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Daylight and absenteeism – Evidence from Norway☆

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ABSTRACT

Based on administrative register data from Norway, we examine the impact of hours of daylight on sick-leave absences among workers. Our preferred estimates imply that an additional hour of daylight increases the daily entry rate to absenteeism by 0.5 percent and the corresponding recovery rate by 0.8 percent, ceteris paribus. The overall relationship between absenteeism and daylight hours is negative. Absenteeism is also sensitive to weather conditions. Heavy snowfall raises the incidence of absence during the winter, while warm weather reduces the probability of returning to work during the summer.

1. Introduction

The purpose of this paper is to examine the impact of hours of daylight on absenteeism due to illness. Daylight could affect sick leave through both the valuation of leisure and through physical and mental wellbeing. To our knowledge, no previous study has examined the relationship between hours of daylight and the value of leisure. However, based on the American Time Use survey, Connolly (2008) shows that there is a causal relationship between weather conditions in general and the enjoyment of leisure. On rainy days, men shift on average 30 min from leisure to work. There is also ample evidence regarding daylight-related seasonal fluctuations in mental health. For example, on the basis of US data collected at four different latitudes, Rosen et al. (1990) find that the prevalence of winter-type seasonal affective disorders is significantly higher at northern latitudes where the periods of darkness are longest. Lingjærde et al. (1986) present similar evidence for Norway showing that there is a higher prevalence of winter depression in the northern than in the southern counties. And recent evidence from Greenland indicates that the frequency of suicides rises during the summer months in areas with midnight sun, suggesting that long periods of constant light may also have negative effects on mental health through sleep deprivation (Björkstén et al., 2009). These findings suggest that natural daylight variations help synchronize the internal body clock to the earth's 24-h light–dark rotational cycle (Czeisler et al., 1999; van Bommel and van den Beld, 2004).

There is to our knowledge no empirical evidence regarding daylight and worker absenteeism. Such evidence may improve our understanding of regional and seasonal variation in absenteeism, and may also shed light on workers' sick leave behavior in general. There is a small related literature on the relationship between meteorological variables, such as temperature, air pressure, humidity,

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and precipitation and worker absenteeism; see, e.g., Pocock (1972), Smith (1977), and, more recently, Markham and Markham (2005) and Shi and Skuterud (2011). This literature shows that weather conditions potentially affect absenteeism both through their impacts on commuting/attendance costs and through their impacts on particular health conditions. There is also a related literature on the determinants of absenteeism more generally, showing that workers' absence behavior is sensitive with respect to financial incentives (Henrekson and Persson, 2004; Johansson and Palme, 2005; Ziebarth and Karlsson, 2010). This finding suggests that there is a choice-element in absenteeism and, hence, also a potentially decisive role for the utility of leisure. Our paper is also more vaguely related to a broader economics literature focusing on behavioral aspects of daylight variations and sleep patterns, featuring a wide range of topics, such as youth suicide (Hansen and Lang, 2011), academic performance (Carrell et al., 2011) and stock market performance (Kamstra et al., 2000).

In the present paper, we examine the effects of daylight-hours on worker absenteeism in Norway. Due to its geographical location, Norway is an ideal country for investigating daylight effects. The country extends from 58° to 71° north, crossing the Arctic Circle, and the number of daylight-hours varies over the year and across regions from 0 to 24 h. Still, thanks to the Gulf Stream, the north/south temperature differential is modest, facilitating identification of daylight effects. We exploit administrative registers with daily physician-certified absence data for employees in 10 large municipalities. The municipalities are selected to ensure a maximum of idiosyncratic variation in daylight patterns. In order to isolate the impacts of daylight from other (potentially correlated) sources of seasonal and cross sectional variation in absenteeism we use both day-fixed and municipality-fixed effects in our empirical analysis. In addition, we control for local weather-conditions.

Our main finding is that hours of daylight significantly raise the probability of ending a sick-leave spell, ceteris paribus The overall absence rate declines monotonically with hours of daylight.

2. Data

The data we use are collected from administrative registers, and comprise all physician-certified absence spells – their starting dates and their stopping dates – for all employees in 10 Norwegian municipalities from 2002 through 2005.[1] We use these data to compute daily incidence rates (percent of those who were present yesterday who are absent today) and recovery rates (percent of those who were absent yesterday who are present today) at the municipality level. To eliminate the potentially disturbing sources of idiosyncratic seasonal variation in absence behavior arising from variation in seasonal employment, we exclude employees in the construction industries, in tourism, and in farming and fisheries. The delimitation to physician-certified absences is forced upon us by data availability. Absence spells are normally certified by a physician when they exceed three days. This implies that we do not observe very short absence spells, and that the starting dates may be recorded with some measurement error (in most cases the spell will have started 1–3 days earlier than the date reported in our data). The stopping dates will typically be determined some days prior to the actual return-to-work date.[2] Hours of daylight is a continuous variable ranging from 0 to 24 h, calculated as a function of the day of year and the municipalities' latitude. It is calculated for all calendar days and in all municipalities.

Fig. 1 gives an overview of the seasonal pattern in absence behavior in the most northern and the most southern municipalities (based on averages taken over all four years in the dataset). Note first from panel a that there are significant differences in daylight patterns across these two groups of municipalities. The average absence rates plotted in panel b show that the absence rate is 15–20 percent higher in the north than in the south. Yet, the seasonal pattern is more or less the same in the two regions, implying that the north–south absence-differential is relatively constant. This similarity is deceptive, however, as the seasonal pattern in the underlying entry and recovery rates vary substantially across the two regions; see panels c and d. The positive north–south differential in incidence rates is larger during the summer than during the winter, whereas the opposite is the case for the negative differential in recovery rates. This is more clearly illustrated in Fig. 2, where we focus on relative north–south differentials. It is evident that both incidence- and recovery differentials correlate strongly and positively with daylight differentials. For the overall absence rate, the picture is less clear, since the impacts of incidence and recovery differentials pull in opposite directions – more daylight apparently raises the frequency of absences, but also reduces their duration.

Table 1 gives an overview of the data used in our empirical analysis. To disentangle daylight-effects from weather characteristics that are potentially correlated to daylight, we have collected daily data on local weather conditions, including temperature, precipitation, wind speed, and cloudiness. Table 1 shows that there are indeed some significant differences in weather conditions between the southern and the northern municipalities, particularly with respect to temperature, precipitation, and windiness. In the statistical analysis, we control for these differences.

The data used in our statistical analysis comprise daily aggregate absence observations for all the 10 municipalities. Our data window covers the period from January 1, 2002 to December 31, 2005, but some observations are lost due to missing weather information. In total, we have 13,642 municipality-day observations that can be used in the statistical analysis.

[1] The municipalities are Oslo, Lillehammer, Stavanger, Bergen, Trondheim, Stjørdal, Bodø, Tromsø, Vardø, and Alta.

[2] For this paper, we have not had access to information about the specific diagnoses. These diagnoses are in any case not always very informative with respect to the underlying health problem, as they are used very differently by different physicians; see Maeland et al. (2012).

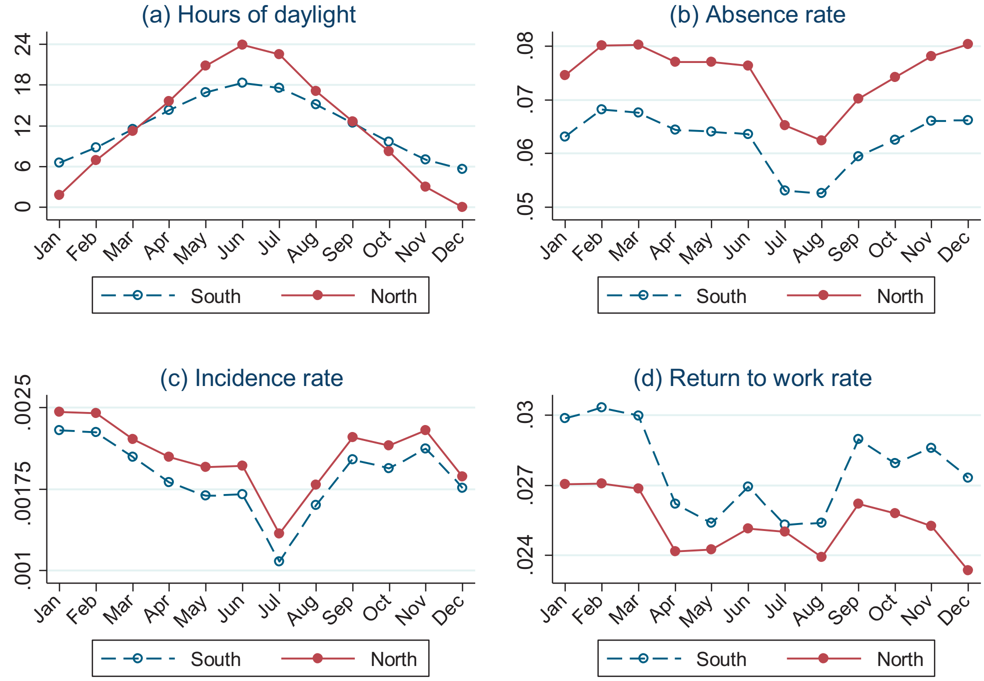

Fig. 1. Daylight and absenteeism in Norway's Northern and Southern municipalities. *Note*: South includes Stavanger, Oslo, Bergen, and Lillehammer. North includes Tromsø, Alta, and Vardø.

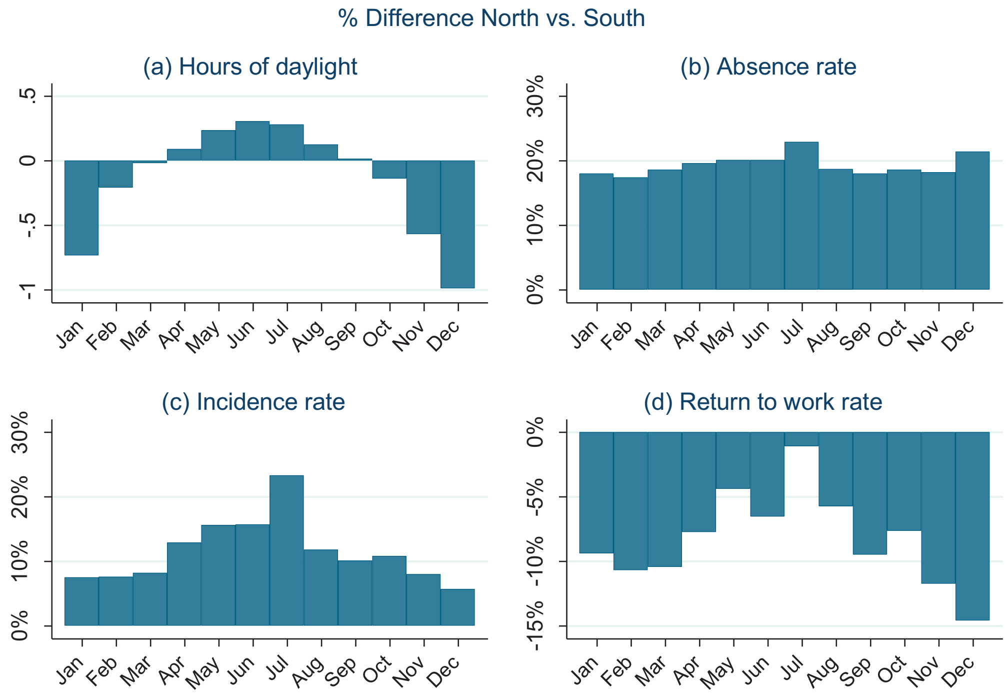

Fig. 2. Relative differences in daylight and absenteeism between Norway's Northern and Southern municipalities.

3. Empirical analysis

In the empirical analysis, we use two dependent variables: (i) the daily rate of entry into certified absence (i.e., the fraction of employees who were not absent "yesterday" who are absent "today") and (ii) the daily rate of recovery (i.e., the fraction of employees who were absent "yesterday" who are not absent "today"). For both outcomes, we estimate weighted (by the number of employees) linear regression models with day-fixed and

Table 1
Descriptive statistics: sickness absence, hours of daylight and weather conditions in the municipalities used for estimation.

	Stav-anger	Oslo	Bergen	Lilleh-ammer	Trond-heim	Stjørdal	Bodø	Tromsø	Alta	Vardø
No. workers	42,357	230,624	96,212	9983	64,707	7313	19,003	26,633	6078	896
Sickness absence (daily averages)										
Absence rate	5.45	6.15	6.83	7.56	7.08	7.18	6.90	7.56	8.87	8.01
Inflow rate	0.17	0.19	0.20	0.17	0.18	0.17	0.18	0.22	0.20	0.19
Recovery rate	2.84	2.83	2.65	2.06	2.28	2.15	2.46	2.71	2.08	2.14
Daylight hours										
Average	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
Max.	18.1	18.5	18.6	18.9	20.0	20.0	24.0	24	24	24
Min.	5.8	5.5	5.4	5.1	4.0	4.0	0	0	0	0
Weather conditions (averages)[a]										
Temp. (°C)	8.6	7.2	8.7	4.5	6.3	6.4	5.6	3.8	2.9	2.8
Precip.	3.4	2.1	7.1	2.1	2.3	2.4	3.2	3.2	1.2	1.7
Clouds	4.3	4.3	4.6	4.3	4.2	4.2	4.4	4.5	4.1	4.9
Wind (m/s)	6.4	4.0	5.4	2.9	3.8	5.4	8.1	4.6	5.1	7.9
Worker characteristics (averages)										
Age	41.2	40.7	42.1	43.7	42.2	43.0	42.0	41.4	40.8	41.5
Female (%)	50.4	50.5	50.3	52.0	49.7	48.1	50.9	51.2	52.6	51.7
Years of educ.	13.5	13.8	13.7	13.8	13.9	13.1	13.4	13.7	13.2	12.2
Public sector (%)	34.6	31.5	35.9	46.4	40.1	36.1	47.8	48.2	43.3	56.5
Degrees North	58	59	60	61	63	63	67	69	69	70

[a] Temperature is measured in degree Celsius, precipitation in millimeters per day, wind speed in meters per second, and cloudiness in the fraction of the visual sky that is covered by clouds (measured in 1/8 s, such that 0 is a clear sky and 8 is a sky fully covered by clouds).

municipality-fixed effects, implying that it is *only* the idiosyncratic seasonal variation in daylight hours that is used to identify the effects of interest. We control for local weather conditions by means of 5-day moving averages (from three days before to one day after the day of interest) for the four meteorological variables listed in Table 1; see the note to that table for details on measurement. The reason why we use a 5-day moving average here is related to the inaccuracy in the exact starting and stopping dates described in the previous section. The impacts of the weather variables are estimated separately for the summer (April–September) and winter (October–March) seasons.[3] Thus, our empirical strategy amounts to tracing out the variations in the seasonal absence patterns that can be attributed to daylight variations, while controlling for cross-sectional long-term differences (municipality-fixed-effects), for longitudinal fluctuations and shocks experienced by all municipalities on the same dates (day-fixed-effects), and for local weather conditions.

Let d_{it} be the number of daylight hours in municipality i at time (day) t, let w_{it} be a vector of corresponding weather observations. Our baseline empirical model is specified as follows:

$$y_{it} = c + \alpha(d_{it}) + w_{it}\gamma + \delta_t + \kappa_i + u_{it}, \tag{1}$$

where y_{it} is one of the two outcome measures outlined above, $\alpha(d_{it})$ is a function of daylight hours, δ_t is a day-fixed effect, κ_i is a municipality-fixed effect, and u_{it} is residual.

[3] In some specifications, we have also included data for pollen intensity, but this did not affect the results to any noticeable extent. Since pollen information is missing for a large number of cases, we have dropped this variable from the estimations reported here.

We try out alternative functional forms for $\alpha(d_{it})$, i.e., a linear, a quadratic, and a "nonparametric" step-function. The latter is a vector of 15 dummy variables indicating the number of daylight hours. The categories are [0,4], (4,5], (5,6], (6,7], (7,8], (8,9], (9,10], (10,13], (13,14], (14,15], (15,16], (16,17], (17,18], (18,19], (19,24], where "[x" means *including x* and "(x" means *greater than x*.

Fig. 3 presents the resultant estimated daylight-impacts, with 95 percent confidence intervals based on municipality-clustered standard errors; see Bertrand et al. (2004). While all the models indicate that recovery rates rise with hours of daylight, the effects on incidence are imprecisely estimated and also less robust. The discrepancy between the different models reflects a combination of statistical uncertainty and differences in the foundation for identification. While the parameter estimates of the polynomial models are dominated by the variation within a central area of the daylight distribution (for which there are much more observations than toward the tails), the nonparametric model circumvents this implicit weighting. All the models indicate a weak positive relationship between daylight and the incidence rate to absenteeism, however.

At this point, it may be of some interest to see how the estimated daylight-impacts are influenced by the selection of control variables. This is illustrated for the linear model in Table 2. Had we not controlled for municipality and national seasonal fluctuations, we would have drawn exactly the opposite conclusions of what we presented above, for both incidence and recovery. Hence, in order to identify the isolated impact of *daylight hours*, it is essential to control for local levels differences as well as for seasonal fluctuations that correlate with the daylight pattern. It is also notable that the introduction of weather controls

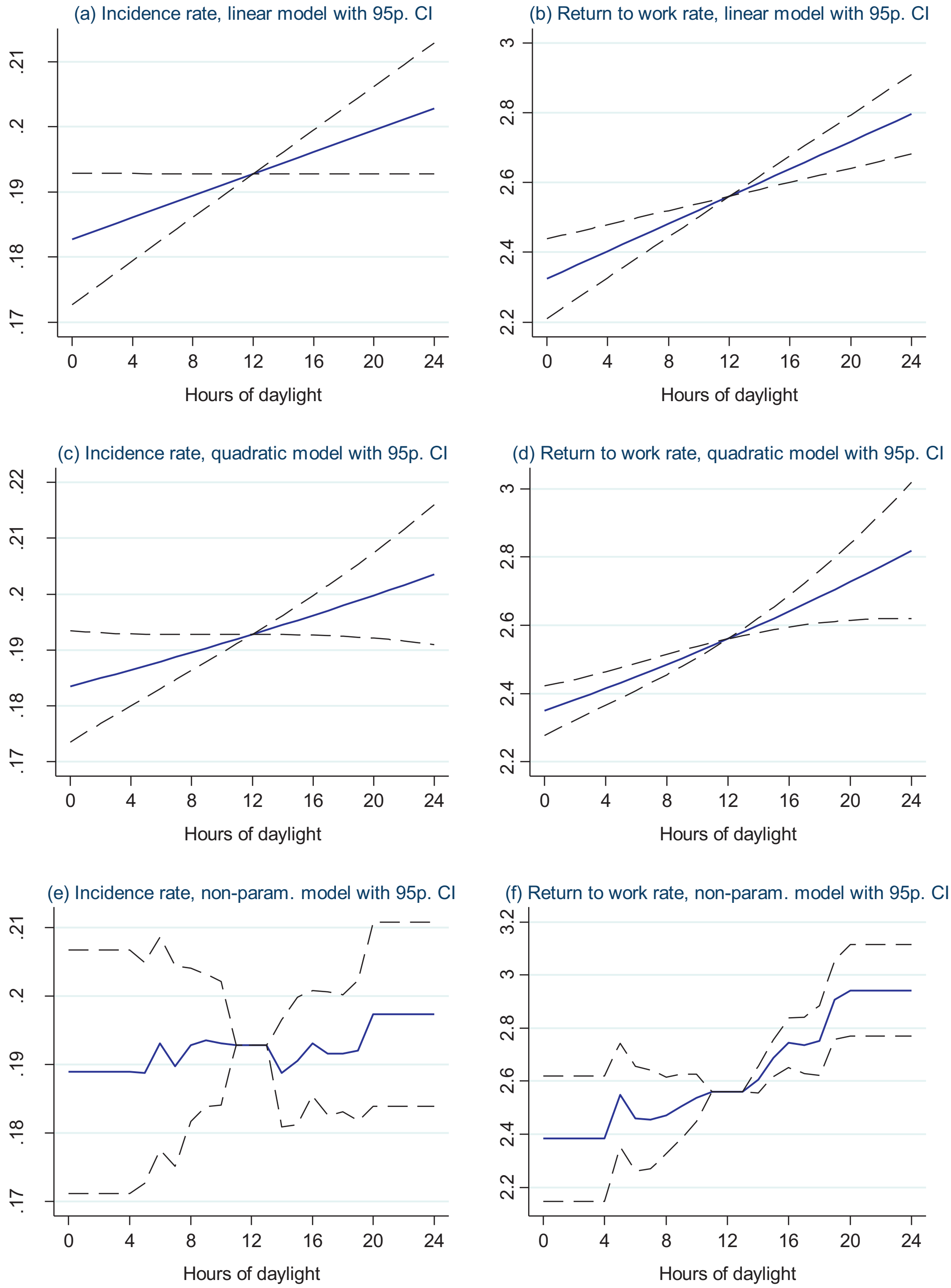

Fig. 3. The estimated impacts of daylight hours on daily entry to and exit from sick leave. *Note*: The rates are normalized to equal the true national mean at 12 h of daylight (which occurs at the same time everywhere, i.e., around 20–21 March and 22–23 September each year)

makes the relationships between daylight and absenteeism weaker.

Tables 3 and 4 presents the estimation results for our preferred models (with all control variables included) in more detail, including the estimated effects of meteorological variables. The estimated influences of weather variables are the same regardless of how we represent the daylight effects, and most of the variables have small and/or insignificant effects on absenteeism. It seems clear, however, that periods of heavy snowfall raise the incidence of absence during the winter, while warm weather reduces the probability of returning to work during the summer. These findings, which are both in line with existing evidence (Markham and Markham, 2005), indicate a role

Table 2
The estimated relationship between hours of daylight and workers' absenteeism, using a linear specification.

	Incidence				
	I	II	III	IV	V (preferred)
Daylight hours	−0.00429*** (0.00054)	−0.00073 (0.00080)	0.00105*** (0.00024)	0.00108*** (0.00031)	0.00084* (0.00043)
	Recovery				
	VI	VII	VIII	IX	X (preferred)
Daylight hours	−0.02181*** (0.00521)	0.00395 (0.00860)	0.01749*** (0.00505)	0.025619*** (0.00636)	0.019630*** (0.00485)
Controls (both in models for incidence and for recovery)					
Municipality	No	Yes	Yes	Yes	Yes
Year and month	No	Yes			
Weak and weak day	No	No	Yes		
Day	No	No	No	Yes	Yes
Weather	No	No	No	No	Yes

Notes: Dependent variables are defined as follows: For incidence: The percent of employees who where present "yesterday" who are absent "today". For recovery: The percent of employees who where absent "yesterday" who are present "today". *(**)(***) Significant at the 10(5)(1) % level. Standard errors clustered on municipality in parentheses. The dataset covers 10 Norwegian municipalities, in total 503,806 workers, from day to day over the years 2002–2005. The preferred model controls for municipality fixed effects, calendar day fixed effects as well as weather. Hours of daylight is calculated daily for each municipality, based on latitude.

for opportunity costs in decisions about absenteeism. On the other hand, we also find that cloudy skies reduce the recovery rate throughout the year, perhaps indicating that weather conditions also affect (mental) health.

Table 3
The estimated relationship between hours of daylight and workers' incidence rate to absenteeism, using a linear, quadratic and non-parametric specification.

	Linear model	Quadratic model	Non-parametric model
Daylight	0.00084** (0.00043)	0.00083* (0.00042)	–
Daylight-squared/100	–	0.00049 (0.0019)	–
Temperature winter	0.00014 (0.00029)	−0.00014 (0.00029)	0.00017 (0.00023)
Temperature summer	−0.00021 (0.00042)	−0.00021 (0.00042)	−0.00022 (0.00039)
Precipitation winter	0.00018*** (0.00004)	0.00018*** (0.00004)	0.00018*** (0.00004)
Precipitation summer	0.00003 (0.00009)	0.00003 (0.00009)	0.00004 (0.00008)
Cloudiness winter	−0.00017 (0.00024)	−0.00017 (0.00024)	−0.00017 (0.00023)
Cloudiness summer	0.00045* (0.00023)	0.00045* (0.00024)	0.00045* (0.00022)
Wind winter	−0.00052 (0.00054)	−0.00052 (0.00054)	−0.00052 (0.00053)
Wind summer	−0.00003 (0.00026)	−0.00002 (0.00026)	0.00002 (0.00025)
Adj. R-squared	0.9765	0.9765	0.9737
# Obs.	13,642	13,642	13,642

Notes: The dependent variable is defined as the percent of employees who where present "yesterday" who are absent "today". *(**)(***) Significant at the 10(5)(1) % level. Standard errors clustered on municipality in parentheses. Daylight is represented by 15 dummy variables (see Fig. 3 for coefficient estimates). The range of each explanatory variable is reported in brackets. The dataset covers 10 Norwegian municipalities, in total 503,806 workers, from day to day over the years 2002–2005. The model controls for municipality fixed effects, calendar day fixed effects as well as weather. Hours of daylight is calculated daily for each municipality, based on latitude.

To check whether there are differences in daylight-responses between men and women, we have estimated the linear specification separately for the two sexes. It turns out there are no differences at all. For incidence, we estimate a daylight effect of 0.00081 for men and of 0.00089 for women. For recovery, we estimate a daylight effect of 0.02054 for men and of 0.01957 for women. The coefficients for men and women are not statistically different. Using and interaction term, the p-values on the sex-difference in the response to daylight is 0.914 for incidence and 0.891 for recovery.

How is overall absenteeism affected by daylight hours? To answer this question, we use the estimated incidence and recovery profiles shown in Fig. 3 to compute steady state absence rates; i.e., the absence rates consistent with inflow = outflow (these are equal to the inflow rate divided by the sum of the inflow rate and the outflow rate). The results are depicted in Fig. 4. They indicate a downwards

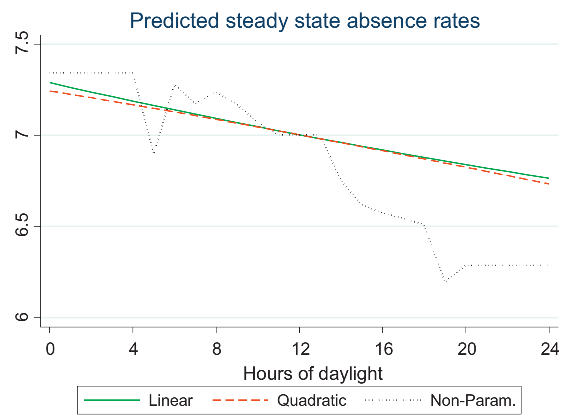

Fig. 4. Steady state absence rate predicted by the linear, quadratic and cubic models. *Note*: The absence rates are normalized to equal the true national mean at 12 h of daylight.

Table 4
The estimated relationship between hours of daylight and workers' recovery rate from absenteeism, using a linear quadratic and non-parametric specification.

	Linear model	Quadratic model	Non-parametric model
Daylight	0.01963***	0.01956***	–
	(0.00485)	(0.00475)	
Daylight-squared/100	–	0.01679	–
		(0.03562)	
Temperature winter	0.00014	0.00015	−0.00018
	(0.00281)	(0.00280)	(0.00297)
Temperature summer	−0.01486**	−0.01489**	−0.01274**
	(0.00722)	(0.00716)	(0.00574)
Precipitation winter	0.00167	0.00168	0.00179
	(0.00134)	(0.00136)	(0.00137)
Precipitation summer	0.00022	0.00020	0.00064
	(0.00087)	(0.00087)	(0.00085)
Cloudiness winter	−0.01165***	−0.01140***	−0.01122***
	(0.00314)	(0.00343)	(0.00375)
Cloudiness summer	−0.01558***	−0.01533***	−0.01491***
	(0.00408)	(0.00443)	(0.00284)
Wind winter	−0.00020	−0.00025	−0.00014
	(0.00739)	(0.00746)	(0.00822)
Wind summer	0.00123	0.00135	0.00134
	(0.00581)	(0.00577)	(0.00516)
Adj. R-squared	0.9632	0.9632	0.9633
# Obs.	13,642	13,642	13,642

Notes: The dependent variable is defined as the percent of employees who where absent "yesterday" who are present "today" *(**)(***) Significant at the 10(5)(1) % level. Standard errors clustered on municipality in parentheses. Daylight is represented by 15 dummy variables (see Fig. 3 for coefficient estimates). The range of each explanatory variable is reported in brackets. The dataset covers 10 Norwegian municipalities, in total 503,806 workers, from day to day over the years 2002–2005. The model controls for municipality fixed effects, calendar day fixed effects as well as weather. Hours of daylight is calculated daily for each municipality, based on latitude.

sloping relationship between daylight hours and absenteeism.[4] Again, there is a difference between the linear and quadratic specifications, on the one hand, and the nonparametric specification, on the other, whereby the latter predicts a steeper decline at higher hours of daylight.

4. Conclusion

Absenteeism is affected by daylight as well as weather conditions. More hours of daylight implies lower overall absenteeism, ceteris paribus The recovery rate increases significantly with daylight, whereas there are weaker indications that also the spell frequency rises somewhat. This may be two sides of the same coin; a higher rate of incidence implies that the threshold for claiming sick declines with hours of daylight, which again implies that average seriousness – and, hence, duration – declines. However, if this was the only explanation, we would probably have seen a significant rise in the total absence rate, since it would indicate that the higher recovery rate only applied for the additional – lower-threshold – absences. Instead, we find that overall absenteeism declines with daylight hours. The relationship identified between weather conditions and absenteeism indicate that absence decisions to some extent are sensitive with respect to the costs of going to work; heavy snowfall raises the incidence of absence during the winter, whereas warm weather reduces the return-to-work rate during the summer.

Can differences in daylight hours explain the north–south differential in absenteeism among Norwegian workers? No, they can't. There are admittedly somewhat higher absence rates in the north during winter times due the long hours of darkness. But the differences are small, and they are more or less neutralized by the relatively lower absence rates during summer times.

Conflict of interest

There are no conflicts of interest in relation to this research.

References

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Quarterly Journal of Economics 119 (1) 249–275.

van Bommel, W.J.M., van den Beld, G.J., 2004. Lighting for work: a review of visual and biological effects. Lightning Research and Technology 36, 255.

Björkstén, K.S., Kripke, D.F., Bjerregaard, P., 2009. Accentuation of suicides but not homicides with rising latitudes of Greenland in the sunny months. BMC Psychiatry 9, 20 (electronic article).

Carrell, S.E., Maghakian, T., West, J.E., 2011. A's from Zzzz's? The causal effect of school start time on the academic achievement of adolescents. American Economic Journal 3 (3) 62–81.

Connolly, M., 2008. Here comes the rain again: weather and the intertemporal substitution of leisure. Journal of Labor Economics 26 (1) 73–100.

Czeisler, C.A., Duffy, J.F., Shanahan, T.L., Brown, E.N., Mitchell, J.F., Rimmer, D.W., Ronda, J.M., Silva, E.J., Allan, J.S., Emens, J.S., Dijk, D.-J., Kronauer, R.E., 1999. Near-24-hour period of the human circadian pacemaker. Science 284, 2177–2181.

Hansen, B., Lang, M., 2011. Back to school blues: seasonality of youth suicide and the academic calendar. Economics of Education Review 30, 850–861.

Henrekson, M., Persson, M., 2004. The effects on sick leave of changes in the sickness insurance system. Journal of Labor Economics 22, 87–113.

Johansson, P., Palme, M., 2005. Moral hazard and sickness insurance. Journal of Public Economics 89, 1879–1890.

Kamstra, M.J., Kramer, L.A., Levi, M.D., 2000. Losing sleep at the market: the daylight saving anomaly. American Economic Review 90 (4) 1005–1011.

Lingjærde, O., Bratlid, T., Hansen, T., Grotestam, K.G., 1986. Seasonal affective disorder and midwinter insomnia in the far north: studies on two related chronobiological disorders in Norway. Proceedings of the Collegium Internationale Neuro-Psychopharmacologicum 9, 187–189.

Maeland, S., Werner, E.L., Rosendal, M., Jonsdottir, I.H., Magnussen, L.H., Ursin, H., Eriksen, H.R., 2012. Diagnoses of patients with severe subjective health complaints in Scandinavia: a cross sectional study.

[4] The impact of daylight hours on the steady state absence rate may alternatively be estimated directly, based on a regression with the absence rate as the dependent variable. We do not view this as recommendable, though, since, from a behavioral viewpoint, it is the flows (transitions) – and not the stocks – that can be expected to respond to changes in the environment. As a robustness exercise, we have nevertheless done this, based on a first-order autoregressive model, and then used this model to compute the steady state relationship between daylight and absenteeism. The results are similar to those based on separate estimations of inflow and outflow shown in Fig. 4. For example, when we use a quadratic (cubic) daylight function, the estimated steady state absence rates vary from 7.44 (7.67) for zero hours of daylight to 6.84 (6.61) for 24 h of daylight.

ISRN Public Health 2012 , http://dx.doi.org/10.5402/2012/851097 (Article ID 851097).

Markham, S.E., Markham, I.S., 2005. Biometeorological effects on worker absenteeism. International Journal of Biometeorology 49, 317–324.

Pocock, S.J., 1972. Relationship between sickness absence and meteorological factors. British Journal of Preventive and Social Medicine 4, 238–245.

Rosen, L.N., Targum, S.D., Terman, M., Bryant, M.J., Hoffman, H., Kasper, S.F., Hamovit, J.R., Docherty, J.P., Welch, B., Rosenthal, N.E., 1990. Prevalence of seasonal affective disorder at four latitudes. Psychiatry Research 31 (2) 131–144.

Shi, J., Skuterud, M., 2011. Reported Sickness Absenteeism and the Weather: A Test of a Shirking Model of Efficiency Wages. Mimeo, University of Waterloo, Canada.

Smith, F.J., 1977. Work attitudes as predictors of attendance on a specific day. Journal of Applied Psychology 62, 16–19.

Ziebarth, N.R., Karlsson, M., 2010. A natural experiment on sick pay cuts, sickness absence, and labor costs. Journal of Public Economics 94 (11–12) 1108–1122.