# Reported Sickness Absenteeism and the Weather: A Test of a Shirking Model of Efficiency Wages*

Jingye Shi† and Mikal Skuterud‡

October 2011

**Abstract**

The inherent unobservability of shirking activity presents a serious challenge to obtaining direct evidence of the efficiency wage hypothesis. We begin with a model of shirking absenteeism in which employees' marginal utility of outdoor leisure is increasing in health. In equilibrium, the positive relation between weather quality and sickness absenteeism reflects the behavior of the inframarginal workers who are the least sick, implying a form of shirking. Using time-use data identifying the weekend and weekday evening outdoor recreational activities of wage and salary workers, we construct an index of weather quality. Linking this index over the summer months with data from the Canadian Labour Force Survey (LFS), which distinguishes reasons for part-week absences, we identify a clear tendency for absenteeism for personal reasons to rise with weather quality. However, comparing this relation across workers facing different shirking incentives, such as between salaried employees, who are typically paid for time off, and hourly-paid employees, who are not, offers little evidence to support the efficiency wage hypothesis.

**Keywords:** Efficiency wages; shirking; absenteeism; weather.
**JEL Classification: D82; J22; J31**.

*Skuterud acknowledges financial support from the Social Science and Humanities Research Council of Canada (No. 410-2011-0281).

†Doctoral candidate, Economics Department, University of Waterloo; jyshi@uwaterlo.ca

‡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 theoretical appeal of efficiency wage theory, most notably the shirking version of Shapiro and Stiglitz (1984), is incontrovertible. Relying on the single substantive assumption that employers are unable to perfectly monitor the effort levels of their employees, but capable of dismissing employees found shirking, the model can, in a setting with perfectly homogeneous workers, account for both equilibrium wage dispersion and involuntary unemployment. The continued interest in the research literature, and the extensive treatment of efficiency wage theory in current graduate texts in macroeconomics and labor economics, are evidence of the persistent and widespread appeal of the efficiency wage hypothesis.

Empirical evidence of efficiency wages is, however, decidedly mixed. While early studies focusing on inter-industry wage differentials were largely supportive (Dickens and Katz (1987); Krueger and Summers (1988)), more recent evidence linking these differentials to firm productivity and monitoring technologies (e.g., Neal (1993)), as well as employer surveys directly probing the rationale behind firm wage policies (Blinder and Choi (1990)), has raised doubt in the literature regarding the real-world relevance of the theory. This evidence, however, leaves much to be desired. As is well recognized in the literature, wage and productivity differentials are highly endogenous, potentially driven by unobservable factors, such as the latent abilities of workers and technologies of firms, that have little to do with the mechanisms of efficiency wage models. To *directly* test the efficiency wage hypothesis, one needs to directly measure the shirking behavior that efficiency wages are intended to inhibit. But, of course, it is the intrinsic unobservability of this behavior that lies at the heart of the efficiency wage hypothesis.

In this study we present an efficiency wage model of absenteeism in which the marginal utility of leisure of employees is increasing in two state-dependent parameters: a sickness level and the weather. In equilibrium, the relation between reported sickness absenteeism and the weather reflects the behavior of employees who are, on the margin, the least sick, implying a form of shirking. Pooling 12 years of employee data from Canada's monthly Labour Force Survey (LFS), which regularly queries reasons for short-term absences, we examine this relation across workers living in 56 Canadian cities facing different economic incentives to shirk contractual work hours. While we find clear evidence of a positive relationship in the summer months between the quality of outside weather conditions and reported sickness absenteeism, which appears largely driven by the behavior of hourly-paid workers, who are least likely to have contractual paid sick days, our findings offer little to support the mechanisms underlying the efficiency wage hypothesis.

The main limitation of our strategy is that we are only able to identify marginal changes, as opposed to levels, in one particular type of shirking activity – skipping work to take advantage of good weather. However, we believe our approach provides a more credible test than what is found elsewhere in the current literature in two important respects. First, the absenteeism-weather relation we focus on better captures the malfeasant employee behavior that concerns efficiency wage theory than what has been used elsewhere. Most notably, unlike the employee dismissal rates examined by Cappelli and Chauvin (1991), which we take to be the most credible attempt to directly measure shirking in the current literature, our measure potentially captures not only shirking that is detected, but also that which goes undetected. Second, once we condition on where an individual lives and the time of the year, weather conditions are unambiguously exogenous, thereby avoiding the identification issues that complicate the extant evidence.

In the following section of the paper we provide a more complete review of the existing empirical efficiency wage literature, as well as the separate empirical literatures using absenteeism and weather data. We then turn to the theoretical efficiency wage model on which we justify our empirical strategy. In Section 4, we describe our empirical methodology, including the data we employ. Section 5 then discusses the results, followed by a concluding section, which summarizes the main findings.

## 2 Existing Literature

Thirty years after Shapiro and Stiglitz (1984), the most frequently cited evidence of efficiency wages is still Krueger and Summers' (1988) analysis of inter-industry wage differentials. In particular, their finding of a negative relationship between these differentials and employee turnover, has been seen to be indicative of the types of pure wage premia implied by the theory. In their critical review, Murphy and Topel (1990) are skeptical arguing that systematic wage differences across industries are entirely consistent, both theoretically and empirically, with the sorting of workers on unobservable dimensions and, in conclusion, call for more direct tests relating these wage differentials to characteristics of industries that provide incentives for employers to pay wage premia. Following on this suggestion, Neal (1993) relates inter-industry wage differentials to a PSID measure of the frequency to which employees' work is monitored, while Chen and Edin (2002) compare wage premia of Swedish production workers paid piece rates, and therefore no incentive to shirk, as opposed to wage rates based on time. While the results of Chen and Edin are overwhelmingly mixed, Neal's findings tend to contradict the predictions of the shirking model of efficiency wages.[1]

The problem is that these are ultimately still indirect tests. A direct test of the shirking efficiency

[1] An earlier study by Leonard (1987) similarly relates wage differentials to a measure of supervisory intensity, but using firm-level data, and also finds little support for efficiency wage theory.

wage model would need to relate the instrument – a wage premium – to the outcome it is intended to influence – shirking activity. But of course, shirking is by its very nature unobservable. Relating wage rates to industry or firm-level productivity, as in Huang et al. (1998) and Wadhwani and Wall (1991) respectively, provides more direct evidence, but still falls short of measuring shirking directly (to say nothing of the difficulty of sorting out the direction of causality in these variables). To our knowledge Cappelli and Chauvin (1991), who examine employee dismissal rates using firm-level data, is the only study within the efficiency wage literature to directly measure malfeasant employee behavior. But even here, the analysis comes up short, since dismissal rates are driven not only by the extent of shirking activity within a workplace, but potentially also by the willingness or ability of employers to detect this behavior.

In this paper, we identify shirking activity be exploiting the link between the weather and reported sickness absenteeism. We are not the first to interpret variations in absenteeism as differences in employees' incentives to shirk. Leigh (1985), Audus and Goddard (2011), Arai and Thoursie (2005), and Askildsen, Bratberg and Nilsen (2005) interpret procyclical rates of sickness absenteeism as consistent with an increased cost of shirking during recessions, when lost jobs are less easily replaced. Using data from a large Italian bank, Ichino and Riphahn (2005) identify a sharp rise in employee absenteeism precisely when probationary periods end and legislative protections against firing kick in. Frick and Malo (2008) interpret variation in absenteeism rates across EU countries as resulting primarily from different sickness benefits. And Bradley, Green and Leeves (2007) interpret changes in absenteeism among Australian teachers who change schools as evidence of how workplace absence norms affect shirking incentives. The identification in these papers is, however, complicated by the possibility that observed variations in absenteeism reflect genuine health. Procyclical absenteeism is consistent with the cost of dismissal influencing shirking incentives, but also with evidence of countercyclical health (Ruhm 2000; Charles and DeCicca 2008). Group-interaction effects are consistent with local or workplace absence norms influencing shirking incentives, but also with contagious illnesses. And sick pay provision, whether from a company or legislative, are ultimately endogenous, potentially driven by the preferences of workers or voters with varying health. The only empirical papers in the econonomics literature to consider an independent role of health in determining absenteeism are those concerned with gender differences (Paringer 1983; Vistnes 1997; and Ichino and Moretti 2006). And interestingly, these papers consistently find that health factors are, if anything, more important in explaining observed absenteeism than economic factors that might affect shirking incentives.

We are also not the first in the economics literature to exploit the exogeneity of the weather. Roll (1984) and Angrist, Graddy and Imbens (2000) use weather conditions at sea and in Central

Florida to identify demand functions for fish and oranges, respectively. Boustan, Fishback and Kantor (2010) use extreme weather events to instrument migrant flows, while Burke and Leigh (2010) use adverse weather shocks to instrument output contractions. A much larger literature, however, is the research relating the weather to stock market returns and trading activity, which has been interpreted as evidence of the psychological effects of the weather, specifically tastes for risk, and against the efficient markets hypothesis of fully rational price setting (e.g., Saunders (1993); Hirshleifer and Shumway (2003); Jacobsen and Marquering (2008)). Lastly, Connolly (2008) 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 nature of the hours adjustments, in particular whether they reflect sickness absenteeism, overtime, vacation days, or even private time-in-lieu-of arrangements with employers, her results do not necessarily tell us anything about shirking activity.[2]

# 3 Model

Our model of shirking absenteeism builds on 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 provides a clean 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

[2] Searching across disciplines we have found three papers 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 correlation is interpreted as either the effect of weather on physical or mental health (e.g., influence of humidity on arthritic pain) or on the cost of getting to work (e.g., during a snow storm). The possibility of weather influencing shirking incentives is only ever mentioned as an afterthought. For example, in the discussion of his results, Mueser writes: "It is easy to imagine that when it was sunny and beautiful outside the chore of earning a livelihood was put off."

indoors. When spent outdoors, we assume $\delta = (1-\theta)\,\lambda$, where $\theta$ reflects an individual's level of sickness and $\lambda$ 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, $\theta$ and $\lambda$, are assumed randomly (uniform) and independently distributed in the population over the interval [0,1].[3]

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 $\theta^z$.[4] The employer's technology for monitoring employee sickness detects an individual's true sickness level $\theta$ with probability $\alpha$ 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.[5]

[3]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.

[4]$\theta^z$ 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.

[5]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 $\theta$ and $\lambda$) of being employed and unemployed in any period, respectively,

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:

$$\delta^c = \frac{w - \alpha\, b - (1-\alpha)\, s + \rho\,(1-a)\ [V(E) - V(U)]}{w - \alpha\, b - (1-\alpha)\, s + h} \tag{3.1}$$

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. Since the weather, unlike all the remaining exogenous variables of the model, only affects the outdoor sickness threshold $\theta^o$, 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. Given the practical difficulty of determining the legitimacy of sickness in the vicinity of $\theta^z$, observed relation between the weather and sickness absenteeism more clearly reflect the type of malfeasant behavior that efficiency wage models are concerned with. This leads to the first proposition (proofs of all propositions can be found in the Appendix).

**Proposition 1 (Weather-absenteeism relation)** *Marginal improvements in outdoor weather quality above some critical level $\lambda = \delta^c$, lead to an increase in sickness absenteeism that is unambiguously illegitimate.*

Although the weather-absenteeism relation is necessarily positive, its magnitude does vary with other shirking incentives. In particular, if existing shirking incentives are low, such as where the risk of being detected shirking is high, an improvement in the weather induces relatively healthy people to shirk. 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 $\theta^o$ adjusts upwards more, resulting in a larger increase in absenteeism than if shirking incentives were high to begin with.

---

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 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 $s > b$).

**Proposition 2 (Interaction effects in partial-equilibrium model)** *The marginal effect of the weather on sickness absenteeism is larger where existing shirking incentives are low, that is where the threshold marginal utility of leisure for choosing to be absent from work ($\delta^c$) 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.*

The assumed distributions of the sickness and weather parameters insure that $\delta^c < 1$, which implies that $\rho(1-a)[V(E) - V(U)] < h$ and $\partial\delta^c/\partial w > 0$. The wage rate, therefore, provides employers with an instrument to control the extent of shirking absenteeism. To model optimal wage-setting behavior, we assume the following sequence of events: (i) employers randomly offer $\bar{n}$ contracts providing wage $w$ for $h$ hours of work; (ii) all received offers are accepted (since $s > b$ and $V(E) - V(U) > 0$); and (iii) individuals receive sickness ($\theta$) and weather ($\lambda$) realizations and decide whether or not to attend work. This implies that although employers have just as much information about the current period's weather as their employees, they are unable to use the weather to influence wage-setting, since they must set wages prior to the weather being realized. As a result, Proposition 1 holds whether one thinks about the partial- or full-equilibrium model, that is, whether efficiency wages are paid or not. However, as we show below, the marginal effect of other shirking incentive parameters on the weather-absenteeism relation can be sharply different if the firm is able to use the wage to influence shirking incentives.

Turning to the full-equilibrium model, suppose firm revenue is an increasing and concave function of the number of contracted employees who turn up for work, given by $R(n)$ (normalizing the price of output to one). Assuming employers know the unconditional distribution of weather, and that there is no outdoor absenteeism when $\lambda \leq \delta^c$, their expected profits in any period are:

$$
\begin{aligned}
\mathrm{E}\{\pi(w,\bar{n})\} \quad = \quad & \int_0^{\delta^c} R(\theta^i \bar{n})\, d\lambda + \int_{\delta^c}^1 R\left((\theta^i - \theta^o)\bar{n}\right)\, d\lambda - \\
& \int_0^{\delta^c} \left[\left(\theta^i w + (1-\theta^i)k + (1-\theta^z)s + (1-\alpha)(\theta^z - \theta^i)s\right)\bar{n}\right] d\lambda - \\
& \int_{\delta^c}^1 [(\theta^i - \theta^o)w + (1 - \theta^i + \theta^o))k + (1-\theta^z)s + (1-\alpha)(\theta^z - \theta^i + \theta^o)s)\bar{n}]\, d\lambda
\end{aligned}
$$

where the four cost terms within both pairs of square parentheses reflect the costs associated with wages, monitoring, legitimate sick pay, and illegitimate sick pay, respectively. Solving the integrals, replacing the sickness thresholds with $\delta^c$ and simplifying, the employer's problem amounts to choosing $\bar{n}$ and $w$ to maximize:

$$
\mathrm{E}(\pi) \quad = \quad R(\Delta^c \bar{n}) - (\Delta^c(w - k - (1-\alpha)s) + (1 - \alpha\theta^z)s + k)\,\bar{n} \tag{3.2}
$$

subject to $\Delta^c = 2\delta^c - 1 - \delta^c \log(\delta^c)$ and equation (3.1). Since $w$ enters the profit function both directly and through $\Delta^c$ (via $\delta^c$), the firm faces the usual efficiency-wage model tradeoff in setting the wage, between lowering labour costs directly and limiting shirking incentives. The solution yields the two first-order conditions:

$$\frac{\partial \mathrm{E}(\pi)}{\partial w} = R'(\cdot)\,\frac{\partial \Delta^c}{\partial w}\,\bar{n} - \left[(w - k - (1-\alpha)s)\frac{\partial \Delta^c}{\partial w} + \Delta^c\right]\bar{n} = 0 \tag{3.3}$$

$$\frac{\partial \mathrm{E}(\pi)}{\partial \bar{n}} = R'(\cdot)\,\Delta^c - [\Delta^c\,(w - k - (1-\alpha)s) + (1 - \alpha\,\theta^z)s + k] = 0 \tag{3.4}$$

which together implicitly define the equilibrium wage rate:

$$(\Delta^c)^2 - \frac{\partial \Delta^c}{\partial w}\,[(1 - \alpha\,\theta^z)s + k] = 0. \tag{3.5}$$

Total differentiation of equation (3.5), to identify employer wage adjustments, together with equation (3.1), reveals that employer wage responses vary dramatically across other shirking incentive parameters. In particular, optimal wage adjustments are larger when both shirking incentives and direct costs increase, as in the case of an increase in sick pay $s$, than when only shirking incentives are affected, as in the case of the job acquisition rate $a$.[6] In fact, assuming efficiency wages are paid, an exogenous increase in sick pay $s$, leads employers to more than fully adjust wages, so that shirking incentives in the new equilibrium are actually lower. This distinction yields the final proposition.

**Proposition 3 (Interaction effects in full-equilibrium model)** *If employers augment the shirking incentives of employees through wage adjustments, that is pay efficiency wages, the weather-absenteeism relation is: (i) unambiguously decreasing in the job acquisition rate, but is attenuated relative to the partial-equilibrium case; (ii) unambiguously increasing in the generosity of sick pay; and (iii) either increasing or decreasing in the probability of being dismissed when shirking.*

Since more generous sick pay is associated with a *higher* weather-absenteeism relation in the full-equilibrium model, but a *lower* relation in the partial-equilibrium model, an estimate of this interaction provides evidence of the real-world relevance of efficiency wages. Moreover, since a positive association between the weather-absenteeism relation and the dismissal probability $\alpha$ is only possible in the full-equilibrium model, an estimate of this interaction potentially provides additional evidence. Lastly, since both models predict a negative effect of the job acquisition rate $a$, this interaction provides a falsification test of the general incentive structure of our model. Not only is this strategy more likely to capture the type of malfeasant shirking behavior that concerns

[6]To see this, note that both $s$ and $a$ enter equation (3.1), but only $s$ enters the firm's profit function, given by equation (3.2).

efficiency wage theory, but it also avoids any reliance on trying to estimate wage premiums, which is fraught with complication.

# 4 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 incentives. To do this, we first need to quantify the weather.

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

To do this, we link data on five weather elements – temperature, relative humidity, wind, cloud cover, and precipitation – in 56 Canadian cities with time-use data from three waves (1992, 1998 and 2005) of Statistics Canada's General Social Survey (GSS).[7] 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.[8] Although the data

[7]The weather data are publicly available from Environment Canada's National Climate Data and Information Archive (NCDIA).

[8]Even after restricting the sample to employees reporting a regular daytime schedule eliminates, nearly 10% of

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.[9] 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 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.[10]

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 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.[11] 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.[12] This leads to the following linear

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.

[9] 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.

[10] 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.

[11] 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 (%).

[12] 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

specification, which we estimate by probit regression:

$$Prob(outdoors_{ict} = 1) = \Phi\Big[\beta_0 + \beta_1 p_{ct} + (1 - p_{ct}) \cdot (\alpha_1 h_{ct} + \alpha_2 h_{ct}^2 + \alpha_3 w_{ct} + \alpha_4 w_{ct}^2 + \alpha_5(h_{ct} * w_{ict}) + \alpha_6(h_{ct}^2 * w_{ct}) + \alpha_7 d_{ct} + \mathbf{z}_c\gamma + \mathbf{x}_t\delta\Big]. \quad (4.6)$$

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, so that we can interpret the marginal weather effects 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 nothing to change our results.

Table 1 reports the main results of estimating (4.6). As expected, warmer weather results in a higher propensity for high-utility 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 cloud cover, result in less outdoor recreation.[13]

Having estimated (4.6), 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 $\lambda$ in our analysis of the sickness absenteeism data.[14] To provide us with some assurance of the meaningfulness of this index, in Fig-

plastic garbage cans tip over." This accounts for fewer than 1% of the observations in our data."

[13]Stepwise analysis beginning with a very general specification that allows thermal and aesthetic effects under physical conditions and includes quartic terms in the 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.

[14]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 (4.6) dropping activities where the location is ambiguous, such as swimming. The main effect of doing so is to change shift up the intercept rather than the shape of function. As indication of this, the optimal humidex and

ure 1 we plot it using average daily weather conditions between 1976 and 2008 from six Canadian cities – Toronto, Vancouver, Saint 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 tend to be warmer and drier. Integrating the city profiles from April to November, Toronto enjoys the highest average weather quality, followed by Vancouver, Montreal, Winnipeg, Edmonton, and St. John's.

### 4.2 Weather-absenteeism relation

Our data on sickness absenteeism come from Canada's monthly Labour Force Survey (LFS). These data have three important advantages. First, although surveys suggest faking sick days is commonplace, the empirical correlation between weather and reported sickness absenteeism is almost certainly very small.[15] We, therefore, need large amounts of data to identify it with any meaningful precision. 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, unlike the Current Population Survey (CPS) (the U.S. equivalent), the LFS identifies not only the usual (contractual) and actual weekly hours worked of employed respondents in the survey reference week (the week containing the $15^{\text{th}}$), but also the main reason for absence in cases where actual hours fall below usual hours. We are, therefore, able to distinguish sickness absenteeism from other types of absenteeism, 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 week. In addition, the weather data are observed hourly, so we are able to examine the differential

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.

[15] 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.

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.[16] 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 restrictions leave us with a final sample of 1,823,074 employees.

Since illegitimate sickness absences are more likely to be short-term, we begin our analysis of the LFS data by distinguishing absences that are 8 hours or less in duration from longer term part-week or full-week absences. We then further 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 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.[17]

A potential 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 what needs to be true here is that they increase in incidence when outdoor weather conditions improve. In this case, one would clearly have to infer malfeasance on the part of the supervisor, since condoning the use of sick days for the purpose of enjoying good weather is surely not accepted personnel policy anywhere. As it turns out, the weather-absenteeism relation we identify in the data almost exclusively reflects the behavior of hourly-paid 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 test the propositions in Section 3, we need to distinguish between workers facing different

[16] 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.

[17] In fact, our results tend to support this conjecture – absence due to family responsibilities are somewhat more strongly related to the weather than own illness, though in both cases we identify statistically significant positive effects of the weather.

incentives to shirk. To do this, we define 4 covariates. First, exploiting the rotating sampling structure of the LFS, in which respondents are potentially resampled for 6 consecutive months, we estimate unconditional month-to-month job acquisition rates for the unemployed separately by city and month. Second, to proxy the generosity of sick pay, 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.[18] Third, although we have defined the theoretical parameter $\alpha$ as simply a detection probability, we can straightforwardly extend the interpretation to the joint probability of detection and 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, we expect unionized workers 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 any discontinuity in absence behavior at 3 months when job protections usually kick in.

Distinguishing short- and 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:

$$Prob(absence_{ict} = j) = \frac{\exp(\mu_{ictj})}{1 + \exp(\mu_{ict1}) + \cdots + \exp(\mu_{ict4})} \tag{4.7}$$

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

$$\begin{aligned}\mu_{ictj} = \Big[ & f_j(weather_{ct}) + \theta_{1j} ar_{ct} + \theta_{2j} hr_{ict} + \theta_{3j} un_{ict} + \theta_{4j} ten_{ict} + \theta_{5j} ten_{ict}^2 + \theta_{6j} \mathbf{1}[ten_{ict} \geq 3] + \\ & \mathbf{ind}_{ict} \lambda_{1j} + \mathbf{occ}_{ict} \lambda_{2j} + \mathbf{z}_c \lambda_{3j} + \mathbf{x}_t \lambda_{4j} \Big].\end{aligned} \tag{4.8}$$

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 $t$; $ar_{ct}$ 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; $\mathbf{1}[ten_{ict} \geq 3]$ 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

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

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 $\mu_{ictj}$. We have tried estimating the function using various polynomials and it is clearly nonlinear. However, little is gained substantively beyond a simple quadratic.[19]

Propositions 2 and 3 are concerned with the marginal effect of the weather across other shirking incentive parameters. To test these propositions, we estimate (4.8) 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 ($un_{ict}$), and the post-probation dummy ($\mathbf{1}[ten_{ict} \geq 3]$). In the absence of efficiency wages (Proposition 2), we expect that the weather effect is highest where shirking incentives are lowest 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, if employers pay efficiency wages, the $hr_{ict}$ interaction should be negative, as employers use wages to limit the relative shirking incentives of salaried workers. In addition to this evidence, we also estimate a wage premium for each individual in the data by regressing their effective hourly wage rate on 8 education categories, a quartic in age, and a vector of city dummies. We then estimate (4.8) including and excluding the residual from this wage regression as an additional regressor to examine whether the estimated interaction effects change significantly, implying that wages are being used by employers to augment shirking incentives.

# 5 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 as expected the magnitude of the effect appears very small. The unconditional variation in the weather is, however, overwhelmingly seasonal, which explains both the tendency for short-term absences for reasons other than sickness or vacations to strongly decline with weather quality (Easter and Thanksgiving, two Canadian statutory holidays, 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

[19]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 on request

vary with season, it is important that we identify the weather-absenteeism relation conditional on the time of year.

The differences in short-term personal absences across job acquisition rates, union status, probation status, and estimated wage premiums are all consistent with the expected shirking incentive effects of these variables – personal absenteeism is higher when job acquisition rates are high, when job protection is high, and when wage premiums are low. 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, a wage premium may be induce less reported sickness absenteeism, but it could also be a consequence of good health. And workers paid an hourly-rate may be on average less healthy for reasons that have nothing to do with shirking incentives. It is precisely the difficulty in interpreting these differences as shirking incentives that motivates our use of the weather-absenteeism relation.

In Table 3 we present the results from estimating the baseline multinomial logit model defined by equations (4.7) and (4.8). The main finding is that the weather appears only to affect the incidence of short-term personal absences. In all the remaining cases, the coefficients on the weather index are statistically insignificant. Moreover, the direction of the weather effect on personal absences is consistent with Proposition 1, that is weather conditions more conducive to outdoor recreation result in more sickness absenteeism. The marginal effect is, decreasing, but positive up to an index value of 0.162, which falls above the 90$^{\text{th}}$ percentile of the weather quality distribution.[20] At the mean of the data, a one standard deviation increase in the weather quality index increases the probability of a short-term absence for personal reasons from 2.9% to 3.1%. This is clearly not a large effect, but given the substantial sample size, it is statistically significant at the 5% level.

Before considering how this weather effect on personal absences varies across employees facing different shirking incentives, we explore the effect further in two ways. First, rather than regressing on the overall average daytime weather quality from Monday through Friday, we consider the marginal effects 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 more personal absenteeism. The results in Table 4 suggest that Friday weather matters most, although the estimates are only marginally significant. That is, marginal improvements in the weather on Fridays, but not on any other day of the week, appear to increase personal absenteeism. This is consistent with the notion that past weather has a larger impact on the today's marginal utility of leisure than does future weather, which at least in the short-term can be forecasted reasonably well. Interestingly though, Monday weather appears to influence other types of short-term absences, as

[20] Estimating the model with a cubic or quartic weather function results in the marginal effect being positive over the full support of the weather distribution. These results are available on request.

well as long-term absences, although except for vacations, the estimated marginal effects are actually decreasing over most of the weather distribution (the negative quadratic term tends to dominate). This suggests the results for Mondays are capturing higher absenteeism on days other than Monday during weeks when Monday's weather is poor relative to the average weather during the rest of the week.

Following on this idea that the marginal utility of the weather is higher when recent past weather has been worse, 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 marginal utility of the current weather. Specifically, the estimates suggest that conditional on average weekend weather of 0.05 (roughly the 15$^{\text{th}}$ percentile), the probability of a personal absenteeism increases by 4.9% (from 2.04% to 2.14%) when the average workweek weather increases from 0.05 to 0.06. When average weekend weather is 0.15 (roughly the 90$^{\text{th}}$ percentile), on the other hand, a one-point increase in average workweek weather (from 0.15 to 0.16) increases personal absenteeism by only 3.5% (from 2.56% to 2.65%).[21]

Finally, 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) present the results from excluding and including, respectively, the estimated wage premium as an additional regressor. Due to the quadratic specification, the ranking of the marginal effects potentially changes over the empirical support of the weather quality index. 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$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the weather distribution separately for each of the four interacting variables. In the case of the job acquisition rate, this is done by comparing the profile between a job acquisition rate at the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles (or 0.13 compared to 0.23). Last, in cases where the ranking of the marginal effects switches, we indicate the point at which the marginal effects are equal with a vertical solid line.

In the case of the 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$^{\text{th}}$ percentile of the weather quality distribution (an index value of roughly 0.069). Efficiency wages will, of course,

[21] 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 the marginal utility of workweek weather is increasing in weekend weather over the entire distribution of the workweek weather.

tend to attenuate both effects (Proposition 3), so without conditioning on the wage premium, these results are not inconsistent with the efficiency wage hypothesis. However, conditioning on the wage premium, does essentially nothing to change these results, even though the wage premium in itself does appear to have the expected effect of reducing personal absenteeism. Therefore, although we do find a clear positive relation between overall personal absenteeism and job acquisition rates, the results do not support the idea that, in choosing to shirk contractual work hours, workers think about the likelihood of finding a replacement job in the event that their malfeasance is detected and they are dismissed.

A cleaner test of the efficiency wage hypothesis is with regard to the effect of sick pay on shirking incentives. 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 $35^{\text{th}}$ percentile (an index value of about 0.078) of the weather quality distribution. 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 $95^{\text{th}}$ 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 0.03 to 0.035, a 17% increase. This does not suggest that employers use wages to influence shirking incentives, since in this case (Proposition 3) we should see a greater responsiveness to weather improvements among workers with more sick pay. Moreover, the results are virtually identical whether or not we condition on the wage, suggesting further that wage rates are not influencing shirking incentives.

Lastly, the results in the final two columns of Table 6, point to very different responses to weather improvements between pre- and post-probation employees, but the implications for efficiency wage theory is more mixed. Specifically, marginal weather improvements below the median weather quality (an index value of 0.095) have a bigger impact on the personal absence rates of post-probation employees, whereas weather improvements above the median weather quality have a larger impact on pre-probation employees. Assuming a higher probability of dismissal among pre-probation employees, the results below the median are therefore consistent with Proposition 3, and the payment of efficiency wages, while the results above the median are consistent with both the partial or full-equilibrium model. One could argue that the types of outdoor activities that we are imagining employees substituting towards when they skip work, are more likely to be induced by marginal weather improvements at the upper end of the distribution, in which case the result is not particularly informative. We might expect, for example, that going from bad to not so bad weather induces less workday activity on the golf course, than going from good to great weather. However, once again, we obtain virtually the identical result whether or not we condition on the wage premium, suggesting once again that wages are not influencing the relative shirking incentives of pre- and post-probationary employees.

# 6 Summary

We argue that the existing efficiency wage literature, in particular the popular shirking version of the model, offers only indirect evidence of the efficiency wage hypothesis. To test the model directly one needs to identify shirking behavior, and not only that which is detected by employers. Using a theoretical model of shirking absenteeism in which the marginal utility of outdoor leisure is decreasing in sickness, we argue that the empirical relation between reported sickness absenteeism and the weather captures the behavior of employees who are the most healthy, implying a form of shirking. Moreover, the model provides us with a series of predictions related to other shirking incentive parameters, allowing us to test the efficiency wage hypothesis.

To model the weather's influence on the marginal utility of outdoor leisure, we link time-use data identifying the weekend and weekday evening outdoor recreational activities of wage and salary workers with weather data. We then relate the resulting weather quality index from this analysis to a large sample of wage and salary workers identifying short-term absences for personal reasons. The results point to a small, but statistically significant, positive relation between the quality of the weather and reported personal absenteeism. However, comparing the magnitude of this weather effect between employees facing different shirking incentives, offers little evidence to support efficiency wage hypothesis. Most notably, the results suggest that shirking absenteeism, at least that which is induced by the weather, occurs almost exclusively among those workers receiving the least sick pay, which we show is theoretically inconsistent with employers using wages to influence shirking incentives.

## REFERENCES


Angrist, Joshua D., Kathryn Graddy and Guido W. Imbens (2000), "The Interpretation of Instrumental Variables Estimators in Simultaneous Equations Models," *Review of Economic Studies* 67(3): 499-527.

Arai, Mahmood and Peter Skogman Thoursie (2005), "Incentives and selection in cyclical absenteeism," *Labour Economics* 12:269-80.

Askildsen, Jan Erik, Espen Bratberg and Øivind Anti Nilsen (2005), "Unemployment, labor force composition and sickness absence: a panel data study," *Health Economics* 14: 1087-1101.

Audas, Rick and John Goddard (2001), "Absenteeism, seasonality, and the business cycle," *Journal of Economics and Business* 53: 405-19.

Barmby, Tim, John Sessions, and John Treble (1994), "Absenteeism, efficiency wages and shirking," *Scandinavian Journal of Economics* 96(4): 561-66.

Blinder, Alan S. and Don H. Choi (1990), "A Shred of Evidence on Theories of Wage Stickiness," *Quarterly Journal of Economics* 105(4): 1003-15.

Boustan, Leah Platt, Price V. Fishback and Shawn Kantor (2010), "The Effect of Internal Migration on Local Labor Markets: American Cities during the Great Depression," *Journal of Labor Economics* 28(4): 719-46.

Bradley, Steve, Colin Green, and Gareth Leeves (2007), "Worker absence and shirking: evidence from matched teacher-school data," *Labour Economics* 14: 319-334.

Burke, Paul J. and Andrew Leigh (2010), "Do Output Contractions Trigger Democratic Change?" *American Economic Journal: Macroeconomics* 2: 124-57.

Capelli, Peter and Keith Chauvin (1991), "An Interplant Test of the Efficiency Wage Hypothesis," *Quarterly Journal of Economics* 106(3): 769-87.

Cerveny, Randall S. and Robert C. Balling Jr. (1998), "Weekly cycles of air pollutants, precipitation and tropical cyclones in the coastal NW Atlantic region," *Nature* 39: 561-3.

Charles, Kerwin Kofi and Philip Decicca (2008), "Local labour market fluctuations and health: is there a connection and for whom?" *Journal of Health Economics* 27: 1532-50.

Chatterji, Monojit and Colin Tilley (2002), "Sickness, absenteeism, presenteeism, and sick pay," *Oxford Economic Papers* 54: 669-687.

Chen, Paul and Per-Anders Edin (2002), "Efficiency Wages and Industry Wage Differentials: A Comparison Across Methods of Pay," *Review of Economics and Statistics* 84(4): 617-31.

Connolly, Marie (2008), "Here comes the rain again: Weather and the intertemporal substitution of leisure," *Journal of Labor Economics* 26(1): 73-100.

de Freitas, C.R., Daniel Scott and Geoff McBoyle (2008), "A Second Generation Climate Index for Tourism (CIT): Specification and Verification," *International Journal of Biometeorology* 52: 399-407.

Dickens, W.T. and L.F. Katz (1987), "Industry-Industry Wage Differences and Theories of Wage Determination," National Bureau of Economic Research Working Paper No.2271 (July).

Frick, Bernd and Miguel Malo (2008), "Labor market institutions and individual absenteeism in the European union: the relative importance of sickness benefit systems and employment protection legislation, *Industrial Relations* 47(4): 505-29.

Hirshleifer, David and Tyler Shumway (2003), "Good Day Sunshine: Stock Returns and the Weather," *Journal of Finance* 58(3): 1009-32.

Huang, Tzu-Ling, Arne Hallam, Peter F. Orazem, and Elizabeth M. Paterno (1998), "Empirical Tests of Efficiency Wage Models," *Economica* 65(257): 125-43.

Ichino, Andrea and Enrico Moretti (2006), "Biological gender differences, absenteeism and the earnings gap," NBER Working Paper Series, no. 12369.

Ichino, Andrea and Regina Riphahn (2005), "The effect of employment protection on worker effort: absenteeism during and after probation," *Journal of the European Economic Association* 3(1): 120-43.

Jacobsen, Ben and Wessel Marquering (2008), "Is It The Weather?" *Journal of Banking and Finance* 32: 526-40.

Krueger, Alan B. and Lawrence H. Summers (1988), "Efficiency Wages and the Inter-Industry Wage Structure," *Econometrica* 56(2): 259-93.

Leigh, J.P. (1985), "The effects of unemployment and the business cycle on absenteeism," *Journal of Economics and Business* 37: 159-70.

Leonard, Jonathan S. (1987), "Carrots and Sticks: Pay, Supervision, and Turnover," *Journal of Labor Economics* 5(4): S136-S152.

Markham, Steven E. and Ina S. Markham (2005), "Biometeorolgical effects on worker absenteeism," *International Journal of Biometeorolgy* 49: 317-24.

Mueser, Roland E. (1953), "The weather and other factors influencing employee punctuality," *Journal of Applied Psychology* 37(5): 329-37.

Murphy, Kevin M. and Robert H. Topel (1990), "Efficiency Wages Reconsidered: Theory and Evidence," in Y. Weiss and G. Fishelson, *Advances in The Theory and Measurement of Unemployment*, New York: St. Martin's Press, pp.204-40.

Neal, Derek (1993), "Supervision and Wages Across Industries," *Review of Economics and Statistics* 75(3): 409-17.

Paringer, Lynn (1983), "Women and absenteeism: health or economics?" *American Economic Review* 73(2): 123-27.

Pocock, S.J. (1972), "Relationship between sickness absence and meteorological factors," *British Journal of Preventive and Social Medicine* 26: 283-45.

Roll, Richard (1984), "Orange Juice and Weather," *American Economic Review* 74(5): 861-80.

Ruhm, Christopher J. (2000), "Are recessions good for your health?" *Quarterly Journal of Economics* 115(2): 617-50.

Saunders, Edward (1993), "Stock prices and Wall Street weather," *American Economic Review* 83(5): 1337-45.

Shapiro, Carl and Joseph E. Stiglitz (1984), "Equilibrium unemployment as a worker discipline device," *American Economic Review* 74: 433-44.

Vistnes, Jessica Primoff (1997), "Gender differences in days lost from work due to illness," *Industrial and Labor Relations Review* 50(2): 304-23.

Wadhwani, Sushil B. and Martin Wall (1991), "A Direct Test of the Efficiency Wage Model Using UK Micro-Data," *Oxford Economic Papers* 43(4): 529-48.

# APPENDIX

## 1. Proofs of Theoretical Propositions

*Proof of Proposition 1:*

The expected proportion of employees $\bar{n}$ who choose to shirk is
$\Pr(\theta < \theta^o) + \Pr(\theta^i < \theta < \theta^z) = (\theta^o) + (\theta^z - \theta^i)$, given that $\theta$ is uniformly distributed over the positive unit interval. But since $\theta^i$ depends only on the threshold marginal utility of leisure $\delta^c$, given by equation (3.1), and $\theta^z$ is an exogenous constant, a marginal improvement in the weather $\lambda$ only affects the extent of outdoor shirking $\theta^o$. Given that $\theta^o = (\lambda - \delta^c)/\lambda$, we have:

$$\frac{\partial \Pr(\theta < \theta^o)}{\partial \lambda} = \begin{cases} 0, & \text{if } \lambda \leq \delta^c \\ \delta^c/\lambda^2, & \text{if } \lambda > \delta^c \end{cases} \tag{6.9}$$

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

*Proof of Proposition 2:*

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 (3.1), we have:

$$\frac{\partial \delta^c}{\partial a} = \frac{\left(\frac{dw}{da}\right)[h - \rho\alpha(1-a)V] - \rho\alpha V(d+h)}{(d+h)^2} \tag{6.10}$$

$$\frac{\partial \delta^c}{\partial s} = \frac{\left(\frac{dw}{ds} - (1-\alpha)\right)(h - \rho\alpha(1-a)V)}{(d+h)^2} \tag{6.11}$$

$$\frac{\partial \delta^c}{\partial \alpha} = \frac{\left(\frac{dw}{d\alpha} + s - b\right)[h - \rho\alpha(1-a)V] + \rho(1-a)V(d+h)}{(d+h)^2} \tag{6.12}$$

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 $\partial\delta^c/\partial\alpha > 0$.

*Proof of Proposition 3:*

Applying the implicit function theorem to the solution of the profit maximization problem in equation (3.5) and using equation (3.1) to identify optimal employee responses to these adjustments yields:

$$\frac{\partial w}{\partial a} = \frac{\rho\,\alpha\,V(d+h)\,[f + 2\Delta^c\,(d+h)]}{2\,[h - (1-a)\rho\,\alpha\,V]\,[f + \Delta^c\,(d+h)]} \tag{6.13}$$

$$\frac{\partial w}{\partial s} = \frac{2(1-\alpha)f + 2\Delta^c(1-\alpha)(d+h) + (1-\alpha\theta^z)(d+h)}{2\,[f + \Delta^c(d+h)]} \tag{6.14}$$

$$\frac{\partial w}{\partial \alpha} = \frac{-\,[2(s-b)(f + \Delta^c d) + d\theta^z s]}{2\,[f + \Delta^c(d+h)]} \tag{6.15}$$

where $f = (1-\alpha\theta^z)s + k$. Substituting these optimal wage responses into equations (6.10), (6.11),and (6.12), yields:

$$\frac{\partial \delta^c}{\partial a} = \frac{-\rho\,\alpha\,V f}{2\,[f+\Delta^c(d+h)]\,(d+h)} < 0 \tag{6.16}$$

$$\frac{\partial \delta^c}{\partial s} = \frac{(1-\alpha\theta^z)\,[h-\rho\,\alpha\,(1-a)V]}{2\,[f+\Delta^c(d+h)]\,(d+h)} > 0 \tag{6.17}$$

$$\frac{\partial \delta^c}{\partial \alpha} = \frac{-\theta^z s\,h + (2-\theta^z s\,\alpha)\rho(1-a)V}{2\,[f+\Delta^c(d+h)]\,(d+h)} \gtreqless 0. \tag{6.18}$$

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. 74 observations are dropped as they predict failure perfectly. $^{***}$,$^{**}$,$^{*}$ 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* | | | | |
| 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 |
| *Wage premium* | | | | |
| Above median | 0.0284 | 0.0248 | 0.0936 | 0.1419 |
| Below median | 0.0290 | 0.0165 | 0.0757 | 0.1280 |
| *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 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. 348 observations due to perfect collinearity.
**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 | 6.5575** | 2.4478 | -8.5562 | -0.5693 |
| | (2.6224) | (3.6911) | (13.5421) | (3.0552) |
| Weather$^2$ | -20.2142** | -0.9761 | 1.1187 | 7.3205 |
| | (9.0606) | (14.0277) | (58.7870) | (11.4778) |
| Job acquisition rate | 0.4018*** | 0.2981* | -0.3501 | 0.1840 |
| | (0.1301) | (0.1650) | (0.5552) | (0.1299) |
| Hourly paid | 0.1191*** | -0.1912*** | -0.2068*** | -0.0668*** |
| | (0.0155) | (0.0178) | (0.0166) | (0.0096) |
| Unionized | 0.2345*** | 0.1226*** | 0.1088*** | 0.2953*** |
| | (0.0156) | (0.0181) | (0.0149) | (0.0087) |
| Tenure | 0.0002 | 0.0042*** | 0.0028*** | 0.0039*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0001) |
| Tenure$^2$/100 | -0.0002*** | -0.0007*** | -0.0006*** | -0.0007*** |
| | (0.00005) | (0.00006) | (0.00004) | (0.00003) |
| Tenure over 3 months | 0.1531*** | 0.5751*** | 0.2037*** | 0.7889*** |
| | (0.0234) | (0.0390) | (0.0219) | (0.0195) |
| Pseudo R$^2$ | | | 0.1657 | |
| 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 city, month, industry and occupation. 348 observations due to perfect collinearity. ***,**,* 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 | 2.2375 | 13.1377*** | 39.8204*** | 10.2158*** |
| | (2.2524) | (3.1367) | (11.5919) | (2.6680) |
| Monday-weather$^2$ | -9.8282 | -51.1590*** | -200.9854*** | -39.0970*** |
| | (8.6385) | (12.2899) | (61.2195) | (10.4876) |
| Tuesday-weather | -0.5801 | -2.4749 | 12.5052 | 0.5255 |
| | (2.5807) | (3.4517) | (11.9143) | (2.5222) |
| Tuesday-weather$^2$ | 11.2100 | 17.2040 | -66.0488 | 2.6776 |
| | (9.6677) | (13.1779) | (61.7932) | (9.9894) |
| Wednesday-weather | -1.5219 | -4.8344* | -14.5973 | -2.3748 |
| | (2.4094) | (2.9157) | (14.2424) | (2.4321) |
| Wednesday-weather$^2$ | 5.2409 | 18.4709 | 66.7904 | 8.2860 |
| | (9.2984) | (11.3210) | (70.7346) | (9.6140) |
| Thursday-weather | 2.0000 | -6.9326** | -18.5416 | -5.0625* |
| | (2.2841) | (3.3506) | (16.0903) | (2.8958) |
| Thursday-weather$^2$ | -9.5339 | 26.5969** | 92.0991 | 21.8189* |
| | (9.1171) | (13.0901) | (81.8273) | (11.5197) |
| Friday-weather | 4.5120* | 5.2101* | -11.5948 | -2.2374 |
| | (2.3643) | (2.8269) | (11.7471) | (2.3184) |
| Friday-weather$^2$ | -17.8365* | -17.2289 | 30.8694 | 8.2519 |
| | (9.1961) | (10.9881) | (55.8560) | (9.0901) |
| Pseudo R$^2$ | | | 0.1683 | |
| 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 includes the same set of controls as in Table 3. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively. 348 observations due to perfect collinearity.

**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 | 14.2333*** | 4.6366 | -4.9514 | -2.6632 |
| | (4.3952) | (6.6440) | (24.5429) | (5.8157) |
| Weather$^2$ | -67.6934*** | -19.0015 | -21.3904 | 22.0613 |
| | (23.4491) | (34.7819) | (146.8662) | (30.2773) |
| Weather*Previous weekend weather | -49.4974** | 1.0504 | -40.8981 | 5.8030 |
| | (22.1935) | (26.5284) | (105.7293) | (21.5337) |
| Weather$^2$*Previous weekend weather | 354.2457** | 68.7352 | 254.6248 | -75.8161 |
| | (146.3282) | (182.4440) | (831.7071) | (153.1947) |
| Pseudo $R^2$ | | | | |
| N | | | | |

**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 includes the same set of controls as in Table 3. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively. 348 observations due to perfect collinearity.
**Source:** 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

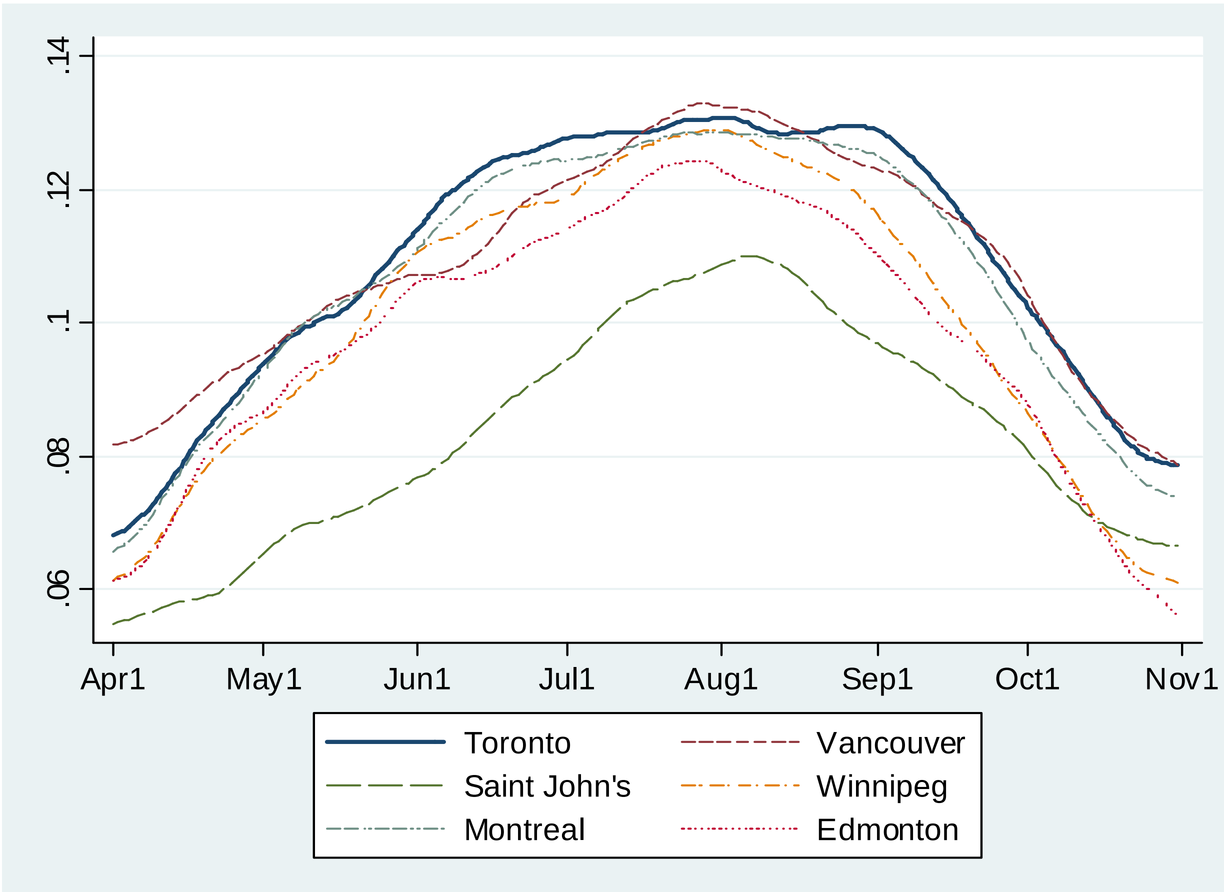
Table 6: Multinomial logit estimates of the probability of short-term absence due to personal reasons

| | Interaction variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Job acquisition rate | | Hourly paid | | Unionized | | $>3$ months tenure | |
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Weather | 6.3409* | 6.3403* | 9.6266*** | 9.6516*** | 6.2005** | 6.2097** | 1.2569 | 1.2864 |
| | (3.5510) | (3.5513) | (2.9625) | (2.9642) | (2.6641) | (2.6650) | (3.1566) | (3.1582) |
| Weather$^2$ | -21.3657 | -21.3534 | -39.4463*** | -39.5892*** | -17.2689* | -17.3069* | 8.0726 | 7.9945 |
| | (14.2818) | (14.2836) | (11.1085) | (11.1172) | (9.3302) | (9.3333) | (12.2773) | (12.2798) |
| Weather*Interaction | 2.1781 | 2.2044 | -4.2680*** | -4.2934*** | 1.3791 | 1.3699 | 5.8169** | 5.7917** |
| | (9.0417) | (9.0446) | (1.5252) | (1.5262) | (1.4372) | (1.4366) | (2.2781) | (2.2777) |
| Weather$^2$*Interaction | -0.8071 | -0.9367 | 27.6538*** | 27.8262*** | -10.1186 | -10.0673 | -31.0472*** | -30.9860*** |
| | (39.6891) | (39.7042) | (7.3080) | (7.3123) | (6.6914) | (6.6892) | (10.3029) | (10.3005) |
| Job acquisition rate | 0.1956 | 0.1966 | 0.4004*** | 0.4025*** | 0.4018*** | 0.4039*** | 0.4017*** | 0.4038*** |
| | (0.4557) | (0.4559) | (0.1302) | (0.1303) | (0.1302) | (0.1303) | (0.1301) | (0.1302) |
| Hourly paid | 0.1192*** | 0.1145*** | 0.2455*** | 0.2414*** | 0.1194*** | 0.1148*** | 0.1193*** | 0.1147*** |
| | (0.0155) | (0.0154) | (0.0739) | (0.0740) | (0.0155) | (0.0154) | (0.0155) | (0.0154) |
| Unionized | 0.2345*** | 0.2394*** | 0.2336*** | 0.2387*** | 0.2064*** | 0.2117*** | 0.2345*** | 0.2395*** |
| | (0.0156) | (0.0155) | (0.0156) | (0.0155) | (0.0714) | (0.0713) | (0.0156) | (0.0155) |
| Tenure | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Tenure$^2$/100 | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** | 0.0002*** |
| | (0.00005) | (0.00005) | (0.00005) | (0.00005) | (0.00005) | (0.00005) | (0.00005) | (0.00005) |
| Tenure over 3 months | 0.1531*** | 0.1526*** | 0.1539*** | 0.1534*** | 0.1534*** | 0.1529*** | -0.0808 | -0.0794 |
| | (0.0234) | (0.0234) | (0.0234) | (0.0234) | (0.0234) | (0.0234) | (0.1183) | (0.1183) |
| Wage premium | – | -0.0414** | – | -0.0426*** | – | -0.0413** | – | -0.0415** |
| | | (0.0162) | | (0.0162) | | (0.0162) | | (0.0162) |
| Pseudo R$^2$ | 0.1658 | 0.1660 | 0.1659 | 0.1662 | 0.1660 | 0.1662 | 0.1658 | 0.1660 |
| 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 includes the same set of controls as in Table 3. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively. 348 observations due to perfect collinearity.

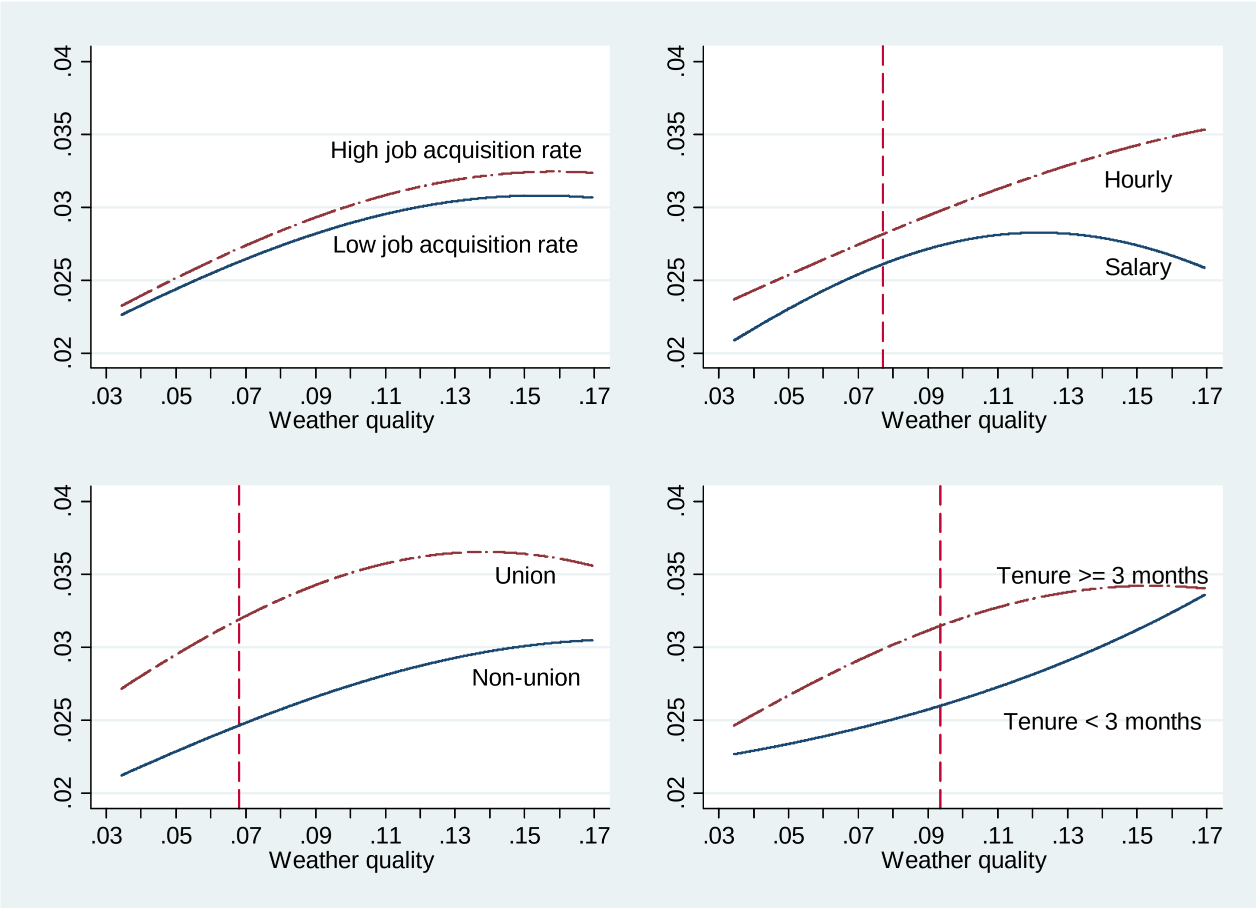
**Source:** 1997 to 2008 Labour Force Survey (LFS) and Canadian National Climate Data and Information Archive (NCDIA).

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




**Notes:** Vertical axis plots the predicted probability of of outdoor recreation from (4.6) 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.