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DISCUSSION PAPER SERIES

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Temperature and Joint Time Use

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ABSTRACT

Temperature and Joint Time Use*

We combine exogenous variation in temperature at the county-day level in the U.S. with daily time use data to examine the effect of temperature on joint time use. We show that low temperatures reduce time spent with friends but increase time spent with family. Conversely, high temperatures increase time alone but reduce time with family. We also provide evidence of the effect of temperature on joint time use being location-dependent. We rationalize this finding using a model in which the chosen time allocation is the outcome of a dual-self decision process with an indoor and an outdoor self. The two selves have different tastes for time alone, time with family, and time with friends. Weather conditions can change the influence of each self, and thereby the corresponding preferences for joint time use. We test the predictions of the model empirically by drawing on methods from the household economics literature. The test results support the hypothesis that weather affects joint time use insofar it affects where the activities take place.

JEL Classification: D70, I31, J22, Q51, Q54

Keywords: temperature, joint time use, social interactions, dual-self model, indoors, outdoors

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1 Introduction

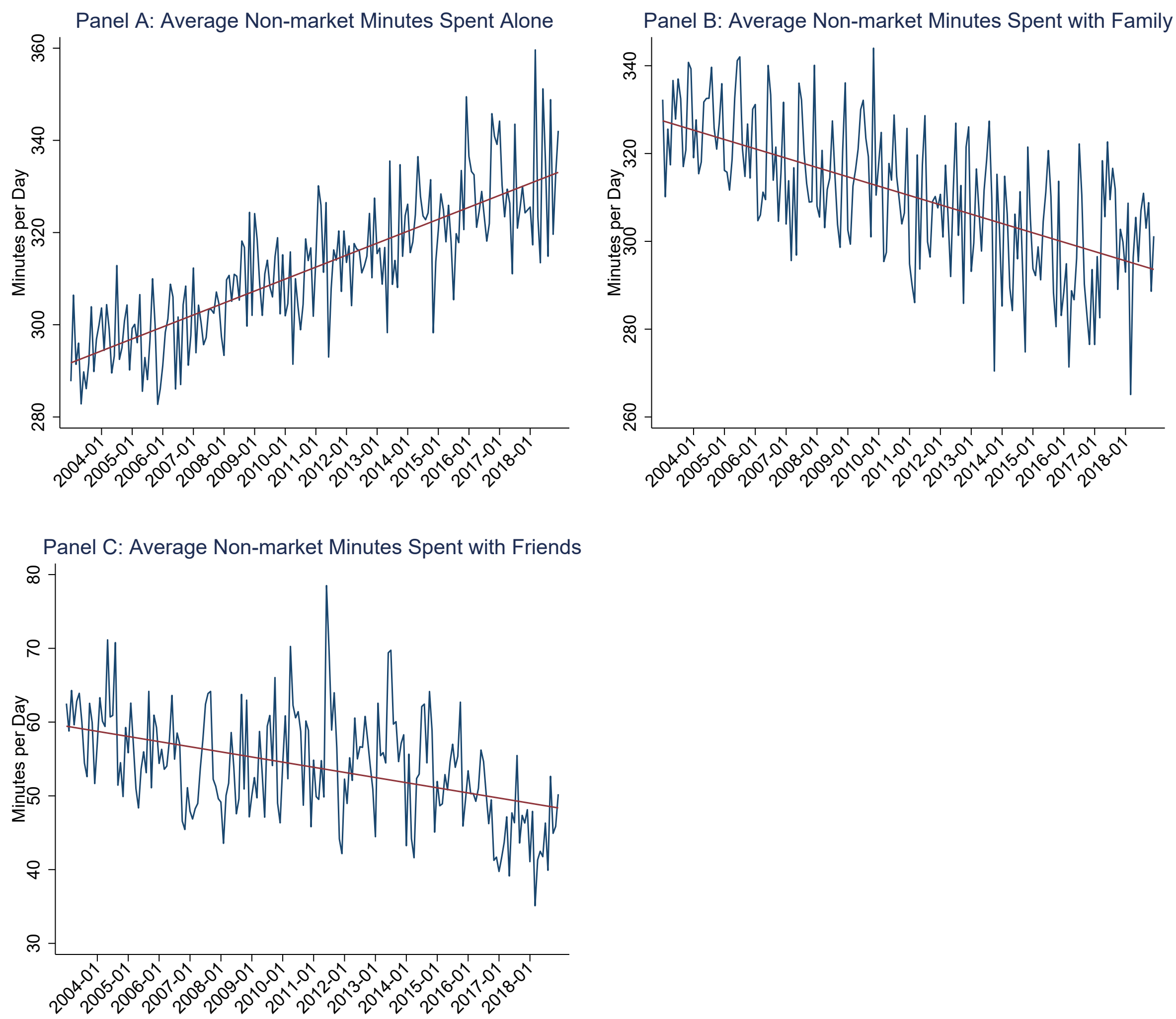
Social interactions through joint leisure cement social ties and are fundamental to individual well-being as well as economic success. The economics literature has recognized that *'those interested in maximizing society's welfare should shift their attention from an emphasis on increasing consumption opportunities to an emphasis on increasing social contacts'* (Kahneman and Krueger, 2006). Previous evidence has highlighted the positive role of in-person contact with friends (Kahneman et al., 2004; Kesselring et al., 2021), how exchanges with family and friends both improve daily mood (Russell et al., 2012) and how life satisfaction of married individuals increases most with time together with the spouse (Hamermesh, 2020).[1]

In the last decades, there have been important changes in the way individuals allocate their time. As shown in panel A of Figure 1, the average time that individuals spend alone in the United States gradually increased from 4 hours and 53 minutes per day in 2004 to 5 hours and 32 minutes in January 2019, representing an increase of 13.3%. Moreover, as shown in panels B–C, the increase in time spent alone has been compensated by a decrease of 30 and 10 minutes per day in the average time that individuals spend with family and friends, respectively. Research has shown that individuals who spend prolonged periods of time alone are more likely to develop health problems, have a higher mortality risk and lower well-being, and experience loss of life satisfaction (Hamermesh, 2020; Luo et al., 2012; Patterson and Veenstra, 2010). It is therefore not surprising that the media has widely reported that *'rebuilding social connection must be a top public health priority for the nation'* (Vivek, 2023).

Time use choices are ultimately driven by individual preferences, and these preferences are not necessarily stable. First of all, contextual factors may directly influence individual preferences for time with family or friends. Moreover, these factors may also change the nature of the underlying activity and thereby indirectly influence the individual's time with

[1] The literature has also shown the impact of social networks in shaping labor market outcomes such as employment status (Bayer et al., 2008; Bentolila et al., 2010; Cappellari and Tatsiramos, 2015; Topa, 2001) and salaries (Dustmann et al., 2015; Marmaros and Sacerdote, 2002; Montgomery, 1991).

Figure 1: Time Allocation Trends



Notes: The figure shows the average non-market time that individuals spent with family, friends, and alone for every month-year during the period of analysis in panels A–C, respectively. We also show the predicted time spent with family, friends, and alone over the same period by tracing a trend line in each of the panels.

others. After all, preferences for joint time cannot be seen separately from the nature of the underlying activity (Hamermesh, 2020; Polivka, 2008). For example, the same individual may prefer time alone when reading a book, surfing the internet, or using social media, but time together for playing sports or traveling, among others.[2] Changing the nature of activities also changes jointness.

One prominent factor that can change *both* an individual's overall preferences for togetherness and the nature of the individual's activities is the weather. For instance, some have argued that physical temperature promotes feelings of psychological warmth and trust (Williams and Bargh, 2008), while physical warmth and social warmth are partly substitutable in daily life (Bargh and Shalev, 2012). Moreover, Connolly (2008) and Graff Zivin and Neidell (2014) found that people switch from outdoor to indoor activities to reduce exposure to bad weather. Ambient weather conditions determine therefore the discomfort associated with particular (outdoor) activities and can influence social interactions and joint time use. As the average global temperature is increasing, and extreme temperatures are becoming more prevalent (Deschênes and Greenstone, 2007), it is important to understand if, and to what extent, individuals adjust whom they spend time with to different temperatures. Our paper investigates this research question.

The first part of the paper combines data on the exogenous variation in temperature at the county-day level from the National Oceanic and Atmospheric Administration (NOAA) with daily time use data from the American Time Use Survey (ATUS) to offer empirical evidence of the causal impact of temperature on the time that individuals spend with family, friends, and alone. We estimate a model that fully accounts for the non-linear relationship between temperature and social interactions by including a set of dummies representing 3°C temperature intervals which cover the full temperature distribution. In the specification,

[2] Changes in the set of activities that individuals have available, such as the ones brought by the rise of mobile phones and social media, may therefore partly explain the trends in time allocation reported in Figure 1. In fact, prior evidence has associated the use of technologies such as the internet or digital media with an increase in the time that individuals spend alone (Stepanikova et al., 2010; Thulin and Vilhelmson, 2019; Vilhelmson et al., 2017).

we control for county, year-month, and day-of-the-week fixed effects (among other controls) to account for time-invariant characteristics at the county level, seasonality, and potential differences in how individuals allocate their time within the week, respectively.

We show that low temperatures leave time spent alone unchanged, and increase the time spent with family at the cost of time spent with friends. In contrast, high temperatures increase time spent alone at the cost of time spent with family. We also find that the effect of temperature on social interactions is location-dependent. Low temperatures reduce the time individuals spend outdoors alone, with family, and friends as well as indoors with friends, and these drops are fully compensated by an increase in the time spent indoors *with family*. High temperatures instead reduce the time spent indoors with family, which is compensated by an increase in the time individuals spend outdoors with family, and indoors and outdoors *alone*.

The second part of the paper formalizes how temperature influences jointness through its effect on the nature of activities. This also generalizes our understanding of joint time choices beyond the case of weather conditions. We first develop a flexible decision model that fits in the tradition of Gary Becker.[3] We define the individual's time budget as total time minus market work and sleep. We label this 'free time' or 'leisure' in the broad sense, although it can also include acts of childcare and household chores. Individuals allocate this time budget to (*i*) indoor leisure alone, (*ii*) indoor leisure with family, (*iii*) indoor leisure with friends, (*iv*) outdoor leisure alone, (*v*) outdoor leisure with family, and (*vi*) outdoor leisure with friends. The model states that the chosen time allocation is the outcome of a dual-self decision process with an *indoor* self and an *outdoor* self. The two selves have different tastes for time alone, time with family, and time with friends. Moreover, the influence of each self on the joint time choice is not fixed. It can vary with weather conditions —as well as with other extra-environmental factors. We thus allow that favorable weather conditions activate the outdoor self, and thereby the corresponding tastes for (outdoor) time alone, time with

[3] Gary Becker pioneered the analysis of important concepts such as time allocation (Becker, 1965) and social interactions (Becker, 1974) through the framework of economic theory.

family, and time with friends.

We finally test this model —and the corresponding interpretation— by drawing on methods from the household economics literature, based on Chiappori (1988, 1992) and Bourguignon et al. (2009). More specifically, we study the demand for different types of leisure (total leisure alone, total leisure with family, and total leisure with friends) through a flexible quadratic demand system. We consider three versions of the demand system: one 'unrestricted' by theory, one consistent with our dual-self interpretation, and finally one that shuts down the effect of temperature on leisure. The test does not need price variation (which is difficult to obtain between time variables) and is robust to mismeasurement of the indoor or outdoor dimension. There is however a minimum requirement of *two* factors that can shift time between indoor and outdoor activities. So, while most of the paper focuses on one weather variable (temperature), the test of the theory model also relies on a second variable (rainfall). The test results support the hypothesis that weather affects joint time use insofar it affects *where* the activities take place.

Most studies of joint time use focus on the demand for togetherness within a household. Sullivan (1996), Hamermesh (2000), and Hallberg (2003) documented demand for togetherness between spouses, by comparing synchronization of work schedules within couples to synchronization of work schedules between random individuals. The former were more synchronized, reflecting a desire for togetherness. Fewer papers have studied the demand for togetherness between households-friends. Two exceptions are Hamermesh et al. (2008) and Georges-Kot et al. (2017). Hamermesh et al. (2008) exploited the fact that only a few time zones in the U.S. (e.g., Arizona) do not switch to the daylight-saving time regime in summer. The authors found that these households adapt their activities to daylight saving time, nonetheless. Georges-Kot et al. (2017) exploited variation in the timing of school holidays in France. The timing of winter and spring breaks is shifted by one week across regions, with permutations every year. The authors found that families without children also adapt their paid leave to school holidays. Finally, Craig and Brown (2014) studied the degree of substitution between leisure with friends and leisure with family. The authors found that weekend work puts downward pressure on joint leisure, but that some individuals recoup joint leisure with friends in the next workweek —at the cost of joint leisure with family.

We note that this is one of the few papers that document joint time use and integrate it in a decision-theoretic framework.[4] While structural analyses of joint time use are scarce, some multi-person decision-making models have been extended with time together. Michaud and Vermeulen (2011) admitted leisure complementarity between spouses in the collective model of Chiappori (1992). Fong and Zhang (2001), Browning et al. (2020), and Cosaert et al. (2023) made a formal distinction between leisure alone and joint leisure with the spouse. To our knowledge, Jenkins and Osberg (2004) is the only other paper that has leisure alone, leisure with family, as well as leisure with friends as separate arguments in the utility function. We model time choices as *individual* decisions because the 'who with' dimension of our paper captures broad types of social leisure (family, friends) rather than interactions with a particular person.[5]

Lastly, we note that this is the first paper in showing evidence on the causal non-linear relationship between temperature and joint time use. The only studies that have explored the effect of temperature on time allocation have focused on the intertemporal substitution between hours of work and leisure. For example, Graff Zivin and Neidell (2014) showed that extreme warm temperatures reduce hours of work and that individuals undertake more indoor leisure and less outdoor leisure when temperatures are extreme. Moreover, Krüger and Neugart (2018) found that low temperatures lead to women reallocating work to leisure time, Somanathan et al. (2021) showed that workers are more likely to be absent from work on warm days, while Fan et al. (2023) found that extreme temperatures reduce outdoor activity (park visitation).

This paper also fits in the broader literature on the economic and health implications

[4]It is also the first paper that lets weather conditions affect the joint time choice.

[5]Interactions with a particular person would require modelling of collective or non-cooperative decision-making and addressing issues of time synchronization.

of temperature. Prior studies have found that extreme temperatures reduce productivity, economic growth, and agricultural and industrial output (Burke et al., 2015; Carleton and Hsiang, 2016; Chen and Yang, 2019; Dell et al., 2012, 2014; Hsiang, 2010; Jain et al., 2020; LoPalo, 2023; Miller et al., 2021; Somanathan et al., 2021; Zhang et al., 2018). Moreover, previous evidence has shown that warm temperatures reduce wages and income per capita (Dell et al., 2009; Deryugina and Hsiang, 2014; Neidell et al., 2021) but have a modest effect on profits (Deschênes and Greenstone, 2007). For health outcomes, previous evidence has shown that extreme temperatures lead to higher mortality rates (Barreca et al., 2015, 2016; Barreca, 2012; Burgess et al., 2014, 2017; Currie and Deschênes, 2016; Deschênes and Greenstone, 2011; Deschênes and Moretti, 2009; Heutel et al., 2021), a worse emotional state (Baylis, 2020; Baylis et al., 2018), and a deterioration in the physical and mental health of individuals (Burke et al., 2018; Deschênes, 2014; Graff Zivin and Shrader, 2016; Guirguis et al., 2018; Mullins and White, 2019; Noelke et al., 2016; White, 2017).[6]

The remainder of the article is organized as follows. We discuss the data in Section 2 and our empirical strategy in Section 3. The results of the empirical analysis are reported in Section 4. In Section 5, we propose a simple but flexible theoretical model, with a dual-self interpretation, of the relationship between temperature and joint time choices. We then test this model more formally in Section 6. Finally, Section 7 concludes.

2 Data and Sample Statistics

2.1 American Time Use Survey Data

We use data from the American Time Use Survey (ATUS), which is sponsored by the Bureau of Labor Statistics and conducted by the U.S. Census Bureau. This dataset is based on a

[6] Additional evidence has found an important effect of temperature on fertility (Barreca et al., 2018; Barreca and Schaller, 2020; Eissler et al., 2019), birth weight (Deschênes et al., 2009), human capital (Graff Zivin et al., 2018, 2020), food consumption (Bhattacharya et al., 2003) and migration (Deschênes and Moretti, 2009).

U.S. representative and randomly selected sample of individuals pertaining to households that completed an interview for the Current Population Survey (CPS), which is the primary source of labor force statistics for the U.S. population. The American Time Use Survey's primary purpose is to understand how individuals allocate their time, and it serves this goal by collecting cross-sectional data based on time diaries that describe how individuals spent their time on the day before the interview. More specifically, the time diaries provide detailed information on all the activities in which individuals got involved the day prior to the interview, their start and stop times, and the place *where* individuals did these activities. Importantly for our analysis, the time diaries also report *with whom* individuals spent this time, as well as the relationship between the interviewed individuals and the people with whom the activities were done.[7] This enables us to use as outcome variables precise measures on the amount of time individuals spent with family members, friends, and alone throughout the analysis. The outcome variables include 'pure' leisure, childcare, and household chores, but are net of market work and sleep.

Besides time allocation information, the American Time Use Survey dataset provides rich information on the socio-demographic characteristics of individuals. For example, it contains data on the gender, ethnicity, age, educational level, and the civil status of individuals, as well as on their household characteristics such as whether there are children in the household. Moreover, the dataset provides information on socio-economic characteristics of individuals such as their income or labor status. Lastly, the dataset provides information on the county of residence of individuals, which we use to link it with the temperature data in the analysis. We describe the weather data in more detail in the following section.[8] As there are more than 3,000 counties in the U.S., this allows us to exploit exogenous variation on weather conditions at an accurate geographical level.

[7] More specifically, the time diaries provide information on who was physically present during each activity.

[8] For 41.59% of individuals we do not observe the county of residence, but only the metropolitan statistical area where they live. In these cases, we assign individuals to the most populated county within their metropolitan area.

2.2 Weather Data

The daily weather data come from the National Oceanic and Atmospheric Administration (NOAA), and contain information on weather conditions for all available weather stations in the United States.[9] For example, the dataset provides information on the maximum, minimum, and average temperatures, as well as on the rainfall and snowfall on a daily basis for each weather station reporting information. There are more than 9,000 stations in the U.S., which allows us to exploit detailed exogenous variation on weather conditions across the country. Given that the smallest geographical unit for which there is information in the American Time Use Survey dataset is the county of residence of individuals, we aggregate the weather data at the county level by taking the average of each weather condition on a particular day for the stations within each county. We construct this information for every day over the period of time for which we have information on the American Time Use Survey dataset, and do not impose any sample restriction to the weather dataset. This allows us to use variation in weather conditions across more than 14.5 million county-day observations.

2.3 Sample Descriptive Statistics

Throughout the analysis, we use the sample of individuals who completed a time diary between 2004 and 2019, which provides us with a large sample of approximately 125,000 individual-day observations representative of the U.S. population. This allows us to estimate precisely the effect of temperature on social interactions.

Column 1 of Table 1 provides summary statistics of our sample. As shown, there is a higher proportion of females and white individuals in our sample. Moreover, individuals are 47 years old on average, and generally have some college education. Regarding our outcomes of interest, we provide descriptive evidence on whom individuals spend their non-market time with between 4 A.M. of the diary day and 4 A.M. of the day after. Non-

[9] We use the Global Historical Climatology Network – Daily (GHCN-Daily) dataset (Menne et al., 2020). Also see Menne et al. (2012) for a detailed description.

market time excludes working time as well as sleep spells. We measure all our outcomes of interest in minutes per day. As shown, individuals spend on average more than 5, 5, and 1 hours of their non-market time per day alone, with family, and friends, respectively. Moreover, most of the time individuals spend alone and with others is indoors. Columns 2–3 provide summary statistics for the subsamples of individuals who have a temperature below and above the average temperature during our period of analysis. As shown, individuals are remarkably similar in socio-demographic characteristics regardless of the temperature they are exposed to. Regarding weather conditions other than temperature, individuals have higher rainfall and snowfall when temperature is lower on average. Lastly, regarding our outcomes of interest, we do not find important differences for individuals who face a temperature above or below the mean, except that individuals spend more time alone and with others outdoors when facing temperatures above the mean. While it is useful to summarize how time allocation may vary when temperature is lower or higher than the mean, it is also important to acknowledge that these descriptive statistics do not offer any causal evidence, and do not take into account non-linearities in the relationship between temperature and time allocation. In the next section, we present the empirical strategy we follow to identify the causal non-linear impact of temperature on joint time use.

3 Empirical Strategy

Our empirical analysis exploits accurate daily variation in temperature across counties in the United States to investigate the non-linear effect of temperature on social interactions. We do so by estimating the following model:

$$y_i = \alpha + f(Tmax_{c(i),t(i)}) + \phi_{c(i)} + g(t(i)) + \varepsilon_i \tag{1}$$

where y_i is the outcome of interest for individual i. Throughout the analysis, we use three main dependent variables: the number of minutes individuals spent with family, friends,

Table 1: Descriptive Statistics

	Full Sample	Temperature < Average	Temperature > Average
	(1)	(2)	(3)
Female	0.56	0.56	0.56
	(0.50)	(0.50)	(0.50)
Age	46.99	46.78	47.15
	(17.73)	(17.62)	(17.81)
White	0.79	0.80	0.78
	(0.41)	(0.40)	(0.42)
Education Level: Less than High-school	0.15	0.14	0.15
	(0.35)	(0.34)	(0.36)
Education Level: High-school	0.24	0.24	0.24
	(0.42)	(0.42)	(0.42)
Education Level: College	0.62	0.63	0.61
	(0.49)	(0.48)	(0.49)
Precipitation (tenths of mm)	28.04	30.86	25.75
	(75.42)	(72.24)	(77.85)
Snowfall (mm)	1.56	3.47	0.00
	(12.17)	(17.96)	(0.12)
Non-market Minutes Spent Alone	312.17	312.04	312.27
	(265.67)	(264.65)	(266.49)
Non-market Minutes Spent Alone Indoors	294.73	298.28	291.84
	(257.16)	(258.35)	(256.15)
Non-market Minutes Spent Alone Outdoors	17.43	13.76	20.43
	(55.35)	(48.95)	(59.90)
Non-market Minutes Spent with Family	314.28	313.17	315.19
	(293.02)	(290.66)	(294.93)
Non-market Minutes Spent with Family Indoors	301.10	304.31	298.48
	(282.42)	(283.28)	(281.69)
Non-market Minutes Spent with Family Outdoors	13.18	8.86	16.70
	(54.13)	(43.03)	(61.50)
Non-market Minutes Spent with Friends	65.41	63.25	67.17
	(151.35)	(148.17)	(153.88)
Non-market Minutes Spent with Friends Indoors	60.31	59.64	60.86
	(142.43)	(141.75)	(142.98)
Non-market Minutes Spent with Friends Outdoors	5.10	3.61	6.31
	(35.92)	(29.02)	(40.66)
Number of Observations	124,935	56,146	68,789

Notes: The table presents the summary statistics of some socio-demographic characteristics of individuals, weather conditions they are exposed to, and outcomes of interest. We present averages and standard deviations in parentheses. Column 1 presents unweighted descriptive statistics for the full sample. Columns 2–3 present summary statistics for individuals who are exposed to a temperature below and above the sample temperature mean, respectively.

and alone on a particular day, respectively. Our explanatory variables of interest are given by a function that depends on the maximum temperature in the county of residence (c) of individual i on the diary date (t): $f(Tmax_{c(i),t(i)})$. More specifically, we use a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. This set of indicators covers the full temperature distribution and we use as the benchmark interval the one between 17 and 20 Celsius degrees. This allows us to explore the non-linear effect of temperature on social interactions, consistent with the empirical models that have been used by previous literature (Graff Zivin and Neidell, 2014). $\phi_{c(i)}$ is a set of dummies accounting for time-invariant characteristics at the county level which may be correlated with both the maximum temperature and the *who with* dimension of time use. $g(t(i))$ includes a set of dummies for the interactions between month and year indicators, to account for common trends in the outcome variables over the years of analysis as well as for potential seasonality in how individuals spend their time within the year. $g(t(i))$ also includes a set of dummies for the day of the week of the diary as well as whether the day is a bank holiday, as individuals may spend a different amount of their time with family, friends and alone on the different days of the week. After controlling for county, year-month, day of the week, and bank holiday fixed effects, we still have variation in our independent variables of interest —our maximum temperature indicators— because temperature varies at the county-day level.[10] Lastly, ε_i is the error term, which varies at the individual level. We allow for an arbitrary correlation of standard errors at the state-month level. The identification assumption of the analysis is that the error term is independent of the within-county variation in maximum temperature conditional on the set of controls we include in our specification.

[10]In the robustness tests, we also show that the estimates are robust to controlling for a set of covariates accounting for weather conditions other than maximum temperature, a set of covariates controlling for exogenous socio-demographic characteristics of individuals, second-order interactions between the county dummies and season fixed effects, and state–year indicators.

4 Empirical Results

This section provides evidence of the causal non-linear impact of temperature on the time individuals spend with family, friends, and alone. For this purpose, we estimate our baseline specification and present the estimates of our variables of interest —the indicators on the maximum temperature in the county of residence of individuals on the date of the diary— in Figure 2. The time individuals spend alone on very cold days is roughly similar to that spent on days where the maximum temperature falls in the 17 to 20 Celsius degrees interval. The time alone estimates for low temperature dummies are small and not statistically significant. However, low temperatures increase the time with family at the cost of time with friends. At the lower end of the temperature distribution, individuals spend much more time with family and less time with friends. Then, as the temperature increases from very low values to our benchmark (17 to 20 Celsius degrees), we find a gradual increase in time with friends and a corresponding decrease in time with family. In contrast, at days with extremely high temperatures, we show that individuals spend less time with family and more time alone compared to the time they spend at days when the temperature is within our baseline interval level. Extremely high temperatures do not seem to change the time individuals spend with friends relative to the benchmark temperature interval. Overall, our baseline estimates show that temperature affects with whom individuals spend their time.

It is also important to explore whether the effect of temperature on time spent with family, friends, and alone depends on where the activities take place. While the American Time Use Survey does not provide direct information on whether the activity takes place indoors or outdoors, we classify activities by adopting the definition proposed in Graff Zivin and Neidell (2014). This definition uses broad information on where the activity takes place as well as detailed information on the type of activity to classify it as indoors or outdoors. In particular, we define all activities as indoors unless its location or type clearly indicate that an activity is done outdoors. For example, if individuals report doing the activity 'outdoors away from home' or while 'walking' or 'cycling', we classify it as outdoors. Moreover, if the type of activity can only be done outdoors, such as exterior cleaning, gardening, or moving the lawn, among others, we classify the activity as outdoors as well. Similar to Graff Zivin and Neidell (2014), we therefore assign activities into indoors when their location or type is ambiguous. Our estimates thus represent a lower bound of the effect of temperature on time spent outdoors.

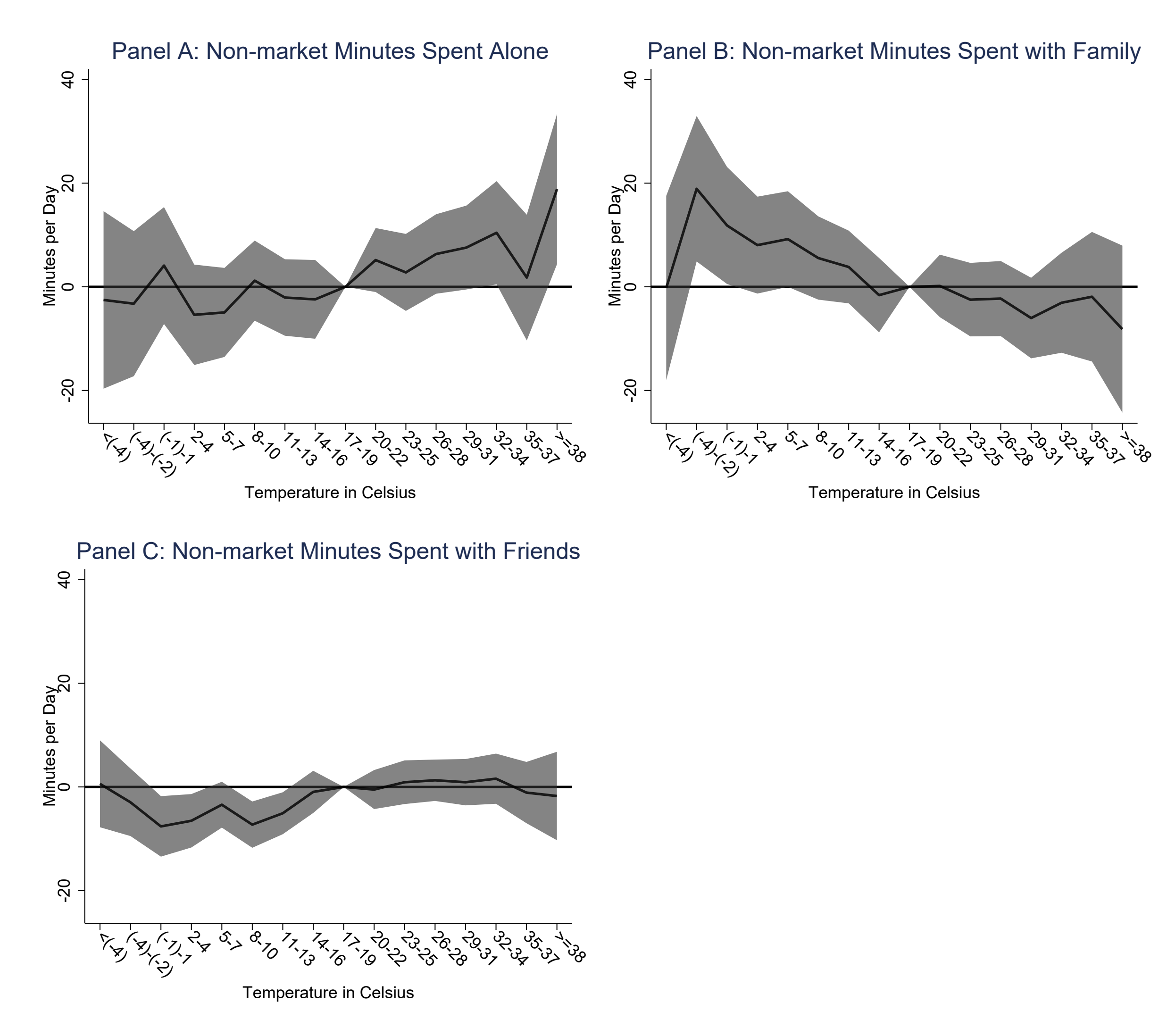
We report our estimates of the effect of temperature on joint time use, indoors and outdoors, in Figure 3. As shown, extremely low temperatures reduce the time spent outdoors with family, friends, and alone. This is compensated by an increase in the time spent indoors, but this increase applies only to the category of time with family. At the lower end of the temperature distribution, the time with friends increases as it gets warmer again, and this increase is mainly driven by time spent with friends *outdoors*. By contrast, warm temperatures reduce time spent with family indoors, and this is compensated by an increase in the time individuals spend outdoors with family as well as indoors and outdoors *alone*.[11] These results demonstrate that temperature not only has an effect on the time that individuals spend with family, friends, and alone, but that the location of activities is an important mediator of these changes in joint time use.

4.1 Robustness Tests

In this section we examine whether the baseline estimates are robust to the implementation of multiple sensitivity tests. First, we study whether the baseline estimates are sensitive to the inclusion of additional covariates such as individual or weather characteristics that may affect the temperature and time allocation relationship. In Appendix B.1, we estimate a specification that is similar to our baseline model but that also controls for a set of exogenous socio-demographic characteristics of individuals, such as the individual's age, gender,

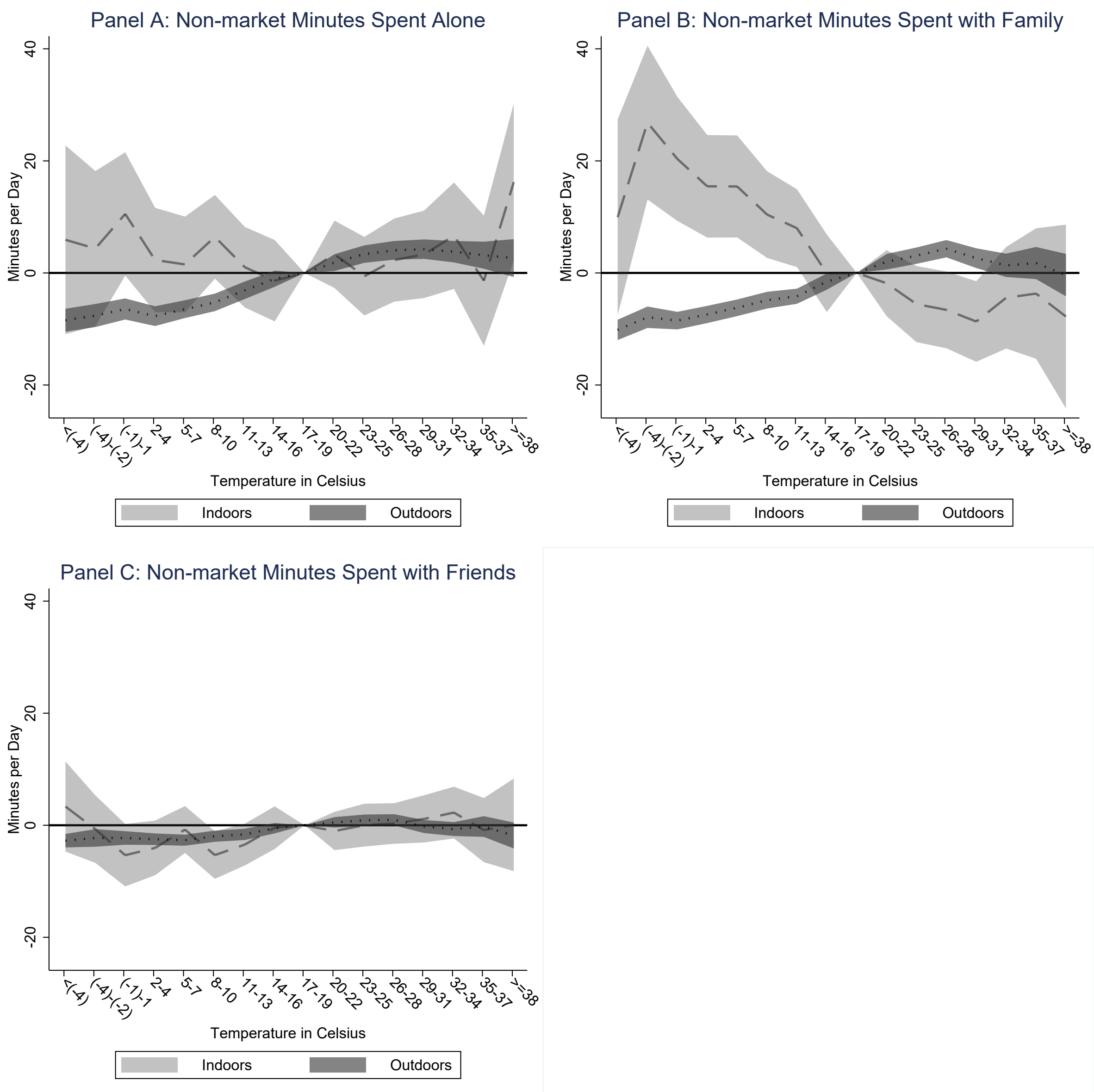
[11] In Appendix A, we examine whether our baseline estimates vary by household type. We classify our sample into individuals living alone and with at least one family member, and estimate our baseline model while exploring heterogeneity for these two types of individuals. We find that extreme temperatures increase (decrease) time spent alone (with family) for individuals living alone. This joint time use adjustment mainly occurs through changes in indoors non-market time. We also show that our baseline estimates for time spent with family and friends are primarily driven by individuals living with family.

Figure 2: The Effect of Temperature on Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark interval the one between 17 and 20 Celsius degrees. We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date in panels A–C, respectively. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

Figure 3: The Effect of Temperature on Indoors and Outdoors Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark interval the one between 17 and 20 Celsius degrees. We also present the 95% confidence intervals of the estimates. We use as the dependent variable the indoors and outdoors time that individuals spend alone, with friends, and with family on the diary date in panels A–C, respectively. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

ethnicity, and level of education. In Appendix B.2, we instead include as additional controls weather conditions other than the maximum temperature, such as the minimum temperature and the amount of rainfall and snowfall, in the county of residence of the individual on the diary date.

Second, we investigate whether the effect of temperature on time allocation we found might be driven by changing policies or conditions at the regional level, such as changes in labor regulation. We account for these by including as additional controls second-order interactions between the state and year dummies. We present the estimates in Appendix B.3.

Lastly, another possible concern is that the estimates on the impact of temperature on joint time use may be driven by seasonality. While we have accounted for this in our baseline specification by including year-month dummies, we further address this possibility by including as additional controls second-order interactions between the county and season dummies. The four season dummies take value 1 for the periods December–February, March–May, June–August, and September–November, and 0 otherwise, respectively. We present the estimates in Appendix B.4. As shown in Appendices B.1–B.4, the baseline estimates we reported in Figures 2–3 are robust to all these sensitivity checks.

4.2 Adaptive Behavior

Another possible question is whether the effect of temperature on joint time use depends on the frequency with which individuals have been exposed to different temperatures. We explore this possibility from several angles. First, we estimate specifications similar to the baseline model but with additional controls for temperature conditions in the days before the diary date. For example, in Appendix C.1.1, we include as controls a set of indicators that take value 1 if the maximum temperature in the county of residence of the individual the day before the diary date fell within temperature intervals of 3 Celsius degrees. Appendices C.1.2 and C.1.3 are similar to Appendix C.1.1, but instead account for temperature conditions two and three days before the diary date, respectively. As shown, the estimates on the effect of temperature of the diary date on joint time use remain largely unchanged when we account for the temperature conditions in the days prior to the diary date. This suggests that our baseline estimates are not driven by short-term adaptive behavior.

Second, we explore potential adaptive behavior by investigating if the effect of temperature on joint time use depends on how long individuals have been exposed to warm (cold) temperatures during the summer (winter) season. In Appendix C.2, we estimate the baseline model while restricting our sample to the summer period (June to August). We show the estimates of the set of indicators covering temperatures higher than the benchmark interval (i.e. between 17 and 20 Celsius degrees), for the first and second part of the summer. We define the first part of summer as that going from June 1 until July 14, and the second half as that going from July 15 until August 31. While this sample restriction reduces substantially the sample size we can use to estimate the effect of temperature on joint time use, it is interesting to explore how the estimates vary throughout the summer. As shown, the effect of warm temperatures on overall, indoors, and outdoors joint time use does not seem to depend on a particular half of the summer. Moreover, the coefficients are rather imprecisely estimated, therefore providing suggestive evidence at best. In Appendix C.3, we re-estimate the analysis of Appendix C.2, now restricting the sample to winter and focusing on how the estimates vary in the first and second part of this season. We define the first part of winter as November and December, and the second part as January and February. As shown, cold temperatures increase time spent with family indoors and reduce time spent alone and with family outdoors irrespective of the half of the winter we study. The estimates are of similar magnitude in the first and second part of the winter. Overall, we find no strong evidence suggesting adaptive behavior of individuals to temperature conditions within the different seasons.

Lastly, we study adaptive behavior by comparing the effect of temperature on joint time use for individuals living in cold and warm counties in Appendix C.4. It is important to bear in mind that this subanalysis also reduces considerably our sample size and thus the statistical power we can exploit. We define cold (warm) counties as those with an average temperature lower (higher) than the mean of the sample. To facilitate the presentation of the results, we first report in Figures C.11 and C.12 the estimates of the set of indicators covering temperatures lower than the benchmark interval (i.e. 17–20 Celsius degrees). As shown, low temperatures increase time spent with family indoors independently of whether individuals live in cold or warm counties, although the estimates are higher in magnitude (and less precise) for individuals living in warm counties. We also find that cold temperatures reduce time spent alone, with family and friends outdoors and in a similar way regardless of whether individuals live in a cold or warm county. In Figures C.13 and C.14, we report the estimates of the set of indicators covering temperatures higher than the benchmark interval (i.e. 17–20 Celsius degrees). As shown, high temperatures reduce time spent with family indoors only for individuals living in cold counties. Instead, warm temperatures increase time spent alone and with family outdoors irrespective of whether individuals live in warm or cold counties. The estimates thus suggest that the effect of temperature on certain types of time allocation may vary according to the temperature conditions individuals are used to, but also that this adaptive behavior cannot fully explain the relationship between temperature and joint time use.

5 A Dual-Self Model of Joint Time Use

So far, we provided causal evidence on the relationship between temperature and joint time use. We found that an individual's time with family generally decreases as it gets warmer, and that this is compensated by an increase in the time with friends (in the lower half of the temperature distribution) or time alone (in the upper half of the temperature distribution). We also confirmed important shifts in the location of activities, by temperature. We now offer a dual-self interpretation that can rationalize this finding. The dual-self representation posits that individual preferences for leisure alone, leisure with family, and leisure with friends differ by the indoor or outdoor nature of activities, which in turn depends on weather conditions. To formalize the intuition, we extend consumer theory with the *who with* (as advocated by Hamermesh (2020)) and *where* dimensions of leisure. In the next section, we resort to tools from the household economics literature to formally test the dual-self interpretation of joint time use.

Set-up. We let an individual divide their non-work time L between leisure alone l_a, leisure with family l_{fa}, and leisure with friends l_{fr}.[12] Leisure vector $l \in \mathbb{R}^3_+$ consists of the elements l_a, l_{fa}, and l_{fr}. We further decompose l_a, l_{fa}, and l_{fr} by the location of activities. Let $l^I \in \mathbb{R}^3_+$ denote the vector of 'indoor' leisure $(l^I_a, l^I_{fa}, l^I_{fr})'$ and let $l^O \in \mathbb{R}^3_+$ represent the vector of 'outdoor' leisure $(l^O_a, l^O_{fa}, l^O_{fr})'$. We further admit *hybrid* activities that take place partly indoors and partly outdoors.[13] We denote this hybrid leisure by $l^H = (l^H_a, l^H_{fa}, l^H_{fr})' \in \mathbb{R}^3_+$. Each minute of leisure can be classified as indoor, outdoor, or hybrid; so we have that $l^I + l^O + l^H = l$.

Each person is endowed with a pair of utility functions U^I and U^O. There can be (up to) two selves within the individual; for instance one with a stronger preference for indoor leisure (U^I) and one with a stronger preference for outdoor leisure (U^O). Moreover, these selves must not necessarily agree on the valuation of leisure alone, leisure with family, and leisure with friends. Which preference or 'self' is active depends on the decision environment, specified below. Preferences take the form:[14]

$$U^I(l^I, l^O, l^H)$$

$$U^O(l^I, l^O, l^H)$$

[12] Leisure is broadly defined as time not working or sleeping, so it also captures household chores and childcare.

[13] For instance, a typical city trip will consist of indoor (hotel, pubs, museums, ...) and outdoor (visiting the city's parks, shopping streets, ...) activities.

[14] This general formulation allows that the tastes U^I can also partially depend on l^O, while U^O can depend on l^I. This captures the possibility of spill-overs between indoor and outdoor activities. Times l^H generate benefits for both selves simultaneously.

Preferences of the form $U^I(l^I)$ and $U^O(l^O)$ are special cases of the general model. Then the preference of the indoor self (which values only l^I) differs a lot from that of the outdoor self (which values only l^O).

Finally, each individual has a personal time constraint:

$$\sum_{i=I,O,H} l_a^i + l_{fa}^i + l_{fr}^i = L$$

For simplicity, we assume that leisure choices are weakly separable from consumption and other uses of time. Our set-up can be seen as the second stage of a two-stage budgeting procedure. In the first stage, an individual selects their market work (which also immediately determines their total consumption opportunities) and total leisure. In the second stage, they allocate this total leisure over time alone, time with family, and time with friends. We focus on the second stage in the present paper.

A joint time use model with weather variation. The dual-self model states that leisure choices are the result of a within-individual decision process with an indoor self and an outdoor self. Formally, there must exist utility functions U^I and U^O and weights μ^O so that the leisure demands (l^{I*}, l^{O*}, l^{H*}) solve

$$\max_{l^I, l^O, l^H} U^I(l^I, l^O, l^H) + \mu^O U^O(l^I, l^O, l^H) \tag{2}$$

$$s.t.$$

$$\sum_{i=I,O,H} l_a^i + l_{fa}^i + l_{fr}^i = L$$

with $l^I = (l_a^I, l_{fa}^I, l_{fr}^I)'$, $l^O = (l_a^O, l_{fa}^O, l_{fr}^O)'$, and $l^H = (l_a^H, l_{fa}^H, l_{fr}^H)'$. This follows the literature on 'cooperative' multiple selves (Ambrus and Rozen, 2014; May, 1954). Applied to our set-up, the individual maximizes an overall welfare index that aggregates the utility flows of each self. Flexible weights μ^O determine the relative influence of the outdoor self in the decision-making process.[15] Generally speaking, μ^O increases the degree to which final outcomes reflect the preferences of the outdoor self.

We are now ready to formulate explicit hypotheses with respect to the decision-making structure in (2).

(H1) The individual's leisure choice is determined by program (2). Temperature changes the relative decision power of the selves (μ^O) but not the preferences of each self (U^I or U^O).

(H2) The indoor and outdoor selves have identical preferences: $U^I(\cdot,\cdot,\cdot) = U^O(\cdot,\cdot,\cdot)$.

Hypothesis H1 formalizes consistency with program (2) and, more importantly, specifies *how* weather variables enter the model. It states that weather can change the *influence* but not the *preferences* of each self.[16] Weather can affect the leisure choice but only through its effect on μ^O. Hypothesis H2 zooms in on the selves' preferences. It formalizes the alternative possibility that indoor and outdoor selves have identical preferences. In other words, individual-level preferences for joint time are independent of the indoor or outdoor nature of the underlying activities. Our dual-self interpretation of joint time use is supported if H1 holds and H2 does not. If H1 is rejected, then the leisure choice is the result of a more flexible (but less tractable) model than the one presented here. If H2 is accepted, then preferences for leisure do not differ meaningfully across activities so the distinction between indoor and outdoor selves becomes vacuous.

[15] The dual-self model of joint time use is formally similar to the collective model proposed by Chiappori (1988, 1992). The collective model was developed to describe consumption and labor supply by spouses with distinct preferences. The main assumption behind the collective model is Pareto efficiency: consumption is the Pareto efficient outcome of an intra-household bargaining process between spouses.

[16] A priori, it is less clear how weather variables could affect individual preferences for time alone, time with family, and time with friends *conditional on the activity taking place inside/outside.* Connolly (2008) found for instance that a rainy day was associated with less leisure and more work, but that the overall effect of weather variables was statistically small.

6 Empirical Tests of the Dual-Self Interpretation

We bring our model to the data by testing hypotheses H1 and H2. We first test whether the time choices observed in our data satisfy the dual-self model (H1). We then investigate whether the data can also be rationalized with one single self —independent of the indoor or outdoor nature of activities (H2).

Testing the dual-self model. The main empirical challenge in testing the dual-self model is that there is no independent price variation in the data, associated with l_a, l_{fa}, and l_{fr}, to help us identify the value of different uses of time. A priori, it is unclear how weather conditions change the shadow prices of different types of joint time use. In addition, as mentioned before, there is no *direct* information about the indoor or outdoor nature of activities in the American Time Use Survey. We constructed a (lower bound) proxy for outdoor time at the end of Section 4, but the quality of the approximation may vary across individuals. For instance, activities done at some 'Other place' may be 100% indoors for some individuals and 100% outdoors for others.

To bring the model to the data, we resort to well-known tools from the collective household literature (Chiappori, 1988, 1992).[17] A major advantage of this empirical strategy is that it still works in the absence of price variation and even if the *where* dimension of leisure remains unobserved. The latter implies that the test is robust to measurement error in the location dimension. To implement the test of our dual-self model, we need *at least two* variables that can plausibly shift time between indoor and outdoor activities. Let T denote the maximum temperature on the diary day in the county of residence of the individual. While most of the paper has focused on temperature, the following analyses will also incorporate

[17] In this literature, strategies to test consumption models typically belong to one of two classes. The first class relies on price variation (i.e., to detect violations of Slutsky symmetry and its extensions). In our set-up, it is not straightforward to associate different uses of time with different costs. Wages help pin down the opportunity cost of leisure but not, separately, the costs of leisure alone, leisure with family, and leisure with friends. The second class of tests relies on so called 'distribution factors'. In a household context, a variable is a distribution factor *if it does not enter individual preferences nor the overall household budget constraint but it does influence the decision process* (Bourguignon et al., 2009).

a precipitation variable (R).[18] We measure rain R in tenths of millimetres rainfall on the diary date in the county of residence of the individual. In addition, we show in Appendix D that temperature and rainfall do not change the total time that individuals allocate to non-market activities. Let $l_n(L,T,R)$ capture the demand for leisure ($n = a, fa, fr$) in function of total leisure time L and extra-environmental factors T, R. These 'aggregate' demands $l_n(L,T,R)$ refer to leisure alone, leisure with family, and leisure with friends *at the level of the individual*, not at the level of each self. These demands can be estimated from the data.

H1 hypothesizes simultaneously that (i) observed leisure choices solve program (2) and that (ii) the functions U^I and U^O in (2) are independent of T, R. Applying the terminology of the (formally similar) collective household literature, joint leisure is the efficient outcome of a decision process with two selves —one for indoor and one for outdoor activities— where each self's preference is invariant to weather factors $d = T, R$. Following this literature, if (i) and (ii) jointly hold, the data must pass the 'factor proportionality' conditions discussed in Bourguignon et al. (1993, 2009). This condition states that the ratio of marginal effects of T and R must be identical for all demands $m, n = a, fa, fr$:

$$\forall m,n : \frac{\partial l_m(L,T,R)/\partial T}{\partial l_m(L,T,R)/\partial R} = \frac{\partial l_n(L,T,R)/\partial T}{\partial l_n(L,T,R)/\partial R}.$$

The proportionality property can be implemented with a minimum of two factors.

If H1 holds, we cannot reject our dual-self interpretation. H2 goes one step further by stating that one self suffices to rationalize the data. In other words, one can set $U^I(\cdot,\cdot,\cdot) = U^O(\cdot,\cdot,\cdot)$. However, under hypothesis H1 and absent effects on total L, this implies that variation of T, R must leave joint leisure choices unaffected. This translates into the following

[18] The effect of rainfall on the nature of activities has been shown in seminal work by Connolly (2008). In Appendix E, we also estimate the effect of rainfall on the time that individuals spend alone, with family, and friends. We further study if the location of activities mediates these effects. As shown, more rain leads to less outdoor time spent alone, with family, and friends, and more indoor time spent with family.

conditions for all demands $n = a, fa, fr$:

$$\forall n : \frac{\partial l_n(L,T,R)}{\partial T} = \frac{\partial l_n(L,T,R)}{\partial R} = 0.$$

Indeed, without preference variation between the selves ($U^I(\cdot,\cdot,\cdot) = U^O(\cdot,\cdot,\cdot)$), time shifts between indoor and outdoor activities will never affect overall togetherness.[19]

Parametric specification. In our empirical application, following Bourguignon et al. (2009), we model the demand for leisure n as a quadratic in (L, T, R). We assume that temperature T and rainfall R influence μ^O but not the total amount of time L.[20] We then estimate the following system of leisure functions:

$$l_n = p_n + q_n L + r_n L^2 + s_n T + t_n R + u_n T^2 + v_n R^2 + w_n LT + x_n LR + y_n TR \tag{3}$$

with l_n leisure alone ($n = a$), leisure with family ($n = fa$), and leisure with friends ($n = fr$). For the estimation, we augment these equations with demographic characteristics and control variables such as county, year-month, day-of-the-week, and holiday-day dummies. In the quadratic demand system specified above, our hypotheses translate as follows:

(H1) The weather factors have the same proportional impact across leisure demands. Applied to the quadratic functions, this requires (at least) one of the following two conditions to hold:

$$l_n = p_n + q_n L + r_n L^2 + \lambda_n[sT + tR + uT^2 + vR^2 + wLT + xLR + yTR] \tag{4}$$

$$l_n = p_n + q_n L + r_n L^2 + \lambda_n[T + \tau R] + \varphi_n[T + \tau R]^2 + \omega_n L[T + \tau R] \tag{5}$$

[19]It is worth to note that μ^O has *no* impact on time choices in the special scenario where $U^I(\cdot,\cdot,\cdot) = U^O(\cdot,\cdot,\cdot) = U(\cdot,\cdot,\cdot)$ (i.e., when the preferences of the selves coincide). In that case, we can write the objective function as $(1+\mu^O)U(\cdot,\cdot,\cdot)$ and this rescaling leaves the optimal joint time unchanged.

[20]We also show this in Appendix D.

(H2) The weather factors have no impact on the leisure demands:

$$s_n = t_n = u_n = v_n = w_n = x_n = y_n = 0$$

In the formulation of H1, parameters $s, t, u, v, w, x, y, \tau$ are constant across goods. Either the terms with weather factors enter all demand functions proportionally (4), or the demand functions are quadratic in the same simple function $T + \tau R$ (5). We refer to Bourguignon et al. (1993, 2009) for a formal derivation of (4) and (5) from the quadratic demand system, under the restrictions of factor proportionality. We first estimate the system of three leisure equations in (3) simultaneously by ordinary least squares. We subsequently test the coefficient restrictions implied by (4), respectively (5), from hypothesis H1. We finally test whether all coefficients of those terms that include T or R are zero (H2).

Results and discussion. Figure 4 plots the predicted values for leisure alone, leisure with family, and leisure with friends in function of the maximum daily temperature. The patterns are fully in line with the empirical evidence of the causal impact of temperature on time use from Section 4. However, the main objective of estimating (3) is to test our dual-self interpretation of the result established in Section 4. We do this by testing the conditions of H1 and H2. The first hypothesis states that weather affects joint leisure (only) insofar it influences an index of indoor or outdoor activities. The χ^2–values of the log-likelihood ratio tests of H1 are $\chi^2(6) = 3.48$ and $\chi^2(7) = 3.14$; with corresponding p-values of 0.7462 and 0.8716. Thus we cannot reject (any of) the possible implications of H1. This lends support to our dual-self interpretation of joint time choices, in which each self has 'stable' preferences for togetherness. The second set of conditions states that weather variables do not affect joint time choices. The χ^2–value of the log-likelihood ratio test associated with H2 is equal to $\chi^2(14) = 53.15$; the related p-value is close to zero. We thus reject the hypothesis that one self, independent of the indoor or outdoor nature of activities, rationalizes the data. Individual preferences for togetherness cannot be seen separately from the indoor or outdoor nature of activities.

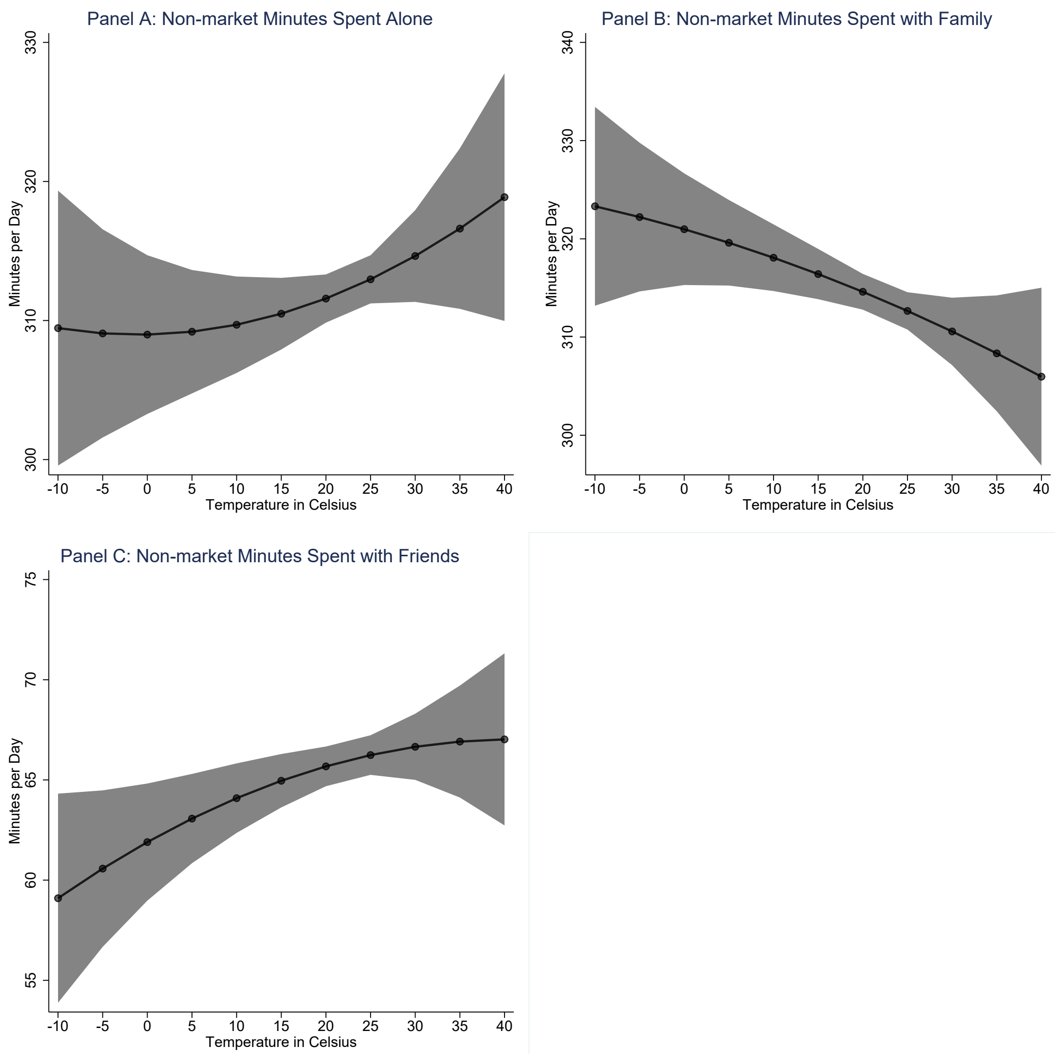
In sum, joint leisure can be represented as the outcome of an implicit decision process with two selves. One (indoor) self is mainly in charge of activities that take place indoors and another (outdoor) self is responsible for joint time choices outdoors. This incorporates the *where* and *who with* dimensions of leisure time in an empirically tractable microeconomic model. It also suggests a mechanism that links both dimensions. The outdoor self will have a larger impact on time use under favorable (less extreme) weather conditions. Combined with the results in Section 4, the theory suggests that the indoor self almost exclusively favors time with the family while the outdoor self values time alone, time with friends, *as well as* time with family.

The more general insight from this analysis is that any exogenous shock to total indoor or outdoor time can also, indirectly, affect togetherness. This suggests that loneliness, companionship in the family, and social ties all depend, at least in part, on the *environment in which* individuals allocate their time. The weather condition is one of the first determinants that come to mind when predicting the distribution of leisure time to indoor and outdoor activities (Graff Zivin and Neidell, 2014). Yet, our basic insight extends beyond specific weather circumstances. Any shock to the location of leisure activities can affect the allocation of joint time. So, although we validated our model with weather data, the theory can be applied to various other settings. Other circumstances that hamper outdoor activities, thereby potentially limiting the joint time decision, include mobility problems, severe pollution, lack of safety and various forms of discrimination.

7 Conclusions

This paper examines the effect of temperature on joint time use by exploiting exogenous variation in temperature at the county-day level in the United States and combining this

Figure 4: Theoretical Predictions of Time Use in Function of Temperature



Notes: The figure shows the predicted values of the empirical application of our theoretical model in function of the maximum daily temperature. We show predicted values for the full temperature distribution and also present their 95% confidence intervals. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date in panels A–C, respectively. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, as well as for a set of socio-demographic characteristics. We cluster standard errors at the state-month level.

information with daily time use data from the American Time Use Survey. The paper also provides an interpretation of the results in a decision-theoretic framework that we test empirically.

In the first part of the analysis, we examine the non-linear relationship between temperature and social interactions by estimating a model that includes a set of indicators referring to temperature intervals of 3 Celsius degrees and covering the full temperature distribution. In the specification, we control for county, year-month, and day-of-the-week fixed effects (among other controls) to account for time invariant county characteristics, seasonality, and differences in time allocation over the week, respectively. We show that low temperatures reduce the time individuals spend with friends and increase the time they spend with family. By contrast, high temperatures increase time spent alone at the cost of time with family. We also find that the non-linear relationship between temperature and time spent with others is location-dependent. Low temperatures increase time spent with family indoors, which is compensated by decreases in the time individuals spend outdoors alone, with family, and with friends, as well as a reduction in the time spent with friends indoors. High temperatures decrease the time spent with family indoors, which is compensated by an increase in the time that individuals spend outdoors with family, and outdoors and indoors alone.

The second part of the analysis provides a decision-theoretic framework to interpret the effect of temperature on joint time use. Temperature enters the model as an extra-environmental variable that shifts the attention to (or away from) outdoor activities. In this framework, weather variation can influence joint time because the individual's preferences for joint activities depend at least in part on the nature and location of the activities. The theoretical predictions of our dual-self model, with indoor and outdoor preferences for joint time use, are supported by the data. The rationale is as follows: favorable weather conditions increase the influence of the outdoor self, and this raises overall time alone and with friends. The outdoor self appears to value all three types of time use whereas the indoor self mainly values time with family. Any exogenous shock to individuals' total indoor or outdoor leisure can therefore also change *with whom* individual spend most of their time. Individual preferences for joint leisure are not invariant to exogenous changes in the environment.

The time variables in this research are aggregates of more detailed time use data on recreation, household chores, childcare, and other activities net of sleep and market work. An interesting avenue for future research is to decompose non-market time (e.g., into 'pure' leisure, caregiving, chores) and estimate temperature effects for each category separately. However, it will be empirically challenging to classify each non-market activity in exactly one category. Some activities, like childcare or shopping, may simultaneously produce leisure for the individual and benefits for the household. Another avenue for future research is to split up time with family into time with the spouse, with children, with the individual's parents or with other relatives. While this may yield deeper insight into temperature effects across different types of social interactions, it would also exacerbate issues of timing and time synchronization (e.g., between spouses in a time constrained couple) that we abstract from in our analysis.

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Appendix of Temperature and Joint Time Use

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May 24, 2023

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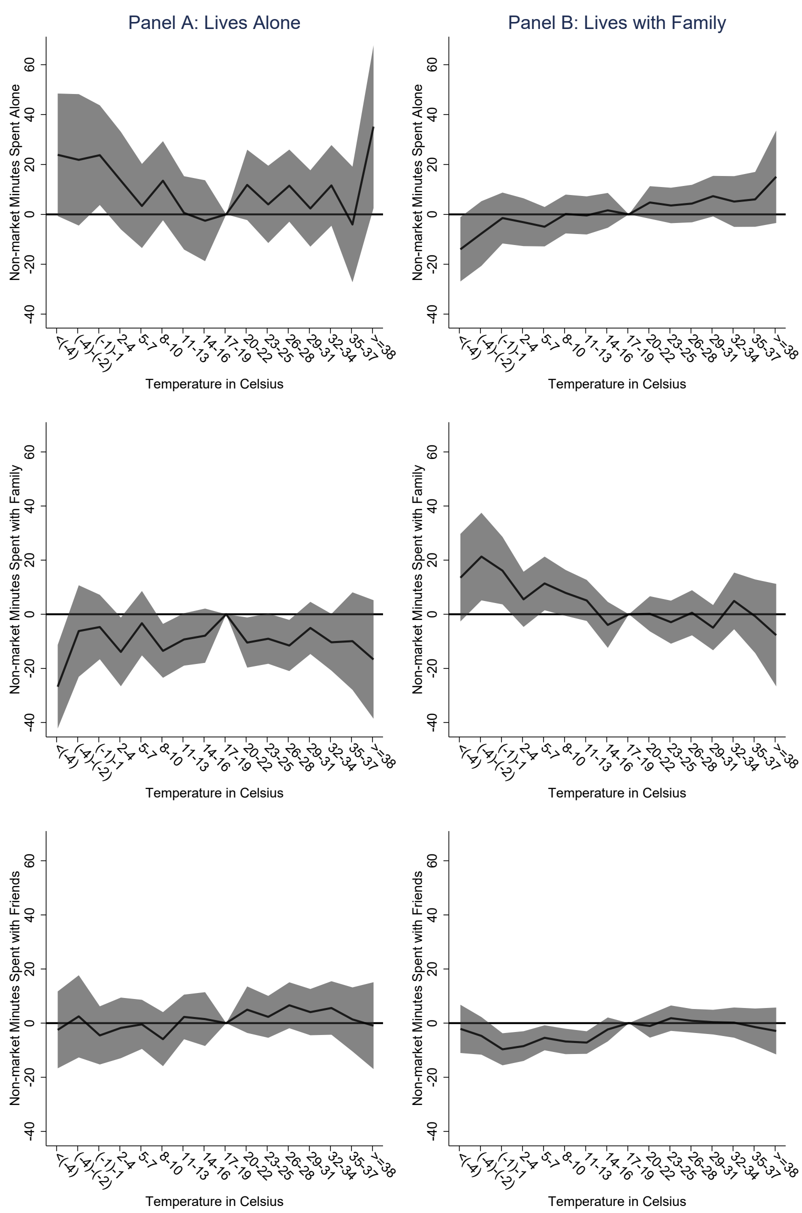
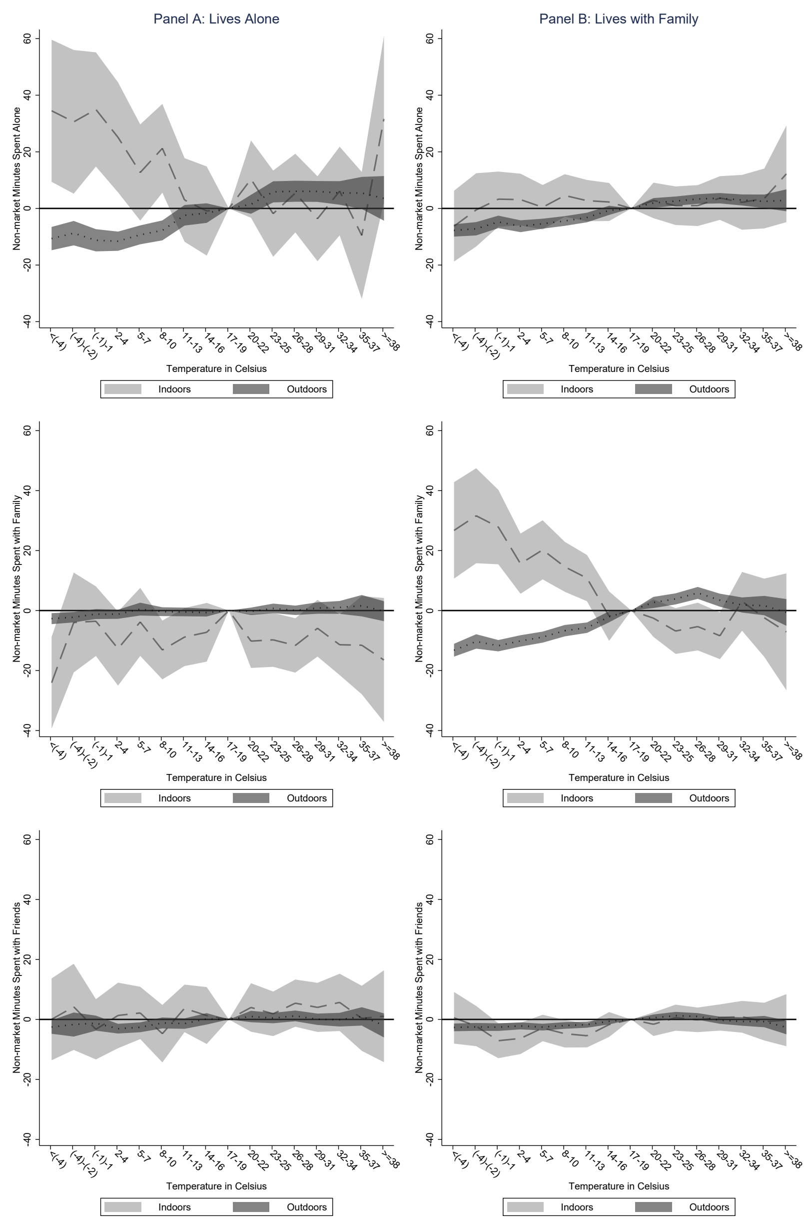
A Household Type

Figure A.1: The Effect of Temperature on Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark interval the one between 17 and 20 Celsius degrees. We also present the 95% confidence intervals of the estimates. We estimate the baseline model while exploring heterogeneity for individuals living alone and with family in panels A and B, respectively. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects. We cluster standard errors at the state-month level.

Figure A.2: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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B Robustness Tests

B.1 Individual controls

Figure B.1: The Effect of Temperature on Joint Time Use

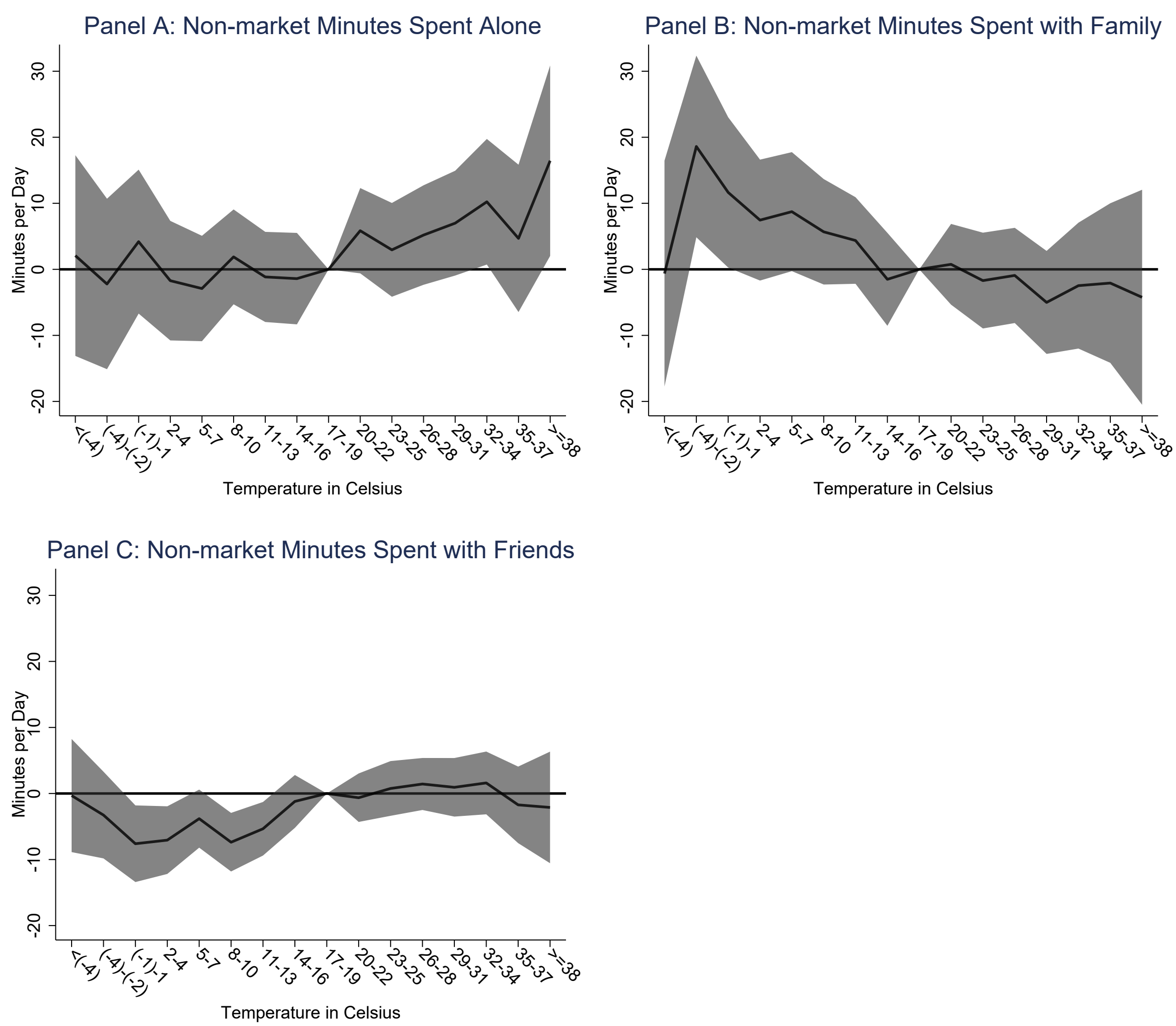

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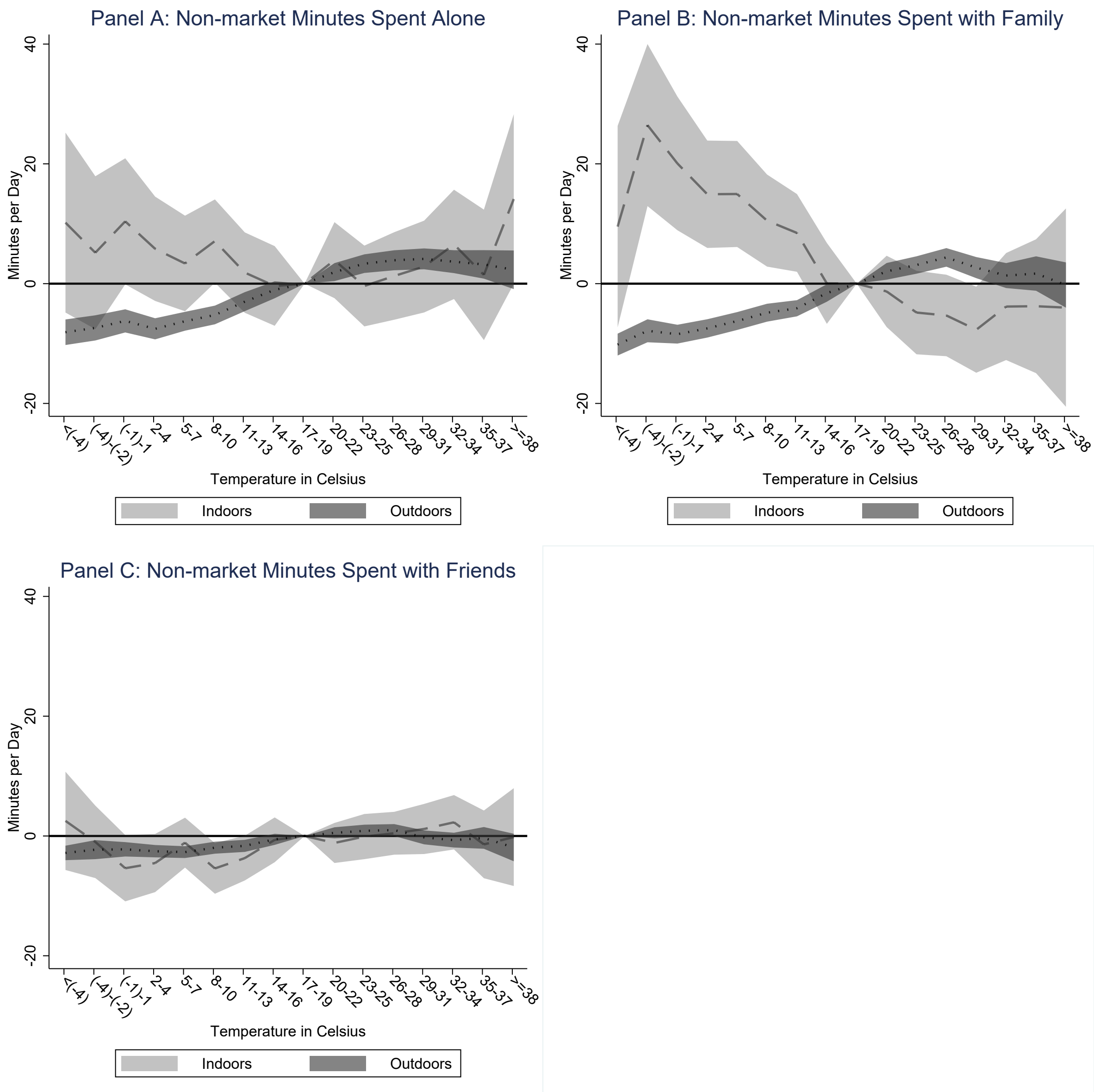
Figure B.2: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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B.2 Weather controls

Figure B.3: The Effect of Temperature on Joint Time Use

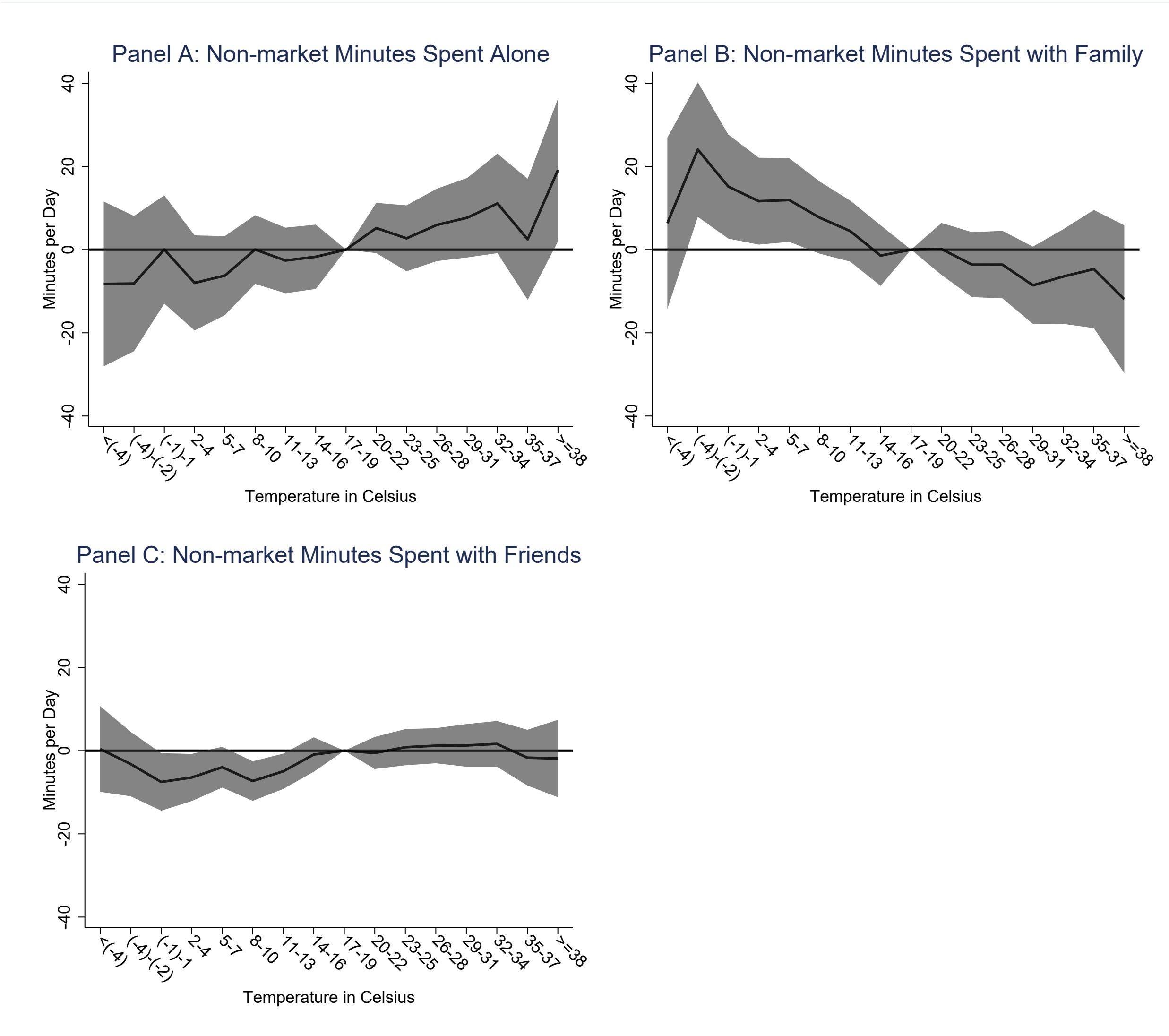

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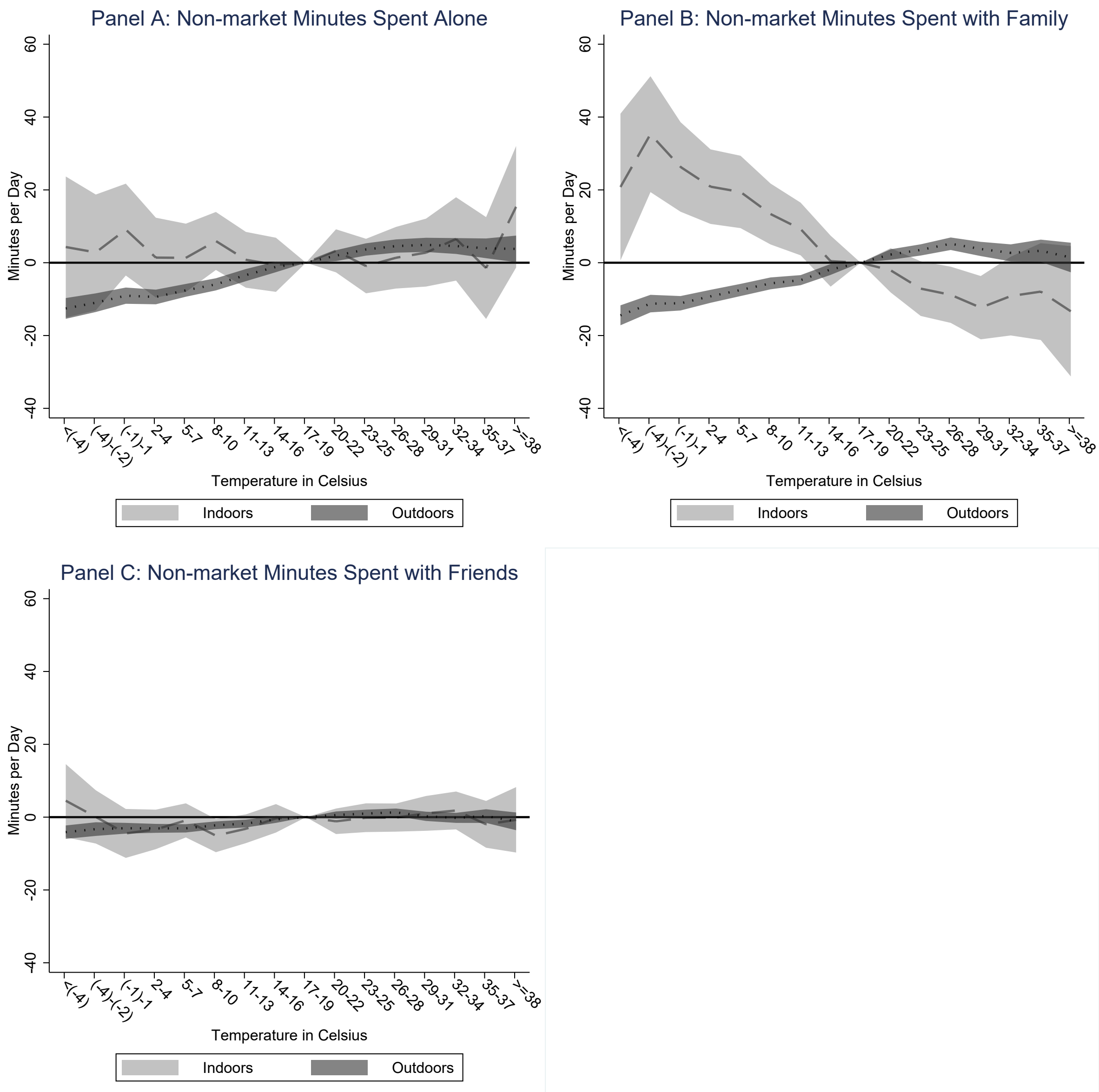
Figure B.4: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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B.3 State-year Shocks

Figure B.5: The Effect of Temperature on Joint Time Use

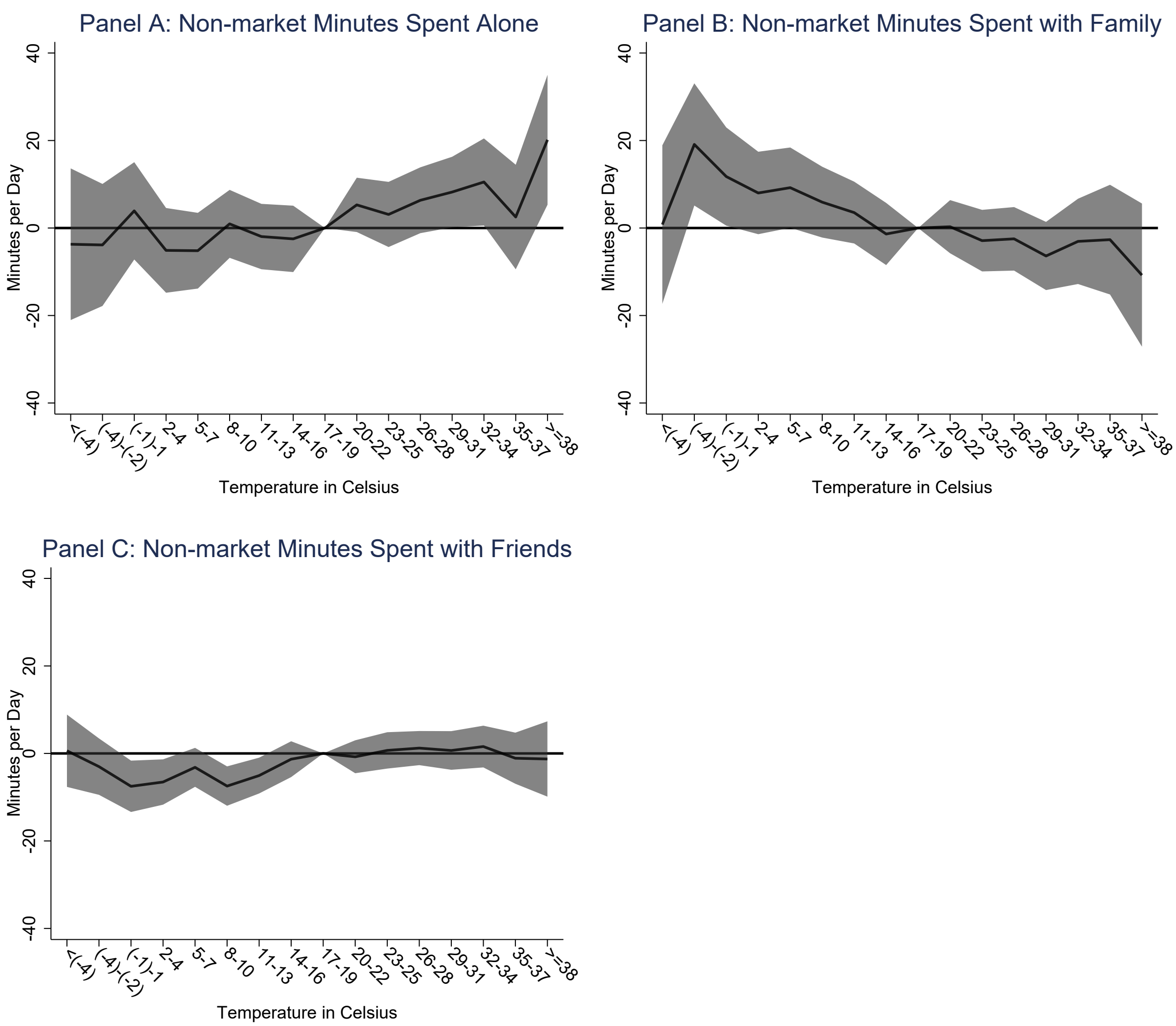

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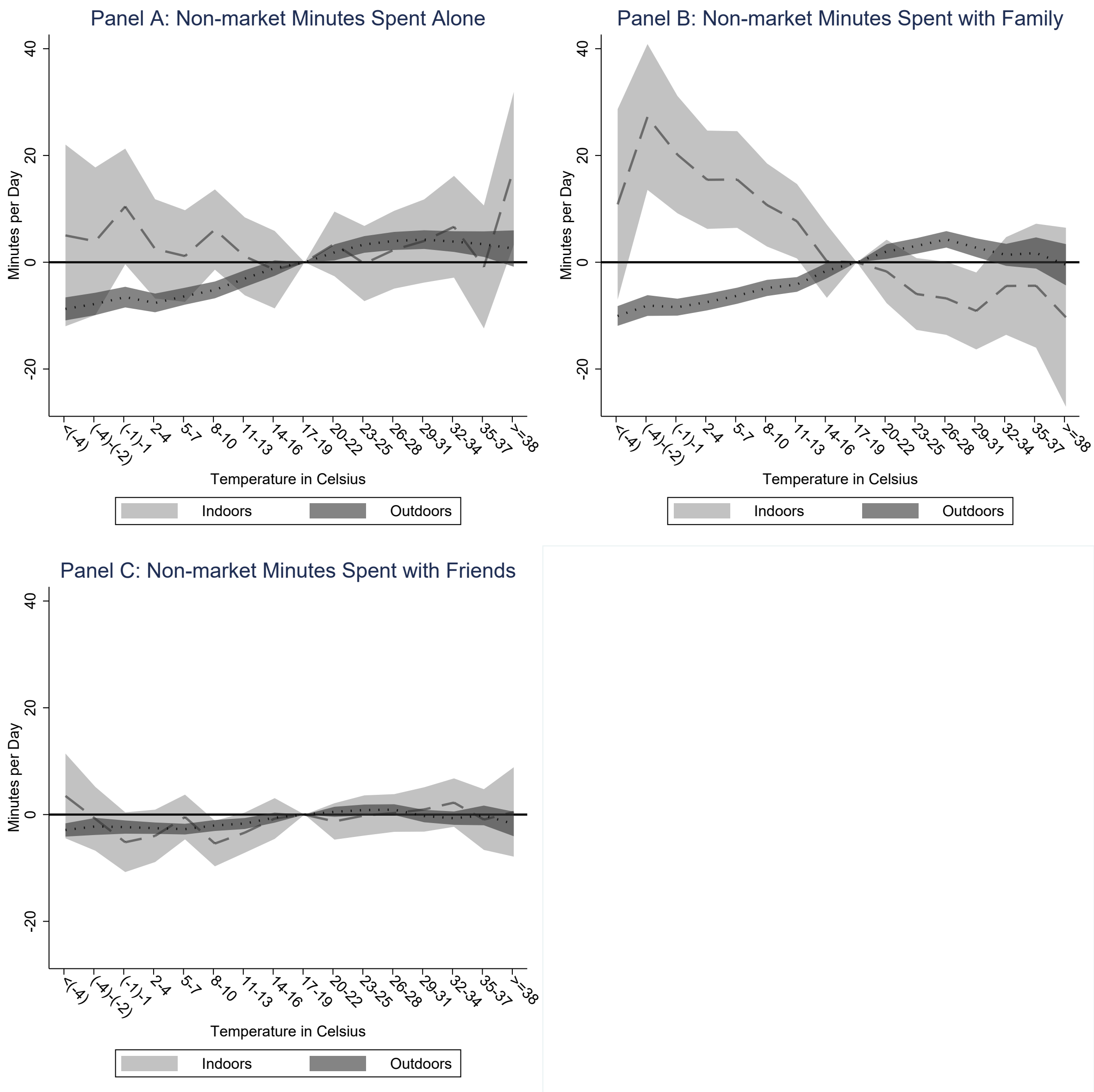
Figure B.6: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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B.4 Seasonality

Figure B.7: The Effect of Temperature on Joint Time Use

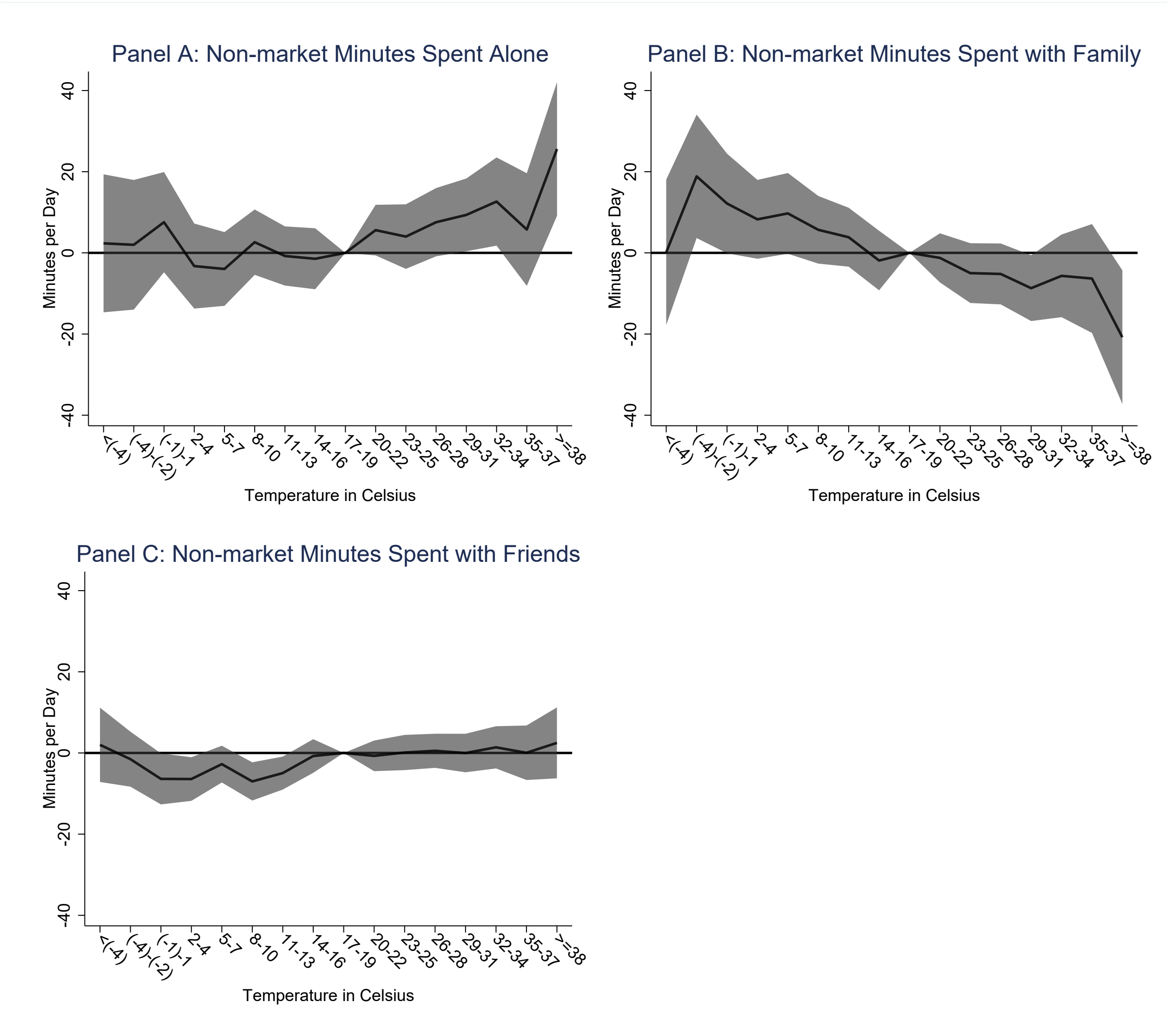

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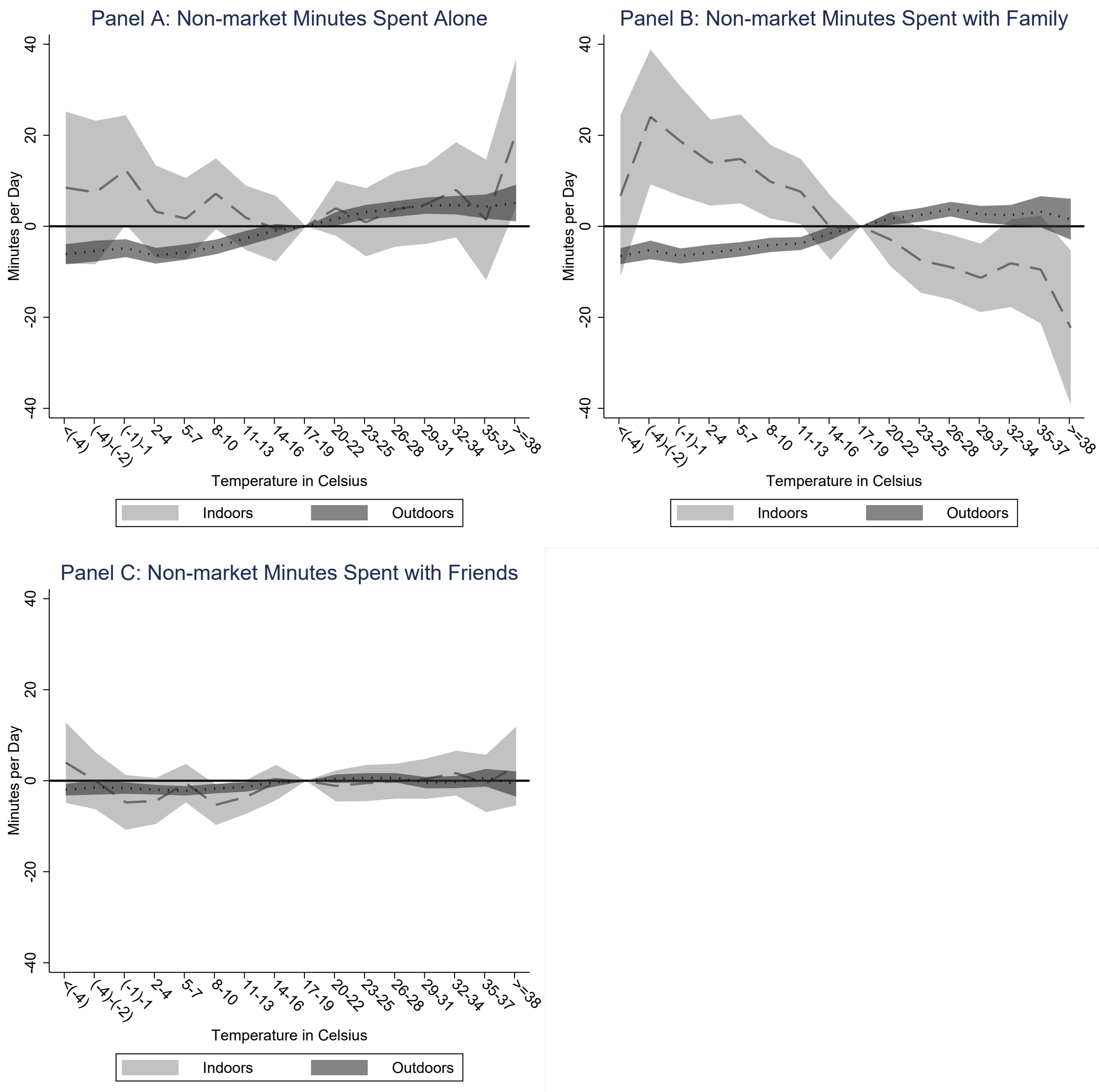
Figure B.8: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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C Adaptive Behavior

C.1 Controlling for Temperature in Prior Days

C.1.1 Controlling for Temperature in the Day Before the Diary Date

Figure C.1: The Effect of Temperature on Joint Time Use

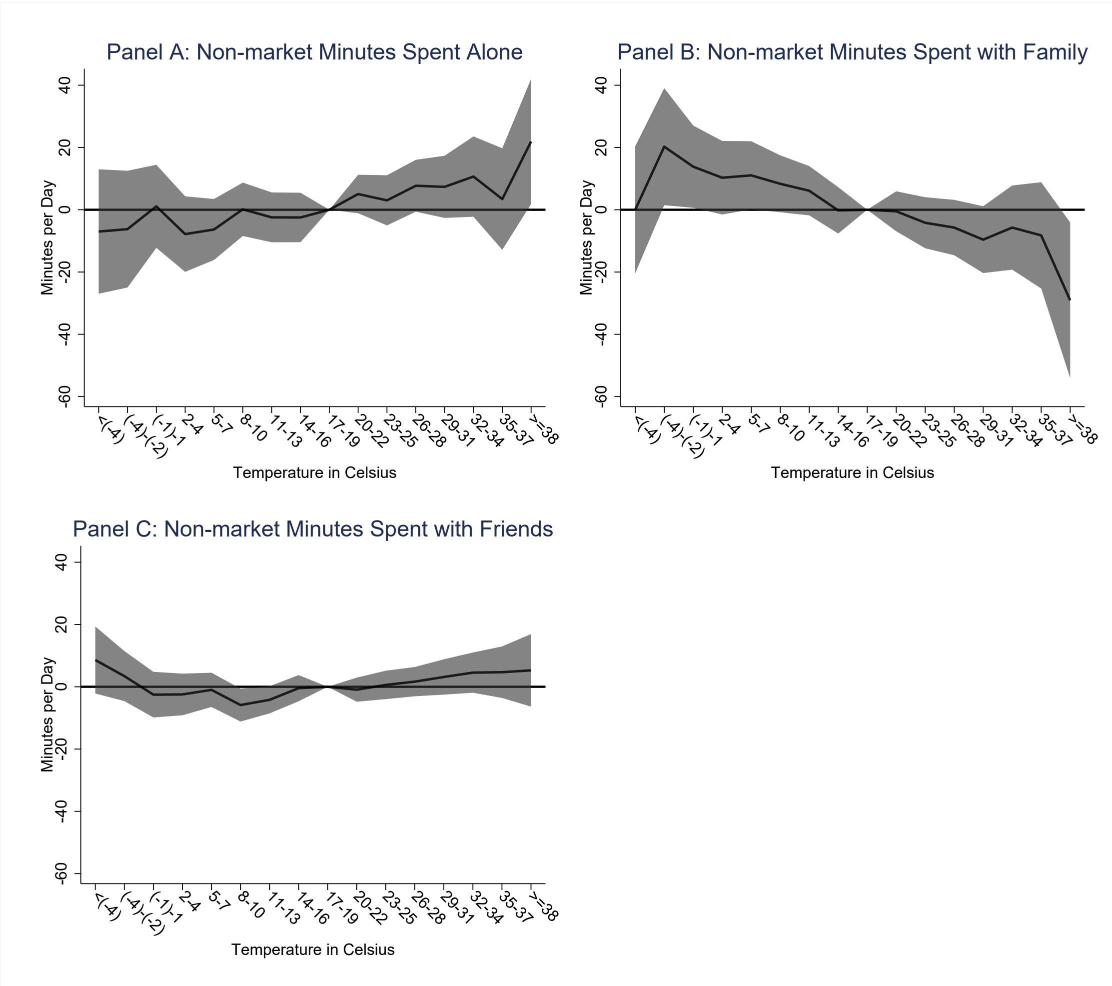

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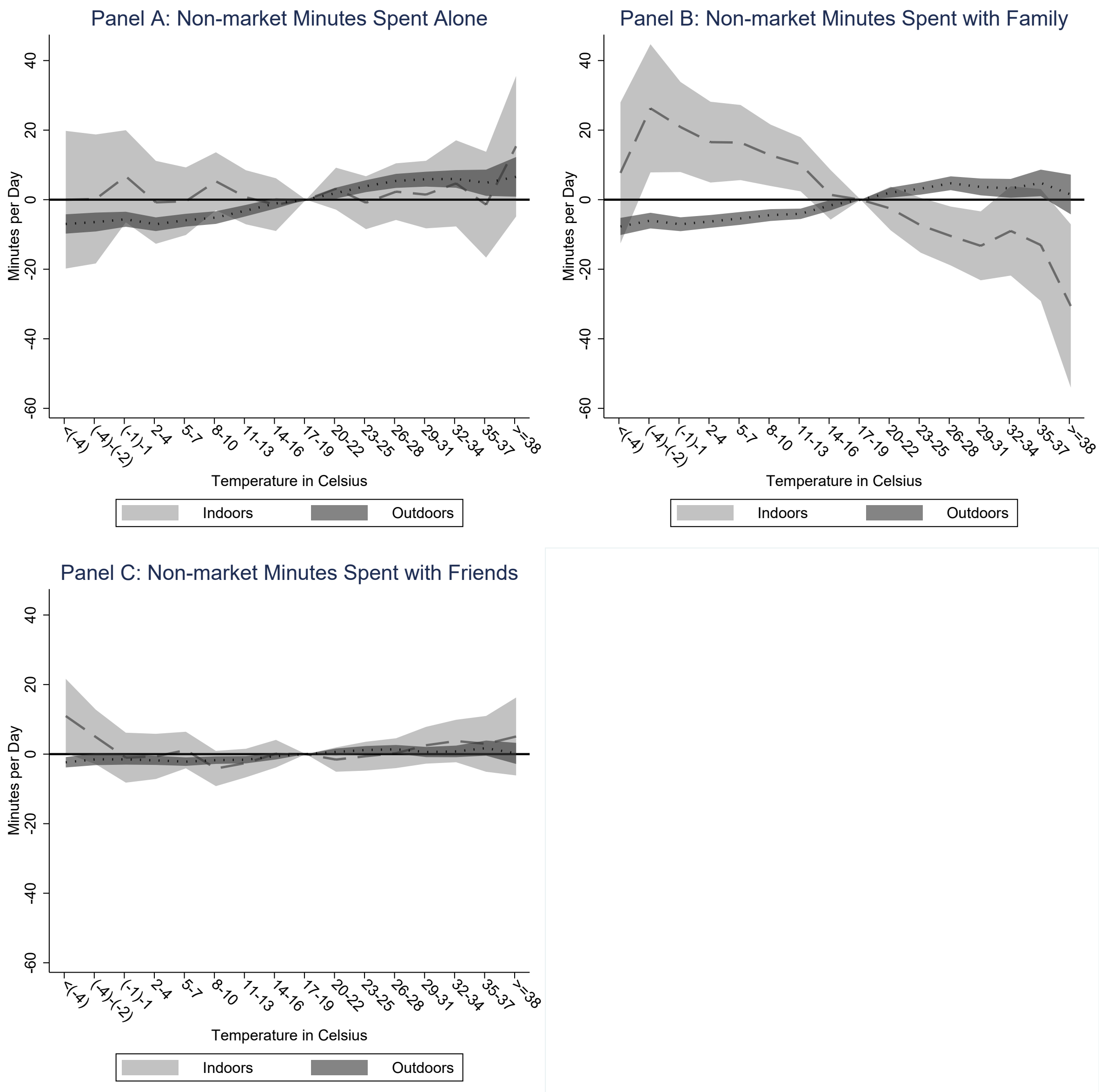
Figure C.2: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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C.1.2 Controlling for Temperature Two Days Before the Diary Date

Figure C.3: The Effect of Temperature on Joint Time Use

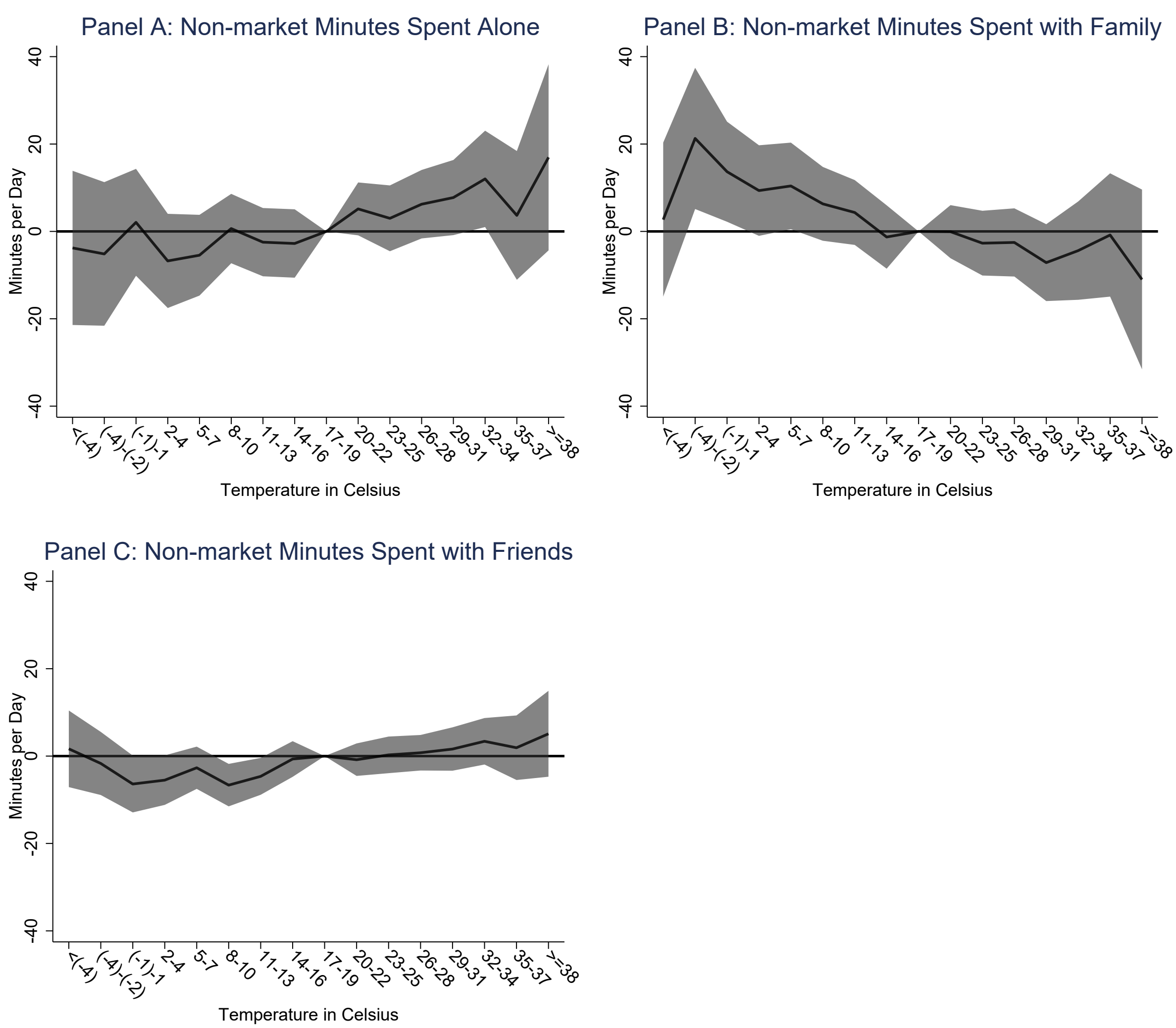

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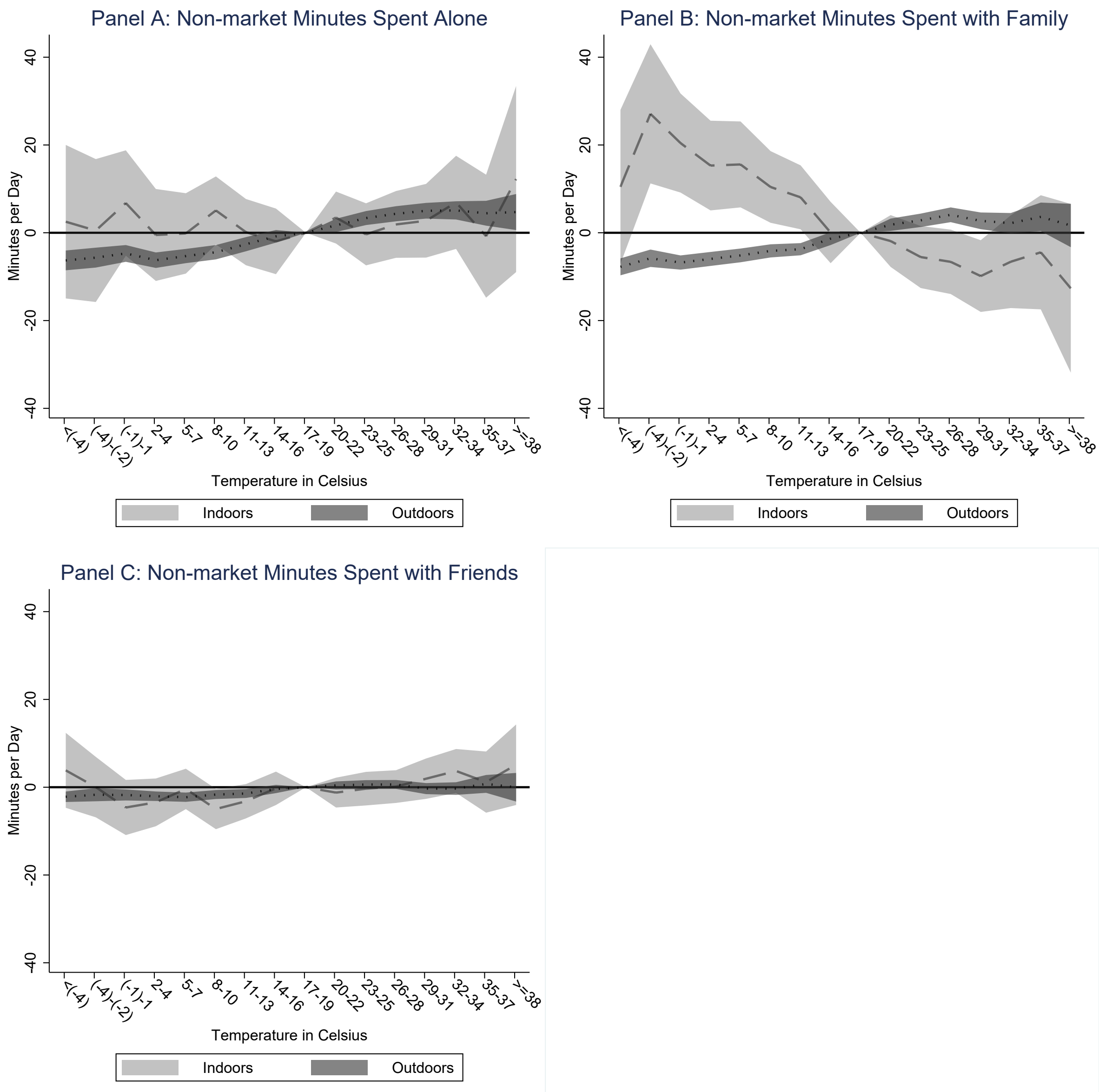
Figure C.4: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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C.1.3 Controlling for Temperature Three Days Before the Diary Date

Figure C.5: The Effect of Temperature on Joint Time Use

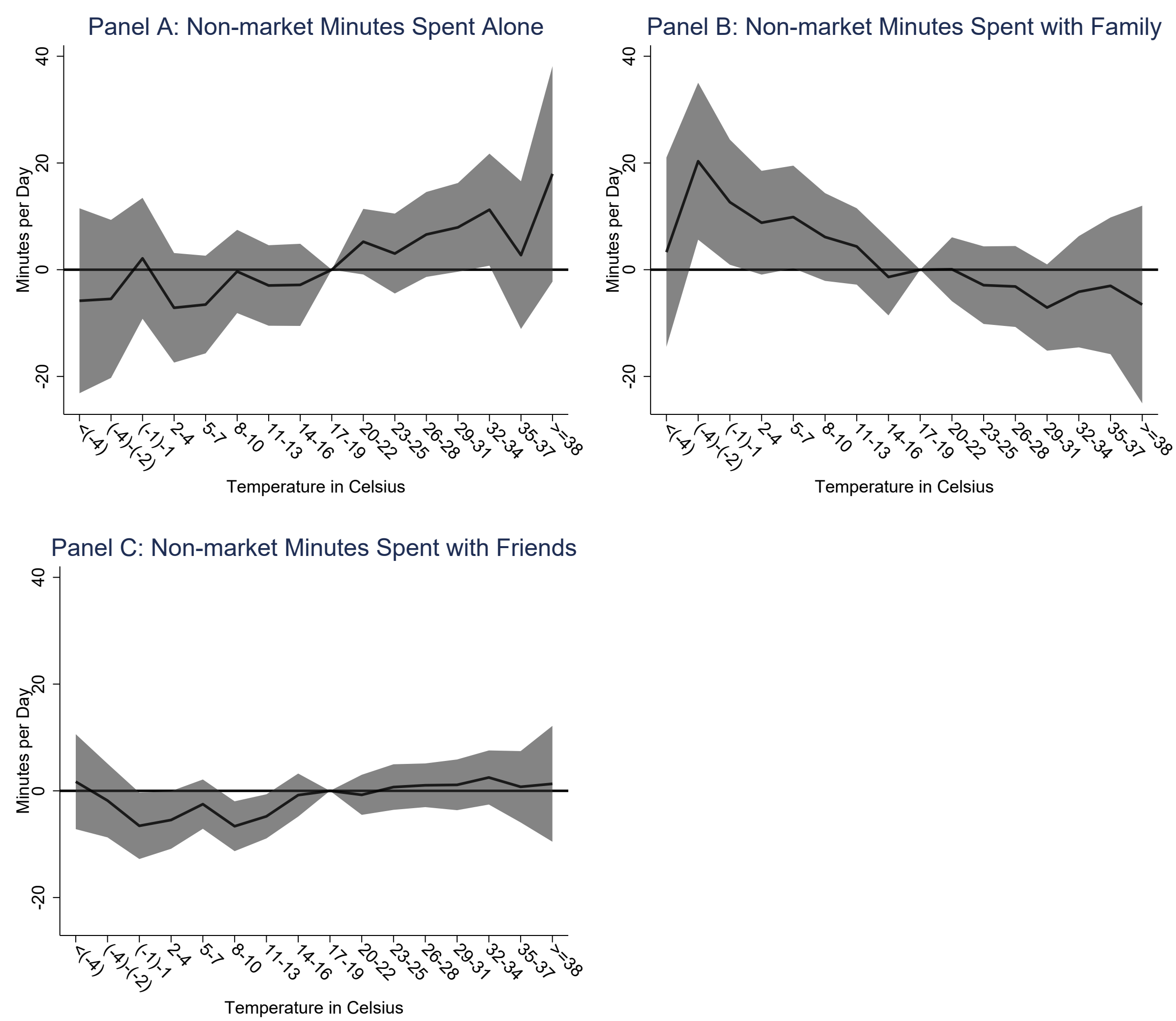

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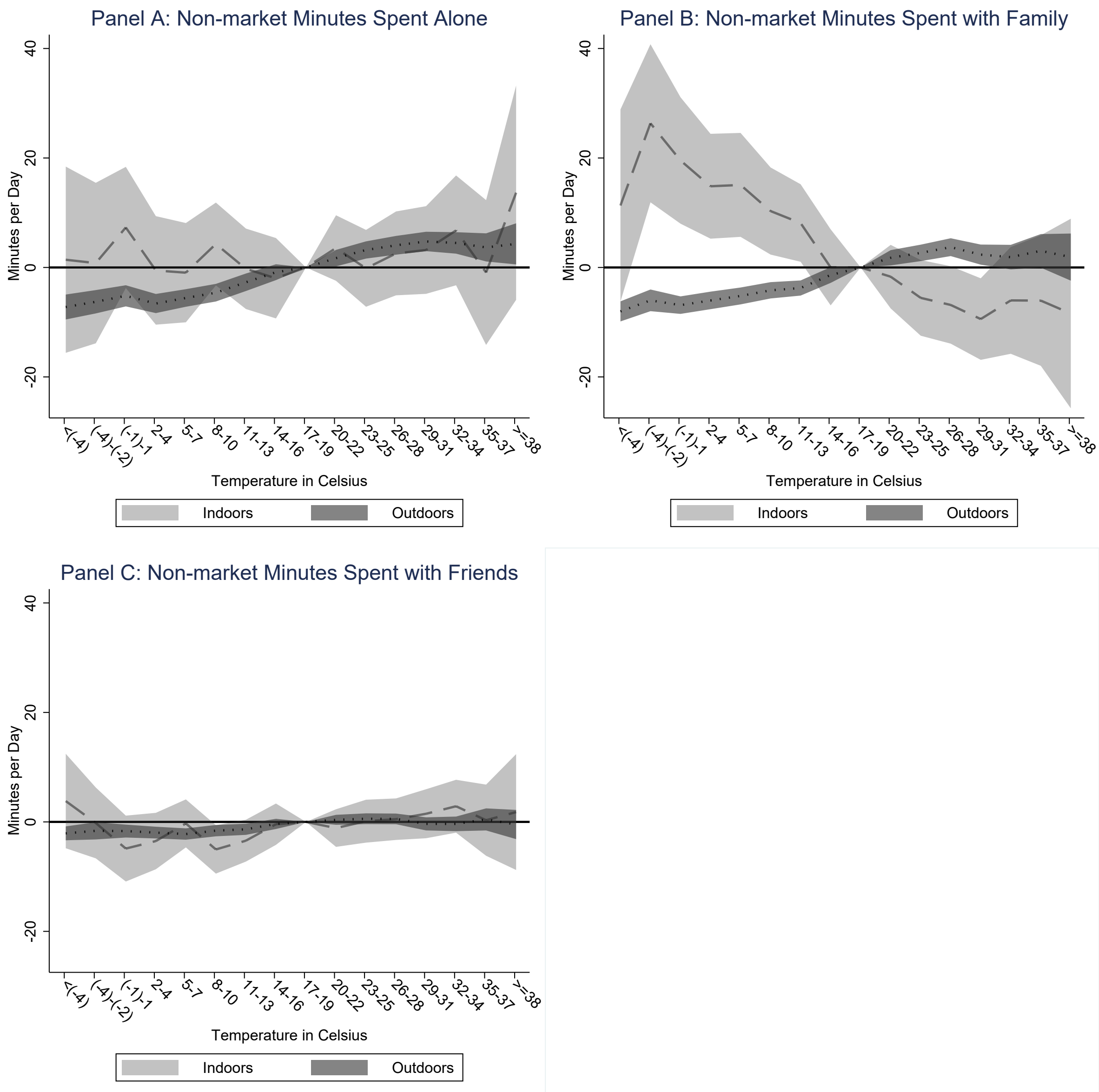
Figure C.6: The Effect of Temperature on Indoors and Outdoors Joint Time Use



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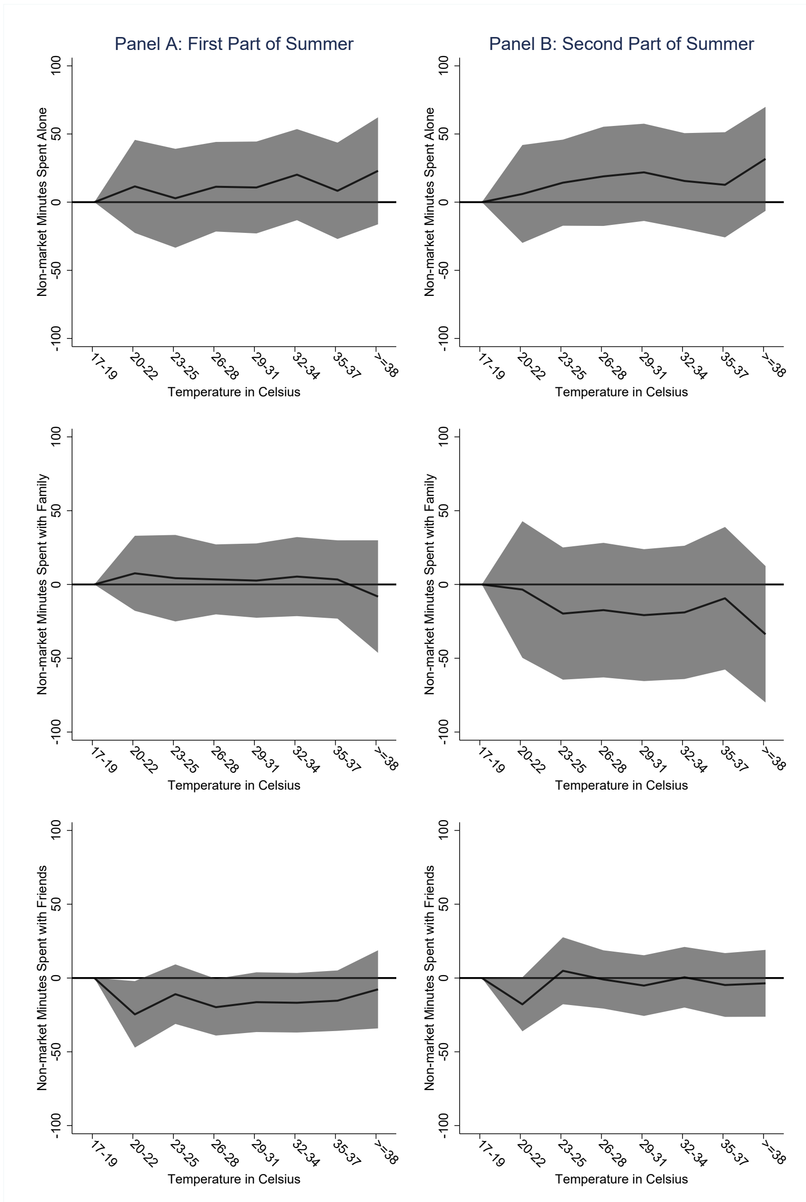
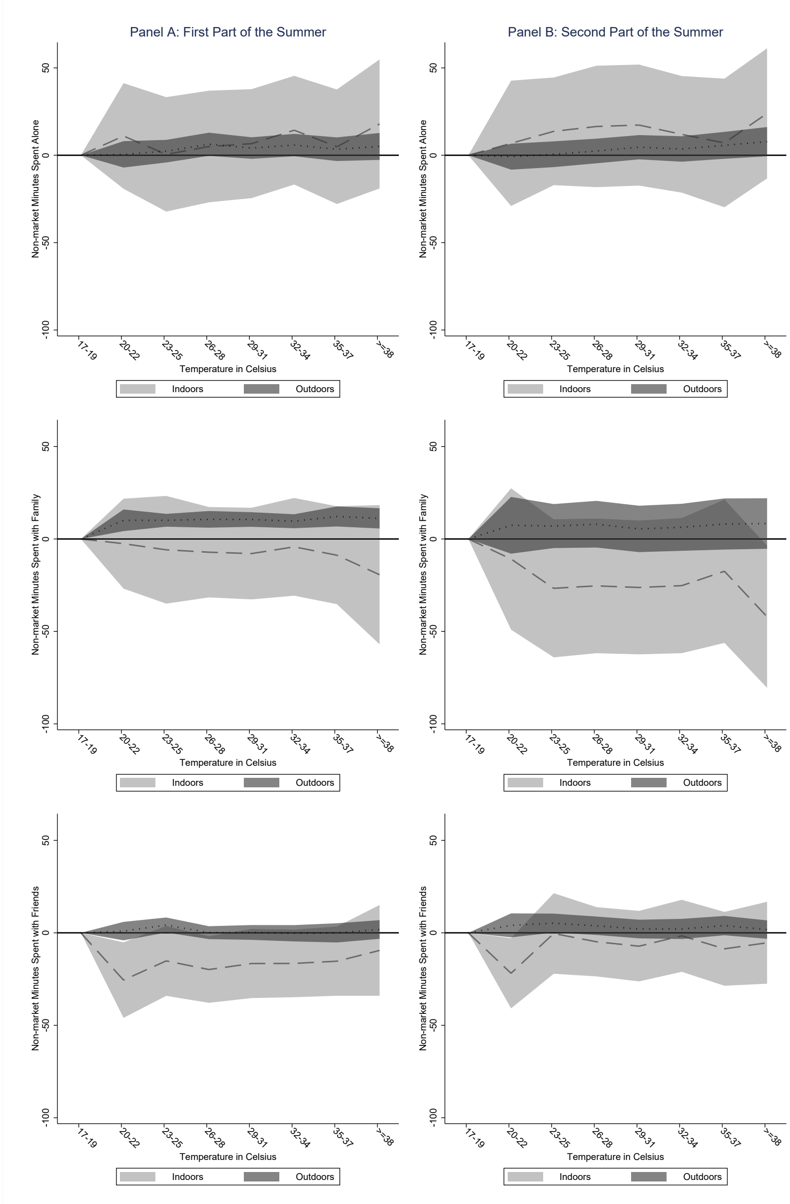
C.2 Adaptive Behavior During Summer

Figure C.7: The Effect of Temperature on Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark the interval between 17 and 20 Celsius degrees. Panel A presents the estimates of our variables of interest for the first part of the summer (i.e. from June 1 until July 14), while Panel B for the second part of the summer (i.e. from July 15 until August 31). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

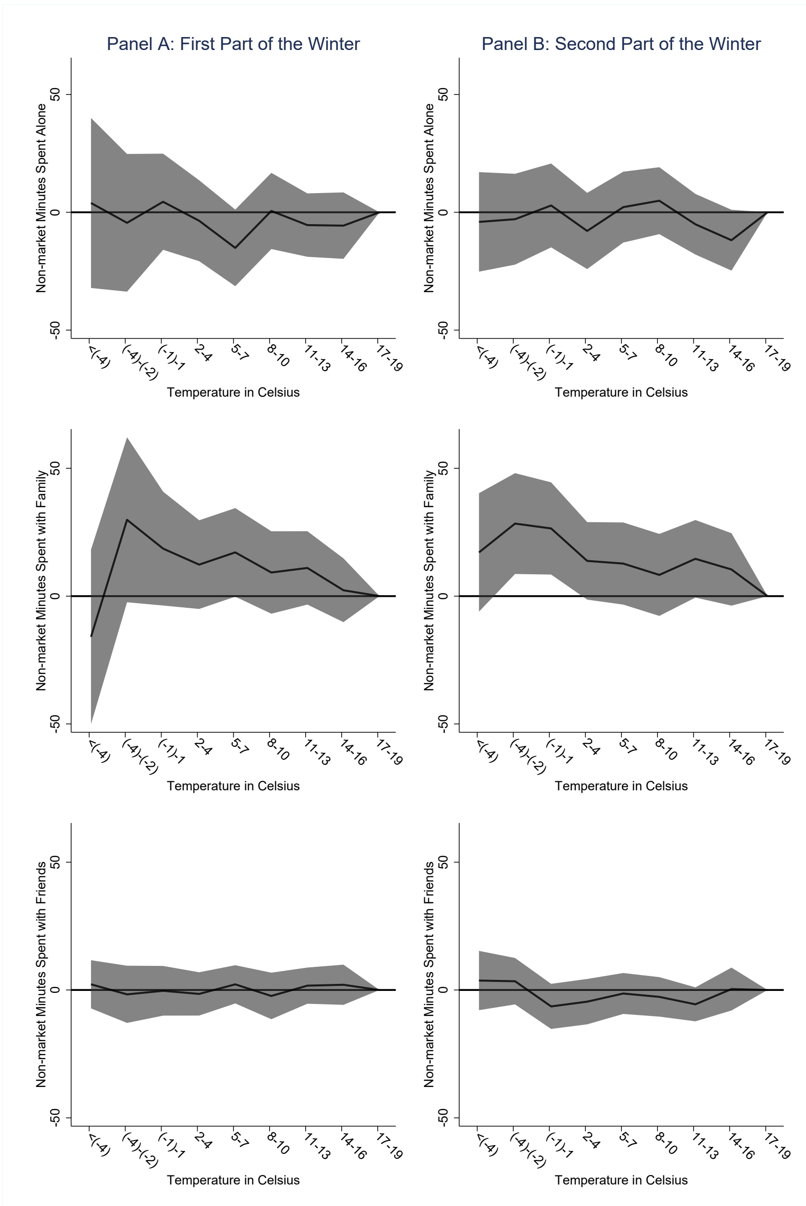
Figure C.8: The Effect of Temperature on Indoors and Outdoors Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark the interval between 17 and 20 Celsius degrees. Panel A presents the estimates of our variables of interest for the first part of the summer (i.e. from June 1 until July 14), while Panel B for the second part of the summer (i.e. from July 15 until August 31). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the indoors and outdoors time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

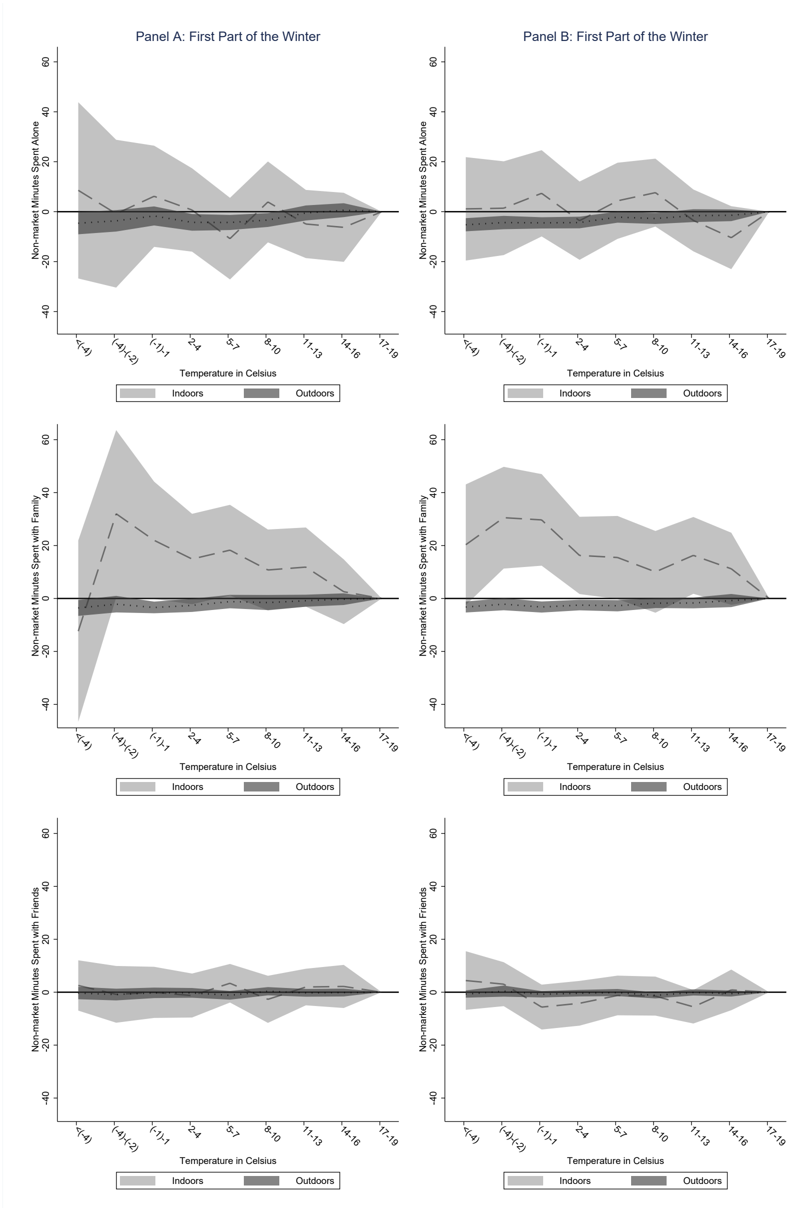
C.3 Adaptive Behavior During Winter

Figure C.9: The Effect of Temperature on Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark the interval between 17 and 20 Celsius degrees. Panel A presents the estimates of our variables of interest for the first part of the winter (i.e. November and December), while Panel B for the second part of the winter (i.e. January and February). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

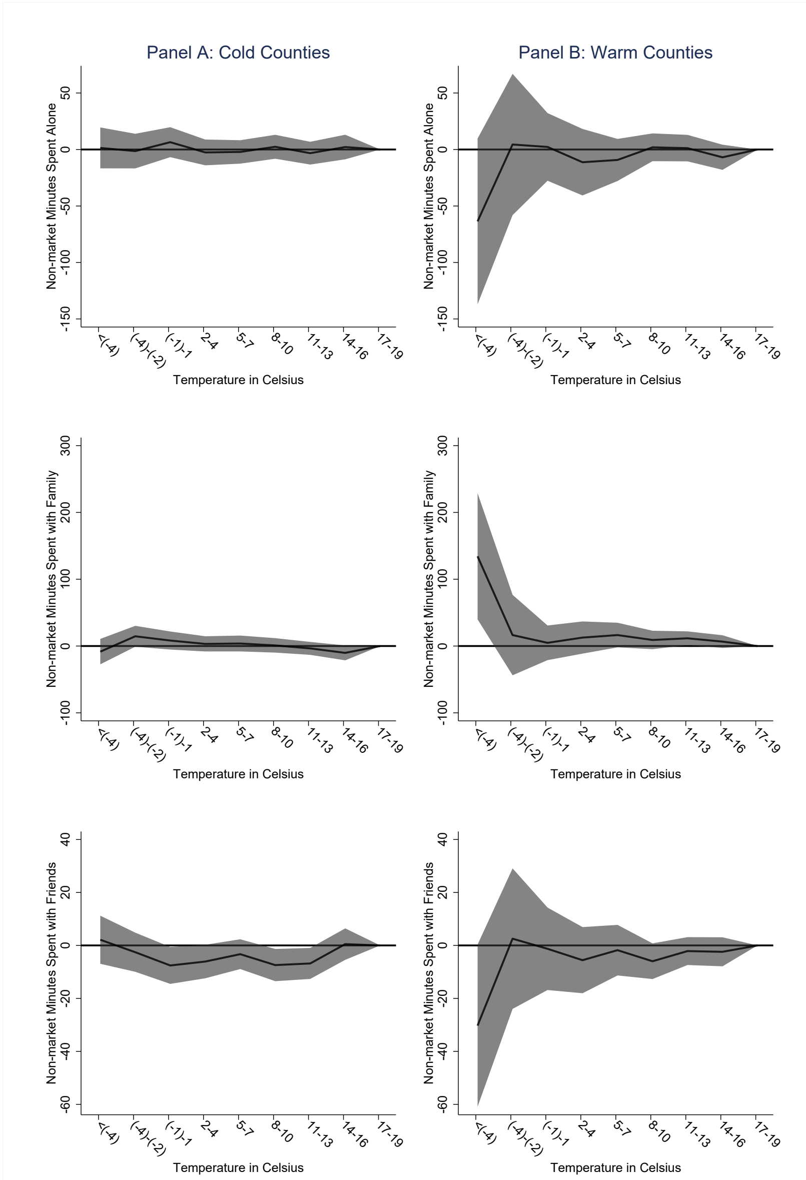
Figure C.10: The Effect of Temperature on Indoors and Outdoors Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark the interval between 17 and 20 Celsius degrees. Panel A presents the estimates of our variables of interest for the first part of the winter (i.e. November and December), while Panel B for the second part of the winter (i.e. January and February). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the indoors and outdoors time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

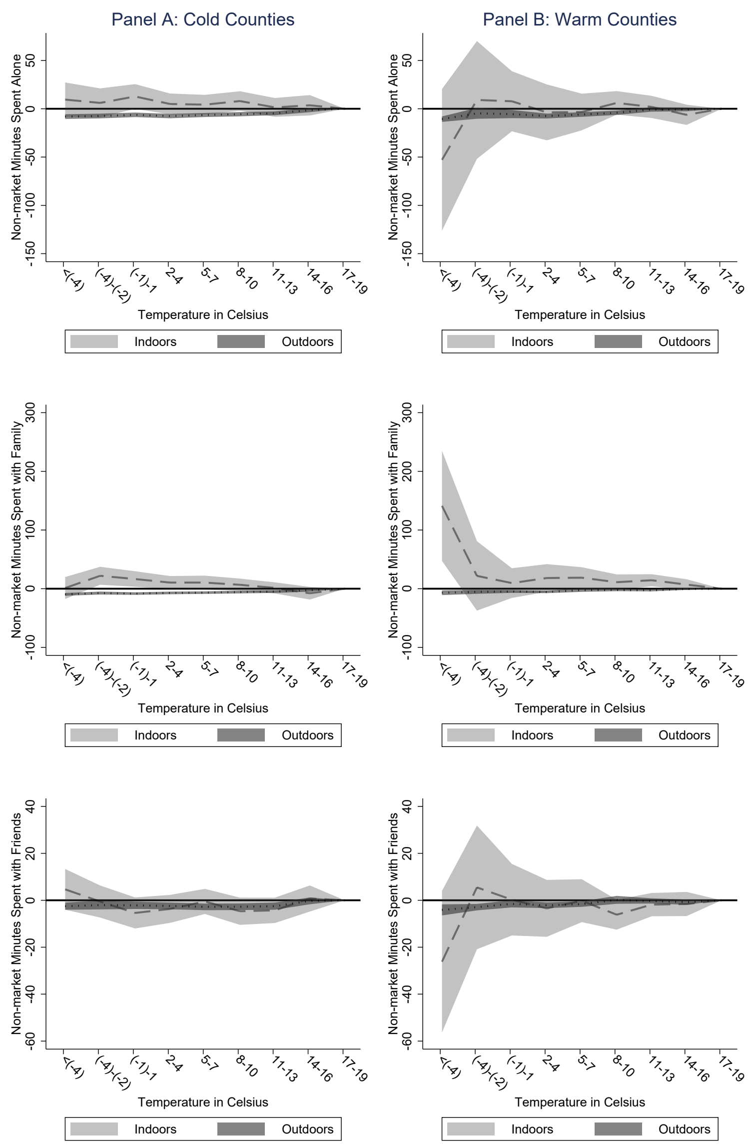
C.4 Adaptive Behavior: Warm and Cold Counties

Figure C.11: The Effect of Temperature on Joint Time Use



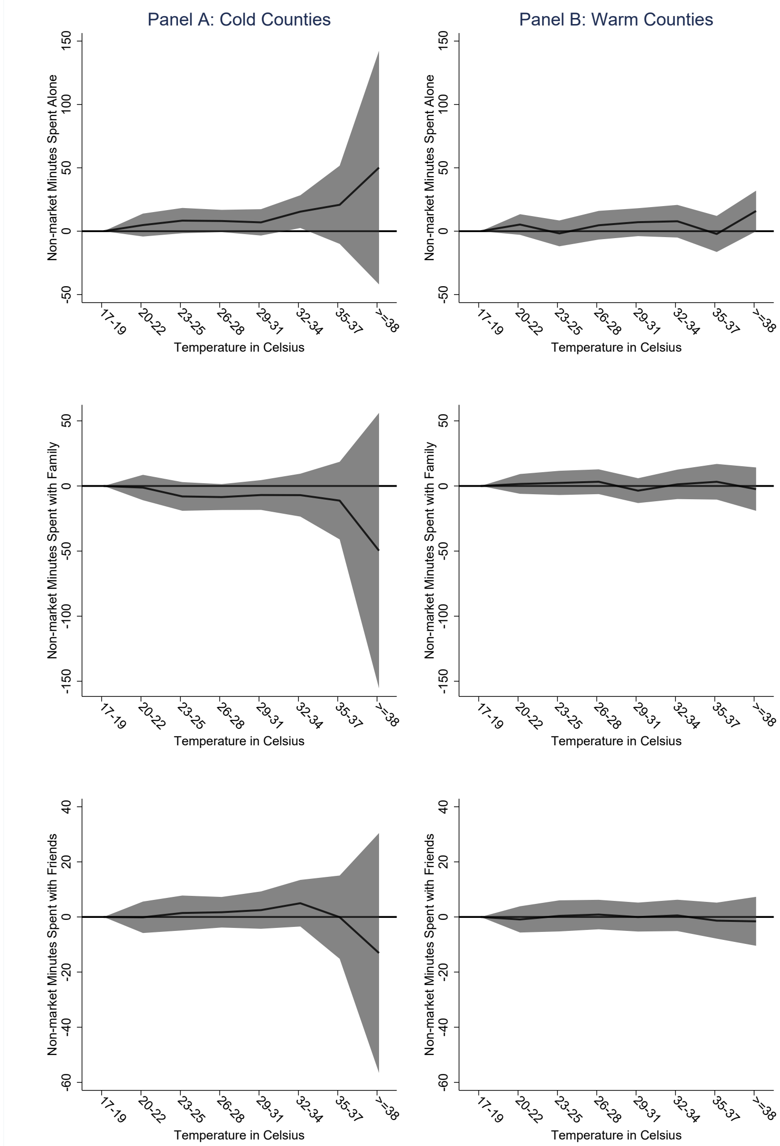
Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution. Panel A presents the estimates of temperatures lower than the benchmark interval (i.e. between 17 and 20 Celsius degrees) for cold counties (i.e. with an average temperature lower than the mean of the sample), while Panel B for warm counties (i.e. with an average temperature higher than the mean of the sample). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

Figure C.12: The Effect of Temperature on Indoors and Outdoors Joint Time Use



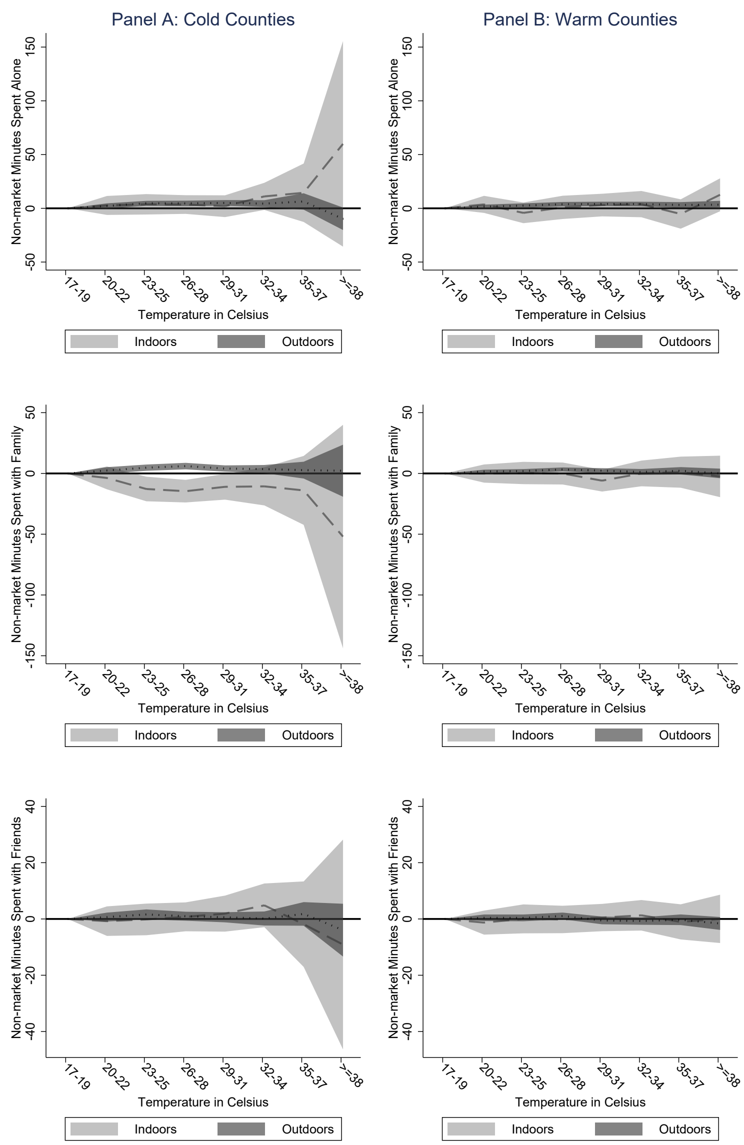
Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution. Panel A presents the estimates of temperatures lower than the benchmark interval (i.e. between 17 and 20 Celsius degrees) for cold counties (i.e. with an average temperature lower than the mean of the sample), while Panel B for warm counties (i.e. with an average temperature higher than the mean of the sample). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the indoors and outdoors time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

Figure C.13: The Effect of Temperature on Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution. Panel A presents the estimates of temperatures higher than the benchmark interval (i.e. between 17 and 20 Celsius degrees) for cold counties (i.e. with an average temperature lower than the mean of the sample), while Panel B for warm counties (i.e. with an average temperature higher than the mean of the sample). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

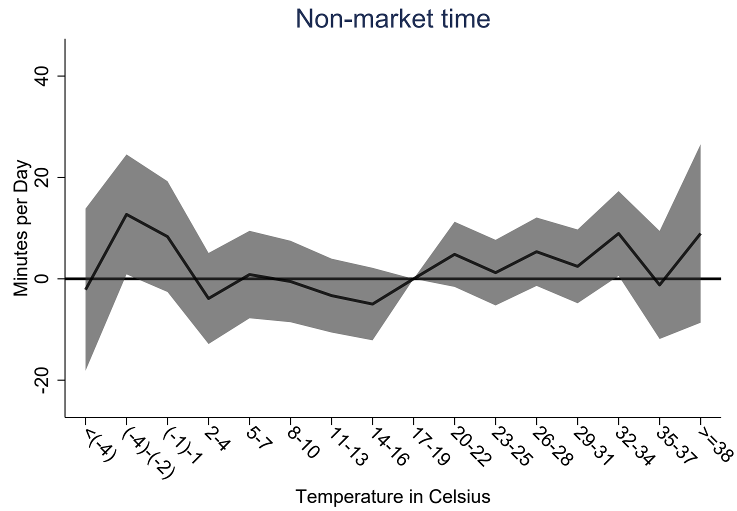
Figure C.14: The Effect of Temperature on Indoors and Outdoors Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution. Panel A presents the estimates of temperatures higher than the benchmark interval (i.e. between 17 and 20 Celsius degrees) for cold counties (i.e. with an average temperature lower than the mean of the sample), while Panel B for warm counties (i.e. with an average temperature higher than the mean of the sample). We also present the 95% confidence intervals of the estimates. We use as the dependent variable the indoors and outdoors time that individuals spend alone, with friends, and with family on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

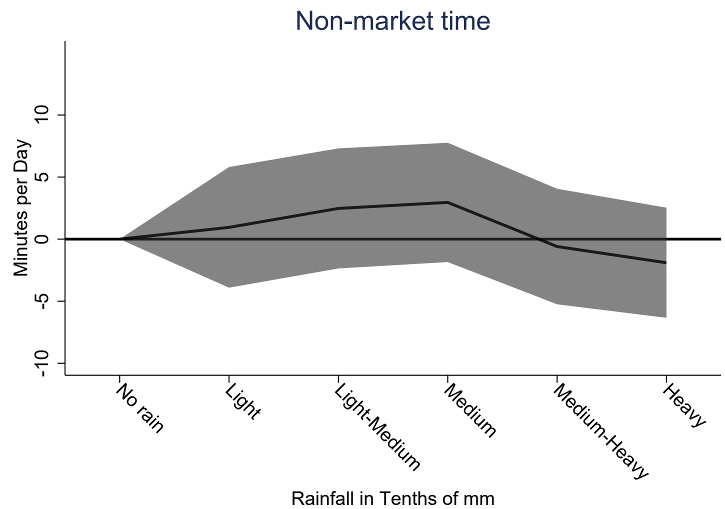
D Non-market Time

Figure D.1: The Effect of Temperature on Non-market Time



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 if the maximum temperature in the county of residence of the individual on the date of the diary falls within temperature intervals of 3 Celsius degrees. The set of indicators covers the full temperature distribution and we use as the benchmark interval the one between 17 and 20 Celsius degrees. We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend on non-market activities on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

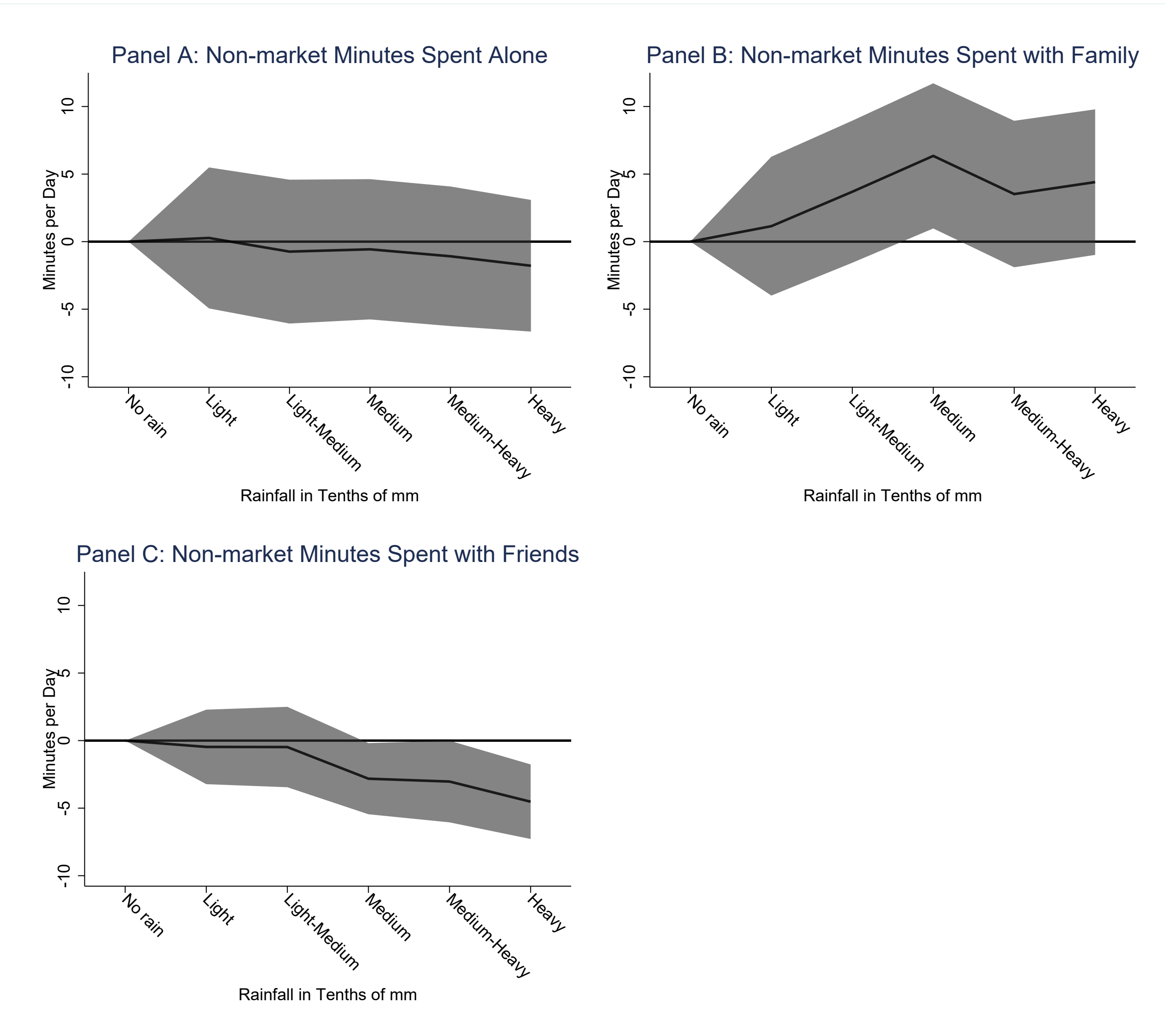
Figure D.2: The Effect of Rainfall on Non-market Time



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 depending on the amount of rainfall in the county of residence of the individual on the date of the diary. The set of indicators covers the full rainfall distribution and we use as the benchmark days with no rain. We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend on non-market activities on the diary date. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

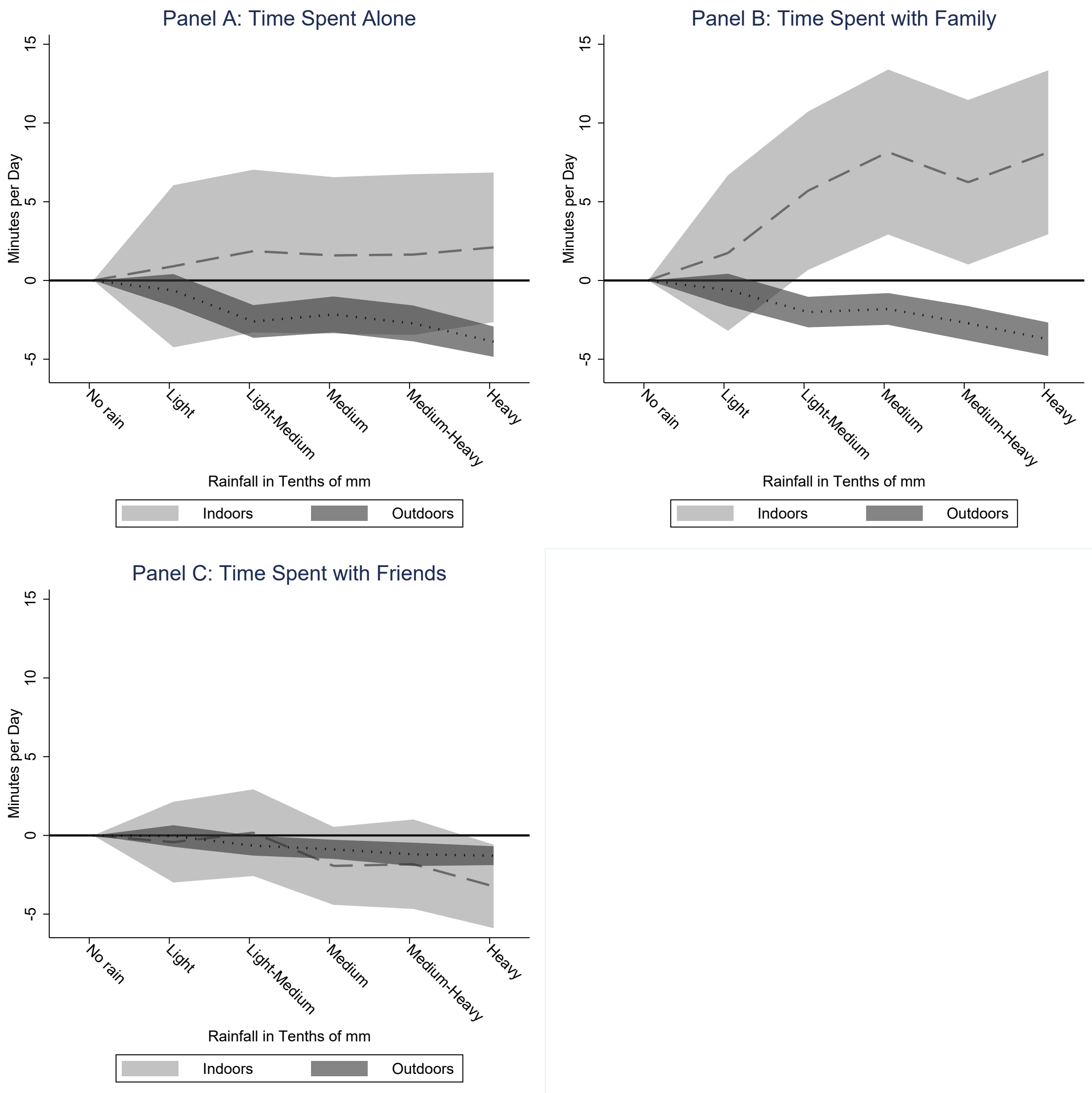
E Estimates on Rainfall

Figure E.1: The Effect of Rainfall on Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 depending on the amount of rainfall in the county of residence of the individual on the date of the diary. The set of indicators covers the full rainfall distribution and we use as the benchmark days with no rain. We also present the 95% confidence intervals of the estimates. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date in panels A–C, respectively. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

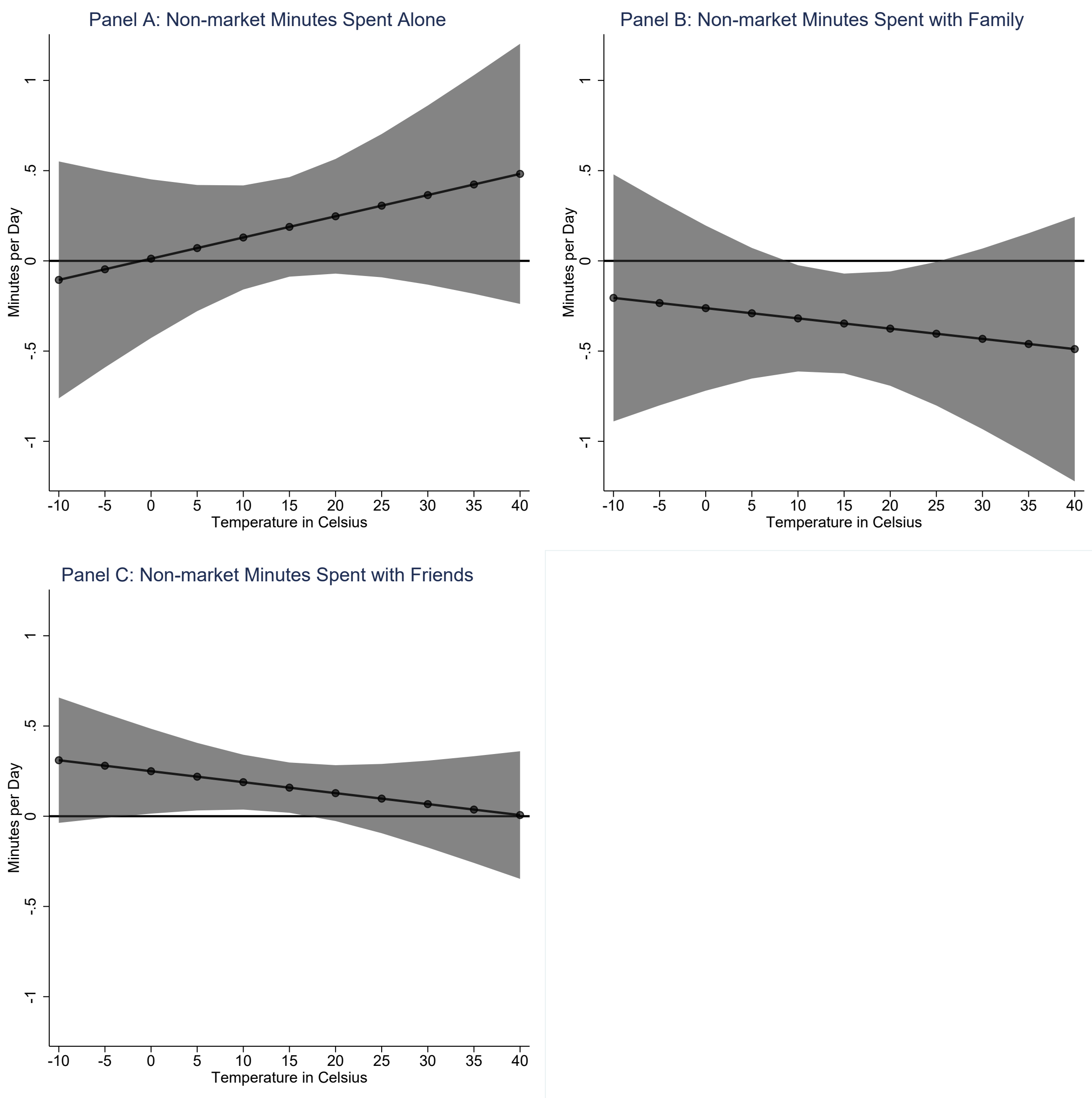
Figure E.2: The Effect of Rainfall on Indoors and Outdoors Joint Time Use



Notes: The figure shows the estimates of the effect of a set of dummies that take value 1 depending on the amount of rainfall in the county of residence of the individual on the date of the diary. The set of indicators covers the full rainfall distribution and we use as the benchmark days with no rain. We also present the 95% confidence intervals of the estimates. We use as the dependent variable the indoors and outdoors time that individuals spend alone, with friends, and with family on the diary date in panels A–C, respectively. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, and cluster standard errors at the state-month level.

F Marginal Effects of Temperature on Time Use

Figure F.1: Marginal Effects of Temperature on Time Use



Notes: The figure shows the marginal effects of the maximum daily temperature from the empirical application of our theoretical model. We show marginal effects for the full temperature distribution and also present the 95% confidence intervals. We use as the dependent variable the time that individuals spend alone, with friends, and with family on the diary date in panels A–C, respectively. We control for county, year-month, day-of-the-week, and holiday-day fixed effects, as well as for a set of socio-demographic characteristics. We cluster standard errors at the state-month level.