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The Anatomy of US Sick Leave Schemes: Evidence from Public School Teachers

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Abstract

We study how public school teachers use paid sick leave. Most US sick leave schemes operate as individualized credit accounts: Paid leave is earned, and unused leave accumulates. We construct a unique dataset of daily leave balances and behavior among 982 teachers for 2010–2018. Sick leave use increases during flu season, and evidence indicates that the average teacher does not use sick leave for leisure, though some subsets of teachers (e.g., the young and inexperienced) do. Usage increases with leave balance; the elasticity is around 0.4. Further, teachers with higher balances are less likely to work sick, particularly during flu season.

Keywords: sick leave, teacher, presenteeism, moral hazard, labor supply

JEL classification: I12, I13, I18, I28, J22, J28, J32

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[‡]Please see Appendix Section **??** for a full list of acknowledgments. Further, please note that all nonauthored technical reports and websites are referenced in Appendix Section **??**.

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1 Introduction

Paid leave presents inherent tradeoffs for employers. On the one hand, there is a classic moral hazard problem: The availability of sick pay induces workers to call in sick, which is costly for employers (Fevang et al., 2014; Maclean et al., 2025; Schmutte and Skira, 2025; Barone, 2025). On the other hand, sick workers have lower marginal productivity and working sick (presenteeism) may spread contagious diseases to coworkers and customers, possibly increasing future absences and decreasing customer demand (Barmby and Larguem, 2009; Adda, 2016; Pichler et al., 2021). Because employer costs for leave and employee productivity under presenteeism vary across firms, some employers will not offer sick pay unless required to do so (Maclean et al., 2025).

Among the 38 OECD countries, only the United States, Canada, and South Korea lack federal mandates ensuring universal employee access to paid sick leave (Raub et al., 2018). In 2020, the US passed **?**, the Families First Coronavirus Response Act, the first federal sick leave mandate in US history, which provided up to two weeks of emergency sick leave for COVID-19-related reasons. Nonetheless, approximately 70 million (four in ten) workers were not covered even under the emergency mandate, which expired at the end of 2020 (Long and Rae, 2020).[1] As of March 2022, 23% of all US workers lacked access to *any* paid sick days, with the rate being highest (38%) in service industries BLS (2022). Among those with access to paid leave, the average private sector allotment is less than 10 days per year BLS (2023), much less than the allotments common in European countries, for example.[2]

In addition to the substantial differences in leave-related regulations and generosity, the primary features of short-term sick leave schemes differ fundamentally between the US and most European countries. In the US, the following three features are nearly ubiquitous: (i) Workers own individual paid leave accounts, whereby leave is earned through work per-

[1]The act reduced the spread of COVID-19 (Pichler et al., 2020), but unmet sick leave needs nevertheless tripled during the pandemic (Jelliffe et al., 2021).

[2]Some specific examples: In the UK, workers are guaranteed access to 28 weeks of paid sick leave per year, with a minimum payment of £118.75 per week. France guarantees 12 months of paid leave over a three-year period at a 50% minimum replacement rate. Both countries impose a three-day waiting period and allow separate employer contributions that can make reimbursement much more generous. In Germany, workers can take the first six weeks of sick leave at 100% wage replacement; wages are replaced at 70% for the next 72 weeks (Ziebarth and Karlsson, 2014).

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formed, (ii) leave is deducted when employees take paid time off work, and (iii) unused leave accumulates over time.[3] In many cases, including the setting we study, employees are compensated for unused paid leave upon retirement in an effort to prevent moral hazard. This scheme starkly contrasts with the most common European ones, the design of which resembles unemployment insurance and workers' compensation in the US—no individualized leave credits, but rather replacement rates as a share of salary.

The structural differences between US and European sick leave schemes give rise to divergent employee incentives and potentially different behavioral responses.[4] Understanding how workers in the US use their leave is vital for ongoing debates about national mandates and scheme design; however, most empirical research on the economics of sick leave focuses on Europe.[5] Because of these institutional differences, the research on worker responses to changes in sick leave policies in Europe may not be informative about US workers' behavior. The few studies on sick leave using US data do not focus on the role of institutional features, such as leave balances, nor do they utilize administrative data to examine daily leave-taking behavior (e.g., Gilleskie, 1998, 2010; Callison and Pesko, 2022; Maclean et al., 2025).

Our main contribution is to study how the institutional features of the typical US paid leave scheme influence employee leave taking. To this end, we begin with a theoretical model of leave behavior, which helps us characterize key trade-offs created by the typical US leave scheme. To empirically test several predictions of the model, we use a newly formed dataset compiled from several administrative sources. These data describe the daily labor supply of public school teachers in central Kentucky.[6] In addition to demographics, education, salary,

[3]These features are present in most proposed and passed leave mandates, such as the Healthy Families Act, the 14 state-level US sick pay mandates, and the paid leave policies considered by the Biden administration in 2021 (NPWF, 2021; Findlay, 2021; Healthy Families Act, 2023).

[4]For example, though both types of schemes disincentivize leave taking, European workers generally face a penalty in the present (e.g., a lower paycheck). In contrast, consequences for US workers typically materialize in the future (e.g., in lower available balances or retirement benefits).

[5]Several studies find positive labor supply elasticities (Johansson and Palme, 2005; Ziebarth and Karlsson, 2010, 2014; De Paola et al., 2014; Fevang et al., 2014; Böckerman et al., 2018; Marie and Vall Castelló, 2023). Other papers investigate interaction effects between sick leave and other social insurance programs (Fevang et al., 2017), the role of probation periods (Ichino and Riphahn, 2005), culture (Ichino and Maggi, 2000), social norms (Bauernschuster et al., 2010), gender (Ichino and Moretti, 2009; Herrmann and Rockoff, 2012), physicians as gatekeepers (Markussen and Røed, 2017), compulsory "dialogue meetings" (Markussen et al., 2018), and coworkers (Hesselius et al., 2009).

[6]By studying teachers, we contribute to a small literature on how teacher absence affects student achievement

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job descriptions, and work experience, the dataset contains two features that make it truly unique among US datasets. The first is *daily* information on every sick, personal, emergency, and unpaid day taken by *each* teacher from 2010 to 2018. The second is a daily account of each teacher's leave balance over the same eight school years. As these features are generally unobserved, a secondary contribution of our work is to document leave use and balance accumulation patterns under a leave scheme typical of the US. As we study the sick leave behavior of Kentucky public school teachers, we believe that our findings have clear external validity for all 3.8 million US public school teachers (NCES, 2021) and other state and federal employees, who all work under very similar leave schemes. Given the breadth and diversity of this employee base, we also believe that our findings shed light on how the design of a federal sick leave scheme would relate to employee behavior.

Motivated by our theoretical model, we examine three aspects of how US workers use paid and unpaid leave. First, we examine when teachers use their various types of leave, with a particular focus on whether sick leave is used for illness and/or for leisure. As is the case with all studies of sick leave, we cannot perfectly observe illness or recreation, but we do observe events that shift the probability of illness or raise the utility of absence. We therefore test whether these events alter the frequency of leave taking. As an exogenous shifter of the probability of illness, we use weekly data on local flu hospitalizations as a proxy for exposure to flu activity. As exogenous shifters of the utility of absence, we use the school days (i) before and after scheduled holidays, (ii) following the Super Bowl, (iii) when the University of Kentucky Men's Basketball (UKMBB) team is playing in the NCAA tournament, and (iv) during horse racing meets at Keeneland, a popular local race course. We study the impact of these exogenous shifters on the various types of leave use using regression models with rich sets of teacher and date fixed effects.

Our results indicate that teachers are more likely to use sick leave during flu season: With a 10% increase in the severity of a local flu wave (measured by hospitalizations), leave taking rises by 1.5%. We find no conclusive evidence in the full sample that sick leave is used for leisure.

To our knowledge, this paper is the first to use precise daily leave data on US employees,

(e.g., Ehrenberg et al., 1991; Duflo et al., 2012; Carlsson et al., 2015), which is naturally related to work on the measurement and effects of teacher quality (e.g., Taylor and Tyler, 2012; Chetty et al., 2014).

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which are needed for the statistical tests described above. We thus contribute to the literature on the determinants of leave-taking behavior, such as the "Monday effect" in workers' compensation, which refers to the spike in back injury and sprain claims on Mondays (Card and McCall, 1996; Campolieti and Hyatt, 2006). Skogman Thoursie (2004) implements a test very similar to ours: He uses Swedish administrative data to show that Swedish men were more likely to call in sick the day after popular skiing competitions were broadcast at night during the Winter Olympics in Calgary. We also find evidence of absenteeism related to such "temptation days" in some of our subgroup analyses; *male* teachers, for example, are statistically more likely to take a sick day when UKMBB is playing in the NCAA tournament. We provide more details on this analysis below.

Second, we examine how employees' leave usage changes with their balances. As balances increase, so too does the use of leave. On average, with a 10% increase in leave balance, a teacher's probability of taking leave on any particular day grows by 4.5%. We show that this relationship is strongest at the bottom of the balance distribution, as teachers seek to avoid reaching a zero balance, a threshold beyond which additional leave is unpaid. Our estimate of the elasticity of sick leave use to balance changes (the balance–use elasticity), is the first of its kind in the literature. While researchers studying European-style sick leave schemes frequently estimate replacement rate–use elasticities, which tend to lie near 1.0 (Johansson and Palme, 1996, 2002, 2005; Ziebarth and Karlsson, 2010, 2014; De Paola et al., 2014; Fevang et al., 2014; Böckerman et al., 2018), the balance–use and replacement rate–use elasticities are difficult to compare mainly because an additional leave credit in the US system carries value—namely, monetary value at retirement—even for an employee who opts not to use it. A higher replacement rate benefits only employees who opt to take time away from work.

Third, we investigate whether teachers with low leave balances exhibit presenteeism, that is, turning up to work sick. Our first set of results indicates that teachers (i) do not systematically use sick leave for leisure and (ii) use more leave as they accrue higher balances; presenteeism can explain the intersection of these results. Presenteeism is notoriously difficult to measure because employees actually come to work, and sickness is typically unobserved. Even with survey data, self-reports are susceptible to inherent response biases and framing effects. For this reason, the economic literature on presenteeism is very small; Gilleskie (1998) is a notable exception. Most papers model presenteeism theoretically (Pichler and Ziebarth, 2017) or indirectly infer its existence from reductions in infection rates when employees gain access to

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sick leave (Stearns and White, 2018; Pichler et al., 2020, 2021; Marie and Vall Castelló, 2023). Given this measurement challenge, we exploit the granular nature of our data to propose a novel proxy for presenteeism: sick leave spells that include brief returns to work. We find that presenteeism increases with lower leave balances and is strongest during flu season. In a separate analysis, we also show that an individual's leave taking increases when the share of her colleagues with a low balance increases, which suggests spillover effects from presenteeism.

Our findings provide important evidence for ongoing policy discussions concerning sick leave mandates in the US. As mentioned, the US is one of three OECD countries that does not guarantee universal access to sick leave for employees. Despite bipartisan voter support for a national mandate (NORC, 2018; NPWF, 2020), over the past two decades Congress could not pass the **?**. Similar to the scheme studied in this paper, the Healthy Families Act envisions individual sick leave accounts with a seven-day annual balance.[7] Since 2009, 14 states, the District of Columbia, and dozens of large cities have passed similarly designed regional mandates (see **?** for an overview). We inform this debate by documenting how leave is actually used, at least in the public sector. We find that sick leave use increases when severe flu cases are more prevalent and that, while some subgroups may use leave for leisure, the magnitude of misuse is relatively small. We also document a crucial positive externality of paid leave: Workers with larger sick leave balances are less likely to come to work ill, which reduces the spread of illness in workplaces.

2 Data and Institutional Background

Our empirical analysis draws on several administrative sources that we compile into a unique dataset to study teacher paid leave use. The Online Data Appendix details the original data files, merge methods, and sample selection criteria. First, we combine the following:

1. A statewide, annual longitudinal data file, collected and maintained by the Kentucky Department of Education (KDE), on all Kentucky school teachers, including their demographic information, education, years of experience, school, and job title (KLDS, 2025).

[7]Some federal policy options discussed under the Biden administration included medical and family leave, which differs from the short-term sick leave schemes studied here (**?**). Medical leave refers to long-term sick leave (or temporary disability insurance; see Campbell et al., 2019), while family leave primarily comprises parental leave for childbirth.

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2. Daily administrative leave data provided by Scott County School District (SCSD) in Kentucky.[8] The file contains the date, current leave balance, and type of leave taken for every school day of the 2010/2011–2017/2018 school years.

3. School calendar data and details from other publicly available district documents containing, for instance, salary schedules, snow days, vacation days, and school year opening and closing days.

4. Weekly influenza and pneumonia admission data from the universe of hospitals and ambulatory facilities in Scott County and the seven bordering counties. This information is drawn from Kentucky's Health Facilities and Services Data, collected and maintained by the Kentucky Cabinet for Health and Family Services (HFSD, 2021).

5. Event dates for (i) horse races at Keeneland racecourse, (ii) Super Bowl Monday, and (iii) UKMBB games in the NCAA tournament.

We refer to the final data file as the Kentucky School Teacher Leave Dataset (KSTLD). The KSTLD is an unbalanced panel that contains complete records of all SCSD teachers employed from the 2010/2011 school year through the 2017/2018 school year; there are 790,615 observations from 982 unique teachers. The KSTLD contains detailed administrative information on the exact dates when teachers took sick, personal, or emergency leave, all unpaid leave days, and the total number of paid leave days available for use on each day of the eight school years in our sample. We are unaware of any other dataset used in the economic literature that contains such detailed administrative records on daily leave taking, along with the leave balance at the employee-day level.

2.1 SCSD Teacher Demographics and School Characteristics

Table 1 collapses the KSTLD to the teacher–year level. The average teacher in our data is 39.4 years old, but ages range from 21 to 74 years; 83% are female, and nearly 97% are white, non-Hispanic. Eighty-five percent have a master's degree or higher. Their experience ranges

[8] Kentucky has a total of 172 school districts across its 120 counties. Scott County, in central Kentucky, is the 17th most populous county in the state, with 53,517 residents in 2019, and has a single public school district (Census, 2020). Currently, SCSD is the state's 11th largest district, composed of 18 schools, approximately 9,800 students, and 2,000 faculty and staff (Great Schools, 2025).

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from 0 to 37 years, with an average of 11.7 years. Accordingly, we see variation in the base salary consistent with a deterministic salary schedule (see Online Data Appendix, Table **??**); the average base salary is $50,257 per school year but has a standard deviation of $7,964. Half of all the teachers work in elementary schools, and 23% (24%) work in middle (high) schools.

The SCSD teachers are fairly representative of teachers nationwide. According to a 2016 survey of 40,000 US public school teachers, 77% are female, 80% are white, average experience is 14 years, and 57% have postbaccalaureate degrees (NEA, 2018).

2.2 Leave Allocation and Accumulation

The Kentucky legislature provides a general framework for the allocation and accumulation of paid leave for KDE employees; see **?**. Most notably, Kentucky teachers earn at least 10 sick days per school year, and districts must allow teachers to accumulate unused sick days without limit. Districts can supplement this offer with additional sick and/or personal/emergency days.

A full account of the rules governing the use of both paid and unpaid leave in the SCSD, with links to official district documents, is in Appendix Section **??**. Here, we summarize only the essential details: In the SCSD, each teacher is credited with ten new sick days at the beginning of each school year. These personalized sick days are recorded in an individual account and can be taken for any medical reason, e.g., own or child sickness, doctor appointments, check-ups, scheduled surgeries, maternity leave.[9] Additionally, each teacher earns two emergency days and one personal day at the beginning of each school year. Both emergency and personal days may be requested for nonmedical reasons, though the former tend to be used for last-minute emergencies while the latter can be used for any reason and are often scheduled in advance. Teachers using sick or emergency days for reasons other than those listed above are subject to a variety of penalties (see Appendix Section **??**). Finally, as is common for public school teachers throughout the US, SCSD teachers are not required to work during a (roughly) ten-week period in the summer. Teachers are thus not provided with extra paid *vacation* days other than the one personal day.

[9]Kentucky runs no public temporary disability insurance or family and medical leave program. Consequently, in addition to the rules outlined in this section, *the Family and Medical Leave Act of 1993 (FMLA)* applies. FMLA provides up to 12 weeks of *unpaid* leave in case of pregnancy, own disease, or disease of a family member (cf Thomas, 2020). In Appendix Section **??**, we discuss the typical maternity experience of teachers in Kentucky.

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For all three types of paid leave, unused days roll over and increase a teacher's *sick* leave balance in the following year. This balance grows without limit over the course of a teacher's career.[10] Upon retirement, teachers are compensated for unused leave in two ways: (i) They receive a lump sum worth one-third the value of their unused days at their current wage, and (ii) their annual retirement income increases in proportion to the number of unused days.[11] The retirement scheme is detailed in full in Online Appendix Section **??**. Importantly, if a teacher stops working in Kentucky public schools prior to retirement eligibility (i.e., at age 55 years or after 27 years of service), then all unused sick days are forfeited. This feature of the scheme provides a key incentive for administrators to verify that sick leave is being used appropriately and not for leisure—for teachers who leave the profession early, *used* leave credits are costly for the district/state (e.g., equivalent to the cost of a substitute teacher), while *unused* leave credits cost nothing. Related research studies the substitutability of disability claims, retirement, and unemployment (Riphahn, 1997; Koning and Van Vuuren, 2010).

2.3 Descriptive Statistics on Leave Use

Table 1 Panel C shows teachers take on average 9 leave days per school year, approximately two-thirds of the 13 days credited each year. Most (7.6 per year) are sick days. Teachers average 0.7 personal and 0.6 emergency days per year. Teachers can take fractional days off: In 22% of all leave instances, teachers take only a half-day off (not shown). On average, teachers take time off on 10.3 work days per school year (including fractional and full days off), which yields a daily leave rate of about 6%.[12] In each academic year, 5% of the teachers take no leave. The total annual leave distribution, presented in Appendix Figure **??**, has the characteristic long right tail documented elsewhere (e.g., Markussen et al., 2011); 6% of all teachers take more than 20 days of leave per year, accounting for 22% of all leave use.

Panel D of Table 1 reports that the mean balance entering a school year is 52 days. There

[10]Teachers can also donate days to one another, though this is fairly rare: Fewer than 2% of "spent" credits are donated. The rules governing leave donations are outlined in Appendix Section **??**.

[11]We show in Appendix Figure **??** that, under some assumptions, the discounted present value of an unused sick day ranges between \$90 and \$350, depending on years of service. For more than 25 years of service, the discounted present value of an unused sick day exceeds the daily wage.

[12]All school years contain 189 school days. Because some teachers are not employed for the full year, the average number of school days per year in the sample is 172.6.

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is substantial heterogeneity in balances over the course of the year and across teachers. Figure 1 plots with dark gray bars the histogram of leave balance *at the start* of each school year. Roughly 67% of teacher–years start with a balance below the sample mean. Note that all teachers who start the school year on time earn a minimum of thirteen leave days; thus, we do not observe teachers with zero days at the beginning of the year.[13] Figure 1 also shows the histogram of leave balances *at the end* of the school year in light gray bars. One clearly observes a balance distribution that shifts left as few teachers gain leave (e.g., receive a donation) over the course of the year. The figure highlights that for many teachers, leave balances can be a binding constraint; 5.5% of the teachers finish the year with zero paid leave days remaining, while 16% finish with fewer than 5.

Finally, given the design of the sick leave scheme, one would expect leave balances to increase with experience. Figure **??** shows the average leave balance at the start of the school year by teacher experience; Table 1 Panel D reports related sample means. For those entering their first year of full-time teaching, the mean balance is 14 days, while the mean is 37 (73) days for those with 5–10 (15–20) years' experience.[14] There is variation both within and across experience categories; the experience-specific balance distributions display substantial overlap. At the teacher–year level, the experience–balance correlation coefficient is 0.53.

2.4 Supplemental Data

The KSTLD contains several variables believed to influence the likelihood of leave use: local hospital admissions for influenza and pneumonia, indicators for days immediately before and after scheduled school breaks (e.g., holidays), and indicators for two nationally recognized sporting events. In Appendix Section **??**, we describe why each of these variables is likely to influence leave behavior, their original data sources, and how the variables are coded.

In addition, the KSTLD includes an indicator of a distinctly local sporting event: the opening of the popular horse racing track, Keeneland. Located in Fayette County (home to the

[13] Annual leave allotments for teachers starting after the first day of school are prorated. In Figure 1, we include only teachers starting on the first day. In Table 1 Panel D, the minimums fall below 13 because we do include late-starting teachers.

[14] The mean balance at the start of year one is greater than 13 because many teachers work as aides before being hired as permanent teachers. While those years do not count as experience for salary reasons, accrued sick leave balances do carry over when such employees transition to full-time status.

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city of Lexington), just 20 minutes from the center of Scott County, Keeneland is an internationally renowned horse-racing track whose programming serves as popular social events for central Kentuckians. Races are held Wednesday through Sunday during most weeks in October (the fall meet) and April (the spring meet), with daily attendance of approximately 15,000. Scott County residents are particularly fond of Keeneland. According to Bollinger (2015), more Keeneland attendees come from Scott County than from any Kentucky county besides Fayette. In 2014, approximately 20% of Scott County's population attended the fall meet. In total, the KSTLD contains 130 days and 73,695 teacher-day observations for which Keeneland meets are in session ($\sim$9% of the sample), roughly a third of which fall on Friday, the most popular weekday to attend. This variable is particularly interesting for our sample because Keeneland meets are as much social as sporting events, meaning their appeal reaches all demographics.

3 Theoretical Model

We present a simple model of optimal leave use. We do not estimate this model but rather—in an effort to frame our empirical analysis—use it to highlight the trade-offs faced by teachers operating under this leave scheme.

In the model, a teacher maximizes discounted lifetime utility by choosing how much leave to take in each period. In this expository framework, a lifetime is two periods plus retirement. The model preserves several essential features of the US teachers' sick leave system that beget the trade-offs teachers face when deciding to take leave. First, teachers are paid for their accumulated unused sick leave at retirement. Second, the cost of taking leave is discontinuous and nonlinear at a balance of zero. Third, teachers experience time-varying idiosyncratic shocks—that may or may not be related to health—that affect contemporaneous utility from taking leave. Fourth, the decision to take leave in one period affects a teacher's leave balance in the next period. In sum, the model frames a teacher's sick leave decision as a trade-off between utility today and (i) lower retirement consumption and (ii) the risk of using unpaid leave tomorrow.

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Consider a teacher who derives utility from consumption, C_t, and leisure, L_t, such that

$$\begin{aligned} U &= U(C_t, L_t | b_t, \epsilon_t) \\ L_t &= 365 - 189 + d_t \\ C_t &= I_t - \mathbf{1}\{d_t > b_t\} \cdot [\gamma + \tfrac{(d_t - b_t)}{189} I_t]. \end{aligned} \quad (1)$$

In the second line, leisure refers to the total number of days a teacher is not at work. The variable d_t measures total annual leave days. If the teacher takes no leave, then she works the 189 days she is contracted for, and all others $(365 - 189)$ are reserved for leisure. She gains additional leisure by taking leave. In the third line, consumption is determined primarily by annual income, I_t, which is a deterministic function of experience and education (see Appendix Figure **??**). Period t leave use does not affect period t consumption as long as it does not exceed the balance, b_t. Should $d_t > b_t$, that is, if the teacher takes unpaid leave, she incurs two penalties. First, C_t is reduced by the daily wage rate, $I_t/189$, times the number of unpaid leave days, $d_t - b_t$. Second, she incurs a nonmonetary cost, γ, caused by the increased administrative and approval costs incurred from taking any leave in excess of her available balance.[15]

At the beginning of period 1, the teacher receives a shock, ϵ_1—which could be related to illness, preferences, or both—that shifts her marginal utility from leisure, $U_L(\epsilon_1)$, where $\partial U_L / \partial \epsilon > 0$. The teacher then makes a leave decision, d_1. Because this decision affects the teacher's balance entering the next period, b_2, forward-looking, utility-maximizing teachers must consider how their choices today affect their balance and subsequent choices tomorrow. We formulate this problem using a simple dynamic model where a teacher works (and makes leave decisions) for two periods (e.g., school years) and then retires. To understand the key trade-offs associated with leave taking, one needs to consider her optimal level of leave, d_1^*, in the first period alone.

Using Bellman's equation, we can write the period 1 value function as:

$$V_1(d_1, b_1, \epsilon_1) = U(C_1, L_1(d_1) | b_1, \epsilon_1) + \delta E \left[\underbrace{U(C_2, L_2(d_2^*) | b_2, \epsilon_2) + V_R(b_3)}_{V_2(d_2, b_2, \epsilon_2)} \right] \quad (2)$$

[15] District administrators communicated to us that while taking unpaid leave is allowed, it is discouraged except in a small set of circumstances. Please see Appendix **??** for additional context.

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where

$$b_2 = \max(b_1 - d_1 + 13, 13) \quad ; \quad b_3 = \max(b_2 - d_2, 0)$$
$$V_R(b_3) = \sum_{t'=3}^{T} \delta^{t'-2} U(C_R(b_3), 365) \quad ; \quad d_2^* = \underset{d_2}{\operatorname{argmax}}\, V_2(d_2, b_2, \epsilon_2).$$

In words, the discounted present value of leave decision d_1 has three components: The first is contemporaneous utility, $U(\cdot_1)$, and the second discounted expected utility in period 2, $\delta E[U\cdot_2]$, which is influenced by d_1 through b_2—i.e., more leave use in period 1 lowers the balance entering period 2. In period 1, the teacher does not know ϵ_2 and, therefore, can calculate only her *expected* utility. Upon learning ϵ_2 at the start of the following period, she knows that she will choose the optimal d_2^*. The third component is the discounted expected value of retirement, $\delta E[V_R]$. Again, this value is influenced by d_1 through its effect on b_2, which ultimately influences a teacher's balance upon entering retirement, b_3. For the value of retirement, V_R, we assume exponential discounting of utility received from full leisure (i.e., $L = 365$) and a deterministic stream of payments, $C_R(b_3)$, received in periods $t' = 3$ until death in period T. Importantly, C_R is strictly increasing (linearly) in b_3.[16]

The teacher chooses d_1 such that $\partial V_1/\partial d_1 = 0$. Note that U is discontinuous and, therefore, not differentiable where $d_t = b_t$. Thus, we first assume, without loss of generality, that $d_1 \leq b_1$. Second, note that because $\partial U_L/\partial \epsilon > 0$, $\exists$ z such that if $\epsilon_2 > z$, then $d_2 > b_2$.[17] As (i) more leave in period 1 necessarily lowers b_2 and (ii) entering period 2 with a lower balance necessarily lowers z, we know that $\partial z/\partial d_1 < 0$. Finally, let ϵ_2 be drawn from the distribution F, such that $Pr(\epsilon \leq a) = F(a)$.

[16]The rules governing retirement pay, including those determining how leave balances influence retirement pay, can be found in Appendix Section **??**.

[17]As d_2 lowers b_3 and $\partial V_R/\partial b_3 > 0$, the only rationale for higher leave use is contemporaneous utility gains.

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With this added structure, we rewrite Equation (2) and the first-order condition as

$$V_1(d_1, b_1, \epsilon_1) = \underbrace{U(C_1, L_1(d_1)|b_1, \epsilon_1)}_{A} + \delta \left[\underbrace{F(z)}_{B} \underbrace{\int_{-\infty}^{z} V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2) d\epsilon_2}_{C} + \underbrace{(1 - F(z))}_{(1-B)} \underbrace{\int_{z}^{\infty} V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2) d\epsilon_2}_{D} \right] \tag{3}$$

$$\partial V_1 / \partial d_1 = 0 = A' + \delta \left[BC' + (1 - B)D' + B'(C - D) \right] \tag{4}$$

Equation (4) clearly illustrates the trade-offs faced by teachers making leave decisions. A' measures the benefit of an additional leave day: greater contemporaneous utility, as $U_L > 0$. The term in brackets describes the discounted future costs of the teacher's taking leave today.

The first cost is BC', where $B = Pr(d_2 \leq b_2)$ and C is the discounted expected value of the choice d_2 when $d_2 \leq b_2$. In this circumstance, the teacher retires with accumulated leave and is, therefore, paid for that leave. Thus, BC' captures the first cost of taking leave, namely, that financial benefits in retirement are sacrificed (in expectation) for the sake of contemporaneous leisure. In Appendix Section **??**, we show more formally that the primary determinant of C' is $\partial V_R / \partial d_1$.

The second cost is $(1 - B)D'$, where $(1 - B) = Pr(d_2 > b_2)$ and D is the discounted expected value of the choice d_2 when $d_2 > b_2$. In this circumstance, the teacher (i) incurs both monetary and nonmonetary costs in period 2 (i.e., $\gamma + \frac{(d_2 - b_2)}{189} I_2$) and (ii) retires with zero accumulated leave, which means she receives no additional pay in retirement. D' then measures how (i) and (ii) change with additional leave use today, conditional on $d_2 > b_2$. We show in Appendix Section **??** that d_1 affects only (i). Thus, $(1 - B)D'$ captures the second cost of taking leave; namely, that for agents exceeding their balance in the future, more leave use in period 1 leads to larger (expected) utility losses in period 2. Note further that in the case where $d_2 > b_2$, the trade-off is between current leisure and current consumption, rather than future consumption.

The third cost is $B'(C - D)$, where B' measures how $Pr(d_2 \leq b_2)$ changes with more leave use today and $(C - D)$ is the lifetime utility gap between the states where $d_2 \leq b_2$ and $d_2 > b_2$. Thus, $B'(C - D)$ captures the final cost of leave taking: an increase in the probability of ex-

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ceeding one's future balance and, therefore, suffering financially in period 2 *and* in retirement.

Importantly, as a teacher's leave taking approaches the point where $d_2 = b_2$, there is not only a discontinuous, nonlinear change in her value function but also a change like the trade-off she faces from one of intertemporal utility smoothing to one that is entirely contemporaneous. As long as $d_2 < b_2$, the decision to take leave involves some intertemporal smoothing where taking leave increases utility today at the expense of future consumption. Once $d_2 > b_2$, the trade-off is solely contemporaneous, between consumption and leisure. This shift is mathematically delineated in Appendix Section **??**. Furthermore, the change in the value function is discontinuous at $d_2 = b_2$ because nonmonetary costs γ are realized. The change is nonlinear because the contemporaneous wage that is sacrificed when $d_2 > b_2$ is different from, and typically larger than (see Appendix Figure **??**), the discounted present value of lost retirement benefits when $d_2 < b_2$.

In the empirical section that follows, we answer three questions about the determinants of teacher leave use. The model above motivates each of these questions.

In Section 4.1, we ask: *When and why do teachers take leave?* We test whether sick leave use responds to observable events that (i) raise the likelihood of illness and/or (ii) are recreational in nature. In relation to the model, both event types are forms of shocks, ϵ_t, that raise the (contemporaneous) marginal utility of leisure, A' in Equation (4). A more nuanced model could allow separate illness and recreation shocks, $\{\epsilon_t^I, \epsilon_t^R\}$, which increase U_L at different rates, $\{\alpha_I, \alpha_R\}$. Qualitatively, our empirical analysis in Section 4.1 tests the relative size of α_I and α_R, where factors such as being detected using a sick day for recreation would lower α_R.

In Section 4.2, we ask: *Do larger leave balances induce more leave taking?* The model helps clarify why leave use would increase as balances grow, given that retirement pay increases almost linearly with accumulated leave at retirement. As one's balance increases, $B = P(d_2 \leq b_2)$ approaches 1 and, therefore, $(1 - B)$ approaches zero. With a higher balance, the effect of one more leave day on the future probability of not exceeding one's balance, B', also approaches zero. Thus, higher balances reduce *two* of the costs of taking leave today in Equation (4)—$(1 - B)D'$ and $B'(C - D)$. Each of these relates to the likelihood of being forced to use unpaid leave in the future. In summary, we expect more leave use when balances are higher.

Finally, in Section 4.3, we ask: *Does a larger leave balance reduce presenteeism?* Recall that in the model, illness induces a large ϵ_t shock, which creates tension between (i) the util-

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ity benefit of greater leave use today, $A' = U_L(\epsilon_t)$, and (ii) the discounted expected future cost, $\delta\left[BC' + (1-B)D' + B'(C-D)\right]$. Teachers respond to an illness shock by taking additional leave until these marginal benefits and costs equalize. We explained above that when a teacher's balance is high, $(1-B)$ and B' are small, or the risk of losing future utility by running out of leave is less salient. A *lower* balance can then be thought to increase the marginal cost of leave, resulting in less leave use and potentially forcing sick teachers to work.

4 Empirical Analysis

4.1 When and Why do Teachers Take Leave?

To answer these questions, we regress leave use on several exogenous variables hypothesized to influence the probability of illness or the utility of absence. Our first empirical specification is:

$$y_{it} = \beta_0 + ln(admits_w)\beta_1 + Z_t\beta_2 + X_{it}\beta_3 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it} \tag{5}$$

where the dependent variable y_{it} is a binary indicator of whether teacher i took any (i.e., full or partial) leave on day t. Separate regressions allow for differential effects on the following types of leave use: any, sick, emergency, personal, and uncompensated.

The first independent variable of interest, $ln(admits_w)$, is the natural logarithm of the local flu admit count during the week, w, of day t. In alternative specifications, we replace this variable with a series of vintile dummies, $\Sigma_{k=2}^{20} V_{w,k}^a \beta_{2,k}$, to allow a more flexible relationship between the number of flu hospitalizations and teacher leave behavior. We use this indicator of contagious disease exposure, which varies in a plausibly exogenous fashion over time, to test whether teachers are more likely to use sick leave (or any other type of leave) in response to an increased risk of illness.

To investigate how teachers respond to events that shift the utility of absence, we include a vector of indicator variables, Z_t, for the school days (i) before and after holidays, (ii) when Keeneland is open (plus an indicator for a Keeneland Friday), (iii) when UKMBB plays in the NCAA tournament, and (iv) falling on a Monday after a Super Bowl. Again, these events are

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plausibly exogenous as they are predetermined and do not respond to employee leave taking.

Equation (5) also includes day-of-week (DOW_t), month (δ_m), and year fixed effects γ_y. We control for time-invariant teacher characteristics (e.g., teacher-specific preferences for leave taking or persistent chronic conditions) through teacher fixed effects, α_i. Thanks to our rich administrative data, we can also control for time-variant teacher characteristics such as education, years of experience, age, school type, and annual salary, X_{it}. We cluster standard errors at the teacher level. We do *not* include leave balance in this specification to avoid biases due to endogenous "bad controls" (see Angrist and Pischke, 2009); addressing this issue is the focus of Section 4.2.

4.1.1 Leave Use in Response to Flu Activity

Table 2 contains estimation results from Equation 5. Each column represents a separate ordinary least squares (OLS) regression. The column header indicates the type of leave used as the dependent variable. As hypothesized, higher flu activity, measured by the (log) number of admissions to local hospitals, significantly increases the probability that teachers take leave. The overall effect (column (1)) is clearly driven by sick leave (column (2)) as opposed to the other types of leave. The figures suggest that a 10% increase in local flu hospitalizations increases the probability that a teacher takes leave by roughly 0.09 percentage points (ppt). As the baseline leave rate is roughly 6%, this reflects a 1.5% increase in leave taking.[18]

To allow a more flexible relationship, we reestimate Equation 5, replacing the single continuous $ln(admits_w)$ variable with 19 binary ventile indicators; the baseline category is flu hospitalizations in the lowest ventile.[19] In Appendix Figure **??**, we plot the ventile coefficients from

[18]In the absence of localized high-frequency data on the number of flu cases, we interpret this admission variable as an *ordinal* measure of local flu intensity, rather than a cardinal approximation of flu rates among the general population. An increased prevalence of flu should increase hospitalizations. Still, there is no clear algebraic relationship between hospital rates in week t and the total number of cases among public school teachers in that area. First, influenza hospitalization rates exhibit considerable variation between years but are generally low; e.g., the influenza hospitalization rate for the 2022–2023 season was 62.5 per 100,000 individuals (CDC). Because the small number of severe cases is concentrated among vulnerable populations, conditional on local aggregate flu rates, there may be additional idiosyncratic variation in the share of cases that lead to hospitalization. Second, one would need to know (or assume) the daily infection probability of a public school teacher to be able to assess whether all incremental sick days during higher flu activity are, in fact, triggered by flu infections.

[19]Ventiles are defined across all school years, excluding days in which school is not in session. Appendix Table

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the regression where *any leave use* is the dependent variable. Throughout the distribution, we observe a strictly positive relationship, reinforcing that sick leave use increases incrementally with the risk of catching a contagious disease (or with the severity of the disease of potential exposure). If we define "flu season" arbitrarily using the top five ventiles, then flu season increases the probability of taking leave over its baseline by approximately 1.75 ppt. The leave rate in the bottom ventile is 0.04; thus, flu season increases leave taking by 44%.

4.1.2 Leave Use in Response to Higher Utility from Absence

Returning to Table 2, the next set of coefficients tests for recreational leave taking. Rows 2 and 3 contain the coefficients on indicators for school days just before and after school holidays (as defined in the previous section). We would interpret a higher incidence of leave taking on these days as uses of leave for leisure, as it would likely reflect teachers extending their vacations; we find the opposite. Teachers are significantly *less* likely to take sick, personal, or unpaid leave around the holidays. There is a small increase in emergency leave use immediately preceding a holiday, but the impact on total leave is negative and significant both before and after holidays. While our primary interpretation of this finding is a failure to reject the null that leave is not used for leisure, the result also illustrates how social contracts alleviate friction in this principal–agent problem. Note that teachers are often strictly forbidden from taking personal days preceding and/or following a holiday. In such instances, though sick and emergency days are not forbidden, the restriction may dissuade teachers from using nonpersonal leave out of concerns that administrators might suspect the leave is actually personal.

Rows 4 and 5 of Table 2 test whether teachers are more likely to take leave during the Keeneland spring and fall meets. The first column suggests higher leave use on race days, but the effect is statistically different from zero only for Fridays race days. On a typical Friday when Keeneland is not open, there is a 7.5% chance that a teacher takes leave. All else equal, a Keeneland race day raises the likelihood of Friday leave by 0.82 ppt (11%). Comparing columns (2) through (5), we observe that the statistical significance of the Keeneland Friday effect on any leave use in column (1) is driven mainly by the use of personal leave, though sick leave accounts for approximately one-third of the magnitude of the effect. Even on Keeneland Wednesdays and Thursdays, personal leave use is elevated by a statistically

?? contains the admit range within each ventile.

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significant amount. Keeneland race days have no statistical effect on sick leave use. Indeed, events such as the Keeneland race days are precisely the reason personal leave is allocated. Furthermore, note that the significant, positive impact of Keeneland race days on personal leave use validates our statistical test, as it proves that teachers do in fact value the events but remain unwilling to use sick leave inappropriately to attend.

Rows 6 and 7 test whether leave is more commonly taken on school days when UKMBB plays in the NCAA tournament or on Super Bowl Mondays. Neither type of event has a significant positive effect on any type of leave in the full sample. For both event types, the observed increase in personal leave is closer to reaching statistical significance than the increases in leave of other types; the p-values are 0.12 and 0.20, respectively. Again, using personal leave in this manner is well within district rules, which means we cannot reject the null of appropriate use.

The next several rows of Table 2 show how leave use varies by day of the week. As Wednesday is excluded, the parameter estimates show that leave use is statistically more common on all other days of the week, with Mondays and Fridays having the highest likelihood of leave use. The average Wednesday leave rate is 0.053; all else equal, leave use is 16% more common on Monday and 43% more common on Friday. The Friday effect is statistically larger than the Monday effect at the 1% level.

Mondays and Fridays are the most popular leave days among teachers nationwide (**?**), which some have argued suggests "leisure behavior" (Miller et al., 2008). This may be the case, but conversations with both district administrators and teachers suggest alternative explanations. For example, for a variety of reasons, it is commonly thought that Friday is the least disruptive day for a teacher to take leave.[20] Accordingly, teachers reported to us that routine medical and dental appointments, both acceptable justifications for sick leave use, are "virtually always" scheduled on Fridays. The same is true for minor outpatient procedures, from which teachers also benefit from having the weekend to recover. Regarding Mondays,

[20]Teachers often create lesson plans in weekly blocks, with Fridays used primarily for review and testing, both of which are easier for a substitute teacher to do than introducing new material. Students are also the least focused on Fridays as they anticipate the weekend, which leads administrators to hold nontraditional school activities (e.g., assemblies, pep rallies, band/choral concerts) on Fridays. Again, the marginal educational value of having a classroom teacher manage children during these events, rather than a substitute, is small. Interestingly, this phenomenon is not limited to teaching. A project management software company also found that Fridays were the least productive day of the week (**?**).

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several studies across industries suggest that returning to work after the weekend is associated with psychological stress that may warrant occasional time off. Card and McCall (1996) and Campolieti and Hyatt (2006) document that in the US and Canada, respectively, worker compensation injuries are most common on Mondays because of psychological strain.[21] Another possible explanation for the Monday effect is that injuries are more common over the weekend (Roberts et al., 2014; Stonko et al., 2018). Given that primary care offices are typically closed on weekends (O'Malley, 2013), there are numerous medical reasons for the rise in sick leave use on Mondays.[22]

These alternative explanations are compelling but cannot rule out that heightened leave use around the weekend suggests leisure behavior. Thus, another way to consider this data pattern is to calculate how common these alternative-explanation events would need to be to fully explain increased Monday and Friday leave utilization. In the raw data, the average teacher takes leave on 2.56 Fridays per year. If teachers were to take approximately 30% fewer Fridays off (i.e., 0.77 fewer Fridays per year), then the Friday leave rate would be statistically indistinguishable from the Wednesday rate, all else equal. In other words, the above events (e.g., preplanned doctor visits, professional development) would need to account for 0.77 missed Fridays per year per teacher for the high Friday leave rate to *not* imply leave for leisure. A similar analysis shows that, on average, a teacher would need to take 0.29 fewer Mondays off per year to eliminate the Monday effect. Adding these results together suggests that in the "worst-case scenario," characterized by neither weekend injuries nor Friday doctor visits, teachers may be using up to one day per person per year for leisure to extend weekends.

Finally, the table also shows that leave is taken least in August and June, the first and last months of the school year. Leave use is increasing in experience, which is consistent with teachers having access to a larger leave balance (as we explore in more detail in Section 4.2).

4.1.3 Robustness and Heterogeneity

Appendix Table **??** contains the results from several robustness checks. Column (1) repeats our main results from Table 2, where "any leave" is the dependent variable, for comparison.

[21] Willich et al. (1994) shows, consistent with this conclusion, that employee heart attacks peak on Mondays.

[22] An attentive referee pointed out that presenteeism, not shirking behavior, might vary over the course of a week, such that it is lowest on Mondays and Fridays.

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Column (2) shows that all the estimates are robust to the use of calendar-week fixed effects. For the results reported in column (3), the regression includes flu intensity leads and lags as quasi-placebo tests. Neither leads nor lags of flu intensity have a significant impact on leave use, which reinforces that flu admits capture some measure of increased prevalence, not just seasonal patterns in leave use. Column (4) reports qualitatively similar results with admits measured in levels.

In Appendix Tables **??**-**??**, we explore heterogeneity in these results. A brief description follows.

Gender and Children. Table **??** compares split-sample results for women and men. The effects of flu admissions on any leave use are significant for women, but not men. We cannot pin down a specific mechanism for this difference. Still, since women generally disproportionately shoulder child- (Ranji and Salganicoff, 2014) and eldercare (Grigoryeva, 2017), it is plausible that women teachers take more sick leave during flu season for these reasons. Unfortunately, our data do not contain information on whether the teachers have children, are married or where the teachers live. Twelve of the 15 schools are located in the city center, and the other three are within 7 miles of it, which suggests that childcare facilities are in close proximity. Regarding leave for leisure, Keeneland race days have a statistically significant effect on men's sick leave use, but not women's. Furthermore, men are more likely to take any leave on days when UKMBB plays in the NCAA tournament. Although the statistical significance of this result is driven by personal leave, sick leave accounts for approximately one-third of the magnitude of the overall effect. Additionally, the "Friday effect" specific to sick leave is over 50% larger for men than women. Consistent with the economics of the sick leave literature (e.g., Ichino and Moretti, 2009), we also find that female teachers take more days off than male teachers on average—a difference of approximately 3.5 days annually.

Age, Experience, and Entry/Exit. Table **??** contains split-sample results for teachers under and over age 40. The only notable difference between younger and older teachers is that the latter are significantly more likely to use sick leave on days when UKMBB plays in the NCAA tournament. That said, the two point estimates are not statistically different from one another. The same is true for teachers with more than five years of experience (see Table **??**). Further, some inexperienced teachers commit the "rookie mistake" of calling in sick on a Keeneland

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Friday. Similarly, Table **??** shows that the teachers not observed in the data for all sample years are statistically more likely to use sick leave on Keeneland Fridays.

Education and School Type. Table **??** compares teachers with a master's and those with a bachelor's. Aside from the stronger response to flu hospitalizations among the former, the results are similar. In alternative specifications, we use elementary school rankings from **?** to test whether teachers in lower-ranked elementary schools (i) use more leave (as in Boyd et al., 2005) or (ii) use more leave for leisure. We find evidence of neither. We also stratify the results by secondary vs. elementary and rural vs. urban elementary school teachers and find no significant differences in leave use. All of these results are available upon request.

Leave Duration. The literature on demand for health care distinguishes discretionary from nondiscretionary care (Finkelstein et al., 2013), finding much smaller elasticities for inpatient care (Manning et al., 1987). Similarly, the duration of sick leave proxies for different underlying health shocks (Ziebarth, 2013): Less severe illnesses require short-term and severe illnesses longer-term leave. Moreover, the events that we hypothesize may change the utility of absence from work are all likely to lead to a single day off work. Thus, in Appendix Table **??**, we reestimate Equation (5) for two subsamples: (i) The top panel considers one-day spells only (i.e., excludes all teacher days in an illness spell of 2 or more days), and (ii) the bottom panel considers only spells of 4 days or more (i.e., excludes all teacher days in an illness spell of 1, 2, or 3 days).[23] We see a statistically significant increase in the likelihood of any leave use when UKMBB plays in the NCAA tournament and after the Super Bowl for short but not long spells. The Keeneland Friday, Monday, and Friday effects are also larger for short than for long spells. That said, flu admissions are *also* predictive of sick leave use *only* in the short-spell sample. This is in part because a nontrivial share of the long spells appear to be due to maternity (6%; see Appendix Section **??** for details on how we proxy for maternity). If we also drop maternity leaves, the coefficient on flu admissions for the long-spell sample becomes statistically different from zero and matches the magnitude of that for the short-spell sample (not shown).

In summary, we find a statistically significant increase in leave use with greater flu activity, consistent with the motivation for provision of paid sick leave. In the full sample, we find

[23]See Section 4.3 for how we define a leave spell and its length.

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no statistical evidence that sick leave is used for leisure. Among some subgroups, there is statistical evidence that sick leave is used at higher rates during some recreational events. We acknowledge that leave may be taken for leisure activities we cannot observe (e.g., a family member's birthday). We also acknowledge that taking sick leave for some of the leisure events we examine (e.g., Keeneland racing meets) presents the possibility of being "caught" in a small community where reputations matter. Tests for elevated sick leave use during "private" events that increase the utility of absence may reveal different results.

4.2 Do Larger Leave Balances Induce More Leave Taking?

In the SCSD, each teacher receives ten sick, one personal, and two emergency leave days at the start of each school year. Unused days accumulate without limit. This scheme raises some obvious policy questions: Is this annual allotment of sick leave credit appropriate, too high, or too low? Should leave accumulation be limited? To shed light on these questions, we assess how teachers' leave balances influence their leave taking. Our theoretical model in Section 3 suggests that leave use should rise as the balance grows. Here, we test that prediction empirically.

4.2.1 Empirical Approach

To estimate the balance–use elasticity, we begin with the following statistical model:

$$y_{it} = \beta_0 + sinh^{-1}(Balance_{i,t-10})\beta_1 + X_{it}\beta_2 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it}. \tag{6}$$

The outcome variable, y_{it}, is binary and measures whether any leave (i.e., full or partial) of any type (i.e., sick, personal, emergency, or unpaid) was taken on day t. $Balance_{i,t-10}$ measures the total leave balance (i.e., sick plus personal plus emergency) of teacher i ten school days before day t. We transform $Balance_{i,t-10}$, which takes the value of zero at times, using the inverse hyperbolic sine (IHS) function. Other variables are as previously defined.

This specification addresses several endogeneity concerns that would arise were a leave indicator regressed on current balance alone. First, a teacher's balance is positively correlated with her age and experience. As a teacher ages, her health and family structure may change, which can influence leave taking; thus, age and experience are among the controls in X_{it}, which

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accounts for two potential sources of omitted variable bias. Second, because the leave balance is a function of prior-year leave taking, chronically ill teachers (or even those with very strong preferences for time off) will have lower balances but will also be more prone to taking time off in the current year. We address this by including teacher fixed effects, α_i, which net out time-invariant unobservables, allowing the parameters to be identified from within-teacher variation. Third, we measure the leave balance ten days before the observation day to avoid the mechanical association between a teacher's leave balance and her leave use during a sickness spell; that is, if a teacher is sick on day t and stays home, she (i) has a lower balance on day $t+1$ by construction and (ii) is likely to take leave again on day $t+1$.

With these controls, two remaining sources of variation in teachers' leave balances identify our estimates. The first is the start of the new school year, when balances increase by 13 days regardless of the previous year's balance. The second source of variation is created by severe illness shocks, which teachers have little control over and which oblige them to extended time away from school, leading to lower future balances.

4.2.2 Main Estimates

Table 3 contains estimates of the balance–use elasticity. Moving from left to right in the table, we observe how the previously described sources of bias affect the estimate. Column (1) shows results from a naive regression that ignores the three endogeneity concerns above. Column (2) adds linear and quadratic age and experience controls, which have little impact on the estimate. Note that the point estimates in columns (1) and (2) are negative—the opposite of the hypothesized sign—and statistically significant.[24] However, both the selection and mechanical association concerns described above would lead to downward bias in the balance–use elasticity. In column (3), we control for selection by adding individual fixed effects, which causes the sign to turn positive. In column (4), we replace the current balance with the balance ten days in advance of t, which further reduces bias, increasing the point estimate.

Because the balance variable is transformed with the IHS function, which approximates the natural log away from zero, and the dependent variable (whether teacher i took leave of any type on day t) is binary, our coefficient of interest, β_1, can be interpreted as suggesting that

[24] Consistent with these findings, Appendix Figure **??** shows that the unconditional correlation between leave balance and use on any given day is negative.

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with a 10% increase in a teacher's leave balance, leave taking rises by 0.27 ppt. This reflects a roughly 4.56% increase over baseline in the likelihood of taking leave on any given day, yielding an elasticity of 0.456.

4.2.3 Heterogeneity and Robustness

In Appendix Table **??**, we allow heterogeneity by gender, age, and experience. The elasticity estimates vary little across these observables.

Next, we test whether the balance–use elasticity varies at different points in the balance distribution, which is important for policy design. For example, an elasticity operating entirely through the bottom of the balance distribution would suggest that when teachers run out of paid leave credit, they reduce their leave taking, which may indicate working while sick. The policy prescription for this issue would prioritize keeping teachers away from a zero balance, which could be done through the granting of larger starting balances to new employees. To this end, we repeat the ventile approach used in Section 4.1, dividing the balance distribution into twenty equal bins. Appendix Table **??** reports the balance range in each ventile. Dummy variables representing the top 19 bins replace the continuous balance regressor of interest in Equation (7) as follows:

$$y_{it} = \beta_0 + \Sigma_{k=2}^{20} V_{i,t-10,k}^{b} \beta_{1,k} + X_{it}\beta_2 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it}. \quad (7)$$

Figure 2 plots the ventile coefficients. We observe a strictly positive relationship between leave balance and use. Notably, the likelihood of taking leave jumps substantially between the baseline bin (0–5.5 days) and the second bin (5.5–9 days)—it increases by 4 ppt, or 64% over baseline. This finding is not a strict mechanical artifact of teachers' inability to take leave when their balance is zero. Our dependent variable, any leave of any type, includes unpaid leave, which teachers can use when their balance is zero. That said, incentives change nonlinearly when teachers hit a zero balance because unpaid leave operates under a distinct framework, which we discuss in detail in Appendix Section **??**. This framework imposes some costs on teachers that do not exist for paid leave, meaning teachers are considerably less inclined to use unpaid leave.

For bins two through four (the latter contains a maximum of 13 days, the total number

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allocated per school year), the likelihood remains almost constant, increasing linearly over the remainder of the balance distribution. Teachers in the highest three ventiles have leave balances of more than 92 days, with 144 days on average. All else equal, these "high-balance" teachers are 148% more likely to take leave on any given day than the teachers in the baseline bin and 47% more likely than the teachers in bins two through four.

Estimates from this more flexible specification clearly show that the balance–use relationship is strongest at the bottom of the balance distribution. This effect could be driven by an unwillingness to take unpaid leave, either because teachers do not want to sacrifice pay or because the district imposes additional costs for taking unpaid leave. Also notable is that the IHS function we employ is nearly identical to the natural log function, which is the basis for interpreting our coefficients as elasticities, everywhere *except* near zero.[25] In light of these realities, Table **??** examines how the balance–use elasticity changes with alternative transformations (Panel A) and when we exclude observations with zero balance (Panel B) or a balance in the bottom ventile (Panel C). The main takeaways from this analysis are the following: (i) Across all the specifications and samples considered, we estimate elasticities between 0.38 and 0.52. (ii) The "log plus 1" transformation yields slightly larger elasticities than the IHS, but the difference diminishes as balances near zero are removed from the sample. Finally, (iii) the elasticities are smallest and most uniform when the bottom balance ventile is dropped.[26]

Finally, in Appendix Section **??**, we describe efforts to identify in the data what are likely maternity leaves. For reasons discussed in that section, we reestimate the balance–use elasticity after removing the observations of all teachers in the year when they used maternity leave and the prior year. The resulting elasticity is 0.38.

Furthermore, we show that while leave use increases with balance throughout the balance distribution, it decreases strongly when the balance nears zero. This finding is logical, as leave use with a balance of zero results in pay being withheld from a teacher's typical paycheck. This finding suggests some discretion in leave use (see Section 4.1). While some teachers may

[25] Recent research has explored potential pitfalls of (and alternatives to) the use of the common "log plus 1" and IHS transformations of the dependent variable (Chen and Roth, 2024; Mullahy and Norton, 2024) but does not address situations such as ours where an independent variable is transformed.

[26] Results are not shown, but we also confirm that our main findings are robust to our (i) including calendar week fixed effects and (ii) limiting the sample to teachers employed throughout the full eight-year sample period (i.e., for the sample with no evidence of dynamic selection).

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use leave for leisure, this practice is not systematic enough to produce statistically significant effects for the full sample. That said, we cannot rule out teacher use of sick leave for nonsystematic leisure (i.e., leisure not correlated with the observable events we study) or a contribution of such behavior to the positive balance elasticities we find.[27] Teachers might also use discretion in deciding whether to take leave *when sick*—the topic of the next section.

4.3 Does a Larger Leave Balance Reduce Presenteeism?

Presenteeism, or working while sick, is a well-documented phenomenon that is notoriously difficult to measure because neither administrative nor survey data typically describe how an employee "feels" while working. When surveys do ask employees about going to work sick, framing and response biases become relevant concerns. We take two approaches to studying presenteeism. First, we attempt to measure presenteeism directly from the data. Second, we infer presenteeism from within-school illness spillovers.

To begin, we propose a novel proxy for presenteeism behavior using our daily administrative data: we flag instances in which teachers briefly return to work during a leave spell. Consider a teacher who takes leave on day t, goes to work on day $t+1$, and then again takes leave on day $t+2$. We propose that leave taking on the nearby days t and $t+2$ likely indicates an extended sickness spell, meaning the teacher likely worked while ill on day $t+1$.

There are two potential issues with categorizing day $t+1$ as presenteeism. The first relates to measurement error. All days classified as presenteeism would not necessarily reflect true presenteeism (type-1 error). Some instances of true presenteeism would not be categorized as such (type-2 error).[28] We address this issue when interpreting our findings below.

The second issue is econometric. The goal is to test whether larger leave balances reduce presenteeism; however, our presenteeism proxy requires that employees take leave, which we showed in the previous section is increasing in the leave balance. Thus, a regression of presenteeism days on leave balance at the daily level will yield estimates biased upward (toward

[27]In untabulated results, we estimate Equation 5 separately for high- and low-balance (i.e., top- and bottom-tercile) teachers. We find no statistical (or economically relevant) differences in leisure parameters between the two groups.

[28]In the above example, a teacher could be sick on day t and miss on $t+2$ for unrelated reasons (e.g., child illness), meaning she was not ill herself on day $t+1$. Similarly, presenteeism could involve working sick for a day and then taking consecutive days off or taking consecutive days off and then working while sick.

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zero). We address this econometric issue by conducting our analysis at the illness-spell level. Consider the following proposition:

Proposition 1 *An "illness spell" begins on the first day that a teacher takes leave and continues until she returns to teaching for two consecutive full days. The spell ends on the last day that leave is taken.*

We then classify illness spells by whether they contain work (i.e., a presenteeism spell).[29] Column (1) of Table **??** reports the number of spells of various lengths in our data (measured as the number of school days contained in the spell). Column (2) reports the percentage of all spells falling in each spell-length grouping and column (3) the percentage of all leave days falling in each spell-length grouping. Finally, column (4) reports the percentage of spells in each spell-length grouping that contain a presenteeism event.

The table highlights that most spells (79%) are just a day long, representing half of all leave taken. Spells lasting longer than a week are rare (less than 2% of all spells) but do represent a sizable proportion of total leave taken (19%). Important for our analysis is that our presenteeism proxy requires that a spell be at least three days long. Thus, our econometric analysis focuses on spells longer than two days. Among these, nearly 52% contain presenteeism.

Using this measure of presenteeism, we test whether an increase in a teacher's leave balance reduces the probability of a presenteeism event, *conditional* on her having a spell longer than two days. To do so, we estimate the following model:

$$Presenteeism_{it} = \beta_0 + \Sigma_{k=2}^{20} V_{i,t-10,k}^{b} \beta_{1,k} + Z_t \beta_2 + X_{it} \beta_3 + \delta_m + \gamma_y + \alpha_i + \epsilon_{it} \quad (8)$$

where our outcome is the binary presenteeism measure above. All other variables are defined as above, and $\Sigma_{k=2}^{20} V_{i,t-10,k}^{b}$ measures the leave balance ten days before the start of the spell in ventile indicators.[30] We plot the regression coefficients, $\beta_{1,k}$, in Figure 3 Panel A. The figure suggests that across the balance distribution, higher balances reduce presenteeism; however, because the reference ventile has relatively few presenteeism events, many of the coefficients are not statistically different from zero. The negative balance–presenteeism relationship is

[29] A spell may begin or end with partial leave without being classified as a presenteeism spell. If an interior day contains any instance of partial leave, then the spell is classified as a presenteeism spell.

[30] The balance ventiles are defined for the sample used in estimation, that is, the distribution of balances ten days prior to spells lasting three or more school days.

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particularly strong for balances above the 10th ventile, with a maximum balance of 24.5 days.

Though the above suggests that high balances protect teachers from presenteeism, the relevance for administrators (or a social planner) depends on the severity and transmissibility of the disease. The impact of presenteeism on student learning might be negligible for very minor ailments, and negative illness spillovers are less likely for noncommunicable diseases. Accordingly, we expand on the findings above by reestimating the model for times of high and low flu activity, as measured by $admit_t$. Specifically, we estimate the model separately for spells for which the total number of flu admits during the spell was above the sample median (defined as “flu season”) and for all other spells (“not flu season”). The results are robust to alternative cutoffs. As we are splitting a sample of only 3,061 illness spells, we also reduce our number of leave-balance bins to 12.

Figure 3 Panel B shows the results, plotting the bin coefficients separately for times inside and outside flu season. For spells outside flu season (i.e., in the early fall or late spring), we see an almost perfectly flat relationship between presenteeism spells and a higher leave balance. For spells during flu season (i.e., mostly in January and February), we see a decrease in the coefficients as the balance grows: The larger a teacher’s leave balance, the less likely she is to call in sick, come back to work (for up to one day), and call in sick again—what we deem presenteeism. The flu season coefficients become (and stay) significantly different from zero after the seventh ventile, which contains a maximum of 30 days of leave. Interestingly, these findings show that high balances not only protect against presenteeism but do so when the negative externality associated with presenteeism (i.e., illness spread) is greatest.

As mentioned previously, we advise caution in interpreting these findings given the possible measurement error in our presenteeism proxy. First, consider type-1 measurement error, or false assignment of presenteeism when none exists. The flu season results are less likely to be driven by type-1 error because, during this season, absences are more likely to be illness-related than at other times of the year. Moreover, as the balance–presenteeism elasticity is identified by marginal changes in the available amount of leave, a priori, there is little reason to expect the measurement error to vary with such marginal changes.

Second, the previous section shows that the balance–use elasticity is highest at the bottom of the balance distribution; that is, teachers take significantly less leave when their balance is close to zero. Thus, we might expect marginally larger balances to impact presenteeism most at

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the bottom of the balance distribution. We find larger effects at the top. This finding probably reflects an imperfection in our presenteeism proxy—namely, the illness spell must be at least three days long for presenteeism to be possible. Teachers with very low balances rarely take multiple days off. As a result, our measure will misclassify presenteeism (type-2 error) more often at the bottom of the balance distribution (where teachers are more likely to work sick without taking *any* days off) than at the top.

In light of these measurement errors and distributional issues, we extend our exploration of presenteeism with a final statistical model that adds to Equation 6 a new regressor that measures the share of teachers within the school (excluding teacher i) with a leave balance below 10 on day t. Our motivation here is twofold. First, a test of whether teacher i's leave use increases in response to many teachers in her school having a low balance can be viewed as an indirect test of the existence of presenteeism, without the need for presenteeism to be explicitly measured. As Section 4.2 establishes that own-leave use declines with own-leave balance, a finding that own-leave use is positively associated with deficits in *others'* leave balances would suggest that others may be engaged in presenteeism. Because such a finding could also be explained by peer effects or a school culture of heavy leave use, we also replace the school-type fixed effects in Equation 6 with school-specific fixed effects. Second, policymakers (or school administrators) should seek to prevent presenteeism events only if negative externalities result; the most plausible of these are illness spillovers and poor teaching quality. Thus, this exercise can be viewed as an empirical test for the existence of presenteeism that results in spillovers.

Our initial results from this exercise are in column (1) of Table 4. As expected, the share of a teacher's colleagues with a low balance is a significant, positive predictor of her own leave use, conditional on her own leave balance and various other factors. This finding is consistent with other teachers in teacher i's school exhibiting presenteeism in response to their own low balances, resulting in increased illness and, therefore, leave use by teacher i. A plausible alternative is that we are simply capturing spurious correlation caused by within-school illness waves. To account for this potential source of omitted variable bias, in column (2), we control for both the share of teachers in the school taking leave on day t and the average share taking leave over the previous 5 days (both of which exclude teacher i), as well as the natural log of the number of flu admits at local medical facilities that week. Similarly to what we do in Section 4.2, in column (3), we also measure the share of teachers with a low balance *10 days*

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prior to day t, rather than on day t. In both instances, our results remain robust.[31]

5 Discussion and Conclusion

This paper is the first to study paid leave use by US employees using high-quality administrative data on daily leave behavior and dynamically updating leave balances. We study the behavior of nearly 1,000 public school teachers over eight school years. The paid leave scheme faced by our sample grants employees leave credits on individual accounts, allows them to take leave credits when necessary (under some constraints), allows unused leave credit to accumulate over tenure with the employer, and compensates the workers for unused leave upon retirement. Such schemes are common in the US—indeed, nearly ubiquitous for US public employees—but are less common elsewhere.

Our empirical work focuses on three key questions, motivated by a simple, theoretical model of leave use under the scheme just described. Our first question is: *When and why do employees use leave under these schemes?* In particular, *do employees use sick leave as it is intended or for leisure?* We show that sick leave use increases significantly when environmental hazards increase, for instance, during flu season. Further, we find no statistical evidence in the full sample that teachers use sick leave to extend vacation periods, attend popular local horse racing events, or watch nationally televised sporting events. The local horse racing events do increase teachers' likelihood of taking Friday leave by 11%, though the effect is driven mainly by *personal* leave use, which is allowed under district rules. We find some evidence that specific subgroups of teachers use leave for leisure (e.g., older teachers are more likely to call in sick during the NCAA tournament), but the aggregate effect of such behavior on teacher absence is minimal.

From the perspective of the policymaker, who sometimes must consider marginal increases or decreases in scheme generosity, our results do not support arguments for less generosity on

[31] In additional analysis that is available upon request, we also find that (i) these results are driven entirely by sick leave use; i.e., if the dependent variable is defined based on personal and emergency leave *only*, then a teacher's working with low-balance colleagues is *not* predictive of her own leave use, and (ii) her working with low-balance colleagues is a significant, positive predictor of both (own) short and long leave spells, the latter of which might be more indicative of illness.

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the basis of waste under the current scheme.[32]

Our second question is: *Do larger leave balances induce more leave taking?* We provide clear evidence that the answer is "yes" and that the balance–use elasticity is between 0.38 and 0.45. We also show that leave use is most responsive to balance increases at the bottom of the balance distribution, consistent with workers' desiring to avoid unpaid leave. The likelihood of taking a sick day increases discontinuously as a balance grows from 0–5 days to 5–13 days; it then increases at a relatively constant rate over the remainder of the balance distribution.

Finally, we ask: *Do high balances decrease teachers' likelihood of working while ill?* We use two models to show that higher leave balances protect against such presenteeism. First, we rely on our daily administrative sick leave data—similar data may be collected by public agencies and private firms and used by researchers in the future—to define a novel proxy for presenteeism on the basis of temporary returns to work within a series of absences. Using this measure, we show that a larger sick leave balance reduces teachers' probability of working sick, conditional on their having an illness spell. Moreover, this statistical link is most pronounced for spells during flu season, when the negative externality of presenteeism is strongest. Measurement error concerns are weakest for these spells. Second, we show that a high share of coworkers having a low balance predicts a teacher's own leave use, implying that her coworkers engage in presenteeism. This finding corroborates and complements our finding that higher balances not only prevent presenteeism but also protect against the spread of contagious diseases.

Taken together, these findings suggest the potential for welfare-improving adjustments to the design of the most popular US teacher sick leave scheme. Note our findings that (i) leave use declines when paid leave balances approach zero and (ii) high-balance employees are significantly less likely to display presenteeism than those with low balances. Both findings suggest that keeping employees away from very low balances would reduce presenteeism, making workplaces safer. Note also our finding that leave is rarely misused in aggregate. Collectively, these results suggest that policymakers could reduce presenteeism at minimal cost by offering employees more paid leave at the beginning of their careers, with fewer marginal

[32]A related debate in the Kentucky legislature in 2018 motivated this research. In an effort to reduce state pension expenses, then governor Matt Bevin proposed reducing the benefits associated with accumulated sick leave upon retirement. The backlash from educators was severe and included a teacher's strike. Many popular news outlets report that this policy misstep played a key role in Bevin's election loss (Stevens, 2019).

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credits earned over time.[33] As an example, first-year teachers could be offered an initial a balance of 40 days (as opposed to 13, in the example we study here) but their flow of leave over their next 9 years of employment reduced to 10 days. Under such a scheme, teachers would have received the same number of leave credits by year 10 as in the current system, but many fewer teachers would ever have a balance near zero.[34]

Ideally, our results would clarify under what circumstances the typical US or European sick leave scheme is preferable from a welfare perspective. Unfortunately, such analysis is beyond the scope of this paper. Recall that the typical European sick leave scheme resembles the design of UI in the US, specifying the maximum days' coverage per illness episode and reimbursing employees for missed days at some fraction of the salary. A worker in such a scheme might face a 60% replacement rate, so when she takes a day off, she sacrifices 40% of her daily wage. In the US, when a worker with a high leave balance misses work, she faces no immediate monetary cost, and forgone retirement benefits are discounted. Any formal welfare analysis must evaluate which system better maximizes the likelihood that ill employees stay home while minimizing the likelihood that well employees come to work. Because we lack individual-level data on illness and our empirical model does not allow us to shift the financial consequences of leave taking from the future to the present, we cannot answer this question.[35]

We can make one general statement about the welfare implications of the two schemes from a worker's perspective. Compared to sick pay schemes with partial replacement rates, US-style schemes disproportionately benefit healthy workers for several reasons. First, workers who take less than their full allotment of leave effectively receive 100% replacement of wages. Second, workers who stay through retirement receive partial compensation for unused days. Third, relatively healthy workers are not explicitly taxed to fund the leave of workers

[33]Outside of teaching, several states currently mandate that employees earn a minimum of 1 hour of paid leave per 30–40 hours of work. Our conclusions here suggest that policymakers should instead increase the initial accrual rate but lower the accrual rates over employees' tenure. Alternatively, policymakers could provide an upfront amount of paid leave credit to be earned or repaid over time.

[34]This change may also ease the hardship of lost income during maternity for young teachers. That said, teachers who plan to leave the profession early may be the most likely to take advantage of the new program. For this reason, monitoring such as that described in Appendix Section **??** may be needed to prevent employees from rapidly using all of their leave before switching jobs or careers.

[35]Other differences between the two systems, such as waiting periods and monitoring intensity, further complicate a formal comparison.

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who may require longer spells. In contrast, people in poor health, for example, with chronic conditions or severe diseases, who need more sick days than their annual allotment of leave, incur the financial and administrative burdens of unpaid leave and are likely better off under a European-style system.

Finally, while this study fills a key gap in our understanding of leave behavior under the most common US sick leave scheme, we acknowledge several limitations. We view these limitations as opportunities for future work rather than challenges for this analysis, as most center on the generalizability of our results to a heterogeneous set of employees and occupations. First, teachers may fundamentally differ from other workers in their use of sick leave. If teachers feel a stronger sense of duty to be present, are more emotionally attached to their work, or are more conscientious than employees in another sector, they may respond differently to sick leave incentives. Second, Scott County is a small community, meaning (i) reputations may be more important and (ii) the likelihood that an employee is discovered to be using sick leave for leisure may be greater than in a larger community. Both factors may deter leave use for leisure. Third, most of the paid leave granted to teachers in our setting is specifically for medical absence, not vacation. (Teachers are expected to take vacation during school breaks.) We consider this a positive feature of our setting, as decision-makers face very clean trade-offs; however, in some leave schemes, workers receive "paid time off" (PTO) credits, which can be used for vacation *or* illness. Behavior may differ in these settings. Fourth, an instruction day in K–12 schools cannot easily be shifted intertemporally the way research, report writing, sales calls, or even most physical labor can. On school days, children in a classroom need instruction and supervision. Leave-taking behavior (and responses) may differ in occupations where five days of labor can be, in a sense, compressed into four onerous working days.

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Tables

Table 1: Kentucky Public School Teacher Data, Teacher Demographics

	Mean	SD	Min	Max
A. Socio-Demographics				
Age	39.4	10.2	21	74
Female	0.835	0.371	0	1
Race				
Hispanic	0.009	0.095	0	1
Black	0.020	0.140	0	1
Asian	0.004	0.066	0	1
Education				
Bachelors	0.152	0.359	0	1
Masters	0.462	0.499	0	1
Rank 1 or above	0.386	0.487	0	1
B. Employment				
Experience	11.701	8.165	0	37
First Year	0.053	0.224	0	1
1-5 years	0.222	0.415	0	1
6-10 years	0.217	0.412	0	1
11-15 years	0.201	0.401	0	1
16-20 years	0.149	0.356	0	1
21-25 years	0.088	0.283	0	1
26+ years	0.071	0.256	0	1
Base Salary	50,257	7,964	30,877	66,930
Extra Salary	1,520	3,173	0	30,143
School				
High School (3)	0.240	0.427	0	1
Middle School (3)	0.226	0.418	0	1
Elementary School (8)	0.491	0.500	0	1
Other (3)	0.043	0.204	0	1
C. Leave Days				
Total annual leave taken	9.037	8.299	0	106
Sick	7.642	7.843	0	103
Personal	0.698	0.819	0	4
Emergency	0.590	0.662	0	3
Uncompensated	0.107	0.745	0	13.5
Total days with *any* leave taken	10.279	8.744	0	106
Share of days with *any* leave taken	0.060	0.052	0	0.72
No leave taken	0.045	0.207	0	1
3 or fewer days of leave taken	0.185	0.389	0	1
20+ days of leave taken	0.061	0.238	0	1
D. Leave Balance				
Start of year Balance	51.70	47.35	2.5	348.25
if experience $= 0$	14.25	6.15	5	52.5
if experience $\in [1, 5)$	29.47	16.87	2.5	165.25
if experience $\in [5, 10)$	37.35	25.17	4.5	205.25
if experience $\in [10, 15)$	50.44	34.85	5	189
if experience $\in [15, 20)$	72.66	52.12	5.5	252
if experience $\in [20, 25)$	89.39	64.97	8	289.75
if experience $\in [25, \infty)$	106.07	74.67	5	348.25

Notes: Observations are teacher–years (NT=4,577). There are 982 teachers, 293 of whom are present in all 8 years. SD stands for "standard deviation."

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Table 2: What Explains Leave Use? Full-Sample Results

	Any	Sick	Emergency	Personal	Uncomp
ln(admits)	0.0094 ***	0.0093 ***	0.0008 **	-0.0009 **	0.0002
	(0.0023)	(0.0022)	(0.0004)	(0.0004)	(0.0003)
Holiday					
day prior	-0.0045 ***	-0.0039 ***	0.0023 ***	-0.0029 ***	-0.0002 *
	(0.0014)	(0.0012)	(0.0005)	(0.0003)	(0.0001)
day following	-0.0092 ***	-0.0081 ***	0.0002	-0.0013 ***	-0.0001
	(0.0011)	(0.0010)	(0.0003)	(0.0002)	(0.0002)
Keeneland	0.0021	0.0015	0.0000	0.0008 **	-0.0003 **
	(0.0014)	(0.0013)	(0.0004)	(0.0004)	(0.0001)
× Friday	0.0062 ***	0.0019	-0.0001	0.0044 ***	0.0000
	(0.0021)	(0.0018)	(0.0007)	(0.0009)	(0.0002)
UK Basketball	0.0042	0.0034	0.0001	0.0015	-0.0006 **
	(0.0029)	(0.0025)	(0.0011)	(0.0010)	(0.0003)
Super Bowl Monday	0.0048	0.0027	0.0000	0.0014	0.0004
	(0.0046)	(0.0042)	(0.0012)	(0.0011)	(0.0005)
Day of the week					
Monday	0.0086 ***	0.0068 ***	0.0008 ***	0.0010 ***	-0.0001
	(0.0010)	(0.0009)	(0.0002)	(0.0002)	(0.0001)
Tuesday	0.0020 **	0.0020 ***	0.0002	-0.0001	-0.0001
	(0.0008)	(0.0007)	(0.0002)	(0.0002)	(0.0001)
Thursday	0.0038 ***	0.0025 ***	0.0011 ***	0.0003	0.0000
	(0.0007)	(0.0007)	(0.0002)	(0.0002)	(0.0001)
Friday	0.0230 ***	0.0132 ***	0.0041 ***	0.0057 ***	0.0000
	(0.0013)	(0.0011)	(0.0003)	(0.0003)	(0.0001)
Month					
August	-0.0202 ***	-0.0179 ***	-0.0006	-0.0016 ***	-0.0002
	(0.0042)	(0.0039)	(0.0006)	(0.0005)	(0.0005)
September	-0.0038	-0.0033	-0.0005	0.0003	-0.0004
	(0.0039)	(0.0037)	(0.0006)	(0.0005)	(0.0004)
October	-0.0037	-0.0034	-0.0002	0.0002	-0.0003
	(0.0040)	(0.0038)	(0.0007)	(0.0005)	(0.0004)
November	-0.0010	-0.0006	-0.0013 **	0.0012 **	-0.0005
	(0.0039)	(0.0037)	(0.0006)	(0.0005)	(0.0004)
December	0.0005	0.0007	-0.0012 **	0.0014 ***	-0.0004
	(0.0039)	(0.0037)	(0.0006)	(0.0005)	(0.0004)
Feburary	0.0053 ***	0.0037 **	0.0005	0.0008 **	0.0003 *
	(0.0018)	(0.0017)	(0.0004)	(0.0003)	(0.0002)
March	0.0017	-0.0024	0.0021 ***	0.0015 ***	0.0006 **
	(0.0021)	(0.0019)	(0.0004)	(0.0004)	(0.0003)
April	0.0036	-0.0009	0.0019 ***	0.0015 ***	0.0014 ***
	(0.0027)	(0.0025)	(0.0005)	(0.0004)	(0.0004)
May	-0.0004	-0.0058 **	0.0027 ***	0.0015 ***	0.0013 ***
	(0.0029)	(0.0027)	(0.0005)	(0.0004)	(0.0004)
June	-0.0222 ***	-0.0212 ***	0.0014	-0.0019 ***	-0.0002
	(0.0041)	(0.0038)	(0.0010)	(0.0004)	(0.0003)
Experience	0.0060 **	0.0049 **	0.0006 **	0.0003	0.0003
	(0.0024)	(0.0023)	(0.0002)	(0.0002)	(0.0003)
Age	0.0028	0.0015	0.0010 **	0.0008 **	-0.0003
	(0.0029)	(0.0028)	(0.0004)	(0.0004)	(0.0003)
Dep. Var. Mean	0.060	0.051	0.005	0.004	0.001

Notes: KPSTD data. Observations are teacher–days (NT=790,085). Each column is one OLS regression as in Equation (5) and includes individual fixed effects, indicators for calendar year, school type (i.e., high school, middle school, elementary school), and education (all not shown). The standard errors in parentheses are clustered at the teacher level.

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Table 3: Balance–Use Elasticity

	(1)	(2)	(3)	(4)
$sinh^{-1}(balance_{t-10})$	-0.012 ***	-0.013 ***	0.010 ***	0.027 ***
	(0.0007)	(0.0008)	(0.0017)	(0.0018)
Sociodemographic controls	X	X	X	X
Day-of-week fixed effects	X	X	X	X
Month, year fixed effects	X	X	X	X
Individual fixed effects			X	X
10-day lead				X

Notes: KPSTD data. Observations are teacher–days (NT=739,738). In all models, the dependent variable is an indicator of any leave use, the sample mean of which is 0.0595. In columns (1)–(5), each column is one regression as in Equation (6). Additional controls include indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, and annual salary.

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Table 4: Evidence of Presenteeism

	(1) Any use	(2) Any use	(3) Any use
Share with balance < 10	0.029 **	0.026 **	0.027 **
	(0.0127)	(0.0127)	(0.0131)
$\ln(balance_{t-10})$	0.028 ***	0.028 ***	0.028 ***
	(0.0018)	(0.0018)	(0.0018)
Share using leave on day t		0.058 ***	0.058 ***
		(0.0085)	(0.0085)
Ave. share using leave, past 5 days		0.007	0.011
		(0.0178)	(0.0177)
$\ln(admits_t)$		0.007 ***	0.007 ***
		(0.0023)	(0.0023)
Sociodemographic controls	X	X	X
School fixed effects	X	X	X
Month, year, and DOW fixed effects	X	X	X
Individual fixed effects	X	X	X
10-day lead			X

Notes: KPSTD data. Observations are teacher–days (NT=739,628). In all models, the dependent variable is any leave use, the sample mean of which is 0.0595. Each column is one regression. Controls and fixed effects are identical to those included in Equation (5), but school-type fixed effects have been replaced by school fixed effects. In column (3), the share of teachers in the school with a balance of less than 10 is measured with a 10-day lead.

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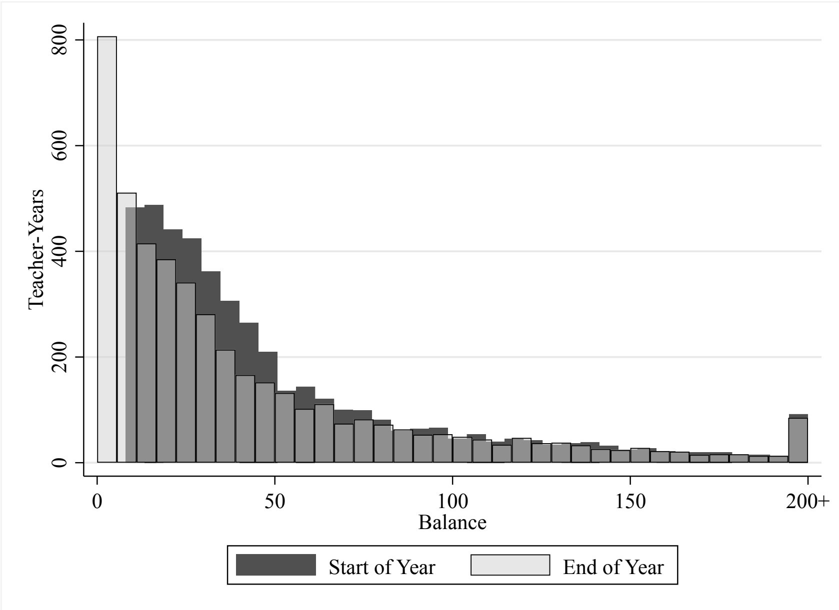
Figures

Figure 1: Mean Teacher Balance, Start vs. End of School Year



Notes: KPSTD data, aggregated to teacher–year, yielding a total of 4,580 observations. Histograms of two variables are reported: (i) teacher leave balance on the first day of the school year and (ii) teacher leave balance on the last day of the school year.

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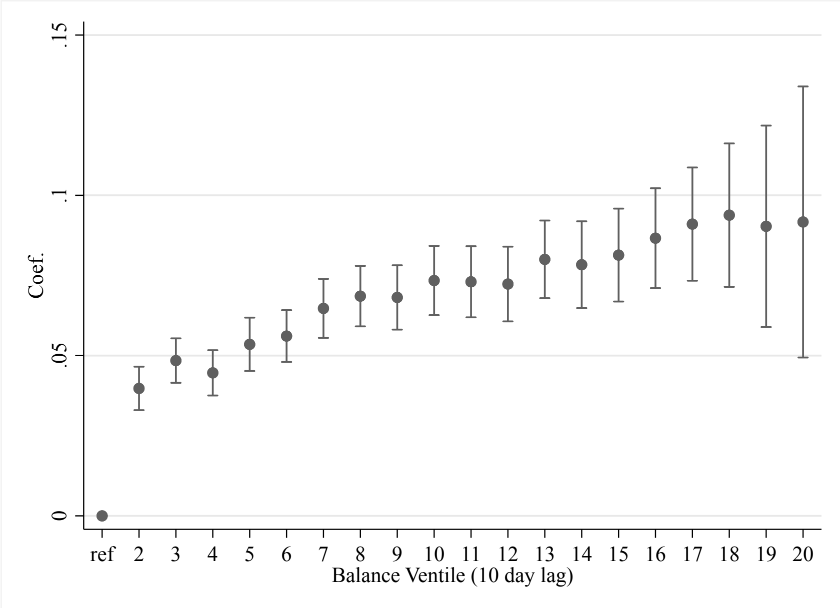
Figure 2: Impact of Balance Ventile on Leave Probability



Notes: KPSTD data. Observations are teacher–days (NT=790,615). The graph shows 10-day-lead leave-balance ventile coefficients and 95% confidence intervals. The dependent variable is whether any leave was taken on a particular day, the sample mean of which is 0.0595. The regression is as Equation (7) and includes controls for teacher education, age, experience, and salary and year, month, and day-of-week indicators. The regression also includes teacher fixed effects. Standard errors are clustered at the teacher level.

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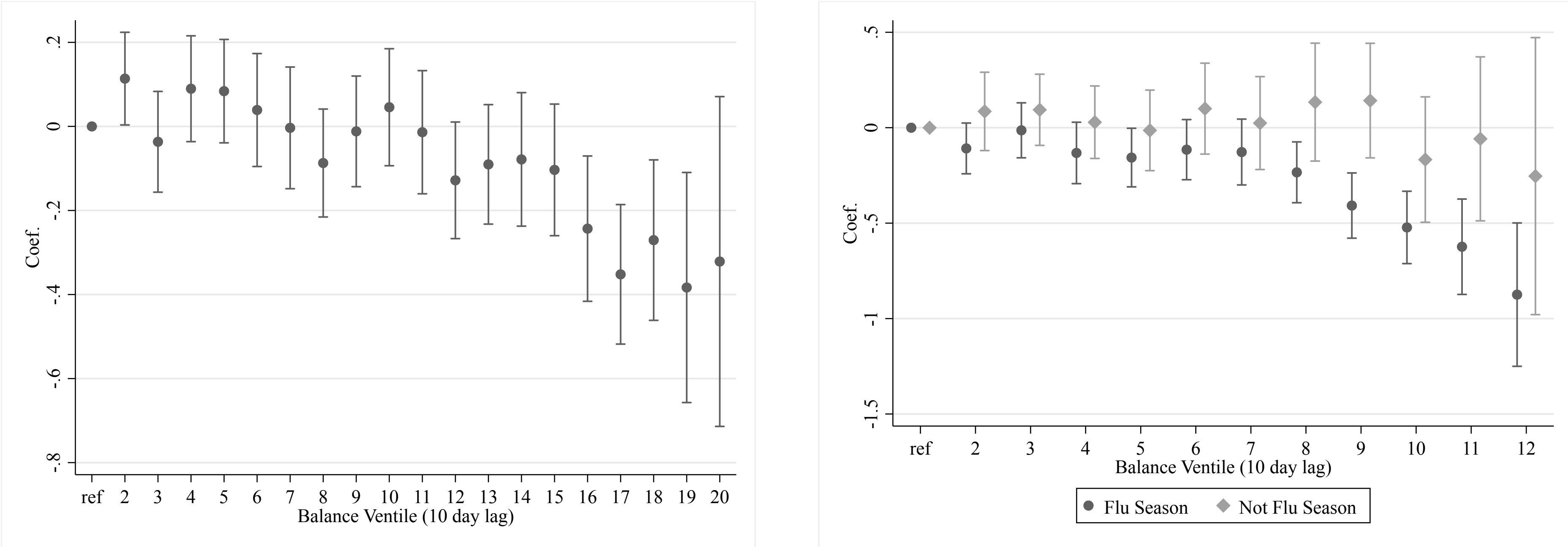
Figure 3: Impact of Balance Ventile on Presenteeism



Panel A

Panel B

Notes: KPSTD data, collapsed to the illness-spell level. The graphs show leave-balance ventile coefficients (from Equation (8)) and 95% confidence intervals. The outcome variable is whether the spell contains a presenteeism event (see Table **??**). Regressions include controls for teacher education, age, experience, and salary and year, month, and day-of-week indicators. Teacher fixed effects are included, and standard errors are clustered at the teacher level. Panel A includes all illness spells in a single regression. Panel B separates spells during flu season from those outside of flu season.