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Abstract

How do people in developing countries respond to extreme temperatures? Using individual-level panel data over two decades and relying on plausibly exogenous variation in weather, we estimate how extreme temperatures affect time use in China. Extreme temperatures reduce time spent working, and this effect is largest for female farmers. Hot days reduce time spent by women on outdoor chores, but we find no such effects for men. Finally, hot days dramatically reduce time spent on childcare, reflecting large effects on home production. Taken together, our results suggest time use is an important margin of response to extreme temperatures.

Keywords: time use, extreme weather, gender

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1 Introduction

Despite a growing interest amongst economists and social scientists in the effects of extreme temperatures, evidence remains concentrated in developed countries. The relative scarcity of evidence in developing countries limits our understanding of the economic damages from rising temperatures in two important ways (Greenstone and Jack, 2015; Jack, 2017). First, damage functions in developing countries may differ because of income differences, non-linearity in dose-response functions (Hsiang, Oliva and Walker, 2019), and differences in the availability and adoption of adaptation technologies (Graff-Zivin and Neidell, 2014). Second, in developing countries relevant outcomes may differ. For example, changes in home production and informal labor may assume greater importance (Parente, Rogerson and Wright, 2000).

In this paper, we use individual-level panel data from nine major provinces in China to estimate the causal effect of extreme temperatures on time use. This unique data set was constructed by confidential matching of gridded weather data with a geolocated panel of households tracked over two decades, from 1989 to 2011. To recover the causal effects of extreme temperatures, we use random daily variation in weather faced by individuals over time, conditional on individual fixed effects, a secular time trend, and province-level seasonal trends. We report three principal findings. First, extreme temperatures negatively affect time spent working, but there is substantial heterogeneity on dimensions of research and policy interest. Effects are larger amongst farmers, particularly female farmers. Second, extreme heat reduces time spent by women on household chores, with no compensatory increases by men. Finally, time spent on childcare falls by almost 30% for every additional day with an average temperature above 80°F, but this effect is only present in households without cooling technologies.

Our research makes several contributions to the literature. First, we add to a recent body of evidence on the effects of extreme temperatures in developing countries.[1] Within this literature, to the best of our knowledge, we are the first to examine how heat affects allocation of the time budget, which is especially important in households with

[1] For a non-exhaustive list, see Burgess et al. (2017); Geruso and Spears (2018) on mortality, Colmer (2018); Jessoe, Manning and Taylor (2017); Santangelo (2016) on labor reallocation, Fishman, Carrillo and Russ (2019); Garg, Jagnani and Taraz (2018) on human capital, Chen and Yang (2017); Zhang et al. (2018) on industrial output and Masuda et al. (2019); Somanathan et al. (2015) on labor productivity. For a broader review, see Heal and Park (2016).

small cash budgets.[2] Second, this paper is among the first to study optimizing time-use responses to an exogenous shock using panel data.[3] Previous work in this space has relied on using repeated cross-sections (Garg, Jagnani and Taraz, 2018; Graff-Zivin and Neidell, 2014). In our setting, repeated cross sections might systematically omit temperature-sensitive individuals during periods of extreme weather. By instead using a panel, we are able to rule out such time-varying sample selection correlated with the treatment of interest. Third, our estimated weather effects provide a lower bound on the magnitudes of climate effects. Lemoine (2018) shows that the effect of climate on costly adaptive actions, like changes in time allocation, can be approximated by the sum of responses to forecast and realized weather. Finally, we investigate the heterogenous effects of temperature by gender: our finding that women's time use is more sensitive to extreme temperatures than men's may have important implications for the distribution of damages from extreme temperatures.[4]

The rest of the paper is organized as follows. Section 2 details the various data sources used in this paper. Section 3 discusses the research design and Section 4 presents the corresponding results. Section 5 provides a brief discussion and concluding remarks.

2 Data

Data on Time Use: We obtain time-use data from the China Health and Nutrition Survey (CHNS), an ongoing large-scale longitudinal survey. It is conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention. The baseline data was collected in 1989 and nine subsequent surveys have been implemented every two to four years since. The survey uses a multistage, random-clustered sampling process to draw a sample from nine provinces and six large

[2]See Graff-Zivin and Neidell (2014) for the effects of temperature on time-use in the United States.

[3]Krueger and Mueller (2012) use a panel to examine time-use responses to endogenous re-employment. Cherchye, De Rock and Vermeulen (2012) study household labor supply using panel time-use data, with identifying variation from the number and age of children.

[4]The observed heterogeneity in temperature responses does not necessarily imply heterogeneity in damages. For example, the differential impact of extreme temperature on women could be offset by intra-household transfers. Nonetheless our findings suggest that there is *scope* for temperature-driven heterogeneity in damages.

cities, covering about 7,200 households with over 30,000 individuals.[5]

The CHNS is valuable for our empirical analysis for two reasons. First, though the CHNS instruments were mainly designed to investigate the health and nutrition status of Chinese families, one section of the survey collects data on individuals' time allocation to working, household chores, childcare and other activities. Most of the questions relating to time allocation to a specific activity are framed as, for instance, "during the past week, for how many hours did you work" or "during the past week, how much time (minutes) did you spend per day, on average, to prepare and cook food for your household."[6] Our analysis focuses on data collected from nine rounds of the CHNS, conducted from 1989 to 2011. When analyzing temperature impacts on time spent on childcare, household chores and working, we use data from survey years 1989-2011, 1997-2011, and 1991-2011, respectively, depending on the availability of the questions on time use. Importantly, each interview date is known, which allows us to link the interview date with weather data to capture how individuals' time use responds to short-run weather variation. In Appendix Tables A.1, A.2, and A.3 we provide descriptive statistics on the datasets used to estimate the effects on work, household chores and childcare respectively.

Second, CHNS covers a large sample size from different climate zones which allows us to obtain greater spatial variation in temperature exposure. There is substantial spatial variation in weather conditions in China (see Appendix Figure A.1). Our sample covers nine provinces: Heilongjiang, Liaoning, Shandong, Henan, Jiangsu, Hubei, Human, Guangxi, and Guizhou, which are highlighted in Appendix Figure A.1.[7]

Weather Data: Weather data, including temperature, precipitation, and relative humidity at the daily level are collected from the ERA-Interim archive, which is a global atmospheric reanalysis dataset constructed by the European Centre for Medium-Term Weather Forecasting (Dee et al., 2011). This dataset provides consistent estimates of

[5]Detailed descriptions of the survey design and sample profiles are available through `https://www.cpc.unc.edu/projects/china` and Popkin et al. (2010).

[6]While the survey question is somewhat ambiguous on whether respondents interpret the question as the previous calendar week or the past seven days, research in survey methods suggests that most respondents interpret such questions as the "past seven days" (Gryczynski et al., 2015). As a robustness check, we also consider the previous calendar week. The results are qualitatively similar.

[7]Three large cities, Beijing, Shanghai, and Chongqing, are excluded from our samples because CHNS sampled them only in 2011.

weather conditions from 1979 to the present. Our analysis uses ERA-Interim weather data on a 0.125 x 0.125 degree latitude-longitude grid from 1989 to 2011. For each county, we construct the daily average temperature, daily total rainfall, and daily mean relative humidity by averaging over all weather grid points within the county boundaries. There is reasonable consensus in the environmental economics literature that use of such reanalysis data is the preferred way to consistently estimate marginal effects of weather (Auffhammer et al., 2013; Schlenker and Lobell, 2010). Appendix Figure A.2 shows the spatial distribution of temperature in the nine provinces covered by the CHNS survey during the study period.

Linked Temperature-Time Use Data: The county-level household locations recorded by the CHNS are confidential. To merge the weather data to the CHNS data, we submitted our county-level weather data and a data linkage request to the Carolina Population Center at the University of North Carolina (CPC). CPC in turn provided us the matched dataset with anonymized county identifiers with one caveat: to prevent backward induction of county identities, CHNS introduced small normally distributed errors in our weather variables. Since this is measurement error is small and classical by construction, the resulting attenuation bias is minimal. In Appendix Table A.4, we compare descriptive statistics from our original weather data and the linked CPC data; they are strongly similar.

3 Research Design

To investigate how temperature influences individuals' time-allocation decisions, we flexibly estimate the effect of weather the week prior to the interview on time use during the same period following the approach laid out in Deschênes and Greenstone (2011) and Hsiang (2016):

$$
\begin{aligned}
ActivityTime_{icpwmy} = & \sum_{k=1}^{K} \beta_k Tempbin_{cpwmy}^{k} + \delta Z_{cpwmy} + \xi X_{icpy} \\
& + \alpha_i + \lambda_{ym} + \gamma_{pm} + \epsilon_{icpwmy}
\end{aligned}
$$

where $ActivityTime_{icpwmy}$ is the number of hours allocated to a given activity for individual i, in county c of province p, during week w in month m of year y. The variable $Tempbin^{k}_{cpwmy}$ measures the number of days in the bin that an individual is exposed to during week w in month m of year y. To construct $Tempbin^{k}_{cpwmy}$, we first group the average daily temperature of the county where the individual lives into 13 temperature bins, with the hottest bin covering temperatures above 80°F, the coldest bin covering temperature below 25°F, and 5°F temperature increments in-between. Second, we count the number of days experienced by the individual living in county c of each temperature bin k during week w in month m of year y. The 56-60°F temperature bin is omitted. The coefficient β_k can be interpreted as the marginal effect of shifting a day from the reference bin (56-60°F) to bin k (for example, above 80°F).

Individual fixed effects are represented by α_i and capture all time-invariant observable and unobservable individual attributes that affect time allocation decisions. The λ_{ym} are year-month fixed effects to control for nationwide trends in time spent on working, household chores and childcare. Since people living in different climate zones might, for example, harvest crops at a different time, our model also includes province-month fixed effects, γ_{pm}, to control for seasonal trends.

Z_{cpwmy} includes county-level weather controls that might be correlated with temperature, including precipitation, humidity, and sunset time. To allow flexible relationships between precipitation and time allocation, we create 11 precipitation bins with 0.1 inches per bin. We also control for quadratic polynomials in average relative humidity and average sunset time during week wmy.

X_{icpy} includes individual-level controls that may be related to time allocation preferences. This includes linear and quadratic terms for age, employment status, years of education, annual net household income of individual i, and the ownership of cooling technologies, fridges and washing machines. Some of these variables are likely endogenous and the corresponding coefficients cannot be interpreted causally. These controls are included to improve precision.

Our parameters of interest, β_k, reflect responses to short-run temperature variations. The identifying assumption is exogeneity of daily average temperature with respect to time-varying unobservable determinants of time use, conditional on a battery of fixed effects and other weather variables. Intuitively, the identifying variation in temperature comes from unusual or unseasonable weather not captured by these controls. Standard errors are clustered at the county level.

4 Results

In this section we document how people in China adjust their time use in response to extreme temperatures. We report three principal findings: (1) extreme temperatures reduce overall time spent working, and this effect is most pronounced for agricultural work; (2) extreme heat particularly reduces time spent by women on household chores; and (3) time spent on childcare is sensitive to extreme heat, but this effect is only present in households without cooling technologies like fans and air-conditioners. Finally, we discuss a number of checks on the robustness of our results.

Time Spent Working: In Figure 1, we show the results by temperature bin on the overall time spent working across all adults in our sample. As noted in Section 3, we interpret each coefficient as the marginal effect of one day in a given week being moved from the omitted bin (56°F-60°F, normalized to zero) to the given bin. Figure 1 shows that extreme temperatures on both the hot and cold ends of the temperature distribution reduce overall time spent working. During a given week, an extra day below 25°F reduces time spent working by 1.8 hours, while an extra day above 80°F reduces time spent working by 1.2 hours. These two coefficient estimates are 4.5% and 3% of the sample mean, respectively. Theory suggests these effects on work may reflect multiple mechanisms, including changes in productivity, the cost of effort, and available tasks (e.g. those due to temperature effects on crops).

However, this result across the full sample of adults masks substantial heterogeneity. In Figure 2 we explore this heterogeneity. Comparing Panel (A) to Panel (B), we find that the effects of extreme temperatures are larger for farmers than non-farmers. Within the sample of farmers, the effects are larger for women than for men. We formally test for this difference in Appendix Table A.5. An extra day above 80°F in a given week decreases time spent working by female farmers by 1.94 hours, and the difference relative to male farmers is statistically significant at the one percent level.

Time Spent on Household Chores: In Figure 3, we estimate the effects of extreme temperatures on time spent on household chores by gender (Panel A) and by location of household chores (Panel B). The interpretation of coefficients is the same as before. We find that an additional extremely hot day reduces time spent on household chores for women but the same hot day has no discernible effect on men. Testing formally for this difference in Appendix Table A.6, we find that in response to another day above 80°F during the week, relative to the omitted bin, women spent about 0.4 hours less on chores. Importantly, we note that while women spend less time on household chores, there is no corresponding effect in time spent on household chores by men, suggesting that extreme heat results in not just lower market work as documented above, but also lower home production. As expected, in Panel (B), we note that most of the reduction in time spent on home production comes from outdoor tasks as opposed to indoor tasks.

Time Spent on Childcare: Next, we examine the effects of extreme temperatures on childcare. In Figure 4 we estimate this effect separately for households with and without cooling technologies. For households without some form of cooling technology (ACs or fans), one additional day with a mean temperature above 80°F, instead of between 56°F and 60°F, reduces time spent on child care by over 4 hours each week (see Appendix Table A.7).[8] Measured against the baseline mean of 14.24 hours, the point estimate corresponds to a 29% effect. Remarkably, this entire effect disappears when we consider households that have adopted some form of cooling technology, suggesting that in this setting, adaptation decisions of households may disproportionately favor investments in infants and young children.

Robustness Checks: In Figure 5 (and correspondingly in Appendix Table A.8) we report robustness checks for our model of work time. Results are robust to using a degree-day specification, using a poisson regression, limiting our sample to a balanced panel of individuals, and including province$\times$year$\times$month fixed effects.

[8]We note that while the point estimate is large and statistically significant at the 5% level, the 95% confidence interval covers a wide-range of magnitudes.

5 Discussion and Conclusion

The vulnerability of marginal populations to extreme weather poses a particular risk for global anti-poverty goals (Barrett, Garg and McBride, 2016). In this paper, we use individual panel time-use data over two decades to study how different groups alter their time allocations in response to extreme temperatures. We show that extreme temperatures reduce time spent working, and that these effects are largest for female agricultural workers. Moreover, hot days with a daily mean temperature above 80°F reduce women's time spent on household chores (with no corresponding effect for men). Such days also reduce childcare time for households without cooling technologies. Continued increases in air conditioning takeup in China (Auffhammer, 2014; Auffhammer and Wolfram, 2014) and other developing countries (Davis and Gertler, 2015; Wolfram, Shelef and Gertler, 2012) may reduce future responsiveness on this margin.

Our research has important implications for climate research and policy. First, it suggests that broadening the outcomes studied may be vital in developing countries. For the rural poor in the developing world, adjustments to time use may be important, particularly as adjustments on other margins may be constrained or impossible. Some time-use adjustments, like childcare, can have important long-run implications. Second, the distribution of effects can differ substantially across important socio-demographic lines like gender. This suggests that effects may be non-uniform even within households. More research into the distribution of extreme weather effects is surely needed.

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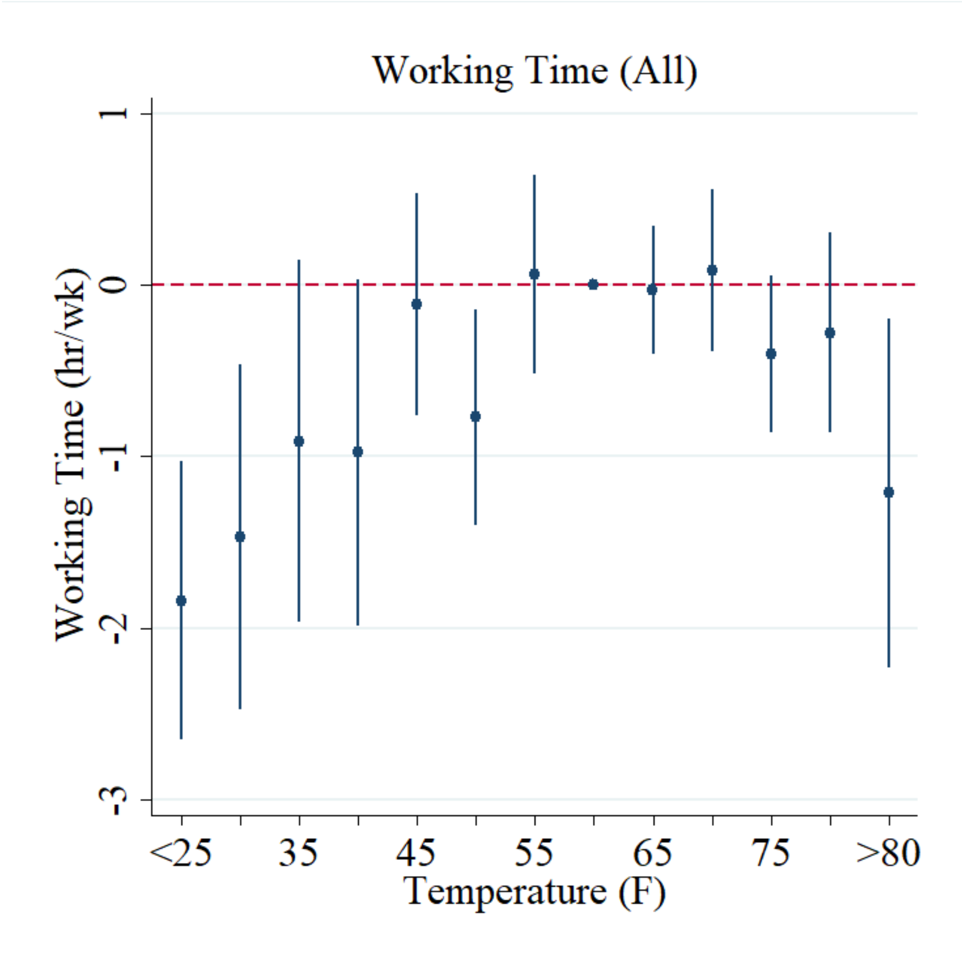
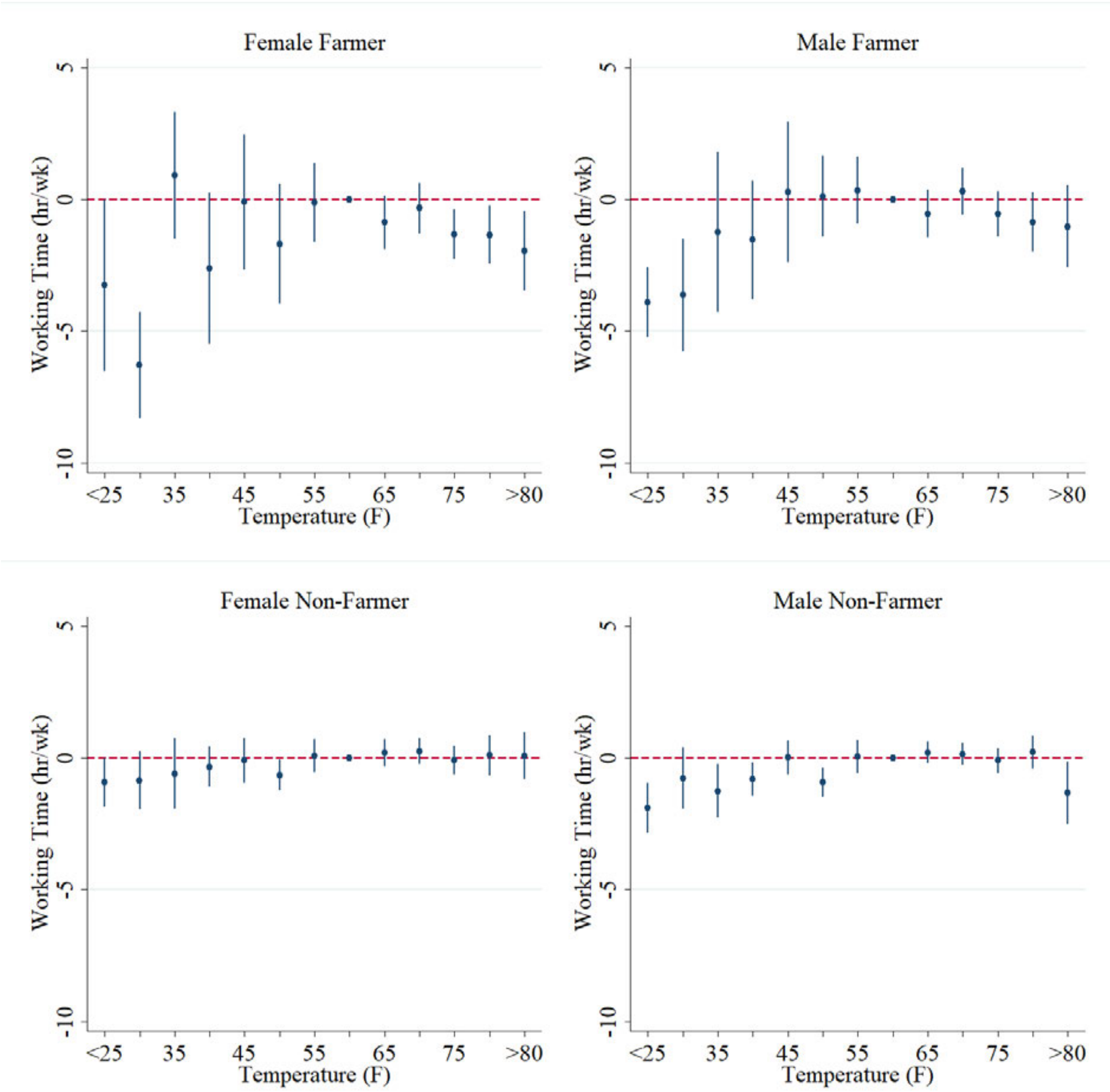
Figures

Figure 1: Effects of Temperature on Working Time



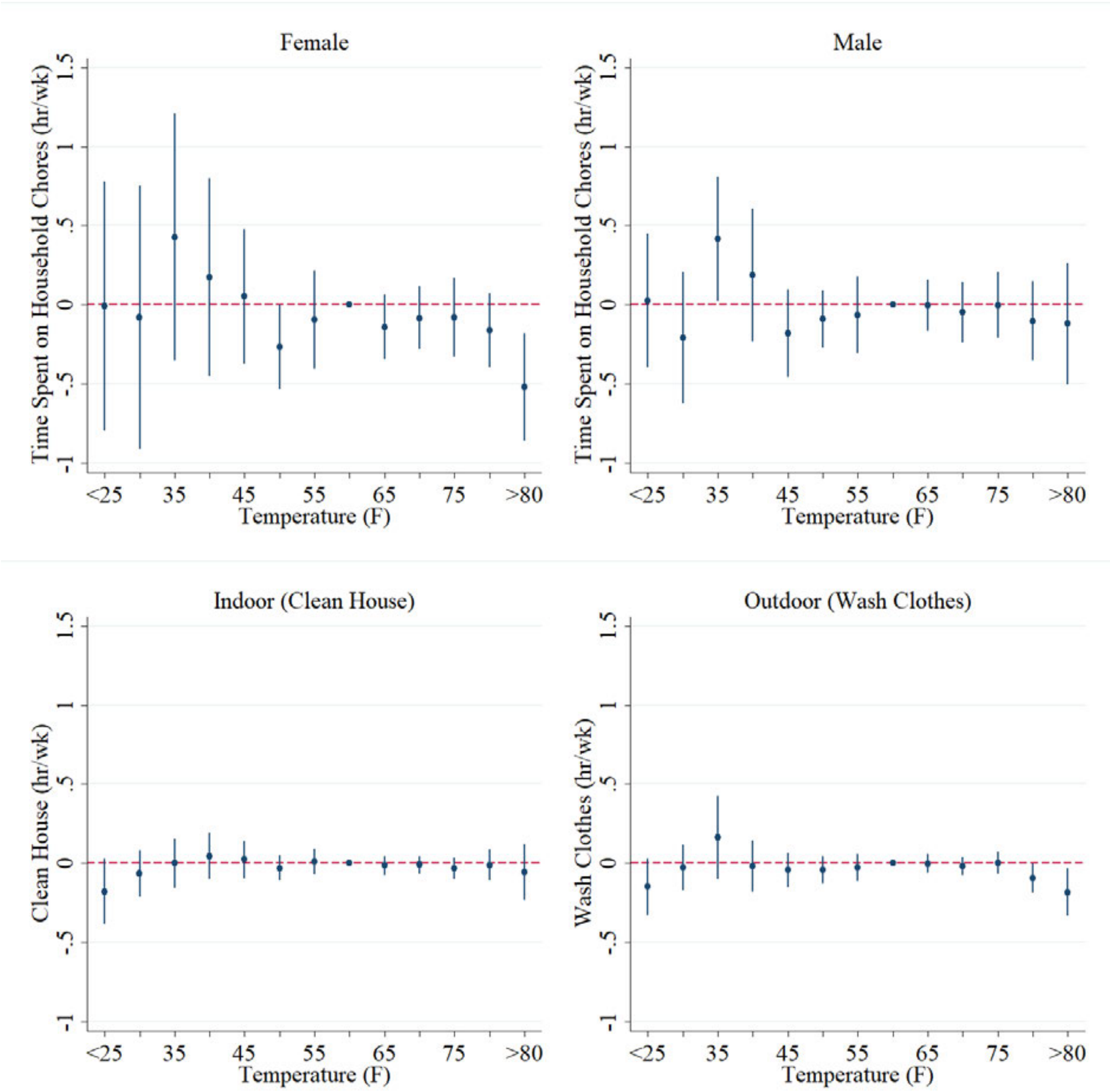
Note: This figure plots coefficient estimates for individuals' working time adjustment in response to different temperature bins corresponding to specification in Column (1) of Table A.5. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Figure 2: Effects of Temperature on Working Time: By Occupation and Gender



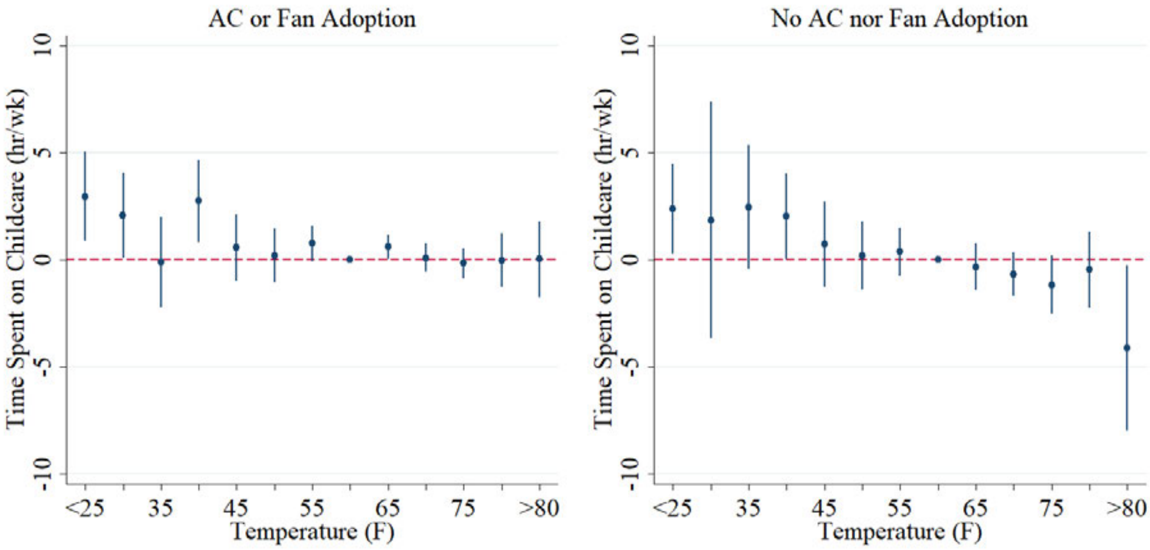
Note: All four graphs correspond to the same regression in Column (2) of Table A.5. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Figure 3: Effects of Temperature on Time Spent on Household Chores



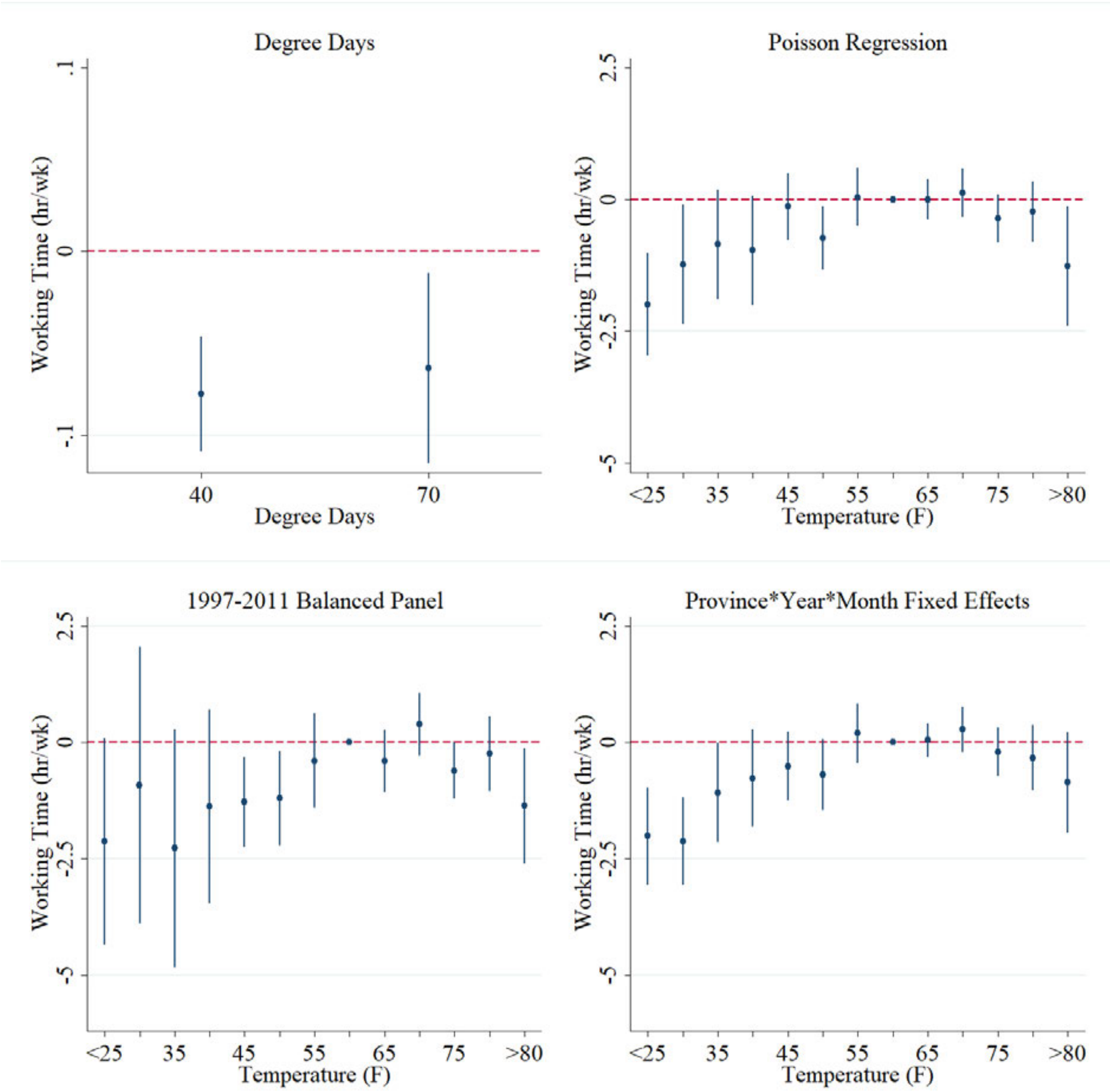
Note: The top panel plots the relationship between temperature and time allocated to household chores by gender, corresponding to specification in Column (1) of Table A.6. The bottom panel plots the relationship between temperature and time allocation on indoor tasks (cleaning house) and outdoor tasks (washing clothes), corresponding to the specification in Column (2) and Column (3) of Table A.6, respectively. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Figure 4: Effects of Temperature on Childcare by AC/Fan Adoption



Note: This figure plots the relationship between temperature and time allocated to taking care of children under 6 years old, corresponding to the specification in Column (1) of Table A.7. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Figure 5: Robustness Checks

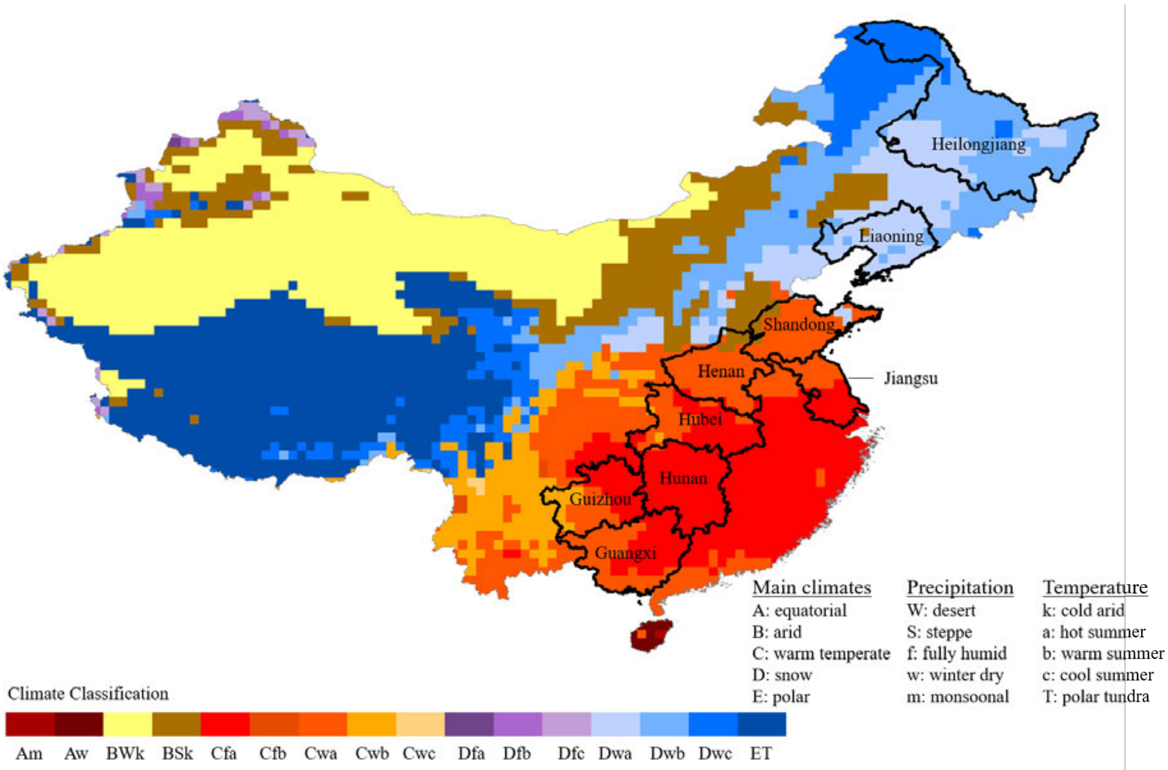


Note: These four graphs presents coefficient estimates for different temperature bins corresponding to alternative specifications in Column (1)-(4) of Table A.8. In the degree days specification, we use 40°F and 70°F when calculating the heating and cooling degree days. Vertical lines represent 95% confidence intervals. The temperature bin 60°F-65°F is the omitted category.

Online Appendix

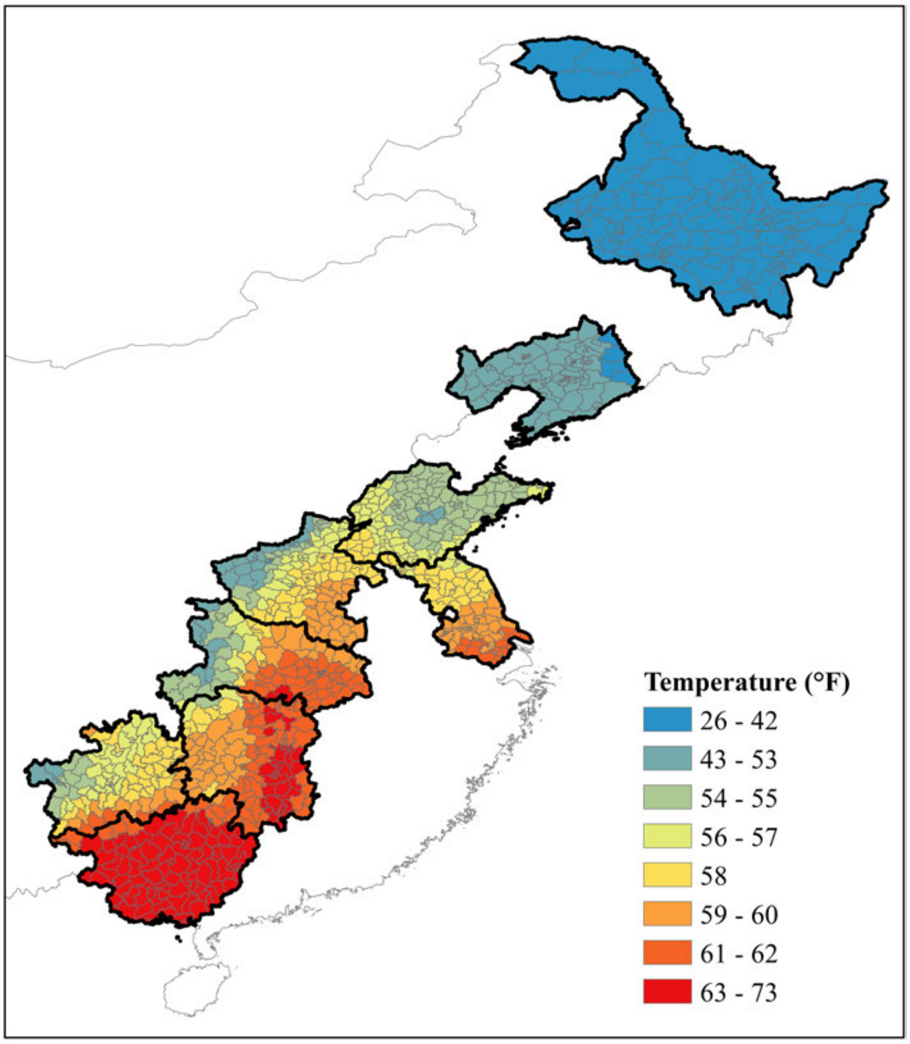
Additional Figures

Figure A.1: China's Climate Zones



Note: This maps presents climate zones across the mainland of China. Administrative boundaries of the nine provinces covered in the emipiral analysis are highlighted in black. Climate zones are classified based on the Köppen-Geiger climate classification, available through http://koeppen-geiger.vu-wien.ac.at/shifts.htm.

Figure A.2: Average Daily Temperature by County



Note: Average daily temperature in Fahrenheit in all counties of the nine provinces covered by the CHNS survey during the study period (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011). Temperatures are categorized into eight groups based on quantiles.

Additional Tables

Table A.1: Summary Statistics (Working Time)

	mean	sd	min	max
Working Time (hr/wk)	40.41	19.26	0.00	156.00
Female	0.42	0.49	0.00	1.00
Age	42.76	11.69	18.00	84.20
Year of Education	8.56	3.83	0.00	18.00
Net Household Income (1,000 yuan/yr)	27.06	35.80	-564.00	900.60
Employment Status	0.99	0.07	0.00	1.00
AC/Fan Ownership	0.83	0.37	0.00	1.00
Washing Machine Ownership	0.71	0.45	0.00	1.00
Fridge Ownership	0.56	0.50	0.00	1.00
Farmer	0.33	0.47	0.00	1.00
Average Humidity (%)	93.14	3.30	79.11	99.45
Average Sunset Time (hr)	18.05	0.65	15.65	19.63
N	26269			

Based on sample of 26,269 individuals during survey year 1991 to 2011 when data on working time is available. Individual characteristics are from CHNS and weather variables are from the ERA-Interim archive. Our estimation results are robust to dropping the top 1% of the observations in terms of working time.

Table A.2: Summary Statistics (Time Spent on Household Chores)

	mean	sd	min	max
Household Chores (hr/wk)	12.34	11.63	0.00	134.40
Clean House (hr/wk)	1.89	2.60	0.00	115.50
Wash Clothes (hr/wk)	2.40	3.10	0.00	107.33
Purchase Food (hr/wk)	2.39	3.46	0.00	116.32
Cook (hr/wk)	5.66	6.39	0.00	105.12
Female	0.55	0.50	0.00	1.00
Age	49.23	15.10	18.00	100.80
Year of Education	7.05	4.25	0.00	18.00
Net Household Income (1,000 yuan/yr)	25.59	33.40	-564.00	900.60
Employment Status	0.63	0.48	0.00	1.00
AC/Fan Ownership	0.80	0.40	0.00	1.00
Washing Machine Ownership	0.65	0.48	0.00	1.00
Fridge Ownership	0.54	0.50	0.00	1.00
Average Humidity (%)	93.33	3.32	79.11	99.45
Average Sunset Time (hr)	18.06	0.65	15.65	19.63
N	40826			

Based on sample of 40,826 individuals during survey year 1997 to 2011 when data on household chores is available. Household chores include four tasks – cleaning house, washing clothes, purchasing food and cooking. Individual characteristics are from CHNS and weather variables are from the ERA-Interim archive. Our estimation results are robust to dropping the top 1% of the observations in terms of time spent on household chores.

Table A.3: Summary Statistics (Time Spent on Childcare)

	mean	sd	min	max
Childcare (hr/wk)	14.24	20.80	0.00	148.00
Age	39.93	14.45	18.20	85.10
Year of Education	6.58	4.07	0.00	18.00
Net Household Income (1,000 yuan/yr)	19.19	28.86	-26.60	383.37
Employment Status	0.75	0.43	0.00	1.00
AC/Fan Ownership	0.80	0.40	0.00	1.00
Washing Machine Ownership	0.58	0.49	0.00	1.00
Fridge Ownership	0.39	0.49	0.00	1.00
Average Humidity (%)	93.30	3.34	79.11	99.29
Average Sunset Time (hr)	18.11	0.63	15.82	19.63
N	5936			

Based on sample of 5,936 individuals during survey year 1989 to 2011 when data on childcare is available. Time spent on childcare is defined as time spent on taking care of children under six years old. Individual characteristics are from CHNS and weather variables are from the ERA-Interim archive. Our estimation results are robust to dropping the top 1% of the observations in terms of time spent on child care.

Table A.4: Summary Statistics of Weather Variables

	mean	sd	min	max
Panel 1: Weather Variables Provided to CHNS				
Temperature (°F)	55.08843	20.41572	-27.90515	96.18461
Precipitation (inch)	2.78724	6.45893	0.00000	233.15747
Humidity (%)	92.90370	5.31594	60.47364	99.94583
Sunset Time (hr)	18.34055	0.94822	15.33463	20.02283
Panel 2: Noise Added to Weather Variables				
Temperature Noise (°F)	0.00118	0.33946	-1.79692	1.81050
Precipitation Noise (inch)	0.00039	0.22174	-1.79915	1.86726
Humidity Noise (%)	0.00065	0.22686	-1.64472	1.64568
Sunset Time Noise (hr)	-0.00005	0.04877	-0.29068	0.28398
Panel 3: New Weather Variables With Noise Added by CHNS				
Temperature_New (°F)	55.08960	20.41914	-27.68640	95.78651
Precipitation_New (inch)	2.78763	6.46340	-1.56230	233.17691
Humidity_New(%)	92.90436	5.32079	60.28096	101.09986
Sunset Time_New (hr)	18.34050	0.94960	15.13215	20.07031
Number of Linked County-Date Observations	322,176			

Observations included in this table are daily weather conditions of counties that could be linked to the CHNS dataset during survey year 1989 to 2011.

Table A.5: Time Spent on Working

	(1) Work (All)	(2) Work by Individual Characteristics
<25	-1.841***	-1.899***
	(0.405)	(0.474)
25-30	-1.469***	-0.784
	(0.502)	(0.579)
31-35	-0.911*	-1.262**
	(0.527)	(0.504)
36-40	-0.977*	-0.816**
	(0.505)	(0.312)
41-45	-0.115	0.004
	(0.322)	(0.326)
46-50	-0.770**	-0.936***
	(0.314)	(0.269)
51-55	0.063	0.037
	(0.288)	(0.312)
61-65	-0.032	0.189
	(0.186)	(0.207)
66-70	0.085	0.138
	(0.236)	(0.207)
71-75	-0.401*	-0.102
	(0.227)	(0.237)
76-80	-0.277	0.204
	(0.291)	(0.308)
>80	-1.214**	-1.331**
	(0.508)	(0.588)
female × farmer		-1.530
		(2.437)
<25 × female		0.965***
		(0.199)
25-30 × female		-0.075
		(0.429)
31-35 × female		0.654
		(0.488)
36-40 × female		0.467
		(0.372)
41-45 × female		-0.111
		(0.413)
46-50 × female		0.276
		(0.322)
51-55 × female		0.039
		(0.340)
61-65 × female		0.005
		(0.252)
66-70 × female		0.110
		(0.215)
71-75 × female		0.002
		(0.242)
76-80 × female		-0.114
		(0.258)
>80 × female		1.400***
		(0.514)
<25 × farmer		-2.010***
		(0.439)
25-30 × farmer		-2.839**
		(1.190)

Table A.5 Time Spent on Working (Continued)

	(1) Work (All)	(2) Work by Individual Characteristics
31-35 × farmer		0.015
		(1.527)
36-40 × farmer		-0.721
		(1.093)
41-45 × farmer		0.268
		(1.309)
46-50 × farmer		1.052
		(0.722)
51-55 × farmer		0.306
		(0.648)
61-65 × farmer		-0.733
		(0.530)
66-70 × farmer		0.170
		(0.419)
71-75 × farmer		-0.451
		(0.505)
76-80 × farmer		-1.071*
		(0.613)
>80 × farmer		0.299
		(0.683)
<25 × female × farmer		-0.316
		(1.834)
25-30 × female × farmer		-2.579**
		(1.165)
31-35 × female × farmer		1.505
		(1.415)
36-40 × female × farmer		-1.547*
		(0.798)
41-45 × female × farmer		-0.272
		(1.029)
46-50 × female × farmer		-2.081**
		(0.962)
51-55 × female × farmer		-0.514
		(0.661)
61-65 × female × farmer		-0.338
		(0.467)
66-70 × female × farmer		-0.757*
		(0.435)
71-75 × female × farmer		-0.780
		(0.484)
76-80 × female × farmer		-0.364
		(0.376)
>80 × female × farmer		-2.314***
		(0.677)
farmer		-13.583***
		(2.343)
N	26269	26269
adj. R^2	0.33	0.38

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, and ownership of fans or AC, fridges and washing machines; (3) individual fixed effects, year-month fixed effects, and province-month fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$. Standard errors are clustered at the county level.

Table A.6: Time Spent on Household Chores

	(1) HHChore by Gender	(2) CleanHouse	(3) WashClothes
<25	0.026	-0.178*	-0.149
	(0.210)	(0.103)	(0.090)
25-30	-0.209	-0.065	-0.029
	(0.207)	(0.074)	(0.071)
31-35	0.416**	-0.001	0.162
	(0.196)	(0.078)	(0.131)
36-40	0.188	0.045	-0.016
	(0.210)	(0.072)	(0.081)
41-45	-0.180	0.024	-0.042
	(0.138)	(0.057)	(0.053)
46-50	-0.090	-0.030	-0.042
	(0.091)	(0.038)	(0.043)
51-55	-0.064	0.009	-0.028
	(0.120)	(0.040)	(0.044)
61-65	-0.002	-0.015	-0.001
	(0.081)	(0.029)	(0.030)
66-70	-0.045	-0.009	-0.019
	(0.095)	(0.027)	(0.029)
71-75	-0.001	-0.031	0.003
	(0.105)	(0.033)	(0.034)
76-80	-0.102	-0.012	-0.095**
	(0.126)	(0.049)	(0.045)
>80	-0.120	-0.055	-0.183**
	(0.192)	(0.087)	(0.075)
<25 × female	-0.035		
	(0.458)		
25-30 × female	0.129		
	(0.534)		
31-35 × female	0.012		
	(0.387)		
36-40 × female	-0.015		
	(0.399)		
41-45 × female	0.235		
	(0.231)		
46-50 × female	-0.176		
	(0.150)		
51-55 × female	-0.031		
	(0.166)		
61-65 × female	-0.137		
	(0.133)		
66-70 × female	-0.038		
	(0.105)		
71-75 × female	-0.079		
	(0.136)		
76-80 × female	-0.059		
	(0.117)		
>80 × female	-0.400**		
	(0.169)		
N	40826	24993	23410
adj. R^2	0.47	0.17	0.10

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, ownership of fans or AC, fridges and washing machines; (3) individual fixed effects, year-month fixed effects, and province-month fixed effects. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A.7: Time Spent on Childcare

	(1)
	Childcare by AC/Fan Adoption
$<$25	2.366**
	(1.051)
25-30	1.839
	(2.748)
31-35	2.457*
	(1.432)
36-40	2.026**
	(0.990)
41-45	0.731
	(0.991)
46-50	0.202
	(0.785)
51-55	0.367
	(0.559)
61-65	-0.329
	(0.551)
66-70	-0.672
	(0.501)
71-75	-1.168*
	(0.676)
76-80	-0.470
	(0.887)
$>$80	-4.134**
	(1.924)
$<$25 × AC/Fan	0.584
	(0.441)
25-30 × AC/Fan	0.211
	(2.401)
31-35 × AC/Fan	-2.569
	(1.778)
36-40 × AC/Fan	0.709
	(0.900)
41-45 × AC/Fan	-0.181
	(1.197)
46-50 × AC/Fan	-0.015
	(0.987)
51-55 × AC/Fan	0.375
	(0.798)
61-65 × AC/Fan	0.931
	(0.606)
66-70 × AC/Fan	0.751
	(0.465)
71-75 × AC/Fan	1.001
	(0.757)
76-80 × AC/Fan	0.430
	(0.721)
$>$80 × AC/Fan	4.154**
	(1.772)
AC/Fan	-3.451
	(2.821)
N	5936
adj. R^2	0.32

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, ownership of fans or AC, fridges and washing machines; (3) individual fixed effects, year-month fixed effects, and province-month fixed effects. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table A.8: Robustness Check

	(1) Degree Days	(2) Poisson	(3) Balanced Panel 1997-2011	(4) Province*Year*Month
DD40	-0.078***			
	(0.015)			
DD70	-0.064**			
	(0.026)			
<25		-1.989***	-2.130*	-2.017***
		(0.496)	(1.087)	(0.523)
25-30		-1.237**	-0.925	-2.122***
		(0.579)	(1.457)	(0.467)
31-35		-0.857	-2.277*	-1.083**
		(0.529)	(1.253)	(0.528)
36-40		-0.969*	-1.374	-0.772
		(0.530)	(1.022)	(0.521)
41-45		-0.142	-1.289**	-0.512
		(0.326)	(0.473)	(0.366)
46-50		-0.738**	-1.206**	-0.699*
		(0.310)	(0.497)	(0.378)
51-55		0.039	-0.400	0.188
		(0.281)	(0.501)	(0.319)
61-65		-0.001	-0.409	0.047
		(0.191)	(0.326)	(0.182)
66-70		0.123	0.385	0.272
		(0.236)	(0.330)	(0.240)
71-75		-0.358	-0.610*	-0.214
		(0.234)	(0.302)	(0.259)
76-80		-0.236	-0.247	-0.337
		(0.295)	(0.396)	(0.353)
>80		-1.263**	-1.368**	-0.868
		(0.575)	(0.609)	(0.535)
N	26269	26161	8920	26264
adj. R^2	0.33		0.33	0.35

All specifications control for (1) county-level weather conditions including precipitation, linear and quadratic terms of relative humidity level and sunset time; (2) individual-level time-varying characteristics including linear and quadratic terms for age, years of education, annual net household income, employment status, ownership of fans or AC, fridges and washing machines; (3) individual fixed effects. Column (1)-(3) include year-month fixed effects and province-month fixed effects, while Column (4) controls for province-month fixed effects instead. Pseudo R^2 of the Poisson regression in Column (3) is 0.33. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < .01$