Gone Fishing! Reported Sickness Absenteeism and the Weather*

Jingye Shi† and Mikal Skuterud‡

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Abstract

A fundamental challenge in informing employer-employee agency problems is measuring employee shirking activity. We identify the propensity of employees to misreport health in order to exploit favorable weather by linking Canadian weather data and survey data on short-term spells of sickness absenteeism among indoor workers during the non-winter months. The results point to a clear tendency for reported sickness absenteeism to rise with the recreational quality of the weather. Comparing across workers suggests larger marginal weather effects where shirking costs are higher, which we show is consistent with employees' marginal utility of outdoor leisure increasing in the interaction of their health and weather quality. We discuss the implications of our findings for flexible vacation policies and survey respondents' trust in the confidentiality guarantees of statistical agencies.

Keywords: Absenteeism; weather; employee shirking.
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†Assistant Professor, Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, Sichuan, China; sjy@swufe.edu.cn

‡Corresponding author: Associate Professor, Department of Economics, University of Waterloo, 200 University Avenue West, Waterloo, Ontario, Canada, N2L 3G1; skuterud@uwaterloo.ca

1 Introduction

The principal-agent problem of contracting employee work effort that is imperfectly monitored arises in a number of areas of economic theory, including models of remuneration by seniority (Lazear 1979); involuntary unemployment (e.g. Shapiro and Stiglitz 1984); performance-based pay (MacLeod and Malcomson 1998); and labour hoarding (Depken, Redmount and Snow 2001). Given the importance of this mechanism in the theoretical work, the empirical research on the agency problem is remarkably scant. In part this reflects the limited availability of personnel data, as Baker and Holmstrom argue in their review article "Internal Labour Markets: Too Many Theories, Too Few Facts" (1995). But more fundamentally it reflects the inherent difficulty of empirically capturing the employee effort levels that underlie the models.

Using direct measures of employee- or firm-level productivity is unquestionably the preferred approach, but these measures are notoriously problematic and the studies that use them tend to be case studies, introducing external validity issues. It is also unlikely to isolate the type of malfeasant shirking behaviour that concerns variants of the models where the employee effort decision entails disciplinary risk. To inform employee incentives to engage in malfeasant behaviour, economists have relied on two measures: employee disciplinary rates (e.g., Cappelli and Chauvin 1991; Ichino and Maggi 2000) and absenteeism rates (e.g., Arai and Thoursie 2005; Ichino and Riphahn 2005; Bradley, Green and Leeves 2007). The difficulty is that disciplinary rates capture only shirking activity that is identified by employers, not that which goes undetected, while reported absenteeism, particularly sickness absenteeism rates, may be entirely legitimate. One can, therefore, never be sure whether differences in these rates across workers facing different shirking costs reflect actual shirking activity, as opposed to differences in employers' willingness or ability to detect and punish shirkers or differences in employee health that may be correlated with these costs.

In this paper, we identify a different type of shirking activity that potentially addresses both of these shortcomings – employees misreporting health in order to exploit weather conditions favourable to high-utility outdoor recreation.[1] We begin by considering a shirking model of sickness absenteeism in which employees' marginal utility of outdoor leisure is increasing in the interaction of

[1] We have found three papers, all outside economics, that examine the absenteeism-weather link: one from psychology (Mueser 1953), one from epidemiology (Pocock 1972); and one from environmental science (Markham and Markham 2005). In all cases, the possibility of weather influencing shirking incentives is mentioned only as an afterthought. For example, Mueser writes: "It is easy to imagine that when it was sunny and beautiful outside the chore of earning a livelihood was put off." Our paper is also related to Connolly (2008), who relates daily hours of work to the incidence of rain and finds evidence of intertemporal labor supply responses to weather. But with no information in her data on the reported reason for absence, in particular whether they reflect sickness absenteeism, overtime, vacation days, or even private time-in-lieu-of arrangements with employers, her results do not tell us anything about shirking activity. Two much closer papers to this one are those by Skogman Thoursie (2004, 2006), who examines the use of the Sweden's national sickness insurance program around birthdays and sporting events.

two state-dependent parameters: health and outdoor weather quality, the intuition being that ideal weather conditions for engaging in outdoor recreation are valued more when one is physically (and perhaps also mentally) healthy. This assumption leads to two main propositions. First, increases in sickness absenteeism associated with marginal improvements in weather quality reflect the decisions of the inframarginal workers (those workers who in the absence of the weather improvement would be present at work) who are the healthiest, implying an increase in absenteeism that is unambiguously illegitimate. Second, comparing across workers, marginal weather improvements should have the largest impact on sickness absenteeism where shirking costs are highest. The reason is that where existing incentives to misreport health are the weakest, such as where sick pay is not offered or job protection is weak, existing sickness absenteeism levels will be lowest and the inframarginal workers will be the healthiest, thereby benefitting most from the weather improvement.

We examine the empirical relevance of these propositions using a two-step approach. First, we construct an index of weather preferences by linking temperature, relative humidity, precipitation, wind speed and cloud cover data to time-use data identifying the weekend and weekday evening outdoor recreational activities of employees with regular daytime work schedules. We then examine the empirical relation between the resulting index of the recreational quality of the weather (hereafter referred to simply as "weather quality") and the incidence of short-term spells of sickness absenteeism reported in survey data, comparing the magnitude of this relation across workers facing different levels of sick pay, job protection, and job-finding rates. We employ Canadian data throughout and restrict attention to: (i) workers employed indoors, to avoid the possibility of the weather influencing the marginal disutility of work; and (ii) non-winter months, since weather is more likely to have confounding direct health effects during the winter. Of course, certain weather conditions may be associated with poorer health in the non-winter months as well, such as extreme heat and the incidence of allergies and headaches, but these weather conditions should be captured as lower weather quality using our methodology for constructing an index, since they will result in decreased outdoor recreation.

Conditioning on city of residence and calendar week, we identify a clear tendency for short-term sickness absences to rise with weather quality. Moreover, this relation is clearly stronger when the weather on the previous weekend is of poorer quality, suggesting pent-up demand for recreational activities. Comparing between workers facing different shirking costs, the estimates also appear consistent with our second theoretical proposition, that weather improvements will have their largest marginal impacts on sickness absenteeism where existing shirking incentives are weakest, such as where sick pay is least generous and job protection is weakest. This finding provides evidence in support of our theoretical assumption that weather and health are complementary in raising employees' marginal utility of outdoor leisure. It also suggests to us that we are not capturing implicit employer-employee agreements to use contractual sick days for non-health-related reasons, since the estimated effects are largest for hourly-paid and probationary employees, who are least likely to have such contractual arrangements. Taken together, these results point to the importance of flexible vacation entitlement policies, which enable employees to exploit complementarities in their marginal utility of leisure, such as that between their health and the weather. They also suggest that survey respondents are misreporting health to Canada's national statistical agency, which raises questions about respondents' trust in the confidentiality guarantees of statistical agencies.

In the following section we describe in more detail our theoretical model of shirking absenteeism. We then outline our empirical methodology, including the data we employ, and in Section 4, discuss the results. We conclude by summarizing our main findings and discussing their implications.

2 Model

Our model of shirking absenteeism extends the model of Barmby, Sessions and Treble (1994) by making employees' marginal utility of leisure depend not only on their level of sickness, but also on outdoor weather conditions. Since the types of high-utility outdoor recreational activities that we imagine workers substituting towards when the weather improves, tend to be more enjoyable when one is healthy, we expect workers' marginal utility of outdoor leisure to be decreasing in sickness. Consequently, shirking absenteeism in our model occurs in equilibrium at both ends of the sickness distribution – among the relatively sick *and* among the most healthy facing the best weather conditions. Given the inherent ambiguity of distinguishing legitimate from illegitimate sickness, we argue that the latter more clearly reflects behavior that is malfeasant in nature, and therefore the type of behavior that could result in dismissal. Moreover, since only shirking activity at the bottom end of the sickness distribution varies with weather fluctuations, the weather suggests an empirical strategy for identifying shirking activity.

In any period, we assume ex-ante identical risk-neutral individuals receive utility $U = (1 - \delta)y + \delta(T - h)$, where T is a time endowment; h are hours worked; and y is income. In making labor supply decisions, individuals weigh the relative marginal utility of leisure spent outdoors and indoors. When spent outdoors, we assume $\delta = (1 - \theta)\,\lambda$, where θ reflects an individual's level of sickness and λ is an index of weather quality. In contrast, when spent indoors, the marginal utility of leisure is assumed independent of the weather, but is increasing in sickness, specifically $\delta = \theta$. An individual, therefore, prefers outdoor to indoor leisure if $\theta < \lambda/(1 + \lambda)$, where the state-dependent parameters θ and λ are assumed randomly (uniform) and independently distributed in the population over the interval [0,1].[2]

Individuals receiving an employment contract, who opt to satisfy the contractual hours obligation h, receive wage w. Employees who choose not to show up for work, on the other hand, and whose true sickness level is either legitimate or goes undetected, receive sick pay $s < w$. The threshold sickness level beyond which absence is deemed legitimate is given exogenously by θ^z.[3] The employer's technology for monitoring employee sickness detects an individual's true sickness level θ with probability α at cost k sufficiently small that the technology is always employed. In the event that illegitimate absence ($\theta < \theta^z$) is detected, a shirking employee is not only dismissed and forced to sustain himself on an unemployment benefit $b < s$ in the current period, but must also begin the following period unemployed facing an exogenous job acquisition rate $a < 1$.

Given this setting, the lifetime utility of an infinitely-lived individual beginning period one with an employment contract can be written:

$$U = \begin{cases} U^{na} = (1-\delta)\, w + \delta\,(T-h) + \rho\, V(E), & \text{if not absent in period 1} \\ U^{a} = (1-\delta)\, s + \delta\, T + \rho\, V(E), & \text{if absent and not dismissed in period 1} \\ U^{u} = (1-\delta)\, b + \delta\, T + \rho\, a\, V(E) + \rho\,(1-a)\, V(U), & \text{if absent and dismissed in period 1} \end{cases}$$

where $\rho\,\epsilon[0,1]$ is a time preference discount rate and $V(E)$ and $V(U)$ are continuation values from period 2 forwards if beginning period 2 with or without a contract, respectively. In deciding whether to shirk the contractual work obligation h in the first period, employees not only take into account the risk of a lower income level b in the current period, but also that they are always better off beginning the next period in the employed state, whether or not they choose to be absent in that period.[4]

[2] The assumption that the sickness and weather parameters are distributed independently is questionable to the extent that the weather affects health directly or weather preferences are correlated with health and individuals can influence the weather they face by choosing where they live. Empirically, the former would tend to bias the estimated weather-absenteeism in the opposite direction to what we hypothesize, since more desirable weather is likely associated with better health. Nonetheless, we try to limit this bias by excluding winter months from the analysis and including a full set of month fixed effects. As for the the latter issue, the model is, best thought of as explaining variations in sickness absenteeism across days within a city. All the estimated regressions, therefore, also include a a full set of city fixed effects.

[3] θ^z can be thought of as being determined endogenously by the employer as it trades off the costs of absenteeism among healthy and productive employees and what Chatterji and Tilley (2002) refer to as the "presenteeism" of unhealthy, unproductive, and perhaps also contagious employees.

[4] Formally, it is straightforward to show that $V(E)$ necessarily exceeds $V(U)$. Defining $E(U^e)$ and $E(U^u)$ as the expected utilities (over the distributions of θ and λ) of being employed and unemployed in any period, respectively, we have:

$$\begin{aligned} V(E) - V(U) &= \sum_{t=1}^{\infty} \rho\, \Big[1 - \alpha\,(\theta^o + \theta^z - \theta^i) - a\Big]^{t-1} [E(U^e) - E(U^u)] \\ &= \frac{1}{1 - \rho\,[1 - \alpha\,(\theta^o + \theta^z - \theta^i) - a]}\, [E(U^e) - E(U^u)] \end{aligned}$$

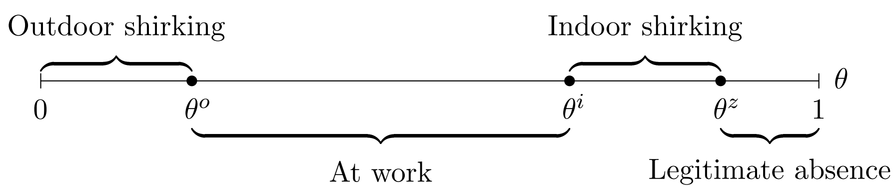
which is necessarily positive since $[E(U^e) - E(U^u)] > 0$, which follows from the fact that the being unemployed gives $U = (1-\delta)b + \delta\, T$ with certainty, whereas being employed results in some probabilistic mixture of this utility level and

The expected lifetime utility of an illegitimately ill employee who chooses to shirk is $U^s = \alpha\, U^u + (1-\alpha)\, U^a$. Shirking occurs if $U^s > U^{na}$, which defines a threshold for the marginal utility of leisure given by:

$$\delta^c = \frac{w - \alpha\, b - (1-\alpha)\, s + \rho\,(1-a)\,\left[V(E) - V(U)\right]}{w - \alpha\, b - (1-\alpha)\, s + h} \tag{2.1}$$

beyond which employees prefer to be absent from work. A worker who prefers outdoor leisure will, therefore, choose to be absent if sickness lies below the outdoor sickness threshold $\theta^o = (\lambda - \delta^c)/\lambda$, while a worker preferring indoor leisure will choose absence if sickness exceeds the indoor sickness threshold $\theta^i = \delta^c$. As long as $\theta^i > \theta^o$, so that at least someone shows up for work, we are insured that $\lambda - \delta^c - \lambda\,\delta^c < 0$ or $\theta^i > \lambda/(1+\lambda) > \theta^o$. The proportion of employees who shirk is then $(\theta^o) + (\theta^z - \theta^i)$, where the first and second term capture outside and inside shirking absenteeism, respectively. This is illustrated in Figure 1.

Figure 1: Optimal employee behaviour over sickness



Notes: The sickness level θ is uniformly distributed between 0 and 1 with 0 indicating perfect health.

Since the weather, unlike all the remaining exogenous variables of the model, only affects the outdoor sickness threshold θ^o, one can readily see that any relation between the weather and reported sickness absenteeism, must reflect the behavior of the inframarginal employees who are the most healthy. A formal proof of this proposition is provided in the Appendix. Given the practical difficulty of determining the legitimacy of sickness in the vicinity of θ^z, the relation between weather and sickness absenteeism more clearly reflects malfeasant shirking behavior. This provides theoretical justification for interpreting the empirical link between weather and reported sickness absenteeism that we estimate as shirking activity. The key advantage of this strategy is that unlike employee disciplinary rates, the weather-absenteeism relation potentially captures shirking activity, whether or not it is detected by employers.

Although the weather-absenteeism relation is necessarily positive, its magnitude does vary with other shirking incentives. In particular, if existing shirking costs are high, such as where sick pay is less generous, an improvement in the weather induces relatively healthy people to shirk, in

the choice of utility levels associated with absence or non-absence, where the former (and the latter more obviously) necessarily exceeds the unemployed utility level (since it provides equal leisure T and income $s > b$).

comparison to where existing shirking costs are low. But since their marginal utility of outdoor leisure is high, as a consequence of the interaction of weather and sickness in utility, the sickness threshold θ^o adjusts upwards more, resulting in a larger increase in absenteeism. The marginal effect of the weather on sickness absenteeism is, therefore, expected to be larger where shirking costs are high, that is where the threshold marginal utility of leisure for choosing to be absent from work (δ^c) is high. This implies that we should see a larger weather-absenteeism relation: (i) when job acquisition rates are low; (ii) where sick pay is less generous; and (iii) where the probability of being dismissed when shirking is high. Once again, formal proofs of this proposition are provided in the Appendix.[5]

3 Empirical Identification

Our main empirical objective is to link, at the level of the individual employee, data on sickness absenteeism and local weather conditions and examine how this relation varies across employees facing different shirking costs. To do this, we first need to quantify the weather.

3.1 Weather quality index

The key mechanism driving shirking activity in our model is the effect of the weather on employees' marginal utility of outdoor leisure (combined with a monitoring friction). What we have in mind is that certain weather conditions either enable high-utility outdoor recreational activities or make these activities sufficiently enjoyable to justify the risk inherent in shirking. To capture this idea empirically, we model how various weather elements come together to jointly influence the likelihood of workers with regular daytime work schedules engaging in outdoor recreation on weekends and weekday evenings. For most activities, the functional form of this weather quality index is likely highly nonlinear with sharp discontinuities. For example, for most golfers the utility gain of playing when it is 25℃ compared to 15℃ probably exceeds the gain from 25℃ to 35℃. But both of these gains are probably small if they are coupled with significant precipitation. This type of index has been studied by geographers interested in identifying the ideal climate for particular tourism-related activities, such as sedentary time at the beach (e.g., Mieczkowski 1985; Morgan et al. 2000). We are, however, interested in an index of weather preferences over a broader set of recreational activities. Moreover, unlike these studies, which rely on surveys asking respondents to rank hypothetical

[5] We have also examined the robustness of these results in an efficiency wage setting similar to that examined in Barmby, Sessions and Treble (1994). Interestingly, in this setting, where employers use the wage rate to influence the extent of sickness absenteeism, the weather-absenteeism relation is largest where sick pay is most, not least, generous (the results in terms of job acquisition and dismissal probabilities remain the same). Evidence that the weather-absenteeism relation is decreasing in sick pay, as we find, therefore provides some indirect evidence against the efficiency wage hypothesis. This theoretical analysis is available from the authors on request.

weather conditions (sometimes in situ), we prefer to identify the index using revealed preferences.

To do this, we link data on five weather elements – temperature, relative humidity, precipitation, wind speed and cloud cover – in 56 Canadian cities with time-use data from three waves (1992, 1998 and 2005) of Statistics Canada's General Social Survey (GSS). The time-use data identify the detailed activities of survey respondents continuously over a randomly assigned 24-hour period. Linking the activities of respondents at the top of each hour with local weather conditions at precisely the same point in time and extracting the weekend (9am-9pm) and weekday evening (6pm-9pm) records between April 1 and October 31, we obtain a sample 33,908 observations on 5,686 wage and salary workers currently employed in a job with a regular full-time daytime schedule.[6] Although the data do not directly identify whether activities are indoors or outdoors, we are able to identify a set of 13 recreational activities that we expect are overwhelmingly outdoors and could potentially, given the right weather conditions, provide participants with sufficient utility gains to justify shirking.[7] Together these activities account for 6.1% of the 33,908 top-of-the-hour weekend and weekday evening observations in our sample. Moreover, the time-use survey queries respondents as to which of all the activities they engaged in over the 24-hour period they "enjoyed most." Using this information, we can estimate the probability of identifying a particular activity as the most enjoyed, conditional on a respondent at some point during their reference day engaging in that activity, separately for each activity in the data. Taking the average of these probabilities over sets of activities, there is clear evidence that the set of 13 outdoor activities we have identified do indeed tend to capture the types of high-utility activities we are interested in.[8]

To determine the functional form of our weather index, we have explored nonparametric and stepwise methods. Our preferred approach, however, is to lean on theory from the biometeorology literature to arrive at a transparent and parsimonious specification. In their construction of a weather index for tourism related activity, De Freitas, Scott and McBoyle (2008) distinguish between three facets of the weather: thermal, aesthetic and physical, where physical elements, such as rain and strong winds, tend to nullify the effects of thermal sensation and aesthetic features of the

[6] Even after restricting the sample to employees reporting a regular daytime schedule, nearly 10% of the top-of-the-hour observations are market work activities. In order to focus as much as possible on behavior when workers are not constrained by work schedules, we drop these observations. It turns out, however, that the resulting weather index is not sensitive to whether or not these observations are included.

[7] They are: gardening; walking, hiking, jogging, or running; golf; fairs, festivals, circuses or parades; bicycling; pleasure drives; fishing; boating; and rowing, canoeing, kayaking, wind surfing or sailing; zoos; camping; hunting; horseback riding, rodeo, jumping, and dressage.

[8] Specifically, among the 13 activities we define as outdoors, they are on average the most enjoyed in 41% of cases. In comparison, the average probability among recreational activities that are overwhelmingly indoors, such as watching television, is only 16.1%. Note that, in averaging the probabilities over activities, we weight activities by their relative incidence. For example, every incident of horseback riding in the data is identified as the most enjoyed activity in the day, but there are a trivial number of observations on this activity, so that it contributes essentially nothing to the average probability.

weather. To capture thermal sensation, we use two terms: quadratic humidex (℃) and quadratic wind speed (km/hr), as well as their interaction to capture the cooling effects of the wind.[9] The aesthetic facet is captured using a measure of the proportion of the sky covered by cloud, recorded in the data on a 10-point scale. Lastly, we define physical weather conditions as the existence of any precipitation or a wind speed in excess of 38km/hr.[10] This leads to the following linear specification, which we estimate by probit regression:

$$\begin{aligned} Prob(outdoors_{ict} = 1) = \Phi\Big[&\beta_0 + \beta_1 p_{ct} + (1 - p_{ct}) \cdot (\alpha_1 h_{ct} + \alpha_2 h_{ct}^2 + \alpha_3 w_{ct} + \alpha_4 w_{ct}^2 + \\ &\alpha_5 (h_{ct} * w_{ict}) + \alpha_6 (h_{ct}^2 * w_{ct}) + \alpha_7 d_{ct} + \mathbf{z}_c \gamma + \mathbf{x}_t \delta\Big]. \end{aligned} \tag{3.2}$$

where $outdoors_{ict}$ is a dummy variable indicating individual i, residing in city c, at hour t was engaged in an outdoor activity; p_{ct} is a dummy indicating physical conditions; h_{ct}, w_{ct}, and d_{ct} are the humidex, wind speed and cloud cover, respectively; $\mathbf{z}_c$ is a row vector of city dummies; and $\mathbf{x}_t$ is a vector of month (April to October) and hour dummies (9am-9pm). Once we condition on where individuals live, as well as month and hour (since constraints like park opening hours may create spurious correlations between the weather and activities), the weather is necessarily orthogonal to any individual heterogeneity. Consequently, we can interpret the marginal effects of weather as pure causal effects, even in the absence of any demographic control variables. Although there is evidence of a correlation in weather and the day of the week (Cerveny and Balling 1998), which we also find in our data, the correlations are tiny, so that adding indicators of day of the week to $\mathbf{x}_t$ does essentially nothing to change our results.

Table 1 reports the main results of estimating (3.2). As expected, warmer weather results in more outdoor recreation up to some threshold temperature, the value of which depends on the amount of wind. Wind primarily has the effect of flattening the humidex function, so that increases in the humidex, whether they lie above or below the threshold, have smaller marginal effects. Over the entire estimated function, the "bliss point" combination of weather conditions is a humidex of 27.2 ℃, a wind speed of 14.7 km/hr, and clear skies. Also, for virtually our entire sample, physical conditions (rain and high wind speed), which negate the effects of the humidex, wind speed and

[9]The humidex was developed by J.M. Masterton and F.A. Richardson of Canada's Atmospheric Environment Service in 1979 and is similar to the heat index widely reported in the U.S.. The formula we use is:

$$h = T + \frac{5}{9} \cdot \left(\frac{6.112 \cdot 10^{\frac{7.5 \cdot T}{237.7+T}} \cdot H}{100} - 10 \right)$$

where T is the dry bulb temperature (℃) and H is relative humidity (%).

[10]The wind speed threshold corresponds to 8 or a "strong breeze" on the Beaufort Scale. At this speed: "Large tree branches are set in motion; whistling is heard in overhead wires; umbrella use becomes difficult; and empty plastic garbage cans tip over." This accounts for fewer than 1% of the observations in our data.

cloud cover, result in less outdoor recreation.[11]

Having estimated (3.2), we can go back to our weather data and for every city-day-hour observation, predict a probability of being outdoors ($outdoors_{ijt} = 1$). It is these fitted values that we use as our measure of the state-dependent weather quality index λ in our analysis of the sickness absenteeism data.[12] To provide us with some assurance of the meaningfulness of this index, in Figure 1 we plot it using average daily weather conditions between 1976 and 2008 from six Canadian cities – Toronto, Vancouver, St. John's, Winnipeg, Montreal, and Winnipeg. Since the predicted values are based on a common city-time reference group, the variations purely reflect differences in weather conditions, as opposed to variations in outdoor recreation preferences across cities or time. The results are entirely consistent with popular perceptions. Vancouver enjoys better Spring weather, but summers in Toronto and Montreal dominate slightly, due to slightly warmer temperatures and less precipitation. Integrating the city profiles from April to October, Toronto enjoys the highest average weather quality, followed by Vancouver, Montreal, Winnipeg, Edmonton, and St. John's.

3.2 Weather-absenteeism relation

Our data on sickness absenteeism come from Canada's monthly Labour Force Survey (LFS). These data have three important advantages over other possible data sources. First, although surveys suggest faking sick days is commonplace, the empirical correlation between weather and reported sickness absenteeism is almost certainly very small.[13] Moreover, it seems reasonable to expect that partial day absences, such as leaving work early, will be underreported in the data, thereby attenuating the correlation. We, therefore, need large amounts of data to identify it with any meaningful precision and make comparisons of its magnitude across groups of workers. Pooling April to October monthly LFS files between 1997 and 2008, we obtain a sample of 1.8 million employees currently employed in one of the 56 cities for which we have weather data. Second, the LFS identifies not only the number of hours respondents were absent from work in the survey

[11] Stepwise analysis beginning with a very general specification that allows thermal and aesthetic effects under physical conditions and includes quartic terms in all the continuous variables, produces very similar relative rankings of weather conditions. Specifically, the resulting weather index has a correlation of 0.95 with the index implied by the results in Table 1.

[12] A complication in the estimation is that our narrow set of 13 activities almost certainly misses many outdoor activities. For example, many of the swimming episodes in the data are presumably outdoors. As a result, weather fluctuations that lead individuals to substitute from an indoor activity to swimming outside will be missed and the estimates attenuated. To examine the robustness of the estimated index to this potential bias, we have tried estimating (3.2) dropping activities where the location is ambiguous, such as swimming. The main effect of doing so is to shift up the intercept rather than the shape of function. As indication of this, the optimal humidex and wind speed are 27.3 ℃ and 16.4 km/hr, respectively, when we exclude all ambiguous leisure activities, as well as all home production activities, many of which may also be outdoors.

[13] For example, a recent online survey by Careerbuilder.com found that one-third of 6,800 employees surveyed had called in sick with a fake excuse at least once over the past year.

reference week (the week containing the 15$^{\text{th}}$), but unlike the Current Population Survey (CPS) – the U.S. equivalent – also queries the main reason for the absence. We are, therefore, able to distinguish sickness absenteeism from other types of short-term absences, which may be legitimately influenced by the weather, such as vacations and inclement weather. Lastly, and perhaps most important, the greater the variation in the weather, the more likely it is to provide sufficient utility increments to induce shirking absenteeism. In this sense, Canada offers a more ideal setting to study the absenteeism-weather correlation than more temperate U.S. and European climates. As residents of Canada, we personally know the temptation unseasonably sunny and warm spring weather can have on even the most disciplined among us.

The main limitation of the LFS data, however, is that we observe total hours absent in the survey reference week, as opposed to daily or hourly absenteeism. Nonetheless, we know that there is substantial serial correlation in weather patterns, that is weather variations tend to persist over periods longer than a day, so substantial variations exist even when we aggregate weather over a workweek. In addition, the weather data are observed hourly, so we are able to examine the differential effect of, for example, good weather on a Friday compared to a Monday. However, in the baseline case, we simply use the average unweighted value of the weather quality index from 9am to 5pm between Monday and Friday.

To avoid possible direct effects of the weather on the marginal disutility of work, which would tend to attenuate the estimated absenteeism-weather relation, we further restrict our sample to workers primarily employed indoors.[14] Since the 4-digit industry and occupation codes we rely on to distinguish indoor workers are only available for each respondent's main job (the job in which they work the most hours), but the absenteeism data are for all jobs, we also exclude multiple job holders from the sample. This restriction leaves us with a final sample of 1,822,726 employees.

Our expectation is that absences exceeding one day in duration are less likely to be illegitimate. Our analysis of the 1995 Survey of Work Arrangements indicates that among wage and salary workers who usually work the same number of hours each day, 75.5% report working between 7 and 8 hours per day. We therefore distinguish absences in our LFS data that are 8 hours or less in duration from longer term part-week or full-week absences. It turns out that slightly more than 80% of the short-term absences observed are between 7 and 8 hours in duration, suggesting that the vast majority are exactly one-day absences. To further isolate illegitimate absences, we also distinguish between three reported reasons for a short-term absence: (i) own illness or other personal reasons (taking care of kids, elderly people, and other family responsibilities); (ii) vacation; and (iii) other reasons (labour dispute; temporary layoff; holiday; weather; job started or ended

[14]The largest groups of workers excluded are those employed in the primary resources, construction, and transportation industries. The Appendix contains a complete list of the groups excluded.

during week; working short-time; maternity leave; or other reason). A positive relation between our weather index and the incidence of short-term personal absences (reason (i)), is taken as evidence of shirking absenteeism. Although we are able to distinguish own illnesses from other personal reasons in the data, in our view attributing an illegitimate absence to a child's illness is no less malfeasant than attributing it to one's own illness. Attributing absence to the illness of family members may in fact be less risky, since it is presumably more difficult to detect. Together, own illnesses and other personal reasons account for roughly 20% of all short-term absences.[15]

A concern with our strategy is that we are capturing implicit agreements between supervisors and employees to use contractual sick days for illegitimate reasons. We have no doubt that these types of agreements exist, but the question is how in these cases workers respond to the question: "What was the main reason for the absence?" and how their responses get coded in the data. In our view, whether they are coded as sickness or something else depends exactly on whether the absence was malfeasant. If they are de facto vacation days, so that there is no ambiguity regarding their malfeasance from the employee's perspective, it seems unlikely that sickness will be identified as the "main reason" for the absence. A perfectly healthy employee who has the approval of a supervisor to spend a sunny afternoon golfing is clearly more likely to express the activity – playing golf – than sickness as the main reason for absence, in which case the absence will be coded in the data as either vacation or in the residual "other reason" category. If, on the other hand, employees have some uncertainty about the legitimacy of their absence, it seems more likely that sickness will be mentioned in their response and their absence coded as such. This seems particularly the case if absences are due to weather conditions favourable to outdoor recreation, as opposed to "mental health" or "recuperation" days, which should not be statistically correlated with our weather index (or at least not positively correlated with weather quality as we are hypothesizing). As it turns out, the weather-absenteeism relation we identify in the data is much more prevalent among hourly-paid and probationary employees. Since these are exactly the types of employees who are least likely to have contractual sick days, our results also suggest that we are not identifying implicit agreements.

To distinguish employees facing different shirking costs, we define four covariates. First, exploiting the rotating sampling structure of the LFS, in which respondents are (potentially) resampled for 6 consecutive months, the probability of an unemployed worker transitioning to employment in the following month is estimated using a probit model conditional on his or her education, age, duration of current ongoing unemployment spell, month, and city. Unemployment-employment transition rates are then predicted at the individual-level and used to identify the influence of job acquisition rates on the weather-absenteeism relation. Second, to proxy the generosity of sick pay,

[15] In fact, the empirical results from distinguishing the two types of absences support this conjecture – absences due to family responsibilities are clearly more strongly related to the weather than are absences due to own illness.

we exploit information on whether respondents are paid on an hourly basis or salaried. Our analysis of data from the 1995 Canadian Survey of Work Arrangements shows that, even after conditioning on gender, education, union status, industry, occupation, and geography, hourly paid workers are significantly less likely than salaried workers to be entitled to paid sick leave, providing us with some confidence in our use of this proxy.[16] Third, although we have defined the theoretical parameter α as simply a detection probability, we can straightforwardly extend the interpretation to the joint probability of: (i) detection; and (ii) dismissal given detection. To capture variation in the latter probability, we exploit two variables. First, since unionized workers are more likely to have access to a formal grievance process, they are expected to face a lower dismissal probability. Second, typically probationary periods for new employees in Canada are 3 months in duration. Following Ichino and Riphahn (2005), we exploit job tenure data available in the LFS and identify potential discontinuities in absence behaviour at 3 months when job protections usually kick in.

In order to distinguish short- from long-term absences, as well as three alternative reasons for short-term absence, we employ a multinomial logit model. Specifically, we model the probability of absence for reported reason j as:

$$Prob(absence_{ict} = j) = \frac{\exp(\mu_{ictj})}{1 + \exp(\mu_{ict1}) + \cdots + \exp(\mu_{ict4})} \tag{3.3}$$

where $j = 1, \ldots, 3$ are personal, vacation, and other reason for short-term absence, respectively; $j = 4$ is a long-term absence; and μ_{i0} is normalized to zero, so that no absence during the survey reference week ($j = 0$) is the reference category. The linear logit index μ_{ictj} for $j = 1, \ldots, 4$ is specified as follows:

$$\begin{aligned}\mu_{ictj} = \Big[& f_j(weather_{ct}) + \theta_{1j} ar_{ct} + \theta_{2j} hr_{ict} + \theta_{3j} un_{ict} + \theta_{4j} ten_{ict} + \theta_{5j} ten^2_{ict} + \theta_{6j} \mathbf{1}[ten_{ict} \geq 3] + \\ & \mathbf{dem}_{ict}\lambda_{1j} + \mathbf{ind}_{ict}\lambda_{2j} + \mathbf{occ}_{ict}\lambda_{3j} + \mathbf{z}_c\lambda_{4j} + \mathbf{x}_t\lambda_{5j} \Big].\end{aligned} \tag{3.4}$$

where $weather_{ct}$ is the average value of the weather quality index between 9am and 5pm from Monday to Friday in city c in week t; ar_{ict} is the job acquisition rate; hr_{ict} and un_{ict} are dummies indicating hourly-paid and unionized, respectively; ten_{ict} is months of job tenure; $\mathbf{dem}_{ict}$ is a vector of individual demographic control variables consisting of age (quartic), education (8 categories), and gender; $\mathbf{1}[ten_{ict} \geq 3]$ is an indicator function identifying a discontinuity in absence probabilities at 3 months of job tenure; and $\mathbf{ind}_{ict}$ and $\mathbf{occ}_{ict}$ are vectors of industry and occupation dummies, respectively. The only remaining issue is how to specify the weather function $f_j(\cdot)$. From the theory, we know that the marginal effect of the weather on the probability of absence is nonlinear. But the function $f_j(\cdot)$ identifies the effect on the underlying linear index μ_{ictj}. We have tried

[16]These results are available upon request from the authors.

estimating the function using various polynomials and it is clearly nonlinear. However, little is gained substantively beyond a simple quadratic.[17]

To identify variation in the weather-absenteeism relation across workers, we estimate (3.4) adding interactions of the weather functions $f_j(\cdot)$ with either the job acquisition rate (ar_{ct}), the hourly-rate dummy (hr_{ict}), the union dummy (un_{ict}), or the post-probation dummy ($\mathbf{1}[ten_{ict} \geq 3]$). Our expectation is that the weather effect is largest where shirking costs are highest implying that the ar_{ct} interaction is negative; the hr_{ict} interaction is positive; the un_{ict} interaction is negative; and the $\mathbf{1}[ten_{ict} \geq 3]$ interaction is negative. However, in estimating these interaction effects, we cannot rule out the possibility that the hourly-paid status, union status and even the job acquisition are related to the wages employers pay or heterogeneity in employee health levels. This would be the case if employers, for example, use hourly-paid status, and hence sick pay generosity, as an instrument to influence existing shirking incentives. Unfortunately, credible instruments for all of these variables are not available to us. Instead, we perform two robustness checks using additional control variables intended to capture the underlying heterogeneity that could bias our estimates. First, we control for the wage using an effective hourly-wage rate provided in the LFS data. Second, we again exploit the rotating sampling structure of the LFS to construct a lagged absenteeism variable equal to the percentage of the previous 5 months the individual reported a short-term absence due to a personal reason. This, however, requires that we restrict our sample to observations in the sixth month of their panel, thereby severely reducing the sample size. To distinguish the effects of this sample reduction from the inclusion of the lagged dependent variable, we also present the results from estimating the model using the smaller sample, but without the lagged absenteeism control.

4 Results

We begin our analysis of the LFS data by comparing unconditional sample mean probabilities of absence across the key covariates thought to influence shirking incentives. The results are presented in Table 2. Comparing the incidence of a short-term absence for personal reasons across quintiles of the weather quality distribution, there is a clear tendency for personal absenteeism to rise with good weather. Although the magnitude of the effect appears small, as a percentage change it is a 33% difference (0.0220 and 0.0295) between the first and fifth quintile. The unconditional variation in the weather is, however, overwhelmingly seasonal. That is, most of the variation in the weather index is between days in April and October, when temperatures are on average lower, and

[17] The main difference in adding higher-order polynomials is the estimated marginal effect of the weather on short-term personal absences becomes very flat, rather than declining, at the upper tail of the weather quality distribution. The results of this specification analysis are available from the authors on request.

in July and August, when they tend to be higher. This seasonality explains both the tendency for short-term absences for reasons other than sickness or vacations to strongly decline with weather quality (Easter and Thanksgiving both potentially fall in the survey reference week and in months – April and October – with relatively poor weather) and for long-term absences to increase with the quality of the weather (vacations in excess of one day are most likely in July and August when the weather is best). Since genuine health status may similarly vary with season, it is important that we identify the weather-absenteeism relation conditional on calendar week.[18]

The differences in short-term personal absences across job acquisition rates, union status and probation status are all consistent with the expected shirking incentive effects of these variables – personal absenteeism is higher when job acquisition rates are high and when job protection is high. A higher incidence of personal absence among hourly-rate workers is, however, unexpected, given that they are less likely to be paid for time off. Of course, it is unclear to what extent any of these differences reflect genuine health. For example, workers paid on an hourly basis may be on average less healthy for reasons that have nothing to do with shirking incentives.

In Table 3 we present the results from estimating the baseline multinomial logit model defined by equations (3.3) and (3.4). The main finding is that the weather quality index only has a statistically significant effect on the incidence of short-term personal absences.[19] The direction of this effect is consistent with the theoretical mechanism we have in mind – weather conditions more conducive to outdoor recreation result in more misreported sickness absence. The marginal effect is decreasing, but positive, up to an index value of 0.162, which falls above the 90^{th} percentile of the weather quality distribution. At the mean of the data, a one standard deviation increase in weather quality increases the probability of a short-term absence for personal reasons in the survey reference week from 2.99% to 3.18%. This is clearly not a large effect, which is perhaps not surprising given our concerns about underreporting of partial day absences. Given the substantial sample size, it is, however, statistically significant at the 5% level.

Before considering how this weather effect on personal absences varies across employees facing different shirking costs, we explore the effect further in two ways. First, rather than regressing on the overall average daytime weather quality between Monday and Friday, we estimate the marginal effect of daytime weather separately for each day. The question is then, for example, conditional on the Monday through Thursday weather, does better weather on Friday result in a higher probability of a short-term personal absence at some point during the reference week. The results are presented

[18] Note that there is no obvious pattern in the rates of short-term personal absences across months in Table 2, suggesting that at least over the non-winter months there is little seasonal variation in health.

[19] This result is somewhat sensitive to functional form. When we estimate a linear weather effect, the weather also has a statistically significant positive effect on short-term vacation absences.

in Table 4. Although most of the individual weather terms are insignificant, joint tests of the linear and quadratic terms suggest only Tuesday weather has a significant effect.[20] Given the incentive to use Fridays and Mondays to extend a weekend to provide a sufficient block of time to enable certain activities, we had expected Monday or Friday weather to matter more. But, of course, this incentive is quite different from the weather-induced behaviour we are identifying here. In addition, it may be that this obvious advantage of Monday and Friday absence is exactly what makes shirking on these days less likely – misreporting health on these days, in comparison to Tuesday, is less credible. Interestingly though, Monday weather appears to influence other types of short-term absences, as well as long-term absences.[21]

Although our theoretical model is purely static, it may be that the influence of the weather on the marginal utility of outdoor leisure depends on recent past weather. This would be the case if, for example, the marginal utility of engaging in recreational activities is decreasing in the time spent in these activities in the recent past. To examine this possibility, in Table 5 we present the results from interacting the quadratic weather function with the average daytime weather index on the weekend preceding the survey reference week. As in Table 3, the current weather appears only to affect personal absenteeism and not other types of absenteeism. Moreover, the interaction of current and past weather suggests that past weather influences the effect of current weather. Specifically, the estimates suggest that conditional on average weekend weather of 0.05 (roughly the 15^{th} percentile), the probability of a personal absence increases by 5.8% (from 2.62% to 2.78%) when the average workweek weather index increases from 0.05 to 0.06. When average weekend weather index is 0.15 (roughly the 90^{th} percentile), on the other hand, a one-point increase in average workweek weather (from 0.15 to 0.16) increases personal absenteeism by only 2.0% (from 3.17% to 3.24%).[22] Note that these results are quite different from the evidence of intertemporal substitution of leisure found by Connolly (2008). Rather, our results are evidence of intertemporal substitution of recreational activities between the weekend and workweek through illegitimate sickness absenteeism.

In Table 6 we present the results from interacting the quadratic weather function with the job acquisition rate; hourly-paid indicator; union indicator; and post-probation indicator. Specifications (1) and (2) report the results from excluding and including, respectively, the wage rate as an additional regressor. Due to the quadratic specification, the relative magnitudes of marginal effects between employees facing high and low shirking costs potentially changes over the support of the

[20] Tuesday weather also stands out when we use a linear weather specification.

[21] Note, however, that with the exception of short-term vacation absences, the estimated marginal effects of Monday weather are actually decreasing over most of the weather distribution (the negative quadratic term tends to dominate).

[22] We have also tried estimating with a linear weather function. In this case the linear weather variable is positive and significant and the interaction variable is negative and marginally significant, implying that the marginal utility of workweek weather is increasing in weekend weather over the entire distribution of workweek weather.

weather index distribution. To make the results more transparent, in Figure 2 we plot the predicted probabilities of personal absence (at the mean of the data) between the 5^{th} and 95^{th} percentiles of the weather index distribution separately for each of the four interacting variables. In the case of the job acquisition rate – the only continuous variable – this is done by comparing the profile between a job acquisition rate at the 25^{th} and 75^{th} percentiles (or 0.13 compared to 0.23). In cases where the ranking of the size of the marginal effects is reversed across the distribution, we indicate the point at which the marginal effects are equal with a vertical solid line.

In the case of both the job acquisition rate and unionization status, the estimated interactions are statistically insignificant, although the point estimates for the unionization dummy are the right sign over most of the weather quality distribution. Specifically, the point estimates imply that the marginal effect of the weather is bigger for non-unionized workers beyond the 30^{th} percentile of the weather quality distribution (an index value of roughly 0.071). Conditioning on the wage does essentially nothing to change these results, even though the wage, in itself, is highly significant.[23]

Using hourly-paid status to proxy sick pay, the estimates point to a higher marginal effect of the weather for hourly-paid workers above the 35^{th} percentile of the weather quality distribution (an index value of about 0.078). Below this point the marginal effects are virtually identical for hourly-paid and salaried workers. Going from the median weather quality (about 0.095) to the 95^{th} percentile, has essentially no effect on the short-term personal absenteeism rate of salaried employees, while it increases the rate for hourly-rate employees from about 0.030 to 0.035, a 17% increase. Moreover, once again the results are virtually identical whether or not we condition on the wage, suggesting that wage rates are not influencing this particular type of shirking behaviour.

The results in the final two columns of Table 6, point to very different responses to weather improvements between probationary and post-probation employees that are statistically significant. And again the results are highly insensitive to the wage. Specifically, marginal weather improvements below the median weather quality have a bigger impact on the personal absence rates of post-probation employees, whereas weather improvements above the median have a larger impact on probationary employees. However, we would expect that the types of outdoor recreational activities that we are imagining employees substituting towards when they misreport illness are more likely to be induced by marginal weather improvements at the upper end of the distribution. And at the top end of the distribution, probationary employees are clearly much more sensitive to weather improvements. Once again, therefore, the estimates appear more consistent with the hypothesis that the marginal utility of outdoor leisure is increasing in the interaction of health and the weather

[23]The sign of the wage effect is positive, which is counter to the efficiency wage hypothesis. However, it is unclear to what extent the wage variation, after conditioning on age, education, hourly-paid status, union status, job tenure, occupation and industry, is correlated with unobserved heterogeneity in health.

than with implicit employer-employee agreements to use sick days for illegitimate reasons.

Finally, in specifications (1) and (2) of Table 7 we present the estimates excluding and including the lagged personal absenteeism variable as described in Section 3.2. Due to the substantial loss in sample size (we are left with roughly 10% of the original sample), the precision of all the estimates drops considerably, so that now none of the interaction effects are statistically significant. Nonetheless, lagged personal absenteeism is in all cases associated with significantly more personal absenteeism in the current period as expected. However, as with the wage rate, the point estimates of the interaction effects remain virtually identical. In comparing hourly-paid and salaried employees, for example, the marginal weather effect is larger among hourly-paid employees when weather index exceeds 0.069 (compared to 0.078). This suggests that hourly-paid employees are more responsive to weather quality improvements over an even larger range of the weather quality distribution. The point at which the weather effect is larger for unionized and probationary employees, however, increases (now 0.099 and 0.111 respectively). The key finding that personal absenteeism of hourly-paid, nonunionized and probationary employees appear most sensitive to marginal weather improvements at the top of the weather distribution is, however, robust to the inclusion of the lagged personal absenteeism variable.

5 Conclusion

We argue that the literature's limited empirical evidence informing principal-agent problems between employers and employees primarily reflects the inherent difficulty of measuring effort levels and in particular malfeasant shirking activity. In our view, the most compelling evidence in the current literature is that examining disciplinary rates. The shortcoming of this approach, however, is that it only identifies shirking activity that is detected and punished. Comparing disciplinary rates across workplaces may consequently reflect the efforts of employers to monitor and punish shirkers, rather than differences in actual shirking activity.

As an alternative strategy, we identify the propensity of employees to misreport sickness in order to exploit weather conditions favourable to high-utility outdoor recreational activities. This strategy has the advantage that it captures shirking activity, whether or not that behaviour is identified by employers. Our empirical results point to a clear tendency for the incidence of short-term sickness absenteeism spells to increase with the recreational quality of the weather. Moreover, the marginal effect of the weather appears largest among workers facing the highest shirking costs, such as hourly-paid employees, who are not paid for time off, and probationary employees, who face the greatest risk of dismissal. We show that this result is consistent with a theoretical model of shirking absenteeism in which employees' marginal utility of outdoor leisure is increasing in the interaction of the recreational quality of the weather and individual health.

We think there are two main implications of our findings. First, our findings point to a complementarity in workers' marginal utility of leisure between an individual-level parameter – health – and an environment parameter – the weather. If employers want to limit unanticipated and misreported absenteeism, because it is more costly than scheduled absenteeism, it may be optimal to provide workers with greater flexibility in choosing their days off so that they are best able to exploit these types of complementarities in their utility functions. One mechanism to do this is to limit constraints on when vacation days are scheduled, including commonplace requirements that vacation entitlements be take taken on consecutive days. And in legislating reductions in working hours, governments may have more potential to reduce absenteeism levels by increasing statutory minimum vacation-day entitlements, rather than introducing new statutory holidays.

A second implication of our results arises from the fact that the reason for absence that we observe in our data is being reported to Canada's national statistical agency, not to respondents employers. The question is, why do respondents appear to misreport sickness when Statistics Canada guarantees them confidentiality. Our estimates can be seen as providing some evidence that despite assurances of confidentiality and Statistics Canada's strong reputation, confidentiality concerns appear to affect data quality. In areas where surveys are querying sensitive information, these response biases may be quantitatively important. Respondent trust in confidentiality guarantees may also have implications for survey response rates, which are increasingly relevant as statistical agencies move toward a greater reliance on voluntary surveys, such as Statistics Canadas recent decision to replace their mandatory long-form Census with a voluntary large-scale household survey.

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APPENDIX

1. Proofs of Theoretical Propositions

The expected proportion of employees $\bar{n}$ who choose to shirk is given by $\Pr(\theta < \theta^o) + \Pr(\theta^i < \theta < \theta^z) = (\theta^o) + (\theta^z - \theta^i)$, given that θ is uniformly distributed over the positive unit interval. But since θ^i depends only on the threshold marginal utility of leisure δ^c, given by equation (2.1), and θ^z is an exogenous constant, a marginal improvement in the weather λ only affects the extent of outdoor shirking θ^o. Given that $\theta^o = (\lambda - \delta^c)/\lambda$, we have:

$$\frac{\partial \Pr(\theta < \theta^o)}{\partial \lambda} = \begin{cases} 0, & \text{if } \lambda \leq \delta^c \\ \delta^c/\lambda^2, & \text{if } \lambda > \delta^c \end{cases} \tag{5.5}$$

which implies reported sickness absenteeism is a discontinuous increasing function of the weather.

The marginal effect of the weather on sickness absenteeism is given by $\partial\theta^o/\partial\lambda = \delta^c/\lambda^2$. Applying the implicit function theorem to equation (2.1), we have:

$$\frac{\partial \delta^c}{\partial a} = \frac{\left(\frac{dw}{da}\right)[h - \rho\alpha(1-a)V] - \rho\alpha V(d+h)}{(d+h)^2} \tag{5.6}$$

$$\frac{\partial \delta^c}{\partial s} = \frac{\left(\frac{dw}{ds} - (1-\alpha)\right)(h - \rho\alpha(1-a)V)}{(d+h)^2} \tag{5.7}$$

$$\frac{\partial \delta^c}{\partial \alpha} = \frac{\left(\frac{dw}{d\alpha} + s - b\right)[h - \rho\alpha(1-a)V] + \rho(1-a)V(d+h)}{(d+h)^2} \tag{5.8}$$

where $V = V(E) - V(U)$ and $d = w - \alpha b - (1-\alpha)s$. Since we know $V > 0$ and $h - \rho\alpha(1-a)V > 0$ (see discussion in text), and that $d > 0$ (since $w > s > b$), in the absence of any employer wage adjustments (wage derivatives are zero), the signs of all three derivatives are unambiguous: $\partial\delta^c/\partial a < 0$; $\partial\delta^c/\partial s < 0$; and $\partial\delta^c/\partial\alpha > 0$.

2. Identification of Outdoor Workers

Four-digit industries: Oilseed and grain farming; Vegetable and melon farming; Fruit and tree nut farming; Greenhouse, nursery and floriculture production; Other crop farming; Cattle ranching and farming; Hog and pig farming; Poultry and egg production; Sheep and goat farming; Animal aquaculture; Other animal production; Timber tract operations; Forest nurseries and gathering of forest products; logging; Fishing; Hunting and trapping; Support activities for crop production; Support activities for animal production; Support activities for forestry; Oil and gas extraction; Coal mining; Metal ore mining; Non-metallic mineral mining and quarrying; Support activities for mining and oil and gas extraction; Electric power generation, transmission and distribution; Natural gas distribution; Water, sewage and other systems; Residential building construction; Non-residential building construction; Utility system construction; Land subdivision; Highway, street and bridge construction; Other heavy and civil engineering construction; Foundation, structure, and building exterior contractors; Building equipment contractors; Building finishing contractors; other specialty trade contractors; Scheduled air transportation; Non-scheduled air transportation; Rail transportation; Deep sea, coastal and great lakes water transportation; Inland water transportation; General freight trucking; Specialized freight trucking; Urban transit systems; Interurban and rural bus transportation; Taxi and limousine service; School and employee bus transportation; Charter bus industry; Other transit and ground passenger transportation; Pipeline transportation of crude oil; Pipeline transportation of natural gas; other pipeline transportation; Scenic and sightseeing transportation, land; Scenic and sightseeing transportation, water; Scenic and sightseeing transportation, other; Support activities for air transportation; Support activities for rail transportation; Support activities for water transportation; Support activities for road transportation; Freight transportation arrangement; Other support activities for transportation; Postal service; Couriers; Local messengers and local delivery; Warehousing and storage; Services to building and dwellings; Waste collection; Waste treatment and disposal; Remediation and other waste management services; Spectator sports; Heritage institutions; Amusement parks and arcades; Other amusement and recreation industries; Recreational vehicle parks and recreational camps.

Four-digit occupations: Mail, postal and related clerks; Letter carriers; Couriers, messengers and door-to-door distributors; Land surveyors; Farmers and farm managers; Agricultural and related service contractors and managers; Farm supervisors and specialized livestock workers; Nursery and greenhouse operators and managers; Landscaping and grounds maintenance contractors and managers; Supervisors, landscape and horticulture; Aquaculture operators and managers; General farm workers; Nursery and greenhouse workers; Supervisors, logging and forestry; Supervisors, mining and quarrying; Supervisors, oil and gas drilling and service; Underground production and development miners; Oil and gas well drillers, services, testers and related workers; Underground mine service and support workers; Oil and gas well drilling workers and service operators; Logging machinery operators; Chainsaw and skidder operators; Silviculture and forestry workers; Fishing Masters and Officers; Fishing vessel skippers and Fishermen/women; Fishing vessel deckhands; Trappers and hunters; Harvesting labourers; Landscaping and grounds maintenance labourers; Aquaculture and marine harvest labourers; Mine labourers; Oil and gas drilling, servicing and related labourers; Logging and Forestry labourers; Tour and travel guides; Outdoor sport and recreational guides; Heavy equipment operators; Public works maintenance equipment operators; Crane operators; Drillers and blasters; Water well drillers; Truck drivers; Bus drivers and subway and other transit operators; Taxi and limousine drivers and chauffeurs; Delivery and courier service drivers; Railway and yard locomotive engineers; Railway conductors and brakemen/women; Railway yard workers; Railway track maintenance workers; Deck crew, water transport; Engine room crew, water transport; Lock and cable ferry operators and related occupations; Boat operators; Air transport ramp attendants.

Table 1: Probit estimates of the effect of the weather on the incidence of outdoor recreational activity

	Coefficient	Standard error
Physical conditions	0.3951^{*}	0.2203
Humidex	0.0767^{***}	0.0021
Humidex^2/100	-0.1704^{***}	0.0508
Wind	0.0252^{*}	0.0130
Wind^2/100	-0.0417^{**}	0.0197
Humidex*Wind/100	-0.2106^{*}	0.1098
Humidex^2*Wind/1000	0.0603^{**}	0.0267
Cloud	-0.0167^{***}	0.0053
Pseudo R^2	0.0662	
N	33,834	
Optimal humidex	27.2 ℃	
Optimal wind speed	14.7 km/hr	

Notes: Standard errors are clustered by city and time (month, day, hour). Regression also controls for city, month and hour. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: Activity data from 1992, 1998 and 2005 General Social Survey (GSS). Weather data from Canadian National Climate Data and Information Archive (NCDIA).

Table 2: Sample mean probabilities of absence

	Short-term absence			Long-term absence
	Personal	Vacation	Other	
Weather quality				
Fifth quintile	0.0295	0.0244	0.0053	0.1656
Fourth quintile	0.0312	0.0218	0.0089	0.1581
Third quintile	0.0312	0.0223	0.0210	0.1299
Second quintile	0.0297	0.0185	0.1042	0.1097
First quintile	0.0220	0.0174	0.2606	0.1250
Job acquisition rate				
Above median	0.0305	0.0227	0.0603	0.1456
Below median	0.0275	0.0193	0.1017	0.1275
Pay status				
Salaried	0.0270	0.0271	0.1021	0.1482
Hourly-paid	0.0300	0.0159	0.0717	0.1251
Union status				
Unionized	0.0326	0.0228	0.0894	0.1885
Non-unionized	0.0272	0.0198	0.0828	0.1142
Probation status				
Over 3 months	0.0288	0.0216	0.0861	0.1415
Under 3 months	0.0279	0.0089	0.0664	0.0544
Month				
April	0.0296	0.0186	0.1478	0.1078
May	0.0337	0.0327	0.0086	0.0937
June	0.0374	0.0250	0.0053	0.0971
July	0.0260	0.0294	0.0041	0.2191
August	0.0254	0.0295	0.0129	0.2271
September	0.0361	0.0187	0.0056	0.0974
October	0.0114	0.0198	0.4685	0.1490

Notes: Short-term absence is defined as total hours absent of 8 hours or less. Weather quality is the average value of the weather quality index from Monday to Friday between 9am and 5pm. Standard errors are clustered by city and month. Regression also controls for city, month, industry and occupation.
Source: 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

Table 3: Multinomial logit estimates of the probability of absence from work during survey reference week

	Short-term absence			Long-term absence
	Personal	Vacation	Other	
Weather	5.8397**	2.4065	-6.6625	-0.7192
	(2.5311)	(3.6250)	(14.0593)	(3.0827)
Weather^2	-18.0552**	-1.3967	-7.3017	7.9204
	(8.7856)	(13.8529)	(60.9238)	(11.5980)
Job acquisition rate	5.2307***	6.4584***	5.6673**	2.6802***
	(0.5097)	(0.6354)	(2.4843)	(0.5120)
Hourly-paid	0.1082***	-0.1827***	-0.1687***	-0.0679***
	(0.0154)	(0.0184)	(0.0160)	(0.0092)
Unionized	0.2261***	0.1134***	0.0809***	0.2931***
	(0.0156)	(0.0181)	(0.0150)	(0.0087)
Tenure	0.0004*	0.0043***	0.0017***	0.0041***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Tenure^2/100	-0.0001	-0.0001	-0.0003***	-0.0007***
	(0.0001)	(0.0001)	(0.00004)	(0.00003)
Tenure over 3 months	0.0997***	0.5259***	0.1320***	0.7313***
	(0.0256)	(0.0391)	(0.0218)	(0.0194)
Pseudo R^2			0.1700	
N			1,822,726	

Notes: Short-term absence is defined as total hours absent of 8 hours or less. Weather is the average value of the weather quality index from Monday to Friday between 9am and 5pm. Standard errors are clustered by city and month. Regression also controls for age, gender, education, city, month, industry and occupation. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

Table 4: Multinomial logit estimates of the probability of absence from work during survey reference week by daily weather quality

	Short-term absence			Long-term absence
	Personal	Vacation	Other	
Monday-weather	1.1701	11.5961***	41.6121***	9.7619***
	(2.0197)	(3.0956)	(11.5863)	(2.6812)
Monday-weather^2	-5.6987	-44.5537***	-207.4685***	-37.0173***
	(7.8533)	(12.2276)	(62.2020)	(10.5830)
Tuesday-weather	0.8708	-0.4580	18.2635	1.1884
	(2.4264)	(3.3008)	(11.8101)	(2.5118)
Tuesday-weather^2	4.7046	7.8856	-96.1747	-0.3330
	(9.1755)	(12.6568)	(61.4790)	(9.9841)
Wednesday-weather	-2.3647	-5.8366**	-14.8015	-2.7336
	(2.2124)	(2.7882)	(13.3083)	(2.4308)
Wednesday-weather^2	6.8555	20.6834*	61.9287	8.8665
	(8.6711)	(10.9077)	(66.6439)	(9.5945)
Thursday-weather	3.5731*	-4.3381	-20.3523	-4.4294
	(2.1574)	(3.1314)	(14.7574)	(2.9146)
Thursday-weather^2	-13.1702	19.1868	111.2558	20.6195*
	(8.5848)	(12.2611)	(75.0729)	(11.5245)
Friday-weather	2.2493	2.6537	-13.7873	-3.0255
	(2.2325)	(2.6220)	(11.0951)	(2.2952)
Friday-weather^2	-9.9515	-8.4189	36.4929	10.8657
	(8.7052)	(10.1489)	(52.8644)	(9.0207)
Pseudo R^2			0.1730	
N			1,821,554	

Notes: Short-term absence is defined as total hours absent of 8 hours or less. Weather is the daily average value of the weather quality from 9am and 5pm. Standard errors are clustered by city and month. Regression also controls for age, gender, education, city, month, industry and occupation. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

Table 5: Multinomial logit estimates of the probability of absence from work during survey reference week conditional on previous weekend weather

	Short-term absence			Long-term absence
	Personal	Vacation	Other	
Weather	13.4784***	4.6701	-4.3531	-2.8219
	(4.3604)	(6.5832)	(25.1010)	(5.8682)
Weather^2	-65.0444***	-19.6809	-24.7849	22.8660
	(23.2283)	(34.4317)	(150.5047)	(30.4340)
Weather*Previous weekend weather	-50.3216**	0.0845	-20.1847	5.6590
	(21.8373)	(25.9500)	(104.1999)	(21.5950)
Weather^2*Previous weekend weather	355.3282**	72.6816	156.3359	-76.3461
	(143.6966)	(179.1534)	(837.6791)	(153.1467)
Pseudo R^2			0.1701	
N			1,810,8911	

Notes: Short-term absence is defined as total hours absent of 8 hours or less. Weather is the average value of the weather quality index from Monday to Friday between 9am and 5pm. Standard errors are clustered by city and month. Regression also controls for age, gender, education, city, month, industry and occupation. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

Table 6: Multinomial logit estimates of the probability of short-term absence due to personal reasons

	Interaction variable							
	Job acquisition rate		Hourly paid		Unionized		> 3 months tenure	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Weather	15.3496**	15.3186**	8.9173***	8.9041***	5.4015**	5.3927**	-0.1290	-0.1379
	(6.3187)	(6.3194)	(2.8543)	(2.8543)	(2.5703)	(2.5702)	(3.2427)	(3.2429)
Weather^2	-74.3030***	-74.1149***	-37.0017***	-36.9083***	-14.7271	-14.6819	12.6539	12.6847
	(27.6820)	(27.6830)	(10.7606)	(10.7601)	(9.0467)	(9.0467)	(12.4938)	(12.4949)
Weather*Interaction	-23.7817	-23.7099	-4.3134***	-4.2984***	1.6340	1.6559	6.5420***	6.5483***
	(14.4926)	(14.4910)	(1.5015)	(1.5002)	(1.4381)	(1.4387)	(2.4676)	(2.4679)
Weather^2*Interaction	140.4293**	139.9816**	27.3392***	27.2084***	-11.3591*	-11.4818*	-33.6835***	-33.7024***
	(64.4837)	(64.4727)	(7.2115)	(7.2056)	(6.6879)	(6.6916)	(10.7260)	(10.7281)
Job acquisition rate	6.0343***	6.0182***	5.2331***	5.2195***	5.2281***	5.2138***	5.2307***	5.2165***
	(0.8941)	(0.8942)	(0.5100)	(0.5097)	(0.5095)	(0.5092)	(0.5095)	(0.5093)
Hourly-paid	0.1084***	0.1146***	0.2420***	0.2479***	0.1085***	0.1148***	0.1083***	0.1146***
	(0.0154)	(0.0155)	(0.0724)	(0.0724)	(0.0154)	(0.0155)	(0.0154)	(0.0155)
Unionized	0.2262***	0.2214***	0.2252***	0.2205***	0.1864***	0.1807**	0.2261***	0.2212***
	(0.0156)	(0.0155)	(0.0156)	(0.0155)	(0.0716)	(0.0717)	(0.0156)	(0.0155)
Tenure	0.0004*	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	0.0004*	0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Tenure^2/100	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tenure over 3 months	0.1000***	0.0993***	0.1004***	0.0998***	0.1000***	0.0993***	-0.1765	-0.1775
	(0.0256)	(0.0256)	(0.0256)	(0.0256)	(0.0256)	(0.0256)	(0.1379)	(0.1379)
Wage rate	–	0.0385**	–	0.0373***	–	0.0392**	–	0.0388**
		(0.0181)		(0.0181)		(0.0181)		(0.0181)
Pseudo R^2	0.1702	0.1707	0.1703	0.1708	0.1703	0.1709	0.1701	0.1707
N	1,822,726	1,822,726	1,822,726	1,822,726	1,822,726	1,822,726	1,822,726	1,822,726

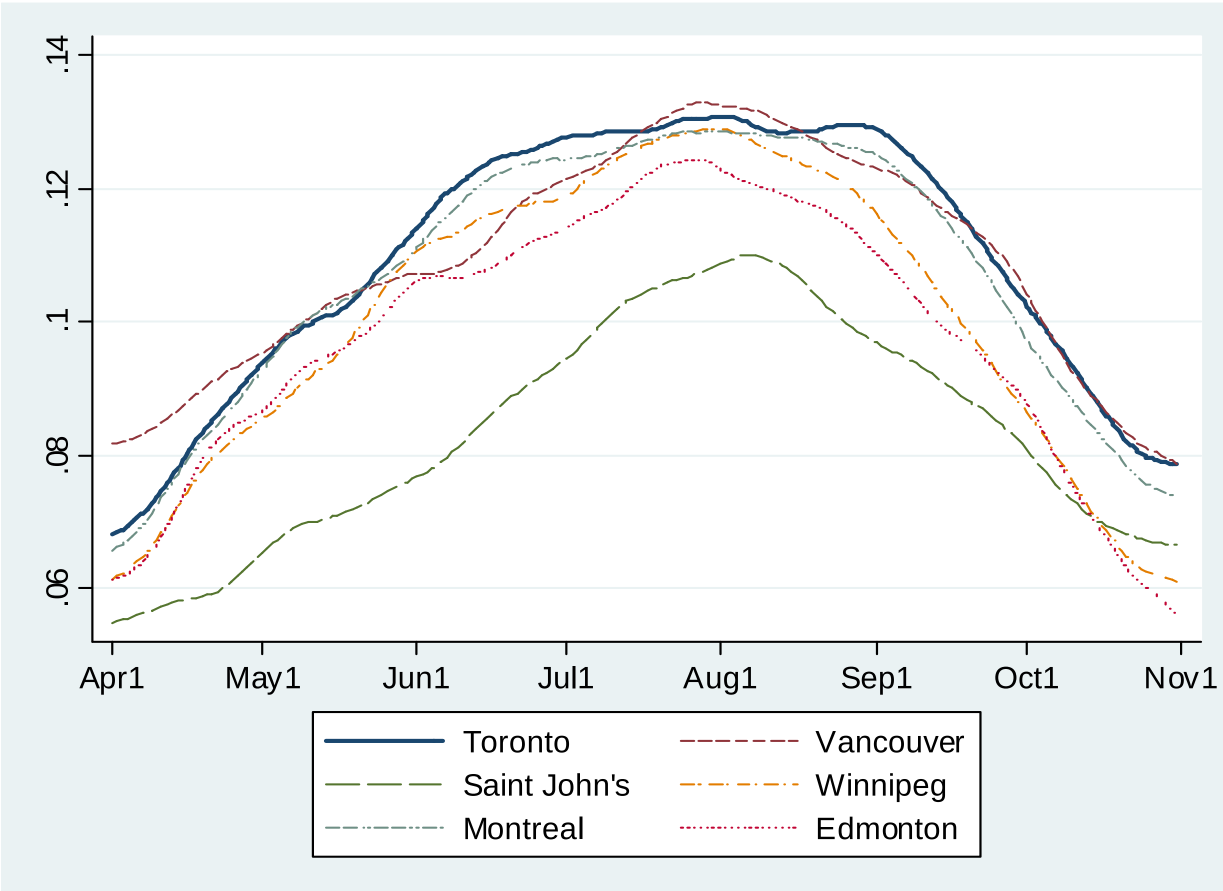
Notes: Short-term absence is defined as total hours absent of 8 hours or less. Weather is the average value of the weather quality index from Monday to Friday between 9am and 5pm. Standard errors are clustered by city and month. Regression also controls for age, gender, education, city, month, industry and occupation. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

Table 7: Multinomial logit estimates of the probability of short-term absence due to personal reasons (conditional on lagged short-term personal absence)

	Interaction variable							
	Job acquisition rate		Hourly paid		Unionized		> 3 months tenure	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Weather	13.6381	16.0039	9.9110*	9.2127*	5.8387	5.6017	-23.6105*	-25.4208**
	(13.2247)	(12.9900)	(5.5605)	(5.3562)	(4.7799)	(4.5700)	(12.6164)	(12.9480)
Weather^2	-68.1225	-77.5830	-36.2868*	-33.7233	-11.7387	-12.2873	113.4201**	119.5946**
	(60.7423)	(59.6836)	(22.3140)	(21.7130)	(17.9585)	(17.2973)	(55.8510)	(57.9497)
Weather*Interaction	-23.4912	-21.5110	-3.0775	-2.6744	5.7712	5.1806	32.0817***	33.4586***
	(32.2682)	(32.2608)	(4.1224)	(4.1383)	(4.3722)	(4.3872)	(12.1564)	(12.5359)
Weather^2*Interaction	112.4648	141.6881	22.2659	19.1225	-28.9107	-25.5496	-138.0124**	-143.6031**
	(149.8534)	(149.4697)	(19.4145)	(19.5146)	(19.8848)	(19.9624)	(54.6416)	(56.7986)
Job acquisition rate	5.9567***	5.6104***	5.8681***	5.0532***	5.8655***	5.0534***	5.8643***	5.0445***
	(1.8364)	(1.8409)	(0.9913)	(0.9709)	(0.9909)	(0.9705)	(0.9900)	(0.9696)
Hourly paid	0.1124**	0.0945**	0.1797	0.1553	0.1122**	0.0942**	0.1129**	0.0950**
	(0.0439)	(0.0445)	(0.2065)	(0.2065)	(0.0438)	(0.0444)	(0.0439)	(0.0444)
Unionized	0.2380***	0.2086***	0.2369***	0.2075***	-0.0167	-0.0241	0.2380***	0.2087***
	(0.0441)	(0.0447)	(0.0441)	(0.0446)	(0.2211)	(0.2221)	(0.0441)	(0.0446)
Tenure	-0.0004	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Tenure^2/100	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Tenure over 3 months	0.0547	0.0425	0.0554	0.0435	0.0543	0.0422	-1.5609**	-1.6461***
	(0.1408)	(0.1420)	(0.1407)	(0.1419)	(0.1406)	(0.1418)	(0.6197)	(0.6344)
Lagged short-term personal absence	–	4.0902***	–	4.0893***	–	4.0900***	–	4.0921***
		(0.1349)		(0.1348)		(0.1348)		(0.1348)
Pseudo R^2	0.1754	0.1801	0.1753	0.1801	0.1754	0.1802	0.1751	0.1799
N	188,797	188,797	188,797	188,797	188,797	188,797	188,797	188,797

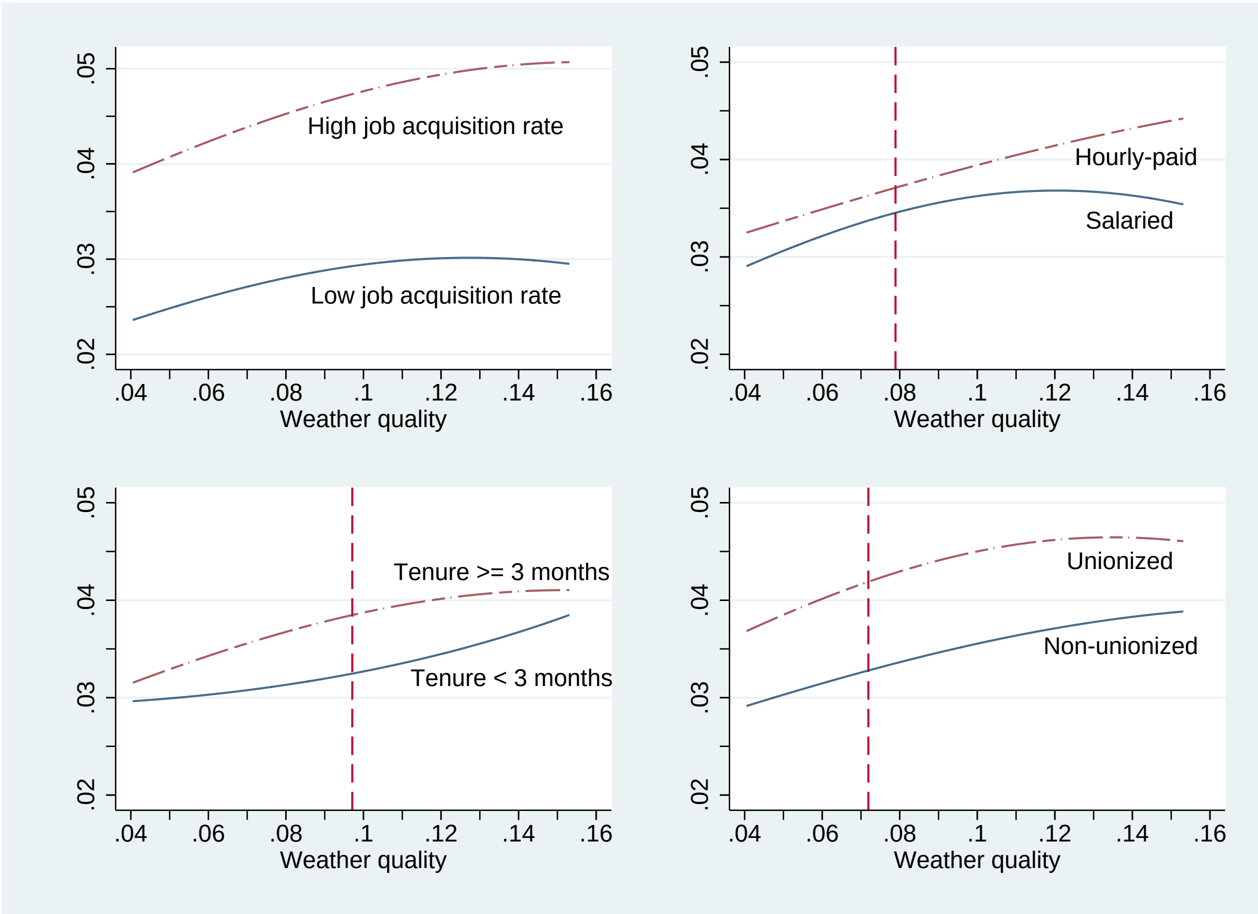
Notes: Short-term absence is defined as total hours absent of 8 hours or less. Weather is the average value of the weather quality index from Monday to Friday between 9am and 5pm. Standard errors are clustered by city and month. Regression also controls for age, gender, education, city, month, industry and occupation. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

Figure 1: April to October weather quality in six Canadian cities



Notes: Vertical axis plots the predicted probability of of outdoor recreation from (3.2) using average daily (9am-9pm) weather conditions between 1976 and 2008. All values are predicted for the reference group (Toronto at 2pm in July), so that all variation purely reflects weather variations, and not variation in weather preferences across cities or time.

Figure 2: Predicted probability of short-term absence due to personal reason relative to no absence, odds ratios



Notes: Predicted probabilities are from estimates in Specification (1) of Table 6. In each case the predictions are for the reference category – Toronto in July at 2pm. All the remaining covariates, except the interaction variables, are similarly set to zero in all cases. High and low job acquisition rates are 0.13 and 0.23, respectively, which are the 15^{th} and 25^{th} percentiles in the sample. The vertical lines indicate the value of the weather index where the slopes of the profiles are equal.