Abstract

This dissertation explores how geography, institutions, and culture affect various socio-economic outcomes. It is composed of two chapters.

Chapter 1 evaluates the economic implications of climate change in the Philippines. How will economic geography change as firms and people adapt to the challenges of a warming planet? I develop a quantitative spatial model wherein rising temperatures and sea-levels disrupt location fundamental amenities and productivities. I allow for heterogenous adaptation among skill groups to incorporate changes in inequality. Taking climate projections at 2100, I estimate aggregate welfare and output to fall by 20% and 14% respectively, with more prominent losses for low-skilled workers. However, large-scale adaptation strategies can attenuate initial damages by as high as 4 percentage points. Back-of-the-envelope calculations suggest the cost-effectiveness of coastline protection over the creation of a new metropolitan area inland.

Chapter 2 inspects the influencing role of gender norms on female labor market performance. Using the 1979 National Longitudinal Survey of Youth (NLSY), I explore how gender norms held at a very young age influence trajectories lifetime trajectories of child penalties on employment outcomes. My findings illustrate that with respect to labor participation and earnings, mothers disproportionately bear impact of children compared to male parents. I also show that short-run penalties on wages and labor hours follow females throughout their careers and persist up to ten years post-child. While all mothers have labor outcomes dip by 18-22% in comparison to their baseline levels a year before childbirth, long-run losses attenuate among females with progressive gender attitudes.

ESSAYS ON DEVELOPMENT AND LABOR ECONOMICS

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Contents

List of Figures

List of Tables

Chapter 1

Economic Consequences of Climate Change: Evidence from the Philippines

1.1 Introduction

Our planet is on a trajectory of anthropogenic warming that is unprecedented in human history. The persistent rise in global average temperatures endangers our delicate meteorological balance, disrupting the predictability of weather systems on which many livelihoods rely. A sobering reality is that low-income countries, which lack sufficient resources to adapt to climate change, will be hit the hardest despite having contributed the least to the world's greenhouse gas emissions.

Rising sea-levels and intensifying heat will spur a growing wave of mass migration given and disrupt key centers of economic activity. In developing countries where a significant share of the labor force relies on agriculture, these responses can register at an even larger scale. On the other hand, climate-induced migration could theoretically lead to hopeful outcomes. For instance, rural workers may relocate to more productive regions when faced with adverse temperature shocks. The demographic shift associated with climate displacement could therefore result in a welfare-improving distribution of economic activity– in some cases, increasing the pace of structural transformation and urbanization (Henderson et al., 2017). Hence, the net effect of global warming remain unclear.[1] This ambiguity necessitates a framework that captures the complex interactions in an economy as the population adjusts to a reality wherein rising seas and warming temperatures become the norm.

In this paper, I first build a model of economic geography that accounts for the spatial interactions of workers in the presence of frictions and externalities. I employ a static quantitative framework borrowing elements from Ahlfeldt et al. (2015) and Allen and Arkolakis (2014). I follow the standard set-up in which workers are born in a location and make a decision about where to reside and work. Trade and migration are costly, and the perceived value of all places endogenously depend both on fundamental components and also equilibrium population levels.

To quantify the welfare effects of climate change, I assume that temperature affects location through its influence on local exogenous productivity and amenities. When temperature profiles change, people and firms move in response to changing fundamentals. This new allocation of firms and labor across space brings about simultaneous adjustments in the economy through endogenous changes in agglomeration and dispersion forces. Additionally, local spillovers are further impacted when portions of land become uninhabitable due to sea-level rise. Thus, welfare accounting is nuanced by the general equilibrating effects of climate shocks on prices, wages, output, and factor reallocation. All the while, adjustments to a new steady state are governed by trade and migration frictions that governs each municipality-pair.

A key contribution of this paper highlights the distributional implications of climate change. I implement this by augmenting the model with heterogeneous workers of low- and high- skill types (Tsivanidis, 2019). I capture the differential responses across subpopulations by recovering type-specific trade and migration elasticities from reduced-form estimates. In doing so, I account for heterogeneous adaptation and present new evidence

[1] A partial equilibrium analysis of the economic effects of climate or weather is the subject of a large body of empirical literature. The works by Dell et al. (2014) and Tol (2009) offers a comprehensive review.

on the uneven impacts of climate change.

Second, I calibrate the spatial equilibrium framework with detailed microdata from the Philippines. The country is an interesting setting since it is already suffering the impacts of global warming through rising temperatures and severe natural disasters. With more than 60% of its population living in coastal municipalities, it remains vulnerable to the threat of rising oceans. The theoretical framework is applied to a rich set of geographic and administrative data recorded at the municipal level. I assemble a long panel of climate histories, geographic attributes, endogenous amenities, migration flows, domestic trade flows, expenditure shares, and average productivity by skill-type to identify key parameters at granular spatial units.

To quantify internal migration frictions, I rely on the decadal Philippine censuses from 1990 to 2010 for detailed coverage of bilateral population flows. Consistent with the literature, I find larger migration costs for low-skilled workers relative to high-skilled workers (Tombe and Zhu, 2019). I supplement this finding with skill-specific wages and expenditure shares collected at higher frequencies from 2003 to 2015 to account for the spatial distribution of income. I complement this data with calibrated parameters from the literature to obtain both relative exogenous productivity and amenities that rationalize the current distribution of economic activity. The recovered objects from the model inversion are strongly and positively correlated with actual location-specific attributes that are deemed desirable. This validation exercise lends credence to the assertion that the quantitative model is empirically relevant, suggesting that the framework is appropriate for general equilibrium counterfactual exercises.

Motivated by my policy simulations, I back out the reduced form effect of climate from the estimated structural fundamentals. I obtain causal estimates of local temperatures on amenities and productivities from a panel regression with a rich set of fixed effects and geographic attributes as controls. I find that skilled workers have larger and more negative semi-elasticities of amenities with respect to temperature, while low-skilled workers elicit higher sensitivities to local productivities. This is consistent with other findings that document higher productivity losses in the agricultural sector (Cruz, 2021; Oliveira and Pereda, 2020; Conte et al., 2021).

I conduct a quantitative evaluation of climate change using high-quality data, and contribute to the literature by simultaneously exploring the effects of rising temperatures and changing sea-levels. With the year 2100 as my reference point, I take the local average of future temperature projections under the Representative Concentration Pathway (RCP) 8.5 and 4.5 (Van Vuuren et al., 2011; IPCC, 2014).[2] The former is a high-emissions pathway with an end-of-century temperature increase of 3.7°C, while the latter is a baseline-emissions pathway with a projected global temperature increase of 1.9°C. Additionally, I simulate the corresponding flooding scenario from a 1.2-meter rise in sea levels using digital elevation maps. Incorporating the effects of sea-level rise is crucial. Over 60% of municipalities are at risk from coastal flooding, which in turn affects local agglomeration and congestion spillovers. For my counterfactuals, I account for these out-of-sample changes in location fundamentals and solve for the new long-run equilibrium levels of wages, output, and welfare.

The principal finding of the paper is that, under baseline frictions, the Philippines faces an aggregate welfare loss of 20%, and a 14% reduction in GDP under average century-end climate projections by the International Panel on Climate Change (IPCC). Climate damages are disproportionate across the population. Losses for low-skilled workers are higher by 6 percentage points than their skilled counterparts. Hence, climate change will exacerbate existing inequalities by 7.5%. Anchoring my results to the standard counterfactual exercises in this literature, I run extreme-case scenarios under extreme trade and migration costs. Welfare losses are amplified by a factor of as high as 1.6 when trade or mobility is restricted, yet a modest attenuating effect on welfare persists

[2]The United Nations' Intergovenmental Panel on Climate Change (IPCC) offers the gold-standard assessment of the current state of the planet and the likely and conservative trajectory for climate change. A future of RCP 4.5 is realized when emissions target are met, while an RCP 8.5 scenario assumes at least a five-fold growth of coal use over the course of the 21st century.

when barriers are removed.

With environmental change unfolding in a long and gradual process, spatial attributes at the end of the century may look very different than today. With this in mind, I execute a set of policy counterfactuals that consider feasible large-scale adaptation strategies. First, I evaluate the climate response of fortifying the shorelines of the three large population centers. This entails a collective engineering effort of building dikes, sea-walls, and levees. Second, I evaluate the welfare implications of an ambitious place-based policy involving the creation of a metropolitan area 80 kilometers north of the capital. New Clarke City can serve as a viable option when coastal residents begin to retreat inland. Results show that enforcing any abatement measures strictly dominate the outcomes simulated in the baseline case. Lower welfare and output losses are driven by the large locational response of low-skilled workers. Back-of-the-envelope calculations suggest that while the creation of a new city can mitigate output losses by around 4%, these gains are insufficient to cover the cost of abatement. In contrast, protecting the shoreline against sea-level rise makes for a cost-effective investment even when using cost estimates at the upper bound.

My research is related to a nascent but growing literature that tackles this topic through a similar methodological approach. Desmet et al. (2021) employ a dynamic spatial equilibrium framework to estimate projected GDP losses from rising oceans. In the same vein, but looking at a single country in Vietnam, Balboni (2019) models a multi-region spatial equilibrium framework to calculate welfare losses from misallocated infrastructure investments that ignore climate risks like sea level rise. More directly related to my work are those by Conte et al. (2021), Rudik et al. (2021), and Oliveira and Pereda (2020) wherein sectoral productivity varies with temperature, and climate-induced migration operates through changes in local amenities.

This paper contributes by taking a general equilibrium assessment of climate change for developing countries, which remains scarce in the literature. While the climate crisis is global, its impacts are local and will be more substantial in some parts of the world

(Hsiang and Kopp, 2018). More importantly, how people respond to environmental threats will be driven by institutional or geographical context. Applying the model to a single country allows me to capture heterogeneous agents, and unearths patterns on changes in inequality. This feature extends the current application of spatial models in evaluating the impacts of global warming. Additionally, my research offers insights into the distributional consequences of varying adaptation costs and actual policy considerations. This is of key relevance to a range of nations with limited resources to deal with the harsh new realities posed by climate change.

The rest of this paper is organized as follows. Section 1.2 presents background information on climate and economic development in the Philippines. Section 1.3 describes the different datasets used in my analysis. Section 1.4 presents reduced-form results. Section 1.5 lays out the quantitative spatial model. Section 1.6 discusses a special two-location case of my model to better build intuition. Section 1.7 calibrates the general model and recovers key structural estimates. Section 1.8 quantifies the effects of climate change under different counterfactual simulations. Section 1.9 concludes.

1.2 Background

1.2.1 Climate and Geography

The Philippines is among the nations most vulnerable to the effects of rising global temperatures.[3] By virtue of its location, its climate is characterized by frequent tropical cyclones, storm surge, and droughts.[4] Historical trends suggest that the country is already witnessing the impacts of global warming. In recent decades, anomalous weather patterns have become more common whereby certain regions are experiencing warmer tem-

[3] According to IPCC (2014), vulnerability is defined as the propensity or predisposition to be adversely affected. While encompassing a variety of concepts, climate vulnerability highlights the lack of capacity to cope and adapt.

[4] The Philippines lie in the Northwestern Pacific Basin, the most active tropical cyclone basin in the world. The country averages 20 cyclones per year. I use cyclones, hurricanes and typhoons interchangeably. But technically, storm systems that occur in the northwestern Pacific Ocean that hit the Philippines are typhoons.

peratures than usual, while typhoons are becoming more frequent and severe. Relative to the rest of the world, the Philippines ranks fifth in terms of its exposure to extreme natural events (Eckstein et al., 2021).[5]

In addition, the country is highly susceptible to rising sea levels. An archipelago of roughly 7,000 islands, the Philippines has the fifth longest coastline in the world.[6] As a consequence of the country's poor infrastructure and challenging topography - characterized by a mix of valleys, plains, and rugged mountains - more than half of its population resides on flat lowlands along the coastal rims. During the Spanish colonial period, the historical advantage offered by natural harbors spurred city formation along the coasts. Since then, urbanization is anchored around these areas with little population movements toward the highlands. The three largest metropolitan areas— Metro Manila, Metro Cebu, and Metro Davao- contain 18% of the national population. If sea levels rise by two meters, some municipalities might could experience a land reduction of as high as 24%.[7]

The Philippines exhibits high temperatures due to tropical maritime air currents that flow through the archipelago. With a mean temperature of 27.1°C, there is considerable variation across the country's geography at varying altitudes. On the other hand, rainfall distribution varies with topography and distance to seas. Regions experience entirely different levels of storm exposure at a given time. Although mean annual accumulated rainfall is approximately 209 millimeters, it ranges across municipalities from 105 to 425 millimeters.

[5]The Germanwatch Climate Risk Score compiles various datasets from 1999 to 2018 to quantify the severity of losses from weather-related events from all over the world. Indicators include fatalities per 100,000 inhabitants, monetary losses per unit of gross domestic product (GDP), and the incidence of heatwaves, hurricanes, wildfires, storms, and floods.

[6]It has a land area of 298,170 square kilometers and a coastline that spans 36,289 kilometers.

[7]While Metro Manila has an average elevation of 7 meters, it sits in the middle of a floodplain. It is also bounded by two bodies of water - Manila Bay on the west and Laguna de Bay on the southeast. Additionally, the Pasig River, a major waterway, runs through the metropolis.

1.2.2 Economy and Population

The most recent Census tallies the Philippine population at around 109 million. It is among Asia's fastest growing economies with an annual GDP growth rate of 4.5% in the early 2000s before hitting pre-pandemic highs of 6.4% for 2010–19. Recent growth can be attributed to a shifting distribution of economic activity from the agricultural sector to manufacturing and services.[8]

Yet despite a period of sustained growth, poverty reduction has not kept pace with the country's economic performance. Poverty rates have fallen by merely 1.3% from 27.9% between 2012 to 2015, and by only 0.3% from 2009 to 2012.[9] Higher incidence of poverty persists, especially among households who depend on agriculture. A significant share of the labor force still remains in low-productive and low-skill sectors. Though moving away from this trend, over a third of the working population is employed in agriculture, fishing, and forestry.

The strong reliance on livelihoods that depend on the natural environment is concerning in a world where climate patterns are becoming less stable. First, considerable evidence shows that agricultural output is vulnerable to seasonal unpredictability, droughts, and heavy rainfall (Costinot et al., 2016; Deschênes and Greenstone, 2007). Not only do higher temperatures reduce yields, but they also pave the way for soil degradation, and the proliferation of weeds and pests. For the Philippines, whose main crops include rice, coconut, corn and sugar – yields are projected to decline by 10% percent for every 1°C increase over 30°C (USAID, 2017). An increase in rainfall variability also plays a role in crop failures and productivity decline.[10]

Second, the fact that over 60% of the population lies along vast coastlines implies a nat-

[8]To paint a picture, agriculture accounts for 19% of total GDP in 1990 but has gradually decreased to 9% over the years. In 2021, agriculture - which also includes fishing and forestry, accounts for 10% of GDP, while, the industrial and service sectors accounted for 30% and 60%, respectively. These estimates are taken from national accounts data.

[9]These figures are based on the national poverty estimates produced by the Philippines Statistics Authority.

[10]Positive rainfall shocks are associated with runoff or flooding that are disruptive to farmland, while negative rainfall shocks disrupt the planting cycle for rain-fed irrigated crops.

ural dependency on ocean health and marine resources.[11]. Around 4% of the labor force is employed in the fisheries sector. But in a rapidly warming planet, ocean acidification directly affects catch potential and fishery yield (WB, 2013).[12] The slightest disruption in ocean dynamics can lead to severe impacts.[13]

By itself, the current sectoral composition puts the nation at an already vulnerable position with regards to climate change. Yet on top of this, large concentrations of people in low-lying deltas also face serious threats from coastal inundation.[14] In the decades ahead, populations in dense coastal zones will be victims of the harsh impacts of sea-level rise. For example, the city of Manila, which is home to 1.8 million people, has witnessed an accelerated sea-level rise of 13.3 millimeters per year. To scale, this figure is nine-times the average rate. Meanwhile, the country's primary agglomeration of Metro Manila is sinking by an annual rate of 10.2 centimeters from 1960 to 2012 (Morin et al., 2016).

Despite these extreme climate risks, internal migration flows are still moving coastward. As in most developing countries, highly productive firms concentrate in large urban areas. Consistent with the findings that agglomeration economies attenuate across space, growth in both skilled and low-skilled occupations is more pronounced around city-centers (Angel et al., 2011). In contrast, rural areas have labor markets that are characterized by low-paying jobs and insecure employment.[15] The large disparities in amenities also serve as a pull for the educated and the high-income population. Ultimately, this dynamic fuels a pattern of rapid and sprawling urbanization that precedes sufficient

[11] The Philippines ranked as the seventh largest producer of fish, 11th largest producer in terms of aquaculture, and third largest producer of seaweeds among the top producers in the world (Food and Agriculture Organization, 2013)

[12] Ocean acidity affects the health of coral reefs, which serve as important feeding and spawning grounds for many fish species. Corals have relatively fixed thermal limits and can be severely damaged from fluctuating water temperatures. Temperature and salinity also affect the distribution of seaweeds and kelp density.

[13] For example, during the 1998-99 El-Niño Southern Oscillation (ENSO), a halving of live coral cover in the Philippines has decreased fisheries production by Php 7 billion which is around 33% of the GDP from this sector from 2000.

[14] A delta is an area where the river sediment is building out into the sea. Large urban areas on deltas are subject to flooding from both storm surges and seasonal river floods.

[15] A job is low-paying if its wage is lower than two-thirds of the median wage. In the 2010 Labor Force Survey, nearly 38% of wage workers earn less than two-thirds of the median wage.

adjustments in infrastructure or housing supply. Absent the threat of climate change, a continuous trajectory towards this path guarantees congested living conditions and worsening amenities.

In the next section, I show how workers from different skill groups are distributed throughout the country. On the one hand, low-skill workers are situated in interior municipalities that specialize in crop production. On the other, skilled workers reside in high-amenity locations that will gradually erode in value. The slow onset of climate change is expected to disrupt the long-run distribution of economic activity. But how effectively the population reorganizes to this new steady state will depend on multiple conflating factors - including but not limited to climate adaptation strategies, and frictions in both goods and labor markets.

1.3 Data

The primary geographic units that I used my analysis are municipalities.[16] The Philippines is partitioned into 1,627 municipalities that are contained within 81 provinces. In 2010, an average municipality has a median population of 32,172 and area of 114 square kilometers.[17] I aggregate the municipalities up to 1,600 to reflect commuting zones where people actually reside and work. Using this level of disaggregation helps capture the localized differences in labor markets, migration frictions, geographic amenities, and climate profiles. For example, the largest agglomeration of Metro Manila is subdivided into 13 municipalities but are treated as one spatial unit in mine. Consistent boundaries are achieved throughout the sample period across all data sources used in this study. I briefly describe my main data sources here, and introduce others in subsequent sections as I use

[16] Municipalities are a second-level administrative division and the most granular geographic unit behind *barangays*.

[17] Average equivalents are 56,881 people and an area of 180 square kilometers. This spatial unit compares to U.S. counties whose median population records at around 26,000. Due to its expansive geography however, county area is not quite comparable as it has a large median estimate of 1,610 square kilometers (622 square miles).

them in the analysis.

1.3.1 Migration Flows and Population

My primary source of migration and population statistics is the Census of Population and Housing from 1990, 2000, and 2010. This provides counts of residential population at *barangay*, municipal, and province levels. Migration histories are recovered from responses to municipality of residence five years prior to the census. By limits of the survey, I only consider permanent migration episodes in my analysis.[18] An individual is tagged as an internal migrant if they registered a different municipality five years ago relative to their current residence. Armed with this information, I build a repeated cross section of migration flows for each origin-destination pair at the municipality-level.[19]

In the absence of employment information in the Census, I treat all respondents of age 16-60 as active labor force participants. The Philippines has a labor force participation rate that is stable around the range of 64-66% from 1990 to 2020.[20] Distinction across skill types is based on completed years of schooling, whereby a person is counted as a skilled worker if they have at least completed high-school. In 2010, this puts the low-skilled and skilled worker shares at 68% and 32%, respectively.

1.3.2 Wages and Expenditure Shares

Employment information comes from the Philippine Labor Force Surveys (LFS). These cross-sectional surveys cover a nationally representative sample of around 40,000 people and provide comprehensive data on wages, hours worked, and industry of occupation across primary and secondary jobs. Other supplemental information such as years of

[18] My obtained estimates do not capture temporary and seasonal migration. I am also omitting people who have moved multiple times or who have moved and returned home.

[19] I exclude external migrants from the analysis as my model focuses on a closed domestic economy. In 2010, 4% of households reported to have at least one member working overseas.

[20] Official statistics define this as the percentage of the total number of persons in the labor force divided by the total population for those 15 years old and over.

schooling, household size, previous work histories, and job search duration are also collected from each respondent. Although administered quarterly, I use the triennial series running from 2004 to 2016 since these data have responses coded up to the municipality. This allows me to compile average wages across skill types and sectors for each municipality.[21]

1.3.3 Trade Flows

I assemble internal trade data from inter-provincial commodity flows shipped through either water or air for years 2000 and 2010. While the raw data contain the quantity and value of every commodity, recorded at the Standard International Trade Classification (SITC) five-digit level, I collapse this information into total bilateral trade flows between 81 provinces.

1.3.4 Weather and Climate

I collect monthly averages of temperature and rainfall from two primary sources. I extract climate variables for all 1,627 municipalities to match the spatial units in my analysis. I rely on TerraClimate as my main source for observed weather patterns. This is a global dataset of interpolated climate data in high spatial resolution of approximately 4 kilometers (1/24 degree).[22] I collected monthly information on actual average temperature, minimum temperature, maximum temperature and accumulated precipitation from 1958 to 2020.

I obtain end-of-century climate conditions from NASA's Earth Exchange Global Daily

[21] Figure A1 and presents the distribution of wages for each survey year for all skill groups. Figure A2 illustrates the distribution on the pooled sample after purging out year fixed effects.

[22] TerraClimate is available to the public through an unrestricted data repository hosted by the University of Idaho's Northwest Knowledge Network. It combines inputs from WorldClim, Climate Research Unit (CRU Ts4.0), and Japanese 55-year Reanalysis (JRA 55) to produce monthly climatological variables from 1958 to recent years (Abatzoglou et al., 2018). TerraClimate exhibits strong correlations against data obtained from individual weather stations in the Global Historical Climatology Network (GHCN).

Downscaled Projections (NEX-GDDP) dataset.[23] Future daily near-surface air temperature and precipitation are available at a spatial resolution of 0.25 x 0.25 degrees. These projections are based on model runs under greenhouse house gas scenarios known as Representative Concentration Pathways or RCPs (Van Vuuren et al., 2011; Taylor et al., 2012). I extract climate conditions in the year 2100 for both business-as-usual and worst-case scenarios (IPCC, 2014). The former is based on RCP 4.5 which assumes a decline in emissions by around 2040 as market forces drive adoption of non-renewable fuels and lower emissions technology.[24] Under this scenario, a warming of 2-3°C is probable. On the other hand, the worst-case or "business as usual" scenario under RCP 8.5 is characterized by increasing emissions, and predicts a 4.3°C warming by the end of the century.

With these in hand, I assemble a municipal-level panel of climate measures. To match the temporal scale of my administrative datasets, I collapse monthly temperature and precipitation to their averages corresponding to the reference year of each survey or census.[25] Moreover, I take advantage of the long time-series to construct an alternative measure of weather shocks that considers absolute deviations relative to the climate norm of a given municipality. These deviations, or anomalies, are calculated relative to the 20-year historical municipal average taken a year before the survey reference period.[26]

1.3.5 Geographic Characteristics

I combine various datasets to build a profile of municipal geographic characteristics. Land areas are calculated from GIS data for each polygon at the second administrative boundary. From each municipality's centroid, I obtain latitude, longitude, and distance to coasts. Soil characteristics are taken from the SoilGrids dataset provided by Interna-

[23]This dataset "downscales" global projections of temperature and precipitation into more granular spatial scales, hence the name.

[24]RCP 4.5 refers to the level of radiative forcing by greenhouse gas emissions stabilizing at 4.5 watt per square kilometer (W/m^2) by 2100.

[25]For example, I take measurements for $t-1$ relative to the LFS survey year, and measurements from $t-6$ to $t-1$ for the Census.

[26]Deviations from the long-run averages mitigate the variability that comes from El Niño-Southern Oscillation cycles.

tional Soil Reference and Information Centre (ISRIC). Topographical variables— including slope, elevation, and ruggedness– were calculated using raster data from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Dataset v4. The digital elevation map has a high-resolution of 3 arc-seconds. I similarly utilize this raster to simulate coastal inundation from a sea-level rise of 1 meter, 2 meters and 5 meters.

1.4 Reduced Form: Climate Affects Migration

The core assumption of the model highlights migration as a coping mechanism for how individuals respond to climate change. Using municipal-level data that span 20 years, I estimate how temperature changes explain migration patterns to date. I empirically estimate from a panel regression

$$y_{nt} = \alpha + \gamma W_{nt} + \beta X_{nt} + \delta_n + \delta_t + \epsilon_{nt}, \tag{1.1}$$

where y_{nt} denotes the migration outcome for municipality n at year t, W_{nt} captures municipality n's climate profile, X_{nt} incorporates location-specific covariates, δ_n denotes municipal fixed effects, and δ_t controls for year fixed effects. For my dependent variables, I analyze the effect of temperature on (i) out-migration rates, (ii) in-migration rates, and (iii) net migration rates. Out-migration rates are calculated as the number of persons who left the municipality divided by municipality-origin population. Meanwhile, in-migration rates are calculated with total in-migrants in the numerator, and the population in the remainder of the country as the denominator. Net-migration rates are the difference between out-migrants and in-migrants in the numerator divided by the total population in the country. The estimates across the three migration statistics are not comparable due to large differences in population base.[27]

My preferred measurement for W is the absolute degree deviation from expected aver-

[27] The relative difference between the population bases will be much greater in the denominator than the relative difference between the numerators.

age temperatures. This is calculated within each spatial-unit relative to its own long-run 20-year historical average. The parameter of interest γ is identified due to the exogenous nature of temperature. By doing so, I highlight the response when the local population is exposed to conditions outside their own preconceived climate normal. Instead of averages, I postulate that people's location preferences are determined by an acceptable range of temperatures. This specification allows for an implicit model of adaptation in a panel model (Tol, 2021).

I estimate the parameters of Eq. 1.1 across skill-groups and present the results in Table 1.1. Following Mahajan and Yang (2020), I include lagged dependent variables in X_{nt} to account for the size of prior migrant stocks.[28] Additionally, I control for the size of municipality in columns 2, 4, and 6. Results suggest that climate uncertainty induces the population to relocate. Locations with extreme deviations from average temperatures are associated with higher out-migration rates, with magnitudes that are 3-4% higher with the inclusion of log population. In addition, municipalities with large temperature deviations tend to lose considerable shares of low-skilled workers compared to skilled-workers.

I find negligible results for in-migration rates and weakly significant coefficients for net migration rates. This is not surprising within the context of my analysis or other findings in the literature (Gröger and Zylberberg, 2016). Climate shocks do not exert any influencing pull towards locations, but rather, exhibit a repelling force from locations. This lends support to the assertion that people more exposed to volatile conditions leave their current locations, though not necessarily to a place that insures them against new shocks. Estimated coefficients when using average temperatures for W in Table A1 also provide similar insights.

The results in this section fit with the literature that exploits within-country variation of weather shocks to estimate its impact on migration (Gröger and Zylberberg, 2016;

[28] Table A2 presents the results without these lags, and insights remain unchanged.

Bryan et al., 2014), and labor markets (Colmer, 2021; Kleemans and Magruder, 2018). Adaptation induces a spatial reallocation of labor, with heterogeneous patterns across populations of varying skill groups. But a partial equilibrium analysis fails to consider the changes in the overall economy. Valuable insights can be gained by quantifying the general equilibrium effects of climate change on prices, output, and reallocation.

1.5 Model

This section presents a spatial equilibrium model that evaluates the aggregate welfare and distributional effects of climate change. The theoretical framework combines insights from the literature on quantitative spatial equilibrium models with costly migration (Tombe and Zhu, 2019; Monte et al., 2018) and incorporates heterogeneous agents (Tsivanidis, 2019; Zárate, 2022). Relative to their work, I allow climate change to to distort location fundamentals that drive amenities and productivity, while explicitly allowing for differential effects across sectors. Because some locations will be more affected than others, this subsequently modifies the types of firms and workers that sort throughout space.

Setup. Consider a country with a discrete set of locations indexed by $n \in \{1, ..., N\}$. In each location, there is a mass of workers of skill-level $g \in \{U, H\} \equiv \mathcal{G}$, where U and H denote low and high skill types respectively. Firms in each location use labor from a single group g to produce a distinct variety, so that varieties are differentiated by both skill and also by location. Locations differ by their type-specific productivities A_{ng} and amenities B_{ng}, and are interlinked through trade and migration. By differentiating the population across g, I incorporate heterogeneity in preferences into the model. Low and high-skilled workers have distinct tastes for the same menu of location-specific amenities. Similarly, the variation in productivities represents implied sectoral advantages. For example, a municipality with rich natural advantages (such as soil quality or proximity to resources) could be attractive for firms of different types. Overall, the equilibrium distribution of economic activity is characterized by preference-based sorting, in which individuals self-select into locations that maximize utility.

Consumer Preferences and Optimal Consumption Demands. Each individual i is born in an origin, denoted by n, and makes a single lifetime decision about where to migrate. After moving to a destination location, indexed by d, agents earn a wage from production and derive utility from consuming local consumption goods and amenities. We solve the consumer's problem in two steps, using backwards induction.

First, conditional on locating in d, the worker's utility follows a standard Cobb-Douglas form:

$$U_{ndg}(i) = \left[\prod_{s \in \mathcal{G}} \left(\frac{C_{ds}}{\beta_s}\right)^{\beta_s}\right] \frac{B_{dg}}{\mu_{ndg}} \epsilon_{ndg}(i), \quad \sum_{s \in \mathcal{G}} \beta_s = 1, \tag{1.2}$$

where C_{ds} denotes a CES aggregate bundle of a variety of goods consumed from sector s, B_{dg} measures the value of local amenities for group g in location d, μ_{ndg} is the skill-specific cost of moving from n to d, and $\epsilon_{ndg}(i)$ is an idiosyncratic shock to worker i. The parameter β_s is the expenditure share on consumption goods produced from sector s.

The consumption bundle for goods produced in sector s and consumed in location d is given by:

$$C_{ds} = \left(\sum_n q_{dns}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{1.3}$$

where the σ measures the Armington elasticity of substitution among varieties. Consumption of the composite good from sector s is assumed to be differentiated by location of origin and sector. As $\sigma \rightarrow \infty$, products become perfect substitutes. The price-index dual to the consumption bundle in Eq 1.3 follows the usual Dixit-Stiglitz form

$$P_{ds} \equiv \left(\sum_n p_{dns}^{(1-\sigma)}\right)^{\frac{1}{1-\sigma}}, \tag{1.4}$$

where p_{dns} is the cost paid for sector s goods in locality d for the variety from n.

Solving for optimal consumption demand, the expression for the indirect utility of worker i is

$$V_{ndg}(i) = \frac{B_{dg} w_{dg} \epsilon_{ndg}(i)}{\mu_{ndg}(\prod_s P_{ds}^{\beta_s})}, \tag{1.5}$$

which is a function of skill-specific wages, goods prices, amenities in location d, and migration costs.

Migration Choices. Given preferences for consumption bundles, workers determine their location choices. Workers are mobile across locations but not across sectors. Workers can relocate within municipalities, but not internationally. While skilled and unskilled workers face the same prices for the same consumption bundle, they earn different wages in each location. In particular, workers of type g are each endowed with one unit of labor, which they supply inelastically to type g firms in location d to earn wages w_{dg}.

A worker who chooses a location different from their origin n incurs a migration cost that is unique to the origin-destination pair. Moving from n to d takes an iceberg cost of $\mu_{ndg} \geq 1$, and is symmetric between locations $\mu_{ndg} = \mu_{dng}$. Each agent determines where to live after receiving a one-time idiosyncratic shock $\epsilon_{ndg}(i)$.

Following Ahlfeldt et al. (2015), I assume that individual preference shocks (ϵ_{ndg}) are iid draws from a Frechet distribution,

$$F^g(\epsilon) = \exp\{\epsilon^{-\theta_g}\}, \quad \theta_g > 1.$$

This rationalizes imperfect spatial sorting and captures the idea that workers from the same skill group can have idiosyncratic reasons for choosing different locations.[29] The parameter θ_g is group-specific and governs the shape of the distribution and dispersion

[29] The usual Fréchet scale parameter, which denotes the group-specific average preference shock of moving to d from location n, is normalized to one without loss of generality.

of preferences, with lower values implying more heterogeneity across locations. People exhibit stronger attachment to particular locations when θ_g is smaller. As θ_g increases, agents receive less variation in their ϵ draws, and are more sensitive to differences in wages, prices, or amenities across locations.

The distributional assumption on the idiosyncratic term implies that indirect utility also follows a Fréchet distribution. Thus, the probability that a worker from skill group g migrates from n to d can be expressed as[30]

$$\pi_{ndg} = \frac{[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_s P_{ds}^{\beta_s})]^{-\theta_g}}{\sum_{d\in N}[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_s P_{ds}^{\beta_s})]^{-\theta_g}}. \tag{1.6}$$

The expression above shows that the probability of choosing a destination is decreasing in bilateral frictions and prices, but increasing in wages and amenities. Using migration probabilities in Eq. 1.6, the supply of workers of skill-type g in location d can be found by summing over the number of migrants that have moved there:

$$L_{dg} = \sum_{n\in N} \pi_{ndg} L_{ng}^0. \tag{1.7}$$

Finally, the ex-ante expected utility for skill group g is given by:

$$E_n^g[u] = \Gamma\left(\frac{\theta_g - 1}{\theta_g}\right)\left(\sum_{d\in N}[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_s P_{ds}^{\beta_s})]^{-\theta_g}\right)^{1/\theta_g}, \tag{1.8}$$

where $\Gamma(\cdot)$ is the Gamma function.

Residential Amenities. Residential amenities in location d are parameterized as:

$$B_{dg} = \overline{B}_{dg}\left(\frac{L_d}{T_d}\right)^{-\eta}, \tag{1.9}$$

[30]Derivation shown in the Appendix.

where L_d and T_d refer to the total municipal population and area respectively. The type-specific amenity value is endogenously determined by population density and an exogenous component $\overline{B}_{dg}$ (i.e. climate, topography, distance to coast, soil quality). Land, T_d, enters amenities as a fixed component, and may potentially decrease through inundation from sea-level rise. The parameter η denotes the congestion elasticity of amenities with respect to population density, where a higher value implies stronger dispersion forces.[31] Amenity spillovers, η, are negative since land is not directly consumed in the model. Exogenous amenities are group-specific to allow for heterogeneity in tastes across skill types.

Production. A representative firm in location d produces varieties in sector s and uses labor as its only input. There are two sectors in this economy: agriculture and non-agriculture. Firms in the agricultural sector only hire low-skill workers, while firms in the non-agricultural sector use skilled workers. To reflect this simplification, I slightly abuse notation and denote sector s as g henceforth. The production function is then given by:

$$Y_{dg} = A_{dg} L_{dg}, \tag{1.10}$$

where A_{dg} is total factor productivity. Intuitively, locations with higher shares of low-skill labor specialize in producing agricultural goods. Firm productivity is determined by location fundamentals and agglomeration forces in location d,

$$A_{dg} = \overline{A}_{dg} \left(\frac{L_d}{T_d} \right)^{\alpha}. \tag{1.11}$$

Exogenous productivity, $\overline{A}_{dg}$, is sector-specific and depends on natural endowments such as soil quality, ruggedness, distance to coast, slope, and climate variables. Agglomeration

[31] An alternative consideration is to allow endogenous productivities and amenities to depend on the composition of high-skill residents instead of total density (Diamond, 2016). This may be relevant to developing countries that lack strong public goods provision.

externalities depend on the size of the local working population density (Rosenthal and Strange, 2004). The greater the value of $\alpha > 0$, the stronger the agglomeration forces.[32] In equilibrium, each location produces goods from both sectors and wages and prices adjust so that zero profits are made in both sectors. Under perfect competition, price of a good is equal to its marginal cost of production:

$$p_{dg} = \frac{w_{dg}}{A_{dg}}.$$

For simplicity, transport costs are identical for shipping goods from both sectors. Given this setting and under perfect competition, the cost to a consumer in location d to purchase a unit of good g from location n is given by:

$$p_{dng} = \frac{\tau_{dn} w_{ng}}{A_{ng}}, \tag{1.12}$$

where τ_{dn} are bilaterally symmetric and follow an iceberg form such that the quantity $\tau_{dn} \geq 1$ must be shipped in order for one unit to arrive.[33]

Goods Gravity. Optimization of Eq. 1.2 implies that workers from n and locating in d consume varieties from sector g, q_{dng}, given by:

$$q_{dng} = \beta_g (p_{dng})^{1-\sigma} P_{dg}^{\sigma-1} w_{dg},$$

with P_{dg} as the CES price index at location d for goods produced by skill type g. Thus, the total expenditure of location d for the type-g differentiated variety from location n is given by:

$$X_{dng} = \beta_g (p_{dng})^{1-\sigma} P_{dg}^{\sigma-1} \left(\sum_g w_{dg} L_{dg} \right), \tag{1.13}$$

[32]The effects of sea-level rise is more impactful if land comes in an as fixed factor in the firm's production function, instead of working through the agglomeration spillovers.
[33]Unlike migration costs, trade costs are not skill-specific.

where final demand for type-g varieties by residents of d is

$$X_{dg} = \sum_{n \in N} X_{dng} = \beta_g \left(\sum_g w_{dg} L_{dg} \right)$$

Taking Eq. 1.12 into Eq.1.13, the expenditure share X_{dng} can be written as:

$$X_{dng} = \beta_g \tau_{dn}^{1-\sigma} \left(\frac{w_{ng}}{A_{ng}} \right)^{1-\sigma} P_{dg}^{\sigma-1} \left(\sum_g w_{dg} L_{dg} \right). \tag{1.14}$$

This is the goods gravity equation following a similar formulation to (Allen and Arkolakis, 2018).

Equilibrium. Given parameters $\{\alpha, \beta_g, \theta_g, \eta, \sigma\}$, exogenous variables $\{A_{dg}, B_{dg}\}$, and endogenous variables $\{w_{dg}, \pi_{ndg}, L_{dg}, p_{dg}, P_{dg}\}$, an equilibrium is defined by solving the following systems of equations:

1 **Labor Market Clearing**: The number of workers supplied to sector g in location d must equal the inflows of type g workers to location d:

$$L_{dg} = \sum_{n \in N} \pi_{ndg} L_{ng}^0. \tag{1.15}$$

2 **Goods Market Clearing**: Total payments to workers in sector g in location d must equal the proceeds from the sale of goods to all locations including itself:

$$w_{dg} L_{dg} = \sum_{n \in N} X_{dng}.$$

Additionally, the total expenditure on goods consumed in location d must equal the total income of workers:

$$\sum_g w_{dg} L_{dg} = \sum_g \sum_{n \in N} X_{ndg}. \tag{1.16}$$

3 **Closed Model**: Populations add up such that $L_d = \sum_g L_{dg}$.

To guarantee uniqueness and existence of equilibrium, the relative strength of agglomeration spillovers should be lower than congestion forces. The standard conditions and its formal proof are provided in Allen et al. (2020).

1.6 An Example with Two Locations

In this section, I present a simplified version of my model to highlight the welfare effects of climate change. I limit the world economy to two regions and vary the intensity of damages to location fundamentals. By doing so, I underscore the uncertainty that comes from a precarious climate future. While harsh outcomes are almost certain, some glimmers of hope emerge under certain conditions or policy regimes. I illustrate this nuance through graphical analysis.

To match the notation in the full model, I define fundamental productivities as A_i and exogenous amenities as B_i. Fundamental characteristics of different locations $i \in \{1, 2\}$ are then negatively affected by global warming.[34] I assume a representative two-region economy with homogeneous workers where location 1 is endowed with better bundles of amenities and productivities, so that $B_1 > B_2$ and $A_1 > A_2$. I denote shocks to each location as ∂W_i and alternately switch the region that is severely affected by climate change.

For my first case, I assume that Region 1 is more impacted by increasing temperatures than Region 2. As $\frac{\partial B_1}{\partial W} < 0$, $B_1 \to 0$ and the same goes for exogenous productivities A_1.

[34] I abstract away from the specifics of a changing climate but one can consider this as a set of various components that include temperatures, rainfall, extreme weather events, risk of droughts, flooding, and wildfires.

Panel A of Figure 1.1 plots the percentage change in welfare effects against the new levels of exogenous objects. Without opportunities to migrate, the population is transfixed and endures negative shocks to their utility. The dashed line in red indicates a persistent and increasing welfare loss as location fundamentals tend to 0 moving further right along the x-axis. This is not surprising since exogenous characteristics depreciate. The underlying mechanisms is straightforward– decreasing wages and amenities depresses overall welfare.

I juxtapose this example with its diametric equivalent and subject Region 2 to intense climate shocks. When the worse-off region is hit harder by climate change, welfare continually declines as locational advantages are eroded (blue line in Panel A of Figure 1.1). In line with intuition, losses are slightly muted when the more productive location remains relatively unscathed. The aggregate economy is better off when the low-productivity and low-amenity location is subject to harsher climate conditions.

I repeat the same set of exercises but allow population to relocate in response to the new climate reality. Panel B of Figure 1.1 show the equivalent results. A side-by-side comparison emphasize that losses are curbed compared to their no-mobility analog. People relocate to dampen the losses from a rapidly changing climate.

But an interesting finding in Panel B of Figure 1.1 is the possibility of achieving positive welfare effects. As depicted by the blue line, I uncover a range of welfare-improving outcomes when low-performing municipalities are hard-hit by climate shocks. The mechanism by which this occurs is consistent with a rural-urban migration story wherein workers relocate to highly productive regions (Barrios et al., 2006; Henderson et al., 2017). In effect, the negative impact of climate change pushes people beyond their migration tipping points, and takes the economy to a more efficient allocation of labor. However, this favorable range of results is short-lived. Moving to the right of the x-axis, losses become inevitable as warming temperatures further devalues a locality's fundamental components. In addition, welfare losses from *Shocks to Region 2* supersedes that of *Shocks to*

Region 1 as exhibited by the crossing point between the two cases. Beyond this point, losses are amplified due to congestion as people increasingly sort to more attractive locations. Similarly, workers leaving low-productive areas attenuates the agglomeration forces in those places.

At the heart of this exercise, I tweak how locations respond to the exogenous objects in my model. The different scenarios proxy for the various ways that future climate could affect the economy. The added perspective of considering aggregate welfare alongside migration frictions underscores the possible gains to reducing barriers to mobility.[35] One can see that moving beyond two locations introduces complexity, as each bilateral location pair has a unique draw of climate-pair sensitivities. Accommodating multiple skill-groups further adds ambiguity as spatial interactions become more intricate.[36] Therefore, to quantify actual welfare effects, I take the full discussed in Section 1.5 to the data.

1.7 Taking the Model to the Data

The structural model provides a framework that facilitates a quantitative assessment of the economic consequences of global warming. Integral to this step is pinning down the relationship between climate variables and amenities and productivities. In this section, I outline the procedure for how I use the structural model with the data to recover amenities and productivity.

I proceed in three steps. First, I characterize bilateral migration frictions using the gravity relationship between geographic distance and labor flows. Second, I borrow structural parameters from the literature to calibrate the model. I then invert the model

[35]Without loss of generality, these frictions can serve in as a stand-in for trade frictions or policy adaptation measures.

[36]The Toy Model subsection of the Appendix presents a two-location model with heterogeneous workers where I vary endowments as being skill-specific and location-specific. Here, I evaluate welfare along the dimensions of migration costs in the x-axis. This highlights the competing trade-offs of each worker with regards to their welfare components - a preference for amenities B_i^g at the expense of productivity w_i^g. When structural fundamentals are clear-cut and have high match (i.e. no trade-offs), migration barriers have dire consequences on welfare.

to obtain the spatial distribution of amenities and productivities that rationalizes the observed data as an equilibrium outcome. In the final step, I empirically estimate the key semi-elasticities of climate on the location fundamentals that support the current equilibrium distribution of labor. Since my model accommodates heterogenous skill-types, I can assess the differential implications of climate change.

1.7.1 Estimating Migration Costs

To derive an estimating equation for migration costs, I parameterize these costs as a function of geographic distance and their observables, $\mu_{ndg} = \exp\{\gamma^g \ln Dist_{nd} + X'_{dn}\beta\}$. A log-linearized version of Eq. 1.6 results in a reduced-form gravity specification:

$$\ln \pi_{ndgt} = \delta_{ngt} + \delta_{dgt} + \gamma^g \ln Dist_{nd} + X'_{dn}\beta + e_{ndgt} \quad \forall g, \tag{1.17}$$

where the dependent variable is the migration probability measured as the share of workers of type g moving from n to d at year t. As is typical in the literature, I interpret geographic distance as a stand-in for movement costs between locations (Bryan and Morten, 2019; Tombe and Zhu, 2019).[37] The fixed effects in the migration gravity model have a structural interpretation as a bundle of wages, amenities, prices, and rents. Destination-year fixed effects control for the migration pull-factors,

$$\delta_{dgt} = \theta_g \ln \left(B_{dgt} w_{dgt} (\prod_g P_{dgt}^{-\beta_g}) \right).$$

while origin-year fixed effects capture push factors

$$\delta_{ngt} = \theta_g \ln \left(\sum_{d \in N} B_{dgt} w_{dgt} \mu_{ndgt}^{-1} (\prod_g P_{dgt}^{-\beta_g}) \right)$$

[37] The bilateral straight-line distance measure is taken from each municipality's centroids.

The destination-year fixed effect controls for location differences across destinations for a given year, while the origin-year fixed effect accounts for the appeal of other alternative locations from the perspective of living at the origin. I also include pair-wise controls, X_{dn}, to remove confounders that may similarly affect the relationship between distance and migration flows. To account for measurement error, I augment Eq. 1.17 with an error term e_{ndgt}.

Migration costs are identified conditional on endogenous origin-specific push factors and destination-specific pull factors. Following the conventions in estimating gravity equations, I employ a Poisson Pseudo Maximum Likelihood estimator to allow for zero migration flows between municipalities. (Silva and Tenreyro, 2006; Correia et al., 2020).

Table 1.2 presents the regression coefficients of Eq. 1.17. Results in Columns 2 and 3 are used to calculate the bilateral migration costs low- and high- skill workers. Estimates reveal that the resistance to migrate strongly increases with distance, with low-skilled workers exhibiting higher aversion to relocate. Consistent with intuition, migration probabilities are higher between locations that belong in the same island and same province. Figure 1.2 presents the distribution of estimated migration costs, $\widehat{\mu_{ndg}^{-\theta_g}}$, between these two subgroups and asserts that they are statistically different.[38] These plots visually confirm that low-skilled workers face larger costs to migration.

1.7.2 Estimating Trade Costs

I run the equivalent regression of Equation 1.17 between the observable trade shares across provinces on the left hand side on the same set of pair-wise controls. The results in Table 1.3 validate a gravity relationship whereby trade flows decrease with greater distances across locations. The distance coefficient of -1.081 is close to the negative unit trade cost elasticity found in the literature (Head and Mayer, 2014).

[38] A Kolmogorov-Smirnov test rejects the hypothesis that the distributions are equal.

1.7.3 Calibration

I set my parameter values borrowing from other papers and, whenever possible, obtain estimates from Philippine administrative datasets. Calibration of the model requires national expenditure shares for agricultural and non-agricultural goods.[39] I obtain this from relying on the Family Income and Expenditure Survey (FIES) for 2003, 2006, and 2009.[40] These are nationwide sample surveys that report a household's income sources, consumption expenditures, and socio-demographic characteristics. In my calibration, I base my estimates on the pooled data from 2003-2009. All wages and expenses are converted to constant 2010 prices using a CPI deflator. The national expenditure shares for agricultural and non-agricultural consumption bundles are 0.352 and 0.648, respectively. For skilled workers, these shares are 0.294 and 0.706, respectively, while the equivalent shares are 0.447 and 0.553 for low-skilled workers.

I set the remaining structural parameters to standard values from the literature. Following Chauvin et al. (2017), I fix the agglomeration parameter to $\alpha = 0.076$. This parameter is higher than what is observed in the US, but is consistent across findings using developing countries' statistics. For my congestion parameter, I use $\eta = -0.10$ based on the estimate obtained from Ahlfeldt et al. (2015). Borrowing from Allen and Arkolakis (2014), I use an elasticity of substitution of $\sigma = 5$. Typically, this number ranges from five to nine when considering goods traded in the same country (Ossa, 2015). I set the inverse dispersion parameter of location preferences using estimates of $\theta_s = 2.054$ and $\theta_u = 2.840$ from Tsivanidis (2019). Table 1.4 summarizes all the parameter values used in this exercise.

[39] I use the term "agricultural" for expositional ease, but the agricultural bundle also contains non-crop yielding goods like dairy, meat, fisheries and marine products.

[40] The LFS mirrors the exact sample of those in the FIES for the coinciding years that they are conducted. Individuals from the separate surveys can be linked to portray a more complete picture of household well-being. The FIES serve as an important source for the calculation of poverty estimates and in the estimation of the Consumer Price Index.

1.7.4 Model Inversion

Along with the calibrated parameters, I take the empirical data on migration flows, residualized wages, and trade shares to invert the model to obtain the structural parameters for two cross-sectional years that span a decade.[41] Model Appendix B3 outlines the set of equations that recovers the unobserved local composite prices and welfare. Thereafter, I use equations 1.9 and 1.11 to recover the fundamental parameters $\{\overline{B}_{dg}, \overline{A}_{dg}\}$ that rationalize the observed data as an equilibrium. Figure A3 present the scatterplots of the recovered structural parameters between 2000 and 2010. Ranging from 0.73 to 0.93, these graphs illustrate a high correlation for the location fundamentals across both years for the same skill group. The spatial distribution of the welfare composites by skill is depicted in Figure 1.3. This map illustrates the relative attractiveness of each municipality in the initial equilibrium in 2010 for each skill-type. Reassuringly, the spatial patterns of the calibrated values appear sensible. Areas that are highly desirable (darker shades of blue) are concentrated and sprawling around Metro Manila in the North-East. In taking both maps into account, it appears that skilled workers have a narrower set of choices in terms of location should they wish to maximize their utility. Whereas low-skilled workers maintain a high ex-ante welfare in the southern island of Mindanao, the same cannot be said for their skilled counterparts. Panels A and B in Figure 1.4 offer a visual representation of the structural parameters in the initial equilibrium. This complements the spatial distribution of welfare in Figure 1.3. Overall, the model performs well at recovering the unobserved fundamentals that affect the welfare components offered by a municipality.

[41] I matched the information from the Philippine Censuses of 2000 and 2010 with the corresponding skill-specific wages from LFS 2004 and 2010. Without a close match for wages for 1990, I am unable to leverage the population flow data from Census 1990. Skill- and municipality-level wage residuals are taken from Mincer regressions that control for work experience, gender, and years of schooling.

1.7.5 Model Validation

In this section, I validate the recovered measures of $\overline{A}_{dU}$, $\overline{A}_{dH}$, $\overline{B}_{dU}$ and $\overline{B}_{dH}$ against actual measures of amenities and natural endowments. This is of crucial importance since I postulate climate to work through these channels. I inspect the bivariate correlation between the recovered fundamentals across a wide set of exogenous geographic characteristics X_{dt} from a regression of the form:

$$y^g_{dt} = \rho^g X_{dt} + \alpha^g_r + \alpha^g_t + u^g_{dt}$$

where the dependent variable y^g_{dt} denotes the recovered measures of skill-specific log productivity and log amenities, α^g_r controls for region fixed effects, and α^g_t controls for year fixed effects. Table 1.5 shows estimates of $\widehat{\rho}^g$, where each coefficient is from a separate regression. The recovered location fundamentals are strongly and positively correlated with cooler temperatures, flatter and less rugged terrain, and predictability in weather. In general, the valuation of natural endowments relative to amenities and productivities tend to move in the same direction for both skill-types. However, I find that low-skilled amenities decline as locations have higher levels of education, elevation, slope and ruggedness. These characteristics have almost twice as large effects on unskilled amenities as they do on skilled amenities. A justification for why rugged locations are less appealing to low-skilled workers may be related to the lack of access to more reliable modes of private transportation.

I also examine the relationship between the recovered fundamentals and endogenous amenities. To account for endogenous amenities across municipalities, I rely on the Barangay Schedule (Form 5) of the decennial Censuses. This dataset records different facilities and services that are available in each village. Examples include access to hospitals, libraries, universities, marketplaces. I aggregate the responses up to the municipality to be consistent with my unit of analysis. Table 1.6 presents bivariate correlations analogous to Table 1.5. Interestingly, there are now divergent patterns across subgroups. While skilled amenities decline as low quality housing increases, they are positive but insignificantly related to low-skill amenity. Other estimates in Table 1.6 lend support to the assertion that I recovered reasonable estimates for my exogenous parameters (i.e. high productivity and amenity values with larger shares of universities, hotels, banks).

1.7.6 Recovering Climate Semi-Elasticities

In this section, I estimate the effect of temperature on location fundamentals. I employ a panel regression and rely on the exogenous variation in temperatures within and across municipalities to identify climate semi-elasticities of amenity and productivity. I parameterize the recovered location fundamentals using the functional form,

$$y_{dt}^{g} = \delta_1^{g} \mathrm{W}_{dt} + \beta X_d + \alpha_r^{g} + \alpha_t^{g} + u_{dt}^{g} \tag{1.18}$$

where the dependent variable, y_{dt}^{g}, represents either (log) exogenous productivity or exogenous amenity, α_t^{g} denotes year fixed-effects, and α_r^{g} denotes region fixed-effects. The parameter of interest, δ_1^{g}, captures how municipal-level fundamentals are affected by climate shocks W_{dt}. Equation 1.18 also include X_d which are time-invariant geographic attributes (i.e. slope, topography, distance to water source). The inclusion of region fixed effects controls for cross-sectional variation at the broader administrative unit. It also captures the general level of economic development, culture, and other natural amenities at the region-level. Meanwhile, year fixed effects account for common time trends such as policy changes, economic cycles, and common climatic events (i.e. El Niño–Southern Oscillation) which could be correlated with my measures of climate.

Mirroring my reduced-form approach, I define climate shocks W as deviations from a location's own historical climate norm. Focusing on deviations highlights the impact of weather predictability on outcomes (Kahn et al., 2021; Burke et al., 2015).[42] Identification

[42] Refer to discussion in Section 1.4 for its advantages.

relies on the quasi-random nature of weather across municipalities. The elasticities are identified conditional on time-invariant geographic attributes.

Table 1.7 presents estimates of the climate semi-elasticities across skill-types following the regression specifications above.[43] A couple of insights can be inferred here. First, deviation from expected temperatures have a larger effect on the productivity channel for low-skilled workers than they do for skilled workers. Temperature variability will make it harder to sustain optimal working conditions, moreso for outdoor labor. This finding is consistent with the literature that explores the impact of temperature across sectors (Rudik et al., 2021; Conte et al., 2021; Somanathan et al., 2021). However, when considering exogenous amenities, skilled workers are deemed more sensitive to warmer temperatures by more than a factor of two compared to their low-skilled counterparts.

Since this step is crucial in understanding how climate profiles affect the baseline economy, I also present alternative estimates employing other specifications in Table A7. In Panel A of this table, I first consider dropping region fixed effects - doing so improves the explanatory power of the estimates shown in Table 1.7. Meanwhile, Panels B and C distinguishes the climate semi-elasticities for each Census year. I find that using a single cross-sectional data point significantly blows up the magnitude of the coefficients. Using the average values for the two years as the dependent variable does not dampen these estimates (see Panel D). Nonetheless, the general narrative persists in that deviation in expected temperatures reduces exogenous productivities (amenities) of low-skilled (high-skilled) workers at larger scales. This robustness exercise justifies the inclusion of a temporal dimension in estimating the effect of temperatures on location fundamentals.

[43] Although the measurement of choice for climate shocks are deviations of temperature from their respective 20-year historical moving average, I also provide the semi-elasticities obtained from using average temperature in Table A8.

1.8 Counterfactuals

The structural model provides a framework that allows me to quantify the implications of a changing climate on aggregate welfare. Relying on projections from the IPCC's Fifth Assessment Report (IPCC, 2014), I simulate the economy forward under the average expected realizations of local temperatures and inundated areas from sea-level rise. I then evaluate how the Philippines will evolve to a new long run economic geography in the year 2100.

As shown in Figure 1.5, the Philippines is expected to experience an average increase in temperature of 3.2°C under a high-emissions pathway (RCP 8.5) and a 1°C increase under a low-emissions pathway (RCP 4.5), relative to its levels in 2020.[44] The atmospheric warming associated with these forecasts corresponds to a local maximum sea-level rise of 1.1 meter and 1.6 meters, respectively.[45] Figure 1.6 illustrates the spatial distribution of sea-level rise in the high emissions case. Under this scenario, around 65% of Philippine municipalities housing 70% of the population will have some portion of their land submerged in water. With majority of the population situated along the coast, it is crucial to understand how labor reallocates under a climate paradigm that is drastically different from the current equilibrium. Implicit in these set of exercises is that agents passes the same semi-elasticities through the end of the century as they do today.

1.8.1 Counterfactual Procedure

Given the obtained exogenous parameters that rationalize the current observed data, I simulate how rising sea-levels and warming temperatures will impact the spatial distri-

[44]While magnitudes seem minuscule, the rate by which warming occurs is alarming. To scale, the temperature increase that will occur in the next 50 years is faster than planet had endured last 6,000 years combined.

[45]While the global maximum sea-level rise under RCP 4.5 and RCP 8.5 are respectively and 62 and 82 centimeters, estimates are higher at specific locations in the world due to varying factors such as land subsidence from natural processes, withdrawal of groundwater and fossil fuels, and changes in regional ocean currents. I use the regional sea-level projections provided by Jackson and Jevrejeva (2016) and Jevrejeva et al. (2016) for the Philippines.

bution of economic activity. With the semi-elasticities from Table 1.7, I use Equation 1.18 to predict the new levels of location fundamentals given the new climate conditions at the end of the century. Thereafter, I use Equations 1.9 and 1.11 to incorporate the effects of sea-level rise. Changes in local sea levels reduce available land, which increases density and amplifies the strength of productivity spillovers. However, this provokes an opposite effect on amenity values - higher density amplifies local congestion forces. I adopt the notation x' for the newly calculated variables under alternative location fundamentals. To simulate new outcomes, I implement the following steps wherein the index t represents an iteration step:

1 With new values of $\{A'_{dg}, B'_{dg}\}^0$, I obtain the new set of wages using the labor demand equation given an initial guess of prices $\{P_{dg}, p_{dg}\}^0$.

2 Using equations 1.22 to 1.25, labor reallocates according to a new realization of welfare, and output is updated under the new counterfactual distribution of skilled and low-skilled labor: $\{L'_{dg}, Y'_{dg}, \omega'_{dg}, W'_{dg}\}^t$.

3 Prices and wages $\{P'_{dg}, p'_{dg}, w'_{dg}\}^t$ are updated consistent with this new allocation.

4 Iteration continues until $(\tilde{w}_{dg}, \tilde{L}_{dg}, \tilde{p}_{dg}, \tilde{P}_{dg}) - (w'_{dg}, L'_{dg}, p'_{dg}, P'_{dg})^t < \epsilon^{\text{tol}}$, where ϵ^{tol} is the tolerance value, set to $(1e-9)$. Otherwise, return to step 2.

Using the new equilibrium allocations, I calculate the expected aggregate welfare across skill-types. Aggregate welfare is the mean welfare across all locations, weighted by their respective initial population shares:

$$E_n^g[u] = \Gamma\left(\frac{\theta_g - 1}{\theta_g}\right)\left(\sum_{d\in N}[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_g (P_{dg})^{\beta_g})]^{-\theta_g}\right)^{1/\theta_g}, \tag{1.19}$$

which is the ex-ante welfare prior to moving.

1.8.2 Average Emissions Scenario

My baseline counterfactual simulates the long-run steady state given average temperatures from RCP 4.5 and RCP 8.5, and a sea-level rise of 1.2 meters. While the average emissions pathway predicts a 2.1°C increase relative to 2022 temperatures, warming happens non-uniformly across space. Figure 1.7 plots the distribution of municipal temperatures across 2010 and 2100. Overall, this figure shows that future temperatures are shifted to right at a higher variance. The accompanying maps in Figure A4 and A5 further illustrate the changing distribution of where the comparatively hot regions are.[46] In 2010, the municipalities with extremely high temperatures are generally dispersed. While the three largest agglomerations have temperatures at the upper tail of the distribution (27.5-28.4°C), it is worth noting that the primate city of Metro Manila situated in the northeast is in a "hot" region, and adjacent municipalities exhibit similar high averages. Ninety years later, the spatial distribution will be vastly different as warmer temperatures become heavily clustered towards the south east.

A cause of possible concern is that extreme temperatures are predominantly concentrated in the southern island of Mindanao - a region that has the highest levels of poverty and concentration of low-skilled workers in the Philippines. As discussed in Section 1.6, this would have multiple implications for welfare depending on how economic activity shifts as labor reallocates. The degree to which rising temperatures encourage workers to move to better locations will depend on migration costs and availability of other suitable locations. Motivated by this, I simulate counterfactual scenarios under extreme cases of free mobility and infinite migration costs. To isolate the impact of climate change, I calculate welfare according to baseline levels of bilateral trade costs and migration costs at 2010 values. These counterfactuals help uncover the driving force behind changes in welfare.

In Figure 1.8, I illustrate the changes in structural fundamentals following the com-

[46]The corresponding changes in precipitation is shown in Figure A6 where overall rainfall has generally declined for the country.

bined effects of temperatures. These scatterplots demonstrate the differences between 2010 and 2100, where a linear down-scaling occurs for all subgroups. Apart from some exceptions in exogenous amenities, municipalities experience a decline in exogenous fundamentals as exhibited by points that lie below the 45° line. These patterns suggest a change in the relative ranking across municipalities by the end of the century, and emphasize the inequity of climate change as some locations become less habitable.

Varying Costs

Table 1.8 presents the simulated results of the future economy given climate conditions at 2100. The impacts of rising seas and temperature on productivity and amenity fundamentals yields an aggregate welfare loss of 19.9% under baseline 2010 frictions. Low-skilled workers are more susceptible to the impacts of climate change with losses that are 5.9 percentage points (p.p.) higher compared to their skilled counterparts who register a welfare reduction of 16.7%. Meanwhile, aggregate output losses are at 14.2%, skilled output losses are 12.9%, while low-skilled losses are at 15.5%. The distributional implications of climate change foreshadows a somber reality, with inequality intensifying by 7.5%.[47] Collectively, these results suggest that locations inhabited by low-skilled workers are disproportionately ravaged by global warming.

Column 2 of Table 1.8 show that when barriers to mobility are reduced, baseline welfare loss is reduced by almost half due to the large gains accrued to low-skilled workers. Output and welfare losses for the low-skilled population are curbed by 8 p.p. and 5.5 p.p. respectively when they are perfectly mobile. With welfare disparities narrowing, inequality improves by 1.3% relative to 2010 levels. However, it is important to note that progress is not uniform with skilled workers merely gaining a percentage point improvement in welfare. This finding suggest two things. First, migration costs play a significant role in the location decisions of low-skilled workers. This is supported by estimates

[47] Inequality is defined as the ratio of skilled welfare to low-skilled welfare.

from the gravity regressions in Table 1.2, whereby given the same set of geographic barriers, low-skilled workers exhibit higher migration resistance relative to their skilled peers. Hence, reducing migration costs is critical to helping low-skilled workers adapt to climate change. Second, removing barriers to mobility suggests a crowding-out effect that drives down the welfare components of skilled-workers. Comparatively modest output gains of 0.3 percentage points in the skilled sector are driven by the counteracting trade-offs between amenities and real wages. As low-skilled workers relocate to large urban areas typically occupied by skilled workers, the influence of congestion externalities become more salient. In response, skilled workers are leave for high amenity locations that are no longer as productive.

Column 3 of Table 1.8 underscores the mitigating influence of migration in adapting to a changing environment. When population is held fixed at its 2010 state, initial welfare losses are inflated by 12.3 percentage points. By nature of how temperatures are spatially distributed at the end of the century, the distortions of climate on exogenous productivity are more prominent for low-skilled workers with GDP losses increasing by 20.3 p.p relative to their counterfactual outcome under baseline frictions. Interestingly, though the equivalent estimate for skilled workers is at 9.7 percentage points, skilled welfare losses increase by 11 percentage points. This suggests that welfare for the skilled-sector is driven by a significant devaluation of amenities. Imposing zero mobility leads to a worsening of outcomes of great proportions and further exacerbates existing inequalities.

Finally, I present in the last two columns of Table 1.8 how trade costs facilitate adjustments to climate change. Relaxing trade frictions can ease the country's ability to shift production away from places with eroding comparative advantage. Output and welfare losses are largely attenuated when trade barriers are reduced to zero. While this scenario is unlikely due to the country's island geography, this exercise highlights the best possible scenario when badly afflicted places can produce less of their own varieties and costlessly source goods from other municipalities. Conversely, imposing infinite trade costs impedes household access to more affordable goods from trade partners. When this occurs, people adapt by moving to locations that could provide cheaper prices for goods, at the expense of local amenities or wages.

Isolating Climate Channels

In this section, I highlight the mechanisms that explain the differences in welfare and output effects across skill groups. Limiting the impacts of temperatures and sea-level rise on a specific fundamental characteristic demonstrate how skilled and low-skilled workers respond heterogeneously to changes to their environment. Table A9 presents the results of this exercise.

If temperatures solely affect exogenous productivity, overall welfare decreases further by 0.4 percentage points. Column 2 highlights that the effects are not shared equally across skill groups. The brunt of the burden falls on low-skilled workers as they suffer decreases in welfare and output by 1.4 p.p. and 2.3 p.p., respectively, relative to initial losses shown in Column 1. Conversely, skilled workers are able to make some headway on welfare and output. This scenario intensifies inequality by 10.5% relative to 2010 levels. The persistent reductions in aggregate and skill-specific output are due to the uniformly damaging effects of rising temperatures on exogenous productivity (see Figure 1.8).

Putting a pin on these findings, I simulate counterfactual outcomes when I isolate the impact of climate on amenities. Results in Column 3 show that low-skilled workers have attenuated their baseline welfare losses when productivity is spared from the impacts of rising temperatures. In contrast, skilled workers fail to benefit and suffer from an additional welfare loss of 0.5 percentage points. It is important to note however that skilled output losses slightly increased. While these magnitudes seem negligible, the non-uniform effects underscore the trade-offs of how skilled workers assess overall utility. Viewing Columns 2 and 3 together reveals how workers balance the welfare components offered by a certain location. While low-skilled workers are highly sensitive to changes in fundamental productivity, skilled workers carry a higher premium on exogenous amenities, which is consistent with the findings in Table 1.7.

So far, I've established the welfare and output implications of temperature and sea-level rise on the baseline economy. Yet, more can be done to disentangle the driving forces behind these effects. In the next few paragraphs, I highlight the changes on the spatial allocation of labor across the country. Unraveling these patterns is of crucial importance since the aggregate and distributional impacts of climate change are driven by the migration responses of workers. Additionally, knowing which location types gain or lose population carry weight for future policy considerations.

Column 2 of Table A10 presents the labor distribution across area-types when temperatures disrupt location fundamentals as consistently assumed in the model. In reading this table, each row considers a binary classification of all municipalities in the country.[48] Each cell from Columns 2 to 5 quantifies the net percentage change in the counterfactual, relative to 2010 population shares presented in Column 1.[49]

I look to Column 2 to investigate the labor distribution that substantiate the overall welfare impacts in the baseline counterfactual. A major finding is that workers exhibit substantial out-migrations from productive urban cities. In the new economy, an additional 12.8% and 10.0% of skilled and low-skilled workers will reside in rural areas compared to their 2010 shares.[50] There are some differences on how skilled and low-skilled groups managed their retreat from the coasts. While skilled workers avoided locating in poor municipalities, low-skilled workers are now more concentrated in poor municipali-

[48]The distribution of municipalities by each of these mutually independent categories are presented in Table A11.

[49]The 2010 population shares assumes represents the baseline distribution without the effects of climate change and sea-level rise. I can interpret these changes as the lower estimate of how climate change induces labor to reallocate across municipalities. They are the lower bound since I am unable to differentiate population movements within the same area-type. Hence, these statistics underestimate overall migration flows since I am not capturing workers who had relocated to the same area classification (i.e. coastal to coastal movements).

[50]Rural population shares can be extracted from the table by taking the difference of 100 and urban population share.

ties at 25.7%.[51] Although compensated by better amenities in new locations, the relatively high rate at which population flees urban areas exerts a negative downward influence on aggregate output. An accompanying map in Figure A7 shows that skilled labor dispersed throughout the country while low-skilled workers are more concentrated.

Considering the results in Table A10 in conjunction with Table A9 can further enrich the analysis. Columns 3 and 4 of Table A10 present the spatial allocation of labor that correspond to counterfactuals that decompose the effect of climate to a single channel. Consistent across the board, coastal municipalities are shown to have declining population shares. Moreover, poorer municipalities largely absorb the displaced low-skilled population than skilled workers. These migration patterns can be attributed to the redistribution of relative locational advantages under the new climate reality in 2100 (see Figures A4 and 1.8). On the aggregate, if productivity is solely impacted and amenity values remain the same, people are dissuaded from moving away from urban areas. The universal preference to locate in cities would then improve agglomeration spillovers but intensify congestion forces. Meanwhile, if amenities are only affected, workers flock to places that are amenity-rich but are less productive.

Inspecting the spatial distribution of labor across subgroups, low-skilled welfare is severely undercut once workers relocate away from the coasts and are displaced to poorer municipalities. Interestingly, low-skilled workers are precluded from achieving better outcomes when amenity disruptions are turned off (column 2 of Table A9). This insinuates higher migration thresholds among low-skilled workers, in that they can withstand larger losses in underlying welfare components. This demonstrates why counterfactual scenarios that include changes to the amenity channel lead to a more efficient allocation of low-skilled labor across the country.

On the other hand, skilled workers attenuate their initial losses as long as they remain in coastal municipalities. The persistent welfare loss exhibited by skilled workers

[51] A municipality is classified as poor if its rate of poverty incidence rate above 40%. I took the poverty incidence rates as given from FIES 2009.

is driven by amenity distortions, which are further amplified when they flee large cities. This is emphasized when jointly reading the results in Column 4 of Table A9 and Column 3 of Table A10. Skilled workers leave productive places to access amenities in either poorer or rural municipalities when the relative advantage of coastal areas are compromised. Since skilled workers exhibit stronger preferences for consuming amenities, their decision to relocate comes at the expense of losses in GDP.

No Sea-Level Rise

I further isolate the impact of climate change on rising temperatures by ignoring the effects of sea-level rise. Effectively, this means that land remains intact for 34% of coastal municipalities.[52] I find that the overall effect of rising seas is second order to the impacts of temperatures. Column 4 in Table A9 shows that the estimates are consistent with intuition. Protecting land from rising oceans attenuates overall losses in baseline output and welfare for both skill groups. Columns 1 and 5 of Table A10 suggest that rising seas have a larger displacing effect among low-skilled workers. Absent sea-level rise, coastal municipalities have increased skilled population share to 74.8%, emphasizing the strong coastal bias of this particular subgroup.

1.8.3 Adaptation Policies

An implicit assumption of my prior counterfactuals is that location fundamentals are stable over time and are only influenced by climate. This assumes that no policies are pursued in improving location fundamentals. This may run in contrast to reality whereby nations anticipate the impacts of a warming planet, and subsequently invest in various abatement policies. With this in mind, I evaluate two adaption interventions in response to the direct threat of sea-level rise. I quantify their effects by implementing upgrades to location fundamentals appropriate to the context of the policy.

[52] Land is now fixed in the denominator for Eqs. 1.9 and 1.11. Thus, isolating the response of agglomeration and congestion forces to labor reallocation.

Building Coastal Resilience

Nullifying the impacts of sea-level rise is far from feasible for a country like the Philippines. However, strengthening coastal protections for large population centers could come close enough. This counterfactual assumes that coastal protections are in place so that sea-level rise will have no outright effects on altering land areas of the three largest metropolitan cities– Metro Manila, Metro Cebu and Metro Davao. This entails various mitigating strategies involving a combination of engineering and ecological options– nurturing aquatic vegetation, construction of flood walls, sea dikes, levies and land reclamation (Borsje et al., 2011; Jones et al., 1994). Column 2 in Table 1.9 evaluates the overall implications of building up coastal resilience. Here, I find low-skilled workers respond favorably as their baseline GDP losses are cut back to 10% from 16% absent any adaptation. Equivalently, skilled workers curb their output losses by 1.0 p.p. from a baseline of 12.9%. The improvement in aggregate GDP highlights the importance of keeping the population in large coastal cities. In terms of aggregate welfare, baseline losses are hampered by 1.1 p.p. with by gains driven by low-skilled workers. This suggests that if large population centers are defended from rising seas, climate-induced migration can facilitate a more efficient allocation of labor towards highly productive areas (Henderson et al., 2017).

Column 3 of Table A13 illustrates that welfare gains are accrued to the population remaining in coastal municipalities. If highly productive regions are protected from rising seas, workers need not relocate to sub-optimal or less developed locations. Increasing the desirability of the three largest Metros precludes 4% of skilled and low-skilled workers from moving to rural areas, compared to the baseline case shown in Column 2. The value of this exercise highlights the importance of keeping large urban centers relevant in a rapidly changing environment. This argument bears more consequence in developing countries where large amenity and productivity disparities exist across locations. All in all, curbing the threats of sea-level rise yields better aggregate and distributional outcomes, as it spares losses of local agglomeration economies from high-density coastal areas.

I conduct a back-of-the-envelope calculation to quantify the output gains from implementing this adaptation strategy against the massive infrastructural cost of fortifying the coastlines. A 2.9 p.p. reduction in aggregate GDP loss implies a project benefit of $6.0 billion in nominal 2010 values. This implies that the project pays for itself as it surpasses the incurred cost of $51 million. I borrow this cost estimate from India's National Coastal Protection Project undertaken from 2007-2012. Civil works and reef construction were involved to protect the combined 1,000 kilometer shorelines of Goa, Maharastra and Karnataka - which implies a per-kilometer cost of $51,000 (ADB, 2017). An alternative sea-wall project in South Korea estimates a per-kilometer cost of $2.2 million in 2005 (Min et al., 2016). This registers a larger bill since it is strictly an engineering endeavor involving walls built parallel to the shoreline.[53] Notwithstanding, evaluating the project using this alternative estimate does not change the viability of coastal area protection.

Place-based Policy: Replicating the coastal mega-city inland

My second policy counterfactual considers a large-scale place-based policy that creates a new metropolis 90 kilometers north of Metro Manila. New Clark City (NCC) will span an area of 9,450 hectares (23,400 acres) located in the municipalities of Capas and Bamban. It was initially conceptualized to stimulate economic activity inland as a viable alternative to the highly congested capital. Discussions regarding this city have been ongoing since 2012, though the plan was only formalized in 2016.[54] While progress have been slow, land contracts have been drafted, issued and awarded to real estate developers (BCDA, 2020). The threats of climate change will only increase the value of this initiative as the city's geographical features offer some advantage against natural hazards. First, the area

[53] In addition, the cost also incorporates social cost, and the loss of wetlands and ecosystem services.

[54] In March 2015, the Philippine Congress approved House Resolution 116 which supports the creation of New Clark City. Officially, groundbreaking rites in April 2016 marked the estimated start date of the project.

has a minimum elevation of 54 metres above sea level and would not be susceptible to flooding. Second, the city is encapsulated by the Sierra Madre mountain range on the east and the Zambales mountain range on the west - both providing a natural defense against typhoons. If sound investments are made in the next 70 years, this area may have location fundamentals that are as competitive as Metro Manila. To achieve a counterfactual simulation that captures this policy, I assume that NCC will have upgraded levels of structural fundamentals in 2100. This is implemented by awarding the comprising municipalities of NCC with geographic amenities and exogenous productivities similar to Metro Cebu.[55] I then predict the new location fundamentals across skill-types in consideration of the local temperatures in NCC. This exercise generates a new city into existence, and thereby shifts the relative advantages of municipalities across space.

Results are provided in Column 3 of Table 1.9. The creation of a large metropolitan area offers substantial benefits to the country. This is evident by the sizeable reduction in both welfare and output losses for both skill groups alike, though larger improvements are achieved by low-skilled workers. A few explanations justify this result. First, offering a new desirable option in the hinterlands induces more migration due to the artificial reduction in bilateral distance to attractive locations. Second, creating a new megacity in the middle of the main island group (Luzon) improves the intensive margin decisions of workers. Expanding the choice sets with the inclusion of an objectively better location can facilitate welfare improving outcomes, though the attenuating effects are muted among skilled workers. Sorting patterns in Column 4 of Table A13 indicate that people are more willing to poorer areas compared to the other alternative counterfactuals evaluated in this paper. Interestingly however, the dispersion of population towards such regions do not impose negative welfare and distributional consequences.

Despite these benefits, a back-of-the-envelope calculation fails to justify this place-

[55]The disparity between the natural amenities and fundamental productivities of Metro Manila and New Clark City are too large to ever be realistic. Thus, I artificially inflate the location fundamentals to levels equal to the second largest city in the country.

based policy given an estimated capital outlay of $12.9 billion (PDI, 2019). While a new metropolis offers a benefit of $7.2 billion, these gains are insufficient to meet the insurmountable costs of the project. Yet, accepting inaction amidst an impending disaster seems reckless especially when livelihoods are at stake. Some hopeful prospect emerge that could make this option attainable if construction technologies become cost-effective, or if cheaper financing sources are more accessible.

Migrants can solicit positive spillovers to the places they go. The distributional effects of climate change can reshape the internal structure of a country's economic geography. An injection of skilled human capital into inland regions can spur new economic clusters in the country. Thus, I close this section by relating the new distribution of labor with the skill composition of each municipality. Figure A8 maps in green, areas that have high shares of skilled workers. There is a considerable increase in "skilled" municipalities compared to the baseline economy in 2010. Moreover, the spatial patterns exhibited in the right panel of Figure A8 lend support to the labor reallocation story presented in Tables A10 and A13. Within the context of my model, climate change will make these areas transition to more productive sectors through the influx of skilled workers.

1.8.4 Robustness

In this section, I run a series of counterfactuals to test the robustness of my baseline results. I estimate the equivalent losses for high- and low-emission cases under RCP 8.5 and RCP 4.5. Results in Table A12 show that relative to 2010 levels, aggregate welfare losses by century-end lie between the range of 20.9% and 21.4%. Meanwhile, output consistently decreases by around 14% for all IPCC projections. I close this set of counterfactuals by simulating the economy in 2050. Bringing the time horizon closer to the present addresses the concern that frictions, preferences, and behavior at 2010 may not perfectly carry through ninety years into the future. With temperature warming and the danger of sea-level rise becoming less prescient, I find the most optimistic outcome thus far.[56] Estimates in column 4 indicate that damages to output attenuates by 3 to 4 percentage points across skill groups. At the same time, welfare losses are mitigated by 6.1 p.p. and 2.8 p.p for skilled and low-skilled groups, respectively.

Finally, I demonstrate how my baseline welfare effects respond to my choice of calibrated parameters. Each panel in Figure 1.9 plots the level of counterfactual outcome when a single parameter is varied while keeping all other structural parameters constant. I report the plots for the Armington elasticity of goods substitution, σ, and the congestion parameter, η. Panel A illustrates that a higher degree of substitutability between varieties (larger values of σ) yield lower climate damages to the economy. As products become perfect substitutes, goods production are allocated more efficiently away from areas made worse off from climate change. Panel B demonstrates that equivalent results along different parameter choice of the congestion externality, η. Moving to the left along the x-axis implies larger depreciation of residential amenities with respect to density. Hence, it's unsurprising to find welfare losses to follow this downward slopping trend. Stronger distaste for congestion implies higher tendencies for workers to migrate out of large productive cities upon the influx of displaced low-skilled workers. Finally, I note that the axis-values along the y-axis falls within a narrow range of my baseline welfare losses. This indicates that my results are robust to parameter specification.

1.9 Conclusion

This paper explores the effects of climate change on a country's internal spatial development amidst frictions in the economy. My research question necessitates a quantitative and general equilibrium model that simultaneously accounts for the influence of changing temperatures and sea-level rise on exogenous productivity and location-specific amenities. Climate shocks imply a spatial shift on the comparative advantages of lo-

[56]Figure A9 illustrate high spatial correlation of temperature profiles between 2050 and 2100.

cations, and that labor, and subsequently economic activity, is reallocated across space. Applying this theoretical framework to a developing country context, I use data-driven estimates of trade and migration costs to capture realistic responses to exogenous environmental shocks across skill groups. I enrich the analysis by simulating possible alternatives where damages are mitigated from the disruptive and inevitable effects of climate change.

My findings depict a dire future for the Philippines. The slow-moving, yet significant threat of sea-level rise and warming temperatures will hamper overall welfare and aggregate GDP by around 20% and 15%, repesectively. Low-skilled workers bear the brunt of the burden, though skilled workers are similarly afflicted since they are strongly concentrated along the coasts. The effects of climate change are heterogeneous. I bring into sharper focus the differential responses across skill-groups when I disentangle the channels through which climate affects location fundamentals. An upheaval on fundamental amenities elicits larger migratory responses from skilled workers, whereas distortions on productivities are of detriment to low-skilled workers. Notwithstanding, the implications of global warming on inequality are potentially catastrophic. The unjust and indiscriminate impact of climate change may further amplify existing disparities, and at worst, create instability in the region.

Failure to confront the climate future undercuts any economic headway made today. Large-scale adaptation strategies are thus necessary to dampen the astonishing losses in aggregate GDP and overall welfare. This paper contributes by evaluating a quantitative assessment of actual policy considerations that many climate-vulnerable nations are considering to invest in. The daunting cost of adaptation remain a challenge, but back-of-the-envelope calculations justify the exorbitant costs of protecting the shoreline of large metropolitan centers. This is in contrast to an ambitious place-based policy of creating a central mega-city inland. This lackluster result may not be surprising. The verdict on changing the spatial distribution of economic activity through place-based policies remains ambiguous in the literature (Neumark and Simpson, 2015). But if liquidity constraints are relaxed, implementing any abatement strategy can induce a better outcome for the economy.

Global warming may intensify high-skill emigration and affect the local stock of human capital, leading to negative externalities (Docquier and Rapoport, 2012). Future improvements to the paper may include a dynamic spatial equilibrium framework with endogenous structural change. Under this direction, there is room to incorporate endogenous population growth, endogenous adaptation, and sectoral switching between firms and workers (Cruz and Rossi-Hansberg, 2021; Desmet and Rossi-Hansberg, 2015; Conte et al., 2021).

Tables

Table 1.1: Effect of Weather on Migration Statistics

	All		Skilled		Unskilled	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Out-migration rates						
Δ Temperature (°C)	0.1848*	0.2375**	0.1282*	0.1639*	0.1890*	0.2434**
	(0.0967)	(0.1133)	(0.0729)	(0.0844)	(0.0988)	(0.1165)
Within R^2	0.002	0.079	0.256	0.306	0.003	0.080
Dependent Variable: In-migration rates						
Δ Temperature (°C)	0.0012*	0.0005	0.0014	0.0010	-0.0021*	-0.0023*
	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0012)	(0.0012)
Within R^2	0.049	0.295	0.329	0.385	0.614	0.618
Dependent Variable: Net-migration rates						
Δ Temperature (°C)	0.0002	-0.0004**	0.0007	0.0005	0.0001	-0.0007***
	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0003)	(0.0002)
Within R^2	0.037	0.136	0.330	0.336	0.003	0.157
Observations	3,200	3,200	3,200	3,200	3,200	3,200
Lagged Dependent Variable	Y	Y	Y	Y	Y	Y
Log Population Controls	N	Y	N	Y	N	Y
Year FE (2)	Y	Y	Y	Y	Y	Y
Province FE (81)	Y	Y	Y	Y	Y	Y
Municipal FE (1,600)	Y	Y	Y	Y	Y	Y

Notes: This table presents the regression coefficients of climate variables on migration rates. The variable, Δ *Temperature (°C)*, denotes temperature deviation from a municipality's own 20-year long-run moving average. Observations are at the municipality-year level. Each column represents a different dependent variable based on the migration statistics of a specific subgroup indicated in the columns. Table A2 presents the corresponding results without the lags. Clustered standard errors at municipality-level are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 1.2: Migration gravity

	(1) All	(2) Skilled	(3) Unskilled
Log Distance	-1.214***	-1.162***	-1.228***
	(0.042)	(0.052)	(0.043)
Same island	0.223**	0.227*	0.216**
	(0.109)	(0.129)	(0.106)
Same province	1.189***	1.426***	1.143***
	(0.128)	(0.148)	(0.133)
Hometown bias	3.869***	3.940***	3.874***
	(0.112)	(0.132)	(0.115)
Absoulte difference in longitude	0.104**	0.017	0.134***
	(0.041)	(0.036)	(0.044)
Absoulte difference in latitude	-0.103***	-0.067*	-0.112***
	(0.027)	(0.035)	(0.026)
Origin x Year FE	Y	Y	Y
Dest. x Year FE	Y	Y	Y
N	7,680,000	7,680,000	7,680,000
N municipalities	1,600	1,600	1,600
N years	3	3	3
Wald χ^2	57,925	45,858	57,673
Pseudo R^2	0.828	0.821	0.829

Notes: This table shows the results of the non-parametric reduced-form migration gravity equation 1.17. Same island is a dummy that equals one when municipality-pairs are not separated a body of water. Same province is a dummy that takes a value of one if location pairs belong to the same province. Hometown bias is a dummy that equals one for own-to-own migration flows. Differences in longitudes and latitudes are calculated from the centroids of each municipality. Table A3 presents the coefficients when no controls is specified in the regression, while Table A4 shows the distance elasticity coefficients for each cross-sectional census year. Two-way clustered standard errors by origin-municipality and destination-municipality are reported in parentheses. Estimates are obtained from Poisson Pseudo Maximum Likelihood regressions with multiway fixed effects, as described by Correia, Guimarães, and Zylkin (2020). $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 1.3: Trade gravity

	(1) All Years	(2) 2000	(3) 2010
Log distance	-1.081**	-1.107***	-1.041**
	(0.424)	(0.366)	(0.453)
Same island	-1.603**	-1.354***	-1.726**
	(0.648)	(0.454)	(0.785)
Same region	0.512	0.512	0.521
	(0.450)	(0.380)	(0.509)
Hometown bias	-9.340***	-9.952***	-8.837***
	(2.046)	(1.844)	(2.161)
Absoulte difference in longitude	0.129	0.102	0.137
	(0.101)	(0.099)	(0.102)
Absoulte difference in latitude	-0.208	-0.014	-0.314**
	(0.135)	(0.106)	(0.154)
Origin x Year FE	Y	N	N
Dest. x Year FE	Y	N	N
Origin FE	N	Y	Y
Dest. FE	N	Y	Y
N	13,112	6,561	6,561
Wald χ^2	145.158	130.221	138.724
Pseudo R^2	0.764	0.810	0.737

Notes: This table estimates the distance elasticity of trade at the province-level ($N = 81$). Same island is a dummy that equals one when province-pairs are not separated a body of water. Same region is a dummy that takes a value of one if location pairs belong to the same region. Hometown bias is a dummy that equals one for own-to-own trade flows. Differences in longitudes and latitudes are calculated from the centroids of the most populated municipality in the province. Two-way clustered standard errors by origin-province and destination-province are reported in parentheses. Estimates are obtained from Pseudo Maximum Likelihood regressions with multiway fixed effects, as described by Correia, Guimarães, and Zylkin (2020). $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 1.4: Summary Table of Parameter Values

Parameter	Description (Source)
$\sigma = 5$	Elasticity of substitution between goods (Allen and Arkolakis, 2014)
$\theta^H = 2.054$	Fréchet shape parameter (Tsivanidis, 2019)
$\theta^U = 2.840$	Fréchet shape parameter (Tsivanidis, 2019)
$\eta = -0.10$	Congestion parameter (Ahlfeldt et al., 2015)
$\alpha = 0.076$	Agglomeration Externalities (Chauvin et al., 2017)
$\beta^{\text{ag}} = 0.352$	Share parameter for agricultural consumption bundle (FIES 2003,06,09)
τ_{nd}	Trade cost (DOMSTAT 2000, 2010)
μ^g_{nd}	Migration cost (Census 1990, 2000, 2010)

Table 1.5: Amenities and Productivities: Inverted Composites vs Geographic Amenities

	Amenity		Productivity	
	(1) Skilled	(2) Low-Skilled	(3) Skilled	(4) Low-Skilled
Panel A: Time-varying characteristics				
Avg. Temperature (°C)	-0.034**	-0.055***	-0.015	-0.028**
	(0.013)	(0.017)	(0.009)	(0.011)
Δ °C relative to long-run average	-0.004**	-0.005*	-0.002*	-0.004**
	(0.002)	(0.003)	(0.001)	(0.001)
Avg. Rainfall (millimeter)	-0.011	-0.027**	-0.006	-0.014**
	(0.008)	(0.011)	(0.005)	(0.006)
Δ Rainfall relative to long-run average	0.056*	0.078	0.005	0.033
	(0.029)	(0.052)	(0.029)	(0.029)
Panel B: Time-invariant characteristics				
Log Elevation (meters)	-0.219*	-0.272**	-0.071	-0.107
	(0.112)	(0.110)	(0.063)	(0.065)
Log Slope (meters)	-0.518*	-0.581*	-0.217	-0.237
	(0.255)	(0.305)	(0.132)	(0.162)
Log Distance to Permanent Water Sources (km)	-0.176***	-0.125*	-0.067**	-0.058
	(0.049)	(0.062)	(0.027)	(0.034)
Multi-Scale Topographic Position Index	-0.443***	-0.698***	-0.229***	-0.322***
	(0.098)	(0.097)	(0.050)	(0.055)
Terrain Ruggedness Index	-0.216***	-0.248***	-0.097***	-0.106***
	(0.060)	(0.065)	(0.032)	(0.035)
Soil Bulk Density (kg/m3)	0.236**	0.402***	0.146**	0.169**
	(0.082)	(0.061)	(0.055)	(0.060)
Latitude	-0.008**	-0.022***	-0.004	-0.011**
	(0.003)	(0.005)	(0.002)	(0.004)
Longitude	-0.089**	-0.085*	-0.039*	-0.077*
	(0.038)	(0.047)	(0.019)	(0.042)
N	3,200	3,200	3,200	3,200

Notes: This table shows the coefficients from regressing the recovered log productivity and amenities on a natural amenity given in each row. Observation is at municipality-year level for 2000 and 2010. Climate variables are annual municipal averages corresponding the Census reference years. Temperature and rainfall deviation are with respect to a municipality's own historical 20-year average. Time-invariant characteristics are sourced from various GIS sources where observations represent municipality averages calculated from raster statistics. From elevation data, multi-Scale Topographic Position Index (mTPI) measures a slope position of a location relative to its surrounding neighborhood. Positive and large values of mTPI mean the cell is higher than its adjacent neighborhood as in being at a hilltop or ridge, while negative values mean that a location is the base of a valley. All regressions include year fixed effects and region fixed effects. Standard errors are clustered at region-level and reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 1.6: Amenities and Productivities: Inverted Composites vs Endogenous Amenities

	Amenity		Productivity	
	(1) Skilled	(2) Low-Skilled	(3) Skilled	(4) Low-Skilled
Share of villages with a health center	0.062***	0.068***	0.031***	0.040***
	(0.010)	(0.013)	(0.006)	(0.008)
Share of villages with street pattern	0.072***	0.039***	0.042***	0.036***
	(0.008)	(0.011)	(0.005)	(0.006)
No. hotels per 1000 residents	0.073***	0.061***	0.045***	0.046***
	(0.007)	(0.009)	(0.004)	(0.005)
No. banks per 1000 residents	0.054***	0.049***	0.034***	0.033***
	(0.005)	(0.007)	(0.003)	(0.003)
No. restaurants per 1000 residents	0.118***	0.049*	0.066***	0.047***
	(0.021)	(0.028)	(0.013)	(0.016)
Estimated slum area in square kilometers	0.177***	0.610***	0.081***	0.289***
	(0.047)	(0.069)	(0.026)	(0.034)
Villages with housing projects (1 0)	0.213***	0.274***	0.117***	0.155***
	(0.015)	(0.020)	(0.008)	(0.010)
% residents with insecure tenure	-0.010*	0.004	-0.007**	-0.002
	(0.005)	(0.006)	(0.003)	(0.003)
% slum households	-0.041***	-0.002	-0.026***	-0.017***
	(0.006)	(0.007)	(0.003)	(0.004)
% houses constructed using weak materials	-0.049***	-0.006	-0.031***	-0.023***
	(0.006)	(0.008)	(0.003)	(0.005)
N	3,200	3,200	3,200	3,200

Notes: This table shows the coefficients from regressing the recovered log productivities and log amenities on an actual amenity given in each row. Each cell represents a single regression of a specific amenity indicated in the row on the dependent variable indicated in the column. Observation is at municipality-year level for 2000 and 2010. Endogenous amenities are obtained from Census village modules. All regressions include year fixed effects and province fixed effects. Standard errors are clustered at province-level and reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 1.7: Effect of Climate on Location Fundamentals

	Amenity		Productivity	
	(1) Skilled	(2) Low-Skilled	(3) Skilled	(4) Low-Skilled
Δ °C relative to long-run average	-0.617*	-0.370	-0.641*	-1.077**
	(0.292)	(0.235)	(0.330)	(0.438)
Overall Adjusted R^2	0.375	0.346	0.349	0.357
Within Adjusted R^2	0.208	0.177	0.166	0.137
N	3,200	3,200	3,200	3,200
N Municipalities	1,600	1,600	1,600	1,600
Year Fixed Effects	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Controls: Natural Amenities	Y	Y	Y	Y

Notes: Main measurement for temperature are anomalies from its own 20-year long-run moving average. The dependent variables are log productivities and log amenities recovered from the model inversion process detailed in Section 1.7.4. Climate variables match the same reference year used for Census 2000 and 2010. Controls for natural amenities include elevation, slope, distance to water sources, ruggedness, soil bulk density and multi-scale topographic position index. Table A6 presents the full set of coefficients. Observation is at municipality-year level for years 2000 and 2010. Standard errors are clustered at the region-level and reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table 1.8: Percentage Changes in Welfare and Output under Average Climate Projections in 2100

	(1) Baseline	(2) Free Mobility	(3) No Migration	(4) Free Trade	(5) No Trade
Welfare, aggregate	-19.9	-15.1	-31.3	-13.3	-23.0
Welfare, skilled	-16.7	-15.7	-27.6	-10.5	-16.8
Welfare, low-skilled	-22.6	-14.6	-34.6	-16.1	-23.3
Inequality	7.5	-1.3	10.6	6.7	8.5
Output, aggregate	-14.2	-10.0	-27.9	-9.2	-21.7
Output, skilled	-12.9	-12.6	-22.6	-8.7	-19.6
Output, low-skilled	-15.5	-10.0	-35.8	-9.6	-25.3

Notes: Table shows the percentage change in welfare, output, and inequality given out-of-sample changes to location fundamentals. The economy is simulated for five counterfactual scenarios: *Baseline* assumes current frictions as identical to 2100, *Free Mobility* purges all migration costs to zero, *No migration* holds the 2010 population fixed in its place, *Free Trade* eliminates all barriers to trade, and *No trade* restrict the flow of goods across municipalities. Average climate projections include land reduction due to sea-level rise and temperature averages from RCP 4.5 and RCP 8.5.

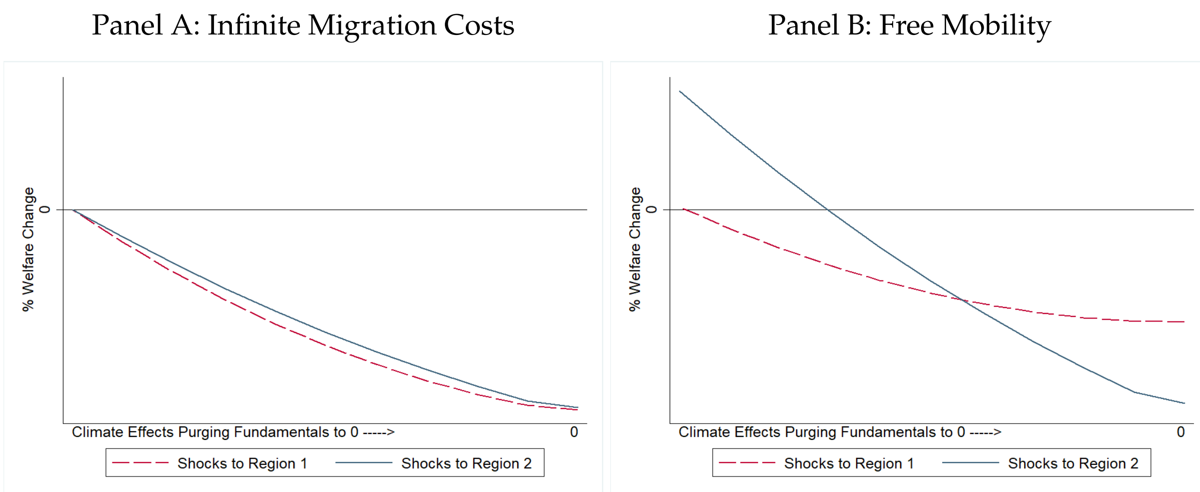
Table 1.9: Percentage Changes in Welfare and Output with Climate Adaptation

	(1) Baseline	(2) (1) + Coastal Protection	(3) (1) + New Inland City
Welfare, aggregate	-19.9	-18.8	-17.8
Welfare, skilled	-16.7	-16.8	-15.8
Welfare, low-skilled	-22.6	-20.4	-19.6
Inequality	7.5	4.5	4.7
Output, aggregate	-14.2	-11.3	-10.7
Output, skilled	-12.9	-11.9	-11.1
Output, low-skilled	-15.5	-10.3	-9.7

Notes: Table shows the percentage decrease in welfare, output, and inequality given out-of-sample changes to location fundamentals. Column 1 reports the baseline scenario consistent with the model presented in Section 1.5 whereby climate affects both amenity valuation and total factor productivity. Column 2 considers the climate mitigating strategy of building up coastal protection on the nation's three largest urban agglomeration. Column 3 considers a place-based policy of creating a new city 80km north of the capital.

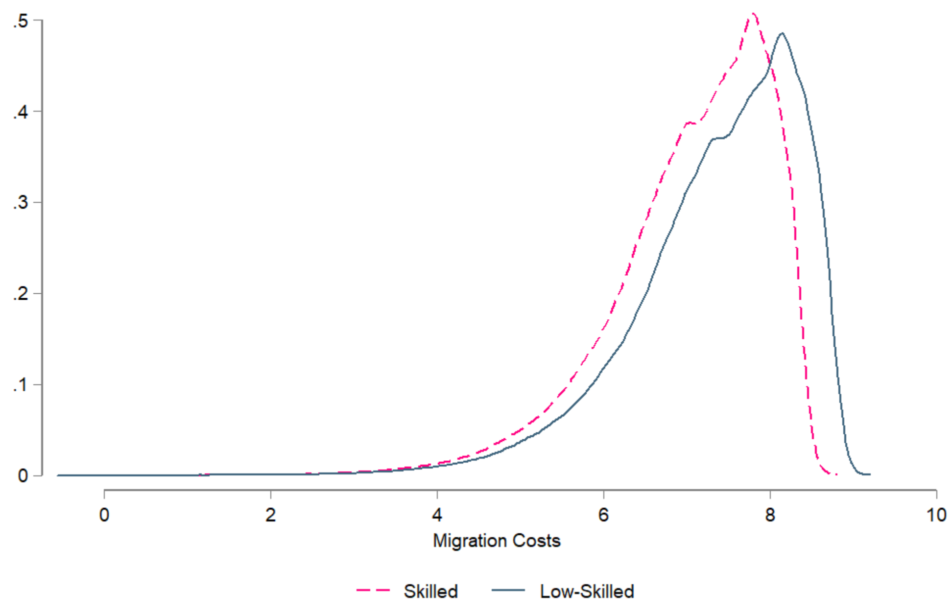
Figures

Figure 1.1: Welfare Change vs Changes in Climate Profiles



Notes: This figure plots the overall welfare effects in the y-axis against the intensity of climate damages to location fundamentals in the x-axis. There are two locations in this economy: a better-off region with a more attractive set of amenities and productivities, and a worse-off region. The blue line simulates the scenario when only the worse-off region is affected by climate change, while the red dashed line simulates the case when the better-off region is solely impacted. *Panel A* presents the percentage welfare changes when agents are not allowed to migrate. Correspondingly, *Panel B* plots the changes in welfare when people can relocate without cost.

Figure 1.2: Distribution of Migration Costs

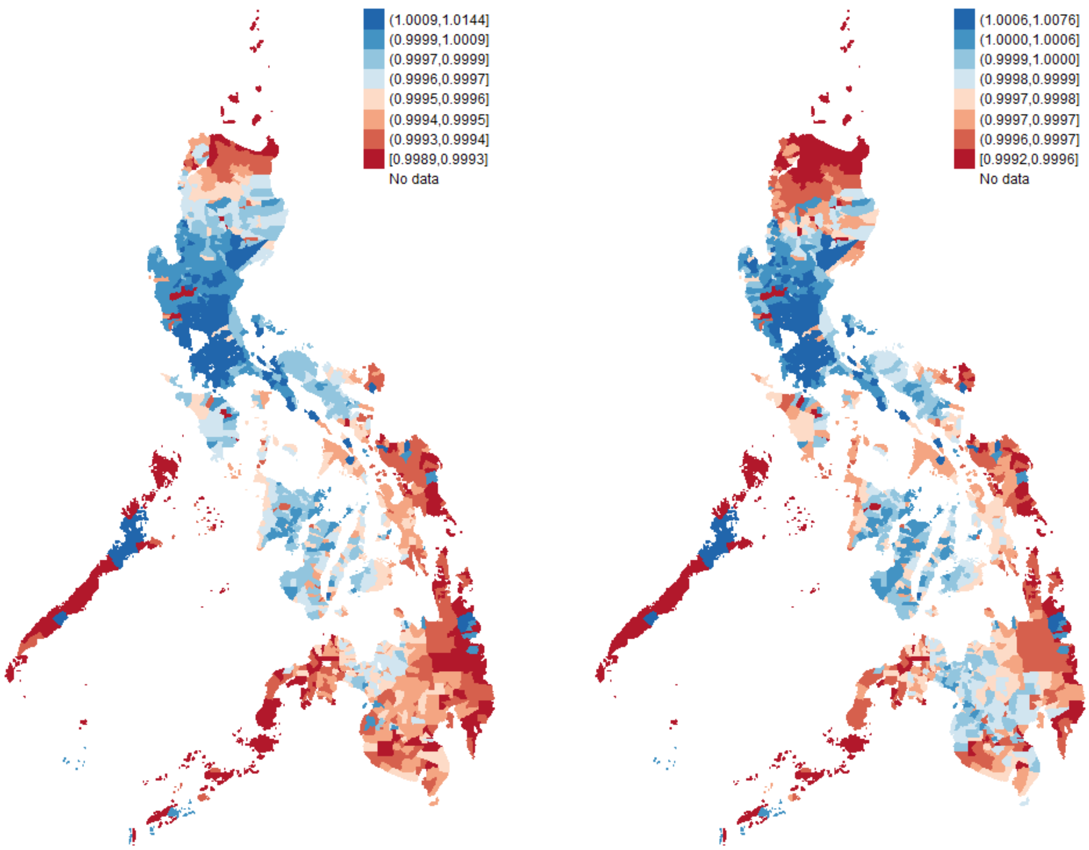


Notes: This figure presents the distribution of migration cost across skill groups estimated from running the regression in Eq. 1.17. The combined test for running a two-sample Kolmogorov-Smirnov test has a p-value of 0.000, which rejects the equality of distributions. The p-value `ksmirnov` calculates are based on the asymptotic distributions derived by Smirnov (1933) on a sample of $n = 5,287,752$.

Figure 1.3: Welfare Composites From Model Inversion

(a) Skilled Workers

(b) Low-skilled Workers

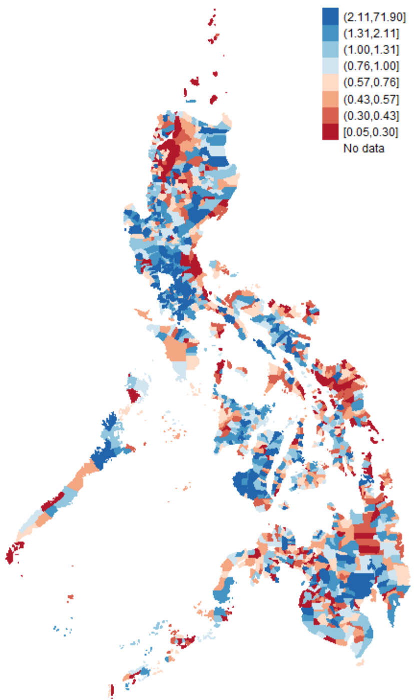


Notes: The left (right) panel shows the ex-ante welfare for skilled (low-skilled) workers. Values are normalized to the mean. Both panels are obtained from inverting the model following the procedures outlined in Section 1.7.4. The spatial distribution of welfare across skill-groups rationalizes the migration flows from the latest Census of 2010 using the corresponding wages and structural parameters in Table 1.4.

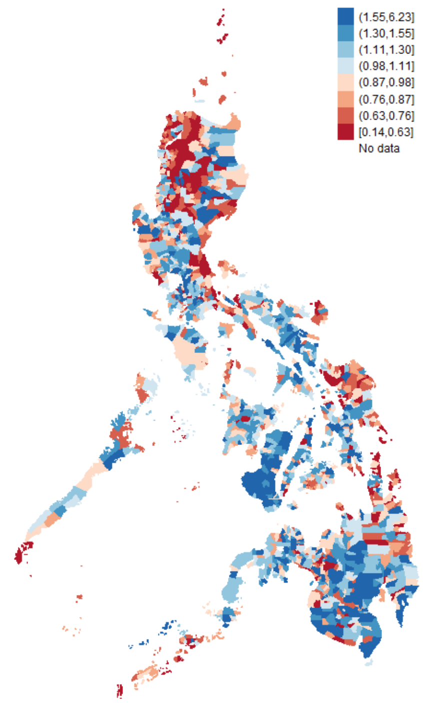
Figure 1.4: Location Fundamentals From Model Inversion

Panel A: **Exogenous Amenity**

(a) Skilled Workers

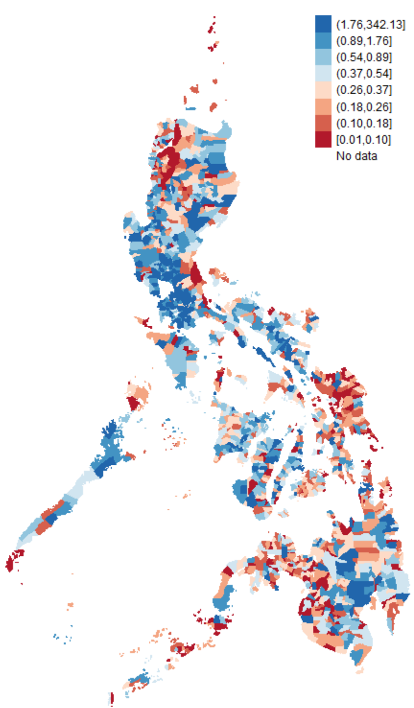


(b) Low-skilled Workers

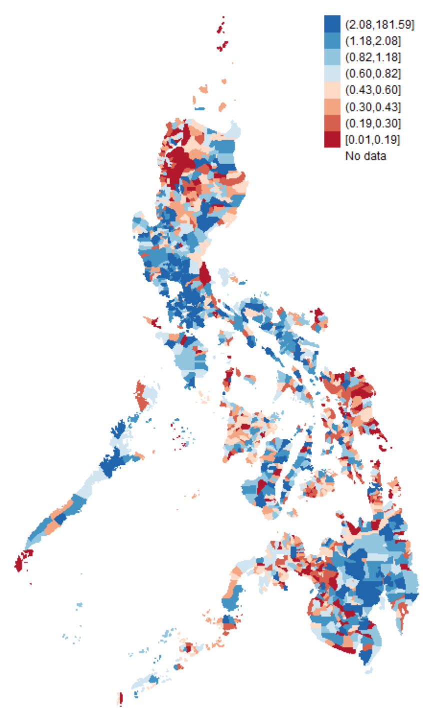


Panel B: **Exogenous Productivity**

(c) Skilled Workers

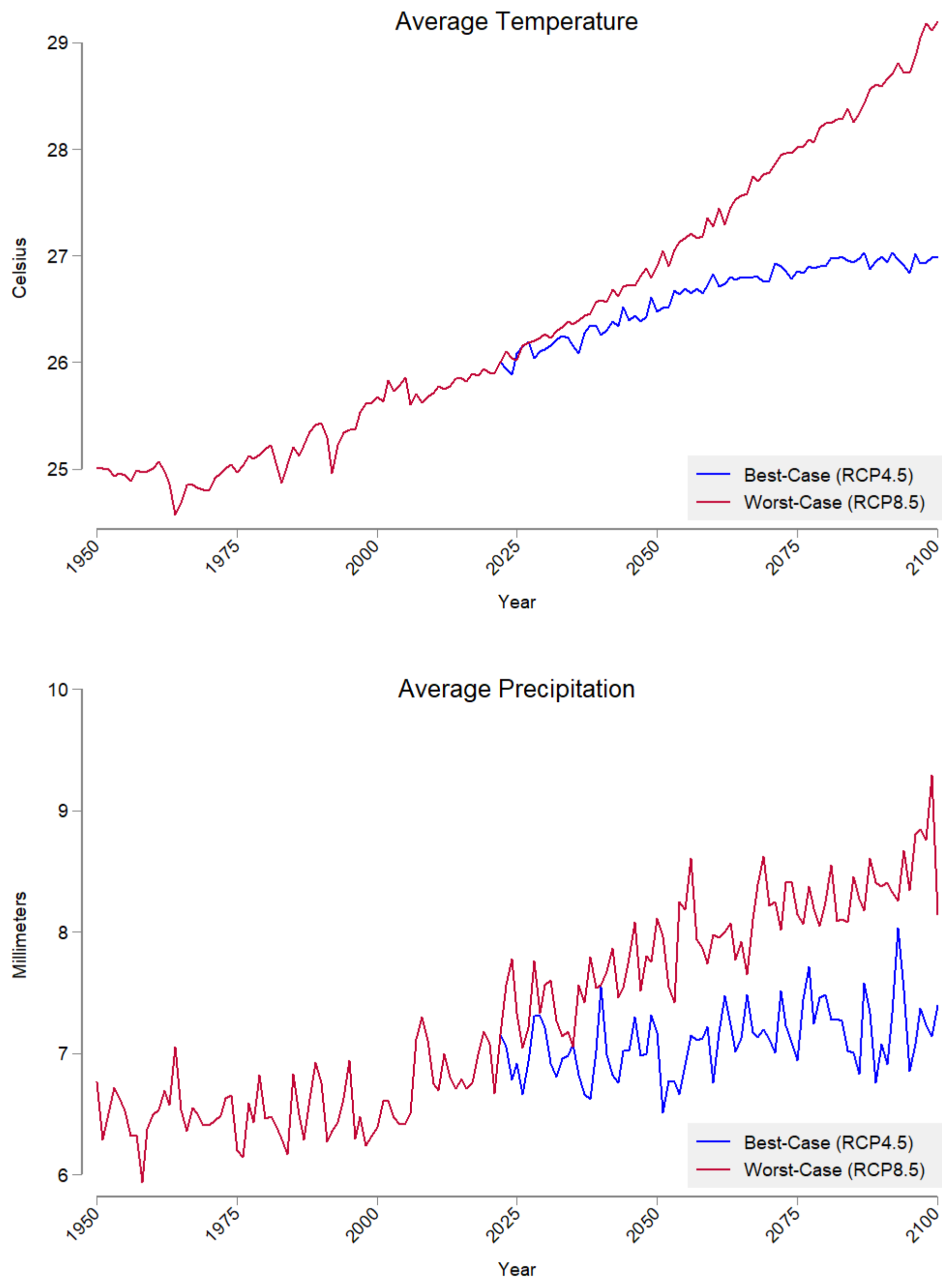


(d) Low-skilled Workers



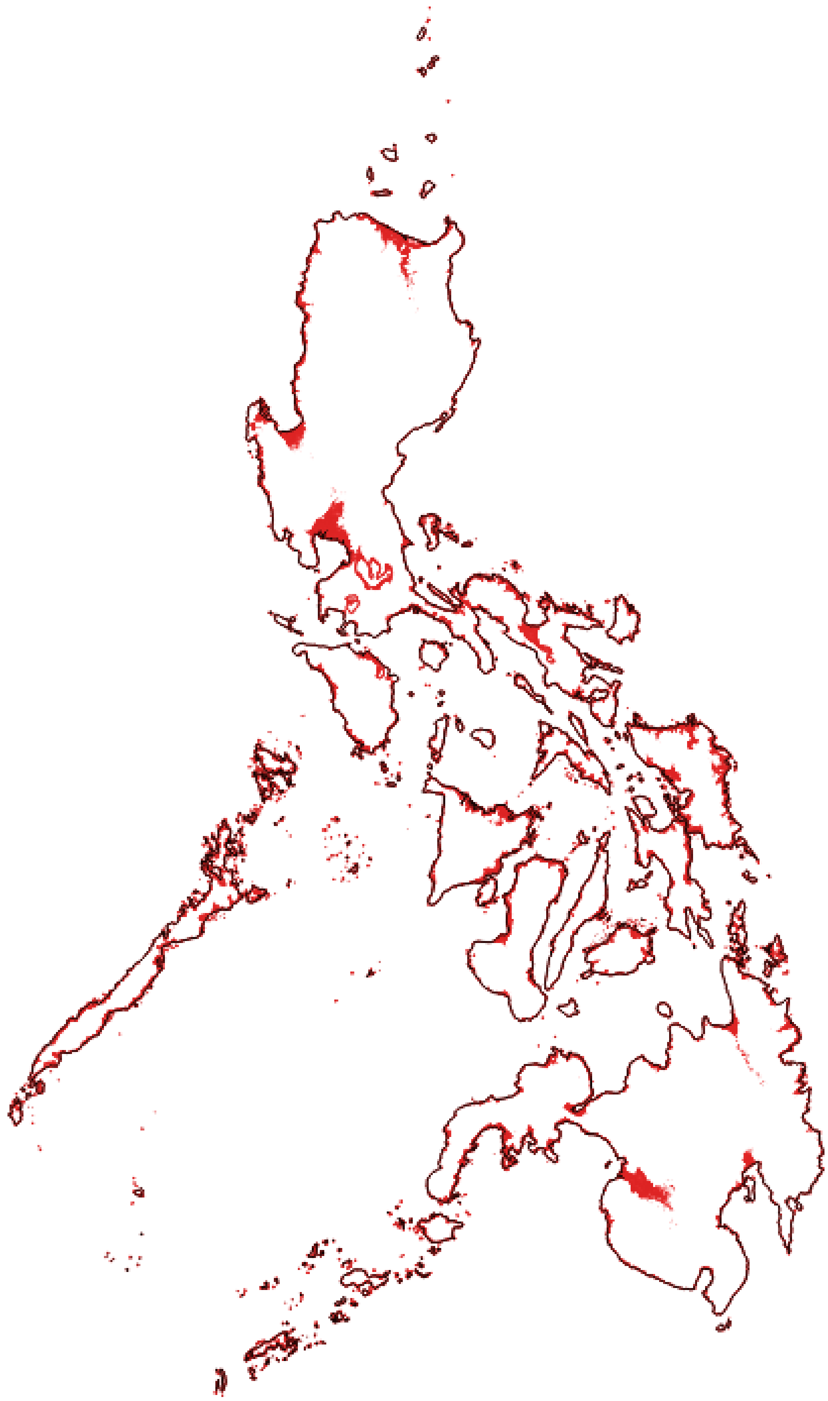
Notes: This figure maps the recovered location fundamentals across municipalities for low-skilled and skilled workers. Darker shades of red (blue) denote lower (higher) values.

Figure 1.5: Climate projections for the Philippines



Notes: This figure shows the national yearly averages of temperature and accumulated precipitation from 1950 to 2100. Statistics are pertaining to observed temperatures are sourced from TerraClimate (until 2021), while climate forecasts are sourced from NEX-GDDP. Climate projections used are based on the average of RCP 4.5 and RCP 8.5.

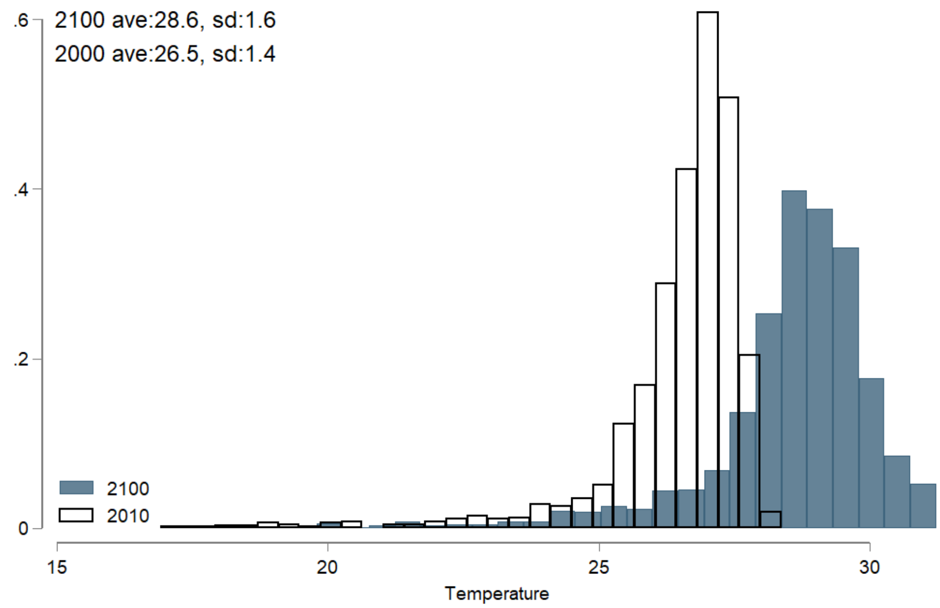
Figure 1.6: Flooded land from a sea-level rise of 2.0 meters



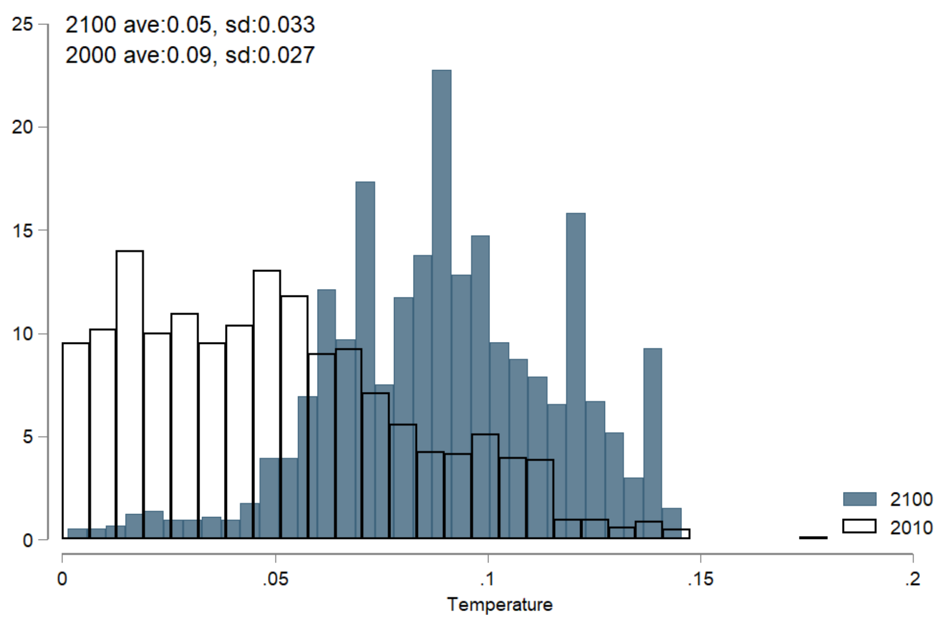
Notes: This figure shows how the country will be affected from an extreme sea-level rise scenario of 2 meters. Shaded regions in red are inundated land calculated from raster files of Shuttle Radar Topography Mission (SRTM) Digital Elevation Dataset v4.

Figure 1.7: Distribution of Municipal Temperatures

Panel A: **Average Temperatures**

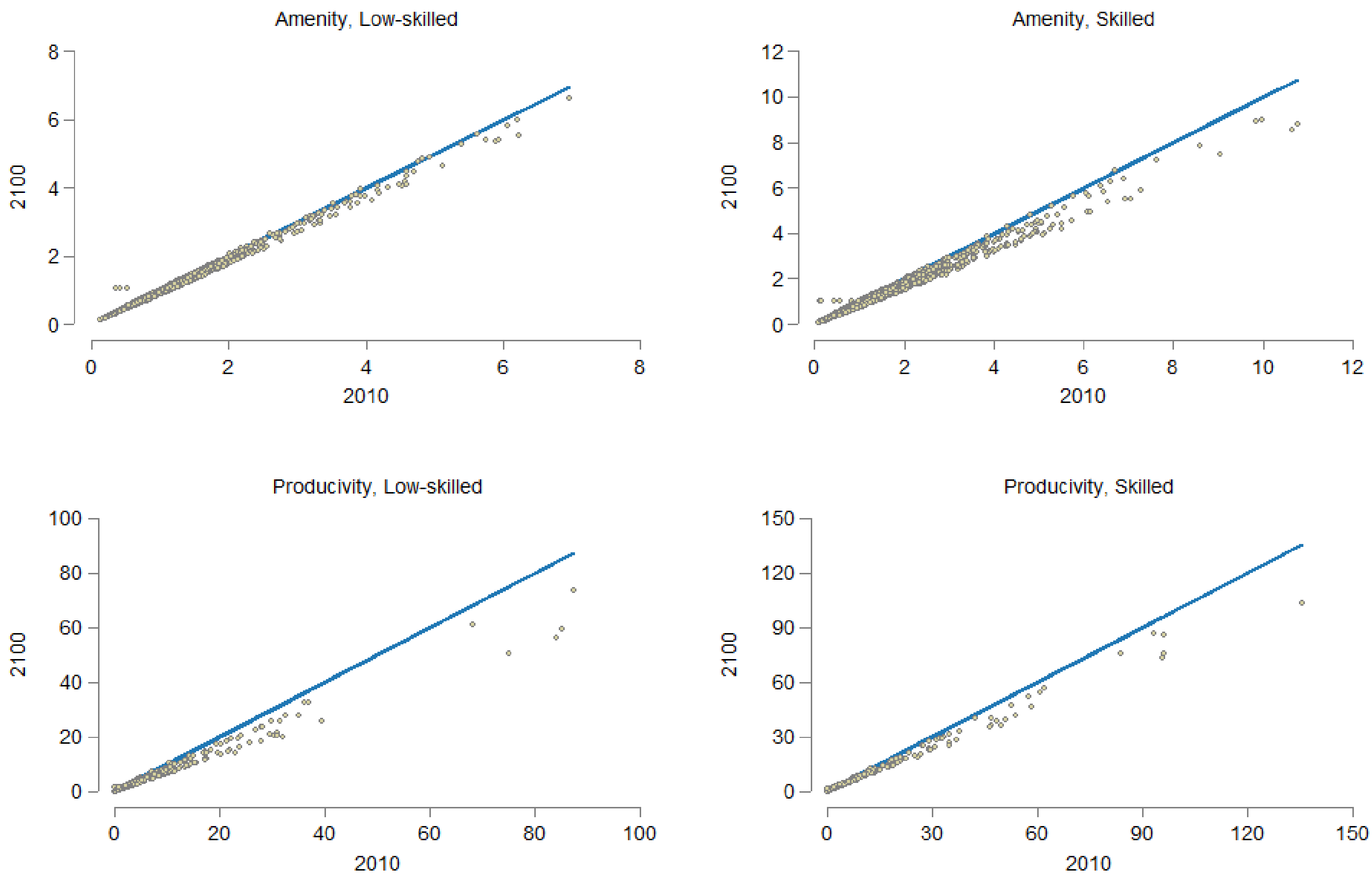


Panel B: **Degree Deviation from Expectations**



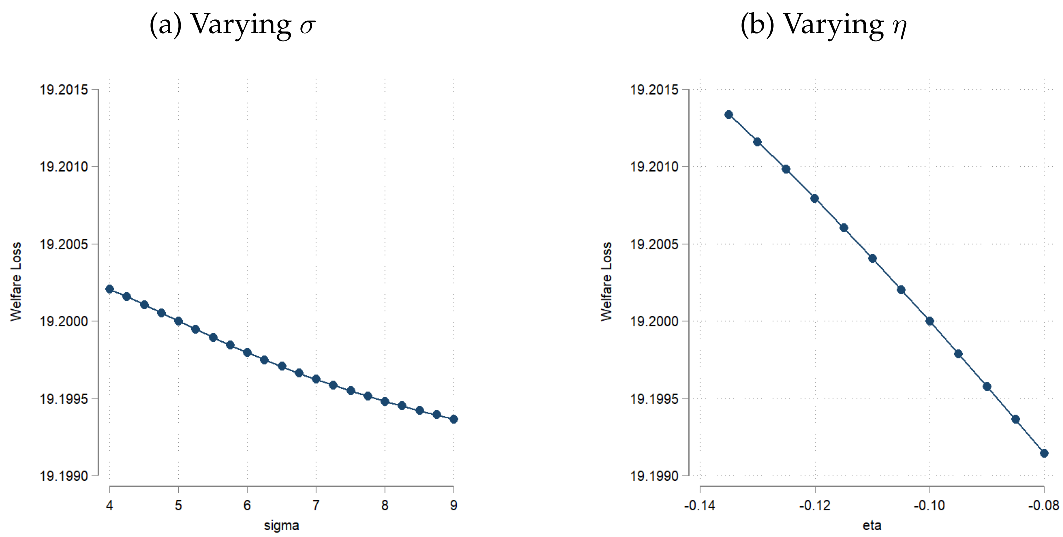
Notes: This figure shows the distribution of yearly average temperatures of each municipality for 2000 and 2010. Panel A presents annual municipality averages calculated from monthly averages. Panel B displays the degree deviation from a municipality's own 20-year long-run average. Statistics are based on observed temperatures from TerraClimate for 2010, while forecasted temperatures are sourced from NEX-GDDP.

Figure 1.8: Structural Parameters, 2100 vs 2000



Notes: This figure maps the relationship between location fundamentals in 2010 and 2100. Each dot represent the values for each municipality. Out of sample changes to exogenous productivities and amenities are based on forecasted temperatures from the average of RCP 4.5 and RCP 8.5, along with the climate semi-elasticities in Table 1.7.

Figure 1.9: Welfare Effects of Climate Change in 2100: Varying Parameters



Notes: This figure plots the welfare loss on the y-axis for different simulations undertaken with different parameter values, where values are listed on the x-axis. Results of each simulation are indicated by separate points on the graph. In each panel, a single parameter is varied (listed in the panel title) and all other parameters are held constant at values taken from Table 1.4.

A Appendix Tables And Figures

Table A1: Effect of Weather on Migration Statistics

	All		Skilled		Unskilled	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Out-migration rates						
Average Temperature (°C)	0.2368*	0.2872**	0.1643*	0.1985*	0.2421*	0.2943**
	(0.1238)	(0.1375)	(0.0933)	(0.1030)	(0.1264)	(0.1412)
Within R^2	0.002	0.079	0.256	0.306	0.003	0.081
Dependent Variable: In-migration rates						
Average Temperature (°C)	0.0013*	0.0007	0.0030**	0.0026*	-0.0018*	-0.0020*
	(0.0008)	(0.0007)	(0.0015)	(0.0014)	(0.0010)	(0.0010)
Within R^2	0.049	0.295	0.426	0.480	0.732	0.735
Dependent Variable: Net-migration rates						
Average Temperature (°C)	0.0002	-0.0006**	0.0008	0.0006	0.0000	-0.0009***
	(0.0003)	(0.0002)	(0.0006)	(0.0006)	(0.0003)	(0.0003)
Within R^2	0.037	0.136	0.330	0.336	0.003	0.158
Observations	3,200	3,200	3,200	3,200	3,200	3,200
Lagged Dependent Variable	Y	Y	Y	Y	Y	Y
Log Population Controls	N	Y	N	Y	N	Y
Year FE (2)	Y	Y	Y	Y	Y	Y
Province FE (81)	Y	Y	Y	Y	Y	Y
Municipal FE (1,600)	Y	Y	Y	Y	Y	Y

Notes: This table presents the regression coefficients of average temperatures on migration rates. Observations are at the municipality-year level. Each column represents a different dependent variable based on the migration statistics of a specific subgroup indicated in the columns. Table A2 presents the corresponding results without the lags. Clustered standard errors at municipality-level are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A2: Effect of Weather on Migration Statistics, No Lagged Controls

	All		Skilled		Unskilled	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Preferred Climate Measurement						
	Dependent Variable: Out-migration rates					
Δ Temperature (°C)	0.0466**	0.0384**	0.0300*	0.0244*	0.0471**	0.0388**
	(0.0215)	(0.0178)	(0.0164)	(0.0145)	(0.0218)	(0.0180)
Within R^2	0.000	0.002	0.000	0.001	0.000	0.002
	Dependent Variable: In-migration rates					
Δ Temperature (°C)	-0.0007	0.0019**	-0.0004	0.0003	-0.0003	0.0016**
	(0.0009)	(0.0008)	(0.0003)	(0.0003)	(0.0007)	(0.0006)
Within R^2	0.000	0.094	0.000	0.026	0.000	0.075
	Dependent Variable: Net-migration rates					
Δ Temperature (°C)	0.0004	0.0017	0.0002	0.0015	0.0005	0.0018
	(0.0012)	(0.0016)	(0.0010)	(0.0012)	(0.0012)	(0.0017)
Within R^2	0.000	0.065	0.000	0.056	0.000	0.065
Panel B: Standard Climate Measurement						
	Dependent Variable: Out-migration rates					
Average Temperature (°C)	0.1447**	0.1253**	0.0773*	0.0635*	0.1482**	0.1288**
	(0.0666)	(0.0588)	(0.0429)	(0.0382)	(0.0680)	(0.0600)
Within R^2	0.001	0.002	0.001	0.001	0.001	0.002
	Dependent Variable: In-migration rates					
Average Temperature (°C)	-0.0026	0.0042	-0.0022***	-0.0004	-0.0007	0.0043*
	(0.0028)	(0.0030)	(0.0006)	(0.0007)	(0.0022)	(0.0023)
Within R^2	0.000	0.094	0.001	0.026	0.000	0.076
	Dependent Variable: Net-migration rates					
Average Temperature (°C)	-0.0028***	0.0007	-0.0028**	0.0004	-0.0028***	0.0008
	(0.0010)	(0.0016)	(0.0013)	(0.0016)	(0.0009)	(0.0017)
Within R^2	0.001	0.065	0.001	0.055	0.001	0.064
Observations	4,800	4,800	4,800	4,800	4,800	4,800
Log Population Controls	N	Y	N	Y	N	Y
Year FE (3)	Y	Y	Y	Y	Y	Y
Province FE (81)	Y	Y	Y	Y	Y	Y
Municipal FE (1600)	Y	Y	Y	Y	Y	Y

Notes: This table presents the regression coefficients of climate variables on migration rates. Panel A reports the coefficients when using temperature deviation from a municipality's own 20-year long-run moving average. Panel B considers the climate measurement of using temperature averages. Observations are at the municipality-year level. Each column represents a different dependent variable based on the migration statistics of a specific subgroup indicated in the columns. Clustered standard errors at municipality-level are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A3: Migration gravity, Robustness

	(1) All	(2) Skilled	(3) Low-skilled
Log Distance	-2.425***	-2.423***	-2.432***
	(0.021)	(0.021)	(0.021)
Baseline Controls	N	N	N
Origin-Year FE	Y	Y	Y
Destination-Year FE	Y	Y	Y
N	7,680,000	7,680,000	7,680,000
N Municipalities	1,600	1,600	1,600
N Years	3	3	3
Wald χ^2	13491	12947	13418
Pseudo R^2	0.824	0.817	0.825

Notes: This table estimates the distance elasticity of migration. Two-way clustered standard errors by origin-municipality and destination-municipality are reported in parentheses. Estimates are obtained from Poisson Pseudo Maximum Likelihood regressions with multiway fixed effects, as described by Correia, Guimarães, and Zylkin (2020). $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A4: Migration gravity, cross-sectional estimates

	(1) All	(2) Skilled	(3) Low-skilled
	Panel A: 1990 only		
Log Distance	-1.205***	-1.140***	-1.221***
	(0.058)	(0.079)	(0.059)
Wald χ^2	25,537	18,648	24,504
Pseudo R^2	0.790	0.784	0.791
	Panel B: 2000 only		
Log Distance	-1.265***	-1.218***	-1.278***
	(0.046)	(0.045)	(0.047)
Wald χ^2	78,367	68,522	77,398
Pseudo R^2	0.843	0.835	0.845
	Panel C: 2010 only		
Log Distance	-1.201***	-1.170***	-1.212***
	(0.030)	(0.033)	(0.031)
Wald χ^2	93,144	80,229	94,128
Pseudo R^2	0.850	0.843	0.852
N Municipalities	1,600	1,600	1,600
N Municipal Pairs	2,560,000	2,560,000	2,560,000
Baseline Controls	Y	Y	Y
Origin FE	Y	Y	Y
Destination FE	Y	Y	Y

Notes: This table estimates the distance elasticity of migration. Same island is a dummy that equals one when municipality-pairs are not separated a body of water. Same province is a dummy that takes a value of one if location pairs belong to the same province. Hometown bias is a dummy that equals one for own-to-own migration flows. Differences in longitudes and latitudes are calculated from the centroids of each municipality. Two-way clustered standard errors by origin-municipality and destination-municipality are reported in parentheses. Estimates are obtained from Poisson Pseudo Maximum Likelihood regressions with multiway fixed effects, as described by Correia, Guimarães, and Zylkin (2020). $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A5: Effect of weather shocks on log wages

	(1) All	(2) Skilled	(3) Unskilled	(4) Non-agri	(5) Agri
Panel A: Standard climate measures					
Avg. temperature ($^\circ C$)	-0.0236***	-0.0077	-0.0277***	-0.0316***	-0.0148
	(0.0073)	(0.0125)	(0.0080)	(0.0101)	(0.0090)
Pseudo R^2	0.606	0.488	0.588	0.530	0.580
F-stat	2682.32	755.24	1804.05	1197.67	139.11
Panel B: Anomalies from own 20-year long-run moving average					
Δ Temperature ($^\circ C$)	-0.0817*	-0.0086	-0.1249**	-0.0361	-0.1543***
	(0.0482)	(0.0742)	(0.0502)	(0.0611)	(0.0516)
Pseudo R^2	0.606	0.488	0.588	0.530	0.580
F-stat	2685.70	753.78	1806.08	1145.70	142.32
Panel C: Panels A and B combined					
Avg. temperature ($^\circ C$)	-0.0215**	-0.0081	-0.0237**	-0.0330***	-0.0069
	(0.0087)	(0.0131)	(0.0099)	(0.0108)	(0.0108)
Δ Temperature ($^\circ C$)	-0.0368	0.0064	-0.0725	0.0250	-0.1373**
	(0.0546)	(0.0769)	(0.0608)	(0.0624)	(0.0631)
Pseudo R^2	0.606	0.488	0.588	0.530	0.580
F-stat	2470.98	680.16	1579.52	1054.91	142.08
Individual controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y
Municipal FE	Y	Y	Y	Y	Y
Clustered SE at Municipal-level	Y	Y	Y	Y	Y
No. Individuals	140,395	49,689	90,660	83,509	56,872

Notes: This table presents the regression coefficients of climate variables on log wages. Each column represents a subsample of the working population. Observation is at the individual-year level. All regressions include individual characteristics which consist of gender, work experience and its squared term, dummies for living in an urban area, high-school level completion, and college degree holder. Clustered standard errors at municipality-level are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A6: Effect of Climate on Location Fundamentals

	Amenity		Productivity	
	Skilled	Low-Skilled	Skilled	Low-Skilled
Δ °C relative to long-run average	-0.6171*	-0.3695	-0.6409*	-1.0772**
	(0.2918)	(0.2347)	(0.3295)	(0.4384)
Elevation (meters)	0.0011***	0.0005	0.0021***	0.0012
	(0.0003)	(0.0004)	(0.0004)	(0.0008)
Slope	0.0999***	0.0743***	0.1390***	0.1181***
	(0.0171)	(0.0162)	(0.0251)	(0.0295)
Distance to Permanent Water Sources (meters)	-0.0002***	-0.0000*	-0.0003***	-0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Terrain Ruggedness Index	-0.2155***	-0.1215***	-0.3011***	-0.1996***
	(0.0204)	(0.0269)	(0.0325)	(0.0498)
Bulk Density (kg/m3)	0.1361**	0.1252***	0.2683**	0.1892**
	(0.0504)	(0.0255)	(0.1003)	(0.0860)
Soil pH in H2O	0.2515	0.4373***	0.5047	0.8222**
	(0.1905)	(0.1470)	(0.3017)	(0.2928)
Overall Adjusted R^2	0.375	0.346	0.349	0.357
Within Adjusted R^2	0.208	0.177	0.166	0.137
Observations	3,200	3,200	3,200	3,200
No. Municipalities	1600	1600	1600	1600
Year Fixed Effects	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Clustered Std. Errors	Y	Y	Y	Y

Notes: Main measurement for temperature are anomalies from own 20-year long-run moving average. The dependent variables are log productivities and log amenities recovered from the model inversion process detailed in Section 1.7.4. Observation is at municipality-year for 2000 and 2010. Climate variables match the same reference year used for Census 2000 and 2010. Standard errors are clustered at region-level and reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A7: Effect of Climate on Location Fundamentals, Robustness

	Amenity		Productivity	
	(1) Skilled	(2) Low-Skilled	(3) Skilled	(4) Low-Skilled
A. No location fixed effects				
Δ °C relative to long-run average	-0.8015***	0.1260	-0.8433**	-1.0007***
	(0.1926)	(0.1543)	(0.3413)	(0.2968)
Overall Adjusted R^2	0.259	0.199	0.213	0.180
Within Adjusted R^2	0.260	0.198	0.213	0.180
Observations	3,200	3,200	3,200	3,200
Year Fixed Effects	Y	Y	Y	Y
Region Fixed Effects	N	N	N	N
B. Year = 2000				
Δ °C relative to long-run average	-2.1139	0.3896	-3.0486	1.4640
	(2.0914)	(1.1672)	(3.6981)	(3.4962)
Overall Adjusted R^2	0.367	0.336	0.322	0.320
Within Adjusted R^2	0.201	0.168	0.171	0.127
Observations	1,600	1,600	1,600	1,600
Region Fixed Effects	Y	Y	Y	Y
C. Year = 2010				
Δ °C relative to long-run average	-4.5374***	-4.7896***	-5.5402***	-8.3942***
	(2.0605)	(1.0512)	(3.6608)	(3.3482)
Overall Adjusted R^2	0.401	0.388	0.353	0.386
Within Adjusted R^2	0.240	0.226	0.173	0.187
Observations	1,600	1,600	1,600	1,600
Region Fixed Effects	Y	Y	Y	Y
D. Dependent Variable: Average value of 2010 and 2000				
Δ °C relative to long-run average	-4.0876***	-3.9721***	-6.0659***	-8.6568***
	(1.0427)	(0.7598)	(1.4837)	(1.8534)
Overall Adjusted R^2	0.416	0.396	0.358	0.384
Within Adjusted R^2	0.248	0.229	0.190	0.190
Observations	1,600	1,600	1,600	1,600
Region Fixed Effects	Y	Y	Y	Y
No. Municipalities	1,600	1,600	1,600	1,600
Controls: Natural Amenities	Y	Y	Y	Y
Clustered Std. Errors	Y	Y	Y	Y

Notes: This table shows the climate elasticities under different specifications indicated by the headers. Controls for natural amenities include elevation, slope, distance to water sources, ruggedness, soil bulk density and multi-scale topographic position index. Standard errors are clustered at the region-level and reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A8: Effect of Climate on Location Fundamentals: Alternative Specifications

	Amenity		Productivity	
	(1) Skilled	(2) Low-Skilled	(3) Skilled	(4) Low-Skilled
Panel A: Standard Climate Measure, Linear				
Avg. Temperature	-0.0625	-0.0414	-0.1317	-0.1926*
	(0.0422)	(0.0386)	(0.0766)	(0.0976)
Overall Adjusted R^2	0.393	0.387	0.367	0.405
Within Adjusted R^2	0.231	0.229	0.189	0.202
Panel B: Standard Climate Measure, Squared				
Avg. Temperature	-0.4033	-0.6727***	-0.6319	-1.4828**
	(0.4121)	(0.2080)	(0.7165)	(0.5395)
Avg. Temperature, squared	0.0055	0.0101**	0.0080	0.0207**
	(0.0068)	(0.0036)	(0.0116)	(0.0097)
Overall Adjusted R^2	0.393	0.390	0.367	0.408
Within Adjusted R^2	0.231	0.233	0.189	0.206
Panel C: Two Moments Combined				
Avg. Temperature	-0.0710	-0.0553	-0.1454	-0.2134
	(0.0564)	(0.0676)	(0.0837)	(0.1536)
Δ °C relative to long-run average	-0.5759*	-0.3470	-0.5583	-0.9776*
	(0.3207)	(0.2408)	(0.3663)	(0.5313)
Overall Adjusted R^2	0.382	0.356	0.358	0.377
Within Adjusted R^2	0.217	0.190	0.178	0.164
Observations	3,200	3,200	3,200	3,200
No. Municipalities	1,600	1,600	1,600	1,600
Controls: Natural Amenities	Y	Y	Y	Y
Region Fixed Effects	Y	Y	Y	Y
Clustered Std. Errors	Y	Y	Y	Y

Notes: Table presents alternative approaches to obtaining the effects of temperature on exogenous productivity and amenity. Panel A uses a linear specification of temperature while Panel B captures the non-linear effects of temperature by including a squared term. Panel C combines my preferred specification with the municipal-level average temperature as an additional control. Observation is at municipality-year level for 2000 and 2010. Climate variables match the same reference year used for Census 2000 and 2010. Controls for natural amenities include elevation, slope, distance to water sources, ruggedness, soil bulk density and multi-scale topographic position index. Standard errors are clustered at region-level and reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Table A9: Percentage Changes in Welfare and Output Different Climate Channels

	(1) Baseline	(2) Amenities fixed at 2010-levels	(3) Productivities fixed at 2010 levels	(4) (1) + No Sea-Level Rise
Welfare, aggregate	-19.9	-20.3	-20.0	-19.2
Welfare, skilled	-16.7	-16.1	-17.2	-16.6
Welfare, low-skilled	-22.6	-24.0	-21.4	-22.4
Inequality	7.5	10.5	5.5	6.1
Output, aggregate	-14.2	-16.0	-12.7	-12.1
Output, skilled	-12.9	-12.9	-13.0	-10.1
Output, low-skilled	-15.5	-17.8	-12.5	-13.2

Notes: Table shows the percentage change in welfare, output, and inequality given out-of-sample changes to location fundamentals. Each column presents the percentage effects relative to 2010 levels under varying mechanisms on how climate affects the economy. Column 1 reports the baseline scenario consistent with the model presented in Section 1.5 whereby climate affects both amenity valuation and total factor productivity. Column 2 limits the impact of climate on productivity while Column 3 limits the impact of climate on amenities. Columns 2 and 3 consider the effects of sea-level rise. The last column re-simulates the baseline case absent the impacts of sea-level rise on land inundation.

Table A10: Labor Reallocation Across Area Types

		Δ %			
	(1) 2010 Population Distribution	(2) Baseline	(3) Amenities fixed	(4) Productivities fixed	(5) w/o Sea-Level Rise
Skilled Population Share (%) in...					
Poor Municipality	10.7	-3.4	-0.2	+1.2	+0.0
Coastal	74.5	-2.5	-2.1	-7.4	+0.3
Coastal x Poor	2.3	-0.9	+0.0	+0.5	+4.2
Urban	55.9	-12.8	+2.3	-12.3	-9.5
Low-skilled Population Share (%) in...					
Poor Municipality	22.7	+3.0	+1.2	+2.8	+1.2
Coastal	71.7	-6.3	-0.8	-5.3	-1.0
Coastal x Poor	6.1	+0.8	+0.8	+0.7	+0.6
Urban	40.8	-10.0	-1.8	-8.8	-3.2

Notes: Table shows the labor reallocation of skilled and low-skilled workers by area classification. The distribution of municipalities by each of these mutually independent categories are presented in Table A11. Column 1 shows the initial percentage shares in the initial period of 2010. Correspondingly, this distribution reflects the underlying labor allocation for Column 3 in Table 1.8. Column 1 reports the baseline scenario consistent with the model presented in Section 1.5 whereby climate affects both amenity valuation and total factor productivity. Column 2 limits the impact of climate on productivity while Column 3 limits the impact of climate on amenities.

Table A11: Distribution of Municipalities by Area Classification Types

	Count		%	
	0	1	0	1
Area Type				
Poor Municipality	1016	584	63.5	36.5
Coastal Areas	1045	555	65.3	34.6
Coastal x Poor	1441	159	90.1	9.9
Urban	1410	190	88.1	11.9

Notes: This table presents a tabulation of municipalities by area category. A municipality is classified as *poor* if its rate of poverty incidence rate above 40%. I took the poverty incidence rates as given from FIES 2009. Municipalities are considered coastal if it has any area where land meets the ocean. *Coastal x Poor* are simply the interaction of the first two rows, and municipalities are considered urban if they belong to are classified by the National Statistics Office (NSO) as either: highly urbanized city, independent component city, and local component city.

Table A12: Percentage Changes in Welfare and Output under Different Projections

	2100			2050
	(1) Baseline	(2) Worst-case RCP8.5	(3) Best-case RCP 4.5	(4) Average
Welfare, aggregate	-19.9	-20.9	-21.4	-15.5
Welfare, skilled	-16.7	-17.7	-15.1	-10.6
Welfare, low-skilled	-22.6	-23.8	-22.1	-19.8
Inequality	7.5	7.9	9.0	11.4
Output, aggregate	-14.2	-14.5	-14.2	-9.9
Output, skilled	-12.9	-13.1	-12.9	-9.9
Output, low-skilled	-14.1	-12.8	-15.4	-10.0

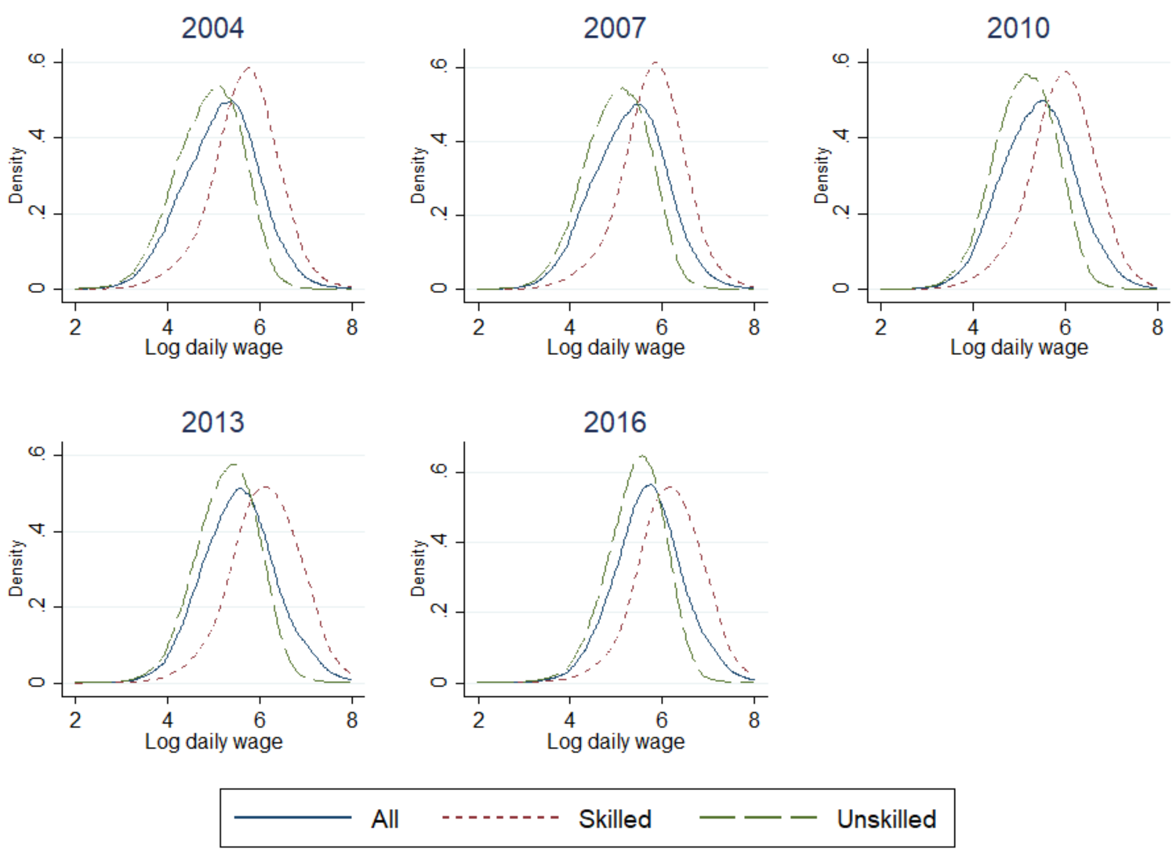
Notes: Table shows the percentage decrease in welfare, output, and inequality given out-of-sample changes to location fundamentals. Columns 2 and 3 consider out of sample changes to exogenous productivities and amenities are based on forecasted temperatures from the average of RCP 8.5 and RCP 4.5, respectively. Column 4 reports the counterfactual baseline welfare losses using the average 2050 climate profiles of RCPs 2.5 and 8.5.

Table A13: Labor Reallocation Across Area Types, with Adaptation

		Δ %		
	(1) 2010 Population Distribution	(2) Baseline	(3) (2) + Coastal Protection	(4) (2) + New Inland City
Skilled Population Share (%) in...				
Poor Municipality	10.7	-3.4	+1.1	+3.0
Coastal	74.5	-2.5	-3.0	-2.8
Coastal x Poor	2.3	-0.9	+0.2	-0.1
Urban	55.9	-12.8	-9.0	-9.7
Low-skilled Population Share (%) in...				
Poor Municipality	22.7	+3.0	+0.7	+3.4
Coastal	71.7	-6.3	-4.0	-0.8
Coastal x Poor	6.1	+0.8	+1.1	+0.8
Urban	40.8	-10.0	-6.1	-8.3

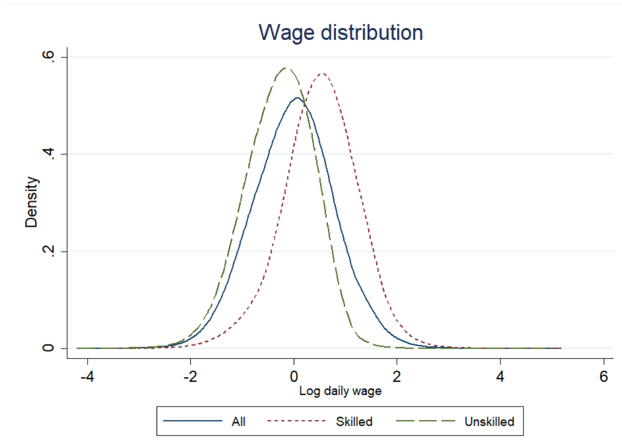
Notes: Table shows the labor reallocation of skilled and low-skilled workers by area classification. The distribution of municipalities by each of these mutually independent categories are presented in Table A11. Column 1 shows the initial percentage shares in the initial period of 2010. Correspondingly, this distribution reflects the underlying labor allocation for Column 3 in Table 1.8. Columns 2 to 5 show the percentage changes relative to the initial population share in Column 1. Columns 2 and 3 are simply the baseline model that considers the effects temperatures in 2100, with and without consideration of sea-level rise. Columns 4 and 5 separately considers climate mitigating strategies of building up coastal resilience on the nation's three largest urban agglomeration, and improving location fundamentals of a new city 80km north of the capital.

Figure A1: Log wages from Labor Force Surveys



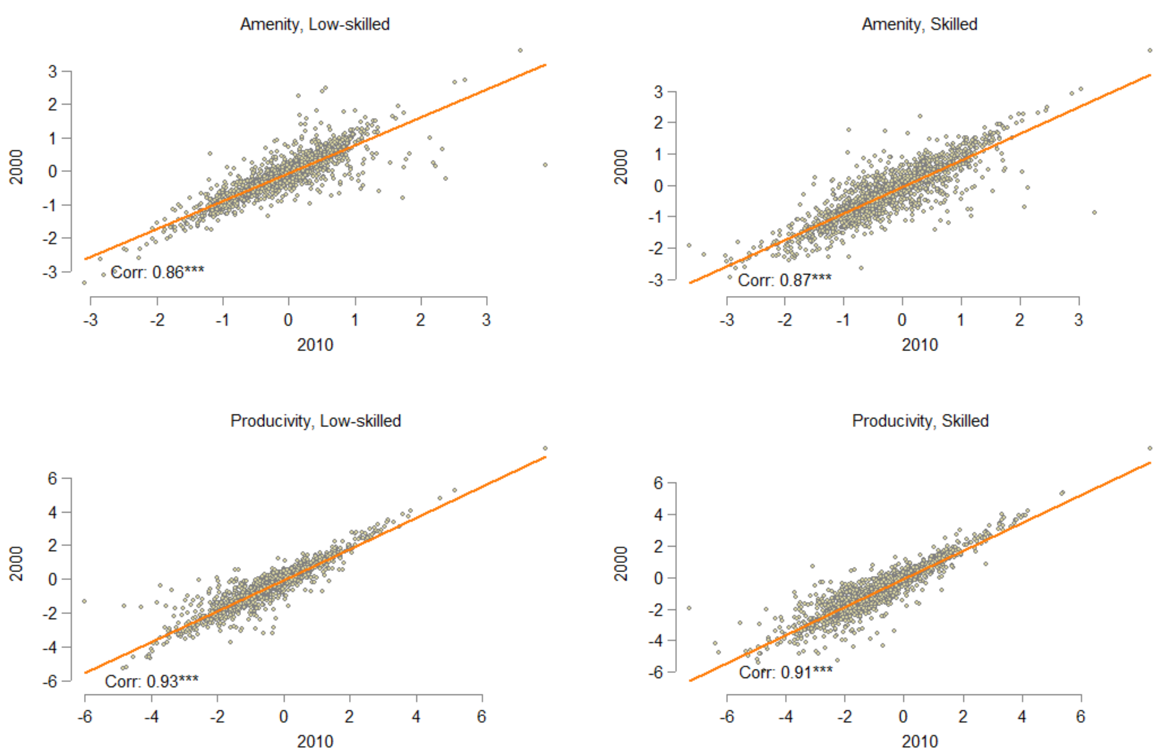
Notes: This figure shows the distribution of cross-sectional wages for each skill-group. Unit of observation is the individual. Source: LFS 2004, 2007, 2010, 2013, 2016

Figure A2: Log wages, pooled



Notes: This figure presents a pooled measurement of wages (log) after purging out year fixed effects. Source: LFS 2004, 2007, 2010, 2013, 2016

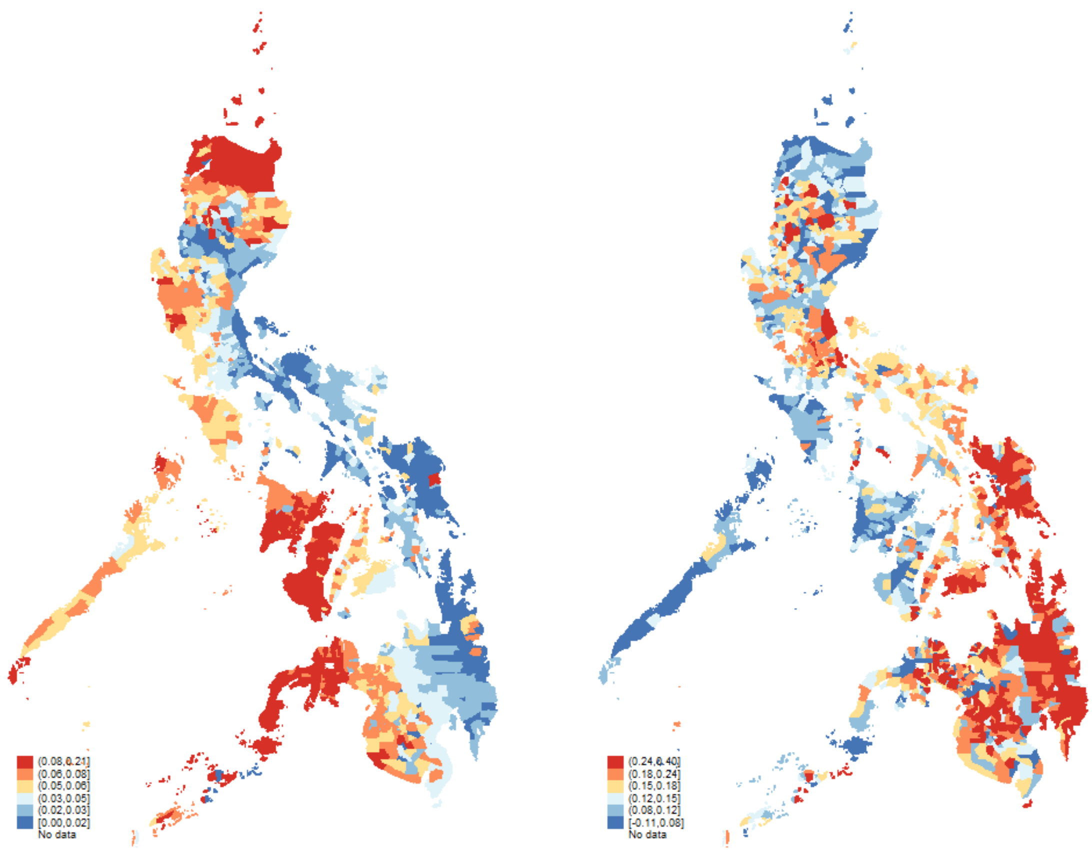
Figure A3: Location Fundamentals From Model Inversion, 2000 vs 2010



Notes: This figure maps the correlation between the recovered log location fundamentals in 2010 and 2000. Each dot represent the values for each municipality.

Figure A4: Temperature Profiles for 2010 and 2100 in Temperature Deviations (°C)

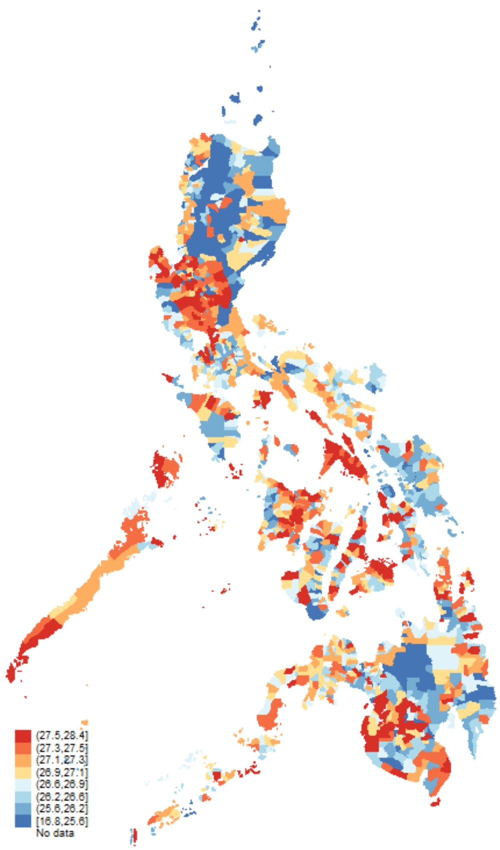
(a) 2010 (b) Δ (2100-2010)



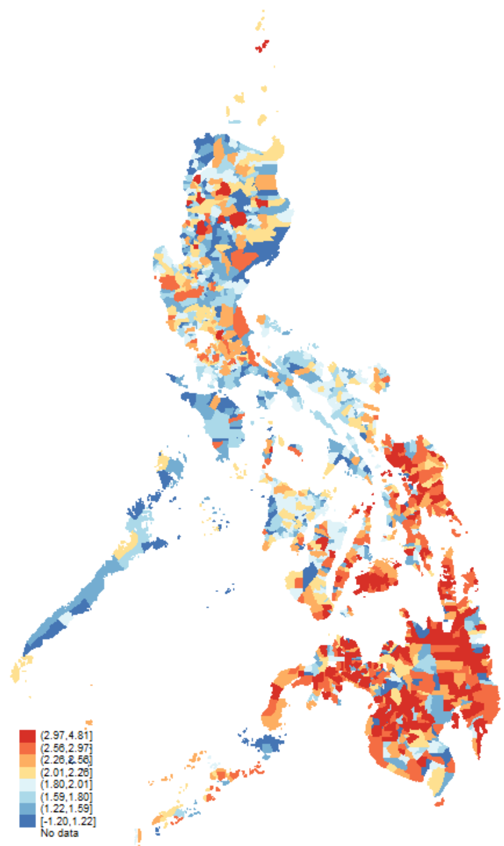
Notes: This figure maps the spatial distribution of temperature deviations from the historical norm in the Philippine. Darker shades of red (blue) denote higher (lower) values. Panel A shows the values for 2010, while Panel B presents the forecasted differences in 2100 relative to 2010. Regions in red (blue) will relatively have unpredictable (reliable) climate patterns than the rest of the country. Temperature deviation are with respect to a municipality's own long-run 20 year average.

Figure A5: Temperature Profiles for 2010 and 2100 in °C

(a) 2010



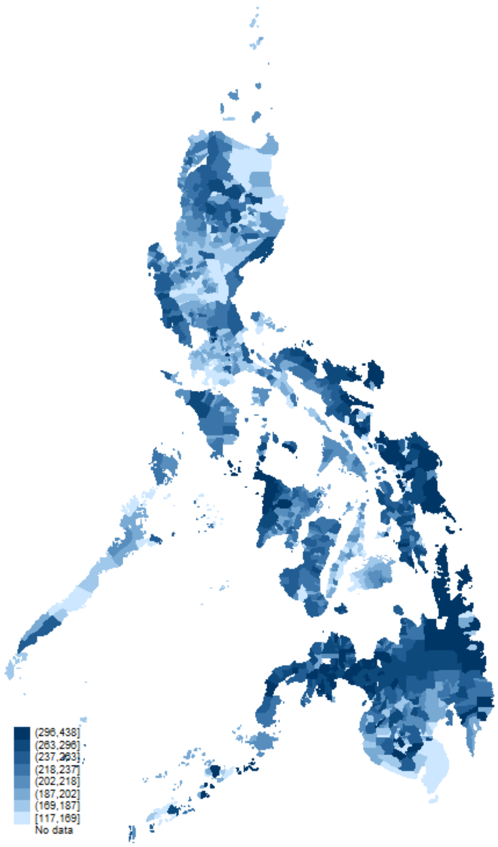
(b) Δ (2100-2010)



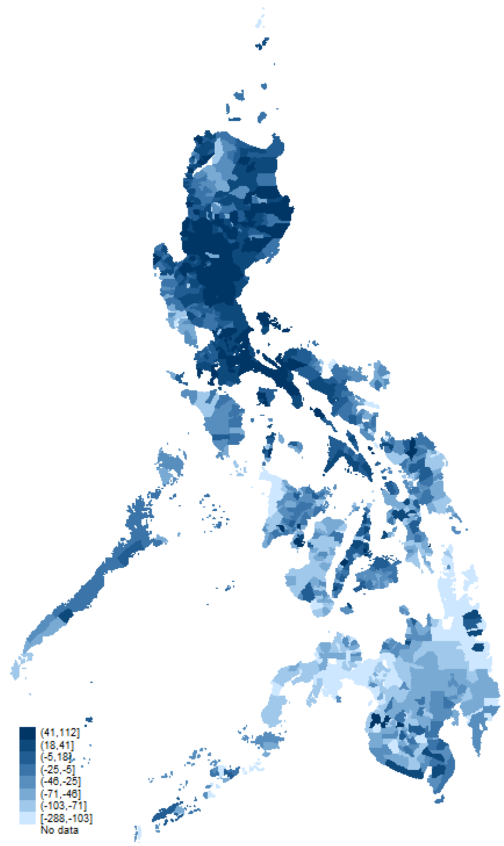
Notes: This figure maps the spatial distribution of average temperatures in the Philippine. Darker shades of red (blue) denote higher (lower) values. Panel A shows the annual average for 2010, while Panel B presents the forecasted difference temperatures in 2100 relative to 2010. Most municipalities will see an increase in temperature. Regions in blue will be relatively cooler than the rest of the country. A corresponding map of rainfall patterns is supplied in Table A6.

Figure A6: Annual average accumulated precipitation for 2010 and 2100 in millimeters

(a) 2010



(b) Δ millimeters in 2100 relative to 2010



Notes: This figure maps the spatial distribution of average yearly accumulated rainfall in the Philippines. Darker shades of blue denote higher values. Panel A shows the annual average for 2010, while Panel B presents the forecasted difference in 2100 relative to 2010.

Figure A7: Labor Allocation for Baseline Counterfactuals

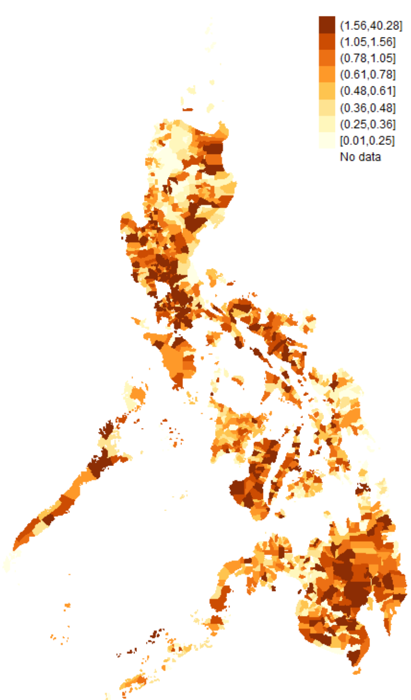
Panel A: **Skilled Workers**

(a) 2010

(b) 2100

Panel B: **Low-skilled Workers**

(c) 2010

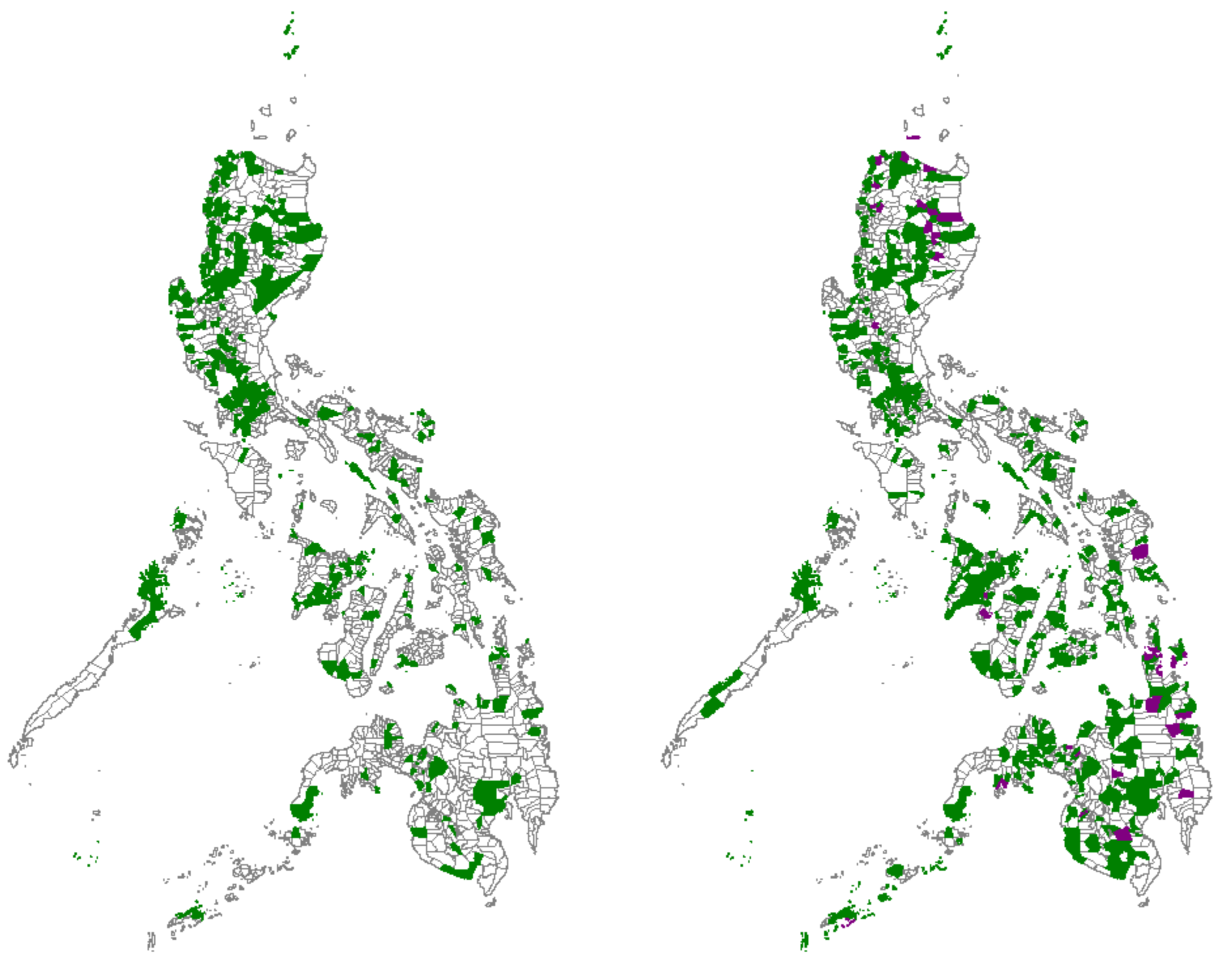


(d) 2100

Notes: This figure maps the spatial allocation of low-skilled and skilled labor. Values are normalized to within-year means. Darker shades of denote higher values.

Figure A8: Skilled Municipalities Across the Country

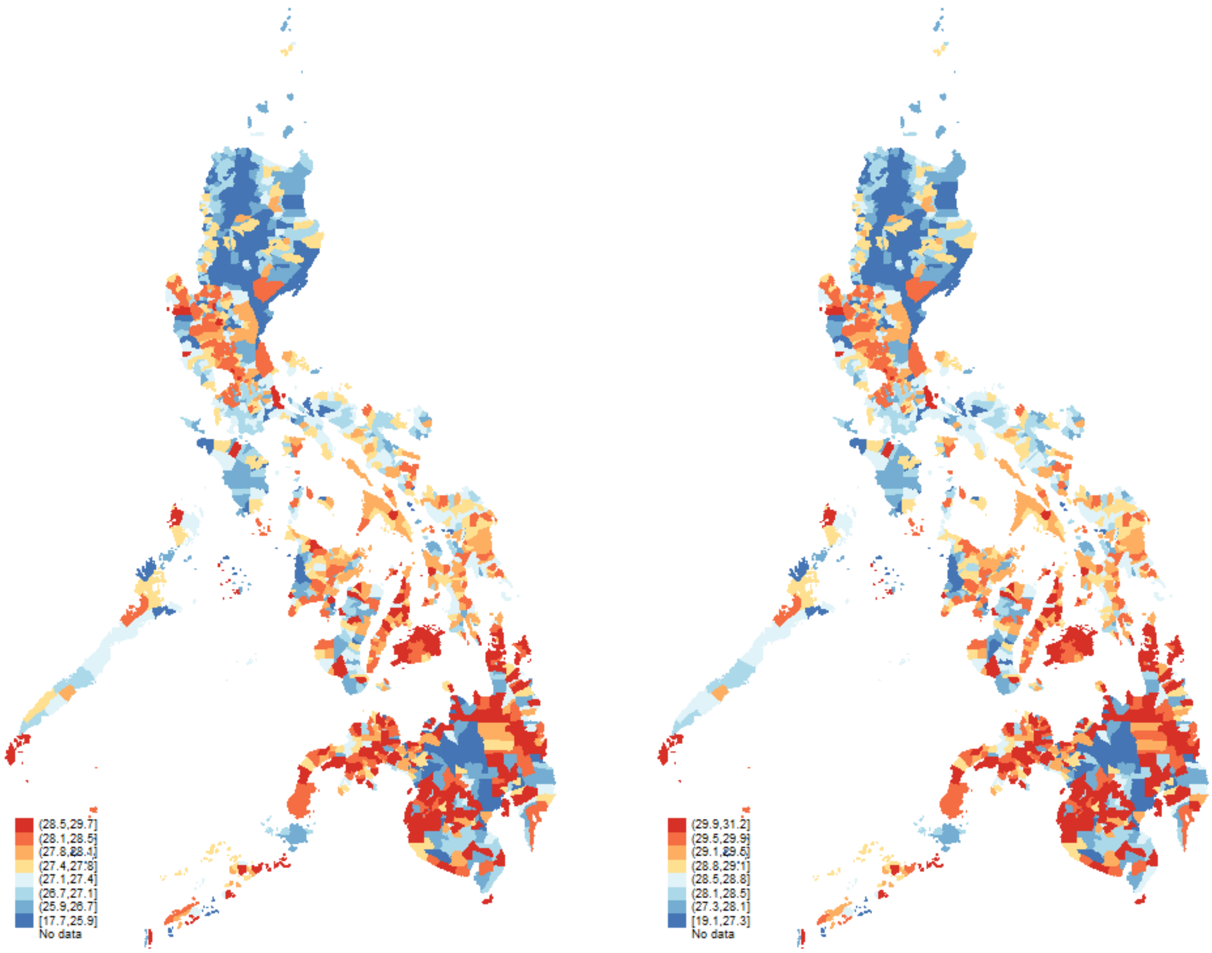
(a) 2010 (b) 2100



Notes: This figure presents in green the localities where skilled working population shares are higher or equal to the national share (34%). Panel A maps the local skill composition in the baseline economy without climate change, while Panel B presents the corresponding information for in 2100 when climate affects both productivity and amenities. In Panel B, areas in purple are the marginal municipalities that breached the skill-share threshold due to either adaptation strategies of coastal adaptation or creating a new city inland.

Figure A9: Temperature Profiles for 2050 and 2100 in °C

(a) 2050 (b) 2100



Notes: This figure maps the spatial distribution of average temperatures in the Philippine. Darker shades of red (blue) denote higher (lower) values. Panel A shows the annual average for 2050, while Panel B shows the 2100 values.

B Model Appendix

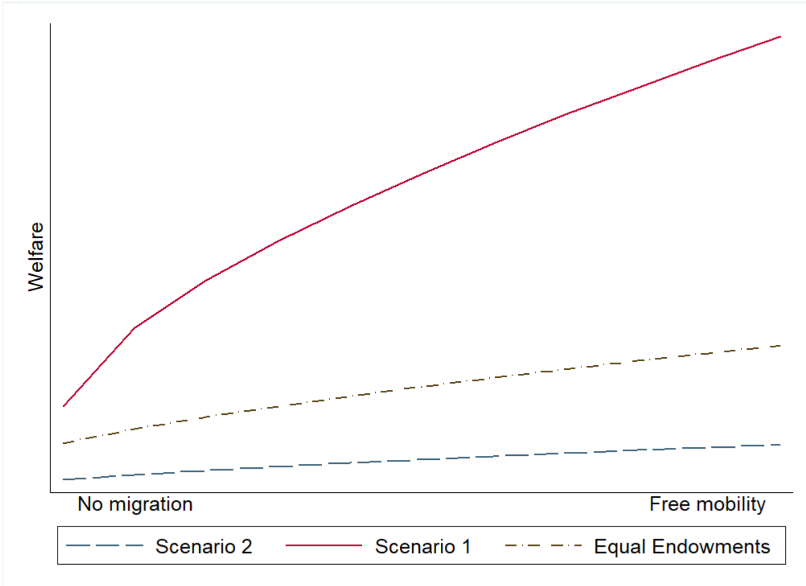
B1. Simple Two Location Case

I consider an alternative exercise that underscores the role of mobility on aggregate welfare when there are heterogenous skill types. To do so, I consider three scenarios under varying assignments of location fundamentals that remain fixed throughout the different levels of migration costs. As a baseline case, I set equal endowments such that $A_1^g = A_2^g$ and $B_1^g = B_2^g$ for $g \in \{U, H\}$. Hence, sorting of low-skill and high-skill workers are simply governed by responses to trade and migration frictions on prices and wages. This equal endowment setting minimizes the role of geography on a location's productivity and attractiveness. However, since congestion and agglomeration forces also come into play, population for both locations equalize in the absence of migration costs ($L_1^H = L_1^U = L_2^H = L_2^U$).

I simulate another scenario - which I'll call *Scenario 1*, where locations hold strong competitive advantage towards a specific sector or skill-type. I set this up such that endowments appropriate for skill g is mutually exclusive to one region. For example, location 1 exhibits cooler temperatures with soil that is more like a bedrock, while location 2 have a temperate climate and possesses soil ideal for crops. In this case, location 1 is unabashedly desirable for high-type workers since $A_1^H > A_2^H$ and $B_1^H > B_2^H$. Correspondingly, location 2 attracts low-skilled workers since $A_2^U{>}A_1^U$ and $B_2^U > B_1^U$. Strong sorting patterns are exhibited here due to dominant preferences for geographic-specific amenities. In addition, match-productivity reinforces the pull of particular locations through its effect on welfare via wages. This imply that migration costs are of paramount. Figure B1 illustrates that removing barriers to mobility have consequential welfare effects.

Finally, I offer a competing case - *Scenario 2*, where the endowments are distributed accordingly: (i) $A_1^H > A_2^H$, (ii) $B_1^H < B_2^H$, (iii) $A_1^U < A_2^U$, (vi) $B_1^U > B_2^U$. Workers face a choice between attractive amenities or high wages in each location. Trade-offs are a feature in this exercise such that no agent can win on all fronts. Since amenities and productivities are affecting welfare in opposite directions, a bit more ambiguity is expected here. Figure B1 suggests that adjusting migration costs have negligible implications on welfare.

Figure B1: Aggregate Welfare Against Migration Frictions



B2. Derivation of Equilibrium Conditions

The general equilibrium can be characterized by a system of equations. From the goods market clearing in Eq. 1.16 and the definition of prices in Eqs. 1.12 and 1.4, we have:

$$\sum_g w_{dg}L_{dg} = \sum_g \sum_{n\in N} \left(\frac{\tau_{dn}w_{dg}}{T_{dg}}\right)^{1-\sigma} P_{ng}^{\sigma-1}\beta_g \left(\sum_g w_{ng}L_n^g\right), \tag{1.20}$$

$$P_{ng} = \left(\sum_{d\in N} \tau_{nd}^{1-\sigma}\left(\frac{w_{dg}}{T_d^g}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}},$$

From the labor market clearing using Eqs.1.6 and 1.7, we have:

$$L_{dg} = \sum_{n\in N} \frac{[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_g P_{dg}^{\beta_g})]^{-\theta_g}}{\sum_{d\in N}[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_g P_{dg}^{\beta_g})]^{-\theta_g}} L_{ng} \quad \forall g. \tag{1.21}$$

Simplifying total income as $I_n = \sum_g w_n^g L_n^g$, I can rewrite Eq. 1.20 in terms of prices

$$I_d = \sum_g \sum_{n\in N} \tau_{dn} p_d^{1-\sigma} P_n^{g\sigma-1}\alpha_g I_n, \tag{1.22}$$

Meanwhile, the denominator in the migration probability can be expressed as

$$W_{ng} = \left(\sum_{d\in N}[B_{dg}w_{dg}]^{\theta_g}[\mu_{ndg}(\prod_g P_{dg}^{\beta_g})]^{-\theta_g}\right)^{1/\theta_g}, \tag{1.23}$$

to denote the welfare of migrants from n as a CES aggregate of their utility for all possible locations. By similar logic, the numerator can be written as a function of welfare of residents who reside in d as

$$\omega_{dg} = \frac{B_{dg} w_{dg}}{\prod_g (P_{dg})^{\beta_g}} \tag{1.24}$$

such that Eq. 1.21 becomes equivalent to:

$$L_{dg} = \sum_n \mu_{ndg}^{-\theta_g} \left(\frac{\omega_{dg}}{W_{ng}} \right)^{\theta_g} L_{ng} \tag{1.25}$$

Rearranging Equations (1.22)-(1.25) yield the systems of equations in Section 1.9.

B3. Model Inversion

The process follow a similar procedure outlined in Allen and Arkolakis (2018) to get local composites of prices and welfare. I rearrange Equations 1.6, and 1.7, 1.12, 1.4 and 1.16 to express the endogenous objects $\{p_{dg}, P_{dg}, \omega_d^g, W_{dg}\}$ in the left-hand side as:

$$p_{dg} = \left(\sum_{n \in N} \tau_{dn}^{1-\sigma} (P_{ng})^{\sigma-1} \beta_g \frac{I_n}{I_d} \right)^{\frac{1}{\sigma-1}} \tag{1.26}$$

$$P_{dg} = \left(\sum_{n \in N} \tau_{nd}^{1-\sigma} (p_{ng})^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{1.27}$$

$$\omega_{dg} = \left(\sum_{n} \mu_{ndg}^{-\theta_g} \left(\frac{L_{ng}}{L_{dg}} \right) (W_{ng})^{-\theta_g} \right)^{-1/\theta_g} \tag{1.28}$$

$$W_{dg} = \left(\sum_{d \in N} \mu_{dng}^{-\theta_g} \omega_{ng}^{\theta_g} \right)^{1/\theta_g}, \tag{1.29}$$

where

$$\omega_{dg} = \frac{B_{dg} w_{dg}}{\prod_g (P_d^g)^{\beta_g}} \quad \text{and} \quad W_{ng} = \left(\sum_{d \in N} [B_{dg} w_{dg}]^{\theta_g} [\mu_{ndg} (\prod_g P_{dg}^{\beta_g})]^{-\theta} \right)^{1/\theta_g}.$$

With these equations at hand, I can recover the unobserved parameters given empirical data on migration flows, residualized wages, and population.

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Chapter 2

Gender Norms and Child Penalties

2.1 Introduction

Observed gender differences in labor market outcomes have steadily declined over the last century. A key channel for why this is the case can be explained by the evolution of gender roles and the attitude shift in female identity with regards to work (Goldin, 2006). As more women find purpose in their careers, female educational attainment and employment participation are rising to match the levels of their male counterparts. But parity has yet to come to fruition. Since the 1990s, convergence in male-to-female earnings has plateaued to levels between 80 and 82% in the United States (Chung et al., 2017).

A compelling explanation to the persistent gender gap can be attributed to the role of women as part of the family unit. A sizeable body of work finds the impact of children to be responsible - with females having lower participation and earnings post-birth (Adda et al., 2017; Daniel et al., 2013; Anderson, 2008). It also becomes apparent that gender wage disparities tend to increase around the female child-bearing age of 25 to 40 years (Goldin, 2014). This phenomenon is known in the literature as "motherhood penalties" since similar impacts on male labor outcomes are not observed among male parents.[1] Despite controlling for differences in human capital, occupational choice, and work histories, a portion of the gender gap still remains unexplained (Altonji and Blank, 1999; Olivetti and Petrongolo, 2017). The disproportionate impact of children by gender is likely driven by the division of responsibilities in the household, where child care typically falls on women (Blau et al., 2020).

These trends motivate a possible source of heterogeneity on the impact of children on female wages and participation. While the role of attitudes and norms is always lurking in the background, more can be done to establish the empirical relevance of these factors to the persistent inequalities we observe in the labor market (Marianne, 2011). Cultural norms and societal expectations may perpetuate gender imbalances if they are strong enough to induce self-imposed barriers to workforce engagement (Alesina et al., 2013). Compliance to gender-specific roles at the onset of parenthood may also partly explain the diverging labor outcomes across mothers and childfree women (Blau and Kahn, 1995).[2]

In this regard, this paper seeks to examine how gender attitudes affect the impacts of children on labor market outcomes. My gender norms measure is taken from the attitudes module of the National Longitudinal Survey of Youth (NLSY) in 1979. I assign all respondents a score based on their self-reported assessment on questions pertaining to women's roles in the household, family, and workplace. I then group these individuals into one of the three gender-norm categories of *Modern*, *Neutral*, and *Traditional*– by doing so, I compare employment effects of parenthood for males and females who share similar

[1] I opt to use the gender-neutral "child penalties" for the remainder of this paper.
[2] The reductions in earnings inequality did not happen uniformly across all females. In the US, the estimated female-to-male earnings ratio for married women with children is significantly lower at 0.57, compared to 0.88 for single women without child. (Blau and Kahn, 1995)

propensities for work and family. Intuitively, parents with modern gender norms should have a more equitable division of domestic responsibilities if such beliefs are truly binding into adulthood. Hence, my analysis indirectly checks if deviation from traditional gender beliefs is associated with male-to-female labor outcomes that are closer to parity.[3]

I use high-quality panel data to employ an event-study design to trace the lifetime trajectories of labor market outcomes around the event of childbirth. I implement the specification of Kleven et al. (2019b) in calculating child penalties to illustrate the dynamic effect of the firstborn on female outcomes relative to males. This methodological choice non-parametrically controls for age and time trends, and under certain conditions recovers causal estimates of child penalties even in the long run. My main results for the full sample demonstrate a long-run child penalty of 13% in wages, 18% in hours worked, 10% in employment and 22% in earnings. These fall within similar ranges obtained for OECD countries (Kleven et al., 2019a). Motherhood dampens workplace engagement and performance in the short-run regardless of one's gender-norm beliefs. Additionally, none of the groups have successfully erased the penalties associated from child-birth.

Heterogeneity in results by norm categories behave according to expectation, with modern parents attaining lower penalties. Long-run trajectories of child penalties in wages, earnings, and weekly hours worked between males and females exhibit slight convergence among people who do not conform to traditional gender roles. A key contribution of this paper suggests that gender attitudes do not positively affect labor market outcomes in a linear manner. This is exhibited by similar outcomes between mothers

[3]This is in line with the predictions of social role theory, which argues that gendered preferences, perhaps childcare among them, stem from strong social norms but become less differentiated across sexes in societies with more gender-equal rights (Schmitt et al., 2017; Cuevas et al., 2021).

with neutral and traditional gender attitudes. Only females with modern gender identities have long-run penalties that are narrower by 2% to 10% than the estimates obtained from the full sample.

I run different sets of robustness checks to validate my main results. A few insights emerge from these exercises. First, I obtain slightly larger penalties when using individuals without children as my control group. I still observe similar long-run trajectories in outcomes and find mothers and non-mothers be identical on pre-trends. Echoing my baseline findings, the gaps for the bottom third percentile of women along the index (those with modern views) have narrower child penalties relative to the placebo control group. These results suggest that women with progressive values have higher preferences for continually engaging in the labor force. Non-mothers with modern-to-neutral gender views have career trajectories similar to that of males, thus further supporting the claim that gender disparities are linked to the role of motherhood. Second, I show that long-run penalties are highly associated with the number of lifetime children. Mothers with only one child have considerably smaller penalties in their labor supply and wages. Interestingly, the path towards gender convergence begins once their child turns three. This gap sharply narrows once the child reaches school-age (5 years old) before tapering off to reach a long-run wage penalty of 7.5%.

This paper seeks to contribute to the literature that explores how preferences for gender-specific roles affect economic outcomes. A large and well-established body of research examines the impact of gender identity on women's labor supply (Fernández and Fogli, 2009; Lippmann et al., 2020; Bertrand et al., 2015). Intuitively, identity is likely to have an effect on workforce participation if a person is guided by one's internal rule of behavior.

The potential mechanism relies on a framework whereby agents suffer a disutility if they were to engage in actions conflicting with the behavioral prescription for their own gender category (Akerlof and Kranton, 2000). My study assumes this similar line of thought, and contributes to the branch of research that focuses on cross-sectional estimates of culture by exploiting the variation in attitudes across birth cohorts and/or across countries (Kleven et al., 2019a; Fernández, 2013). Typically, measurement for norms are proxied from a separate source (i.e World Values Survey) and merged with national censuses products or other administrative data. This paper improves upon this methodological approach by using a longitudinal survey that has individually-linked gender attitudes of respondents alongside their information on demographics, educational attainment and labor outcomes.

My research fits with the recent literature that explores gender inequalities through an event-study design (Kleven et al., 2019b, Kleven et al., 2019a, Berniell et al., 2021). This innovation departs from the standard decomposition approach in studying gender gaps to capture the dynamic effects of labor outcomes around the birth of the first child. My paper is closely related to the works of Kuziemko et al. (2018) and Kleven (2022) who consider the role of gender norms in explaining the persistence of child penalties.

The second half of the paper examines the mechanisms that drive these child penalties. I demonstrate that gender attitudes affect crucial labor market inputs throughout the life-cycle. Previous findings suggest that social norms affect labor outcomes through decisions about the timing of marriage, fertility and educational investments (Fernández et al., 2004). Since the event-study design cannot identify pre-child effects, I conduct correlational exercises that may help explain the observed variation in outcomes of my main results. I first show that modern gender norms are associated with higher educational investments even after controlling for ability and maternal education. This may be suggestive of anticipatory effects to fertility or intended attachment to the labor force post-child. Another mechanism I consider is the occupational sorting channel through which preferences for workplace flexibility may explain the gender wage gap (Olivetti and Petrongolo, 2017). Exploiting the information on fringe benefits and occupation information, I find that progressive women are more likely to be in jobs with better workplace protections after child-birth.

Finally, I attempt to contribute to the literature by employing a causal mediation analysis. The aim is to disentangle the direct effect of gender norms from its indirect effects through a mediator that simultaneously impacts child penalties. The indirect effect can be thought of as one possible channel for why the treatment works, while the direct effect represents all other possible explanations. The value of this exercise increases when the policy maker have a greater degree of control over the mediators than the treatment. However, I did not find strong mechanism effects among years of schooling, marital status, and occupational quality.

All in all, results highlighted here suggest that adherence to social norms explain some portion of the gender disparities in the labor market. Gender identity can induce people to engage in activities that can potentially attenuate or impede one's success in the labor market. I show that there is heterogeneity across women when comparing the outcome trajectories across those with varying beliefs. While gaps still exist for modern females, I find larger disparities among mothers who identified with gender-unequal roles in the household. My findings affirm that given strong preferences, identity formation at a young age has a lasting effect into adulthood.[4]

2.2 Data

I utilize the 1979 cohort of the National Longitudinal Survey of Youth which contains a sample of 12,686 men and women aged 14-21 when they were first interviewed in 1979. Three independent probability samples are included in the NLSY79, of young people born January 1, 1957 through December 31, 1964: (i) a cross-sectional sample designed to be nationally representative of the non-institutionalized civilian population in the United States; (ii) a set of supplemental samples oversampling civilian Hispanics, Blacks, and economically disadvantaged non-black/non-Hispanic youths; and (iii) a sample of individuals actively serving in the military as of September 30, 1978. Respondents in the first two samples were last interviewed in 2016 when they were around 52-58 years old, while those in the military sample are no longer interviewed after 1984. Respondents in the military sample are not considered in this study.

I have the ability to directly observe attitudes towards gender norms in the NLSY rounds of 1979, 1982, 1987, and 2004 for all respondents. This questionnaire contains belief statements concerning female roles around child-care, home production, and labor market participation. Table 1 lists these in detail, along with percentage shares of individuals who either agree or strongly agree with such statements.[5] While males have a strong preference for traditional female roles, the percentage gap between males and fe-

[4]Developmental psychologists claim that gender roles are shaped early in life through the interaction with peers, teachers and/or relatives (Eaves et al., 1989; Collins et al., 2000).

[5]Table A1 presents the equivalent statistics for the subsample of parents in subsequent waves. While attitudes are also collected for the 1979, 1982, 1987, and 2004 rounds, survey attrition remains a concern on the latter rounds that non-missing observations can lead to an imbalanced sample.

males on beliefs is surprisingly large ranging at around 8-18%. Responded sentiments are recorded using 4-point Likert scale of "4=strongly agree", "3=agree", "2=disagree", and "1=strongly disagree", individuals with higher scores are viewed to possess traditional gender norms.

My primary measure of gender norms is taken from the 1979 survey. This decision is borne out of practicality since follow-up surveys beyond 1979 have higher incidences of item non-response and survey attrition. I construct an aggregate measure of gender-norm beliefs following Anderson (2008) and more recently, Dhar et al. (2022). This procedure allows for index construction when data on indicators are missing, thereby maximizing the sample size. I first convert the 4-point scale to its dichotomous equivalent wherein *strongly agree* and *agree* are encoded as one, and *strongly disagree* and *disagree* are encoded as zero. I then collapse responses from all seven questions into a single numerical index using a GLS procedure with weights generated from the inverted-covariance matrix of all the variables in the respective index. Thereafter, I assign the sample into equally sized bins and categorize them into *Modern*, *Neutral* and *Traditional* groups. Alternatively, I also run a principal component analysis (PCA) to construct this index and found identical sample groupings with the GLS approach.[6]

The calculated scores capture gender beliefs when respondents were 13 to 24 years old. Hence, I implicitly assume that gender beliefs held when young have long-run consequences on labor market outcomes.[7] While this may raise some concerns, the prevailing literature lends empirical support that parental influence and social norms developed in

[6]The first principal component explains about 35.1% of the total variance.

[7]Table A2 demonstrates that around 45% report similar gender norms post-birth. Among parents who have changed views, shifts towards more traditional and progressive views are equally split.

childhood have lasting implications into adulthood (Farré and Vella, 2013; Fernández et al., 2004). Table A3 demonstrates how familial background relates to the preference formation of gender norms.

2.3 Sample Restrictions and Summary Statistics

I impose the following restrictions in preparation for an event-study specification with a subsample that comprises of parents:

a) With non-missing hourly wages and hours of work at least once pre- and post-child.

b) Age at first year of birth is 16-45 for females and 16-60 for males.

c) Respondent is first observed by age 20 and last observed when aged 40 or older.

For (a) and (c), this qualification is designed to rule out non-interviews and respondents with incomplete information (i.e. those who are "working" but report zero earnings or labor hours). Note that those who are out of the labor force are justified to have zero labor market outcomes and are included in the analysis.

Applying the aforementioned restrictions would leave me with a sample comprising of individuals who first became parents anytime from 1982 to 2008. While this range is quite large, this is relative to the panel spanning from 1979 to 2016. Sample statistics are presented in Table 2, taken a year before parenthood for 2,383 males and 2,216 females, whereas Table 3 presents time-varying characteristics. On average, fathers have more traditional gender norms than women. They are also older, earn higher wages and have longer work histories relative to women. On the other hand, women have more years of schooling on average and are more likely to be college graduates when they first become parents. The latter is consistent with findings that females accumulate higher educational levels than males (Becker et al., 2010; Blau and Kahn, 2017). Traits generally behave according to intuition when comparing within the same sex across gender-norm categories. People with progressive gender-norms have higher years of schooling, belong to more educated parents, have higher AFQT scores, and hold more skill-intensive occupations. Within each category, gender outcomes are statistically different for hours worked per week, work experiences, and earnings. The differences across males and females are more pronounced for individuals who belong in the traditional group. These summary statistics foreshadow my results wherein male outcomes remain unaffected by parenthood, and females are doing better in terms of labor market outcomes before childbirth.

2.4 Methodology

I adopt an event-study approach to fully exploit the NLSY panel in tracing the labor market effects of children over a 10 year horizon. A difference-in-differences with two way fixed effects estimates the evolution of gender differences across labor market outcomes over time. While labor decisions are expected to change or drop sharply after childbirth, additional insights can be gained as to how these rebound over longer time horizons. In this setting, individuals are on a lifetime path to deciding on when to have kids so that all observations help identify the impact of parenthood. I consider the event of the first childbirth as the "treatment" and measure the effect of parenthood every year from five years prior to having a child to ten years after. Hence, results can be viewed in consideration of all the possible children born after the first one, and the estimated long-run impacts should be interpreted as the total impact of all kids. Outcomes of interest are wages, earnings, hours worked per week, and labor force participation. Wages are taken from the most recent job at interview, while earnings are defined in annual terms and encompass salary and tips. I treat earnings in levels and wages in logs, so that the latter is strictly conditional on employment while the former includes non-participation.

Denote Y_{it}^g as the outcome of individual i of gender g at year τ:

$$Y_{it}^g = \sum_{t=-5}^{10} \alpha_\tau^g \mathbf{1}(t - s_i = \tau) + \beta^{\mathbf{g}'} \mathbf{D}_{it}^{Age} + +\gamma_t^g + \eta_i^g + \nu_{it}^g, \tag{2.1}$$

where s_i refers to the year of person i's first childbirth and $\tau = -1$ serves as the reference period such that α_j are event time coefficients relative to the year before the first childbirth. The second term is a vector of age dummies that nonparametrically controls for life-cycle trends, while the third term refers to year dummies which accounts for period-specific trends such as wage inflation and business cycles. The event time coefficients are identified by exploiting the different timing of births among parents of the same age who has a child aged τ and parents of other children in the same year. The event time dummy at $\tau = -1$ is omitted so the event time dummies measure the impact of children relative to the year just before the first child birth. Finally, I include individual fixed effects η_i^g to control for the unobserved determinants of the timing birth, while ν_{ist}^g denotes the error term. The inclusion of individual fixed effects seeks to mitigate the threat of unobservable confounders and captures other factors (ability and preferences) that may affect outcomes. This implies that parameter estimates of the event-time coefficients α_τ^g reflect the within-person evolution of outcome variables relative to the event of parenthood of gender g. I run separate regressions for males and females to allow for gender-variation in age-specific and year-specific trends.

$$P_{\tau}^{g} = \frac{\hat{\alpha}_{\tau}^{g}}{E[\tilde{Y}_{ist}^{g}|\tau]}. \tag{2.2}$$

As in Kleven et al. (2019b,a), I scale the event-time coefficients as percentages defined in Eq. 2 and report them as plots for all of my main results. Each data point is interpreted as the percentage impact on outcome variables relative to their counterfactual outcome of not bearing any child. Presenting results in annual frequencies for each $\tau = \{-5, ..., 10\}$ flexibly distinguishes the time-varying dynamic effects of children on labor outcomes. This enriches the analysis as I can differentiate between short and long-term impacts across parents and gender norm-categories. For exposition purposes, I refer to the estimates obtained at $\tau = 1$ as short-run, and $\tau = 10$ as long-run.

The event-study specification can provide clean estimates of the impact of having a child on labor supply decisions. Causal identification relies on the assumption that there are no anticipatory effects on outcomes conditional on the fixed effects.[8] That is, time-varying unobservables should not be correlated with both parenthood and the outcome of interest. Identification of short-run penalty relies on smoothness around $\tau = 0$, with no indication that outcomes respond prior to child birth. Meanwhile long-run penalty relies on parallel trends between men and women, conditional on controls for time and lifecycle trends. This is empirically assessed using graphical evidence wherein men and women

[8] See Sun and Abraham (2021) for a formal discussion about the identifying assumptions in an event study design.

have trajectories that move in parallel for $\tau < 0$. While Freyaldenhoven et al. (2019) argues that this diagnostic is not sufficient for establishing causality, I present some robustness exercises common to this literature in Section 6 (Kleven et al., 2019b; Kuziemko et al., 2018).

2.5 Main Results

In this section, I discuss the estimated impact of children on the labor supply decisions of parents. To better highlight the differences across gender norm categories, I present my main results for specification (1) separately for each outcome graphically and report the point estimates for the event time coefficients in the Appendix. As is standard in the child-penalty literature (Kleven et al., 2019b; Kleven et al., 2019a; Berniell et al., 2021), I plot the temporal scaled estimates as defined by Eq. 2 for males and females. Such penalties are interpreted as the percentage deviation from the counterfactual outcome of not having any children. For each outcome variable, I also provide the estimated long-run child penalty at $\tau = 10$ in the bottom right corner:

$$P_{\tau} = \frac{\hat{\alpha}^{m}_{\tau} - \hat{\alpha}^{w}_{\tau}}{E[\tilde{Y}^{w}_{ist}|\tau]}, \tag{2.3}$$

which can be interpreted the percentage by which females are falling behind relative to male parents after ten years. Eq. 3 facilitate ease of interpretation when we comparing long-run results across females by gender-norm categories.

I present my main findings for log wages, weekly hours worked, participation and earnings in Figures 2.1–2.4 respectively for the full sample and the three gender-norm categories. All plots include 95 percent confidence bands around the event coefficients. Note that selection into employment must be considered in interpreting the results for wages and hours worked. If I assume positive selection, estimates obtained for these outcomes can be viewed as a lower bound for the impact of parenthood. A few things stand out at first glance. First, the non-violation of parallel pre-trends and the absence of discontinuities at $\tau = 0$ is encouraging for the event-study specification in lending support for causality. Parallel pre-trends for both genders rule out the possibility that observed penalties are merely driven by gender-specific time trends. The paths substantially diverge after the arrival of their firstborn and are characterized by a sudden drop for females ranging around 12%-20% while male outcomes remain unscathed. Finally, motherhood has a persistent effect on all labor outcomes. Note that calculated penalties across gender attitudes convey patterns consistent with expectation. That is, in terms of labor outcomes, the burden of childcare is more detrimental to females who identified with traditional roles in the household. While mothers belonging to this category do not exhibit strikingly large short-run penalties compared to their "neutral" peers, their performance is unique in that they suffer a gradual increase in penalties two to three years post-child.

Upon closer inspection of Figure 2.1, the short-run impact of children (taken at $\tau = 1$) reduces female wages by 16% relative to their levels prior childbirth ($\tau = -1$). These wage penalties are persistent and never fully converge back to their original levels. The long-run wage penalties - which is interpreted as the outcome percentage gap of females to males due to children, remains at 11-14%. Interestingly, mothers in neutral and traditional categories have similar long-run penalties at 14%. Only females with strong careeroriented preferences have lower child penalties to 10%. While results are slightly more encouraging for mothers in the modern category, it remains quite concerning if this is the best-case scenario for a female to have over the period spanning from 1990 to 2016.

Together with the results in Figure 2.2, it appears that female success in the labor market is determined by the number of hours worked. Here, I find patterns that are more differentiated across gender norms. First, traditional mothers significantly cut back hours by 20-33% relative to their baseline levels pre-child. While the estimating specification does not account for the impact of family size, the sustained decline two to five years post-childbirth for traditional females is likely influenced by their decision to have more kids. Another key insight can be found in the long-run penalties across gender-norm categories taken at $\tau = 10$. I observe that neutral and traditional female penalties - estimated at 20.5% and 18.9% respectively, track similarly behind their male counterparts. That these two are non-discernible suggest some non-linear relationship along one's position in the gender-norm scale and performance in the labor market. This is supported by the finding that modern females have a strikingly lower long-run weekly hours penalty of 9.6%.

I complete the picture by looking at the impact of parenthood on labor force participation. Figure 2.3 illustrates that females in my sample are less inclined to change their extensive margin decisions after having their firstborn, as exhibited by their lower short-run penalties of about 8-15%. These suggest that female wage penalties are unlikely driven by lengthy unemployment spells due to childcare. Meanwhile, female parents who lean liberal have long-run trajectories that converge slightly over time. This is in contrast to both traditional and neutral mothers who not only display impacts that tend to linger over time, but also have long-run child penalties that are almost identical.

Figure 2.4 presents the impact of children on parent's earnings. The impact on total earnings can be viewed as a play on either adjusting hours worked, wages, and other pecuniary sources that are not tied to employment (i.e. non-wage income from businesses and investments before taxes and transfers). Doing so allows me to check if there are unobservable mechanisms that allow a person to have agency over their earning capacity outside wage-employment. While it may be the case to have parents who sort into self-employment or rely on other sources of non labor income, the extent to whether this is gendered in nature is what I hope to address in the inclusion of this outcome. The plots across the board illustrate higher female earning penalties compared to that of wages in Figure 2.1. The observed dip a year after having one's firstborn behaves according to intuition with the largest one-year short-run ($\tau = 1$ vs $\tau = 0$) drop for mothers in the traditional category. Second, within-norm long-run earning penalties are considerably larger ranging from 13% to 38%. The distinct contrast on the earnings effect of children between traditional and modern mothers indicates that females in the latter group may have more flexibility in maximizing salaries or have access to familial wealth.

Children have negligible effects on the labor market outcomes of males. Notably, fathers are spared from short and long-run penalties attributed to having a child. This finding is consistent across male gender attitudes whereby contrary to an immediate disengagement from the labor force post-child, fathers have become even more involved in the labor market. This result is consistent with the literature. A survey among high-income countries found no significant evidence of child penalties for fathers but observes negative long-run implications for female parents (Kleven et al., 2019a). Perhaps uniquely driven by the NLSY 1979 cohort, I observe male wages, hours worked, and earnings to slightly increase for the first four years after childbirth. I motivate these results by taking a similar conjecture to Kuziemko et al. (2018) - that the difficulties of child-rearing may similarly serve as an information shock to fathers, and that society's acceptance of traditional gender roles may supersede any gender-equal priors once held by males.

All things considered, I consistently find that females in the modern-norms category are less likely to suffer in terms of their labor-market outcomes. This may be explained by anticipatory behavior in response to having kids whereby they sort into jobs with better family benefits or accumulate higher levels of human capital. Assuming that this group has been the most assertive in navigating their way through the workplace, I can interpret their penalties as the lower bound. I explore these possibilities by providing descriptive evidence in Section 7. On the flip side, I find a lack of variation in outcomes across traditional and neutral mothers quite surprising. This suggests that for females born from 1957 to 1964, one must skew highly progressive to assert for better labor outcomes than the average.

2.6 Robustness Checks

I present a set of robustness tests to address concerns related to the identification assumption that the timing of the first child's birth is not correlated with labor outcomes, conditional on the included fixed effects. Kleven et al. (2019b) presents the theoretical argument that event study design identifies both short- and long-run effects of children compared to widely used alternative approaches, such as instrumental variables and differences-in-differences. In the same vein, I conduct one of these exercises when the data permits.

Never-parents as control groups

The inclusion of non-parametric controls for age and years in Eq. 2.1 help account for other outcome determinants that do not depend on children. However, if such non-child components are not fully controlled for, the long-run child penalty may be biased. For my main identification check, I conduct a difference-in-differences event study design using same gendered non-parents as controls. Using the individuals without children reflect the non-child trends in a difference-in-differences design. I implement this by assigning placebo births to the subsample of individuals without any children from 1979-2016. Birth years are assigned separately for males and females using a log-normal distribution with mean and variances obtained from the respective empirical distributions of each gender.[9] This exercise provided 1,592 males and 1,159 females as placebo control groups. Results by gender norm-conforming preferences is illustrated in Figure 2.5 for wages and weekly hours worked. Conditional on employment, females without children exhibit event-time trends similar to that of male parents. This suggests that absent the role of parenthood, female labor market performance would come closer to outcomes achieved by men. Taking these results as given, long-run wage penalties are around 2 percentage points larger for the modern and neutral categories when using females without children as the comparison group as opposed to fathers in Figure 2.1. I also observe similar patterns when looking at weekly hours worked. I conduct this same exercise for males in Figure 2.6 where I confirm my previous findings that fathers are less affected by children. My wage penalties for the traditional and neutral mothers are 13.8 and 11.4%, respectively. These

[9]This alternative control group are older in age and are less likely to face a truncation issue of having kids later on. The log-normal distribution is an approximate distribution of the possible age at first child obtained from the actual gender-specific distributions from parents in the sample.

estimates fall within the range of what was estimated by previous literature, wherein a wage differential of 10-15% exist for females with children relative to females without (Waldfogel, 1998; Korenman and Neumark, 1992).

2.7 Mechanisms

This section seeks to expound on the main findings by looking at how gender attitudes affect crucial decisions related to one's success in the labor market. Results discussed here depart from the event-study specification to give space for analyzing how observable individual covariates facilitate lower penalties. Guided by my main results, I explore the interesting variation that exists across gender-norm categories. Empirical findings presented are merely descriptive for the benefit of understanding the heterogeneous impact of children across females with varying preferences for home production. Hence, the sample inspected will be limited to mothers conditional on employment– highlighting outcome differences between modern and non-modern females. Descriptive evidence in this section merely explores the relationship between gender norms and several mechanisms, but not the direct link between the mechanisms and the outcome.

Impact across number of kids

A key limitation of my main results is the lack of nuance on labor market effects attributed to the heterogeneity in fertility decisions of parents. The patterns observed post-birth include the impact of all succeeding children that may have been born after the fist one. To address this, I generate separate estimates for parents with different lifetime number of kids using my baseline specification. Doing so allows me to comment on the extent by which inequalities are driven by family size. Figures 2.7 and 2.8 highlight that my main results are largely influenced by parents with two or more children. While I still observe a sharp drop around the birth of the first child for all mothers, those with one child are able to mitigate the long-run penalties for both wages and weekly hours worked. By contrast, those with two kids and more have penalties that fail to converge over time. A key trend here is the timing for when one-child females begin to reduce the wage penalties from 16.6% to about half at 8% for non-traditional mothers. Impressively, long-run penalties for weekly hours worked have converged to zero for all females across all groups. The path to convergence begins to happen around four to five years after having their firstborn, which perhaps alludes to the gendered division of early childcare. All together, these plots suggest that having an additional child comes at the expense of female labor force attachment.

Educational Investment

The timing of the NLSY attitudes survey is taken around the time when the respondents are close to finalizing their human capital decisions. Compared to other outcomes that indicate anticipatory behavior on fertility, I assume that educational investment seems reasonably influenced by one's gender-norm attitudes in 1979. While reverse causality remains a potential concern in this analysis, I conduct my analysis conditional on a wide set of covariates which include ability, mother's educational category, family income status, urbanity, and race. Table 4 contains results for when years of schooling is regressed on their own gender-norm attitudes. These estimates are obtained at $\tau = -1$ which provides a snapshot of individual characteristics before having a child. Consistent with the findings in Fernández (2013), modern females have more formal schooling when they decide on becoming parents. While not surprising, women with modern attitudes have 0.17 more years of schooling relative to her peers. I run the same analysis using one's raw score along the gender-norm index in Columns 5-8 to arrive at the same conclusion (recall that having a higher score imply norm-conforming behavior to traditional gender roles).

Sorting into Jobs

I also explore if non norm-conforming females are more likely to engage in any sorting behavior around the birth of their first child in comparison to mothers in the neutral and traditional categories. This information is key to answering if preferences for certain jobs shift around the event of parenthood, and if such patterns are significantly differentiated across gender attitudes. I do this by looking at two outcomes - the probability of having family friendly benefits at the current job, and the skill intensity of their current job. This exercise is motivated by the empirical findings that motherhood affects selection into employment around female sorting to "family-friendly" occupations post-child (Cardoso et al., 2016).

Table 5 presents the likelihood of whether a modern working-mother has access to family-friendly benefits in three periods: before childbirth, when her child is between one to five years old, and when her child is older than five. The reduction in sample size is explained by the limitation of the NLSY whereby detailed non-wage compensation was only collected for employees working more than 20 hours per week.[10] I consider an obser-

[10] The NLSY classifies employment as part-time if work hours are less than 20 hours per week. Hence, it is highly likely that observations omitted are not awarded any fringe benefits. The coefficients for modern gender-norms is interpreted as being conditional on full-time employment.

vation as having access to family-friendly amenities if she receives either of the following - flexible work, maternity/paternity leaves, and company provided childcare. Results indicate that even controlling for education and demographic traits, modern females are 2-5% more likely to have access to at least one of these amenities. The propensity is higher and statistically significant at 4.6-5.17% when her child is younger than five years old. Estimates when only considering maternity/paternity benefits suggest some preference for jobs that offer higher levels of employee protection. Perhaps this can be viewed as preemptive to ensuring near-term labor market opportunities.

Finally, I attempt to link my work to the strand of literature that inspects the role of work amenities in explaining gender differentials in labor decisions (Goldin and Katz, 2016; Wiswall and Zafar, 2018). Empirical evidence supports the assertion that females sort into "family-friendly" occupations that have more flexible work schedules (Mas and Pallais, 2017). I explore whether such sorting patterns are true for my sample by considering changes in occupational shifts pre- and post- child. I utilize the 3-digit occupation codes alongside O*Net 1998 data to obtain occupational characteristics. The harmonized occupational information is then merged with the replication files in Deming (2017), and David and Dorn (2013) to obtain composite scores of occupational skill-intensity of math, reasoning and service. The first two are proxies for jobs that are associated with higher compensation in contrast to services-intensity that are usually low-paying and female-dominated. These are scores that are normalized to have mean zero and unit variance. Coefficients obtained in Table 6 indicate that relative to her peers, mothers who lean more progressive are consistently employed in jobs that are associated with higher labor market outcomes as proxied by math and reasoning-intensive occupations. However, I do not observe striking changes around the birth of the first child among modern females when comparing within-period estimates. This could suggest that gender norms, if believed to be influential, are more likely to affect long-run performance in the labor market through one's human capital decision.

2.8 Causal Mediation

Taking the results above, I proceed to highlight the causal mechanisms of gender norms on child penalties through its influence on an intermediate variable, referred to in the literature as *mediators*. This section investigates if my treatment effects are influenced by a mediator that similarly affects the size of the child penalties. Through a causal mediation analysis, I can decompose the total treatment effect of norms on the outcome into indirect and direct effects. I am guided by the findings in the literature and consider (i) educational investment, (ii) occupational quality, and (iii) age at first marriage as potential mediators M that are simultaneously influenced by family background and gender norms (Currie and Moretti, 2003, Fernández et al., 2004). If the overall effect of norms on child penalties are largely explained by mechanism effects, then policy initiatives that directly influence these mediators may be more useful.

Methodological Framework and Assumptions

Figure 2.9 illustrates a simple classical mediation model of how all these variables relate (Baron and Kenny, 1986). Formally, $Y(d)$ and $M(d)$ respectively denote the potential outcome and the potential mediator state under treatment value $d \in \{0, 1\}$. The directional arrow a is the treatment-outcome relationship, or the *direct effect* of the treatment on outcome Y while the causal chain from b to c is the treatment-induced *indirect effect*.[11]

To decompose the total treatment effect, $Y(d)$ must be expressed as a function of both the treatment and mediator, $Y(d) = Y(d, M(d))$, to denote the potential outcome that occurs under treatment value d and potential mediator $M(d)$. The average direct effect, $\theta(d)$, is then defined as

$$\theta(d) = E[Y(1, M(d)) - Y(0, M(d))], \quad d \in \{0, 1\}, \tag{2.4}$$

which is the change in mean potential outcomes when treatment status is varied given a fixed mediator value of $M(d)$. Equation 2.4 effectively shuts off the impact of the treatment on the mediator along with its subsequent effects on the outcome. Likewise, the average indirect effect corresponds to the difference in mean potential outcomes that is due to changes in the mediator under treatment and control states while keeping treatment status fixed at d,

$$\delta(d) = E[Y(d, M(1)) - Y(d, M(0))], \quad d \in \{0, 1\}. \tag{2.5}$$

Equation 2.5 reflects the portion of the total effect attributed to the change on the mediator M that is due to exogenous shift in treatment. The average treatment effect can be

[11] Alternative terms are used in Flores and Flores-Lagunes (2009) where indirect effect is known as the mechanism effect, and the direct effect is referred to as the net effects or the causal effect net of mechanism effects. This paper follows the nomenclature of Pearl (2001).

expressed as a sum of its direct and indirect components at opposing treatment states:

$$E[Y(1, M(1) - Y(0, M(0))] = \theta(1) + \delta(0) = \theta(0) + \delta(1).^{12} \tag{2.6}$$

But a causal interpretation of direct and indirect components requires additional identifying assumptions since $Y(d, M(1-d))$ is never observed for any unit, and only one of the potential values among $Y(1, M(1))$ and $Y(0, M(0))$ is ever observed. I take the approach of estimating the potential outcome-means of equations 2.4 and 2.5 by invoking sequential conditional independence of the treatment and the mediator (Huber, 2020). Formally, this is based on two ignorability assumptions made in sequence, and an overlap assumption:

- **Assumption 1**: $\{Y(d', m), M(d)\} \perp\!\!\!\perp D|X$, for all $d, d' \in \{0, 1\}$ and m in the support of M
- **Assumption 2**: $Y(d', m) \perp\!\!\!\perp M|D = d, X = x$, for all $d, d' \in \{0, 1\}$ and m, x in the support of M and X
- **Assumption 3**: $Pr(D = d|M = m, X = x) > 0$ for all $d \in \{0, 1\}$ and m, x in the support of M and X

The conditions above are stronger than what is typically needed in obtaining non-mediated average treatment effects. Here, causal inference relies on unconfoundedness or selection-on-observables imposed on both treatment and mediator. The first assumption requires treatment, D, to be exogenous of potential outcomes and mediators after conditioning

[12] If there are no interaction effects, the direct and causal mediation effects do not vary as functions of the treatment status, $\delta(0) = \delta(1)$ and $\theta(0) = \theta(1)$.

on covariates X. The second assumption goes beyond and necessitates that the mediator is independent of potential outcomes conditional on both treatment and the same set of control variables. Given X and D, this rules out unobserved characteristics that jointly confounds the relationship between M and Y. Finally, the overlap assumption imposes a non-zero probability of receiving treatment given M and X, so that comparable units in terms of X and M are available across treatment states.

Empirical Implementation

Under this framework, I consider modern gender norms as the treatment D since no individual can control the family circumstances to which they are born to. Empirical evidence indicates that beliefs are inherited from primary caregivers, or to some extent influenced by their geographic and socio-economic background (Bredtmann et al., 2020; Cordero-Coma and Esping-Andersen, 2018; Fogli and Veldkamp, 2011). Thus, conditioning gender norms on a rich set of household and family characteristics at childhood is expected to satisfy the first identifying assumption.

Norms can similarly influence other decisions that predicate labor market success. Sequentially, I do not rule out the possibility that outcome effects are driven by the levels or value of a mediator $M(d)$, through which was affected by either having modern gender attitudes $d = 1$ or non-modern attitudes $d = 0$. For instance, descriptive statistics in Table **??** show that modern beliefs is associated with more schooling and delayed marriage. By employing a mediation analysis, I check if my main results are driven by pertinent decisions pre-childbirth that simultaneously affect outcomes.

I use the parametric algorithm by Hicks and Tingley (2011) and Imai et al. (2010a) to estimate the causal mediating effect of (i) age at first marriage, (ii) years of schooling, and (iii) occupational quality as measured through the composite scores of occupational skill-intensity in math and reasoning.[13] Equations 2.4 and 2.5 are calculated following a two-step procedure. First, the mediator is regressesd on the treatment and pre-treated covariates relevant to the treatment. Thereafter, predicted mediator values for both $d = 1$ and $d = 0$ is assigned to each observation. The second stage of the algorithm models the mediator-outcome relationship wherein the outcome is regressed on the treatment, mediator, and the same set of pre-treated covariates. From this fitted model along with the predicted mediator values, all counterfactual potential-outcome means are estimated (Imai et al., 2010b). Causal interpretation is possible when conditional sequential ignorability holds.

The assumption of sequential ignorability on the mediator is typically harder to satisfy. This entails the inclusion of all pretreatment confounders X that jointly affects the treatment, mediator, and the outcome. This is a strong and untestable assumption, where the remedy at best is including as many pretreatment controls as possible.[14] Conveniently, the NLSY offers a rich resource for household, parental, and familial characteristics that jointly influence gender attitudes, labor market outcomes, and the mediators that I evaluate. I am able to include a number of pretreatment covariates including mother's and father's level of education, mother's employment status, own ability measures (AFQT scores), race, if whether responded lives in urban/rural zones, family size, poverty sta-

[13]This algorithm can be applied to a range of parametric specifications and can accommodate OLS, probit, or logit in either of the mediator and outcome regressions. A nonparametric implementation of this algorithm is possible but not explored in this paper.

[14]See Imai et al. (2010b) for the technical proofs and Huber (2020) for a discussion on the differences among alternative assumptions for causal mediation analysis. Note that conditioning on post-treatment variables will not help satisfy the sequential ignorability assumption in the second stage.

tus, if foreign language is spoken in the household, if birth country is outside the US, access to libraries and if respondent have access to newspapers and magazines at home.

Table 2.7 shows the estimated average indirect or causal mediation effects, average direct effects, and average total effects of gender norms for each of the mediators considered.[15] For my dependent variable, I present the impact of gender beliefs with respect to the absolute value of child penalties at year τ for the labor market outcome specified in the column header. Therefore, a negative coefficient represents a reduction in penalties for mothers with progressive gender norms. I show the average direct and average causal mediated effect a year, and 10 years after childbirth to inspect the persistence of gender beliefs on short-run and long-run child penalties. I limit the sample in this exercise to female mothers since fathers have outcome penalties that are minimally affected by parenthood.

The causal mediation effects are presented as average indirect effects in Table 2.7. These point estimates quantify the impact of modern norms on child penalties as transmitted through either (i) age at first marriage, (ii) years of schooling, and (iii) occupational quality. Regardless of the mediator, it appears that modern norms reduces short-run and long-run child penalties for earnings, hours worked, and labor market participation. The influence of modern gender norms on penalty reduction is larger at $\tau = 10$ than at $\tau = 1$, which is consistent with the findings from my event-study specification.

I find that for years of schooling and occupational quality, modern norms affect child penalties in the same direction as their direct effects. Interestingly, treatment-induced

[15]Direct and indirect effects are calculated using the Stata command `medeff` provided by Hicks and Tingley (2011).

changes on years of schooling account for 21% of the total effect on weekly hours penalty at $\tau = 1$. Meanwhile, changes through occupational quality have the largest impacts on earnings penalty at $\tau = 1$, accounting for 10% of the total effects. However, for the rest of the outcomes evaluated, the indirect mechanism only explains 2-6% of the total effects. Results for age at first marriage unearth some peculiar patterns. First, females with progressive attitudes have short-run earnings penalty that are 1.8% higher than non-modern mothers. In terms of its decomposition, the causal mediating effect of modern norms on marrying age attenuates penalties, but the direct effect that encapsulates all other causal mechanisms increases the earnings penalty by 2.61% at $\tau = 1$. Other than this, results for this specific mediator follow the same trend as years of schooling, and occupational quality (i.e. explains a small portion of the total outcome effects, mechanism and direct effects go in the same direction).

Another thing that stands out are the negligible indirect effects on child penalties where more than 90% of the total effects come from factors other than the selected mediator. This means that other mechanisms unrelated to M explain the variation in outcomes across modern and non-modern parents. For example, families with progressive values may likely locate in urban areas that happen to have higher labor demand or affordable childcare. They may also match with supportive partners who encourage their career aspirations once the child is of school-age, hence achieving lower penalties by $\tau = 10$. Another consideration can be related to time-varying life shocks that can mitigate the impact of norms on the selected mediator (i.e. health issues, disruptions in family life, change in beliefs). All together, one or all of these reasons can explain why the mediated effect of norms on outcomes is relatively small.

Since the calculated range of my point estimates fall within large 95% confidence intervals that include zeros, I close this section by pointing out threats to causal interpretation of the decomposed effects. Going back to the econometric assumptions in Section 2.8, it is worth noting that while each of D, M, and Y can be affected by statistically independent sets of unobservables, sequential ignorability fails when there exist (i) an unobserved pre-treatment covariate that jointly affects both mediator and outcome, or all three including the treatment, (ii) or a post-treatment confounder that does the same (Keele et al., 2015). The possibility of these happening can be hard to rule out given the time frame between preference formation at adolescence and motherhood–i.e. one must believe the absence of common post-treatment confounders that similarly influence child penalties and the mediating variables. Nonetheless, Table 2.7 has shown negligible mechanism effects and lend support to my main results in which gender norms explain a large part of child penalties.[16]

2.9 Conclusion

This paper aims to shed light on the role of social norms as one source for the remaining gender gap. Familial roles around childcare reflect endogenous preferences that are typically unaccounted for in the literature. Yet, the provision of household production among spouses may be influenced by one's inclination for gender-specific roles. By emphasizing one's adherence to these norms, I am able to shed light if whether social pressures to conform stalls the path to equality. Using NLSY79 data, I established the trajectories of

[16]A recent working paper by Kleven (2022) similarly finds a large correlation between traditional gender norms and high child penalties. Over time, as urbanization rates increase in the United States, gender beliefs become more progressive and child penalties decrease.

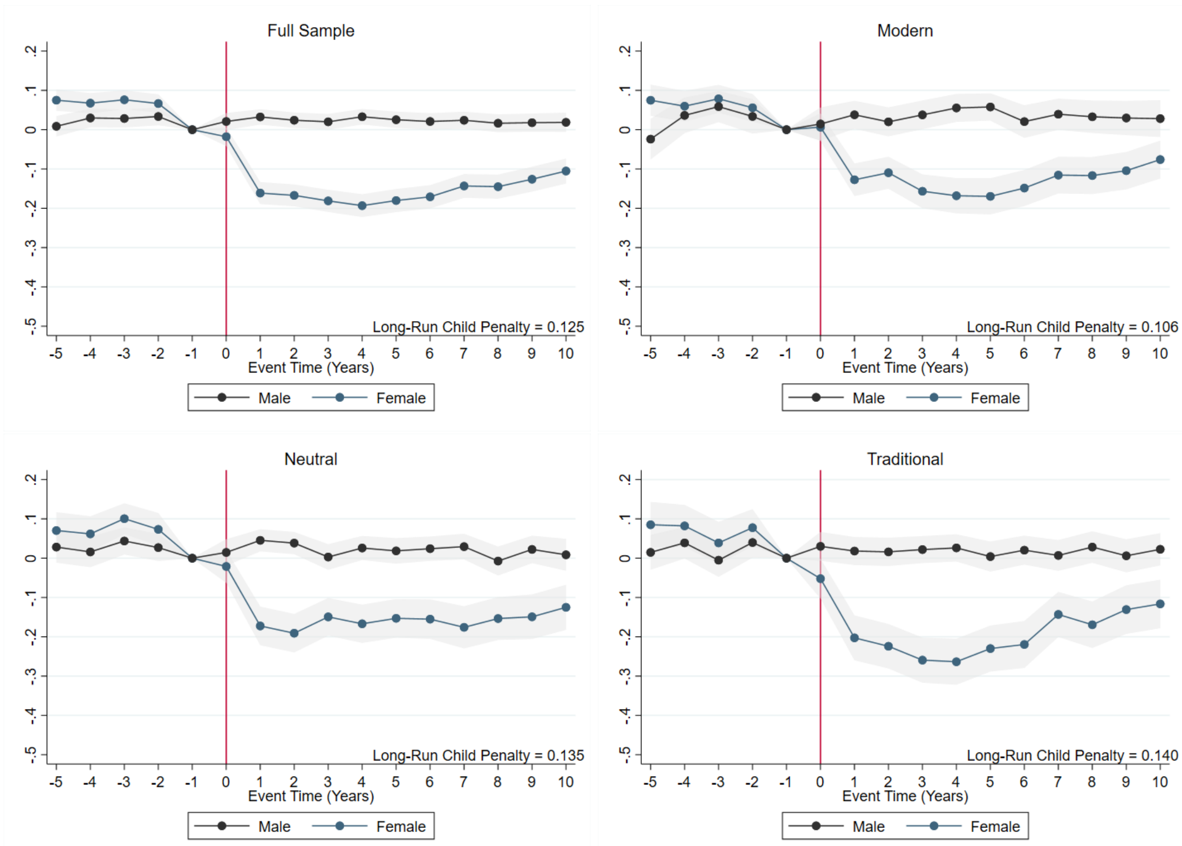
child penalties across gender attitudes and find children to have persisting effect on female labor outcomes, all through 10 years post-birth. The trends observed are similar to the findings on the child penalty literature. First, men and women follow similar career trajectories for at least five years prior to becoming parents. That male penalties range close to zero post-child indicate that they are unaffected by childcare. Although long-run penalties are mitigated by 2-5% relative to the penalties incurred a year after childbirth, all females regardless of their proclivities toward gender equality are unable to have their penalties converge back to zero.

The reduction in earnings inequality did not happen uniformly across all women. I illustrate that the calculated penalties across gender attitudes convey patterns consistent with expectation. That is, in terms of labor outcomes, the burden of childcare is detrimental to females who identified with traditional roles in the household. While mothers belonging to this category do not exhibit strikingly large short-run penalties compared to their "neutral" peers, their performance is unique in that they suffer a gradual increase in penalties two to three years post-child. Moreover, the persistence of penalties are associated with family size. Mothers with only one child have shown some success in mitigating the gender disparities in wages and hours worked. I inspect anticipatory and reactionary choices post-child but did not find any compelling patterns of sorting into occupation. Rather, it appears that modern women are investing more in education when young, and maintain continuous access to family-friendly benefits.

My results are estimated from the birth cohort of 1958 to 1965. It seems reasonable to expect that these gaps disappear in more recent cohorts when female preferences move towards gender-equal norms. Although the current climate allows for more inclusive policies in the workplace, this paper demonstrates how culture and norms sustain gender disparities. When norm-conformity is strongly enforced, policies aimed at narrowing the gender gap may seem futile. Hence, the influence of values education shouldn't be overlooked. This is essential especially in consideration that these gaps persist despite legislative efforts to promote gender equality in the workplace. But it is with hope that beliefs, cultural barriers, and social norms are dynamic. Over the last decades, there has been an observed shift towards more progressive roles as females assert more autonomy in reshaping their roles in society (Goldin, 2006). Gains made today have potentially multiplying effects in future generations through the inter-generational transmission of values (Farré and Vella, 2013; Fernández, 2013; Fernández et al., 2004).

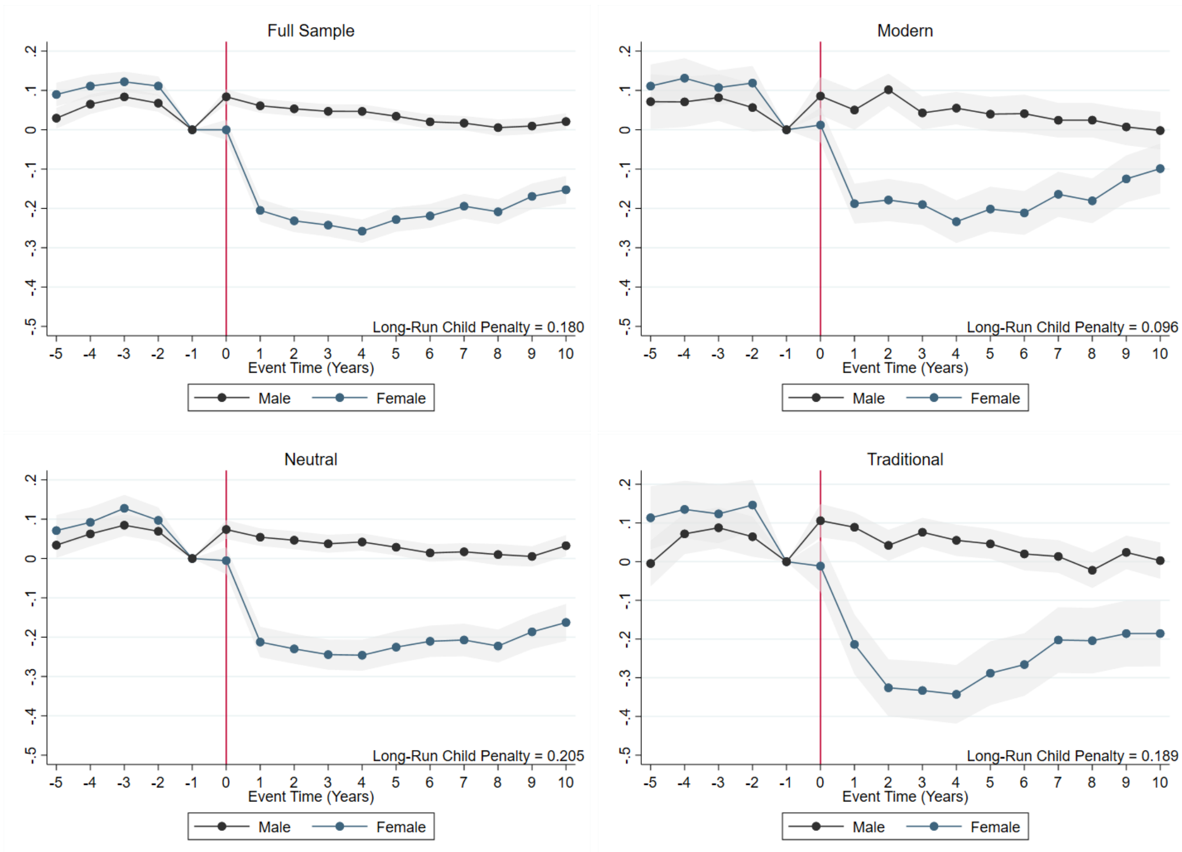
Figures

Figure 2.1: Impacts of children on log wages



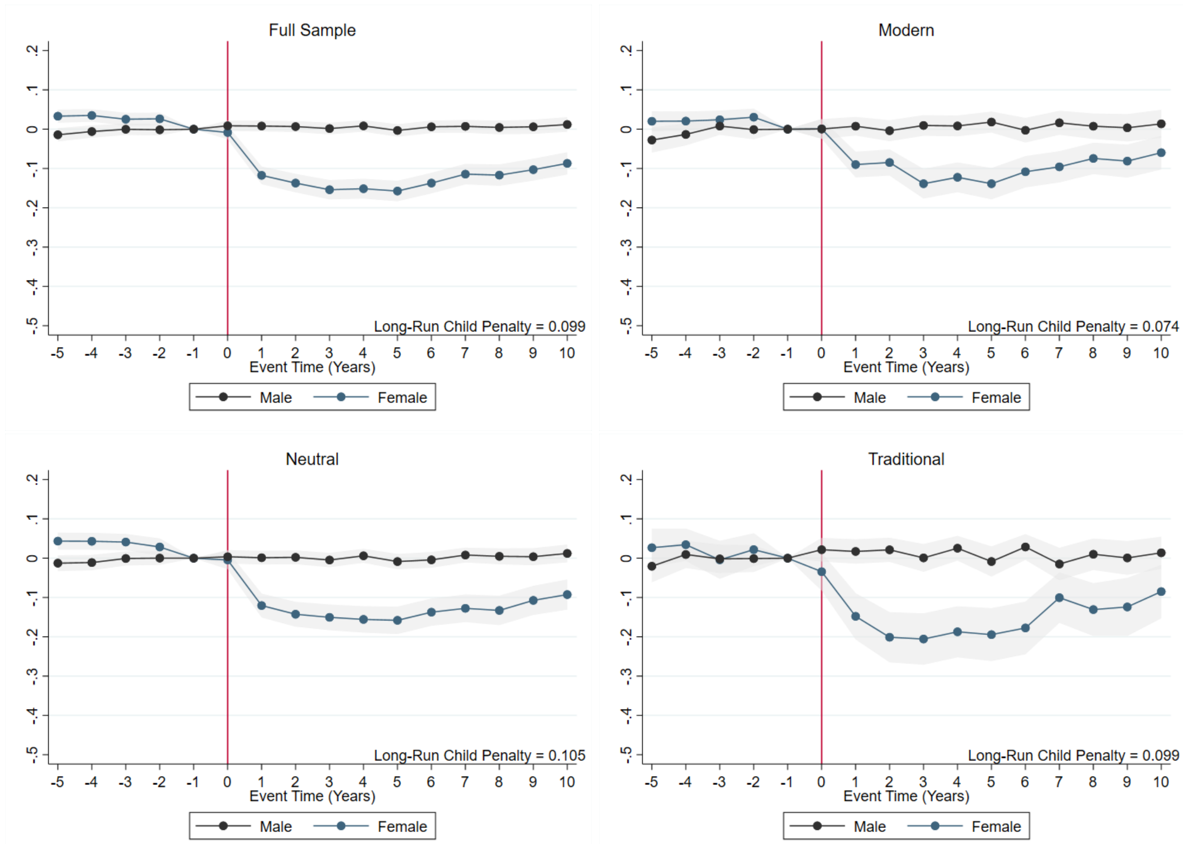
Notes: Effects estimated are conditional on employment. Figure reports event time coefficients from equation as a percentage of the counterfactual outcome absent children, calculated following equation (2). In the bottom right panel of all graphs, long-run child penalty is calculated using Equation (3) from obtained estimates at $\tau = 10$. Raw regression results are reported in Table A3.

Figure 2.2: Impacts of children on weekly hours worked



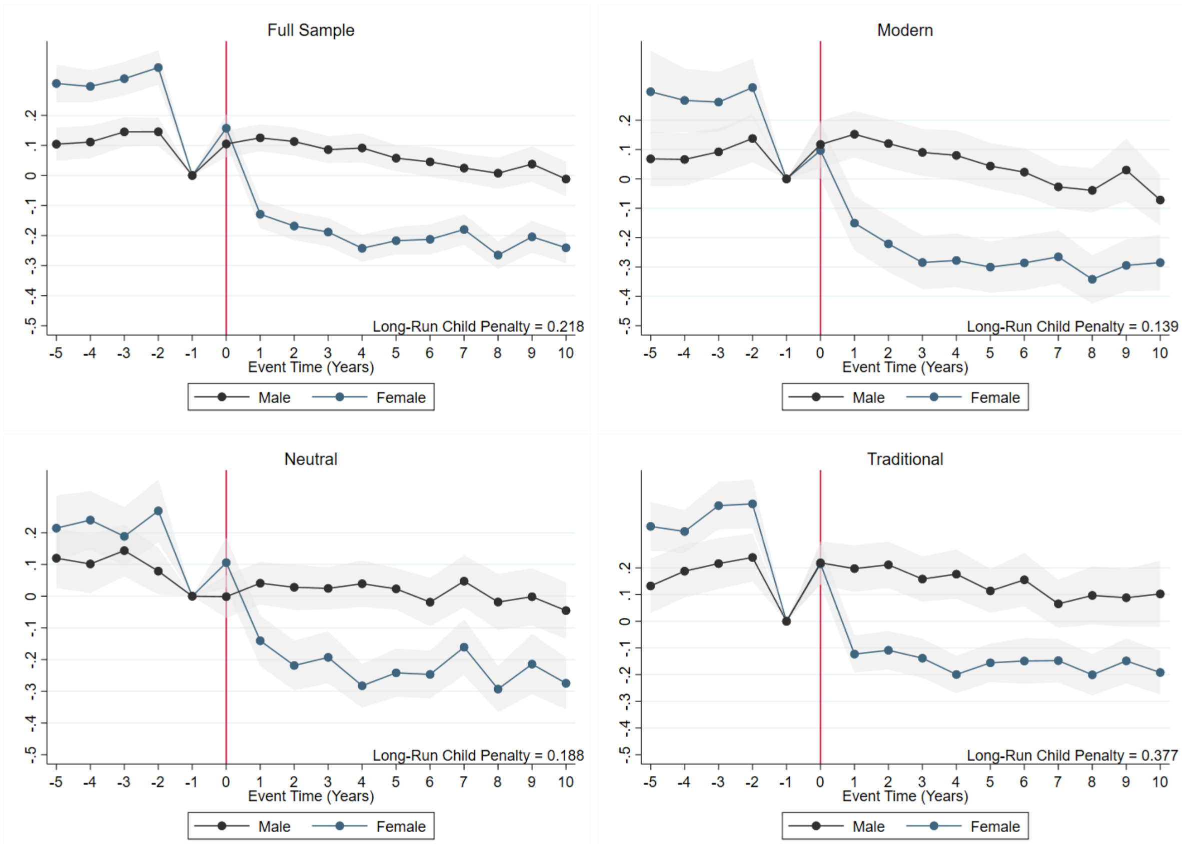
Notes: Effects estimated are conditional on employment. Figure reports event time coefficients from equation as a percentage of the counterfactual outcome absent children, calculated following equation (2). In the bottom right panel of all graphs, long-run child penalty is calculated using Equation (3) from obtained estimates at $\tau = 10$. Raw regression results are reported in Table A4.

Figure 2.3: Impacts of children on participation



Notes:: Figure reports event time coefficients from equation as a percentage of the counterfactual outcome absent children, calculated following Equation (2). In the bottom right panel of all graphs, long-run child penalty is calculated using Equation (3) from obtained estimates at $\tau = 10$. Raw regression results are reported in Table A5.

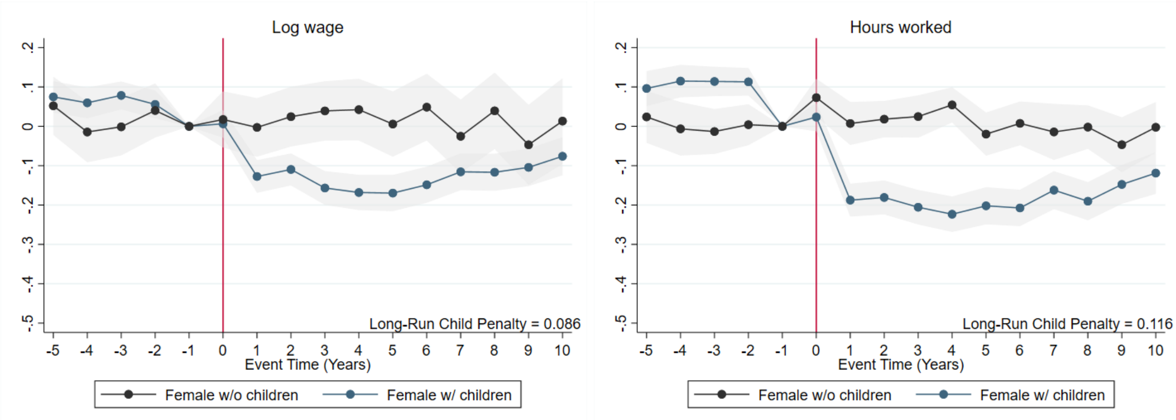
Figure 2.4: Impacts of children on earnings



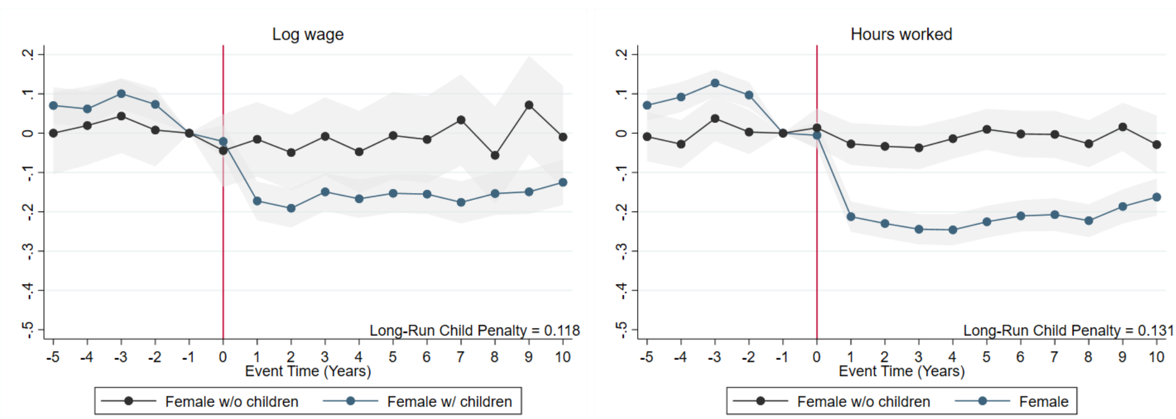
Notes: Figure reports event time coefficients from equation as a percentage of the counterfactual outcome absent children, calculated following Equation (2). In the bottom right panel of all graphs, long-run child penalty is calculated using Equation (3) from obtained estimates at $\tau = 10$. Raw regression results are reported in Table A6.

Figure 2.5: Impacts of Children in a Difference-in-Differences Event Study Design, Females

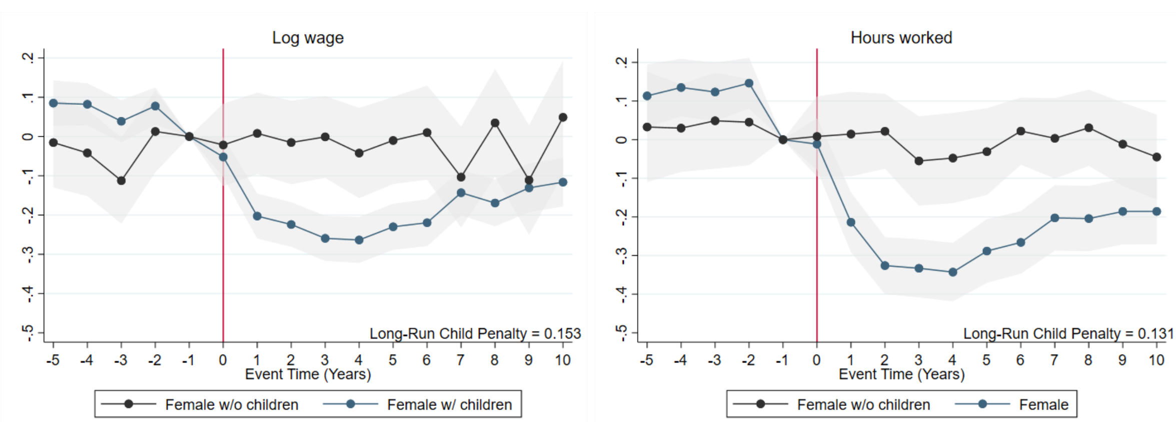
(a) Modern



(b) Neutral

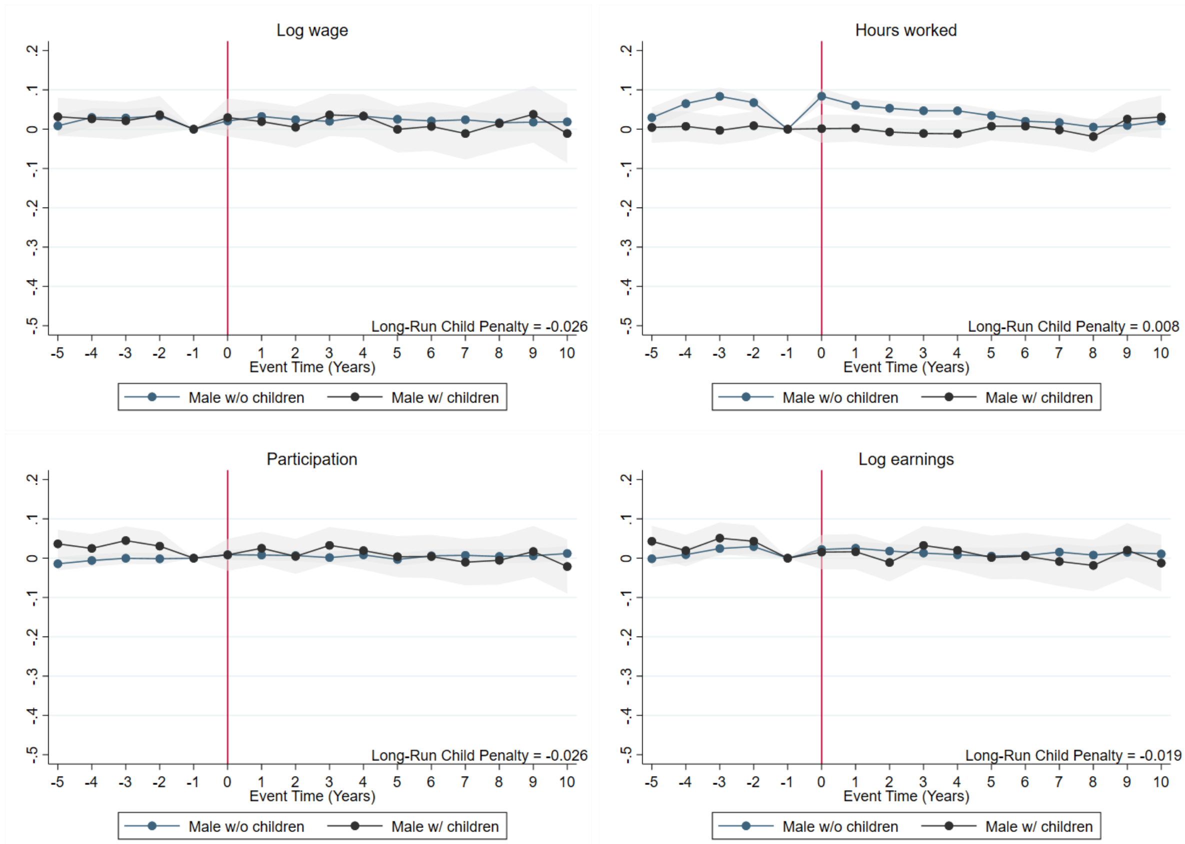


(c) Traditional



Notes: These statistics are obtained from the baseline event study specification (1) except that parents are compared against female counterparts who never had any children. Figure reports event time coefficients as a percentage of the counterfactual outcome absent children. All plots report long-run child penalty calculated at $\tau = 10$.

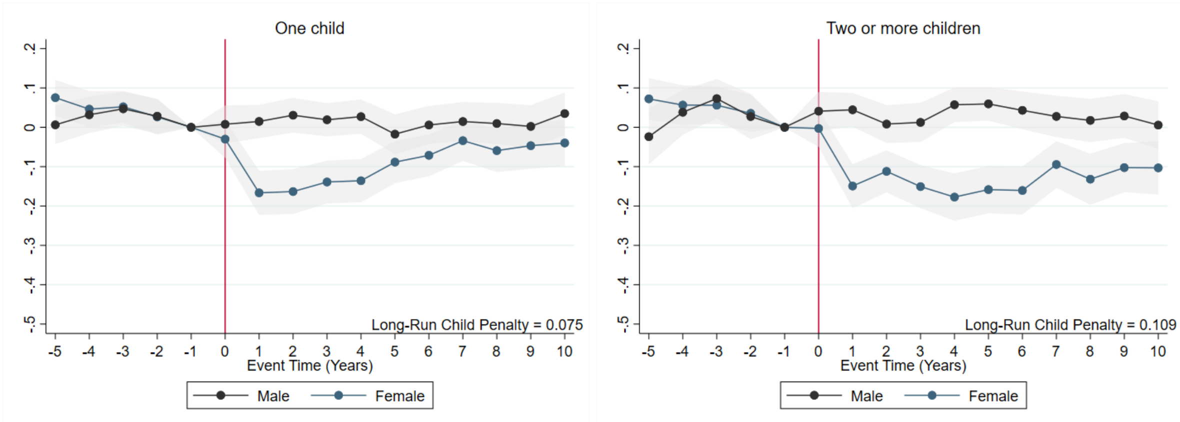
Figure 2.6: Impacts of Children in a Difference-in-Differences Event Study Design, Males



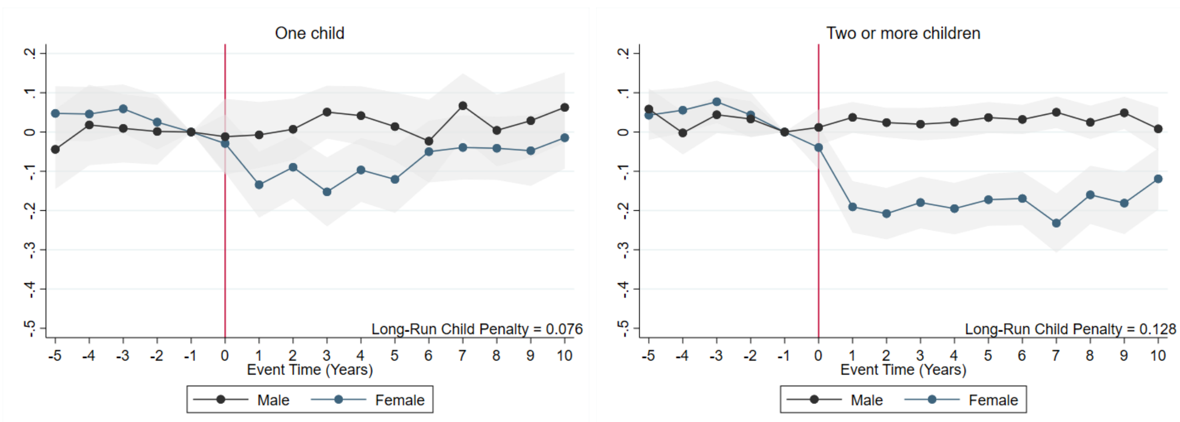
Notes: These statistics are obtained from the baseline event study specification (1) except that parents are compared against male counterparts who never had any children. Figure reports event time coefficients as a percentage of the counterfactual outcome absent children. All plots report long-run child penalty calculated at $\tau = 10$.

Figure 2.7: Penalties relative to number of kids, wages

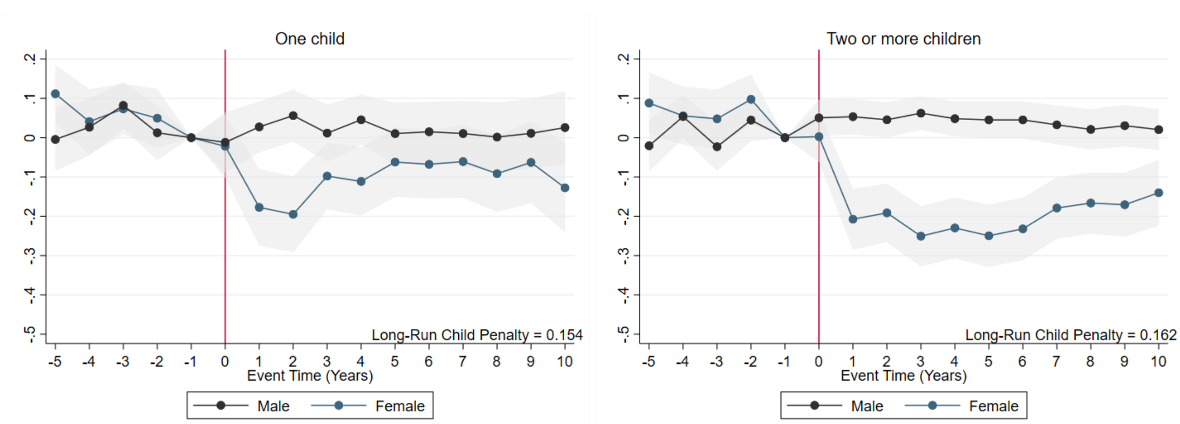
(a) Modern



(b) Neutral



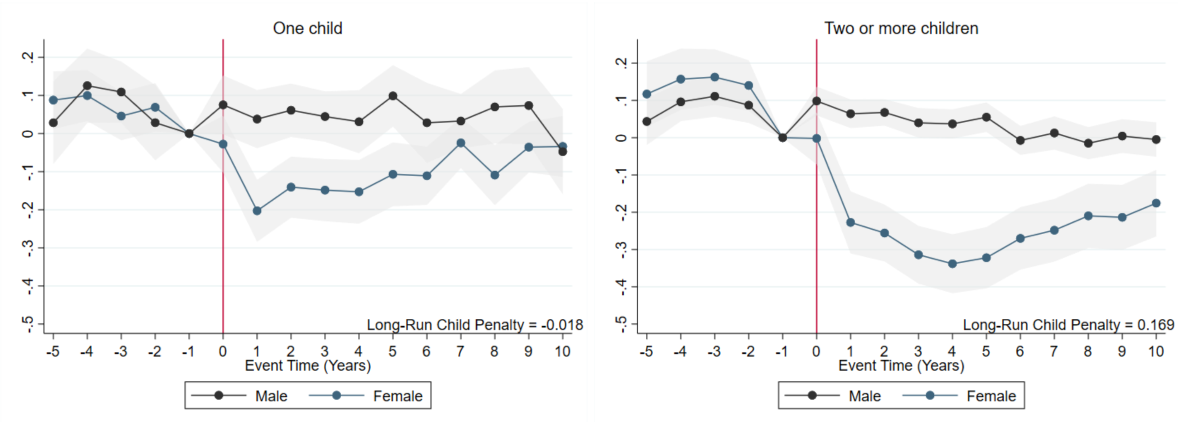
(c) Traditional



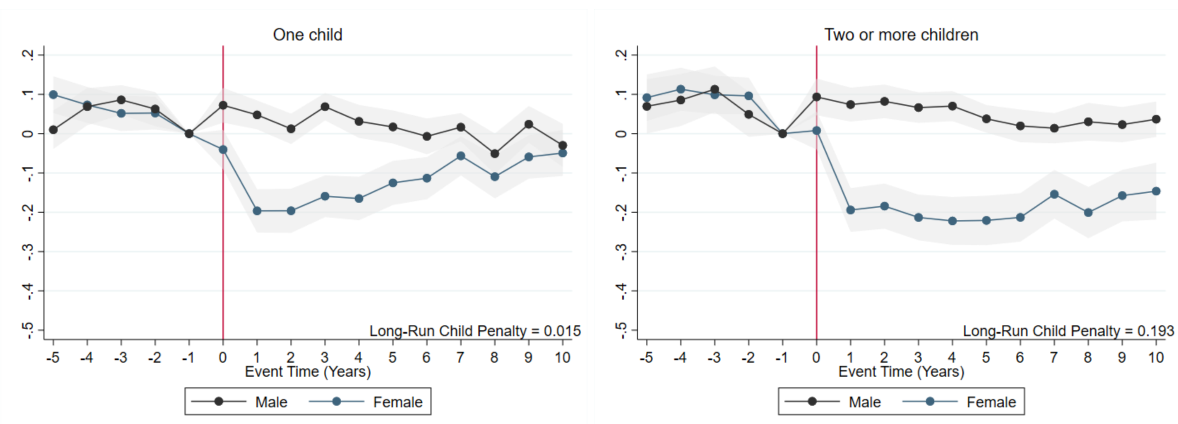
Notes: These statistics are obtained after stratifying the sample by their lifetime number of kids. Figure reports event time coefficients from as a percentage of the counterfactual outcome absent children. All plots report long-run child penalty calculated at $\tau = 10$.

Figure 2.8: Penalties relative to number of kids, Hours worked per week

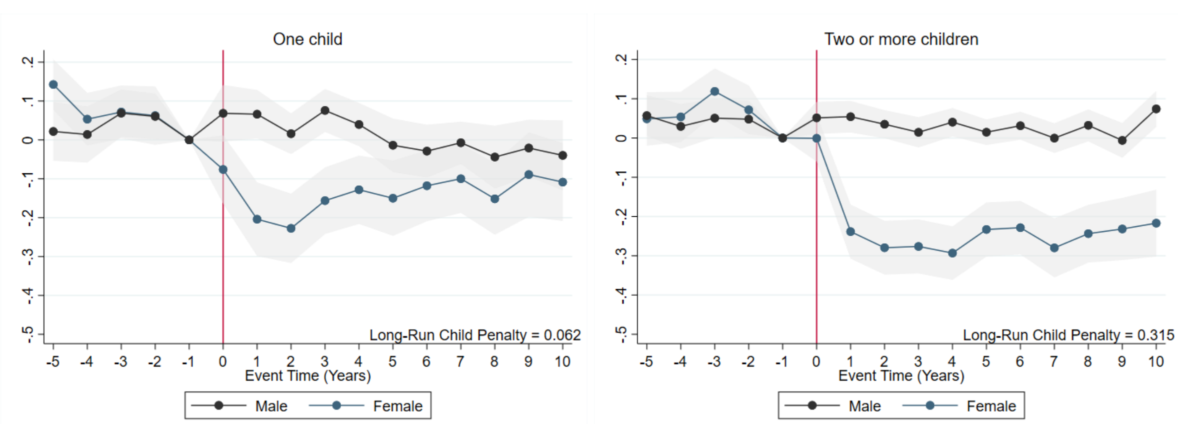
(a) Modern



(b) Neutral



(c) Traditional



Notes: These statistics are obtained after stratifying the sample by their lifetime number of kids. Figure reports event time coefficients from as a percentage of the counterfactual outcome absent children. All plots report long-run child penalty calculated at $\tau = 10$.

Figure 2.9: Mediation Analysis

$$\begin{tikzcd}
\text{Treatment/Intervention, } d \in \{0,1\} \arrow[r, "a"] \arrow[d, "b"] & \text{Outcomes, } Y(d) \\
\text{Mediator, } M(d) \arrow[ur, "c"] &
\end{tikzcd}$$

Notes: This illustrates a causal mediation framework following the classical mediation model of Baron and Kenny (1986) while adapting the potential outcomes notation in Huber (2020). Treatment d sequentially precedes the mediator M. The directional arrow to Y coming from D represents the direct effect of the treatment, while the arrow from M to Y denotes the indirect effect of the treatment that operations through the mediator M.

Tables

Table 2.1: Percent of NLSY79 Respondents Who Either Agree or Strongly Agree with Statement

Questions about women's role in the household	**NLSY79 cohort**	**Full Sample**	**Female**	**Male**
Woman's place is in the home, not the office or shop	23.5	23.9	14.3	32.7
Wife with a family has no time for outside employment	30.3	31.0	23.5	38.0
A non-working wife feels as useful than one who holds a job	33.7	32.9	37.2	28.9
Employment of wives leads to more juvenile delinquency	27.4	28.0	23.6	32.1
Better if man is achiever outside home and woman takes care of family/home	44.3	44.4	36.0	52.2
Men should not share the work around the house with women	19.3	19.1	15.7	22.3
Women are much happier if they stay home and take care of children	33.3	32.8	25.8	39.4
Observations	12,686	4,593	2,215	2,378

Notes: Belief statements are taken from the attitudes module of the NLSY. Respondents answered if they strongly agreed, agreed, disagreed, or strongly disagreed with the statement. The first column reports unweighted shares of the orignal cohort, while the second column only include parents who that satisfy the sample criteria in Section 3 The last two columns reports the equivalent shares across gender.

Table 2.2: Summary Statistics, Time-invariant characteristics

	Full Sample	Females			Males		
	All	Modern	Neutral	Traditional	Modern	Neutral	Traditional
Lifetime count of children	2.31	2.15	2.25	2.39	2.35	2.35	2.39
	(1.12)	(0.95)	(0.98)	(1.14)	(1.21)	(1.14)	(1.24)
Age at firstbirth	26.22	26.12	25.43	25.05	27.27	26.93	26.37
	(5.08)	(5.00)	(4.76)	(4.63)	(5.41)	(5.26)	(5.07)
Year of first job	81.85	81.89	81.96	81.94	82.06	81.72	81.64
	(3.54)	(3.34)	(3.68)	(3.50)	(4.16)	(3.18)	(3.50)
Hispanic	0.19	0.17	0.19	0.23	0.13	0.20	0.23
	(0.40)	(0.37)	(0.40)	(0.42)	(0.34)	(0.40)	(0.42)
Black	0.25	0.28	0.20	0.20	0.31	0.29	0.23
	(0.44)	(0.45)	(0.40)	(0.40)	(0.46)	(0.45)	(0.42)
White	0.55	0.55	0.60	0.57	0.55	0.51	0.53
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Mother's years of schooling	10.95	11.42	10.80	10.65	11.79	10.89	10.33
	(3.25)	(2.85)	(3.16)	(3.38)	(2.97)	(3.33)	(3.52)
Father worked full-time in 79	0.96	0.97	0.96	0.96	0.97	0.97	0.96
	(0.19)	(0.16)	(0.20)	(0.20)	(0.18)	(0.18)	(0.20)
Mother worked full-time in 79	0.69	0.74	0.66	0.66	0.73	0.71	0.63
	(0.46)	(0.44)	(0.47)	(0.47)	(0.45)	(0.46)	(0.48)
Desired count of children in 79	2.60	2.46	2.57	2.88	2.45	2.57	2.71
	(1.50)	(1.53)	(1.33)	(1.79)	(1.26)	(1.35)	(1.63)
Standardized AFQT score	65.75	70.12	67.80	63.15	69.44	63.80	60.98
	(21.71)	(18.46)	(19.54)	(22.01)	(21.82)	(22.83)	(23.46)
Observations	4,593	912	708	595	594	834	950

Summary statistics were computed for the subsample of parents that satisfy the conditions in Section 3. Mean coefficients and standard deviations are reported in parentheses.

Table 2.3: Male and female characteristics before and after childbirth

	Full Sample	Females			Males		
	All	Modern	Neutral	Traditional	Modern	Neutral	Traditional
Characteristics at $t = -1$							
Log wage	5.56	5.58	5.35	5.14	5.91	5.78	5.56
	(2.54)	(2.51)	(2.58)	(2.65)	(2.37)	(2.45)	(2.59)
Log earnings	8.23	8.20	7.96	7.75	8.65	8.53	8.23
	(3.20)	(3.16)	(3.20)	(3.29)	(3.05)	(3.07)	(3.34)
Hours worked per week	35.11	32.91	31.53	31.46	38.21	37.48	38.21
at current job	(16.13)	(14.92)	(15.48)	(16.78)	(15.66)	(15.88)	(16.55)
Labor force participation	0.92	0.93	0.92	0.91	0.94	0.92	0.91
	(0.27)	(0.26)	(0.28)	(0.29)	(0.24)	(0.26)	(0.29)
Part-time status	0.14	0.18	0.19	0.21	0.12	0.10	0.09
	(0.35)	(0.38)	(0.39)	(0.41)	(0.32)	(0.30)	(0.29)
Married	0.54	0.59	0.59	0.54	0.56	0.51	0.48
	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Highest grade completed	12.76	13.26	12.85	12.57	13.26	12.59	12.19
	(2.40)	(2.21)	(2.18)	(2.21)	(2.41)	(2.46)	(2.62)
Family friendly benefits	0.46	0.60	0.57	0.51	0.38	0.38	0.35
in current job	(0.50)	(0.49)	(0.50)	(0.50)	(0.48)	(0.49)	(0.48)
Math-intensive occupation	3.65	3.91	3.72	3.67	3.69	3.47	3.48
	(1.57)	(1.55)	(1.47)	(1.51)	(1.71)	(1.56)	(1.55)
Reasoning-intensive occupation	3.97	4.26	4.01	3.91	4.10	3.79	3.78
	(1.80)	(1.76)	(1.73)	(1.67)	(1.92)	(1.82)	(1.82)
Service-intensive occupation	3.26	3.88	3.98	3.89	2.79	2.72	2.55
	(1.99)	(2.04)	(1.96)	(2.02)	(1.91)	(1.75)	(1.72)
Observations	4,593	912	708	595	594	834	950
Characteristics at $t = -10$							
Log wage	5.58	5.28	5.02	4.78	6.31	6.17	5.87
	(2.73)	(2.79)	(2.93)	(3.01)	(2.30)	(2.35)	(2.60)
Log earnings	8.19	7.78	7.46	7.22	9.20	8.89	8.54
	(3.65)	(3.72)	(3.87)	(3.84)	(3.12)	(3.29)	(3.60)
Hours worked per week	35.40	30.39	27.87	26.79	42.79	42.67	40.74
	(17.81)	(17.07)	(17.79)	(18.51)	(14.42)	(15.77)	(15.31)
Labor force participation	0.85	0.83	0.79	0.75	0.92	0.91	0.89
	(0.36)	(0.38)	(0.40)	(0.43)	(0.28)	(0.28)	(0.32)
Part-time status	0.12	0.19	0.23	0.25	0.03	0.03	0.04
	(0.32)	(0.39)	(0.42)	(0.44)	(0.18)	(0.17)	(0.20)
Married	0.74	0.70	0.74	0.74	0.77	0.74	0.76
	(0.44)	(0.46)	(0.44)	(0.44)	(0.42)	(0.44)	(0.43)
Highest grade completed	13.01	13.45	13.18	12.82	13.42	12.83	12.49
	(2.37)	(2.14)	(2.11)	(2.14)	(2.40)	(2.49)	(2.64)
Family friendly benefits	0.67	0.78	0.80	0.72	0.62	0.60	0.56
in current job	(0.47)	(0.41)	(0.40)	(0.45)	(0.49)	(0.49)	(0.50)
Math-intensive occupation	3.81	3.91	3.81	3.67	4.02	3.73	3.74
	(1.57)	(1.54)	(1.49)	(1.51)	(1.69)	(1.60)	(1.54)
Reasoning-intensive occupation	4.25	4.32	4.23	4.02	4.55	4.21	4.17
	(1.82)	(1.74)	(1.78)	(1.61)	(1.98)	(1.87)	(1.87)
Service-intensive occupation	3.45	4.02	4.28	4.11	3.02	2.83	2.82
	(2.07)	(2.16)	(2.21)	(2.09)	(1.82)	(1.89)	(1.73)
Observations	3,197	629	510	424	424	540	670

Summary statistics were computed for the subsample of parents that satisfy the conditions in Section 3. Mean coefficients and standard deviations are reported in parentheses.

Table 2.4: Gender attitudes and female educational investment on years of schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Modern gender norms	0.1695	0.1733*	0.1440				
	(0.1050)	(0.0937)	(0.0895)				
Gender-norm index				-0.0834*	-0.0217	-0.0826	-0.0584
				(0.0445)	(0.0399)	(0.0663)	(0.0644)
Age-standardized AFQT score		1.0366***	1.0004***		1.0398***	0.0000	0.9824***
		(0.0620)	(0.0765)		(0.0520)	(.)	(0.0759)
Non-traditional gender norms * AFQT			1.0366***			1.0330***	
			(0.0620)			(0.0620)	
Modern gender norms * AFQT				0.0705			0.1005
				(0.1010)			(0.1015)
Mother's educational category:							
7 to 12 yrs	0.5238**	-0.0040	0.0008	0.6739***	0.0722	0.0018	0.0081
	(0.2370)	(0.2478)	(0.2456)	(0.1937)	(0.1878)	(0.2452)	(0.2430)
13 to 15 years	1.5497***	0.5849**	0.5908**	1.6724***	0.6627***	0.5882**	0.5964**
	(0.2935)	(0.2963)	(0.2943)	(0.2394)	(0.2271)	(0.2936)	(0.2913)
16 yrs and over	2.4823***	1.1019***	1.1060***	2.5986***	1.1943***	1.1083***	1.1135***
	(0.2956)	(0.3020)	(0.2999)	(0.2444)	(0.2375)	(0.2997)	(0.2975)
Demographic characteristics	Y	Y	Y	Y	Y	Y	Y
Unique Observations	1460	1413	1413	1989	1925	1413	1413
R-squared	0.4255	0.5520	0.5522	0.4227	0.5556	0.5512	0.5517
F-stat	88.4182	139.2866	125.0167	121.5653	197.3967	139.6432	124.8683

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Gender attitudes and preference for job amenities around birth of first child

	Any family-friendly benefits			Company provided child care			Maternity/Paternity Leaves		
	$t < 0$	$t = [1, 5]$	$t = [6, 10]$	$t < 0$	$t = [1, 5]$	$t = [6, 10]$	$t < 0$	$t = [1, 5]$	$t = [6, 10]$
Modern gender norms	0.0233***	0.0464***	0.0348**	0.0090	-0.0012	0.0004	0.0614***	0.0517***	0.0507***
	(0.0066)	(0.0126)	(0.0137)	(0.0119)	(0.0075)	(0.0062)	(0.0160)	(0.0127)	(0.0129)
Demographic characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Age categories	Y	Y	Y	Y	Y	Y	Y	Y	Y
Education categories	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6739	5805	6381	2468	5584	7772	4216	8173	8259
R-squared	0.7541	0.3507	0.0546	0.0172	0.0212	0.0209	0.0336	0.0720	0.0697

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Gender attitudes and preference for occupational characteristics around birth of first child

	Math-intensive			Reasoning-intensive			Services-intensive		
	$t < 0$	$t = [1, 5]$	$t = [6, 10]$	$t < 0$	$t = [1, 5]$	$t = [6, 10]$	$t < 0$	$t = [1, 5]$	$t = [6, 10]$
Modern gender norms	0.1805***	0.1333***	0.1387***	0.1986***	0.2032***	0.1379***	-0.0411	-0.0467	-0.1321**
	(0.0379)	(0.0385)	(0.0436)	(0.0413)	(0.0414)	(0.0468)	(0.0525)	(0.0552)	(0.0611)
Demographic characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Age categories	Y	Y	Y	Y	Y	Y	Y	Y	Y
Education categories	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	7750	7596	6673	7750	7596	6673	7750	7596	6673
R-squared	0.1636	0.1361	0.1101	0.2466	0.2290	0.1929	0.0427	0.0558	0.0613

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Estimated causal mechanisms of modern gender norms with respect to child penalties

	Earnings		Weekly hours		Participate	
Childbirth: $t = 0$	t+1	t+10	t+1	t+10	t+1	t+10
Mediator: Age at first marriage						
Average Indirect Effect	-.0085	-.0051	-.0125	- .0001	-.0014	.0032
	[-.0166, -.0028]	[-.0122, -.0009]	[-.0234, -.0046]	[-.0069, .0060]	[-.0794, .0346]	[-.0006, .0114]
Average Direct Effect	.0261	-.0435	-.0092	-.0695	-.0234	-.0616
	[-.0305, 0846]	[-.0957, .0105]	[-.0801, .0639]	[-.1531, .0169]	[-.0794, .0346]	[-.1298, .0087]
Average Total Effect	.0177	-.0486	-.0217	-.0696	-.0247	-.0585
	[-.0383, .0792]	[-.1005, .0080]	[-.0916, .0553]]	[-.1540, .0205]	[-.0812, .0360]	[-.1278, .0148]
Mediator: Highest Grade Completed						
Average Indirect Effect	-.0044	-.0114	-.0054	-.0054	-.0029	-.0044
	[-.0152, .0007]	[-.0320, -.0001]	[-.0195, .0019]	[-.0257, .0052]	[-.0124, .0006]	[-.0210, .0046]
Average Direct Effect	-.0745	-.2169	-.0197	-.1599	-.0511	-.1837
	[-.2117, .0671]	[-.3927, -.0353]	[-.1989, .1651]	[-.3699, .0572]	[-.1881, .0904]	[-.3544, -.0074]
Average Total Effect	-.0789	-.2283	-.0253	-.1652	-.0541	-.1881
	[-.2154, .0661]	[-.4039, -.0379]	[-.2033, .1638]	[-.3762, .0616]	[-.1909, .0907]	[-.3597, -.0035]
Mediator: Occupational Quality						
Average Indirect Effect	-.0035	-.0059	-.0024	-.0076	-.0000	.0008
	[-.0141, .0056]	[-.0197, .0012]	[-.0127, .0044]	[-.0263, .0009]	[-.0009, .0006]	[-.0010, .0047]
Average Direct Effect	-.0303	-.0856	.0510	-.0439	-.0094	-.0467
	[-.1258, .0682]	[-.2104, .0432]	[-.0842, .1906]	[-.2204, .1383]	[-.0277, .0095]	[-.0848, -.0073]
Average Total Effect	-.0338	-.0915	.0486	-.0515	-.0094	-.0459
	[-.1273, .0664]	[-.2152, .0414]	[-.0855, .1903]	[-.2268, .1367]	[-.0277, .0097]	[-.0845, -.0055]

Notes: Lower and upper bounds at 95% confidence interval in brackets. All mediators and modern treatment dummy are conditioned on the same set of pretreatment covariates that includes: mother's and father's level of education, mother's employment status, own ability measures (AFQT scores), race, if whether responded lives in urban/rural zones, family size, poverty status, if foreign language is spoken in the household, if birth country is outside the US access to libraries and if respondent have access to newspapers and magazines at home.

Appendix

Table A1: Percent Who Either Agree or Strongly Agree with the Statement

	NLSY Survey Year			
Questions about women's role in the household	1979	1982	1987	2004
Female Subsample				
Woman's place is in the home, not the office or shop	14.3	9.8	8.0	8.4
Wife with a family has no time for outside employment	23.5	15.0	11.7	14.1
A non-working wife feels as useful than one who holds a job	37.2	40.2	51.1	61.8
Employment of wives leads to more juvenile delinquency	23.6	16.6	16.0	24.6
Better if man is achiever outside home and woman takes care of family/home	36.0	27.2	22.5	25.2
Men should not share the work around the house with women	15.7	6.6	5.2	3.9
Women are much happier if they stay home and take care of children	25.8	19.8	22.2	25.4
N	2215	2172	2107	2004
Male Subsample				
Woman's place is in the home, not the office or shop	32.7	23.8	13.2	11.5
Wife with a family has no time for outside employment	38.0	29.6	20.9	19.5
A non-working wife feels as useful than one who holds a job	28.9	24.8	30.6	39.2
Employment of wives leads to more juvenile delinquency	32.1	25.4	21.0	28.3
Better if man is achiever outside home and woman takes care of family/home	52.2	41.4	29.9	27.0
Men should not share the work around the house with women	22.3	15.1	7.3	4.7
Women are much happier if they stay home and take care of children	39.4	33.8	29.8	34.6
N	2378	2318	2230	2067

Notes: Belief statements are taken from the attitudes module from all waves of the NLSY. This table presents the shares of females and males that are in agreement with the belief statements itemized in the first column. Statistics are shown for all survey waves where this information is reported.

Table A2: Persistence of norm categories post-birth

	Female	Male
N	2215	2378
% share unchanged	45.1	44.4
% share that became more progressive	27.7	29.1
% share that became more traditional	27.2	26.5

Changes in norms are calculated by comparing norm-categories before and after childbirth.

Table A3: Gender progressivity vs family characteristics at 1979

	All	Female	Male
AFQT scores	0.0012***	0.0008	0.0012**
	(0.0004)	(0.0006)	(0.0005)
Mother worked full time	0.0664***	0.0757**	0.0437
	(0.0225)	(0.0330)	(0.0298)
Mother's year of schooling	0.0168***	0.0166***	0.0178***
	(0.0040)	(0.0061)	(0.0052)
Lived apart from father (1 0)	0.0512**	0.0200	0.0752**
	(0.0230)	(0.0328)	(0.0316)
Household subscribed to magazines and newspapers (1 0)	0.0550*	0.0859**	0.0357
	(0.0284)	(0.0419)	(0.0373)
Poverty (1 0)	-0.0418	0.0838*	-0.1410***
	(0.0320)	(0.0481)	(0.0416)
Large family size (1 0)	0.0217	0.0028	0.0318
	(0.0213)	(0.0311)	(0.0283)
Urban residence (1 0)	0.0117	-0.0093	0.0163
	(0.0253)	(0.0372)	(0.0334)
N	2208	1098	1110
R^2	0.0380	0.0285	0.0613

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent variable of scores is rescaled so that a higher number denotes modern gender norms.

Table A4: Event-time coefficients with respect to t=-1 for log wages

	Females				Males			
	Full Sample	Modern	Neutral	Traditional	Full Sample	Modern	Neutral	Traditional
t=-5	0.378***	0.393***	0.349***	0.406***	0.0462	-0.134	0.153	0.0766
	(0.0688)	(0.105)	(0.118)	(0.140)	(0.0705)	(0.146)	(0.109)	(0.117)
t=-4	0.342***	0.314***	0.310***	0.400***	0.161**	0.203	0.0865	0.205*
	(0.0664)	(0.104)	(0.114)	(0.132)	(0.0649)	(0.128)	(0.107)	(0.106)
t=-3	0.390***	0.415***	0.509***	0.193	0.156**	0.325***	0.243**	-0.0270
	(0.0621)	(0.0948)	(0.101)	(0.135)	(0.0632)	(0.111)	(0.0973)	(0.115)
t=-2	0.343***	0.296***	0.374***	0.387***	0.185***	0.189	0.152	0.214**
	(0.0611)	(0.0946)	(0.108)	(0.120)	(0.0627)	(0.124)	(0.0979)	(0.105)
t=0	-0.0972	0.0355	-0.114	-0.275**	0.121*	0.0859	0.0861	0.171
	(0.0658)	(0.0989)	(0.114)	(0.135)	(0.0634)	(0.126)	(0.100)	(0.106)
t=1	-0.905***	-0.727***	-0.963***	-1.114***	0.193***	0.229**	0.274***	0.106
	(0.0794)	(0.120)	(0.140)	(0.160)	(0.0586)	(0.109)	(0.0857)	(0.105)
t=2	-0.962***	-0.639***	-1.097***	-1.265***	0.146**	0.122	0.235***	0.0948
	(0.0809)	(0.120)	(0.143)	(0.162)	(0.0603)	(0.115)	(0.0881)	(0.108)
t=3	-1.047***	-0.918***	-0.862***	-1.474***	0.122**	0.231**	0.0180	0.130
	(0.0826)	(0.128)	(0.141)	(0.166)	(0.0616)	(0.113)	(0.102)	(0.104)
t=4	-1.122***	-0.988***	-0.968***	-1.505***	0.201***	0.341***	0.160*	0.157
	(0.0852)	(0.134)	(0.143)	(0.170)	(0.0608)	(0.111)	(0.0962)	(0.105)
t=5	-1.049***	-0.997***	-0.891***	-1.317***	0.155**	0.357***	0.116	0.0244
	(0.0865)	(0.137)	(0.146)	(0.170)	(0.0642)	(0.109)	(0.103)	(0.117)
t=6	-0.994***	-0.873***	-0.902***	-1.256***	0.128*	0.127	0.151	0.123
	(0.0874)	(0.137)	(0.149)	(0.174)	(0.0657)	(0.130)	(0.0981)	(0.113)
t=7	-0.829***	-0.676***	-1.018***	-0.817***	0.147**	0.244**	0.184*	0.0422
	(0.0884)	(0.139)	(0.158)	(0.166)	(0.0675)	(0.124)	(0.104)	(0.120)
t=8	-0.837***	-0.681***	-0.883***	-0.963***	0.101	0.204	-0.0458	0.171
	(0.0898)	(0.140)	(0.160)	(0.171)	(0.0712)	(0.130)	(0.117)	(0.123)
t=9	-0.724***	-0.606***	-0.854***	-0.740***	0.109	0.183	0.140	0.0364
	(0.0918)	(0.140)	(0.165)	(0.178)	(0.0726)	(0.136)	(0.111)	(0.129)
t=10	-0.601***	-0.440***	-0.709***	-0.656***	0.115	0.174	0.0541	0.136
	(0.0924)	(0.142)	(0.166)	(0.177)	(0.0765)	(0.147)	(0.129)	(0.125)
Obs.	58,196	23,992	18,598	15,580	63,466	16,193	22,343	24,812
R-squared	0.063	0.056	0.072	0.074	0.082	0.086	0.096	0.077

All regressions include individual fixed effects, age dummies, year dummies and a constant.
Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Event-time coefficients with respect to t=-1 for weekly hours worked

	Females				Males			
	Full Sample	Modern	Neutral	Traditional	Full Sample	Modern	Neutral	Traditional
t=-5	2.460***	3.147***	1.952***	2.920***	0.977**	2.447**	1.128**	-0.155
	(0.417)	(0.789)	(0.550)	(1.066)	(0.442)	(1.211)	(0.540)	(0.975)
t=-4	3.082***	3.742***	2.546***	3.631***	2.190***	2.501**	2.101***	2.363***
	(0.398)	(0.732)	(0.535)	(1.014)	(0.426)	(1.147)	(0.540)	(0.874)
t=-3	3.430***	3.127***	3.555***	3.386***	2.870***	2.821***	2.932***	2.926***
	(0.366)	(0.647)	(0.482)	(1.058)	(0.390)	(1.036)	(0.478)	(0.898)
t=-2	3.157***	3.475***	2.744***	4.010***	2.362***	1.955*	2.444***	2.213**
	(0.351)	(0.646)	(0.471)	(0.911)	(0.389)	(1.074)	(0.467)	(0.900)
t=0	-0.00207	0.378	-0.166	-0.339	3.164***	3.239***	2.804***	3.933***
	(0.395)	(0.705)	(0.535)	(1.004)	(0.369)	(0.927)	(0.464)	(0.814)
t=1	-6.580***	-6.157***	-6.829***	-6.684***	2.389***	1.970**	2.131***	3.431***
	(0.469)	(0.843)	(0.630)	(1.226)	(0.355)	(0.996)	(0.443)	(0.750)
t=2	-7.700***	-6.040***	-7.646***	-10.54***	2.140***	4.073***	1.876***	1.672**
	(0.485)	(0.922)	(0.640)	(1.211)	(0.366)	(0.838)	(0.466)	(0.808)
t=3	-8.156***	-6.538***	-8.205***	-10.91***	1.911***	1.741**	1.531***	3.067***
	(0.492)	(0.907)	(0.656)	(1.254)	(0.365)	(0.862)	(0.471)	(0.763)
t=4	-8.742***	-8.082***	-8.324***	-11.30***	1.926***	2.263***	1.735***	2.252***
	(0.506)	(0.952)	(0.676)	(1.269)	(0.365)	(0.862)	(0.456)	(0.838)
t=5	-7.746***	-6.989***	-7.644***	-9.515***	1.433***	1.657*	1.194***	1.904**
	(0.530)	(1.002)	(0.696)	(1.386)	(0.352)	(0.922)	(0.434)	(0.812)
t=6	-7.415***	-7.314***	-7.123***	-8.733***	0.842**	1.714*	0.595	0.834
	(0.520)	(0.979)	(0.686)	(1.349)	(0.389)	(1.025)	(0.473)	(0.905)
t=7	-6.533***	-5.653***	-6.955***	-6.606***	0.710*	1.019	0.718	0.566
	(0.536)	(1.002)	(0.706)	(1.406)	(0.381)	(0.938)	(0.465)	(0.903)
t=8	-6.952***	-6.169***	-7.404***	-6.561***	0.229	1.034	0.423	-0.942
	(0.534)	(0.987)	(0.706)	(1.384)	(0.446)	(0.943)	(0.576)	(0.985)
t=9	-5.573***	-4.228***	-6.128***	-5.858***	0.398	0.304	0.221	1.015
	(0.547)	(1.028)	(0.723)	(1.363)	(0.434)	(1.001)	(0.551)	(0.934)
t=10	-4.985***	-3.338***	-5.284***	-5.768***	0.882*	-0.0878	1.376**	0.116
	(0.575)	(1.087)	(0.775)	(1.343)	(0.453)	(1.034)	(0.577)	(1.013)
Obs.	58,196	23,992	18,598	15,580	63,466	16,193	22,343	24,812
R-squared	0.129	0.129	0.134	0.138	0.213	0.221	0.224	0.206

All regressions include individual fixed effects, age dummies, year dummies and a constant.
Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Event-time coefficients with respect to t=-1 for labor force participation

	Females				Males			
	Full Sample	Modern	Neutral	Traditional	Full Sample	Modern	Neutral	Traditional
t=-5	0.0294***	0.0183	0.0383***	0.0234	-0.0130*	-0.0258*	-0.0116	-0.0183
	(0.00763)	(0.0117)	(0.00967)	(0.0216)	(0.00780)	(0.0151)	(0.00943)	(0.0185)
t=-4	0.0311***	0.0186*	0.0380***	0.0305*	-0.00546	-0.0125	-0.0102	0.00841
	(0.00722)	(0.0111)	(0.00963)	(0.0185)	(0.00720)	(0.0132)	(0.00909)	(0.0157)
t=-3	0.0226***	0.0218**	0.0363***	-0.00371	-0.000209	0.00730	-0.000675	-0.00157
	(0.00737)	(0.0107)	(0.00925)	(0.0218)	(0.00677)	(0.0106)	(0.00836)	(0.0164)
t=-2	0.0236***	0.0278***	0.0254***	0.0194	-0.00142	-0.000973	0.000222	-0.000895
	(0.00714)	(0.0100)	(0.00976)	(0.0188)	(0.00674)	(0.0117)	(0.00815)	(0.0156)
t=0	-0.00757	0.000704	-0.00407	-0.0309	0.00802	0.000468	0.00342	0.0197
	(0.00797)	(0.0116)	(0.0106)	(0.0220)	(0.00636)	(0.0119)	(0.00807)	(0.0138)
t=1	-0.107***	-0.0822***	-0.109***	-0.135***	0.00745	0.00714	0.00110	0.0155
	(0.0103)	(0.0151)	(0.0139)	(0.0272)	(0.00642)	(0.0112)	(0.00821)	(0.0144)
t=2	-0.124***	-0.0774***	-0.129***	-0.183***	0.00621	-0.00362	0.00206	0.0193
	(0.0108)	(0.0154)	(0.0145)	(0.0295)	(0.00654)	(0.0127)	(0.00825)	(0.0141)
t=3	-0.140***	-0.126***	-0.136***	-0.187***	0.00146	0.00882	-0.00434	0.000681
	(0.0113)	(0.0175)	(0.0150)	(0.0302)	(0.00691)	(0.0124)	(0.00862)	(0.0162)
t=4	-0.137***	-0.111***	-0.140***	-0.170***	0.00775	0.00770	0.00566	0.0229
	(0.0116)	(0.0175)	(0.0154)	(0.0300)	(0.00679)	(0.0125)	(0.00834)	(0.0145)
t=5	-0.142***	-0.126***	-0.142***	-0.177***	-0.00302	0.0169	-0.00803	-0.00764
	(0.0119)	(0.0183)	(0.0159)	(0.0311)	(0.00744)	(0.0125)	(0.00919)	(0.0177)
t=6	-0.124***	-0.0977***	-0.123***	-0.160***	0.00561	-0.00252	-0.00398	0.0257*
	(0.0120)	(0.0183)	(0.0158)	(0.0308)	(0.00734)	(0.0147)	(0.00942)	(0.0150)
t=7	-0.102***	-0.0859***	-0.114***	-0.0901***	0.00664	0.0149	0.00747	-0.0134
	(0.0118)	(0.0181)	(0.0159)	(0.0292)	(0.00753)	(0.0142)	(0.00887)	(0.0189)
t=8	-0.104***	-0.0660***	-0.117***	-0.116***	0.00403	0.00692	0.00439	0.00900
	(0.0123)	(0.0180)	(0.0168)	(0.0303)	(0.00806)	(0.0151)	(0.00954)	(0.0183)
t=9	-0.0907***	-0.0716***	-0.0943***	-0.109***	0.00555	0.00329	0.00346	0.000590
	(0.0124)	(0.0188)	(0.0165)	(0.0332)	(0.00828)	(0.0161)	(0.0101)	(0.0196)
t=10	-0.0762***	-0.0525***	-0.0808***	-0.0741**	0.0109	0.0123	0.0111	0.0122
	(0.0126)	(0.0191)	(0.0170)	(0.0302)	(0.00856)	(0.0164)	(0.0105)	(0.0186)
Obs.	62,135	25,664	19,813	16,632	68,953	17,542	24,093	27,185
R-squared	0.046	0.045	0.055	0.051	0.055	0.069	0.058	0.052

All regressions include individual fixed effects, age dummies, year dummies and a constant.
Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Event-time coefficients with respect to t=-1 for earnings

	Females				Males			
	Full Sample	Modern	Neutral	Traditional	Full Sample	Modern	Neutral	Traditional
t=-5	3,984***	3,611***	2,934***	4,870***	2,716***	2,661***	2,935***	2,598***
	(436.7)	(1,063)	(585.5)	(678.0)	(444.8)	(758.8)	(753.3)	(808.6)
t=-4	3,750***	2,810***	3,331***	4,527***	3,141***	2,982***	2,903***	3,763***
	(319.2)	(546.5)	(573.2)	(518.9)	(475.9)	(830.9)	(792.8)	(841.2)
t=-3	4,360***	3,513***	2,909***	5,854***	4,473***	3,464***	4,514***	5,803***
	(369.8)	(753.5)	(597.6)	(589.6)	(598.9)	(747.0)	(877.7)	(1,585)
t=-2	4,894***	3,535***	4,599***	5,868***	3,934***	4,020***	2,760***	5,264***
	(503.9)	(556.5)	(1,276)	(582.2)	(455.0)	(749.6)	(704.9)	(944.6)
t=0	3,042***	1,954***	2,347***	4,122***	4,098***	5,169***	1,831**	5,453***
	(362.9)	(658.9)	(596.9)	(612.9)	(554.7)	(1,077)	(775.0)	(916.0)
t=1	-491.8	-1,473**	-225.1	-313.4	4,924***	6,034***	3,386***	5,390***
	(388.9)	(578.6)	(704.9)	(664.5)	(617.6)	(1,125)	(950.9)	(1,107)
t=2	-1,263***	-2,546***	-1,622**	-306.2	4,988***	5,580***	2,598***	7,245***
	(393.4)	(658.7)	(681.4)	(663.8)	(695.5)	(1,138)	(945.8)	(1,578)
t=3	-1,626***	-3,291***	-1,404*	-960.4	4,572***	5,096***	3,128***	5,769***
	(439.3)	(736.7)	(843.2)	(679.5)	(703.1)	(1,236)	(1,081)	(1,343)
t=4	-2,650***	-3,357***	-2,989***	-2,134***	4,187***	4,718***	2,751***	5,266***
	(436.0)	(790.3)	(728.1)	(721.7)	(686.2)	(1,223)	(1,028)	(1,284)
t=5	-2,307***	-3,496***	-2,320**	-1,637**	4,856***	6,006***	3,887***	4,535***
	(493.7)	(832.9)	(912.2)	(791.3)	(911.8)	(1,888)	(1,311)	(1,307)
t=6	-2,581***	-3,133***	-3,299***	-1,793**	3,680***	4,158***	1,817	5,350***
	(511.7)	(1,076)	(711.3)	(873.0)	(861.4)	(1,587)	(1,298)	(1,501)
t=7	-2,056***	-3,525***	-1,218	-1,852**	4,365***	4,057**	4,931***	4,105**
	(538.1)	(872.5)	(970.5)	(899.1)	(966.1)	(1,722)	(1,602)	(1,660)
t=8	-3,231***	-5,043***	-2,925***	-2,307**	3,108***	2,939*	2,347	4,152**
	(540.9)	(681.5)	(958.4)	(981.9)	(1,004)	(1,667)	(1,697)	(1,866)
t=9	-2,401***	-4,190***	-1,519	-2,032**	3,816***	4,177**	3,279	3,843*
	(622.2)	(791.8)	(1,328)	(940.6)	(1,237)	(2,109)	(2,174)	(2,080)
t=10	-3,150***	-3,899***	-3,613***	-2,378**	1,860	1,157	1,084	3,485
	(607.4)	(1,074)	(911.4)	(1,096)	(1,141)	(1,920)	(1,860)	(2,172)
Obs.	62,135	25,664	19,813	16,632	68,953	17,542	24,093	27,185
R-squared	0.106	0.133	0.091	0.106	0.161	0.147	0.172	0.182

All regressions include individual fixed effects, age dummies, year dummies and a constant.
Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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