and manufacturing workers layoff: failure to reallocate within 36 months

Manufacturing Reallocation Failure, All Seasons—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.3, where the dependent variable is the binary outcome on whether the worker experiences a layoff followed by failure to reallocate within 36 months. The independent variables are the number of days in a quarter with daily mean temperature in a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

A number of reasons could explain this high rate of failure to reallocate due to heat shocks. First, after layoffs, other employers may take it as a signal that the worker is a low type and are therefore reluctant to hire. However, this alone does not seem sufficient to explain the high rate of prolonged failure to reallocate even in another sector or municipality within 3 years. Papers examining labor reallocation after trade liberalization[16] suggest that intersectoral reallocation frictions are much more pronounced in developing countries such as Brazil relative to developed countries such as the U.S. Compared with more permanent trade liberalization, here I show that even transitory temperature shocks lead to significant failure to reallocate, possibly due to frictions in the job rematching process.

Third, transitioning to informality could be an important aspect. Workers not reallocating to another formal-sector job after heat-related layoff could be either unemployed or informally employed. Dix-Carneiro and Kovak (2017b) find that the informal sector is an important absorber of formal workers laid off during trade liberalization. Formal jobs are generally considered to be of higher quality, offering more benefits and greater labor production than informal jobs (La Porta and Sheleifer, 2014). Transitioning to the informal sector under extreme heat shocks could have important worker-welfare implications; an area for future research.

Understanding worker reallocation better quantifies the full cost of climate change for the labor market. Especially in developing countries, the long-term formal labor-market "scarring" associated with heat shocks likely implies more pronounced individual welfare losses. Finally, failure to reallocate happens for both growing and nongrowing season heat shocks. Details appear in Section 1.10.

[16] Dix-Carneiro (2014), Goldberg and Pavcnik (2007), Autor et al. (2014).

1.6 Heterogeneity

Having examined mechanisms and labor reallocation, I now turn to the distributional impact of temperature shocks, identifying the most vulnerable groups in the manufacturing workforce. In addition to the worker-level characteristics in RAIS, I further link variables from the *Dictionary of Occupation Titles (DOT)* to study heterogeneity by occupation-task intensity.

Meta-analysis (Hancock et al., 2007) in the ergonomics literature suggests that thermal stress has the highest impact on psychomotor and motor tasks, and the lowest impact on cognitive skills. In more routine-manual task-intensive occupations, workers' heterogeneous sensitivity to heat may also be better revealed. So the hypothesis is that through the direct labor-productivity channel, individual employment effects are significantly higher for workers in routine-manual-intensive occupations.

1.6.1 Empirical Strategy

I follow Autor, Levy, and Murnane (2003) in using data from the DOT to construct occupational task-intensity measures for the U.S. Census Occupational Codes. To match the U.S. Census Occupational Codes to the Brazilian Occupational codes, I first concord across time using data provided by Autor and Dorn (2013), and then map the 2000 U.S. Census Occupational Codes to the International Standard Classification of Occupations (ISCO-88), provided by the Center for Longitudinal Studies in UCL. Finally, the concordance from ISCO-88 to the Brazilian occupational codes CBO is by Muendler et al. (2004). Assuming that Brazil and the U.S. share similar relative task intensity across occupations, I obtain an index for routine-manual task intensity (RMTI) based on the DOT measure of *Finger Dexterity* (Autor, Levy and Murnane, 2003).

Table 1.2: Examples of occupations by RMTI

Occupations: Routine-manual task intensity	
High	**Low**
Fabric treating, printing workers	Mathematicians and actuaries
Spinners, twisters, and related workers	Production and research managers
Lace makers, weavers, dyers,	Machine maintenance mechanics
Dressmakers	Cabinet makers
Telephone, telegraph operators,	Plastic product workers

Based on Brazilian CBO three-digit occupational codes in RAIS.

Table 1.2 gives some common examples of occupations (CBO, 3-digit) in RAIS with the highest and lowest measures of routine-manual-task intensity. Highly routine manual task-intensive occupations such as fabric treating and weavers require more motor or psychomotor skills, whereas low routine-manual-task occupations require more cognitive skills.

The estimation framework follows Equation 1.4 and allows for heterogeneous impact along a variety of worker and plant attributes:

$$\begin{aligned} Y_{ijmt} = \sum \beta_{1k} RMTI_{it} * Tempbin^{k}_{m,t} + \sum \beta_{2k} Z_{it} * Tempbin^{k}_{m,t} + \sum \beta_{3k} * Tempbin^{k}_{m,t} \\ + \beta_{40} RMTI_{it} * Hum_{m,t} + \beta_{41} Z_{it} * Hum_{m,t} + \beta_{50} RMTI_{it} * Rain_{m,t} + \beta_{51} Z_{it} * Rain_{m,t} \\ + f(Rain_{m,t}, Hum_{m,t}) + \alpha_1 Z_{it} + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \varepsilon_{ijmt} \end{aligned} \tag{1.4}$$

Y_{ijmt} is the binary outcome for worker layoff. Weather variables on temperature, rainfall, and humidity are defined as before. $RMTI_{it}$ measures worker i's occupational routine-manual-task intensity. Z_{it} is a vector of worker-level covariates including wage, gender, tenure, and size of the plant. Both $RMTI_{it}$ and Z_{it} are standardized. X_{it} are other worker or plant-level controls. Fixed effects are included at the Quarter*Year, Year*State, Quarter*State, Industry*Year, Industry*Quarter, State*Industry, and Municipality level. Standard errors are clustered at the mesoregion-level.

1.6.2 Results

The key coefficients of interest are β_{1k} and β_{2k}, capturing the differential impact of heat shocks interacting with worker attributes on initial occupational-task intensity, wage, gender, plant size, and tenure. Table 1.3 presents the key coefficients focusing on the interaction with the highest temperature bin ($> 31°C$). I separately examine heterogeneous effects in the nongrowing seasons and in the full sample.

Column 1 shows the estimates for manufacturing worker layoff during the nongrowing seasons, where only the direct labor productivity channel is at work. Here the hypothesis is that as temperatures increase, labor productivity in more routine-manual-intensive tasks will see a larger decrease. Consistent with the ergonomics literature on thermal stress, workers in routine-manual-task-intensive occupations are more likely to experience heat-related layoff. Having a routine-manual-task-intensity measure of one standard deviation beyond the mean increases the effect of an additional extreme heat day by 0.27 percentage points. We also see that the impact of heat shocks are more pronounced for those with less tenure at the plant, which could indicate that workers laid off are more temporary or have lower labor force attachment.

In the full sample presented in column 2, a differential effect no longer emerges according to occupational routine-manual-task intensity. Because in the full sample manufacturing workers are laid off from a combination of direct labor productivity and indirect agricultural channels, a pronounced differential impact is unlikely to occur by occupation. Finally, it is important to note that the source of heterogeneity is consistent with, but not limited to, the direct labor productivity channel. Differential coverage of climate controls in the same establishment, observed in Indian diamond-processing factories by Somanathan et al. (2014), for example, could also explain this

Table 1.3: Manufacturing layoffs: Worker-level heterogeneity

	(1) layoff b/se	(2) layoff b/se
Temp(>31)	0.0271	0.1037
	(0.092)	(0.072)
RMTI*Temp(>31)	0.2685**	0.0625
	(0.103)	(0.077)
Tenure*Temp(>31)	-0.1443*	-0.1162*
	(0.083)	(0.062)
Observations	1061664	14437797
Subsample	NGSeasons	Full
Clustering	**meso**	
Other FEs	**Quarter*State, State*Year, Quarter*Year, Prod*Quarter, Prod*Year, Prod*State**	
Y(mean)	6.304	6.422

Manufacturing Labor Market, Heterogeneity—Following Equation 1.4, the dependent variable Y^{p}_{ijmt} is the binary variable for worker layoff. The independent variables, "RMTI $\times Tempbin^{k}$," are the worker's occupational routine-manual task intensity (normalized), interacted with the numbers of days in a quarter with daily mean temperature within a specific range k. The "$< 17°$C" bin is the omitted category. All regressions include quarter $\times$ state, quarter $\times$ industry, quarter $\times$ year, state $\times$ year, industry $\times$ year, state $\times$ industry, and municipality fixed effects, along with weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

heterogeneity. Alternatively, if occupations differ in the ease with which workers can switch to the informal sector, one could also observe a similar differential impact by occupational-task intensity. Overall, heterogeneity analysis in this section informs identification of vulnerable groups in the manufacturing workforce most affected by heat shocks, and reveals potential distributional impact.

1.7 Additional Evidence

In Section 1.4, I briefly reviewed some possible scenarios in which transitory shocks could lead to significant increases in manufacturing layoff. The simplest explanation is if firing and hiring costs are not prohibitively high, which I test here using Bartik-type shocks in output. Other relevant factors include asymmetrical adjustment costs leading to concave hiring rules (Ilut et al., 2018), worker heterogeneity in heat sensitivity, or willingness to exert effort under heat exposure (Graff Zivin and Neidell, 2014), and downward nominal wage rigidity. In this section, I also explore the role of nominal wage rigidity using historic inflation spikes in Brazil.

1.7.1 The Role of Nominal Wage Rigidity

Brazil experienced high and volatile episodes of inflation after the 1960s. I exploit the inflation spike in the 1990s to check if downward nominal wage rigidity could cause the employment effect of heat shocks. Intuitively, firms may choose to lay off workers when wages are rigid downwards. During periods of high inflation, however, real wages are effectively lower, leading to smaller employment effects of extreme heat shocks. The effect of inflation would not be present if wages are always indexed. Throughout 1985–1999, however, the Brazilian government periodically froze wages and stopped indexation to lower inflation expectations (Duryea and Arends-Kuenning, 2003).

$$\begin{aligned} Y_{ijmt} = \sum \beta_{1k} Inflation_t * Tempbin^k_{m,t} + \sum \beta_{2k} * Tempbin^k_{m,t} + \beta_3 Inflation_t * Hum_{m,t} \\ + \beta_4 Inflation_t * Rain_{m,t} + f(Rain_{m,t}, Hum_{m,t}) + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \tau_m + \varepsilon_{ijmt} \end{aligned} \tag{1.5}$$

Y_{ijmt} is the binary outcome for worker layoff. Weather variables of temperature, rainfall, and humidity are defined as before. $Inflation_t$ is quarterly inflation measured by the Brazilian national price index, *INPC*.[17] Fixed effects are included at the Quarter*Year, Year*State, Quarter*State, Industry*Year, Industry*Quarter, State*Quarter, and Municipality level. Standard errors are clustered at the mesoregion level.

[17] These data are made public by Marc Muendler, http://econweb.ucsd.edu/muendler/.

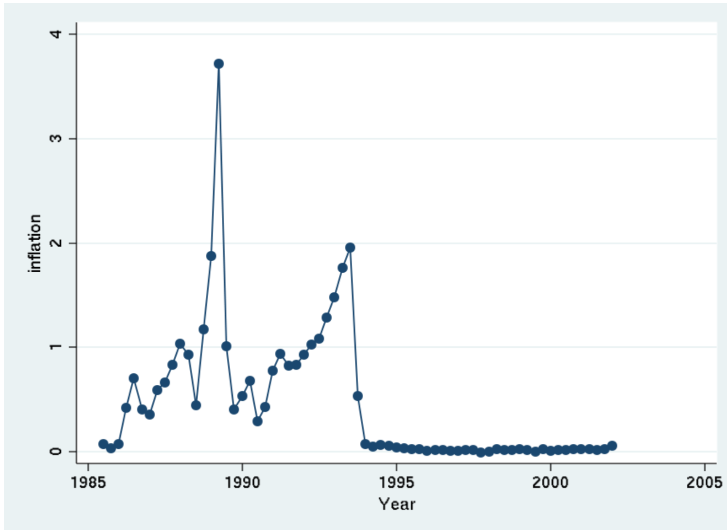


Figure 1.16: Quarterly Brazilian inflation index

This chart shows quarterly inflation measured by the Brazilian national price index, *INPC*, from 1985 to 2002. Raw data are made public by Marc Muendler, http://econweb.ucsd.edu/muendler/.

Figure 1.16 plots the "hyperinflation" period in Brazil using the quarterly inflation index from 1986 to 2002. I match the data from 1990 to 2000 with RAIS and exploit the inflation spike from 1990 to 1995. I interpose the inflation index with heat shocks to see whether the employment impact of extreme heat is smaller during high inflation. My intuition indicates that the employment effect of a labor productivity drop is larger when nominal wages are rigid downward. By effectively lowering real wages, higher inflation dampens the effect on worker layoff. Kaur (2018) pioneered this test and found a similar mechanism in Indian village labor markets.

Table 1.4 shows the results of nongrowing versus growing seasons. Here I focus on the effect of an additional extreme heat day, with daily mean temperatures beyond 31 degrees Celsius. Column 1 shows that during nongrowing seasons, swapping a day with daily mean temperatures below 17°C for one with daily mean temperatures beyond 31°C increases the probability of layoff by 1.4 percentage points, or a 19.45% increase of the baseline layoff propensity (7.17 percentage points). The effect does not vary with inflation, suggesting downward nominal wage rigidity is

Table 1.4: Heat shocks and nominal wage rigidity: Growing vs. nongrowing seasons

	(1) Layoff b/se	(2) Layoff b/se
Temp(>31)	1.3946***	0.1245**
	(0.358)	(0.049)
Temp(>31) × Inflation	0.2678	-0.0956**
	(0.278)	(0.037)
Humidity	-0.0113	-0.0047
	(0.056)	(0.011)
Humidity × Inflation	-0.0775	-0.0100
	(0.068)	(0.016)
Observations	1,377,060	16,182,508
Municipality FE	Yes	Yes
Subsample	NGSeasons	GSeasons
Clustering	meso	meso
Y (mean)	7.17	7.75

Manufacturing Labor Market, Nominal Wage Rigidity—Following Equation 1.5, the dependent variable, Y^{p}_{ijmt}, is the binary variable for worker layoff. The key independent variables, $Tempbin^{k}\times$ inflation, are the number of days in a quarter with daily mean temperature within a specific range k, interacted with the quarterly inflation index. The "< 17°C" bin is the omitted category. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

not a dominant cause of the manufacturing layoffs observed in Section 1.4.2.1. That is, even when the wage floor is flexible, firms still choose to lay off workers under extreme heat during nongrowing seasons. One possibility consistent with this evidence is if workers who are more heat sensitive or who exert less effort when exposed to heat are revealed after heat shocks, they may be laid off regardless of wage rigidity. In contrast, Column 2 shows that layoffs during growing seasons are dampened during high inflation. Intuitively, growing-season layoffs could be caused by lower local demand or higher input price from indirect agricultural channels. Firms are less likely to lay off workers when inflation enables downward real-wage adjustment.

1.7.2 Bartik Shocks in Output

Whether a significant labor productivity shock caused by heat stress would lead to worker layoff depends on specific labor-market institutions in Brazil. In this subsection, I provide relevant institutional details on hiring and firing costs, and check the ease with which firms lay off workers in the presence of temporary output contraction.

Firms in Brazil in general face moderate firing and hiring costs. In the case of layoffs without a special cause, the firm pays 40% of the accumulated job security fund (FGTS) upon layoff (Menezes-Filho and Muendler, 2011), which is about 0.5 month's salary for the average person being laid off in my sample.[18] The firm's penalty for laying off a worker is around 8–19% of the UI benefit paid to the worker (Van Doornik et al., 2017). However, Almeida and Carneiro (2012) also suggest that due to imperfect enforcement, the de facto cost of firing a worker may be less than it appears on paper.

To check the ease with which firms lay off workers in Brazil, I estimate the impact of

[18]The median tenure of workers at the time of layoff in my sample is around 15 months.

Bartik output shocks on firm employment following an approach similar to Hershbein and Kahn (2018). If layoff decisions respond to the regional share of national changes in output, the firing costs are unlikely to be prohibitively high. I use the full sample data in RAIS to construct regional industry employment weights and the Industrial Physical Production Index from the PIM (IBGE) for industry-specific changes in national output during the years 1992–2000.[19] $\phi_{m,k,\tau}$ stands for the regional industry employment share of industry k in municipality m in a prior year (1989). lnB_{kt} is the log of national output in industry k in year t. The Bartik shock in output for municipality m in year t, ΔB_{mt}, is calculated following Equation 1.6. I estimate how the probability of worker layoff responds to Bartik shocks in output following the fixed-effect framework in Equation 1.7.

$$\Delta B_{mt} = \sum^{k} \phi_{m,k,\tau}(lnB_{kt} - lnB_{k,t-1}) \tag{1.6}$$

$$Y_{ikmt} = \beta_1 \Delta B_{mt} + \alpha_1 X_{it} + \theta_{kt} + \Phi_{ks} + \tau_m + \tau_i + \varepsilon_{ikmt} \tag{1.7}$$

Y_{ijmt} is the binary outcome for worker layoff at the yearly frequency. X_{it} is a vector of worker and plant-level controls. I also include controls for industry growth trends, industry specializations, and municipality and worker fixed effects. Standard errors are clustered at the worker and municipality levels. To examine layoff response to output contraction versus expansion, I look at the subsample where the Bartik shock is negative rather than positive. Table 1.5 shows that the probability of layoffs responds strongly to annual output contraction and less so to output expansion, consistent with firms having concave hiring rules (Ilut et al., 2018). In particular, a one-percentage-point (relative) regional output reduction leads to a 0.57 percentage point increase in the probability of worker layoff, whereas an output expansion of the same magnitude only leads to a 0.16 percentage point decrease in the propensity of layoff.

[19] The index is not available for 1991.

Table 1.5: Manufacturing layoff and yearly Bartik shock in output

	(1) Layoff b/se	(2) Layoff b/se
ΔB_{mt}^{output}	-0.5659***	-0.1565**
	(0.153)	(0.075)
Observations	1,488,964	2,537,323
Worker FE	Yes	Yes
Municipality FE	Yes	Yes
Subsample	$\Delta B_{mt} < 0$	$\Delta B_{mt} > 0$
Clustering	**Worker, Municipality**	

Manufacturing Labor Market—Following Equation 1.7, the dependent variable, Y_{ijmt}, is the binary outcome for worker layoff at the yearly frequency. The independent variable, ΔB_{mt}, is the municipality-level Bartik shock in output (see text for details). All regressions include industry $\times$ year, state $\times$ industry, worker, and municipality fixed effects, along with a rich set of firm- and worker-level controls. *** Significant at 1%, ** 5%, * 10%.

1.8 Conclusion

Climate change poses significant challenges to manufacturing labor markets in developing countries, especially given future climate predictions. In this paper, I examine the short- and medium-run employment adjustment margins of heat shocks through individual worker layoff, hiring, and job reallocation. By focusing on heat shocks during the nongrowing seasons of each local labor market in Brazil, I show that the direct labor-productivity channel associated with extreme heat days leads to significant worker layoff. These effects are more pronounced for workers in more routine manual task-intensive occupations. Over time, a significant 24.3% of all manufacturing workers who were laid off due to quarterly heat shocks failed to find another formal job within 36 months, suggesting large worker-level costs over the medium run.

I address several natural extensions in ongoing work. The first is to further understand how climate change affects worker transition into informality and associated implications for worker welfare. Second, I expand work on various adjustment margins that include the firm, industry, and regional perspectives, which helps better explain the adjustment process in general equilibrium. Finally, given more pronounced impact on workers in lower skilled occupations and the large fraction of workers near minimum wage in Brazil, the next step is to quantify how existing social welfare programs interact with climate change and how to better design such programs.

Findings from this research inform a more comprehensive cost assessment of climate-change damages. Worker-level evidence is one step closer to identifying certain groups in the workforce who are more vulnerable to these dramatic environmental changes, and to targeting mechanism-specific interventions. This paper also shows that existing labor-market transitional costs in developing countries could further interact with heat shocks and exacerbate worker welfare loss. Together, this micro-level evidence suggests the importance of incorporating sector, region, and worker-specific estimates of climate-change damages, building on existing tools such as the Integrated Assessment Models (Nordhaus, 2017).

1.9 Acknowledgements

Chapter 1 is being prepared for publication. The dissertation author is the principle researcher on this chapter.

1.10 Additional Figures and Tables

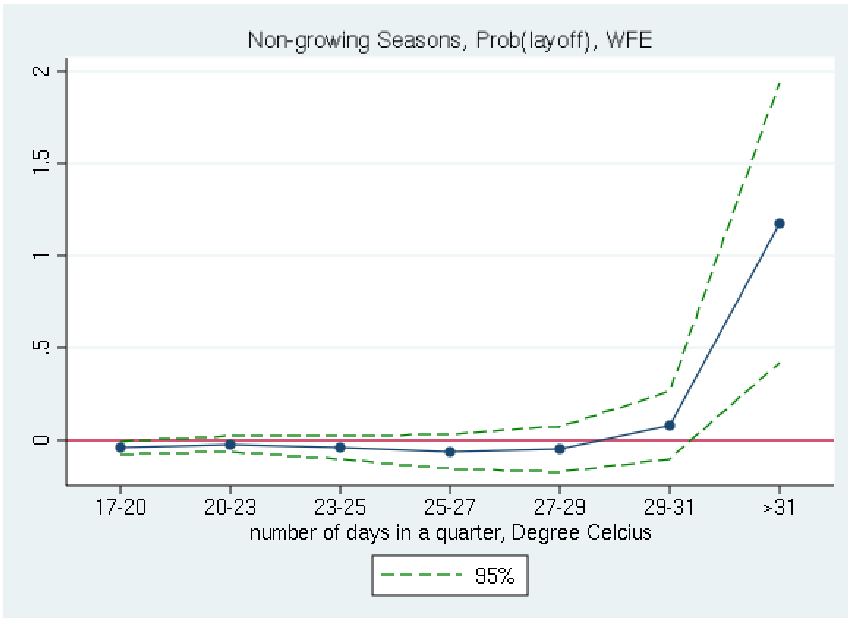


Figure 1.17: Manufacturing worker layoff: nongrowing seasons, with worker fixed effects and lagged weather shocks

Manufacturing Labor Market, Nongrowing Seasons, Worker FE, Lags - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the nongrowing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. In addition, this specification controls for worker fixed effects and average weather shocks for the past three quarters. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

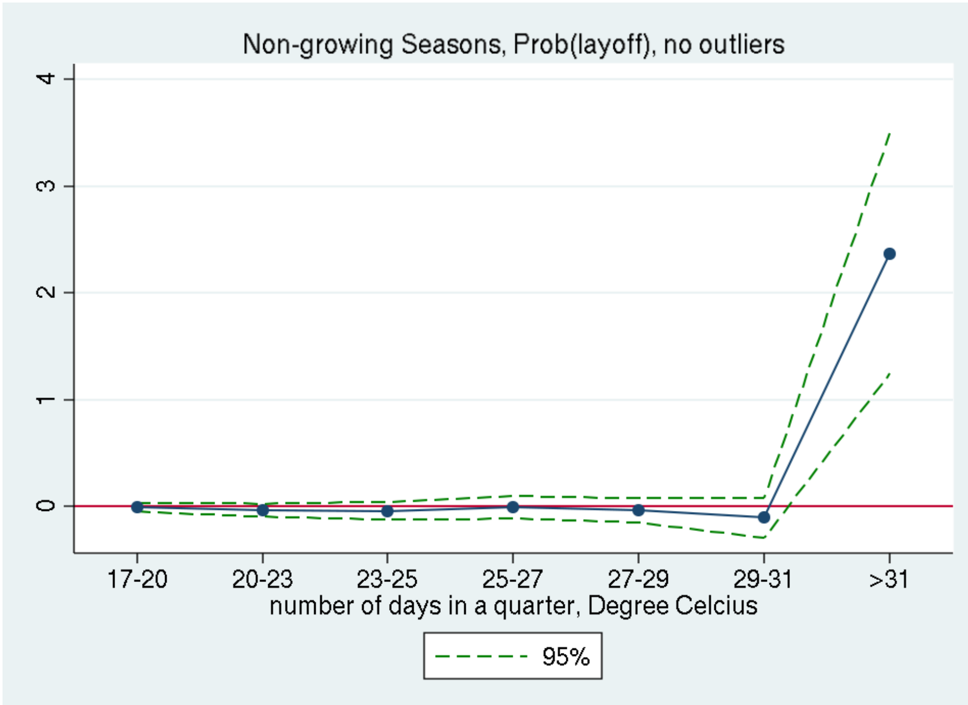


Figure 1.18: Manufacturing worker layoff: nongrowing seasons, excluding outliers (cooksd)

Manufacturing Labor Market, Nongrowing Seasons, Cook's Distance - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. *We drop influential outliers with Cook's distance larger than 4/n, where n is the total number of observations.* The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the nongrowing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. In addition, this specification controls for worker fixed effects and average weather shocks for the past three quarters. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

Table 1.6: Quarterly heat shocks and manuf. worker reallocation, nongrowing seasons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manu-s	Manu-d	Agr-s	Agr-d	Serv-s	Serv-d	**Failure**	**Tot. layoff**
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Temp(>31)	0.530***	0.053**	0.019***	0.006	0.027**	0.033	**0.283*** **	**0.952*** **
	(0.133)	(0.024)	(0.007)	(0.006)	(0.012)	(0.021)	(0.069)	(0.251)
Decomposition	**55.7%**	5.6%	2.1%	0.6%	2.9%	3.45%	**29.7%**	**100%**
N	16322039	16322039	16322039	16322039	16322039	16322039	16322039	16322039
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter × State, State × Year, Quarter × Year, Prod × Quarter, Prod × Year, Prod × State**							

Manufacturing Reallocation, Nongrowing Seasons—Following Equation 1.3, the dependent variable Y^{p}_{ijmt} is the binary variable for whether the worker belongs to a particular postlayoff category, p. The independent variables are the numbers of days in a quarter with daily mean temperature within a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The outcomes for Columns 1–7 are (1) reallocate to the manufacturing sector, in the same municipality, within 36 months; (2) reallocate to the manufacturing sector, in a different municipality, within 36 months; (3) reallocate to the agricultural sector, in the same municipality, within 36 months; (4) reallocate to the agricultural sector, in a different municipality, within 36 months; (5) reallocate to the service/primary sector, in the same municipality, within 36 months; (6) reallocate to the service/primary sector, in a different municipality, within 36 months; and (7) failure to reallocate to any formal employer, within 36 months. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with other weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

1.11 Agricultural Layoff and Hiring: Nongrowing seasons vs. Growing seasons

I briefly examine the formal agricultural labor-market impact to verify the underlying assumption for isolating the direct labor productivity channel. Recall that we identify the direct labor productivity channel by focusing on heat shocks during the nongrowing seasons. A key assumption here is that heat shocks during the nongrowing seasons have no significant impact on agricultural outcomes.

We verify this by looking at agricultural layoff and hiring during growing versus non-growing seasons. As shown in the left panels of Figure 1.19 and Figure 1.20, heat shocks during growing seasons increase the propensity of agricultural layoff and reduce the propensity of hiring, consistent with the literature on temperature and crop yield.[20] Since crop yield decreases with temperature, there would be less demand for agricultural workers.

Crucial for our identification assumption, the right panels of Figure 1.19 and Figure 1.20 show that heat shocks during nongrowing seasons have no significant impact on the agricultural labor market. This is expected if there is little agricultural crop growing activity which is temperature sensitive occurring outside the growing seasons.[21] Together, these results are consistent with the identifying assumption that heat shocks during nongrowing seasons do not operate through agricultural channels. Finally, I do additional robustness check focusing on sugarcane workers only. In Brazil, the sugarcane sector is unionized, 70% formal, and therefore has better coverage in RAIS. The findings are similar (Figure 1.21).

[20](Schlenker and Roberts, 2009; Lobell et al., 2011)

[21]There may still be agricultural workers employed during the nongrowing seasons, engaging in marketing, and looking for opportunities to sale of their crops.

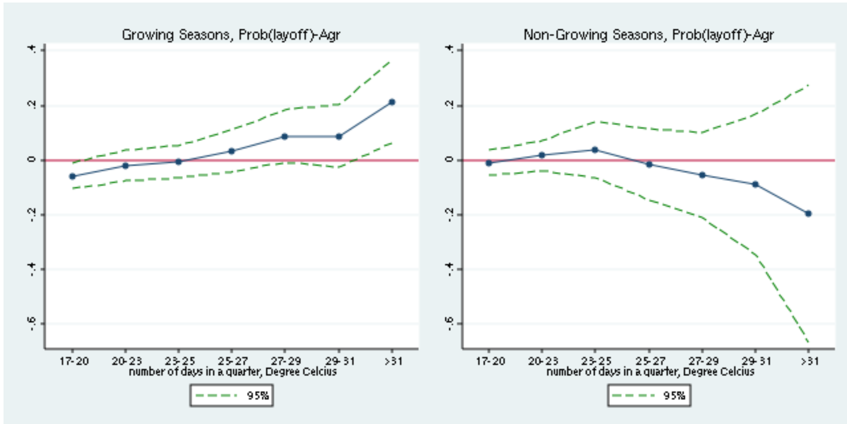


Figure 1.19: Quarterly heat shocks and agricultural layoff

Agricultural Labor Market, Growing seasons versus Nongrowing seasons - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

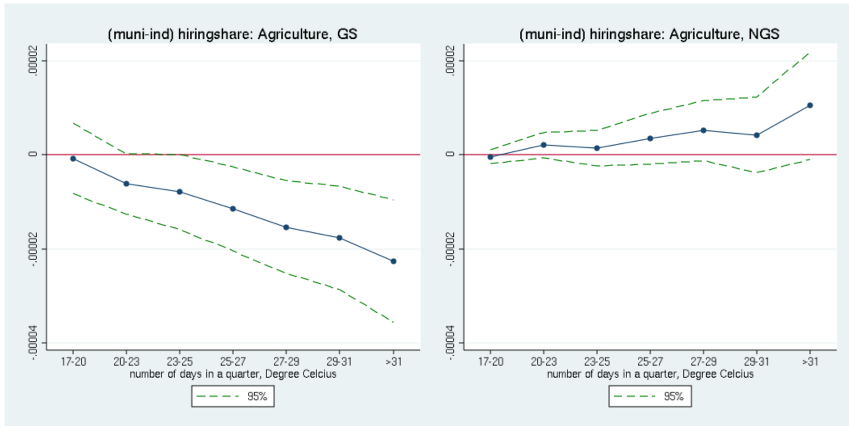


Figure 1.20: Quarterly heat shocks and agricultural hiring

Agricultural Labor Market, Growing seasons versus Nongrowing seasons - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1. The dependent variable is region-industry hiring share, constructed by aggregating the total number of individual accession in each quarter at the municipality-industry level, normalized by each municipality's population in 1999. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "$<17°$C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the hiring share, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, and other weather covariates (see text for details). Standard errors are clustered at the meso-region level.

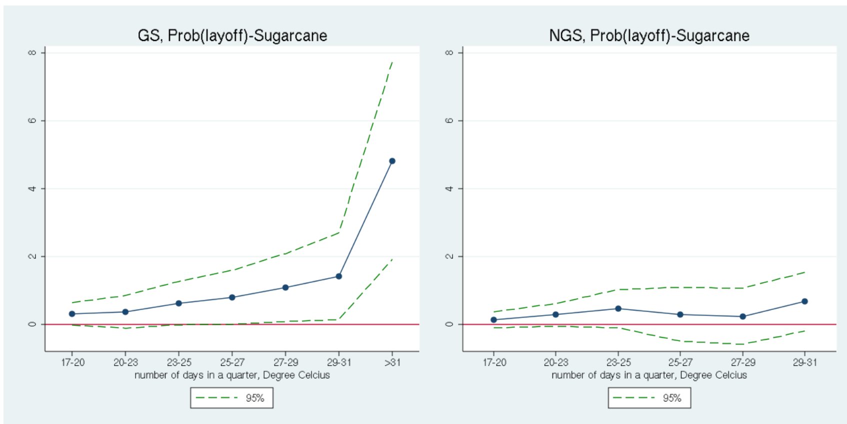


Figure 1.21: Sugarcane worker layoff: growing versus nongrowing seasons

Sugarcane Labor Market, Growing seasons versus Nongrowing seasons - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1.1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

1.12 Reallocation for Agricultural Workers

Table 1.7 shows agricultural worker reallocation post layoff, due to heat shocks during the growing seasons. More intersectoral reallocation happens for agricultural workers, possibly because manufacturing is better represented in the formal sectors. As shown in column 3 and 4 in Table 1.7, 54.1% of all heat-related layoffs find another agricultural employment within the same municipality, while 19.7% workers find another agricultural employment in a different municipality, both within three years. Based on column 1 and 2, roughly 16.8% of heat-related agricultural layoffs find the next job in manufacturing, either in the same or a different municipality.

Table 1.7: Quarterly Heat Shocks and Agr. Worker Reallocation, GS

	(1) Manu-s b/se	(2) Manu-d b/se	(3) Agr-s b/se	(4) Agr-d b/se	(5) Serv-s b/se	(6) Serv-d b/se	(7) Failure b/se	(8) Tot. layoff b/se
Temp(17-20)	0.00098	-0.00006	-0.01737	-0.01957***	-0.00507***	-0.01247***	-0.01427**	-0.06783**
	(0.002)	(0.003)	(0.016)	(0.007)	(0.002)	(0.003)	(0.007)	(0.032)
Temp(20-23)	-0.00102	0.00091	0.00112	-0.00768	-0.00499***	-0.00449	-0.01079	-0.02694
	(0.003)	(0.004)	(0.017)	(0.010)	(0.002)	(0.005)	(0.009)	(0.040)
Temp(23-25)	0.00404	0.00641	0.02841	-0.00115	-0.00619**	-0.00371	-0.01274	0.01506
	(0.003)	(0.004)	(0.019)	(0.010)	(0.002)	(0.005)	(0.009)	(0.043)
Temp(25-27)	0.00785**	0.01090**	0.05281**	0.01085	-0.00350	0.00061	-0.00215	0.07736
	(0.004)	(0.005)	(0.026)	(0.011)	(0.003)	(0.006)	(0.011)	(0.057)
Temp(27-29)	0.01351**	0.02196***	0.11323***	0.03619**	0.00072	0.00732	0.01289	0.20582***
	(0.005)	(0.006)	(0.038)	(0.015)	(0.003)	(0.008)	(0.014)	(0.077)
Temp(29-31)	0.02148**	0.02493***	0.13927***	0.03694**	-0.01006	0.00413	0.01723	0.23393**
	(0.010)	(0.007)	(0.052)	(0.018)	(0.007)	(0.009)	(0.017)	(0.098)
Temp(>31)	**0.02149***	**0.04504*****	**0.21399*****	**0.07791*****	**0.00006**	**0.01003**	**0.02727**	**0.39579*****
	(0.012)	(0.011)	(0.076)	(0.023)	(0.007)	(0.012)	(0.027)	(0.136)
N	1677744	1677744	1677744	1677744	1677744	1677744	1677744	1677744
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter*State, State*Year, Quarter*Year, Prod*Quarter, Prod*Year, Prod*State**							

Agricultural Reallocation, Growing Seasons - Following equation 1.3, the dependent variable Y^{p}_{ijmt} is the binary variable for whether the worker belongs to a particular post-layoff category p. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The outcome for column 1-7 are: (1) Reallocate to the manufacturing sector, in the same municipality, within 36 months (2) Reallocate to the manufacturing sector, in a different municipality, within 36 months (3) Reallocate to the agricultural sector, in the same municipality, within 36 months (4) Reallocate to the agricultural sector, in a different municipality, within 36 months (5) Reallocate to the service/primary sector, in the same municipality, within 36 months (6) Reallocate to the service/primary sector, in a different municipality, within 36 months (7) Failure to reallocate to any formal employer, within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level. *** Significant at the 1 percent, ** 5 percent, * 10 percent.

The majority of the Brazilian agricultural workers are informal and therefore not covered in RAIS. Alternatively, I focus only on sugarcane workers who are highly unionized and better represented in the formal sector (Table 1.8). We see around 72% sugarcane workers reallocate within the agricultural sector in the same or a different municipality. 7.2% and 7.3% reallocate to manufacturing or services in a different municipality. Although failure to reallocate is not significant for the full agricultural sample, a significant 11.2% sugarcane workers fail to find any formal sector employment within the next three years. This failure rate is much lower compared to manufacturing. Out of the many possible explanations, we might expect agricultural workers to be more willing to switch to manufacturing and services due to a higher wage premium, while manufacturing workers may be less willing to switch to agriculture.

Table 1.8: Quarterly Heat Shocks and Sugarcane Worker Reallocation, GS

	(1) Manu-s b/se	(2) Manu-d b/se	(3) Agr-s b/se	(4) Agr-d b/se	(5) Serv-s b/se	(6) Serv-d b/se	(7) Failure b/se	(8) Tot. layoff b/se
Temp(17-20)	0.03543**	0.01736	0.05293	-0.01565	-0.00238	0.00486	-0.00772	0.08482
	(0.015)	(0.017)	(0.067)	(0.030)	(0.006)	(0.009)	(0.011)	(0.108)
Temp(20-23)	-0.01328	0.01325	0.10262	0.03931	-0.00665	0.01228	0.00648	0.15401
	(0.021)	(0.020)	(0.075)	(0.046)	(0.007)	(0.013)	(0.019)	(0.157)
Temp(23-25)	0.01509	0.04480**	0.19791*	0.05176	-0.02086	0.02409	0.01424	0.32702*
	(0.022)	(0.021)	(0.104)	(0.051)	(0.013)	(0.018)	(0.024)	(0.185)
Temp(25-27)	0.00988	0.04089	0.22959*	0.08187	-0.01048	0.02403	0.02206	0.39783*
	(0.023)	(0.031)	(0.119)	(0.053)	(0.009)	(0.019)	(0.030)	(0.227)
Temp(27-29)	0.01994	0.09371**	0.41827**	0.16739**	0.00105	0.04552*	0.05445	0.80034**
	(0.033)	(0.042)	(0.161)	(0.075)	(0.011)	(0.026)	(0.042)	(0.320)
Temp(29-31)	0.04807	0.13761**	0.65303***	0.19977**	0.01136	0.04100	0.06194	1.15278***
	(0.047)	(0.057)	(0.216)	(0.099)	(0.024)	(0.031)	(0.067)	(0.421)
Temp(>31)	0.27051	0.39336***	3.01420*	0.91793***	-0.15311	0.39783***	0.61068***	5.45141***
	(0.172)	(0.144)	(1.803)	(0.185)	(0.102)	(0.111)	(0.226)	(1.985)
N	1677744	1677744	1677744	1677744	1677744	1677744	1677744	1677744
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter*State, State*Year, Quarter*Year, Prod*Quarter, Prod*Year, Prod*State**							

Sugarcane Worker Reallocation, Growing Seasons - Following equation 1.3, the dependent variable Y^{p}_{ijmt} is the binary variable for whether the worker belongs to a particular post-layoff category p. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The outcome for column 1-7 are: (1) Reallocate to the manufacturing sector, in the same municipality, within 36 months (2) Reallocate to the manufacturing sector, in a different municipality, within 36 months (3) Reallocate to the agricultural sector, in the same municipality, within 36 months (4) Reallocate to the agricultural sector, in a different municipality, within 36 months (5) Reallocate to the service/primary sector, in the same municipality, within 36 months (6) Reallocate to the service/primary sector, in a different municipality, within 36 months (7) Failure to reallocate to any formal employer, within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level. *** Significant at the 1 percent, ** 5 percent, * 10 percent.

Chapter 2

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

2.1 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 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 and adaption is relatively costly (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. 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), featuring a mechanism of ”capital-biased productivity”, captures the empirical fact that more productive firms within each sector are also less labor intensive. This approach gives different individual damage functions incorporating 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 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 industrial survey in Indonesia offers an opportunity to test predictions on differential firm exit and within industry resource reallocation. Indonesia is an important

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

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 total factor productivity, capital and 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 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

[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).

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.

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.

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

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

Section 2.2 introduces data sources and relevant empirical facts. Section 2.3 outlines a simple heterogeneous firm model with temperature shocks and comparative statics. Section 2.4 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 2.5 discusses underlying mechanism. Section 2.6 concludes.

2.2 Data Background and Empirical Facts

2.2.1 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.

2.2.2 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 2.3. 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 2.1 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 2.1 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 2.3, 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 2.1: 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

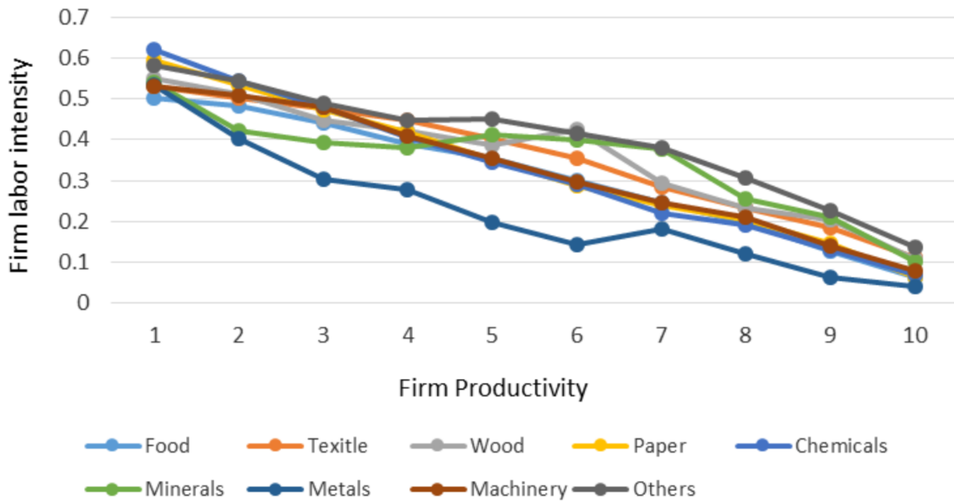


Figure 2.1: Mean Labor Intensity and firm productivity

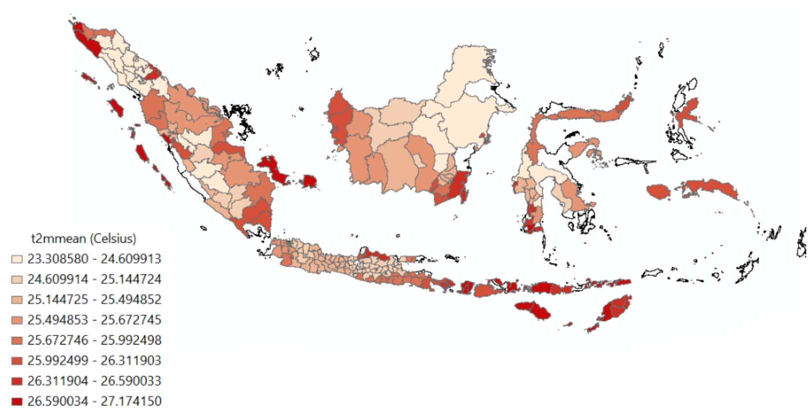


Figure 2.2: Average daily temperature at 2pm

To illustrate the variation in temperature by kabupaten, Figure 2.2 plots the daily mean temperature averaged from 1997-2011. Figure 2.3 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 2.4 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.

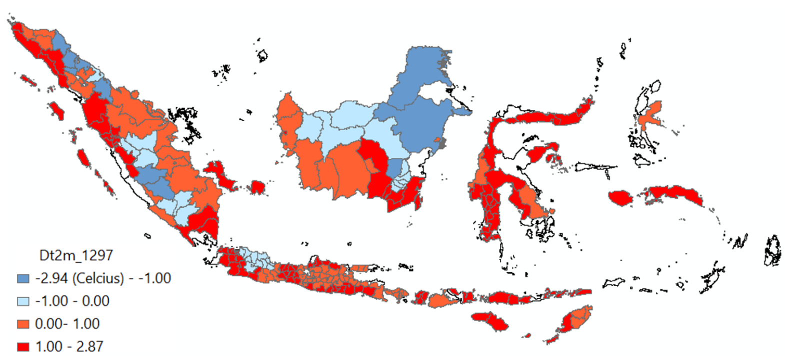


Figure 2.3: Yearly average temperature difference between 2012 and 1997

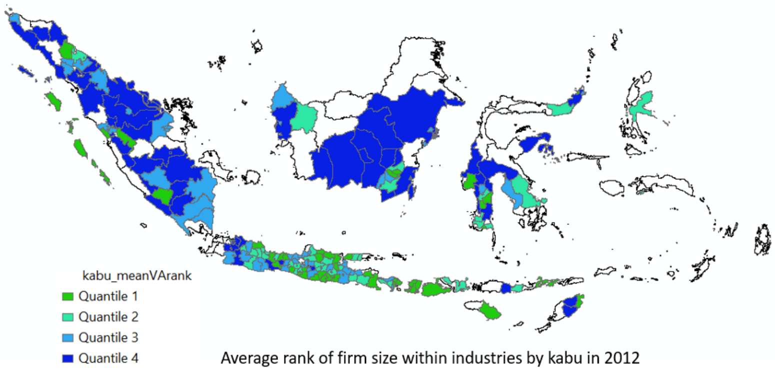


Figure 2.4: Firm size distribution by quantiles within two-digit ISIC industry

2.3 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 2.5 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.

2.3.1 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.

2.3.2 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.

$$U = [\int_{\omega \in \Omega} q(\omega)^{\sigma} d\omega]^{1/\sigma} \tag{2.1}$$

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 $q(\omega) = p(\omega)^{-\sigma} RP^{\sigma-1} = \Gamma p(\omega)^{-\sigma}$.

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.

2.3.3 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).

$$y = A(j)z(\omega, j) * [\alpha_j^{\frac{1}{\rho}}(z(\omega, j)^{\frac{\phi}{2}}k)^{\frac{\rho-1}{\rho}} + (1-\alpha_j)^{\frac{1}{\rho}}(z(\omega, j)^{\frac{-\phi}{2}}F(T)l)^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}} \tag{2.2}$$

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 2.2 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.

2.3.4 Price-Setting

The production function given in equation 2.2 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:

$$q(\omega) = \Gamma(\frac{\sigma}{\sigma-1}c)^{-\sigma} = Gc^{-\sigma} \tag{2.3}$$

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

2.3.5 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:

$$\min_{k,l} e = wl + rk + f, s.t : y = x \tag{2.4}$$

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.

$$\frac{k(\omega,j)}{l(\omega,j)} = (\frac{r}{w})^{-\rho}\frac{\alpha_j}{1-\alpha_j}z(\omega,j)^{\phi(\rho-1)}F(T)^{1-\rho} \tag{2.5}$$

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.

2.3.6 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:

$$c(z^*) = [\frac{f(\sigma-1)}{RP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{-\sigma}}]^{\frac{1}{1-\sigma}} = [\frac{f(\sigma-1)}{G}]^{\frac{1}{1-\sigma}} \tag{2.6}$$

2.3.7 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 2.6 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).

[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.

From Table 2.1, 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 2.5 and assume that factors are substitutes, or $\rho > 1$, we see that the skilled to unskilled worker ratio will increase as temperature increases.

2.4 Empirical Results

2.4.1 Firm Exit

Are less productive firms more likely to exit under temperature shocks? *Prediction 1* derived from the zero profit condition in section 2.3.7 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.

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.

$$P(t_{ij} = \tau+1 \,|\, t_{ij} > \tau, pdty_i^s * temp_{i,\tau+1}, pdty_i^s * rain_{i,\tau+1}, pdty_i^s * humidity_{i,\tau+1}, pdty_i^s * age_i^{2001}, \theta_{jt}) = g(\tau, pdty_i^s * temp_{i,\tau+1}, pdty_i^s * rain_{i,\tau+1}, pdty_i^s * humidity_{i,\tau+1}, pdty_i^s * age_i^{2001}, \theta_{jt}) \tag{2.7}$$

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.

Results

I begin by presenting the results on exit patterns for firms in different initial productivity bins. Table 2.2 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.

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

Table 2.2: 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, $Bin_s XRain$, $Bin_s XAge2001$ and duration dummies are omitted from the table. (d) All coefficients are multiplied by 100 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.

2.4.2 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 2.4.1 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.

Empirical Strategy

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

$$\begin{aligned} y_{it} = \alpha_0 + \sum_s \alpha_{1s} PdtyBin_{is}^{initial} * Temperature_{it} + \sum_s \alpha_{2s} PdtyBin_{is}^{initial} * Humidity_{it} \\ + \sum_s \alpha_{3s} PdtyBin_{is}^{initial} * Rain_{it} + \beta_s PdtyBin_{is}^{initial} * t + \theta_i + \sigma_{jt} + \gamma_{rt} + \varepsilon_{it} \end{aligned} \tag{2.8}$$

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.

Results

Table 2.3 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 2.3: 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 subsection, 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.

2.4.3 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.

Factor Substitution

Taking logs on both side, I transform the equilibrium condition in equation 2.5 to the following equation which directly relates capital to labor ratio with labor productivity $F(T)$:

$$ln[\frac{k}{l}]_{it} = \beta_0 + \theta_1 F(T)_{it} + r_i + \varepsilon_{it} \tag{2.9}$$

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 2.4.2. 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:

$$
\begin{aligned}
y_{it} = \alpha_0 + \sum_s \alpha_{1s} PdtyBin_{is}^{initial} * Temperature_{it} + \sum_s \alpha_{2s} PdtyBin_{is}^{initial} * Humidity_{it} \\
+ \sum_s \alpha_{3s} PdtyBin_{is}^{initial} * Rain_{it} + \beta_s PdtyBin_{is}^{initial} * t + \eta_i + \sigma_{jt} + \gamma_{rt} + \varepsilon_{it}
\end{aligned}
\tag{2.10}
$$

This specification is essentially the same as equation 2.8 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 2.4 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 2.5 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

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

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.

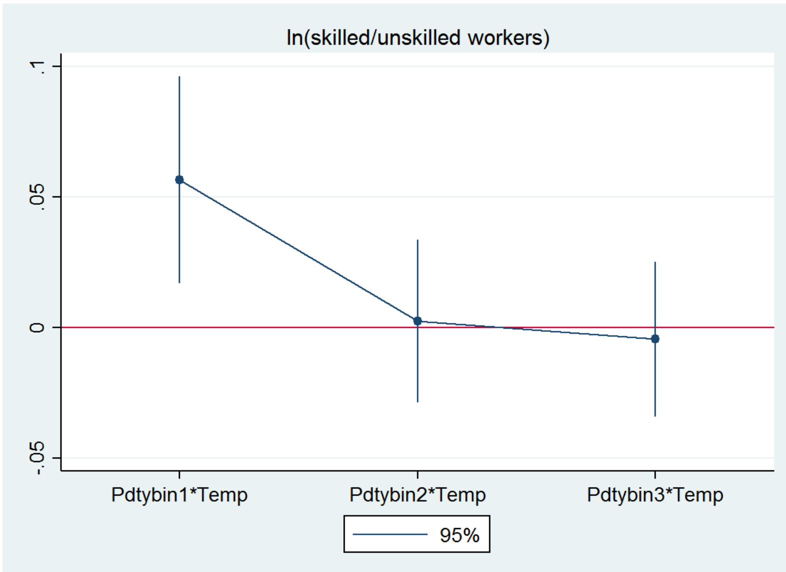


Figure 2.5: Factor substitution to skilled labor

Table 2.4: 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 2.4 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.

Intensive Margins

To look at firm-level changes on the intensive margin, I follow the exact same specification in equation 2.10. 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).

[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.

Figure 2.6 illustrates how value-added output changes as temperature increases for firms in different productivity bins. This corresponds to column (3) in Table 2.5, 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 while the initially least productive firms incur a smaller, marginally significant loss.

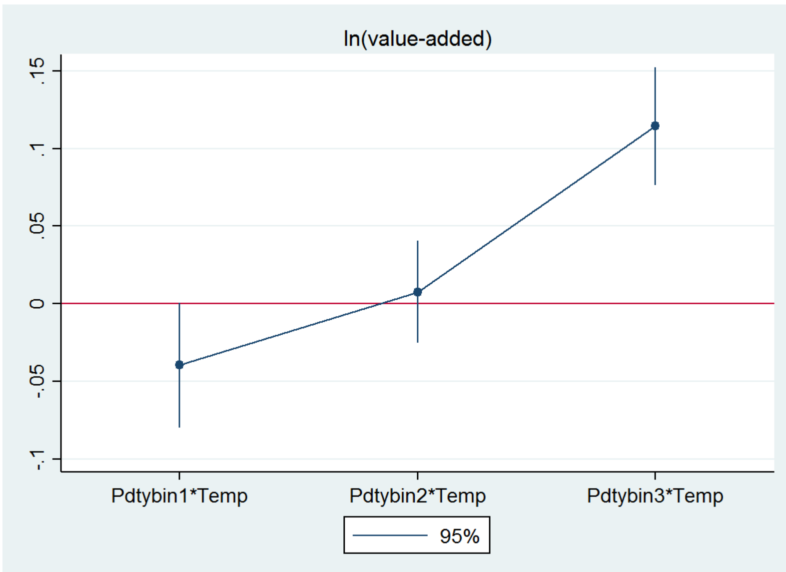


Figure 2.6: Firm-level value-added output

Table 2.5: 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 2.3, column (3), with the firm-level intensive margin results in Table 2.5, 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 2.4.1, 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.

2.5 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.

2.5.1 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 2.6 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.

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

Table 2.6: 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

In Table 2.7, I implement the same fixed effects model as in equation 2.8, excluding the four industries which mainly use agricultural input. These coefficients are comparable to previous results in Table 2.3. 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 2.7: 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

2.5.2 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 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.

2.6 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

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

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.

2.7 Acknowledgements

Chapter 2 is being prepared for publication. The dissertation author is the principle researcher on this chapter.

Chapter 3

Mining Activity and Spatio-Temporal Dynamics of Forest Cover Loss

3.1 Introduction

Deforestation is among the largest sources of carbon emissions related to human activities, highlighted as a key area for international coordination in the Paris Accord. Regional economic growth and associated market fluctuations could have important global environmental footprint. One example is the recent ”commodity super-cycle” and related expansions in mining activities worldwide. So far there lacks a comprehensive assessment of mining-induced deforestation on a global scale, partly because mining sites are often in remote locations and harder to quantify. More generally, reducing forest-based emissions requires a better understanding of not just the sources of forest cover loss but also the institutional and firm-level factors which affect sustainable forest management.

In this paper, we provide global, disaggregated evidence on the forest cover loss around more than 30,000 mining sites and examine the political economy of the environmental impact of mining expansion. First, combining high-spatial resolution data on deforestation and proprietary mining intelligence data, we estimate the elasticity of forest cover loss with respect to mineral price fluctuations. Our results suggest that, on average, the early 2000s ”commodity super-cycle” contributes to roughly 8%-20% of the observed total deforestation around mining sites. Second, incorporating sources of firm-level ownership data, we examine country and firm-level factors which influence sustainable forest management. We find empirical evidence supporting the intuitions of an environmental Kuznets curve, and that the behavior of mining firms from high income countries contributes significantly to the differential impact across host countries. Third, we study impact on local economic activities in nearby communities using nighttime luminosity measures.

Hotelling’s model (Hotelling, 1931), the seminal work on the extraction of exhaustible resources, predicts the price net of marginal cost of extraction rises at the rate of interest whenever production occurs. Under competitive markets, the optimal extraction path coincides with the planner’s solution. [1] However, there exists sources of externality such as public goods or ecosystem services directly and indirectly affected by the extraction of minerals. In their recent modification of the Hotelling model, Anderson et al. (2018) show that drilling activities on the extensive margin respond strongly to price incentives whereas oil production from existing wells does not, due to constraints in reservoir pressure. Instead of directly examining responses of mining activities to global mineral price fluctuations, we study changes in forest cover loss in different buffer zones surrounding mining sites. We interpret the deforestation results within the immediate mining area as tracing out the supply curve. In addition, we use remote sensing satellite imagery to assess environmental impact outside the immediate mining location and quantify associated forest cover loss in nearby communities, illustrating an additional source of environmental externality from commodity price booms.

[1] See Slade and Thille (2009) for a review on the literature of finite resource extraction

Global initiatives aimed at reducing forest-based emissions, such as the UN's REDD++ programs, benefit from understanding the political economy factors that influence deforestation. However, institutions which foster sustainable practices also differ in geographic, demographic and economic features. Existing studies often explore within-country quai-experiments such as institutional changes (Burgess et al., 2012) and regional variations in legal requirements for logging (Alesina et al. 2014) to achieve casual inference. Instead, our paper exploits exogenous global commodity price shocks and compare forest cover loss with different institutional and firm-level determinants before and after the shocks. Our data covers 31 commodities and provides information on the primary commodity produced by each mine, allowing us to exploit the differential timing of prices changes across minerals, and controlling for a rich set of fixed effects at the country, year and mine-level. Most similarly, Berman et al. (2017) also relies on the "commodity super-cycle" for identification, but their paper focuses on civil conflicts in Africa. To our knowledge, this is the first paper to analyze the institutional and firm-level determinants of sustainable forest management with highly disaggregated data on a global scale.

First, we find a positive and significant 77 elasticity of forest cover loss around mines. Conditional on initial forest cover being higher than 40%, increasing the average primary commodity price by one standard deviation increases the percentage of forest cover loss by 0.6 within the 1 kilometer buffer zone. Our estimates also suggest that the early 2000s "commodity super-cycle" contributes to roughly 8%-20% of the observed total deforestation around mining sites, within the 30 kilometer radius. Our results indicate that mining-induced deforestation is not limited to the immediate surroundings of mining pits, but often geographically dispersed, possibly resulting from transportation access or nearby economic activities.

Second, we indirectly examine the political economy of environmental impact of mining expansion. Matching top owner firms of each mining property from our mining intelligence data with a global firm-level database, we investigate the country and firm-level determinants of deforestation during the ”commodity super-cycle”. Our results are robust to a rich set of controls including differential time trends by initial forest cover, time-invariant mine characteristic by year, commodity and mine fixed effects. We find that the elasticity of forest cover loss with respect to price is higher in low income countries, where environmental regulations enforcement could be weaker. The mine’s firm ownership also plays an important role. State ownership interact with the host country’s GDP per capita to influence the elasticity of deforestation. Mine owners from high income countries display larger disparity in the elasticity of forest cover loss when operating in poor versus rich countries. Most strikingly, mining firms from high income countries deforest more during commodity price hikes when operating in poor countries, but not so when operating in rich countries. One possibility is that mining firms from high income countries have the capacity to minimize environmental impact during expansions but do not bother to do so when operating in countries with weaker environmental regulation enforcement.

Our findings on the local economic impact of commodity price booms using nighttime luminosity data reveal an alternative explanation. Nearby economic activities as measured by night lights increase with commodity prices when the mining firm is from a high income country, but decreases with prices when the mining firm is from a low income country. Commodity booms are often associated with employment opportunities and settlements for nearby communities. The differential deforestation rates by mine owners from high income countries at larger radius could therefore also be due to differential logging activities from nearby settlements.

This paper provides first micro-level evidence on a global scale of mining-induced deforestation, contributing to the literature on the environmental impact of mining. Romero and Saavedra (2017) employ a difference in difference strategy to estimate the impact of gold mining on the health of newborns in Columbia. A related body of work document negative health effects of coal use in terms of air pollution and mortality (Beach and Hanlon, 2016) and effective environmental regulations targeted at coal for generation (Tanaka, 2015). There has been less work on the deforestation impact of mining partly because mining occupies smaller, remote areas that are harder to detect. [2] Recent "commodity super-cycles" driven by the rapid growth from emerging markets (Carter et al. 2011, Humphreys, 2010, Reinhardt et al. 2016) renews interest in understanding the environmental footprint of mining expansions. Using remote sensing satellite imagery, Maryati et al. (2012) provide frameworks for evaluating the environmental impact of mining in Indonesia, while Alvarez-Berros and Aide (2015) offer regional assessment of gold mining on deforestation in South America. However, so far to our knowledge, this paper is the first to offer a global assessment of the effect of mining booms on forest cover loss based on high-spatial resolution panel data. Our findings suggest a positive elasticity of forest cover loss with respect to commodity prices, and the losses are spatially dispersed, located both within and outside the immediate areas of mining pits.

Second, our paper speaks to a broader literature on the environmental Kuznets curve by examining institutional and firm-level factors influencing deforestation in a worldwide mine-level panel. Grossman and Krueger (1991, 1995) find economic growth brings an initial phase of environmental deterioration followed by a subsequent phase of improvement. Though intuitive, the interpretation of this inverse U-shaped relationship has been limited due to concerns of simultaneity (Stern, 2004). Andreoni and Levinson (2001) propose a theoretical model with increasing returns in pollution abatement, an explanation not requiring differences in political institutions. Instead of examining pollutant indicators as is traditional in this literature, we quantify worldwide deforestation as another important measure of environmental degradation, exploiting demand-driven global commodity price shocks for identification. We find evidence

[2] See Busch et al. (2017) for a review on the causes of deforestation.

consistent with the environmental Kuznets curve. With firm and mine-level data, we provide further evidence that mining firm ownership plays a key role in driving differences between host country deforestation rates. Our results on forest cover loss outside the immediate mining areas suggest the potential importance of institutions and environmental regulation enforcement.

We begin by describing the data and relevant empirical facts. Section 3.3 presents the baseline estimation framework for the elasticity of forest cover loss. In Section 3.4, we examine institutional and firm-level factors which influence deforestation around mining sites. Section 3.5 provides further evidence on the local economic impact of mining expansions using nighttime luminosity data. Section 3.6 concludes.

3.2 Data and Empirical Facts

3.2.1 Data

First, we obtain proprietary data containing information on more than 30,000 mining sites around the world, provided by SNL Financial. This market intelligence company offers current and historic operating and financial data on mines at the property-level, collected from company annual reports, news articles, etc. For each mine, there is information on main commodities produced, mine characteristics, reserves, work history and owner firm information. However, annual production data is not available for the majority of the properties. We also link each property with other spatial variables using longitude and latitude of the mining sites.

To learn more about the mine owner firms, we further match the SNL data with a global firm-level database, ORBIS-Bureau van Dijk. The ORBIS data is constructed by standardizing balance sheet, income statements and news reports, covering more than 300 million firms worldwide. We are particularly interested in information on firms' domestic and international ownership structure. We match the top three owners of each mining property, and obtain data on these direct owner firms and their global ultimate owners. Key variables of interest include state ownership status, operating revenue and multinational status of both the direct and global ultimate owners.

Data on yearly global forest cover loss around mining properties come from Hansen's Global Forest Change database. The GFC data uses earth observation satellite images from Landsat and characterizes forest cover loss at the Landsat pixel scale. We draw upon this spatially and temporally detailed data and calculate forest cover loss for different buffer zones around all mining properties worldwide, using coordinates provided in the SNL data. The sample period is from 2000 to 2014 [3].

We also gather other sources of spatial data to control for market access to mines. These include: data on the nearest urban agglomerations from the United Nations World Urbanization Prospects, data on the nearest port from the World Port Index, data on the nearest road from the Global Roads Open Access, data on thhe nearest lake from the Global Lake and Wetlands Database, and other spatial data sources from the ESRI.

Commodity price data by year and commodity type come from SNL Financial, supplemented by the IMF Primary Commodity Prices and the Historical Statistics for Mineral and Material Commodities from the USGS. We also use other country-level indices. GDP per capita, rule of law, CPI and corruption ranking indices are from the World Bank's World Development Indicators, supplemented by data from the World Governance Indicators and Transparency International.

[3] A newer version of the GFC data is now available until 2018.

3.2.2 Empirical Facts

In this subsection, we present summary statistics and empirical facts. First, we plot summary graphs for commodity price fluctuations, and forest cover loss around mines. Second, we give illustrative examples of how mining operations and nearby communities look like using satellite imagery from Google Earth. Finally, we provide summary statistics on average mine characteristics.

Figure 3.1 and 3.2 plot the standardized prices of major and minor commodities produced by mines around the world. We see a sharp rise in prices for most commodities starting from the early 2000s [4] and a following drop after the recession. Most previous studies attribute this commodity "super-cycle" to rising global demand, driven by rapid growth and search for natural resources from emerging markets (Carter et al. 2011, Canuto, 2014, Humphreys, 2010, Reinhardt et al. 2016). In our analysis, we use information on the primary commodity produced in each mine and exploit the differential timing of the price changes across minerals.

Next, we show summary graphs of forest cover loss around mines in different buffer zones. Figure 3.3 gives a simple bar chart of the average percentage of forest cover loss around mines, from 2000 to 2014, by radius. The sharpest losses occur around the immediate 1km buffer zone. Figure 3.4 to Figure 3.6 plot the average forest cover loss at 5km from 2000 to 2014, against mine operating country and mine owner country's GDP per capita in 2000. The graphs at 20km can be found in Section 3.8. We see that mine operating countries have a wide range of GDP per capita while mine owning countries are usually richer in comparison. Figure 3.4 is plotted using the full sample, whereas Figure 3.5 and 3.6 restrict to mines with initial forest cover in 2000 being

[4] with the exception of diamonds

higher than 25% and 40% respectively. Focusing on Figure 3.6, average forest cover loss during the sample period ranges from 0 to 66%, with more than half of the sample having forest cover loss less than 5%. There is no apparent correlation between forest cover loss and mine operating country's GDP per capita, whereas a positive correlation exists in the raw data between average forest cover loss and mine owner country's GDP per capita.

Third, we give visual illustrations of open-pit mining sites from different countries borrowing satellite imagery from Google Earth . Mining operations range in shapes and sizes, spanning from less than 1 kilometer to more than 25 kilometers in radius. Figure 3.7 and Figure 3.8 visualize two open pit mines in Argentina and Australia. In Section 3.8, we show additional images for the Batu Hijau Mine in Indoenisa, the Belchatow mine from Poland, the Huckleberry Mine from Canada, the Tagebau Hambach from Germany, the Lavender Pit from Arizona and the Berkeley Pit from Montana. Though often located in remote places near forest, canyons and deserts, many mining sites have nearby towns attached to them. For example, the Cadia-Ridgeway mine in Australia, in Figure 3.8, has a radius of around 0.8km, but the nearby communities have much larger land cover. Mines with irregular shapes such as the Mina Cerro Vanguardia from Argentina could stretch further, taking up to 6 kilometer in radius. With a few exceptions, many mines are contained within the 10 kilometer radius buffer zone, a fact relevant for our latter analysis on the direct and indirect causes of forest cover loss from mining activities.

Finally, Table 3.1 and Table 3.2 provide summary statistics on average mine characteristics and primary commodities produced. We have data on 33,262 unique mining sites, around 20% of which are open pit. 3% of all mine-year observations have state ownership status where as 40% have multinational status. 38.5% of our sample produce gold as the priamry commodity. Other primary commodities include coal, copper, iron ore, nickel, U308, silver, zinc, etc.

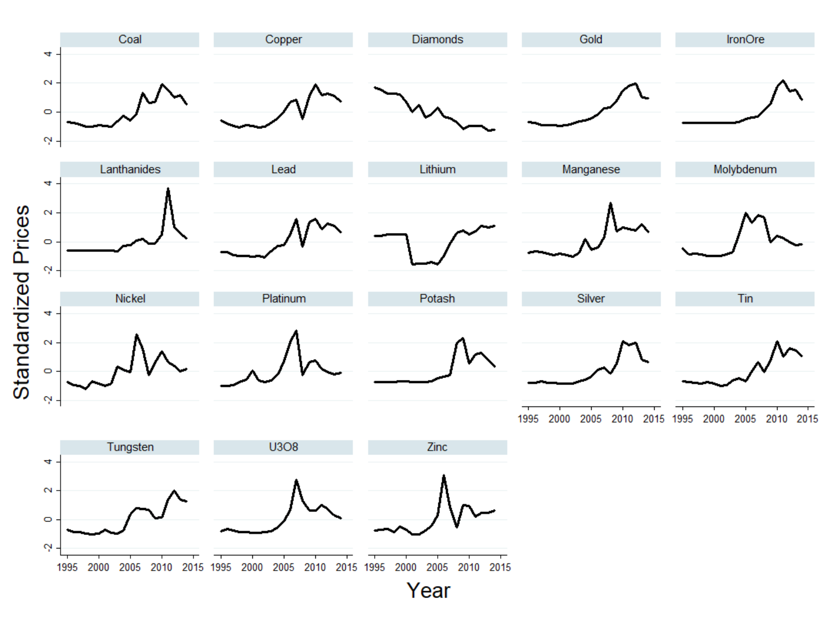


Figure 3.1: Standardized Prices of Major Commodities

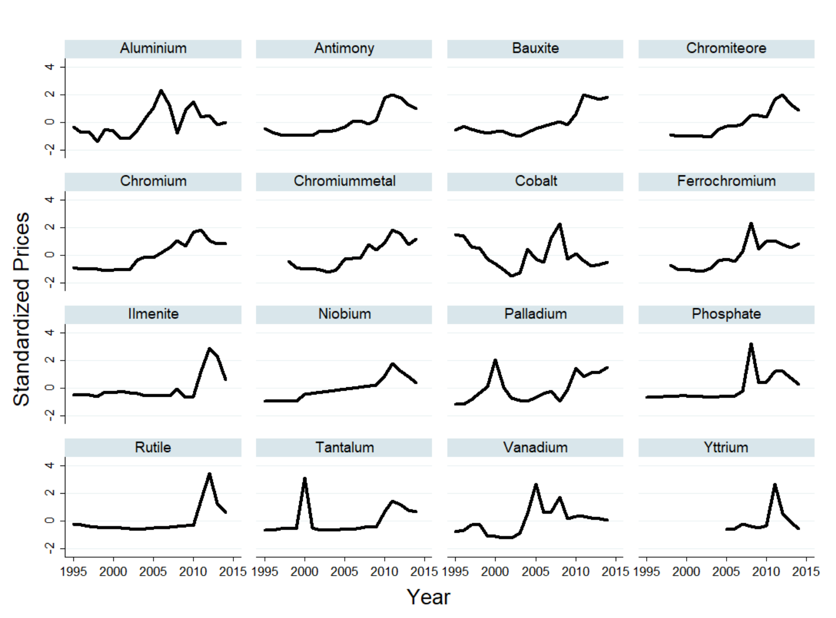


Figure 3.2: Standardized Prices of Minor Commodities

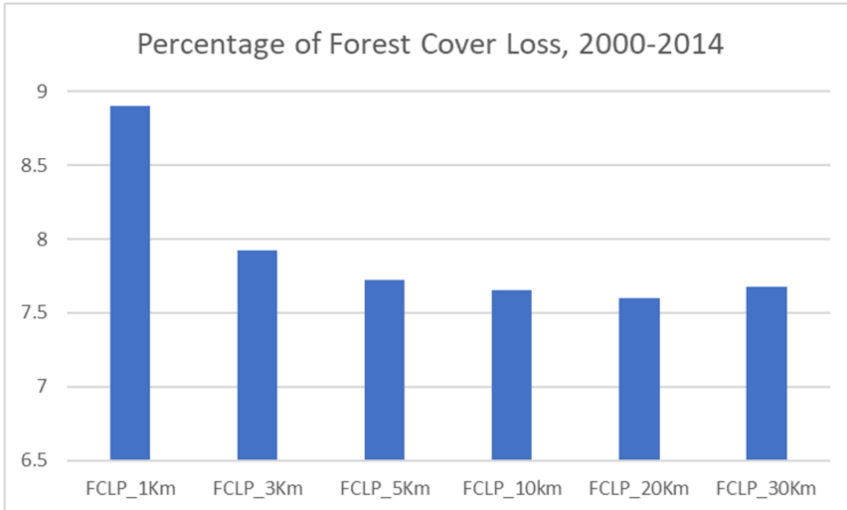


Figure 3.3: Average Forest Cover Loss around Mines by Radius, 2000-14

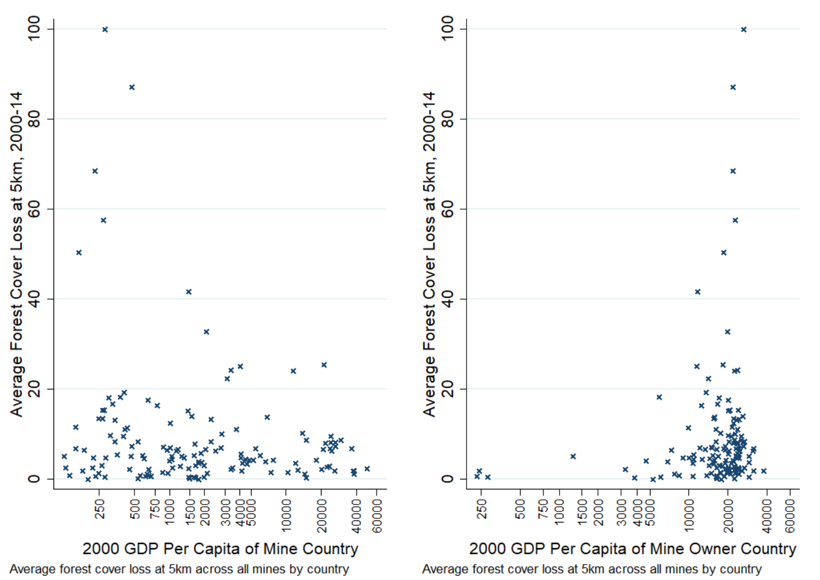


Figure 3.4: Average Forest Cover Loss at 5km by Country, 2000-14

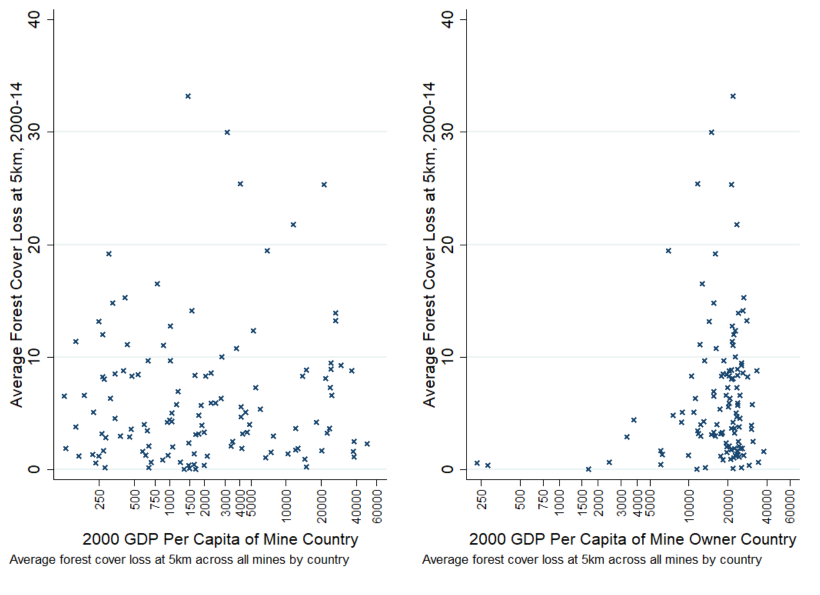


Figure 3.5: Average Forest Cover Loss at 5km by Country, IFC>25%, 2000-14

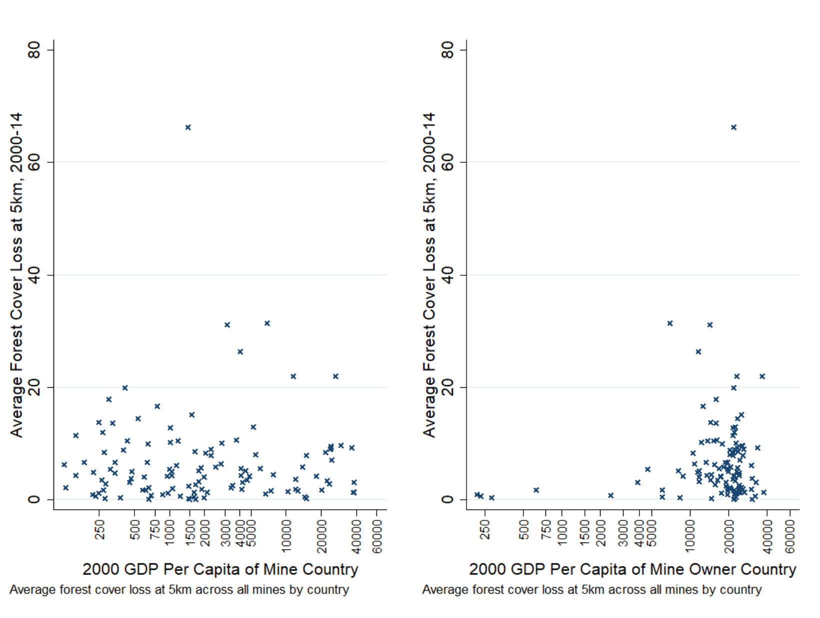


Figure 3.6: Average Forest Cover Loss at 5km by Country, IFC>40%, 2000-14

Figure 3.7: Mina Cerro Vanguardia: gold and silver mine, Argentina

Figure 3.8: Cadia: gold mine, Australia

Table 3.1: Average Mine Characteristics

		Observations
Number of mine countries	159	199572
Number of owner countries	139	130326
Number of mines	33262	199572
Number of commodities	31	199572
Average owner SOE status	0.03	175662
Average owner MNC status	0.4	133614
Average number of commodities per mine	1.82	199572
Whether open pit	0.21	199572

Table 3.2: Share of Primary Commodity

Commodity	**Percentage**	**Observations**
Antimony	0.15	199572
Chromium	0.02	199572
Coal	15.52	199572
Cobalt	0.11	199572
Copper	12.77	199572
Diamonds	4.32	199572
Gold	38.59	199572
Ilmenite	0.42	199572
Iron Ore	5.57	199572
Lanthanides	0.99	199572
Lead	0.75	199572
Lithium	0.58	199572
Manganese	0.59	199572
Molybdenum	0.9	199572
Nickel	3.52	199572
Niobium	0.09	199572
Palladium	0.08	199572
Phosphate	0.8	199572
Platinum	0.98	199572
Potash	0.57	199572
Scandium	0.02	199572
Silver	3.2	199572
Tantalum	0.21	199572
Tin	0.65	199572
Titanium	0.08	199572
Tungsten	0.39	199572
U3O8	5.06	199572
Vanadium	0.14	199572
Yttrium	0.01	199572
Zinc	2.9	199572

3.3 Elasticity of Forest Cover Loss

How do commodity price fluctuations affect land use and forest management around mining sites? What are the country and firm-level determinants of sustainable practices? Since mining sites are often in remote locations, previous studies have been limited in scope and data accuracy, often relying on local observational analysis. In this section, we exploit global demand-driven mineral price changes since 2000, and examine forest cover loss surrounding different types of mining sites worldwide, combining several sources of microdata and high-resolution satellite imagery.

3.3.1 Baseline: Empirical Strategy

The baseline empirical specification is a fixed effect model

$$FCLP\_R_{it} = \beta_1 lpz_{it} + \gamma_t + \gamma_c + \gamma_i + \varepsilon_{it} \tag{3.1}$$

$FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. We draw buffer zones of 1, 3, 5, 10, 20, 30 kilometers radii around each mining site. For the baseline results, we focus on buffer zones where the initial forest cover in 2000 is larger than 40%. lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t. To capture potential common time trends in both commodity prices and deforestation, we include year fixed effects γ_t. To control for time-invariant confounders that are mineral and mine specific, we include commodity fixed effects γ_c and mine fixed effects γ_i. Standard errors are clustered at the country level.

3.3.2 Baseline: Results

We start by examining how the elasticity of forest cover loss with respect to commodity prices varies with distance. Across buffer zones, we find positive and significant elasticity of forest cover loss, suggesting a typical supply curve.

The estimates for different buffer zones are presented in Table 3.3. Across radii, forest cover loss positively increases with the price of the main commodity produced. This elasticity reduces in magnitude as distance from the mining site increases. Conditional on initial forest cover being higher than 40%, column 1 suggests that increasing the average primary commodity price by approximately one standard deviation increases the percentage of forest cover loss by 0.6, within the 1 kilometer buffer zone. This magnitude reduces to 0.2 as we focus on the 30 kilometer buffer zone. Combining column 1 to 6, we interpret these results as tracing out the supply curve, with higher mineral prices leading to more mining activities and associated nearby deforestation.

During the boom in the early 2000s, most commodities experienced price increases roughly equal to 3 standard deviations, corresponding on average to a 1.8 percentage increase in forest cover loss within the 1 kilometer buffer zone, and a 0.6 percentage increase in forest cover loss within the 30 kilometer buffer zone. The average percentage of forest cover loss within the 1 kilometer and 30 kilometer buffer zones during our sample period (2000-2014) was 8.9, and 7.7, respectively. So our estimates suggest the early 2000s ”commodity super-cycle” contributes to roughly 8%-20% of the observed total deforestation around mining sites during this period.

Table 3.3: Percentage of Forest Cover Loss, Initial Forest Cover>40%

	(1) **FCLP** b/se	(2) **FCLP** b/se	(3) **FCLP** b/se	(4) **FCLP** b/se	(5) **FCLP** b/se	(6) **FCLP** b/se
Commodity Price	0.629*** (0.158)	0.453*** (0.144)	0.422*** (0.161)	0.339** (0.133)	0.261** (0.10)	0.194** (0.091)
Observations	51111	54003	54767	55341	55297	55325
Adjusted R^2	0.18	0.2	0.22	0.25	0.32	0.38
Clustering	Country	Country	Country	Country	Country	Country
Fixed Effects			Year, Commodity, Mine			
Initial Forest Cover (Higher than, %)	40	40	40	40	40	40
Radius (km)	1	3	5	10	20	30

Forest Cover Loss, Price Elasticity-Following Equation 3.1, the dependent variable $FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. The independent variable lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t, spanning from 2000 to 2014. We draw buffer zones of 1, 3, 5, 10, 20, 30 kilometers radii around each mine and focus on buffer zones where the initial forest cover in 2000 is larger than 40%. All regressions include year, commodity and mine fixed effects. All coefficients are in percentage points. Standard errors are clustered at the country level. *** Significant at 1%, ** 5%, * 10%.

3.4 Country and Firm-Level Determinants of Deforestation

Previous literature on the political economy of deforestation and environmental Kuznets curve (Alesina et al. 2019, Burgess et al. 2012, Grossman and Krueger, 1995) points to the importance of within-country institutional differences, ethnic diversity and national income as key factors influencing environmental degradation. In this section, we exploit exogenous commodity price shocks and investigate country and firm-level determinants of deforestation during mining expansions on a global scale, using mine-level panel data covering 159 countries. To do this, we match the top owner firms of each mining property from SNL Financial with the global firm-level database, ORBIS-Bureau van Dijk. We first examine the country and firm-level determinants in a double-interaction specification, and then look at triple interaction results.

3.4.1 Double Interaction

$$FCLP\_R_{it} = \beta_1 w_{it} * lpz_{it} + \beta_2 w_{it} + \beta_3 lpz_{it} + \gamma_c + \gamma_i + \theta_{it} + \varepsilon_{it} \tag{3.2}$$

The empirical specification builds on equation 3.1. $FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t. w_{it} is the GDP per capita of the mine's operating country or the dummy for whether the mine is state-owned, in year t. As before, we include commodity fixed effects γ_c, and mine fixed effects γ_i. In addition, we also control for differential time trends by initial forest cover, as well as time-invariant mine characteristics by year fixed effects. Standard errors are clustered at the country level.

Table 3.4 shows how the elasticity of forest cover loss varies with GDP per capita of the mine's operating country. We present results for the 3, 5, 10 and 20 kilometer buffer zones. Across radii, the coefficient on the interaction of main commodity prices and mine operating

Table 3.4: Interaction with Mine Country GDPPC

	(1) **FCLP** b/se	(2) **FCLP** b/se	(3) **FCLP** b/se	(4) **FCLP** b/se
Commodity Price	0.625*** (0.102)	0.575*** (0.151)	0.485*** (0.118)	0.414*** (0.080)
MineGDPPC*ComPrice	-0.624*** (0.214)	-0.493** (0.238)	-0.419* (0.203)	-0.459** (0.164)
Observations	33629	34037	34291	34063
Adjusted R^2	0.14	0.16	0.18	0.26
Clustering	Country	Country	Country	Country
Fixed Effects	Year, Commodity, IFC*Year, MineChar*Year, Mine			
Initial Forest Cover (Higher than, %)	40	40	40	40
Radius (km)	3	5	10	20

Forest Cover Loss, Interaction with Mine Country GDPPC -Following Equation 3.2, the dependent variable $FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. The independent variable lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t, spanning from 2000 to 2014. w_{it} is the GDP per capita of the mine's operating country in year t. We focus on buffer zones where the initial forest cover in 2000 is larger than 40%. All regressions include commodity, mine, IFC (initial forest cover) x year and MineChar x year fixed effects. All coefficients are in percentage points. Standard errors are clustered at the country level. *** Significant at 1%, ** 5%, * 10%.

Table 3.5: Interaction with Owner Firm SOE Status

	(1) **FCLP** b/se	(2) **FCLP** b/se	(3) **FCLP** b/se	(4) **FCLP** b/se
Commodity Price	0.375** (0.148)	0.373** (0.179)	0.301* (0.156)	0.216* (0.123)
OwnerSOE*ComPrice	0.018 (0.302)	-0.063 (0.248)	0.015 (0.226)	0.020 (0.223)
Observations	47981	48677	49255	49287
Adjusted R^2	0.21	0.23	0.26	0.33
Clustering	Country	Country	Country	Country
Fixed Effects	Year, Commodity, IFC*Year, MineChar*Year, Mine			
Initial Forest Cover (Higher than, %)	40	40	40	40
Radius (km)	3	5	10	20

Forest Cover Loss, Interaction with Owner Firm SOE Status -Following Equation 3.2, the dependent variable $FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. The independent variable lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t, spanning from 2000 to 2014. w_{it} is the dummy for whether the mine is state-owned in year t. We focus on buffer zones where the initial forest cover in 2000 is larger than 40%. All regressions include commodity, mine, IFC (initial forest cover) x year and MineChar x year fixed effects. All coefficients are in percentage points. Standard errors are clustered at the country level. *** Significant at 1%, ** 5%, * 10%.

country GDPPC is significantly negative. This shows the elasticity of forest cover loss with respective to price is lower in richer countries. With the same commodity price hike, mines located in countries with higher GDPPC deforest less. The results on state-ownership is less stark. Table 3.5 illustrates double interaction results of commodity prices with the mining firm's ownership status. We categorize a mine to be state-owned if at least one of its top three owners is a State-Owned Enterprise (SOE). There is no significance across radii of the elasticity of forest cover loss varying with state ownership status. However, as we would see later in section 3.4.2, SOE status does matter in the triple interaction setting. In particular, it affects the differential elasticity of forest cover loss between rich versus poor mine operating countries.

3.4.2 Triple Interaction

We now explore how different country and firm-level factors interact with each other to influence the elasticity of deforestation in a triple interaction fixed-effect setting

$$\begin{aligned} FCLP\_R_{it} = \beta_1 z_{it} * w_{it} * lpz_{it} + \beta_2 z_{it} * lpz_{it} + \beta_3 w_{it} * lpz_{it} + \beta_4 z_{it} * w_{it} \\ + \beta_5 z_{it} + \beta_6 w_{it} + \beta_7 lpz_{it} + \gamma_c + \gamma_i + \theta_{it} + \varepsilon_{it} \end{aligned} \tag{3.3}$$

$FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t. w_{it} is the GDP per capita of the mine's operating country in year t. z_{it} is the GDP per capita of the mine owner country, or the dummy for whether the mine is state-owned, in year t. As before, we include commodity fixed effects γ_c, and mine fixed effects γ_i, initial forest cover by year fixed effects, and time-invariant mine characteristics by year fixed effects. Standard errors are clustered at the country level.

We first look at the triple interaction between mine operating country GDP per capita, mine owner country GDP per capita and commodity prices, conditional on having more than 40% initial forest cover. At small radii, focusing on the triple interaction term in Table 3.6, the coefficient is positive and not significant. At higher radii, the triple interaction becomes negatively significant, which tells us that the elasticity of forest cover loss is lower in high income countries and when mining firms are from richer countries. This differential elasticity is starker at higher radii, where presumably the mining operator has more discretion in the rate of deforestation.

Table 3.6: Triple Interaction: MineGDP*OwnerGDP*Price

	(1) **FCLP** b/se	(2) **FCLP** b/se	(3) **FCLP** b/se	(4) **FCLP** b/se	(5) **FCLP** b/se	(6) **FCLP** b/se
Price	0.801*** (0.179)	0.734*** (0.102)	0.685*** (0.146)	0.557*** (0.121)	0.454*** (0.073)	0.333*** (0.076)
MineGDP*Price	-0.788*** (0.269)	-0.600** (0.262)	-0.210 (0.159)	-0.141 (0.181)	-0.293 (0.179)	-0.340* (0.183)
OwnerGDP*Price	0.094 (0.527)	-0.136 (0.232)	-0.161 (0.149)	-0.128 (0.136)	-0.040 (0.105)	0.011 (0.110)
MineGDP*OwnerGDP*Price	1.520 (0.898)	0.256 (0.401)	-0.355 (0.312)	-0.416* (0.233)	-0.430*** (0.139)	-0.425*** (0.133)
Observations	23180	24214	24506	24760	24596	24616
Adjusted R^2	0.14	0.15	0.16	0.18	0.26	0.32
Clustering	Country	Country	Country	Country	Country	Country
Fixed Effects	Year, Commodity, IFC*Year, MineChar*Year, Mine					
Initial Forest Cover (Higher than, %)	40	40	40	40	40	40
Radius (km)	1	3	5	10	20	30

Forest Cover Loss, Triple Interaction: MineGDP*OwnerGDP*Price -Following Equation 3.3, the dependent variable $FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. The independent variable lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t, spanning from 2000 to 2014. w_{it} is the GDP per capita of the mine's operating country in year t. z_{it} is the GDP per capita of the mine owner country in year t. We focus on buffer zones where the initial forest cover in 2000 is larger than 40%. All regressions include commodity, mine, IFC (initial forest cover) x year and MineChar x year fixed effects. All coefficients are in percentage points. Standard errors are clustered at the country level. *** Significant at 1%, ** 5%, * 10%.

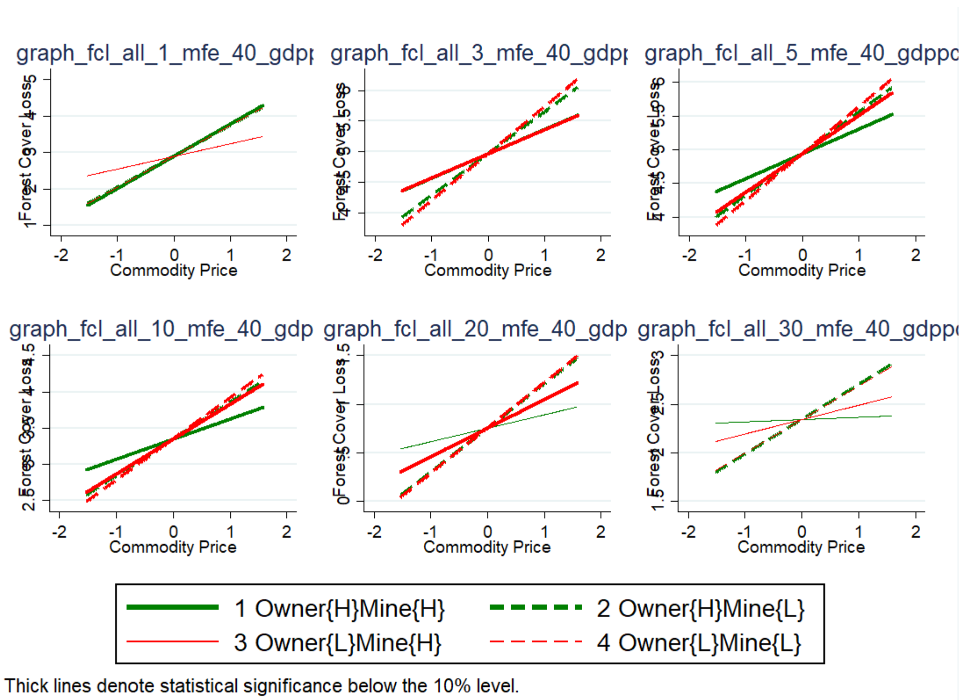


Figure 3.9: Triple Interaction: MineGDP*OwnerGDP*Price

Initial Forest Cover>40%, by buffer radius

Alternatively, Figure 3.9 visualizes this triple interaction by buffer radius. ”High” and ”Low” refers to one standard deviation above and below mean of each variable. Thicker lines denote statistical significance below the 10% level. Generally, mine owners from rich countries display larger disparity in the elasticity of forest cover loss when operating in low versus high income countries. Take the 20 kilometer buffer zone for example: in low income countries, owners from rich and poor countries deforest at the same rate. In high income countries, owners from poor countries have a significantly higher elasticity of forest cover loss with respect to prices. The green solid line at larger radii is flatter and insignificant, suggesting mine owners from rich countries do not deforest much more during commodity price hikes when operating in rich countries. There are many potential explanations for this. One possibility is that mining firms from rich countries have the capacity to minimize environmental impact during mining operation when the institutional incentives for doing so is strong. Alternatively, rich host countries may agree to different standards of environmental conservation for firms from different countries.

Next, we also examine the triple interaction between mine operating country GDP per capita, mine owner's state ownership status and commodity prices. The estimation results are presented in Table 3.7. Across radii, we see positive and significant effects on the triple interaction term. Recall that in section 3.4.1, we see no significant evidence of the elasticity of forest cover loss varying with state ownership status. Table 3.7 shows that state ownership status matters, for the differential elasticity of forest cover loss between rich versus poor mine operating countries. For non-state owned mining firms, the elasticity of forest cover loss is lower in high income countries, echoing previous findings. For state-owned mining firms, perhaps surprisingly, the elasticity of forest cover loss is higher in high income countries.

3.5 Mining Activities and Night Lights

Are the forest cover loss associated with commodity booms a direct effect of mining expansion or an indirect effect from nearby economic activity and population growth? To investigate the relationship between local economic activities and commodity price fluctuations, we look at nighttime luminosity measures from satellite imagery in this section. This data has been used in the literature to capture economic development, particularly for countries with insufficient capacity in national statistics collection.

The main empirical strategy follows fixed-effect models similar as before. Table 3.8 presents estimation results on nighttime luminosity measures for buffer zones of 5, 10 and 25 kilometer radius. Column 2,4,6 follows equation 3.1, controlling for year, commodity and mine fixed effects. Across radii, we see that commodity prices significantly increase local economic

Table 3.7: Triple Interaction: OwnerSOE*MineGDP*Price

	(1) **FCLP** b/se	(2) **FCLP** b/se	(3) **FCLP** b/se	(4) **FCLP** b/se	(5) **FCLP** b/se	(6) **FCLP** b/se
Price	0.709***	0.615***	0.581***	0.490***	0.418***	0.333***
	(0.109)	(0.086)	(0.146)	(0.120)	(0.079)	(0.077)
MineGDP*Price	-0.215	-0.590***	-0.474**	-0.409**	-0.485**	-0.516**
	(0.290)	(0.202)	(0.211)	(0.192)	(0.174)	(0.184)
OwnerSOE*Price	-0.277	-0.066	-0.200	-0.127	-0.099	-0.250
	(0.515)	(0.208)	(0.227)	(0.135)	(0.174)	(0.262)
OwnerSOE*MineGDP*Price	1.628***	0.885**	0.762*	1.031***	1.021***	0.915**
	(0.551)	(0.321)	(0.373)	(0.317)	(0.312)	(0.360)
Observations	28297	29659	30023	30313	30145	30157
Adjusted R^2	0.14	0.15	0.16	0.18	0.26	0.33
Clustering	Country	Country	Country	Country	Country	Country
Fixed Effects	Year, Commodity, IFC*Year, MineChar*Year, Mine					
Initial Forest Cover (Higher than, %)	40	40	40	40	40	40
Radius (km)	1	3	5	10	20	30

Forest Cover Loss, Triple Interaction: OwnerSOE*MineGDP*Price -Following Equation 3.3, the dependent variable $FCLP\_R_{it}$ is the percentage of forest cover loss in year t, measured every three years, at radius R around mining property i. The independent variable lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t, spanning from 2000 to 2014. w_{it} is the GDP per capita of the mine's operating country in year t. z_{it} is the dummy for whether the mine is state-owned in year t. We focus on buffer zones where the initial forest cover in 2000 is larger than 40%. All regressions include commodity, mine, IFC (initial forest cover) x year and MineChar x year fixed effects. All coefficients are in percentage points. Standard errors are clustered at the country level. *** Significant at 1%, ** 5%, * 10%.

activities measured by nighttime luminosity, although the magnitude decreases as we look at larger buffer zones. Next, for the triple interaction between mine operating country GDP per capita, mine owner country GDP per capita and commodity prices, we follow the specification in equation 3.3. The coefficients on the triple interaction are significantly positive. This says that the impact of commodity booms on nearby economic activities is larger if the mine owner is from a rich country and when the mine operating country is rich. Commodity booms are often associated with employment opportunities for nearby mining towns, possibly resulting in local economic booms. Here we focus on the immediate effect, although it would be also interesting to see the medium and long run effects of commodity price booms on local economic development.

Table 3.8: Triple Interaction: MineGDP*OwnerGDP*Price

	(1) **DlSOL** b/se	(2) **DlSOL** b/se	(3) **DlSOL** b/se	(4) **DlSOL** b/se	(5) **DlSOL** b/se	(6) **DlSOL** b/se
Price	-0.009 (0.010)	0.013*** (0.004)	-0.010 (0.010)	0.010*** (0.004)	-0.010 (0.010)	0.008** (0.004)
OwnerGDP*Price	0.076*** (0.012)		0.065*** (0.010)		0.053*** (0.010)	
MineGDP*Price	-0.010 (0.013)		-0.004 (0.011)		0.000 (0.010)	
OwnerGDP*MineGDP*Price	0.028*** (0.005)		0.026*** (0.005)		0.026*** (0.004)	
Observations	49513	130004	49513	130004	49517	130008
Adjusted R^2	-0.04	0.009	0.03	0.08	0.14	0.19
Clustering	Country	Country	Country	Country	Country	Country
Other Fixed Effects	Year, Commodity, Mine, MineChar					
Radius (km)	5	5	10	10	25	25

Nighttime Luminosity, Triple Interaction: MineGDP*OwnerGDP*Price -The dependent variable $DlSOL_{it}$ is the log difference in nighttime luminosity in year t, measured every three years, at radius R around mining property i. The independent variable lpz_{ct} is the average standardized main commodity price for mine i, from year $t-2$ to year t, spanning from 2000 to 2012. w_{it} is the GDP per capita of the mine's operating country in year t. z_{it} is the GDP per capita of the mine owner country in year t. All regressions include year, commodity, mine, MineChar fixed effects. Standard errors are clustered at the country level. *** Significant at 1%, ** 5%, * 10%.

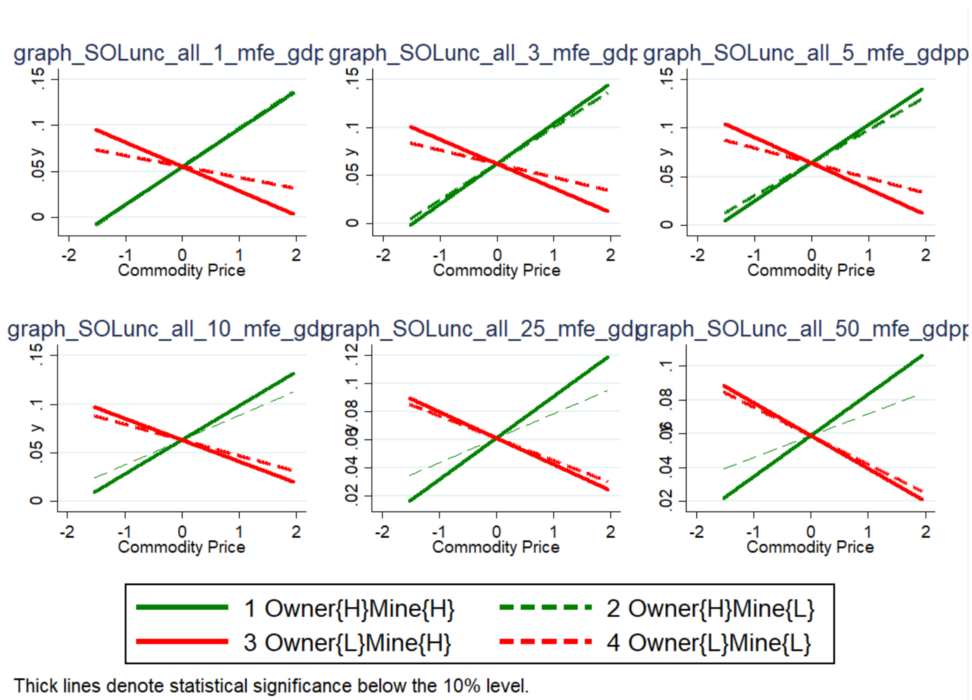


Figure 3.10: Triple Interaction on Night Lights: MineGDP*OwnerGDP*Price

Initial Forest Cover>40%, by buffer radius

We visualize the triple interaction in Figure 3.10. Across radii from 1 to 50 kilometers, nighttime luminosity around mining sites increases with commodity prices when the mine operating country and mine owner country are both high income. For smaller buffer zones with radius below 5 kilometer, the elasticity of night lights is also positive when the mine owner is high income and the mine operating country is low income. [5] However, the effects reverse when the mine owner is from a low income country. Perhaps surprisingly, nighttime luminosity decreases during commodity price booms when the mine owner is from a country with average GDP per capita one standard deviation below sample mean.

In some cases, We could infer the causes of forest cover loss, combining results on nighttime luminosity with previous results in section 3.4. First, recall mine owners from poor

[5] We do not focus on results within the 5 kilometer buffer zone given that the regression fit is very low, possibly because few economic activities happen at night in the immediate area surrounding mines.

countries deforest at a higher rate in both high and low income countries. Given that nearby economic activities do not increase, the forest cover loss more likely results from direct expansion of mining activities. In fact, when mine owners are from poor countries, the price effect on deforestation becomes insignificant when we look at the 30 kilometer buffer zone, as illustrated in Figure 3.9.

When mine owners from high income countries operate in low income countries, we see an increase in both local economic activity and forest cover loss across buffer zones, suggesting both direct expansion in mining operation and local economic growth could contribute to deforestation. Given most mines are less than 10 kilometer in radius, it is likely that the deforestation in larger buffer zones occur due to indirect effects.

3.6 Conclusion

Reducing forest-based emissions as an important strategy to curb global carbon emissions relies on accurate understanding of the causes and factors affecting deforestation. In this paper, we offer global, mine-level evidence on mining-induced deforestation during the ”commodity super-cycle” since 2000. We further explore the political economy of the environmental impact of mining, and find that the elasticity of forest cover loss with respect to price is higher in low income countries. Mining firm ownership plays a key role in understanding the large disparity in deforestation rates between rich versus poor host countries. Further evidence from nighttime luminosity data suggests indirect effects of mining expansion on nearby economic activities may be an important channel through which commodity booms affect deforestation.

This paper offers a natural starting point to evaluate the effectiveness of forest conservation programs on a global scale. A rich recent literature evaluates policies under UN's REDD++

relying on local randomized controlled trials [6], country-level aggregate data [7], and country-specfic quantitative counterfactual estimation [8]. Exploring submission data from the Forest Reference Emission Level (FREL) proposals to the UN, and the World Database on Protected Areas (WDPA) for evaluating forest policies during commodity booms is an area for future research.

[6] Jack and Jayachandran, 2019; Jayachandran, 2013; Jayachandran et al. 2017

[7] Duchelle et al. 2018; Overman et al. 2019

[8] Souza-Rodrigues, 2018

3.7 Acknowledgements

Chapter 3 is coauthored with Ran Goldblatt, Gordon Hanson and Amit Khandelwal, and is being prepared for publication. The dissertation author is the principle researcher on this chapter.

3.8 Additional Figures

3.8.1 Average Forest Cover Loss at 20 km

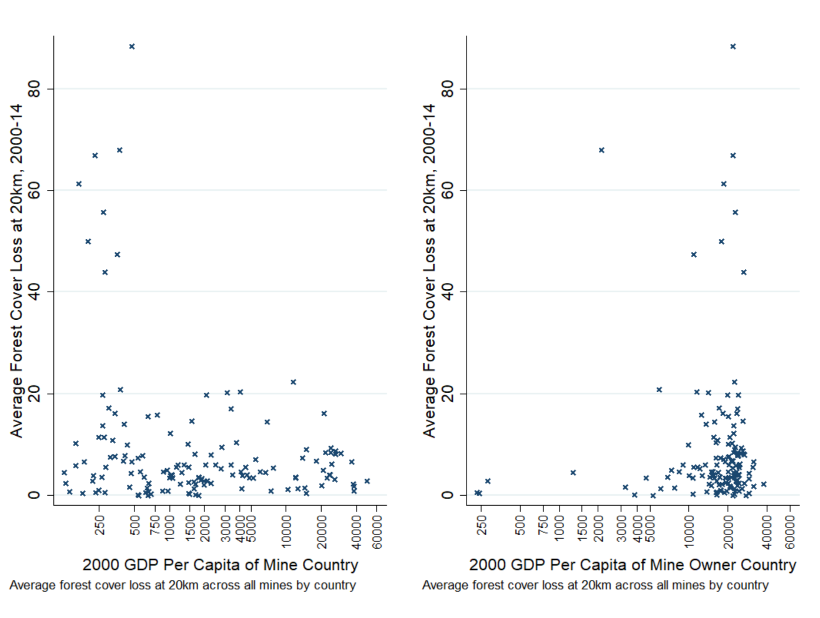


Figure 3.11: Average Forest Cover Loss at 20km by Country, 2000-14

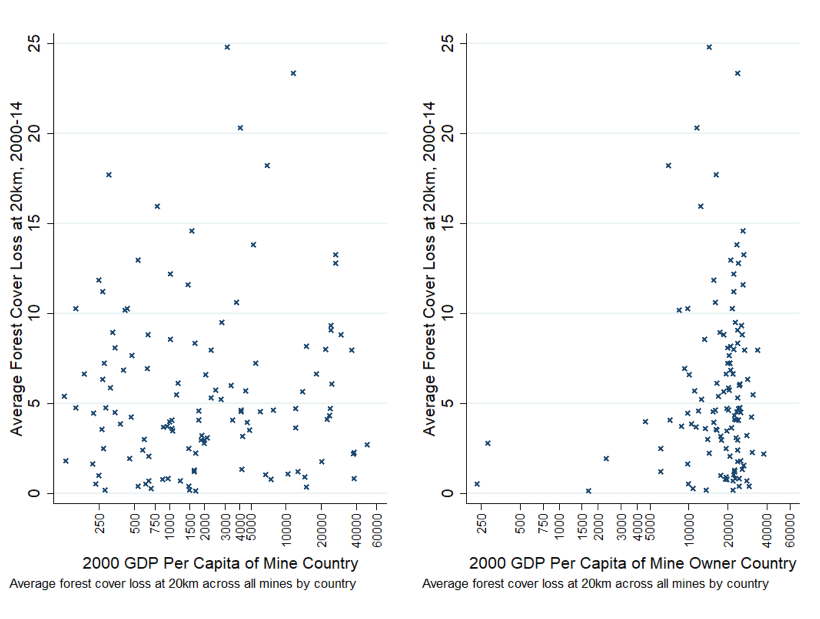


Figure 3.12: Average Forest Cover Loss at 20km by Country, IFC>25%, 2000-14

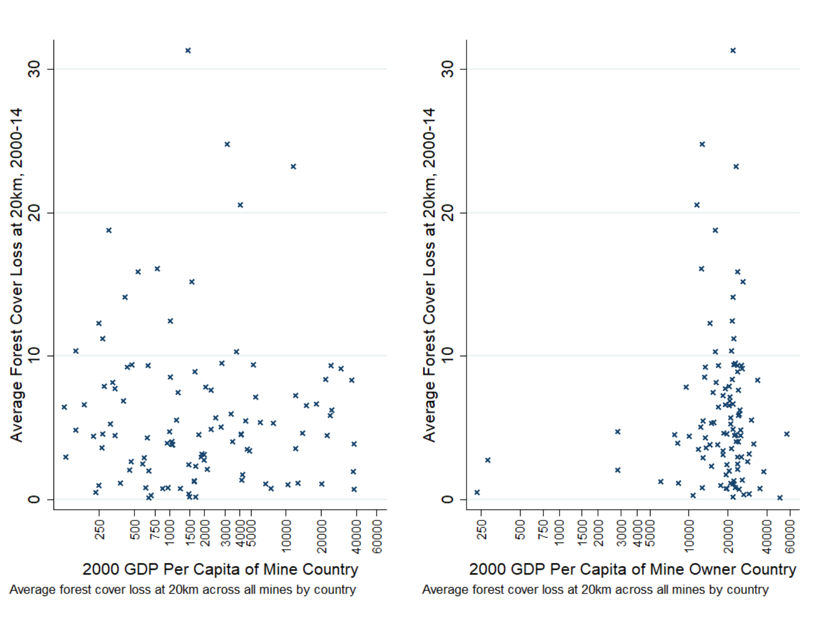


Figure 3.13: Average Forest Cover Loss at 20km by Country, IFC>40%, 2000-14

3.8.2 Google Earth Images of Open Pit Mines

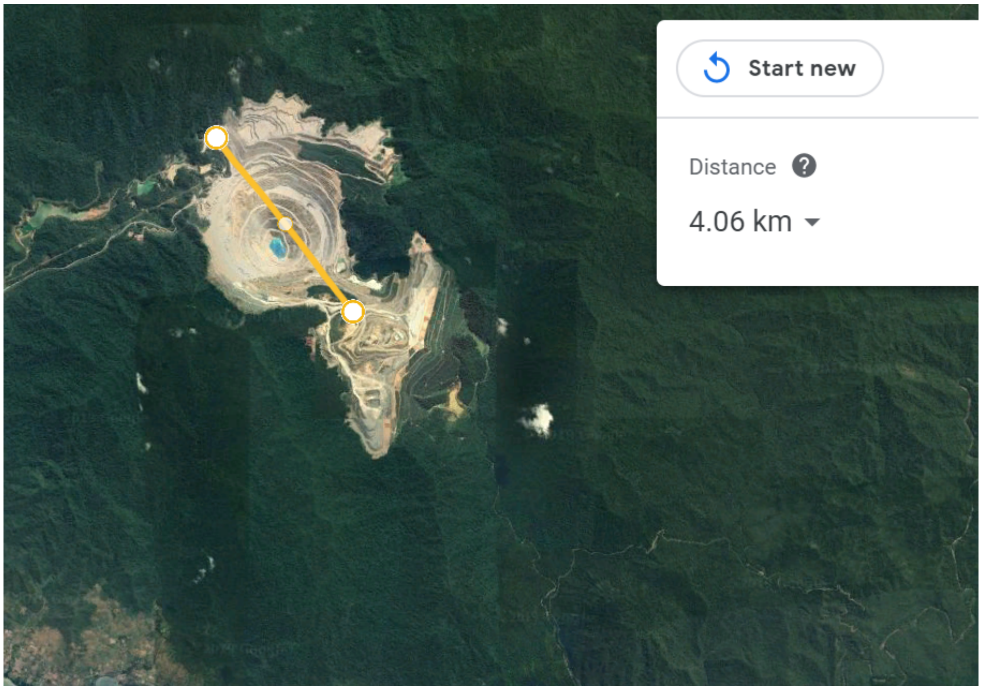


Figure 3.14: Batu Hijau: copper and gold mine, Indonesia

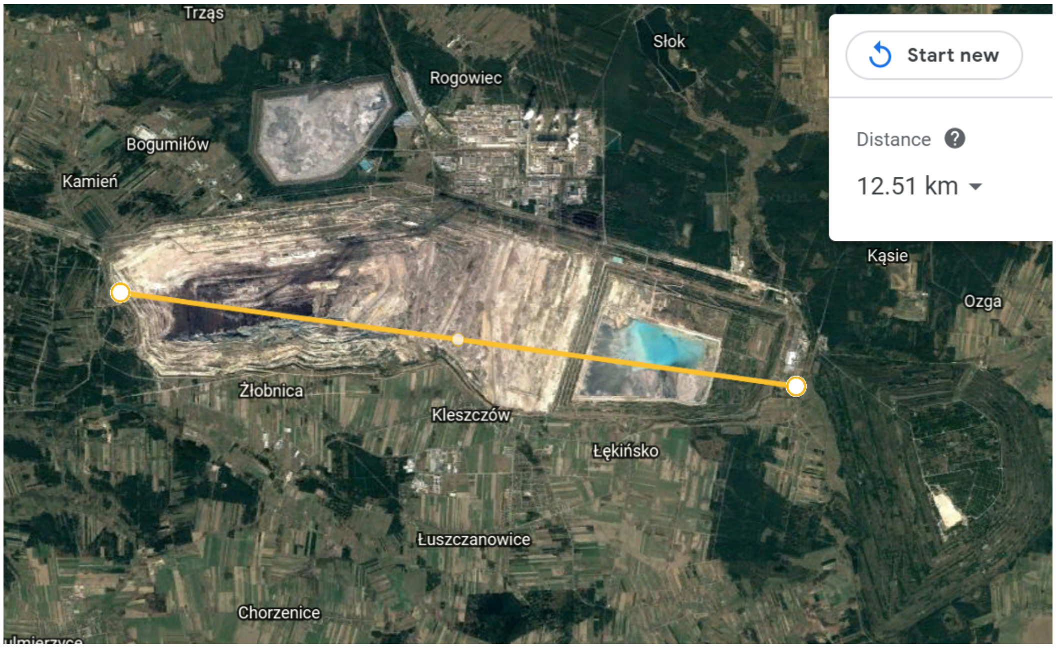


Figure 3.15: Belchatow: coal mine, Poland

Figure 3.16: Tagebau Hambach: lignite mine, Germany

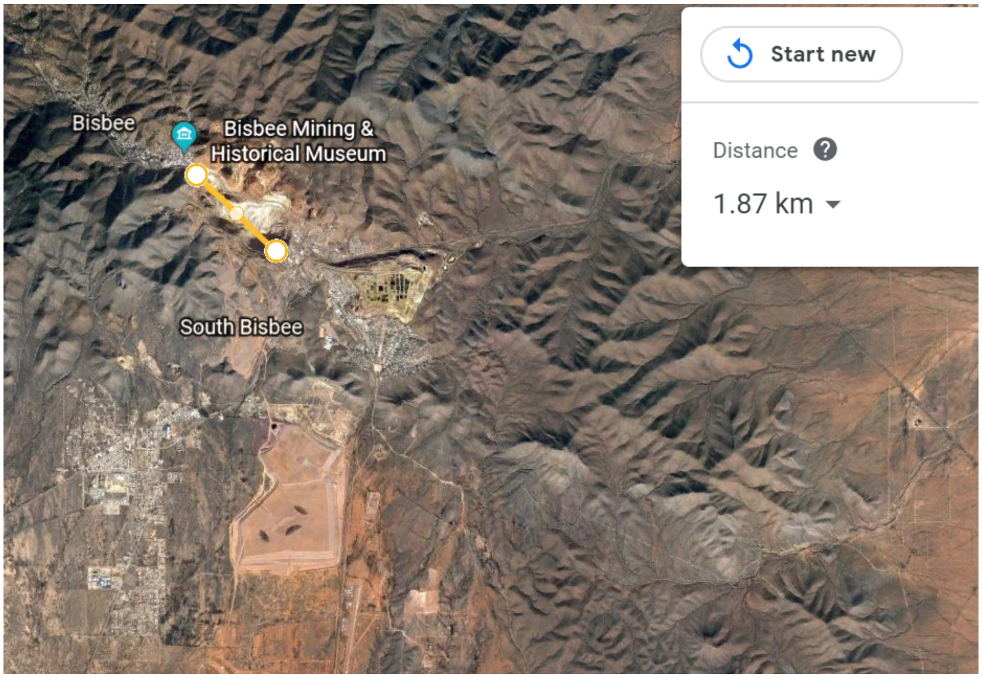


Figure 3.17: Lavender Pit: Arizona

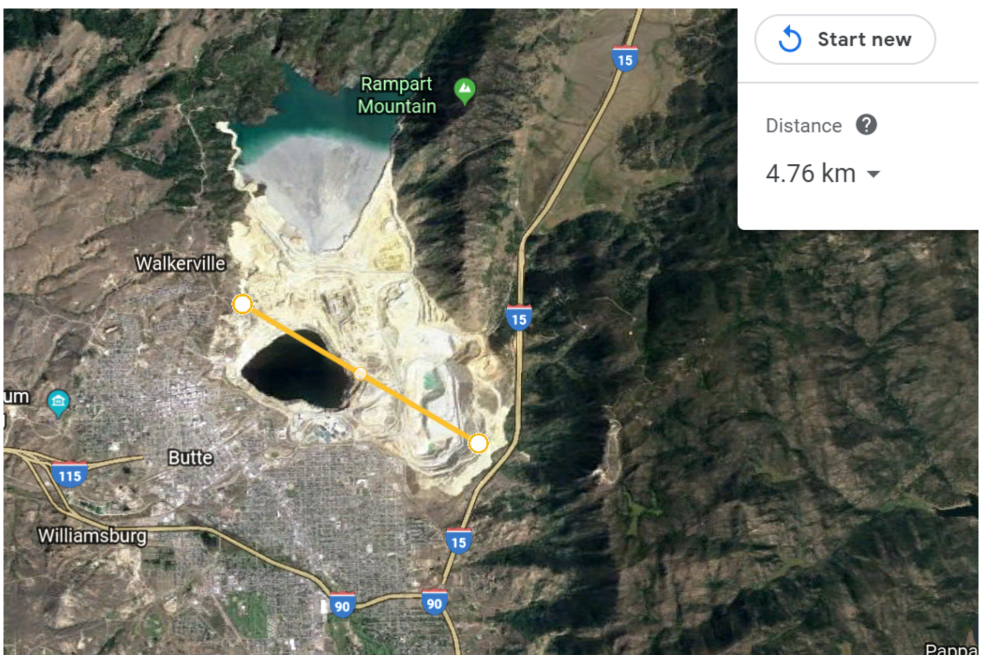


Figure 3.18: Berkeley Pit: copper mine/superfund site, Montana

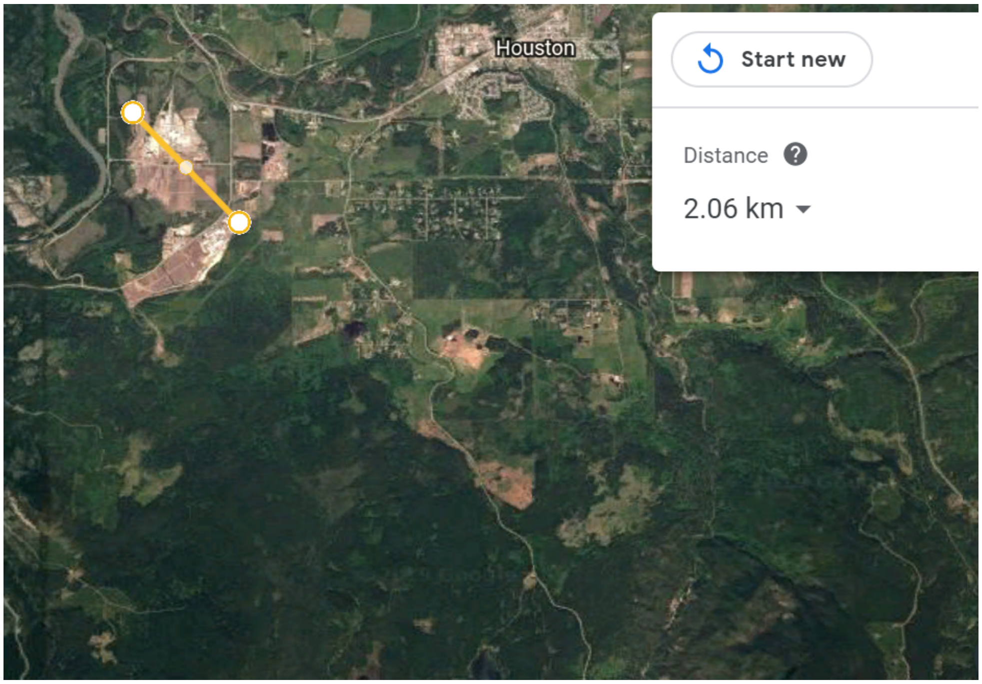


Figure 3.19: Huckleberry Mine: copper/molybdenum/gold/silver, Canada

Bibliography

[1] Google earth.

[2] Daron Acemoglu, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016, 2012.

[3] Achyuta Adhvaryu, Namrata Kala, and Anant Nyshadham. Management and shocks to worker productivity: evidence from air pollution exposure in an indian garment factory. Unpublished working paper, University of Michigan, 2014.

[4] Achyuta Adhvaryu, Namrata Kala, and Anant Nyshadham. The light and the heat: Productivity co-benefits of energy-saving technology. Unpublished manuscript, 2016.

[5] Alberto Alesina, Caterina Gennaioli, and Stefania Lovo. Public goods and ethnic diversity: Evidence from deforestation in indonesia. *Economica*, 86(341):32–66, 2019.

[6] Rita Almeida and Pedro Carneiro. Enforcement of labor regulation and informality. *American Economic Journal: Applied Economics*, 4(3):64–89, 2012.

[7] Nora L Alvarez-Berríos and T Mitchell Aide. Global demand for gold is another threat for tropical forests. *Environmental Research Letters*, 10(1):014006, 2015.

[8] M. Amiti and Joep Konings. Trade liberalization, intermediate inputs, and productivity: evidence from indonesia. *The American Economic Review*, 97(5):1611–1638, 2007.

[9] Soren T Anderson, Ryan Kellogg, and Stephen W Salant. Hotelling under pressure. *Journal of Political Economy*, 126(3):984–1026, 2018.

[10] James Andreoni and Arik Levinson. The simple analytics of the environmental kuznets curve. *Journal of public economics*, 80(2):269–286, 2001.

[11] Max Auffhammer. The relationship between air conditioning adoption and temperature. UC Berkeley Department of Agriculture and Resource Economics, 2011.

[12] David H. Autor and David Dorn. The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–1597, 2013.

[13] David H. Autor, David Dorn, and Gordon Hanson. Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, 129(4):1799–1860, 2014.

[14] David H. Autor, Frank Levy, and Richard J. Murnane. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333, 2003.

[15] Alan Barreca, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S Shapiro. Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159, 2016.

[16] Salvador Barrios, Luisito Bertinelli, and Eric Strobl. Trends in rainfall and economic growth in africa: A neglected cause of the african growth tragedy. *The Review of Economics and Statistics*, 92(2):350–366, 2010.

[17] Brian Beach and W Walker Hanlon. Coal smoke and mortality in an early industrial economy. *The Economic Journal*, 128(615):2652–2675, 2017.

[18] Nicolas Berman, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig. This mine is mine! how minerals fuel conflicts in africa. *American Economic Review*, 107(6):1564–1610, 2017.

[19] Andrew B Bernard, J Bradford Jensen, Stephen J Redding, and Peter K Schott. Firms in international trade. *The Journal of Economic Perspectives*, 21(3):105–130, 2007.

[20] Robin Burgess, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. Weather and death in india. Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript, 2011.

[21] Robin Burgess, Olivier Deschenes, Dave Donaldson, and Michael Greenstone. *Weather, climate change and death in India*. University of Chicago, 2018.

[22] Robin Burgess and Dave Donaldson. Can openness mitigate the effects of weather shocks? evidence from india's famine era. *The American economic review*, 100(2):449–453, 2010.

[23] Robin Burgess, Matthew Hansen, Benjamin A Olken, Peter Potapov, and Stefanie Sieber. The political economy of deforestation in the tropics. *The Quarterly Journal of Economics*, 127(4):1707–1754, 2012.

[24] Marshall Burke and Kyle Emerick. Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3):106–140, 2016.

[25] Marshall Burke, Solomon M. Hsiang, and Edward Miguel. Global non-linear effect of temperature on economic production. *Nature*, 527:235–239, 2015.

[26] Paul J. Burke and Andrew Leigh. Do output contractions trigger democratic change? *American Economic Journal: Macroeconomics*, 2(4):124–157, 2010.

[27] Ariel Burstein and Jonathan Vogel. International trade, technology, and the skill premium. *Journal of Political Economy*, Forthcoming, February 2016.

[28] Jonah Busch and Kalifi Ferretti-Gallon. What drives deforestation and what stops it? a meta-analysis. *Review of Environmental Economics and Policy*, 11(1):3–23, 2017.

[29] A. Colin Cameron, Jonah B. Gelbach, and Douglas L. Miller. Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29:2, 2011.

[30] Otaviano Canuto. The commodity super cycle: is this time different? *Economic Premise, the World Bank*, 150:1–4, 2014.

[31] Tamma A. Carleton. Crop-damaging temperatures increase suicide rates in india. *Proceedings of the National Academy of Sciences*, 114(33):8746–8751, 2017.

[32] Colin A Carter, Gordon C Rausser, and Aaron Smith. Commodity booms and busts. 2011.

[33] Gabriel Chodorow-Reich. The employment effects of credit market disruptions: Firm-level evidence from the 20089 financial crisis. *The Quarterly Journal of Economics*, 129(1):1–59, 2013.

[34] Jonathan Colmer. Weather, labour reallocation, and industrial production: Evidence from india. Work. Pap., London Sch. Econ., London, 2016.

[35] C. Austin Davis. Why did sugarcane growers suddenly adopt existing technology? Working Paper, 2017.

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

[37] Melissa Dell, Benjamin F. Jones, and Benjamin A. Olken. What do we learn from the weather? the new climateeconomy literature. *Journal of Economic Literature*, 52(3):740–798, 2014.

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

[39] Olivier Deschenes, Kyle C. Meng, Peng Zhang, and Junjie Zhang. Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88(3):1–17, 2017.

[40] Olivier Deschłnes and Michael Greenstone. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, 3(4):152–185, 2011.

[41] Rafael Dix-Carneiro and Brian K. Kovak. Trade liberalization and regional dynamics. *American Economic Review*, 107(10):2908–46, 2017.

[42] Rafael DixCarneiro. Trade liberalization and labor market dynamics. *Econometrica*, 82(3):825–885, 2014.

[43] Dave Donaldson and Adam Storeygard. The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, 30(4):171–98, 2016.

[44] Amy E Duchelle, Frances Seymour, Maria Brockhaus, Arild Angelsen, Moira Moeliono, Grace Yee Wong, Thu Thuy Pham, Christopher Martius, et al. Redd+: Lessons from national and subnational implementation. 2018.

[45] Suzanne Duryea and Mary Arends-Kuenning. School attendance, child labor and local labor market fluctuations in urban brazil. *World Development*, 31(7):1165–1178, 2003.

[46] Shuaizhang Feng, Alan B. Krueger, and Michael Oppenheimer. Linkages among climate change, crop yields and mexicous cross-border migration. *Proceedings of the National Academy of Sciences*, 107(32):14257–14262, 2010.

[47] Shuaizhang Feng, Michael Oppenheimer, and Wolfram Schlenker. Climate change, crop yields, and internal migration in the united states. National Bureau of Economic Research No. w17734, 2012.

[48] Anthony C Fisher, W Michael Hanemann, Michael J Roberts, and Wolfram Schlenker. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *The American Economic Review*, 102(7):3749–3760, 2012.

[49] Aaron Flaaen, Matthew D. Shapiro, and Isaac Sorkin. Reconsidering the consequences of worker displacements: Survey versus administrative measurements. Manuscript, University of Michigan, 2013.

[50] Center for Longitudinal Studies UCL. Translation from us occ 2000 to isco-88. Technical report.

[51] Teevrat Garg, Maulik Jagnani, and Vis Taraz. Effects of heat stress on physiology and livelihoods: Implications for human capital accumulation. Working paper, 2017.

[52] Clark L. Gray and Valerie Mueller. Natural disasters and population mobility in bangladesh. *Proceedings of the National Academy of Sciences*, 109(16):6000–6005, 2012.

[53] Gene M Grossman and Alan B Krueger. Environmental impacts of a north american free trade agreement. Technical report, National Bureau of Economic Research, 1991.

[54] Gene M Grossman and Alan B Krueger. Economic growth and the environment. *The quarterly journal of economics*, 110(2):353–377, 1995.

[55] Raymond Guiteras. The impact of climate change on Indian agriculture. Manuscript, Department of Economics, University of Maryland, College Park, Maryland, 2009.

[56] Peter A. Hancock, Jennifer M. Ross, and James L. Szalma. A meta-analysis of performance response under thermal stressors. *Human factors*, 49(5):851–877, 2007.

[57] Matthew C Hansen, Peter V Potapov, Rebecca Moore, Matt Hancher, SAA Turubanova, Alexandra Tyukavina, David Thau, SV Stehman, SJ Goetz, Thomas R Loveland, et al. High-resolution global maps of 21st-century forest cover change. *science*, 342(6160):850–853, 2013.

[58] Geoffrey Heal and . Jisung Park. Feeling the heat: Temperature, physiology & the wealth of nations. *National Bureau of Economic Research*, (w19725), 2014.

[59] J. Vernon Henderson, Adam Storeygard, and Uwe Deichmann. Has climate change driven urbanization in africa? *Journal of development economics*, 124:60–82, 2017.

[60] J Vernon Henderson, Adam Storeygard, and David N Weil. Measuring economic growth from outer space. *American economic review*, 102(2):994–1028, 2012.

[61] Brad Hershbein and Lisa B. Kahn. Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1737–72, 2018.

[62] Harold Hotelling. The economics of exhaustible resources. *Journal of political Economy*, 39(2):137–175, 1931.

[63] Solomon Hsiang, Paulina Oliva, and Reed Walker. The distribution of environmental damages. National Bureau of Economic Research No. w23882., 2017.

[64] Solomon M. Hsiang. 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, 2010.

[65] Chang-Tai Hsieh and Benjamin A. Olken. The missing missing middle. *The Journal of Economic Perspectives*, 28(3):89–108, 2014.

[66] David Humphreys. The great metals boom: A retrospective. *Resources Policy*, 35(1):1–13, 2010.

[67] Cosmin Ilut, Matthias Kehrig, and Martin Schneider. Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news. *Journal of Political Economy*, 126(5):2011–2071, 2018.

[68] B Kelsey Jack and Seema Jayachandran. Self-selection into payments for ecosystem services programs. *Proceedings of the National Academy of Sciences*, 116(12):5326–5333, 2019.

[69] Louis S. Jacobson, Robert J. LaLonde, and Daniel G. Sullivan. Earnings losses of displaced workers. *The American economic review*, pages 685–709, 1993.

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

[71] Seema Jayachandran. Liquidity constraints and deforestation: The limitations of payments for ecosystem services. *American Economic Review*, 103(3):309–13, 2013.

[72] Seema Jayachandran, Joost De Laat, Eric F Lambin, Charlotte Y Stanton, Robin Audy, and Nancy E Thomas. Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science*, 357(6348):267–273, 2017.

[73] Benjamin F. Jones and Benjamin A. Olken. Climate shocks and exports. *The American Economic Review*, 100(2):454–459, 2010.

[74] S. Karjalainen. Thermal comfort and gender: a literature review. *Indoor air*, 22(2):96–109, 2012.

[75] Supreet Kaur. Nominal wage rigidity in village labor markets. *American Economic Review*. Forthcoming.

[76] Tord Kjellstrom, Ingvar Holmer, and Bruno Lemke. Workplace heat stress, health and productivity is increasing challenge for low and middle-income countries during climate change. *Global Health Action*, 2, 2009.

[77] Rafael La Porta and Andrei Shleifer. Informality and development. *Journal of Economic Perspectives*, 28(3):109–126, 2014.

[78] Mark G. Lawrence. The relationship between relative humidity and the dewpoint temperature in moist air: A simple conversion and applications. *Bulletin of the American Meteorological Society*, 86(2):225–233, 2005.

[79] David B. Lobell, Wolfram Schlenker, and Justin Costa-Roberts. Climate trends and global crop production since 1980. *Science*, 333(6042):616–620, 2011.

[80] Sri Maryati, Hideki Shimada, Takashi Sasaoka, Akihiro Hamanaka, Kikuo Matsui, and Hideaki Nagawa. Gis database template for environmental management of mining in indonesia. *Journal of Geographic Information System*, 4(01):62, 2012.

[81] Marc J. Melitz. The impact of trade on intraindustry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725, 2003.

[82] Narcio Aquino Menezes-Filho and Marc-Andreas Muendler. Labor reallocation in response to trade reform. *National Bureau of Economic Researc*, (No. w17372.), 2011.

[83] Julin Messina and Anna Sanz de Galdeano. Wage rigidity and disinflation in emerging countries. *American Economic Journal: Macroeconomics*, 6(1):102–33, 2014.

[84] Jennifer Poole Garey Ramey Tamara Wajnberg Muendler, Marc-Andreas. Job concordances for brazil: Mapping the classificaao brasileira de ocupaoes (cbo) to the international standard classification of occupations (isco-88). University of California, San Diego, unpublished manuscript, 2004.

[85] Raimo Niemelä, Mika Hannula, Sari Rautio, Kari Reijula, and Jorma Railio. The effect of air temperature on labour productivity in call centresa case study. *Energy and Buildings*, 34(8):759–764, 2002.

[86] William D. Nordhaus. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences*, 201609244, 2017.

[87] Han Overman, Anthony R Cummings, Jeffrey B Luzar, and José MV Fragoso. National redd+ outcompetes gold and logging: The potential of cleaning profit chains. *World Development*, 118:16–26, 2019.

[88] Jisung Park. Will we adapt? temperature shocks, labor productivity, and adaptation to climate change in the united states (1986–2012). Discussion paper, Harvard Project on Climate Agreements, 2017.

[89] Topalova Petia, Sebastian Acevedo, Mico Mrkaic, Natalija Novta, Marcos Poplawski-Ribeiro, and Evgenia Pugacheva. *The Effects of Weather Shocks on Economic Activity: How Can Low-Income Countries Cope?* IMF World Economic Outlook, 2017.

[90] June J. Pilcher, Eric Nadler, and Caroline Busch. Effects of hot and cold temperature exposure on performance: a meta-analytic review. *Ergonomics*, 45(10):682–698, 2002.

[91] Jerry D. Ramsey. Task performance in heat: a review. *Ergonomics*, 38(1):154–165, 1995.

[92] Carmen M Reinhart, Vincent Reinhart, and Christoph Trebesch. Global cycles: Capital flows, commodities, and sovereign defaults, 1815-2015. *American Economic Review*, 106(5):574–80, 2016.

[93] Mauricio Romero and Santiago Saavedra. The effect of gold mining on the health of newborns. *Unpublished manuscript. Stanford University, Department of Economics, Stanford, CA*, 2015.

[94] William J Sacks, Delphine Deryng, Jonathan A Foley, and Navin Ramankutty. Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography*, 19(5):607–620, 2010.

[95] T. Sanford, P. C. Frumhoff, A. Luers, and J. Gulledge. The climate policy narrative for a dangerously warming world. *Nature Climate Change*, 4(3):164, 2014.

[96] Gabriella Santangelo. *Firms and farms: The impact of agricultural productivity on the local Indian economy*. Job Market Paper, 2015.

[97] Wolfram Schlenker and David B. Lobell. Robust negative impacts of climate change on african agriculture. *Environmental Research Letters*, 5(1), 2010.

[98] Wolfram Schlenker and Michael J. Roberts. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598, 2009.

[99] Olli Seppanen, William J. Fisk, and Q. H. Lei. Effect of temperature on task performance in office environment. Technical report, Lawrence Berkeley National Laboratory, 2006.

[100] Margaret E Slade and Henry Thille. Whither hotelling: tests of the theory of exhaustible resources. *Annu. Rev. Resour. Econ.*, 1(1):239–260, 2009.

[101] E. Somanathan, R. Somanathan, A. Sudarshan, and M. Tewari. *The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing*, volume 15 of *03*. Indian Statistical Institute, New Delhi, India, 2014.

[102] Eduardo A Souza-Rodrigues. Deforestation in the amazon: A unified framework for estimation and policy analysis. *The Review of Economic Studies*, 2018.

[103] David I Stern. The rise and fall of the environmental kuznets curve. *World development*, 32(8):1419–1439, 2004.

[104] Shinsuke Tanaka. Environmental regulations on air pollution in china and their impact on infant mortality. *Journal of health economics*, 42:90–103, 2015.

[105] the World Bank Group. Climate knowledge portal. Technical report, 2018.

[106] Bernardus Van Doornik, David Schoenherr, and Janis Skrastins. Unemployment insurance, strategic unemployment, and firm-worker collusion. 2017.

[107] Daniel J. Wilson. The impact of weather on local employment: Using big data on small places. Technical report, Federal Reserve Bank of San Francisco, 2017.

[108] Kerstin K. Zander, Wouter J. W. Botzen, Elspeth Oppermann, Tord Kjellstrom, and Stephen T. Garnett. Heat stress causes substantial labour productivity loss in australia. *Nature Climate Change*, 5(7):647–651, 2015.

[109] Joshua Graff Zivin and Matthew E. Kahn. Industrial productivity in a hotter world: The aggregate implications of heterogeneous firm investment in air conditioning. Technical report, National Bureau of Economic Research, 2016. No. w22962.

[110] Joshua Graff Zivin and Matthew Neidell. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26, 2014.