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The Anatomy of U.S. Sick Leave Schemes: Evidence From Public School Teachers

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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 DA1 for a full list of acknowledgments. Further, please note that all nonauthored technical reports and websites are referenced in Appendix Section DA8.

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 (Ichino and Riphahn, 2005; Fevang et al., 2014; Maclean et al., 2025; Schmutte and Skira, 2023). 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 H.R. 6201 (2020), 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).

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

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, 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 work-

(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).

ers' 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 analysis; *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 sets 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 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 at lower leave balances and that this effect 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 Healthy Families Act (2023). Similar to the scheme studied in this paper, the Healthy Families Act envisions individual sick leave accounts and a balance of seven days per year.[7] Since 2009, 14 states, the District of Columbia, and dozens of large cities have passed similarly designed regional mandates (see A Better Balance (2022) 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 an important 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 (White House, 2021). 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.

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 during the 2010/2011 school year up to and including the 2017/2018 school year; there are 790,615 observations from 982 unique teachers. The KSTLD contains detailed administrative information on when exactly teachers took sick, personal, or emergency leave days, 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).

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 A7); 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 Kentucky Legislative Research Commission (2019). Most notably, Kentucky teachers earn a minimum of ten 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 DA2.3. 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 DA2.3). 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 DA2.3, we discuss the typical maternity experience of teachers in Kentucky.

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 DA5. 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 A1, 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 DA2.3.

[11]We show in Appendix Figure A9 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.

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 A2 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 DA3.4, 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 there 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.

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 any Kentucky county besides Fayette. In 2014, approximately 20% of the population of Scott County attended the fall meet. In total, the KSTLD contains 130 days and 73,695 teacher–day observations for which Keeneland meets are in session (∼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. 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.

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

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

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 A7). 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:

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

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

[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 DA2.3 for additional context.

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 $Pr(\epsilon \leq a) = F(a)$.

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

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

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

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.

[16] The rules governing retirement pay, including those determining how leave balances influence retirement pay, can be found in Appendix Section DA5.

[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.

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 DA6, 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 DA6 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 exceeding 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 in the nature of 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 DA6. 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 A9), 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 utility 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 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 A4, we plot the ventile coefficients from 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

[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, but 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 A1 contains the admit range within each ventile.

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 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 (Frontline, 2017), 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, several studies from different industries suggest that transitioning back to work after the weekend comes 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). Combined with the fact 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

[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, as opposed to 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 (Redbooth, 2017).

[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.

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 A2 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. 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 A3-A8, we explore heterogeneity in these results. A brief description follows.

Gender and Children. Table A3 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, but 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 or are married or where the teachers live. Twelve of the 15 schools are located in the city center and the other three 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 A4 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 A5). Further, some inexperienced teachers commit the "rookie mistake" of calling in sick on a Keeneland Friday. Similarly, Table A6 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 A7 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 U.S. News and World Report (2025) 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 A8, 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 DA7.1 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 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 the possibility that leave may be taken for leisure opportunities we simply 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,

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

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 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 cause the sign to turn positive. In column (4), we replace 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 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 A9, 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

[24] Consistent with these findings, Appendix Figure A5 shows that the unconditional correlation between leave balance and use on any given day is negative.

this end, we repeat the ventile approach used in Section 4.1, dividing the balance distribution into twenty equal bins. Appendix Table A1 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:

$$y_{it} = \beta_0 + \Sigma_{k=2}^{20} V^b_{i,t-10,k}\beta_{1,k} + X_{it}\beta_2 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it}. \tag{7}$$

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 DA2.3. 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 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 unpaid leave taking. 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

[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.

realities, Table A10 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 DA7.1, 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 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

[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).

[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.

presenteeism. First, we attempt to measure presenteeism directly from the data. Second, we infer presenteeism from within-school illness spillovers.

To begin, we propose the following novel proxy for presenteeism behavior using our daily administrative data: We flag instances when teachers briefly return to work amid 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) and 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 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 A11 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

[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.

[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.

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 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 3,045 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.

[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.

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 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 error 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 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 almost one thousand 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

[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 on the basis of 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.

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 (for example, older teachers are more likely to call in sick during the NCAA tournament), but the effect of such behavior on teacher absence in the aggregate is very small. 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 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

[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).

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 used inappropriately 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 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

[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 DA2.3 may be needed to prevent employees from rapidly using all of their leave before switching jobs or careers.

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 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

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

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.

References

Adda, J. (2016). Economic activity and the spread of viral diseases: Evidence from high frequency data. *The Quarterly Journal of Economics 131*(2), 891–941.

Angrist, J. D. and J.-S. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion* (1 ed.). Princeton University Press.

Barmby, T. and M. Larguem (2009). Coughs and sneezes spread diseases: An empirical study of absenteeism and infectious illness. *Journal of Health Economics 28*(5), 1012–1017.

Bauernschuster, S., P. Duersch, J. Oechssler, and R. Vadovic (2010). Mandatory sick pay provision: A labor market experiment. *Journal of Public Economics 94*(11), 870 – 877.

Böckerman, P., O. Kanninen, and I. Suoniemi (2018). A kink that makes you sick: The effect of sick pay on absence. *Journal of Applied Econometrics 33*(4), 568–579.

Bollinger, C. (2015). A measure of the economic impact of keeneland racing and sales on lexington-fayette county. *CBER Research Report* (21).

Boyd, D., H. Lankford, S. Loeb, and J. Wyckoff (2005). Explaining the short careers of high-achieving teachers in schools with low-performing students. *American Economic Review: Papers and Proceedings 95*(2), 166–171.

Callison, K. and M. F. Pesko (2022). The effect of paid sick leave mandates on coverage, work absences, and presenteeism. *Journal of Human Resources* (4), 1178–1208.

Campbell, Z., E. Chyn, and J. Hastings (2019). The impact of paid maternity leave: Evidence from Temporary Disability Insurance in Rhode Island. Technical report. mimeo.

Campolieti, M. and D. Hyatt (2006). Further evidence on the Monday effect in Workers' Compensation. *Industrial and Labor Relations Review 59*(3), 438–450.

Card, D. and B. P. McCall (1996). Is Workers' Compensation covering uninsured medical costs? evidence from the "Monday Effect". *ILR Review 49*(4), 690–706.

Carlsson, M., G. B. Dahl, B. Öckert, and D.-O. Rooth (2015). The effect of schooling on cognitive skills. *The Review of Economics and Statistics 97*(3), 533–547.

Chen, J. and J. Roth (2024). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics 139*(2), 891–936.

Chetty, R., J. N. Friedman, and J. E. Rockoff (2014). Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates. *American Economic Rev. 104*(9), 2593–2632.

Darrow, L. A., M. J. Strickland, M. Klein, L. A. Waller, W. D. Flanders, A. Correa, M. Marcus, and P. E. Tolbert (2009). Seasonality of birth and implications for temporal studies of preterm birth. *Epidemiology (Cambridge, Mass.) 20*(5), 699.

De Paola, M., V. Scoppa, and V. Pupo (2014). Absenteeism in the Italian public sector: The effects of changes in sick leave policy. *Journal of Labor Economics 32*(2), 337–360.

Duflo, E., R. Hanna, and S. P. Ryan (2012). Incentives work: Getting teachers to come to school. *American Economic Review 102*(4), 1241–78.

Ehrenberg, R. G., R. A. Ehrenberg, D. I. Rees, and E. L. Ehrenberg (1991). School district leave policies, teacher absenteeism, and student achievement. *J. of Human Resources 26*(1), 72–105.

Fevang, E., I. Hardoy, , and K. Røed (2017). Temporary disability and economic incentives. *The Economic Journal 127*(603), 1410–1432.

Fevang, E., S. Markussen, and K. Røed (2014). The sick pay trap. *Journal of Labor Economics 32*(2), 305–336.

Findlay, S. (2021). Biden and democrats propose national paid leave. Technical report, Health Affairs: Forefront.

Finkelstein, A., E. F. P. Luttmer, and M. J. Notowidigdo (2013). What good is wealth without health? the effect of health on the marginal utility of consumption. *Journal of the European Economic Association 11*, 221–258.

Gilleskie, D. (2010). Work absences and doctor visits during an illness episode: The differential role of preferences, production, and policies among men and women. *Journal of Econometrics 156*(1), 148–163.

Gilleskie, D. B. (1998). A dynamic stochastic model of medical care use and work absence. *Econometrica 66*(1), 1–45.

Grigoryeva, A. (2017). Own gender, sibling's gender, parent's gender: The division of elderly parent care among adult children. *American Sociological Review 82*(1), 116–146.

Herrmann, M. A. and J. E. Rockoff (2012). Does menstruation explain gender gaps in work absenteeism? *Journal of Human Resources 47*(2), 493–508.

Hesselius, P., J. P. Nilsson, and P. Johansson (2009). Sick of your colleagues' absence? *Journal of the European Economic Association 7*(2-3), 583–594.

Ichino, A. and G. Maggi (2000). Work environment and individual background: Explaining regional shirking differentials in a large Italian firm. *The Quart. J. of Econ. 115*(3), 1057–1090.

Ichino, A. and E. Moretti (2009). Biological gender differences, absenteeism, and the earnings gap. *American Economic Journal: Applied Economics 1*(1), 183–218.

Ichino, A. and R. T. Riphahn (2005). The effect of employment protection on worker effort. A comparison of absenteeism during and after probation. *Journal of the European Economic Association 3*(1), 120–143.

Jelliffe, E., P. Pangburn, S. Pichler, and N. R. Ziebarth (2021). Awareness and use of (emergency) sick leave: US employees' unaddressed sick leave needs in a global pandemic. *Proceedings of the National Academy of Sciences 118*(29).

Johansson, P. and M. Palme (1996). Do economic incentives affect work absence? Empirical evidence using Swedish micro data. *Journal of Public Economics 59*(1), 195–218.

Johansson, P. and M. Palme (2002). Assessing the effect of public policy on worker absenteeism. *Journal of Human Resources 37*(2), 381–409.

Johansson, P. and M. Palme (2005). Moral hazard and sickness insurance. *Journal of Public Economics 89*(9-10), 1879–1890.

Koning, P. W. and D. J. Van Vuuren (2010). Disability insurance and unemployment insurance as substitute pathways. *Applied Economics 42*(5), 575–588.

Le Barbanchon, T., R. Rathelot, and A. Roulet (2019). Unemployment insurance and reservation wages: Evidence from administrative data. *Journal of Public Economics 171*, 1–17.

Long, M. and M. Rae (2020). Gaps in the emergency paid sick leave law for health care workers. *Coronavirus (COVID-19). Kaiser Family Foundation*.

Maclean, J. C., S. Pichler, and N. R. Ziebarth (2025). Mandated sick pay: Coverage, utilization, and welfare effects. *Journal of the European Economic Association forthcoming*.

Manning, W. G., J. P. Newhouse, N. Duan, E. B. Keeler, and A. Leibowitz (1987). Health insurance and the demand for medical care: evidence from a randomized experiment. *The American Economic Review 77*(3), 251–277.

Marie, O. and J. Vall Castelló (2023). Sick leave cuts and (unhealthy) returns to work. *Journal of Labor Economics 41*(4), 923–956.

Markussen, S. and K. Røed (2017). The market for paid sick leave. *J. of Health Econ. 55*, 244–261.

Markussen, S., K. Røed, O. J. Røgeberg, and S. Gaure (2011). The anatomy of absenteeism. *Journal of Health Economics 30*(2), 277–292.

Markussen, S., K. Røed, and R. C. Schreiner (2018). Can compulsory dialogues nudge sick-listed workers back to work? *The Economic Journal 128*(610), 1276–1303.

Miller, R. T., R. J. Murnane, and J. B. Willett (2008). Do teacher absences impact student achievement? longitudinal evidence from one urban school district. *Educational Evaluation and Policy Analysis 30*(2), 181–200.

Mullahy, J. and E. C. Norton (2024). Why transform y? the pitfalls of transformed regressions with a mass at zero. *Oxford Bulletin of Economics and Statistics 86*(2), 417–447.

O'Malley, A. S. (2013). After-hours access to primary care practices linked with lower emergency department use and less unmet medical need. *Health Affairs 32*(1), 175–183.

Pichler, S., K. Wen, and N. R. Ziebarth (2020). Covid-19 emergency sick leave has helped flatten the curve in the United States. *Health Affairs 39*(12), 2197–2204.

Pichler, S., K. Wen, and N. R. Ziebarth (2021). Positive health externalities of mandating paid sick leave. *Journal of Policy Analysis and Management 40*(3), 715–743.

Pichler, S. and N. Ziebarth (2017). The pros and cons of sick pay schemes: Testing contagious presenteeism and noncontagious absenteeism behavior. *J. of Public Economics 156*, 14–33.

Ranji, U. and A. Salganicoff (2014). Balancing on shaky ground: Women, work, and family health. *Menlo Park, CA: Kaiser Family Foundation*.

Raub, A., P. Chung, P. Batra, A. Earle, B. Bose, J. Jou, N. D. G. Chorny, E. Wong, D. Franken, and J. Heymann (2018). Paid leave for personal illness: a detailed look at approaches across oecd countries. *WORLD Policy Analysis Center 32*.

Riphahn, R. T. (1997). Disability retirement and unemployment-substitute pathways for labour force exit? an empirical test for the case of germany. *Applied economics 29*(5), 551–561.

Roberts, D. J., J.-F. Ouellet, P. B. McBeth, A. W. Kirkpatrick, E. Dixon, and C. G. Ball (2014). The "weekend warrior": Fact or fiction for major trauma? *Canadian Journal of Surgery 57*(3), E62.

Schmieder, J. F. and T. von Wachter (2016). The effects of unemployment insurance benefits: New evidence and interpretation. *Annual Review of Economics 8*(Volume 8, 2016), 547–581.

Schmutte, I. M. and M. M. Skira (2023). The response of firms to maternity leave and sickness absence. *Journal of Human Resources forthcoming*.

Skogman Thoursie, P. (2004). Reporting sick: are sporting events contagious? *Journal of Applied Econometrics 19*(6), 809–823.

Stearns, J. and C. White (2018). Can paid sick leave mandates reduce leave-taking? *Labour Economics 51*, 227–246.

Stevens, M. (2019). Kentucky's teachers helped deliver a stunning defeat to gov. matt bevin. https://www.vox.com/identities/2019/11/6/20951459/kentucky-democrat-beshear-bevin-teachers. Accessed: 2025-09-17.

Stonko, D. P., B. M. Dennis, R. A. Callcut, R. D. Betzold, M. C. Smith, A. J. Medvecz, and O. D. Guillamondegui (2018). Identifying temporal patterns in trauma admissions: Informing resource allocation. *PLoS One 13*(12), e0207766.

Taylor, E. S. and J. H. Tyler (2012). The effect of evaluation on teacher performance. *American Economic Review 102*(7), 3628–51.

Thomas, M. (2020). The impact of mandated maternity leave policies on the gender gap in promotions: Examining the role of employer-based discrimination. *Available at SSRN 3729663*.

Willich, S. N., H. Löwel, M. Lewis, A. Hörmann, H.-R. Arntz, and U. Keil (1994). Weekly variation of acute myocardial infarction. increased monday risk in the working population. *Circulation 90*(1), 87–93.

Ziebarth, N. R. (2013). Long-term absenteeism and moral hazard—Evidence from a natural experiment. *Labour Economics 24*, 277–292.

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

Ziebarth, N. R. and M. Karlsson (2014). The effects of expanding the generosity of the statutory sickness insurance system. *Journal of Applied Econometrics 29*(2), 208–230.

Tables

Table 1: Kentucky Public School Teacher Data, Teacher Demographics

	Mean	SD	Min	Max
A. Sociodemographics				
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				
Bachelor's	0.152	0.359	0	1
Master's	0.462	0.499	0	1
Rank 1 or above	0.386	0.487	0	1
B. Employment				
Experience	11.713	8.172	0	37
First year	0.053	0.224	0	1
1–5 years	0.221	0.415	0	1
6–10 years	0.216	0.412	0	1
11–15 years	0.201	0.401	0	1
16–20 years	0.148	0.356	0	1
21–25 years	0.088	0.284	0	1
26+ years	0.071	0.257	0	1
Base Salary	50,257	7,964	30,877	66,930
Extra Salary	1,523	3,178	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	9.03	8.30	0	106
Sick	7.64	7.84	0	103
Personal	0.70	0.82	0	4
Emergency	0.59	0.66	0	3
Uncompensated	0.11	0.75	0	13.5
Total days *any* leave taken	10.27	8.74	0	106
Share of days *any* leave taken	0.06	0.05	0	0.72
No leave taken	0.05	0.21	0	1
3 or fewer days' leave taken	0.19	0.39	0	1
20+ days' leave taken	0.06	0.24	0	1
D. Leave Balance				
Balance	51.73	47.38	2.50	348.25
if experience $= 0$	14.25	6.15	5.00	52.50
if experience $\in [1, 5)$	29.47	16.87	2.50	165.25
if experience $\in [5, 10)$	37.28	25.14	4.50	205.25
if experience $\in [10, 15)$	50.49	34.83	5.00	189.00
if experience $\in [15, 20)$	72.66	52.12	5.50	252.00
if experience $\in [20, 25)$	89.21	64.99	8.00	289.75
if experience $\in [25, \infty)$	106.27	74.48	5.00	348.25

Notes: Observations are teacher–years (NT=4,580). There are 982 teachers, 293 of whom are present in all 8 years. SD stands for "standard deviation."

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

	Any	Sick	Emergency	Personal	Uncomp
ln(admits)	0.0094 ***	0.0094 ***	0.0009 **	-0.0009 **	0.0002
	(0.0023)	(0.0022)	(0.0004)	(0.0004)	(0.0003)
Holiday					
day prior	-0.0045 ***	-0.0038 ***	0.0023 ***	-0.0029 ***	-0.0002 *
	(0.0014)	(0.0012)	(0.0005)	(0.0003)	(0.0001)
day following	-0.0092 ***	-0.0081 ***	0.0002	-0.0012 ***	-0.0001
	(0.0011)	(0.0010)	(0.0003)	(0.0002)	(0.0002)
Keeneland	0.0020	0.0015	0.0000	0.0008 **	-0.0003 **
	(0.0014)	(0.0013)	(0.0004)	(0.0004)	(0.0001)
× Friday	0.0062 ***	0.0020	-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	0.0229 ***	0.0132 ***	0.0041 ***	0.0057 ***	0.0000
	(0.0012)	(0.0011)	(0.0003)	(0.0003)	(0.0001)
Month					
August	-0.0203 ***	-0.0180 ***	-0.0006	-0.0016 ***	-0.0002
	(0.0041)	(0.0039)	(0.0006)	(0.0005)	(0.0005)
September	-0.0039	-0.0034	-0.0005	0.0003	-0.0004
	(0.0039)	(0.0037)	(0.0006)	(0.0005)	(0.0004)
October	-0.0038	-0.0035	-0.0002	0.0002	-0.0003
	(0.0040)	(0.0038)	(0.0007)	(0.0005)	(0.0004)
November	-0.0012	-0.0007	-0.0013 **	0.0012 **	-0.0005
	(0.0039)	(0.0037)	(0.0006)	(0.0005)	(0.0004)
December	0.0004	0.0005	-0.0012 **	0.0014 ***	-0.0004
	(0.0039)	(0.0037)	(0.0006)	(0.0005)	(0.0004)
February	0.0053 ***	0.0037 **	0.0005	0.0008 **	0.0003 *
	(0.0018)	(0.0017)	(0.0004)	(0.0003)	(0.0002)
March	0.0017	-0.0023	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	0.0062 **	0.0051 **	0.0006 **	0.0003	0.0003
	(0.0025)	(0.0023)	(0.0002)	(0.0002)	(0.0003)
Age	0.0029	0.0015	0.0010 **	0.0008 **	-0.0003
	(0.0029)	(0.0028)	(0.0004)	(0.0004)	(0.0003)
Dep. Var. Mean	0.060	0.050	0.005	0.004	0.001

Notes: KPSTD data. Observations are teacher–days (NT=790,615). 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.

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=740,235). 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.

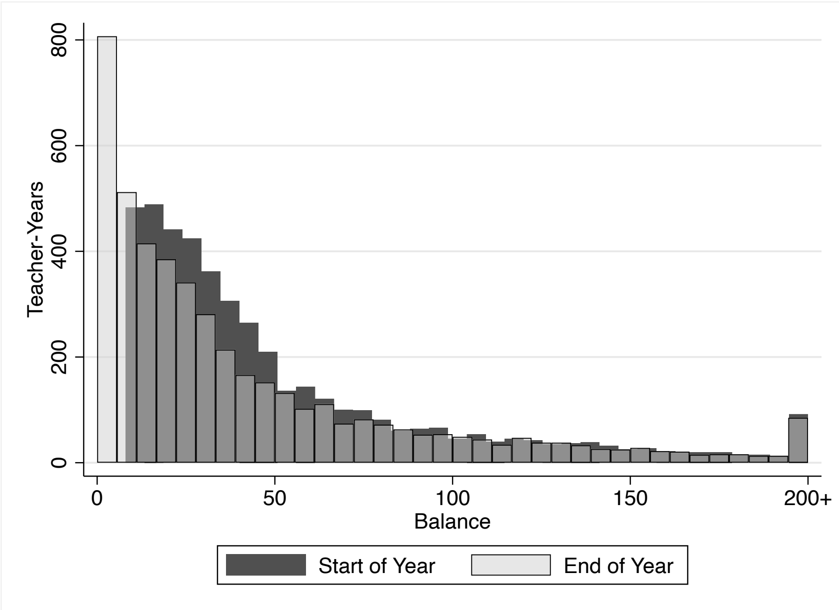
Table 4: Evidence of Presenteeism

	(1) Any use	(2) Any use	(3) Any use
Share with balance < 10	0.030 **	0.027 **	0.027 **
	(0.0127)	(0.0128)	(0.0131)
ln($balance_{t-10}$)	0.028 ***	0.028 ***	0.028 ***
	(0.0018)	(0.0018)	(0.0018)
Share taking leave on day t		0.058 ***	0.058 ***
		(0.0085)	(0.0085)
Ave. share taking 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=740,125). 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 less than 10 is measured with a 10-day lead.

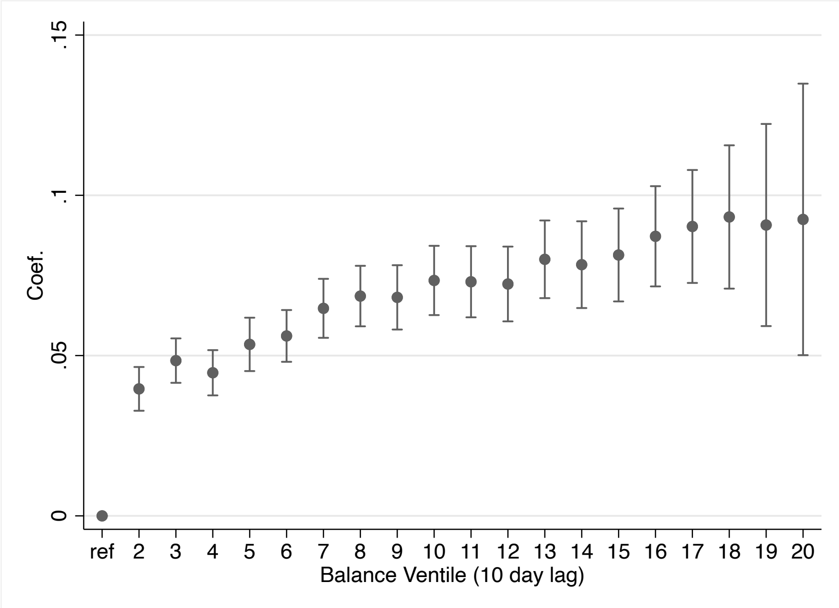
Figures

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



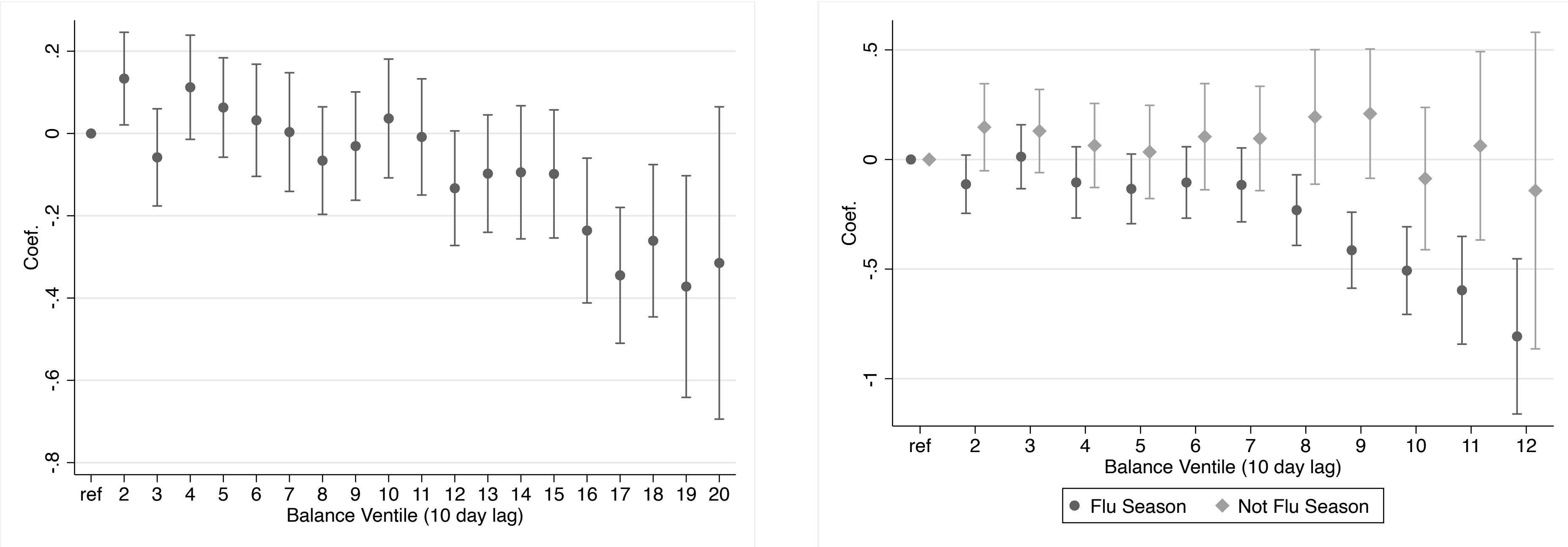
Notes: KPSTD data, aggregated to teacher–year, yielding a total of 4,580 observations. Histograms of two variables are reported: (i) teacher leave balance on the first day of the school year and (ii) teacher leave balance on the last day of the school year.

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.

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 A11). 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.

Appendix – For Online Publication

DA1 Acknowledgments

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DA2 Scott County School District and Its Leave Policy

In this section, we describe the construction of the Kentucky School Teacher Leave Dataset (KSTLD), the main data source for Cronin, Harris, and Ziebarth (2025). We also describe sick leave and other policies relevant for school teachers in the Scott County School District (SCSD).

DA2.1 Scott County School District

Kentucky has a total of 172 school districts and 120 counties. Scott County, in central Kentucky, is the 17th most populous county in the state. In 2020, it had 57,155 residents and a single public school district, SCSD.[1] SCSD is the 12th largest in the state, consisting of 18 schools, with approximately 9,300 enrolled students and 1,364 faculty and staff.[2]

Most SCSD full-time employees are contracted for a 189-day school year. On the remaining 176 days of the year, which include weekends, holidays, and spring, summer, winter, and fall breaks, no work is required. Base compensation is determined by experience and education. For example, Figure A7 contains the 2018–2019 salary schedule. The salary schedule is tied to

[1] https://www.kentucky-demographics.com/counties_by_population

[2] https://www.greatschools.org/kentucky/georgetown/scott-county-school-district/, https://www.scott.k12.ky.us/district_staff.aspx?action=search&location=0&department=0

the 187 instruction days. Teachers are contracted for an additional two "in service" days, for which they receive additional compensation at their daily wage rate. For example, the base compensation for a teacher with 5 years of experience and a master's degree is $47,526, plus $508.30 for two days of service.

There are several ways in which teachers and school administrators can earn more than this base salary. Examples include the following:

- Some teachers take on an additional paid role that require out-of-school work, such as athletic team coach, club leader, or choir director. The associated wage rate varies but is tied to base pay—for example, the high school yearbook coordinator received 107% of base salary.
- For administrators, such as principals and vice principals, base compensation is determined by the salary schedule, but they (i) work more days than teachers and (ii) receive a lump-sum bonus. For example, the typical principal in our data works 230 days per year; thus, if she has 15 years of experience and a master's degree, she earns a $15,000 bonus, plus $67,672.89 for her 230 days, rather than $55,609.46 for 189 days. Assistant principals and guidance councilors are similar but may work fewer days and earn smaller bonuses.
- School psychologists earn the base pay plus 8%.

DA2.2 SCSD Leave Policy

The Kentucky Department of Education (KDE) imposes the following rules on school districts regarding paid leave[3]:

- Districts must provide teachers with a minimum of 10 paid leave days.
- Districts must allow unused leave days to accumulate without limit.
- Starting July 1, 1982, districts *may* compensate teachers at the time of retirement for *up to* 30% of their unused leave days in a lump sum. This lump-sum transfer counts toward the teacher's last year of income when it is factored into retirement (discussed below).

Similarly to many districts, SCSD grants teachers 13 days of paid leave per academic year: 10 sick days, 2 emergency days, and 1 personal day. Below, we detail the rules governing the use of each type of leave, including unpaid leave.

Upon retirement, teachers are paid for any accumulated unused leave. We detail the exact relationship between leave stock and retirement compensation in Section DA5.3 below. For now, simply note that retirement pay is increasing linearly in accumulated stock at the time of retirement, up to a cap of 300 days.

[3] http://www.lrc.ky.gov/Statutes/statute.aspx?id=47842

DA2.3 Types of Leave

There are three types of paid leave—sick, emergency, and personal—as well as unpaid leave. Teachers can also donate and receive donated leave from their colleagues. Different rules dictate the use of each type of leave, as we discuss below.

Paid Emergency and Personal Leave: Paid emergency leave existed through the end of the 2015/2016 school year and allowed teachers to take up to two paid days off work in the event of an emergency. Emergency leave is distinctive from sick leave in that the former can be used for nonmedical reasons (e.g., basement flood, car wreck). Emergency leave is never denied, but teachers must report a reason for requesting leave.

Starting with the 2016/2017 school year, teachers went from receiving one personal day per year to three (i.e., the district stopped distinguishing between emergency and personal leave). Personal days can be reserved in advance and must be approved by a teacher's principal. District documents suggest that personal leave is to be denied only if qualified substitute teachers are unavailable.[4] Note also that the superintendent, at times (e.g., the day before Christmas break), strictly prohibits the use of personal leave. Teachers are not asked to report a reason for taking personal leave. Teachers request emergency or personal leave through a web-based platform called Frontline Education.[5] Teachers report an anticipated absence, and the software creates a job that substitute teachers can select. The teacher and substitute also communicate through the software.

Paid Sick Leave: A teacher can use paid sick leave for any medical problem that she or an immediate family member has. This includes, but is not limited to, own or family member illness/accident, own or family member wellness visits, own or family member recovery from childbirth (or adoption), or mourning the death of an immediate family member. Teachers also apply for sick leave using the Frontline platform.

District documents state that "*upon return to work a certified employee claiming sick leave must file a personal statement or a certificate of a physician stating that the employee was ill or that the employee was absent to attend to a member of the immediate family who was ill.*"[6] In conversations with district administrators, we have been instructed to interpret this to mean that as long as a teacher is in good standing (i.e., has no history of inappropriate leave use) and is missing three consecutive days or fewer (roughly), they will not be asked for a doctor's note (i.e., a personal statement explaining their absence is sufficient). If the teacher requests more sick leave than this, then the superintendent of schools is likely to ask the teacher to supply the district with a doctor's note to receive her full compensation.

Ex ante, sick leave is never denied, but use of sick leave for reasons other than those stated above is strictly prohibited in official district documents. Although clear repercussions for abusive sick leave use are not stated in these documents, private correspondence with district

[4] https://www.dropbox.com/scl/fi/lg4nc6zcl8uq8xpvn54ny/personal_leave.docx?rlkey=eodmi9ohwzx8g2dt0op47zdfe&st=6pxsx5r2&dl=0

[5] https://www.frontlineeducation.com/signin/

[6] https://www.dropbox.com/scl/fi/ct7o0i7ioqdkeef9b6ik3/sick_leave.docx?rlkey=tg6of6lsnf3iiz6n4q747ld70&st=d6w1lpv3&dl=0

administrators provides guidance on what punishments might look like. The administrators gave the example of a teacher taking a sick day and then someone discovering a Facebook post featuring a picture of the teacher on a beach on the same day. For a first-time offense, this would likely result in the sick leave request being denied (i.e., the teacher would be forced to take unpaid leave). For a repeat offender, this offense could result in a 1–3 day unpaid suspension, and eventually, such disregard for district policy would result in termination.

SCSD has no separate system of paid maternity leave. According to the FMLA, employees are entitled to 12 weeks of (unpaid) leave after the birth or adoption of a child. Employees are permitted to use up to 30 days of paid sick leave on the first 30 days of this period. More paid leave can be used if the need is verified by a physician.[7] Employees can also request that the superintendent allow them to take the remainder of the year as unpaid leave,[8] after which, requests must be made in one-year increments.[9]

Unpaid Leave: Unpaid leave primarily takes three forms.[10] The first is short-term nonmedical leave. An example is leave for jury duty, which the district, by law, cannot deny. Another example is leave for a mission trip taken during the school year. A teacher can use personal leave for such an absence, but her principal could approve unpaid leave if she has none remaining.

A second form of unpaid leave is short-term medical leave, which could become necessary for a simple illness if a teacher has used all of her paid leave. Another common reason for such leave is that a teacher on maternity leave runs out of sick days (though this generally results in a flood of donations, as discussed below). Although this is not stated explicitly in district documents, administrators communicated that a request for unpaid short-run medical leave typically results in the district asking the teacher for a doctor's note; failure to provide such a note could result in sanctions (e.g., unpaid suspension).

The final form of unpaid leave is long-term medical leave. Again, this form of leave falls under FMLA rules, and the district treats it much like the maternity leave described above.[11]

Unpaid leave requests also require separate approval and administrative processes distinct from paid leave requests. To the extent that school principals incur administrative costs, some of these will inevitably be passed to the person taking unpaid leave. Additionally, except in the cases delineated above, taking unpaid leave is discouraged.

[7] https://www.dropbox.com/scl/fi/kt04cqklamj9ralswx1dn/maternity_leave.docx?rlkey=zvc8sxxtctcfg2quwrysfdsc0&st=4h532n03&dl=0

[8] This would be registered with an exit code of 0d in the birth year and an entry code of 1b in the following year; see below for codes.

[9] In all instances of early exit due to what appears to be maternity, all leave is used before the exit. If a teacher were to take the following year off due to maternity, the entry code upon reentry would be 2a or 2b; again, see below for codes.

[10] https://www.dropbox.com/scl/fi/ckez9epv05drtygauo3t1/unpaid_leave.docx?rlkey=3wzx5e8zwcyvv83nhea8lf7uk&st=v83ibry1&dl=0

[11] https://www.dropbox.com/scl/fi/ag6cdi1j5rm5zqor6nac6/family_medical_leave.docx?rlkey=jhb3w351cthmd7s0xs9psk9fw&st=u6z81gzw&dl=0

Leave Donations: The district allows teachers to donate sick leave to one another under certain conditions.[12] A summary of the rules are as follows: First, donating teachers must have 15 sick days available, and their donation must not leave their balance below 15. Second, a recipient of donated leave must have suffered a "catastrophic loss" to her person, family, or property that will likely cause an absence of 10+ consecutive work day. Third, the recipient must have exhausted all of her own paid leave. Fourth, donated leave not used consecutively for the original reason the donation was made will be returned to the donor.

DA3 Original Data Sources and Merge

The KSTLD records the individual employment activity of SCSD teachers on every calendar day between August 1, 2010, and June 29, 2018. The district provided retrospective school calendars, indicating whether school was in session each of these days for planned (e.g., holidays) or unplanned (e.g., snow day) reasons. For any day that school is in session, the KSTLD records (among other things) the teacher's stock of available sick leave and her leave activity. All teacher-level information is supplied by SCSD administrators or the KDE. Below, we describe each original data source and the process used to merge and clean the two data files.

DA3.1 Scott County Data

SCSD administrators provided us with two files on teacher attendance. The first file records all paid leave events. The second file records all pay periods in which a teacher's pay was "docked." Both files cover all SCSD employees working in the county at any point between the 2010/11 and 2017/18 school years.

In the paid leave file, an observation is a teacher–event, where the following correspond to an event:

- Taking (any fraction of) a school day off and receiving paid leave.
- A donation or receipt of leave from another SCSD employee.
- Earning leave, which occurs at the start of the school year.

Each event specifies the type (sick, personal, or emergency) and the corresponding date the leave was received/deducted. For every employee, we see the available stock of sick leave *on one date only*.[13] From this point in time, using the full history of leave used and earned, we calculate the stock available to each teacher on every school day from school years 2010/11 to 2017/18.

A separate "dock day" file records unpaid leave. This file also consists of teacher–event observations. Each event records the number of days of work for which the employee's pay is docked, as well as the dollar amount. The following describe possible events:

[12] https://www.dropbox.com/scl/fi/ct7o0i7ioqdkeef9b6ik3/sick_leave.docx?rlkey=tg6of6lsnf3iiz6n4q747ld70&st=74gibv08&dl=0

[13] The exact date depends on the employee's current employment status. For those no longer employed entering the 2018/19 school year, we see their stock at the end of the year *prior to* their exit. For those still employed entering the 2018/19 school year, we see their stock at the end of 2017/18.

- Taking unpaid leave, either because (i) the individual depleted her stock or (ii) the individual requested a paid personal day and it was denied but the individual took the day off nonetheless (for example, requested a personal day on the Friday before Spring Break and was denied). Both of these events represent absence from work, but they have no impact on one's stock of paid leave.

- Salary deductions for incomplete training. A school year is defined by 187 instructional days, plus two mandatory training days. As teacher contracts are defined by a 189-day year, salaries are docked when teachers do not complete these trainings. Trainings do not take place on instructional days; thus, these events do not represent missed instructional days and have no impact on one's stock of sick leave.

The dock day file provides less information about each event than the paid leave file. First, we cannot observe the reason pay is docked. Second, the date provided for each event is the pay date upon which the teacher's pay was docked, not the missed day of school or training. As the KSTLD file records teacher activity on instructional days, we need to (1) separately identify unpaid leave days and incomplete trainings and (2) impute the dates of the unpaid leave days (missed trainings are irrelevant for our purposes).

We make several assumptions. First, according to SCSD officials, all salary deductions for incomplete trainings are imposed on the last paycheck of the school year, in the last week of June. Thus, all dock day events on this paycheck are assumed to be incomplete training penalties and are, thus, dropped from the data.[14] Second, among the remaining events, the unpaid leave day must be taken in the 45- to 30-day window prior to the corresponding pay date. If paid leave is observed in this window, we assume unpaid leave was taken immediately following the last observed paid leave day. If no paid leave is observed in this window, we randomly select a day in this window in which unpaid leave was taken. In both instances, if multiple unpaid days were taken, we assume they were consecutive.

Importantly, note that there are more than 93,000 events in the raw paid leave file, but only 663 events in the dock day file; thus, true unpaid leave represents well below 1% of the total leave taken in the data. Thus, the assumptions discussed above are unlikely to have any significant impact on our findings.

DA3.2 State Data

While the stock of sick leave and teacher activity are measured at the daily level, all the other variables in the KSTLD data file are measured at the employee–academic year level. Most of these data are provided by the Kentucky Center for Statistics (KCS). Specifically, the KCS maintains the Kentucky Longitudinal Data System (KLDS), which follows Kentucky teachers and administrators throughout their careers as educators.[15] From the KCS, we received a subset of the KLDS, corresponding to Scott County teachers and administrators only. Specifically, for

[14] Note that in doing this, we likely inadvertently drop some true unpaid leave that occurs in the last two weeks of school. Thus, we modify this rule on a case-by-case basis. Specifically, if a teacher has no available (paid) leave at any point during this two-week period, then we assume that the dock day event is unpaid leave.

[15] To learn more about the KLDS, visit https://kcews.ky.gov/. Note that the KLDS does not contain information on school staff, such as cafeteria workers, bus drivers, substitute teachers, and administrative assistants.

every individual who taught (at any time) in SCSD during academic years 2010/11 to 2017/18, we receive a full history of KDE employment, going back to 2009, including work outside of Scott County.

Among the variables provided in the KLDS, the following permanent and time-varying (by academic year) variables are included:

- Permanent: gender, race, and degree-granting institution.
- Time-varying: educational rank, experience as an educator in Kentucky, annual base salary, supplemental salary, current district name, name of school, and job title (e.g., middle school teacher, assistant principal, guidance councilor).

DA3.3 Merge

The KCS merged the paid leave file described in Section DA3.1 with the KLDS. The KLDS data contain first and last names, date of birth, and a state identification number (i.e., EPSBID), for 100% of the observations. The paid leave file also contains first and last names and date of birth for 100% of the observations but the EPSBID for just 40%. Thus, observations were first merged by EPSBID, then by first and last name and date of birth.

We eliminated anyone from the SC data who was not a "certified employee," meaning we eliminated those who are not full-time teachers, school administrators (e.g., principals, vice principals, deans), guidance counselors, psychologists, social workers, librarians, or speech therapists. This yielded a data file with 1,046 employees, 4,816 employee–years, and 60,464 leave events. KCS then matched this information to the KLDS. Only 12 individuals could not be located in the KLDS. Among the 1,034 matches, KLDS had time-invariant demographic information for all but 36 individuals; these individuals were excluded from our analysis. The resulting sample contained 998 individuals and 4,730 teacher–year observations; 96.4% of the paid leave events in this sample were correctly matched to the appropriate teacher–year data in the KLDS.

The remaining 3.6% of unmatched data was carefully evaluated on a case-by-case basis. Two situations account for most of this mismatch. First, the KLDS gathers data from school districts on the first day of the school year. Any teacher who begins the school year late is then missing from the KLDS in that year. Furthermore, any teacher who switches schools during the school year is attached only to the first school.[16] Second, young teachers often work as student teachers, teaching assistants, and teacher aids in the year prior to their first year of employment. During this precertification employment year, future teachers bank any unused sick leave, but KLDS does not collect employment information in this year. These individuals then show up in the KLDS, with zero years of experience, in their first year as full-time teachers. After we evaluated each of these cases individually and eliminating inconsistent/irrelevant observations, the final sample contains 982 teachers, 4,580 teacher–years, and 52,695 leave events.

[16] Such cases account for most of the unmatched and demographic-only matched teachers discussed above. If an individual teaches for only one year and begins that year late, she may never enter the KLDS data.

DA3.4 Supplemental Data

The KSTLD contains a number of variables believed to influence the likelihood of leave use. These are discussed below.

Hospital Admissions for Influenza. The first variable measures influenza and pneumonia (I&P) admissions from the Health Facility and Services Data, collected by the Kentucky Cabinet for Health and Family Services. To proxy for local flu intensity, we measure total weekly admissions to Kentucky hospitals (emergency department, outpatient, or inpatient) and ambulatory facilities (surgery centers, urgent treatment centers, etc.) of people from Scott County or any of the seven bordering counties, with an ICD 10 diagnosis code indicating influenza or pneumonia.[17]

Appendix Figure A3 shows total weekly I&P admissions from July 2010 to July 2018. We observe characteristic seasonality patterns of flu, with spikes primarily from December to February, but with variation between years in the exact timing of the peak. The slightly increasing trend in admissions is explained by both population growth and the fact that 2014/15 and 2017/18 were high-infection years nationwide (CDC, 2025). Our regression models flexibly control for this time trend using year fixed effects.

Scheduled Breaks. Also included in the KSTLD are a number of calendar-event indicators, which do not vary between SCSD teachers. Examples include professional development days, early-release days, and federal and local holidays. We extract this information from school calendars supplied by SCSD. We use these variables to create indicators for the days (and weeks) immediately preceding and following scheduled breaks that last three or more days, excluding school cancellation due to weather. Examples include spring and fall break, summer break, and Labor Day (which always occurs on a Monday, creating a three-day weekend). There are 75 such breaks in our data—a little over nine on average each school year.

Nationally Recognized Sporting Events. We create two variables related to the timing of nationally recognized sporting events that may exogenously shift the probability of taking leave for recreational purposes.

The first event variable indicates days when the University of Kentucky Men's Basketball (UKMBB) team plays in the NCAA tournament. UKMBB consistently ranks among the top NCAA basketball programs in attendance[18] and popularity.[19] The dedication of NCAA basketball fans is never more evident than during the NCAA tournament (often called "March Madness"), the apex of the season. In a 2014 survey of US adults, 11% reported that they *would* call in sick to watch the NCAA tournament,[20] while the Bureau of Labor Statistics (BLS) esti-

[17] Bordering counties include Owen, Grant, Harrison, Bourbon, Fayette, Woodford, and Franklin. The population of these counties, plus Scott, is 530,000—12% of the state's population. Regarding diagnosis, we use ICD 9 codes 480–488 for weeks 1/1/2000–9/30/2015 and ICD 10 codes J09–J18 for weeks beyond 10/1/2015.

[18] https://www.ncaa.com/news/basketball-men/article/2020-10-27/25-mens-college-basketball-teams-highest-attendance-2019-20

[19] https://bleacherreport.com/articles/550473-the-duke-blue-devils-and-the-50-best-fan-bases-in-

[20] https://retailmenot.mediaroom.com/2014-03-10-March-Madness-Brings-Madness-to-the-Workplace

mates the average absence rate nationwide is 3%.[21] First-round games are always played on a Thursday and Friday in mid-March. Third-round games are played the following Thursday and Friday, while the championship game is played two Mondays later. First-round games are scheduled throughout the day, and many occur during the school day. UKMBB made the tournament in all years of our sample period except 2013. This totals 13 days (7,327 teacher–day observations) when school was in session and UKMBB was playing in the NCAA tournament.

The second event variable indicates the Monday following the Super Bowl. Commonly referred to as "Super Bowl fever," an annual survey by the Workforce Institute estimates that approximately 10% of the US workforce *plans* to miss work the Monday following the Super Bowl each year.[22] There are six instances of Super Bowl Monday occurring on a school day in our sample period (3,382 teacher–day observations); February 3, 2014 (school closure due to weather), and February 5, 2018 (a scheduled closure), are the exceptions.

DA4 Job Transitions

Of the 4,580 teacher–years described above, 96.7% are "typical" in the sense that the teacher is working on the first day of school and continues to work until the end of the school year. Below, we describe the sources of atypical entry and exit. To aid in this discussion, we describe two variables that we create and the values these variables can take. Note that each teacher–year is ultimately described by both an entry and exit code.

- Variable 1: *entry_code* is a two-digit code containing one number, describing the current year's employment in relation to the prior year, and one letter, describing the timing of one's entry and the status of one's sick leave stock. The codes have the following meanings:

    0. first year employee is observed in the SC data
    1. continued employment, with no gap in service
    2. continued employment, returning from gap in service

    a. working on first day of school with stock from prior years
    b. working on first day of school with no stock
    c. not working on first day of school with stock from prior years
    d. not working on first day of school with no stock

- Variable 2: *exit_code* is similarly defined, although the number describes what the employee does in the following school year, and the letter describes the timing of exit and what happens to one's personal/emergency days.

    0. renewed at the beginning of the following school year—i.e., works for SCSD in the following year.

[21] https://www.bls.gov/cps/cpsaat47.htm#cps_eeann_abs_ft_occu_ind.f.1

[22] https://workforceinstitute.org/a-super-bowl-like-no-other/

1. moves to another KY school district
2. retires from teaching
3. stops teaching in KY

a. works the last day of the year and personal/emergency days converted into future sick leave

b. works the last day of the year and personal/emergency days NOT converted into future sick leave

c. exits prior to the last day of the year and personal/emergency days converted into future sick leave (this never happens, but is included for completeness)

d. exits prior to the last day of the year and personal/emergency days NOT converted into future sick leave

Entry and exit frequencies appear in Appendix Table A12. We discuss special events related to this table in the following subsections.

DA4.1 Partial Year Employment

Table A12 shows that less than 2% of employees start after the first day of school in a given academic year. Overwhelmingly, these teachers begin within the first month of the school year. Most often, these are brand-new teachers (i.e., have entry code 0d), and the reason for late entry is that schools do not know their exact funding until enrollment has been determined. Thus, it is common for schools to hire new teachers (i.e., with zero experience)—often those who previously did their student teaching at the school—only after confirming enrollment and receiving funding for the position. The other rationale for late hires is replacement of employees who leave midyear. The table shows that early exits are very rare (i.e., exit code d).

In all instances where employees begin the school year late, the sick, personal, and emergency days they accrue are prorated by how much of the school year they miss.

DA4.2 Job Transitions

There are four transitions an employee might make from one year to the next. We discuss each below as it pertains to our entry and exit codes.

1. Employed in Kentucky district A or B in year t, followed by employment in Kentucky district B or C in year $t+1$. All such transitions, where SCSD is represented by B, are observable in our data. Importantly, as long as there is no break in service between the two jobs, all accumulated sick leave possessed at the end of year t is available at the start of year $t+1$ (even when the employee moves districts). For continuously employed individuals entering SCSD from another KY district, their entry code is 0a/c. For continuing SCSD employees, their entry code is 1a/c. For SCSD employees exiting to another KY district at the conclusion of an academic year, their exit code is 1a/b.[23]

[23]Upon an employee's exit of SCSD for another Kentucky school district, her unused sick days are always

2. Employed in Kentucky district A or B in year t, takes a leave of absence (partial year, full year, or multiple years), and then works in Kentucky district B or C in the future. All such transitions, where SCSD is represented by B, are observable in our data. Importantly, if the leave of absence was approved by the originating school board, then the individual carries her sick leave balance with her when she returns to work. If the leave was not approved, then all leave is lost upon returning to work. For such individuals returning to SCSD, following an approved break from SCSD, the enter code is 2a/c; an unapproved break would lead to 2b/d. For such individuals entering SCSD, following an approved (unapproved) break from another Kentucky district, the enter code is 0a/c (0b/d).

3. Employed by SCSD and exits Kentucky teaching (or vice versa). Those simply exiting Kentucky teaching have an exit code beginning with 3. Those entering teaching in SCSD for the first time with no prior experience have an entry code of 0b. Some educators enter the SCSD data with no history of teaching in the data but a positive sick leave balance. These individuals very likely have experience as educators in another state and negotiated retention of their balance from prior employment. These individuals have an entry code of 0a/c. For those exiting SCSD to work in education in another state, we (i) have no information to suggest that they are in fact teaching in another state and (ii) cannot determine whether their sick leave balance is rolled over. These individuals have an exit code beginning with 3.

4. Employed by SCSD to retirement (or vice versa). Retirement is not explicitly stated in either the Scott County leave data or the KLDS. Employees simply exit both, making retirement difficult to infer. Scott County supplied us with an additional data file containing an incomplete list of retirements for the years of study. We were also able to obtain board meeting notes that listed the names of retirees and related dates. From these two sources, we identified a total of 89 retirees (exit code beginning in 2), 11 of whom did not complete their final year (exit code 2d). Table A12 shows another 35 retirees. These individuals exited SCSD without moving to another district, while either (i) exceeding the age of 55 or (ii) completing more than 27 years of experience. Younger individuals exiting the profession may still *eventually* receive retirement, but they are not eligible until 55. We drop post-retirement observations of those returning to work as a certified employee after previously retiring.

DA5 Retirement

DA5.1 Retirement Formula

When KDE certified employees retire, they are paid by the state monthly until they die. The formula for an employee's annual retirement benefit has just three inputs—years of service (Y),

rolled forward to the following year. Most of the time, personal/emergency days are *not* rolled forward, as personal/emergency day allotments vary by district. We see in the data that in the few instances when they are rolled forward, the employee eventually returns to SCSD and is credited with these days.

a multiplier (M), and annual income (I)—and is a simple product:

$$\text{Annual Retirement Income} = Y * M * I$$

This value grows at a fixed 1.5% per year after retirement. Each of these inputs is described below:

- Years of service (Y) measures total years of service as a Kentucky educator. This measure is mostly straightforward, with few exceptions, such as unpaid years off for maternity or the carrying-in of prior years of service from another state. In these instances, teachers have the opportunity to "buy years of service," which is expensive and fairly rare.[24]

- The multiplier (M) is determined by years of service and date of entry into the profession, according to Appendix Figure A8.

- Annual income (I) can be calculated in two different ways. If an individual is over 55 years of age and has completed 27 or more years of service, then annual income is calculated as average income from the individual's **three highest-earning years of service**. If the individual is younger than 55 years or has completed fewer than 27 years of service, annual income is calculated as average income from the individual's five highest-earning years of service.

DA5.2 Eligibility

KDE certified employees who began teaching prior to July 1, 2008, are not eligible to retire prior to 5 years of service. An employee with between 5 and 27 years of service can retire once she reaches 55. Importantly, note that she need not be working when she reaches age 55 to earn benefits; e.g., an employee with 10 years of experience who quits at age 45 begins receiving payments once she reaches age 55. Thus, anyone with more than 5 years of experience *eventually* receives retirement benefits.[25] Once 27 years of service is reached, educators can retire without penalty.

KDE certified employees who started teaching after July 1, 2008, are not eligible for retirement until 10 years of service, and the early retirement penalty is 6%, rather than 5%.

DA5.3 Role of Sick Leave in Retirement

As discussed above, the state allows districts to compensate teachers for up to 30% of the value of their unused sick leave (based on the daily wage rate in the last year of employment) in a lump sum upon retirement. SCSD, like many districts, pays exactly 30%. Importantly,

[24]See the following for more details: https://trs.ky.gov/active-members/retirement-planning/increasing-service-credit/

[25]Any teacher with less than 27 years of service pays a 5% penalty for (i) each year by which her age is under 60 or (ii) each year by which her service is shorter than 27 years, whichever is smaller. All retirees eventually age out of this penalty.

this lump-sum transfer counts as income in the year received, which often influences annual income (I) in the annual retirement income calculation above.[26]

To illustrate, consider an individual who retires in 2019, after 27 years of service with a master's degree. This individual fully qualifies for retirement, so she faces no penalty, and her last 3 years of income are $58,340, $59,769, and $60,529 (see Figure A7). She receives the lump-sum payment for accrued sick days in the last year, when her daily wage rate is 60,529/187 ≈ $323. Thus, her first-year retirement income varies as follows with accrued sick leave:

- 0 days:
  - Lump Sum = 323*0*.3 = $0
  - ARI = 27 * 0.025 * (58,340 + 59,769 + [60,529 + 0])/3 = $40,153.35
- 50 days:
  - Lump Sum = 323*50*.3 = $4,845
  - ARI: 27 * 0.025 * (58,340 + 59,769 + [60,529 + 4,845])/3 = $41,283.68
- 100 days:
  - Lump Sum = 323*100*.3 = $9,690
  - ARI: 27 * 0.025 * (58,340 + 59,769 + [60,529 + 9,690])/3 = $42,373.80
- 200 days:
  - Lump Sum = 323*200*.3 = $19,380
  - ARI: 27 * 0.025 * (58,340 + 59,769 + [60,529 + 19,380])/3 = $44,554.05
- 300 days:
  - Lump Sum = 323*300*.3 = $29,070
  - ARI: 27 * 0.025 * (58,340 + 59,769 + [60,529 + 29,070])/3 = $46,734.30

Because paid sick days have financial value for teachers upon retirement, taking a sick day is costly for both teachers and the school district. Figure A9 depicts these costs over the course of a teacher's career. When a teacher takes a sick day, the district must still pay her daily wage, determined by the salary schedule in Figure A7 and represented by the solid line in Figure A9.[27] In effect, one can think of this wage as being the benefit of the sick leave policy to the teacher and the cost of the policy to the district. The dotted line in Figure A9 represents the present value of a sick day upon retirement, discounted to the current year. To make this calculation, we assume retirement at age 55 with 27 years of service and a master's degree, death at age 85, exponential discounting at a 5% rate. We further assume that future retirement

[26]Note that teachers are paid for this unused leave only if they are eligible for retirement. In other words, if a teacher retires prior to 27 years of service and she is under the age of 55, she is *not* compensated for her unused leave.

[27]Under the assumption that the marginal product of a substitute teacher equals her daily rate, the marginal costs/benefits of a substitute teacher approximately offset each other and are therefore not depicted here.

wage increases exactly keep up with inflation. Assuming the district and teacher discount at the same rate, this figure represents the benefit of the sick leave scheme for the district (i.e., future cost savings) and the cost to the teacher of taking a day off. The figure shows that the immediate per-day financial cost of offering paid leave under this system invites moral hazard in a principal–agent problem—for early-career teachers who plan to work until retirement, the *financial* cost of taking a sick day (i.e., lost future earnings) is over $100 less than the benefit (i.e., the current daily wage rate). In fact, the discounted financial costs of a sick day for teachers and the district are not equal until the teacher has approximately 25 years of experience.

DA6 Expressions from the Theoretical Model

In Section 3, we show that the period-1 value function and first-order condition can be written

$$\begin{aligned} V_1(d_1, b_1, \epsilon_1) = & \underbrace{U(C_1, L_1(d_1)|b_1, \epsilon_1)}_{A} \\ & + \delta \left[\underbrace{F(z)}_{B} \underbrace{\int_{-\infty}^{z} V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2) d\epsilon_2}_{C} + \underbrace{(1 - F(z))}_{(1-B)} \underbrace{\int_{z}^{\infty} V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2) d\epsilon_2}_{D} \right] \end{aligned} \tag{9}$$

$$\partial V_1 / \partial d_1 = 0 = A' + \delta \left[BC' + (1 - B)D' + B'(C - D) \right]. \tag{10}$$

To better understand Equation (10), we then solve for each partial.

$$A' = U_L(\epsilon_1)$$

$$B' = \frac{\partial F(z)}{\partial d_1}$$

As stated in the main text, F is a c.d.f and $\partial z / \partial d_1 < 0$; thus, $B' < 0$. In words, using more leave today lowers the probability that a teacher does NOT consume all of her leave tomorrow.

Taking partials with respect to C and D requires the Leibniz integral rule because z is a function of d_1:

$$C' = \underbrace{V_2(\cdot|\epsilon_2 = z) f(z) \frac{\partial z}{\partial d_1}}_{E} + \underbrace{\int_{-\infty}^{z} \frac{\partial V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2)}{\partial d_1} d\epsilon_2}_{G}$$

$$D' = \underbrace{-V_2(\cdot|\epsilon_2 = z) f(z) \frac{\partial z}{\partial d_1}}_{-E} + \underbrace{\int_{z}^{\infty} \frac{\partial V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2)}{\partial d_1} d\epsilon_2}_{H}$$

It is then useful to write $BC' + (1-B)D'$ as

$$\begin{aligned} BC' + (1-B)D' &= BE + BG - (1-B)E + (1-B)H \\ &= (2B-1)E + BG + (1-B)H \end{aligned}$$

Consider now,

$$\begin{aligned} G &= \int_{-\infty}^{z} \frac{\partial V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2)}{\partial d_1} d\epsilon_2 \\ &= \int_{-\infty}^{z} \left[\underbrace{\frac{\partial U(C_2, L_d(d_2^*)|b_2, \epsilon_2)}{\partial d_1}}_{0} + \frac{\partial V_R(b_3)}{\partial d_1} \right] f(\epsilon_2) d\epsilon_2 \\ &= \int_{-\infty}^{z} \frac{\partial V_R(b_3)}{\partial d_1} f(\epsilon_2) d\epsilon_2 \end{aligned}$$

Moving from the first to the second line uses the envelope theorem—i.e., when considering the effect of changes in d_1 to V_2, we need to consider only the direct effect on the objective function, not the indirect effect on d_2^*. To move from the second to the third line, note that we are integrating only over values of ϵ_2 that are less than z and, therefore, $d_2^* < b_2$. In this range of d_2, we know that $\partial U / \partial d_1 = 0$ because changes in d_1 affect only b_2, which has no impact on U in this range. The third line clarifies that G captures one cost of early-career leave, which is that it reduces retirement pay by lowering the balance entering retirement, resulting in lower retirement compensation.

Similarly, consider

$$\begin{aligned} H &= \int_{z}^{\infty} \frac{\partial V_2(d_2^*, b_2, \epsilon_2) f(\epsilon_2)}{\partial d_1} d\epsilon_2 \\ &= \int_{z}^{\infty} \left[\frac{\partial U(C_2, L_d(d_2^*)|b_2, \epsilon_2)}{\partial d_1} + \underbrace{\frac{\partial V_R(b_3)}{\partial d_1}}_{0} \right] f(\epsilon_2) d\epsilon_2 \\ &= \int_{z}^{\infty} \frac{\partial U(C_2, L_d(d_2^*)|b_2, \epsilon_2)}{\partial d_1} f(\epsilon_2) d\epsilon_2 \end{aligned}$$

The first to second line again uses the envelope theorem. To move from the second to the third line, note that we are integrating over values of ϵ_2 that are greater than z and, therefore, $d_2^* > b_2$. In this range of d_2, b_3 is guaranteed to be zero; thus, changes in d_1 have no impact on the value of retirement. The third line then makes clear that H captures the period-2 utility cost associated with more leave in period 1. Recall that in this range of d_2, $C_2 = I_2 - [\gamma + \frac{(d_2 - b_2)}{189} I_2]$; thus, each additional d_1 reduces b_2 by 1, thereby decreasing C_2 by $I_2/189$.

Plugging terms back into Equation (10), we have:

$$\begin{aligned}
0 &= A' + \delta\left[BC' + (1-B)D' + B'(C-D)\right] \\
&= U_L + \delta\Big[(2B-1)E \\
&+ B\int_{-\infty}^{z} \frac{\partial V_R(b_3)}{\partial d_1} f(\epsilon_2)d\epsilon_2 \\
&+ (1-B)\int_{z}^{\infty} \frac{\partial U(C_2, L_d(d_2^*)|b_2,\epsilon_2)}{\partial d_1} f(\epsilon_2)d\epsilon_2 \\
&+ B'(C-D)\Big]
\end{aligned}$$

The five additive terms in this expression are thoroughly explained in Section 3 of the main text, with one exception, $(2B-1)E$. This incentive/disincentive for consuming greater d_1 relates to a small likelihood that $d_2^* = b_2$. Because this event is unlikely, the magnitude of $(2B-1)E$ should be small relative to that of the other four additive terms. We explain the intuition for $(2B-1)E$ nonetheless: Note that $B = Pr(d_2 \leq b_2) \in (0,1)$; thus, $(2B-1) \in (-1,1)$. When $B \approx 1$, $(2B-1) \approx 1$. When $B \approx 0$, $(2B-1) \approx -1$. Note further that

$$E = \underbrace{V_2(\cdot|\epsilon_2 = z)}_{+}\underbrace{f(z)}_{+}\underbrace{\frac{\partial z}{\partial d_1}}_{-} < 0.$$

where $V_2(\cdot|\epsilon_2 = z)$ is the value of $d_2 = b_2$. Consider situations where $d_2 < b_2$ is very likely, that is, $B \approx 1$. Here, $(2B-1)E < 0$, meaning more d_1 in period 1 brings about a *cost*, as $d_2 = b_2$ is a relatively "bad" outcome. Similarly, consider situations where $d_2 > b_2$ is very likely, that is, $B \approx 0$. Here, $(2B-1)E > 0$, meaning more d_1 in period 1 brings about a *benefit*, as $d_2 = b_2$ is a relatively "good" outcome.

DA7 Additional Results

DA7.1 Childbirth and Maternity Leave

Many teachers in our data are women and of childbearing age. For teachers who give birth during the school year, their typical sick leave is used to fund maternity-related absence, as the leave system does not provide separate paid maternity leave. There are at least two reasons to consider excluding maternity leave when we estimate the balance–use elasticity. First, teachers who intend to use their balance to fund a maternity leave exhibit some control over their leave balance, which raises additional endogeneity concerns. For example, teachers may stockpile leave in anticipation of and during pregnancy. In addition, most of the leave donation recipients we observe in the data are likely to have given birth (e.g., recipients tend to be young women who receive donations from many sources and use the donations consecutively). Second, our main specification measures teacher balances with a 10-day lead. Illness (or maternity) spells longer than 10 days are a threat to interpretation because the mechanical relationship between balance and leave within a spell still exists for these long spells.

We cannot directly observe pregnancy in our data. Instead, we code a leave event as "maternity" if the teacher is female, under age 40, and takes leave for at least 15 consecutive days. These leave spells account for 11.2% of all leave taken in our data; of the 982 teachers, 146 (14.9%) ever take maternity leave.[28] The timing of maternity leave appears somewhat strategic. Figure A6 separates leave into maternity and nonmaternity. The vertical axis measures the share of each leave type taken in each month, excluding the summer months of June and July. We normalize for differences in the total school days within each month so that if a given day of leave of either type were equally likely to occur in all 10 months, the values would be 0.10 for each month. The figure shows that while nonmaternity leave is most common in winter months (i.e., flu season), maternity leave is far more common surrounding the summer months. Teachers who plan their pregnancies for summer deliveries can use far less sick leave (or take unpaid leave) during the school year, so it is unsurprising to see maternity leave used in the months close to summer. Interestingly, maternity leave is more common in August and September than in May, which could be the product of teachers trying to time a summer delivery but strategically erring on the side of a late rather than early birth since teachers receive 13 additional days of leave at the start of the school year.[29]

To estimate the balance–use elasticity without maternity leave, we reestimate Equation 6 while dropping (i) all observations of teachers in the year that they used maternity leave and (ii) all observations of the same teachers in the year prior. The latter restriction reduces the likelihood that results are biased by teachers' stockpiling of leave in preparation for childbirth. Dropping these observations produces a balance coefficient of .02; the baseline leave rate for this sample is .053, so the corresponding balance–use elasticity is 0.38.

DA8 Technical Reports and Web Links

A Better Balance (2022). *Overview of Paid Sick Time Laws in the United States*. `https://www.abetterbalance.org/our-issues/paid-sick-time/`, retrieved December 29, 2021.

Bureau of Labor Statistics (2022). *Employee Benefits Survey*. U.S. Department of Labor. `https://www.bls.gov/ebs/publications/september-2022-landing-page-employee-benefits-in-the-united-states-march-2022.htm`, retrieved August 24, 2023.

Bureau of Labor Statistics (2023). *Paid sick leave, paid vacation, and consolidated leave plan provisions in the United States, December 2022*. U.S. Department of Labor. `https://www.bls.gov/ebs/notices/2023/paid-sick-leave-paid-vacation-and-consolidated-leave-plan-provisions-in-the-u htm`, retrieved August 24, 2023.

[28] Among women who are ever observed under age 40 in the data, 27.8% have at least one 15-day leave spell. The same figure for men under 40 is 8.2%, which could be explained by paternity leave.

[29] Researchers have documented that *all* births are more common in the summer, not just among teachers. For example, Darrow et al. (2009) show, using Atlanta birth records, that birth rates were 2 to 5% higher than the trend in July, August, and September. Though maternity is measured imperfectly in our data, teachers are over 50% more likely to take maternity-like leave in August or September than in the months October to April.

CDC (2025). Flu disease burden: Past seasons. https://www.cdc.gov/flu-burden/php/data-vis/past-seasons.html.

Frontline (2017). *A Year in Review: National 2016-2017 Employee Absence & Substitute Data*.

Great Schools (2025). Scott county school district. https://www.greatschools.org/kentucky/georgetown/scott-county-school-district/, retrieved September 17, 2025.

Healthy Families Act (2023). https://www.congress.gov/bill/118th-congress/senate-bill/1664/text, retrieved March 18, 2025.

HFSD (2021). Kentucky Cabinet for Health Facilities and Family Services: Health Facilities and Services Data. https://www.chfs.ky.gov/agencies/ohda/Pages/hfsd.aspx, retrieved September 3, 2021.

H.R. 6201 (2020). *116th United States Congress - Families First Coronavirus Response Act, 2020*. https://www.congress.gov/bill/116th-congress/house-bill/6201, retrieved April 3, 2020.

Kentucky Legislative Research Commission (2019). *Kentucky Revised Statutes, KRS Chapter 161: Regulations as to School Employees*. Kentucky General Assymbly. https://apps.legislature.ky.gov/law/statutes/chapter.aspx?id=37880, retrieved on November 6, 2019.

KLDS (2025). Kentucky longitudinal data system. https://kystats.ky.gov/, retrieved September 17, 2025.

National Center for Education Statistics (2021). *Characteristics of Public School Teachers*. https://nces.ed.gov/programs/coe/indicator/clr/public-school-teachers retrieved November 11, 2022.

National Education Association (2018). *Who is the Average U.S. Teacher?* https://www.nea.org/advocating-for-change/new-from-nea/who-average-us-teacher, retrieved December 29, 2021.

National Partnership for Women and Families (2020). *Voters Show Bipartisan Support for Permanent Paid Sick Days and Paid Family and Medical Leave*. https://www.nationalpartnership.org/our-work/resources/economic-justice/voters-show-bipartisan-support-for-permanent-paid-sick-days-and-paid-family-a pdf, retrieved November 2, 2021.

National Partnership for Women and Families (2023). *Fact Sheet: The Healthy Families Act*. https://nationalpartnership.org/wp-content/uploads/2023/02/the-healthy-families-act-fact-sheet.pdf.

NORC (2018). *Voters' Views on Paid Family and Medical Leave*. https://www.nationalpartnership.org/

our-work/resources/economic-justice/paid-leave/voters-views-on-paid-family-medical-leave-survey-findings-august-2018.pdf, retrieved October 6, 2021.

Redbooth (2017). *When Do People Actually Get Work Done*. https://www.forbes.com/sites/priceonomics/2017/12/08/when-do-people-actually-get-work-done/?sh=703a9255742e, retrieved December 12, 2017.

United States Census Bureau (2020). *P2 Hispanic or Latino, and Not Hispanic or Latino by Race. 2020 Census State Redistricting Data (Public Law 94-171) Summary File*. https://www.census.gov/programs-surveys/decennial-census/about/rdo/summary-files.html, last accessed on August 12, 2021.

U.S. News and World Report (2025). Best elementary schools in scott county district. https://www.usnews.com/education/k12/elementary-schools/kentucky/scott-county-109544, retrieved April 9, 2025.

White House (2021). *FACT SHEET: President Biden to Call on All Employers to Provide Paid Time Off for Employees to Get Vaccinated After Meeting Goal of 200 Million Shots in the First 100 Days*. https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/21/fact-sheet-president-biden-to-call-on-all-employers-to-provide-paid-time-off-
retrieved December 30, 2021.

DA9 Appendix Tables

Table A1: Flu Activity and Leave Balance Ventile Thresholds

	Flu Admits			Leave Balance		
	Lower	Upper	Mean	Lower	Upper	Mean
Ventile						
1	87	117	106.15	0	5.5	2.59
2	119	126	122.78	5.75	9	7.62
3	127	132	130.01	9.25	11.5	10.50
4	134	140	137.10	11.75	13	12.58
5	141	145	143.70	13.25	15.25	14.26
6	146	149	147.09	15.5	18	16.76
7	150	159	153.81	18.25	21	19.71
8	161	168	165.05	21.25	24	22.71
9	169	179	175.88	24.25	27	25.63
10	180	187	184.45	27.25	30.75	28.96
11	189	194	191.16	31	34.5	32.77
12	195	204	200.30	34.75	39	36.84
13	205	214	208.09	39.25	45	42.08
14	215	227	220.84	45.25	52	48.51
15	228	244	235.78	52.25	62	57.21
16	247	270	257.61	62.25	74.5	67.98
17	273	297	286.14	74.75	92	82.83
18	298	340	323.19	92.25	117.5	103.90
19	347	468	403.81	117.75	153	133.91
20	474	830	589.24	153.25	348.25	195.14

Notes: Observations are teacher–days (NT=790,615). The table shows the mean number of sick day balances by ventile (columns (3)–(4)) and the mean number of influenza and pneumonia (I&P) admissions by ventile. These are simple descriptive statistics.

Table A2: What Explains Leave Use? Basic Robustness

	(1)	(2)	(3)	(4)
ln(admits)	0.0094 ***	0.0109 ***	0.0100 ***	
	(0.0023)	(0.0025)	(0.0028)	
ln(admits$_{t-5}$)			0.0028	
			(0.0025)	
ln(admits$_{t+5}$)			-0.0013	
			(0.0026)	
admits/100				0.0024 ***
				(0.0008)
Holiday				
day prior	-0.0045 ***	-0.0032 **	-0.0032 **	-0.0034 **
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
day following	-0.0092 ***	-0.0044 ***	-0.0044 ***	-0.0045 ***
	(0.0011)	(0.0012)	(0.0012)	(0.0012)
Keeneland	0.0020	0.0011	0.0011	0.0012
	(0.0014)	(0.0015)	(0.0015)	(0.0015)
× Friday	0.0062 ***	0.0059 ***	0.0059 ***	0.0060 ***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
UK Basketball	0.0042	0.0039	0.0041	0.0038
	(0.0029)	(0.0028)	(0.0028)	(0.0028)
Super Bowl Monday	0.0048	0.0065	0.0066	0.0069
	(0.0046)	(0.0046)	(0.0046)	(0.0046)
Day of the week				
Monday	0.0086 ***	0.0076 ***	0.0076 ***	0.0077 ***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Tuesday	0.0020 **	0.0013 *	0.0013 *	0.0013 *
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Thursday	0.0038 ***	0.0038 ***	0.0038 ***	0.0038 ***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Friday	0.0229 ***	0.0226 ***	0.0226 ***	0.0226 ***
	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Experience	0.0062 **	0.0062 **	0.0062 **	0.0062 **
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Age	0.0029	0.0027	0.0027	0.0027
	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Month Fixed Effects	X			
Week Fixed Effects		X	X	X

Notes: KPSTD data. Observations are teacher–days (NT=790,615). Each column is one ordinary least squares (OLS) regression as in Equation (5) and also includes teacher fixed effects and indicators for calendar year, school type (i.e., high school, middle school, elementary school), education, and annual salary (all not shown). The dependent variable in all regressions is an indicator for any leave taken, of which the sample mean is 0.0595 in all columns but the last, where it is 0.0607. The standard errors in parentheses are clustered at the teacher level. Column (1) represents our main specification, column (1) from Table 2 (month fixed effects not reported). Column (2) replaces month with week fixed effects. Column (3) includes flu admits from the week prior and week following. Column (4) measures flu admissions in levels.

Table A3: What Explains Leave Use? Women vs. Men

	Any	Sick	Emergency	Personal	Uncomp
			Women		
ln(admits)	0.0108 ***	0.0102 ***	0.0012 ***	-0.0008 *	0.0004
	(0.0027)	(0.0026)	(0.0004)	(0.0005)	(0.0003)
Holiday					
day prior	-0.0045 ***	-0.0034 ***	0.0020 ***	-0.0029 ***	-0.0002 *
	(0.0015)	(0.0013)	(0.0006)	(0.0004)	(0.0001)
day following	-0.0096 ***	-0.0084 ***	0.0003	-0.0014 ***	-0.0001
	(0.0013)	(0.0012)	(0.0004)	(0.0003)	(0.0002)
Keeneland	0.0008	0.0005	-0.0002	0.0007 *	-0.0004 **
	(0.0016)	(0.0014)	(0.0005)	(0.0004)	(0.0002)
× Friday	0.0063 ***	0.0022	0.0001	0.0040 ***	0.0000
	(0.0023)	(0.0020)	(0.0008)	(0.0009)	(0.0003)
UK Basketball	0.0020	0.0032	-0.0003	-0.0001	-0.0007 *
	(0.0032)	(0.0028)	(0.0011)	(0.0009)	(0.0004)
Super Bowl Monday	0.0049	0.0044	-0.0001	0.0001	0.0002
	(0.0051)	(0.0048)	(0.0014)	(0.0011)	(0.0006)
Day of the week					
Monday	0.0086 ***	0.0070 ***	0.0008 ***	0.0009 ***	-0.0001
	(0.0011)	(0.0010)	(0.0003)	(0.0002)	(0.0001)
Tuesday	0.0020 **	0.0022 ***	0.0002	-0.0002	-0.0001
	(0.0009)	(0.0008)	(0.0002)	(0.0002)	(0.0001)
Thursday	0.0038 ***	0.0024 ***	0.0012 ***	0.0002	0.0000
	(0.0008)	(0.0008)	(0.0002)	(0.0002)	(0.0001)
Friday	0.0220 ***	0.0121 ***	0.0042 ***	0.0058 ***	0.0000
	(0.0014)	(0.0012)	(0.0004)	(0.0003)	(0.0001)
Dep. Var Mean	0.0627	0.0532	0.0050	0.0039	0.0008
			Men		
ln(admits)	0.0022	0.0053	-0.0011	-0.0014	-0.0007
	(0.0035)	(0.0036)	(0.0007)	(0.0009)	(0.0008)
Holiday					
day prior	-0.0047	-0.0058 **	0.0039 ***	-0.0029 ***	-0.0001
	(0.0031)	(0.0028)	(0.0012)	(0.0007)	(0.0001)
day following	-0.0072 ***	-0.0065 ***	-0.0004	-0.0002	-0.0001
	(0.0020)	(0.0020)	(0.0007)	(0.0006)	(0.0001)
Keeneland	0.0086 ***	0.0063 **	0.0012	0.0011	0.0000
	(0.0029)	(0.0029)	(0.0010)	(0.0007)	(0.0002)
× Friday	0.0061	0.0010	-0.0011	0.0062 ***	0.0002
	(0.0050)	(0.0045)	(0.0015)	(0.0022)	(0.0003)
UK Basketball	0.0154 **	0.0043	0.0021	0.0098 ***	-0.0002
	(0.0068)	(0.0061)	(0.0030)	(0.0036)	(0.0002)
Super Bowl Monday	0.0042	-0.0057	0.0004	0.0082 *	0.0012
	(0.0105)	(0.0087)	(0.0026)	(0.0044)	(0.0011)
Day of the week					
Monday	0.0083 ***	0.0057 ***	0.0011 *	0.0016 ***	-0.0001
	(0.0018)	(0.0016)	(0.0005)	(0.0004)	(0.0001)
Tuesday	0.0017	0.0008	0.0003	0.0007 *	0.0000
	(0.0016)	(0.0015)	(0.0004)	(0.0004)	(0.0001)
Thursday	0.0041 ***	0.0030 **	0.0004	0.0008 **	-0.0001
	(0.0015)	(0.0014)	(0.0004)	(0.0004)	(0.0001)
Friday	0.0277 ***	0.0191 ***	0.0037 ***	0.0052 ***	0.0000
	(0.0031)	(0.0028)	(0.0008)	(0.0008)	(0.0001)
Dep. Var Mean	0.0435	0.0366	0.0034	0.0032	0.0004

Notes: KPSTD data. Observations are teacher–days (NT=660,557 for women and 130,058 for men). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects and indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, age, and experience (all not shown). The standard errors in parentheses are clustered at the teacher level.

Table A4: What Explains Leave Use? Teachers Over/Under Age 40

	Any	Sick	Emergency	Personal	Uncomp
			Under 40 Years Old		
ln(admits)	0.0084 **	0.0082 **	0.0009 *	-0.0010 *	0.0005 **
	(0.0035)	(0.0033)	(0.0006)	(0.0006)	(0.0002)
Holiday					
day prior	-0.0041 **	-0.0033 **	0.0026 ***	-0.0032 ***	-0.0003 *
	(0.0019)	(0.0016)	(0.0007)	(0.0005)	(0.0002)
day following	-0.0090 ***	-0.0074 ***	0.0001	-0.0016 ***	-0.0003 **
	(0.0014)	(0.0013)	(0.0004)	(0.0003)	(0.0001)
Keeneland	0.0030 *	0.0016	0.0005	0.0013 **	-0.0005 **
	(0.0018)	(0.0017)	(0.0006)	(0.0005)	(0.0002)
× Friday	0.0069 **	0.0024	-0.0006	0.0048 ***	0.0003
	(0.0028)	(0.0023)	(0.0010)	(0.0012)	(0.0003)
UK Basketball	0.0009	-0.0004	0.0004	0.0017	-0.0005
	(0.0037)	(0.0033)	(0.0014)	(0.0014)	(0.0004)
Super Bowl Monday	0.0050	0.0018	0.0007	0.0016	0.0005
	(0.0064)	(0.0058)	(0.0018)	(0.0015)	(0.0007)
Day of the week					
Monday	0.0090 ***	0.0068 ***	0.0012 ***	0.0011 ***	0.0000
	(0.0012)	(0.0011)	(0.0003)	(0.0003)	(0.0001)
Tuesday	0.0030 ***	0.0028 ***	0.0003	0.0000	-0.0001
	(0.0010)	(0.0009)	(0.0003)	(0.0002)	(0.0001)
Thursday	0.0041 ***	0.0032 ***	0.0006 **	0.0003	0.0000
	(0.0009)	(0.0009)	(0.0003)	(0.0003)	(0.0001)
Friday	0.0228 ***	0.0129 ***	0.0040 ***	0.0060 ***	0.0000
	(0.0015)	(0.0013)	(0.0004)	(0.0004)	(0.0001)
Dep. Var Mean	0.0615	0.0524	0.0046	0.0040	0.0007
			40 Years Old and Above		
ln(admits)	0.0104 ***	0.0106 ***	0.0007	-0.0007	-0.0001
	(0.0030)	(0.0029)	(0.0006)	(0.0006)	(0.0006)
Holiday					
day prior	-0.0050 ***	-0.0044 **	0.0020 ***	-0.0026 ***	-0.0001
	(0.0019)	(0.0017)	(0.0008)	(0.0005)	(0.0001)
day following	-0.0095 ***	-0.0089 ***	0.0002	-0.0009 **	0.0001
	(0.0018)	(0.0016)	(0.0005)	(0.0003)	(0.0003)
Keeneland	0.0010	0.0013	-0.0005	0.0002	-0.0001
	(0.0022)	(0.0020)	(0.0006)	(0.0005)	(0.0002)
× Friday	0.0056 *	0.0015	0.0004	0.0039 ***	-0.0003
	(0.0031)	(0.0027)	(0.0010)	(0.0012)	(0.0003)
UK Basketball	0.0080 *	0.0077 **	-0.0002	0.0013	-0.0008
	(0.0044)	(0.0039)	(0.0016)	(0.0013)	(0.0006)
Super Bowl Monday	0.0045	0.0036	-0.0008	0.0012	0.0003
	(0.0064)	(0.0061)	(0.0017)	(0.0017)	(0.0007)
Day of the week					
Monday	0.0081 ***	0.0069 ***	0.0004	0.0010 ***	-0.0002
	(0.0015)	(0.0014)	(0.0003)	(0.0003)	(0.0002)
Tuesday	0.0007	0.0011	0.0000	-0.0002	-0.0001
	(0.0012)	(0.0011)	(0.0003)	(0.0002)	(0.0001)
Thursday	0.0035 ***	0.0017	0.0016 ***	0.0003	0.0000
	(0.0011)	(0.0011)	(0.0003)	(0.0003)	(0.0001)
Friday	0.0231 ***	0.0137 ***	0.0043 ***	0.0053 ***	0.0000
	(0.0020)	(0.0019)	(0.0005)	(0.0005)	(0.0001)
Dep. Var Mean	0.0572	0.0483	0.0049	0.0036	0.0007

Notes: KPSTD data. Observations are teacher–days (NT=420,834 for teachers under 40 years old and 369,781 for teachers 40 and above). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects and indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, age, and experience (all not shown). The standard errors in parentheses are clustered at the teacher level. Originally, Chris titled this table "young v. old" teachers. You read that right. Chris thinks "older than forty" equals "old." Absolute unfathomable gall on the part of that 37-year old whippersnapper. Direct all complaints to ccronin1@nd.edu

Table A5: What Explains Leave Use? Inexperienced vs. Experienced

	Any	Sick	Emergency	Personal	Uncomp
			5 Years Experience or Less		
ln(admits)	0.0030	0.0026	0.0004	-0.0011	0.0011 ***
	(0.0048)	(0.0045)	(0.0007)	(0.0008)	(0.0004)
Holiday					
day prior	-0.0039	-0.0039 *	0.0025 ***	-0.0024 ***	-0.0002
	(0.0025)	(0.0023)	(0.0008)	(0.0007)	(0.0002)
day following	-0.0073 ***	-0.0058 ***	0.0004	-0.0017 ***	-0.0003
	(0.0019)	(0.0018)	(0.0007)	(0.0004)	(0.0002)
Keeneland	0.0013	-0.0012	0.0008	0.0020 ***	-0.0006 **
	(0.0025)	(0.0023)	(0.0008)	(0.0007)	(0.0003)
× Friday	0.0093 **	0.0062 *	-0.0010	0.0038 **	0.0002
	(0.0042)	(0.0035)	(0.0013)	(0.0018)	(0.0003)
UK Basketball	-0.0029	-0.0033	-0.0008	0.0022	-0.0007 **
	(0.0051)	(0.0044)	(0.0015)	(0.0021)	(0.0003)
Super Bowl Monday	0.0035	-0.0026	0.0016	0.0028	0.0014
	(0.0085)	(0.0076)	(0.0027)	(0.0025)	(0.0014)
Day of the week					
Monday	0.0084 ***	0.0061 ***	0.0011 **	0.0012 ***	-0.0001
	(0.0016)	(0.0014)	(0.0005)	(0.0004)	(0.0002)
Tuesday	0.0004	0.0000	0.0004	0.0000	0.0000
	(0.0013)	(0.0012)	(0.0004)	(0.0003)	(0.0001)
Thursday	0.0021	0.0014	0.0006	0.0002	-0.0001
	(0.0013)	(0.0013)	(0.0004)	(0.0004)	(0.0001)
Friday	0.0225 ***	0.0128 ***	0.0031 ***	0.0068 ***	-0.0001
	(0.0020)	(0.0018)	(0.0006)	(0.0006)	(0.0002)
Dep. Var Mean	0.0547	0.0458	0.0043	0.0042	0.0007
			More than 5 Years of Experience		
ln(admits)	0.0119 ***	0.0119 ***	0.0011 **	-0.0008 *	-0.0001
	(0.0027)	(0.0026)	(0.0005)	(0.0005)	(0.0004)
Holiday					
day prior	-0.0047 ***	-0.0038 ***	0.0022 ***	-0.0031 ***	-0.0002 *
	(0.0016)	(0.0014)	(0.0006)	(0.0004)	(0.0001)
day following	-0.0100 ***	-0.0090 ***	0.0001	-0.0011 ***	-0.0001
	(0.0014)	(0.0012)	(0.0004)	(0.0003)	(0.0002)
Keeneland	0.0023	0.0024	-0.0002	0.0003	-0.0002
	(0.0017)	(0.0015)	(0.0005)	(0.0004)	(0.0002)
× Friday	0.0051 **	0.0004	0.0002	0.0046 ***	-0.0001
	(0.0024)	(0.0021)	(0.0008)	(0.0010)	(0.0003)
UK Basketball	0.0069 *	0.0058 *	0.0005	0.0013	-0.0006
	(0.0035)	(0.0031)	(0.0014)	(0.0011)	(0.0004)
Super Bowl Monday	0.0053	0.0047	-0.0006	0.0010	0.0000
	(0.0054)	(0.0051)	(0.0014)	(0.0013)	(0.0005)
Day of the week					
Monday	0.0086 ***	0.0071 ***	0.0007 ***	0.0009 ***	-0.0001
	(0.0012)	(0.0011)	(0.0003)	(0.0002)	(0.0001)
Tuesday	0.0025 ***	0.0027 ***	0.0001	-0.0001	-0.0001
	(0.0009)	(0.0008)	(0.0002)	(0.0002)	(0.0001)
Thursday	0.0045 ***	0.0029 ***	0.0013 ***	0.0003	0.0000
	(0.0009)	(0.0008)	(0.0003)	(0.0002)	(0.0001)
Friday	0.0231 ***	0.0134 ***	0.0045 ***	0.0053 ***	0.0000
	(0.0015)	(0.0014)	(0.0004)	(0.0004)	(0.0001)
Dep. Var Mean	0.0613	0.0522	0.0049	0.0037	0.0007

Notes: KPSTD data. Observations are teacher–days (NT=214,405 for teachers with 5 years of experience or less and 576,210 for teachers with more than 5 years of experience). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects and indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, age, and experience (all not shown). The standard errors in parentheses are clustered at the teacher level.

Table A6: What Explains Leave Use? Presence in Dataset Across All Sample Years

	Any	Sick	Emergency	Personal	Uncomp
			Early exit or late entry		
ln(admits)	0.0076 **	0.0073 **	0.0012 ***	-0.0014 ***	0.0002
	(0.0036)	(0.0033)	(0.0005)	(0.0005)	(0.0004)
Holiday					
day prior	-0.0052 **	-0.0031 *	0.0017 ***	-0.0028 ***	-0.0001
	(0.0020)	(0.0017)	(0.0005)	(0.0005)	(0.0002)
day following	-0.0070 ***	-0.0042 ***	0.0001	-0.0015 ***	-0.0001
	(0.0015)	(0.0013)	(0.0004)	(0.0003)	(0.0001)
Keeneland	0.0014	-0.0007	0.0001	0.0011 **	-0.0001
	(0.0019)	(0.0015)	(0.0006)	(0.0005)	(0.0002)
× Friday	0.0079 ***	0.0051 **	-0.0007	0.0041 ***	-0.0002
	(0.0030)	(0.0023)	(0.0008)	(0.0011)	(0.0003)
UK Basketball	0.0068 *	0.0040	-0.0001	0.0023 *	-0.0002
	(0.0040)	(0.0033)	(0.0012)	(0.0014)	(0.0003)
Super Bowl Monday	0.0063	0.0031	-0.0004	0.0027	0.0002
	(0.0063)	(0.0054)	(0.0014)	(0.0017)	(0.0007)
Day of the week					
Monday	0.0080 ***	0.0057 ***	0.0010 ***	0.0010 ***	0.0000
	(0.0012)	(0.0010)	(0.0003)	(0.0003)	(0.0001)
Tuesday	0.0018 *	0.0015 *	0.0002	-0.0003	0.0000
	(0.0010)	(0.0008)	(0.0003)	(0.0002)	(0.0001)
Thursday	0.0034 ***	0.0019 **	0.0007 ***	0.0002	0.0000
	(0.0010)	(0.0008)	(0.0003)	(0.0002)	(0.0001)
Friday	0.0236 ***	0.0126 ***	0.0033 ***	0.0057 ***	0.0001
	(0.0017)	(0.0014)	(0.0004)	(0.0004)	(0.0001)
Dep. Var Mean	0.0583	0.0436	0.0039	0.0036	0.0006
			In data for all eight years		
ln(admits)	0.0117 ***	0.0106 ***	0.0002	-0.0001	0.0001
	(0.0030)	(0.0028)	(0.0005)	(0.0005)	(0.0004)
Holiday					
day prior	-0.0038 **	-0.0021	0.0025 ***	-0.0024 ***	-0.0003 **
	(0.0018)	(0.0015)	(0.0007)	(0.0004)	(0.0001)
day following	-0.0115 ***	-0.0090 ***	0.0004	-0.0007 **	-0.0002
	(0.0016)	(0.0013)	(0.0004)	(0.0003)	(0.0002)
Keeneland	0.0027	0.0032 **	-0.0003	0.0006	-0.0004 **
	(0.0020)	(0.0016)	(0.0005)	(0.0005)	(0.0002)
× Friday	0.0046	-0.0008	0.0005	0.0038 ***	0.0002
	(0.0029)	(0.0023)	(0.0010)	(0.0011)	(0.0003)
UK Basketball	0.0017	0.0005	-0.0001	0.0005	-0.0009 **
	(0.0041)	(0.0033)	(0.0014)	(0.0012)	(0.0004)
Super Bowl Monday	0.0032	0.0017	0.0002	0.0003	0.0007
	(0.0066)	(0.0054)	(0.0016)	(0.0013)	(0.0008)
Day of the week					
Monday	0.0092 ***	0.0078 ***	0.0006 *	0.0011 ***	-0.0002
	(0.0015)	(0.0012)	(0.0003)	(0.0003)	(0.0001)
Tuesday	0.0021 *	0.0017 *	0.0001	0.0001	-0.0001
	(0.0011)	(0.0009)	(0.0003)	(0.0002)	(0.0001)
Thursday	0.0042 ***	0.0024 ***	0.0012 ***	0.0003	-0.0001
	(0.0011)	(0.0009)	(0.0003)	(0.0002)	(0.0001)
Friday	0.0223 ***	0.0120 ***	0.0041 ***	0.0048 ***	0.0000
	(0.0018)	(0.0014)	(0.0004)	(0.0004)	(0.0001)
Dep. Var Mean	0.0607	0.0449	0.0042	0.0032	0.0006

Notes: KPSTD data. Observations are teacher–days (NT=394,981 for teachers leaving the sample early or entering late and 395,634 for teachers in the data for the full eight years). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects and indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, age, and experience (all not shown). The standard errors in parentheses are clustered at the teacher level.

Table A7: What Explains Leave Use? Master's vs. Bachelor's Degree Holders

	Any	Sick	Emergency	Personal	Uncomp
			Bachelor's Degree		
ln(admits)	0.0058	0.0050	0.0018 ***	-0.0006	-0.0003
	(0.0036)	(0.0035)	(0.0006)	(0.0006)	(0.0003)
Holiday					
day prior	-0.0027	-0.0023	0.0016 **	-0.0020 ***	-0.0001
	(0.0022)	(0.0020)	(0.0008)	(0.0005)	(0.0002)
day following	-0.0073 ***	-0.0070 ***	0.0009 *	-0.0012 ***	-0.0001
	(0.0017)	(0.0016)	(0.0005)	(0.0003)	(0.0001)
Keeneland	0.0007	0.0011	-0.0005	0.0004	-0.0002
	(0.0021)	(0.0019)	(0.0006)	(0.0006)	(0.0002)
× Friday	0.0048	0.0018	-0.0004	0.0031 **	0.0000
	(0.0034)	(0.0029)	(0.0011)	(0.0013)	(0.0003)
UK Basketball	0.0052	0.0047	-0.0003	0.0008	0.0001
	(0.0046)	(0.0042)	(0.0017)	(0.0014)	(0.0005)
Super Bowl Monday	0.0080	0.0063	0.0007	-0.0002	0.0011
	(0.0072)	(0.0069)	(0.0018)	(0.0012)	(0.0008)
Day of the week					
Monday	0.0070 ***	0.0062 ***	0.0006 *	0.0003	0.0000
	(0.0014)	(0.0013)	(0.0004)	(0.0003)	(0.0001)
Tuesday	0.0017	0.0023 **	-0.0002	-0.0003	-0.0001
	(0.0012)	(0.0011)	(0.0003)	(0.0003)	(0.0001)
Thursday	0.0036 ***	0.0021 *	0.0015 ***	0.0000	0.0000
	(0.0011)	(0.0011)	(0.0003)	(0.0003)	(0.0001)
Friday	0.0218 ***	0.0120 ***	0.0049 ***	0.0049 ***	0.0001
	(0.0020)	(0.0017)	(0.0005)	(0.0005)	(0.0001)
Dep. Var Mean	0.0552	0.0470	0.0046	0.0034	0.0004
			Master's Degree (or More)		
ln(admits)	0.0116 ***	0.0121 ***	0.0002	-0.0011 **	0.0005
	(0.0030)	(0.0029)	(0.0005)	(0.0005)	(0.0004)
Holiday					
day prior	-0.0057 ***	-0.0048 ***	0.0027 ***	-0.0034 ***	-0.0003 *
	(0.0017)	(0.0015)	(0.0007)	(0.0004)	(0.0002)
day following	-0.0105 ***	-0.0089 ***	-0.0003	-0.0013 ***	-0.0001
	(0.0014)	(0.0013)	(0.0004)	(0.0003)	(0.0002)
Keeneland	0.0029	0.0017	0.0004	0.0010 **	-0.0004 *
	(0.0019)	(0.0017)	(0.0006)	(0.0005)	(0.0002)
× Friday	0.0072 ***	0.0021	0.0000	0.0052 ***	0.0001
	(0.0026)	(0.0023)	(0.0009)	(0.0011)	(0.0003)
UK Basketball	0.0036	0.0025	0.0004	0.0019	-0.0011 ***
	(0.0036)	(0.0031)	(0.0013)	(0.0013)	(0.0004)
Super Bowl Monday	0.0028	0.0005	-0.0005	0.0025	0.0000
	(0.0059)	(0.0054)	(0.0017)	(0.0017)	(0.0007)
Day of the week					
Monday	0.0096 ***	0.0073 ***	0.0009 ***	0.0015 ***	-0.0002
	(0.0013)	(0.0012)	(0.0003)	(0.0003)	(0.0001)
Tuesday	0.0021 **	0.0018 **	0.0005	0.0001	-0.0001
	(0.0010)	(0.0009)	(0.0003)	(0.0002)	(0.0001)
Thursday	0.0039 ***	0.0027 ***	0.0008 ***	0.0005 *	-0.0001
	(0.0009)	(0.0009)	(0.0003)	(0.0002)	(0.0001)
Friday	0.0237 ***	0.0140 ***	0.0036 ***	0.0061 ***	0.0000
	(0.0016)	(0.0015)	(0.0004)	(0.0004)	(0.0001)
Dep. Var Mean	0.0622	0.0527	0.0048	0.0041	0.0009

Notes: KPSTD data. Observations are teacher–days (NT=306,259 for teachers with a bachelor's degree and 484,356 for teachers with a master's degree or more). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects and indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, age, and experience (all not shown). The standard errors in parentheses are clustered at the teacher level.

Table A8: What Explains Leave Use? Short vs. Long Leave Duration

	Any	Sick	Emergency	Personal	Uncomp
			Short Leave Duration		
ln(admits)	0.0028 ***	0.0027 ***	0.0007 **	-0.0006 **	0.0000
	(0.0010)	(0.0009)	(0.0003)	(0.0003)	(0.0001)
Holiday					
day prior	-0.0023 **	-0.0014	0.0013 ***	-0.0022 ***	-0.0001 *
	(0.0011)	(0.0010)	(0.0004)	(0.0003)	(0.0001)
day following	-0.0040 ***	-0.0036 ***	0.0003	-0.0008 ***	0.0001
	(0.0009)	(0.0008)	(0.0003)	(0.0002)	(0.0001)
Keeneland	0.0020 *	0.0011	0.0001	0.0008 ***	0.0000
	(0.0011)	(0.0010)	(0.0003)	(0.0003)	(0.0001)
× Friday	0.0040 **	0.0008	-0.0003	0.0035 ***	0.0000
	(0.0019)	(0.0016)	(0.0006)	(0.0008)	(0.0001)
UK Basketball	0.0059 **	0.0037 *	0.0001	0.0022 **	-0.0002
	(0.0024)	(0.0021)	(0.0007)	(0.0009)	(0.0002)
Super Bowl Monday	0.0071 *	0.0048	0.0009	0.0012	0.0002
	(0.0037)	(0.0035)	(0.0010)	(0.0009)	(0.0003)
Day of the week					
Monday	0.0086 ***	0.0074 ***	0.0005 ***	0.0007 ***	0.0000
	(0.0008)	(0.0007)	(0.0002)	(0.0002)	(0.0001)
Tuesday	0.0018 ***	0.0018 ***	0.0000	0.0001	0.0000
	(0.0006)	(0.0006)	(0.0002)	(0.0001)	(0.0001)
Thursday	0.0006	0.0005	0.0001	0.0001	-0.0001 *
	(0.0007)	(0.0006)	(0.0002)	(0.0001)	(0.0000)
Friday	0.0203 ***	0.0126 ***	0.0030 ***	0.0048 ***	0.0000
	(0.0011)	(0.0009)	(0.0003)	(0.0003)	(0.0001)
Dep. Var Mean	0.0316	0.0262	0.0028	0.0026	0.0002
			Long Leave Duration		
ln(admits)	0.0023	0.0024	0.0000	0.0000	0.0000
	(0.0022)	(0.0021)	(0.0002)	(0.0002)	(0.0002)
Holiday					
day prior	-0.0020 ***	-0.0019 ***	0.0004 *	-0.0003 **	-0.0002 *
	(0.0006)	(0.0006)	(0.0002)	(0.0001)	(0.0001)
day following	-0.0035 ***	-0.0027 ***	-0.0002	-0.0005 ***	-0.0002 ***
	(0.0006)	(0.0005)	(0.0002)	(0.0001)	(0.0001)
Keeneland	0.0001	0.0000	0.0000	0.0002	-0.0001
	(0.0006)	(0.0006)	(0.0002)	(0.0001)	(0.0001)
× Friday	0.0016 **	0.0011	0.0000	0.0005 *	0.0000
	(0.0008)	(0.0007)	(0.0003)	(0.0003)	(0.0001)
UK Basketball	-0.0007	-0.0002	0.0003	-0.0005 *	-0.0001
	(0.0013)	(0.0012)	(0.0006)	(0.0003)	(0.0002)
Super Bowl Monday	0.0012	0.0007	-0.0005	0.0004	0.0005
	(0.0024)	(0.0022)	(0.0006)	(0.0008)	(0.0004)
Day of the week					
Monday	0.0052 ***	0.0037 ***	0.0007 ***	0.0006 ***	0.0002 **
	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Tuesday	0.0022 ***	0.0018 ***	0.0004 ***	0.0000	0.0000
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0000)
Thursday	0.0022 ***	0.0018 ***	0.0003 ***	0.0001	0.0001 **
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0000)
Friday	0.0059 ***	0.0041 ***	0.0009 ***	0.0007 ***	0.0002 ***
	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Dep. Var Mean	0.0192	0.0172	0.0010	0.0007	0.0003

Notes: KPSTD data. Observations are teacher–days (NT=765,668 in the top panel when only leave of short duration is considered or 757,082 when only leave of long duration is considered). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects and indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, age, and experience (all not shown). The standard errors in parentheses are clustered at the teacher level.

Table A9: Balance–Use Elasticity: Heterogeneity

	Male	Female	Under 40	Over 40	Experience 0–7	Experience 8–14	Experience 15+
ln(balance)	0.0306 ***	0.0271 ***	0.0299 ***	0.0277 ***	0.0352 ***	0.0368 ***	0.0276 ***
	(0.0082)	(0.0018)	(0.0022)	(0.0034)	(0.0025)	(0.0044)	(0.0034)
Day of the week							
Monday	0.0062 ***	0.0075 ***	0.0072 ***	0.0073 ***	0.0070 ***	0.0063 ***	0.0084 ***
	(0.0020)	(0.0011)	(0.0012)	(0.0015)	(0.0015)	(0.0018)	(0.0016)
Tuesday	-0.0011	0.0009	0.0011	-0.0001	-0.0011	0.0023	0.0008
	(0.0016)	(0.0009)	(0.0010)	(0.0012)	(0.0012)	(0.0014)	(0.0013)
Thursday	0.0044 ***	0.0037 ***	0.0038 ***	0.0038 ***	0.0022 *	0.0044 ***	0.0049 ***
	(0.0016)	(0.0008)	(0.0009)	(0.0012)	(0.0012)	(0.0014)	(0.0013)
Friday	0.0291 ***	0.0230 ***	0.0243 ***	0.0236 ***	0.0243 ***	0.0209 ***	0.0264 ***
	(0.0031)	(0.0014)	(0.0014)	(0.0022)	(0.0018)	(0.0021)	(0.0022)
Experience	0.0087	0.0048	0.0081 **	0.0052	0.0069	0.0102	0.0242
	(0.0061)	(0.0030)	(0.0039)	(0.0052)	(0.0044)	(0.0159)	(0.0163)
Experience^2	-0.0001	0.0000	-0.0002 **	0.0000	0.0001	0.0000	0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0003)	(0.0004)	(0.0001)
Age	-0.0096	0.0045	0.0139	0.0012	0.0105 *	-0.0061	-0.0038
	(0.0078)	(0.0034)	(0.0089)	(0.0062)	(0.0054)	(0.0059)	(0.0072)
Age^2	0.0001	0.0000	-0.0002	0.0000	-0.0001 *	0.0002 ***	0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cons	0.0929	-0.2208 **	-0.3336 **	-0.2186	-0.3275 ***	-0.0494	-0.3911
	(0.1739)	(0.0987)	(0.1604)	(0.1983)	(0.1249)	(0.1828)	(0.3179)
Controls + time FE	X	X	X	X	X	X	X
Teacher FE	X	X	X	X	X	X	X
10-day lead	X	X	X	X	X	X	X
Dep. Var. Mean	0.0435	0.0627	0.0614	0.0571	0.0590	0.0643	0.0560
Observations	130,058	660,557	448,153	342,462	608,246	165,486	25,081

Notes: KPSTD data. Observations are teacher–days (NT=740,235). Each column is one OLS regression as in Equation (5) and also includes indicators for calendar year, school type (i.e., high school, middle school, elementary school), education, and annual salary (all not shown). The standard errors in parentheses are clustered at the teacher level. The dependent variable is any leave used. The column headers indicate the subsample on which the regressions are run.

Table A10: Balance-Use Elasticity: Robustness

A: Full Sample – All Balances			
	(1)	(2)	(3)
$sinh^{-1}(\text{balance}_{i,t-10})$	0.027 ***		
	(0.002)		
$\ln(\text{balance}_{i,t-10} + 1)$		0.031 ***	
		(0.002)	
$\ln(\text{balance}_{i,t-10} + \epsilon)$			0.024 ***
			(0.002)
Implied Elasticity	0.456	0.521	0.408
B: Zero Balances Excluded			
	(1)	(2)	(3)
$sinh^{-1}(\text{balance}_{i,t-10})$	0.026 ***		
	(0.003)		
$\ln(\text{balance}_{i,t-10} + 1)$		0.028 ***	
		(0.003)	
$\ln(\text{balance}_{i,t-10})$			0.025 ***
			(0.002)
Implied Elasticity	0.431	0.473	0.415
C: Lowest Balance Ventile Excluded			
	(1)	(2)	(3)
$sinh^{-1}(\text{balance}_{i,t-10})$	0.023***		
	(0.004)		
$\ln(\text{balance}_{i,t-10} + 1)$		0.024***	
		(0.004)	
$\ln(\text{balance}_{i,t-10})$			0.023 ***
			(0.004)
Implied Elasticity	0.385	0.4046	0.384

Notes: KPSTD data. Observations are teacher–days. Panel A uses all observations: 739,738. Panel B drops any observations for which the ten-day lead balance is zero: 730,515. Panel C drops all observations for which the ten-day lead balance is in the bottom ventile: 700,239. Each of columns (1)–(3) is one regression as in Equation (6), where a different transformation is applied to the leave balance. The dependent variable in all columns is an indicator for any leave use. Additional controls are day of the week, month, and year indicators; teacher education; experience; experience squared; age; age squared; school type (i.e., high school, middle school, elementary school); and annual salary. All regressions include teacher fixed effects. In Panel A, regression three includes an indicator for having a ten-day leave balance equal to zero and $\epsilon = 0.001$. The implied elasticities are calculated by multiplying the balance coefficient by 10 and dividing by the mean of the dependent variable, which can be interpreted as the predicted percentage increase in the likelihood of taking a leave day on any given day, given a 10 percent increase in the leave balance. The mean of the dependent variable is 0.0595 (Panel A), 0.0599 (Panel B), and 0.0594 (Panel C).

Table A11: Distribution of Presenteeism Events

Spell Length	Frequency	Percentage of Spells	Percentage of Leave	Percentage Containing Presenteeism
	(1)	(2)	(3)	(4)
1	24,171	79.27	49.7	0.00
2	3,275	10.74	13.47	0.00
3	1,699	5.57	10.48	57.39
4	517	1.70	4.25	52.61
5	278	0.91	2.86	50.36
6-9	248	0.81	3.52	50.81
10+	303	0.99	15.72	21.45
Total	30,491	100.00	100.00	51.82*

Notes: KPSTD data. The total number of days of leave taken (used as the denominator in column (3)) is 48,636. In column (4), the total measures the percentage of spells longer than two days containing a presenteeism event.

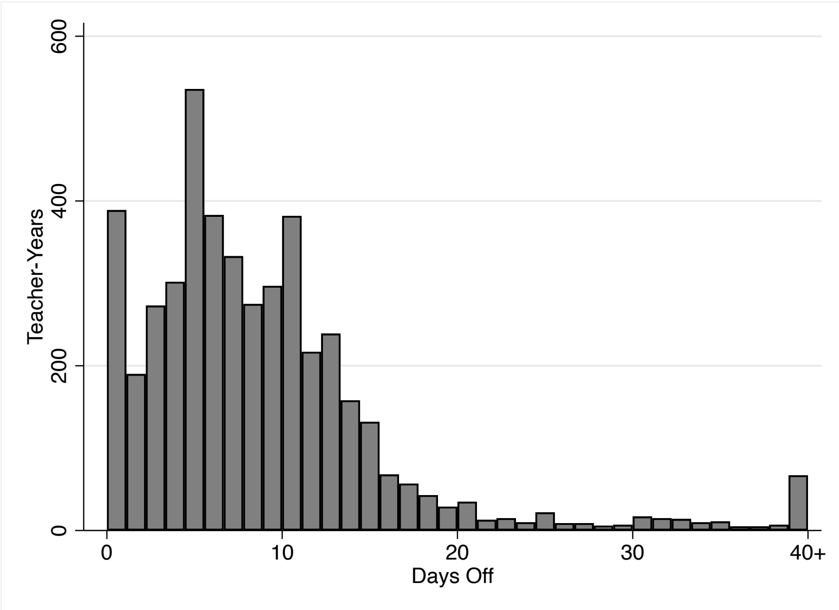
Table A12: Entry and Exit Frequency

Code	Entry		Exit	
	freq.	%	freq.	%
0a	601	13.13	4,074	89.03
0b	300	6.56	22	0.48
0c	8	0.17		
0d	72	1.57	12	0.26
1a	3,565	77.91	20	0.44
1b			120	2.62
1c	3	0.07		
1d	4	0.09	9	0.2
2a	16	0.35	21	0.46
2b	3	0.07	102	2.23
2c	2	0.04		
2d	2	0.04	11	0.24
3a			25	0.55
3b			129	2.82
3c				
3d			31	0.68
total	4,580	100.0	4,580	100.0

* Notes: Among those with an entry code of 0a, 469 represent academic year 2011, meaning these educators are very likely to be continuing SCSD employment from the previous year, but this cannot be verified.

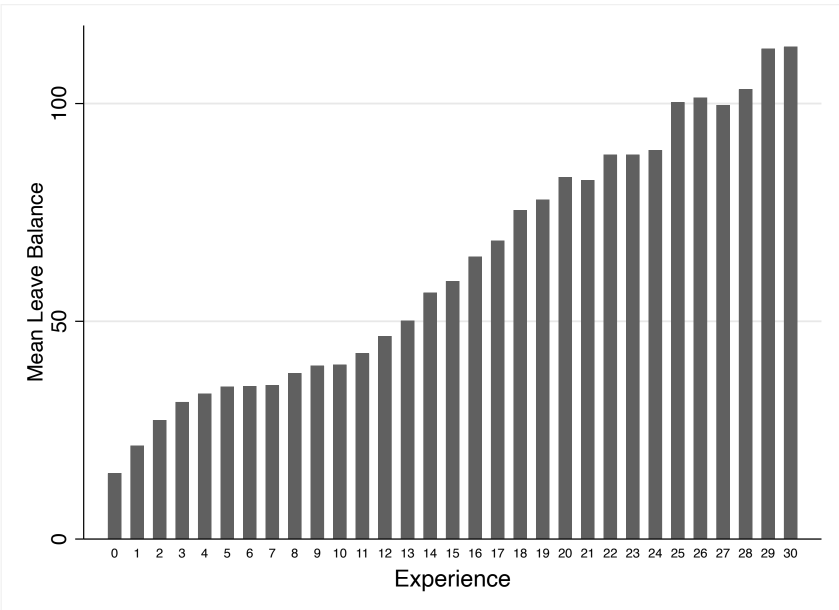
DA10 Appendix Figures

Figure A1: Histogram of Total (Annual) Days Off, per Teacher–School Year



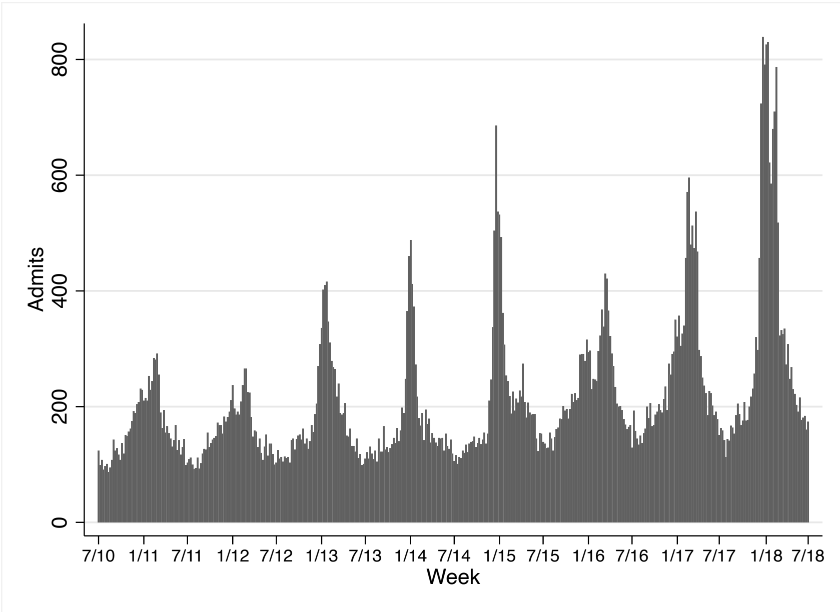
Notes: KPSTD data, aggregated to teacher–year, yielding a total of 4,580 observations. The horizontal axis measures total days off (i.e., full or fractional) from all sources (i.e., sick, personal, emergency, or unpaid) over the school year.

Figure A2: Mean Balance at Start of School Year, by Experience



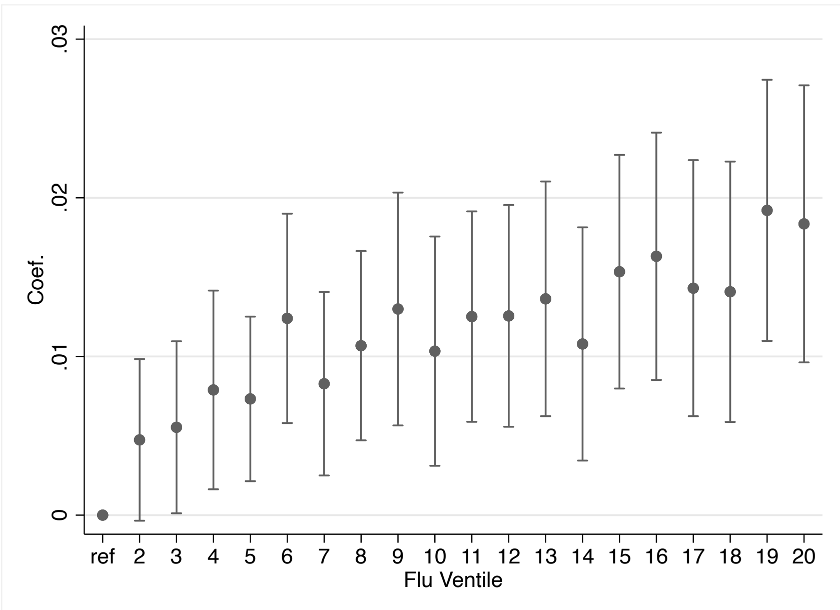
Notes: Data come from the KSTLD. The bars measure mean leave balance at the start of the year for teachers of different experience levels.

Figure A3: Weekly I&P Patients from Scott and Bordering Counties



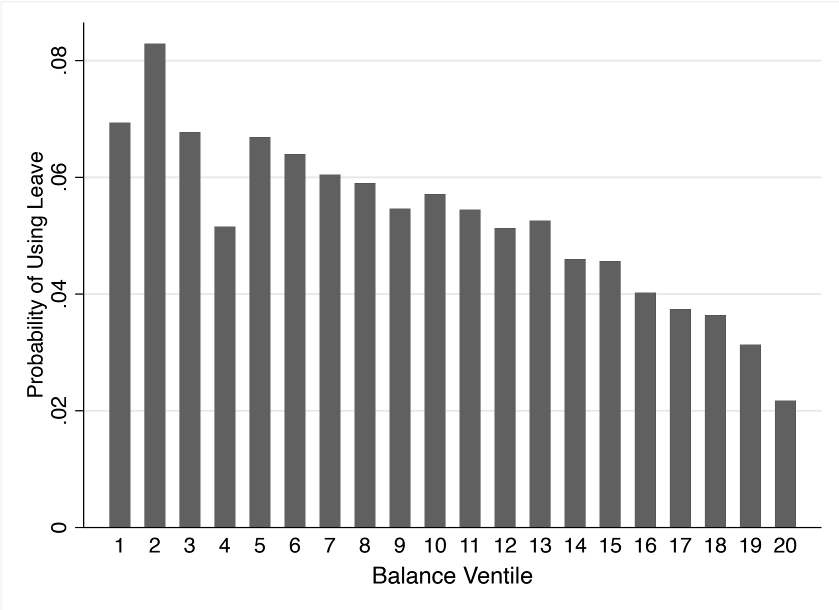
Notes: Cabinet for Health and Family Services in Kentucky, Health Facility and Services Data. Data are all hospital and ambulatory facility admissions with a condition code indicating influenza or pneumonia (ICD 9 codes 480–488 for weeks 1/1/2000–9/30/2015 and ICD 10 codes J09–J18 for weeks beyond 10/1/2015) for residents of Scott County and the seven bordering counties.

Figure A4: Impact of Flu Hospitalization Ventile on Leave Probability



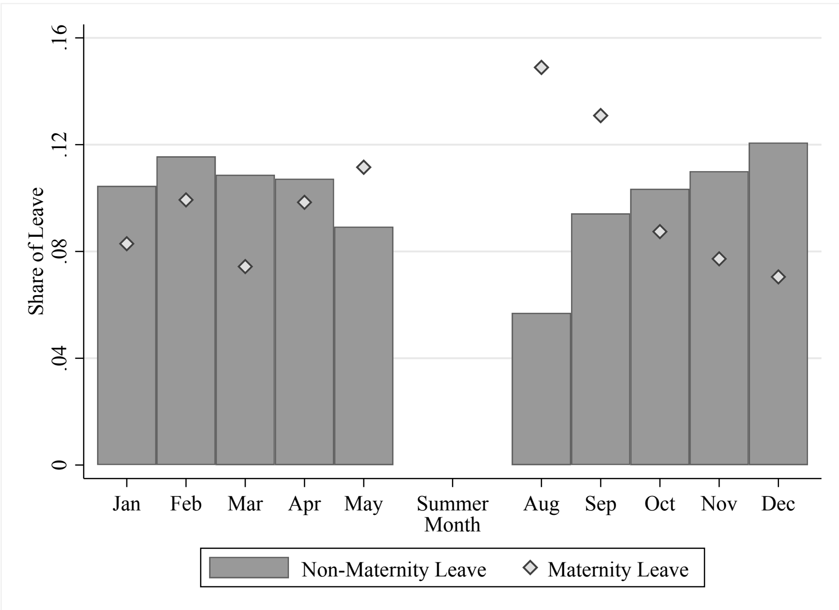
Notes: KPSTD data. Graph shows ventile coeffients $\Sigma_{k=2}^{20} V_{t,k}^{a}$ from a regression as in Equation 5, where $ln(admits_t)$ is replaced by ventile indicators and the leftmost vintile (i.e., fewest flu admits) is the baseline category. The dependent variable is any leave use, which has a sample mean of 0.0595.

Figure A5: Probability of Leave Use by Balance Ventile



Notes: KPSTD data. Each teacher–day is grouped into a ventile according to the balance entering that day. The probability of leave use is then measured as the share of teacher–days in the ventile group that include any type of leave use.

Figure A6: Maternity and Nonmaternity Leave Shares by Month



Notes: KPSTD data. Maternity leave is defined as leave taken by female teachers under age 40 in spells of 15 consecutive days or longer. The vertical axis measures the share of all leave, for pregnancy and not, that occurs in each month. To account for the fact that some months have more school days in them than others, we divide each share by 10 times the share of all observations falling within the month.

Figure A7: 2018–2019 Scott County Public Schools Salary Schedule

Completed Years Experience	RANK III 31	RANK II 21	RANK I 11	RANK I - A 12
0	38,763	42,809	47,279	48,135
1	38,924	42,971	47,438	48,295
2	38,924	42,971	47,438	48,295
3	38,924	42,971	47,438	48,295
4	41,939	46,434	50,922	51,756
5	42,938	47,526	52,105	52,955
6	42,938	47,526	52,105	52,955
7	42,938	47,526	52,105	52,955
8	42,938	47,526	52,105	52,955
9	42,938	47,526	52,105	52,955
10	46,653	51,348	56,137	57,853
11	47,748	52,539	57,429	59,178
12	47,748	52,539	57,429	59,178
13	47,748	52,539	57,429	59,178
14	47,748	52,539	57,429	59,178
15	50,060	55,021	60,045	62,619
16	51,225	56,294	61,414	64,040
17	51,225	56,294	61,414	64,040
18	51,225	56,294	61,414	64,040
19	51,225	56,294	61,414	64,040
20	52,534	57,599	62,673	65,268
21	53,216	58,340	63,461	66,085
22	53,216	58,340	63,461	66,085
23	53,216	58,340	63,461	66,085
24	53,216	58,340	63,461	66,085
25	54,694	59,769	64,840	67,439
26	55,403	60,529	65,652	68,275
27	55,403	60,529	65,652	68,275
28	55,403	60,529	65,652	68,275
29	55,403	60,529	65,652	68,275
30	55,403	60,529	65,652	68,275

41 Rank IV	32,797	(96 to 128 credit hours)
51 Rank V	30,061	(54-95 credit hours)

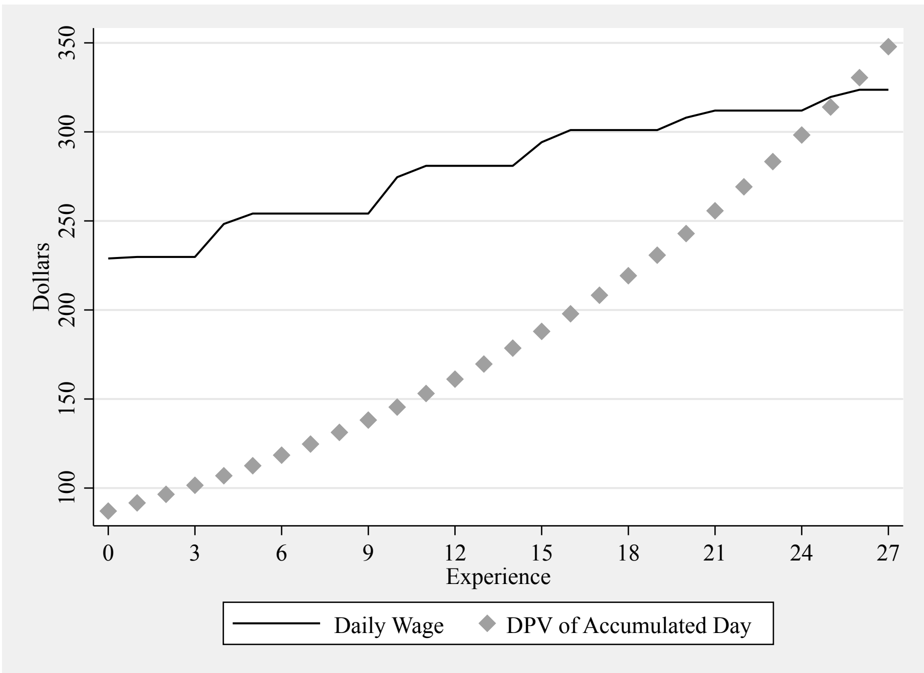
Notes: Rank III corresponds to a bachelor's degree, Rank II a master's degree, Rank I an additional teaching certificate earned post-master's, and Rank I-A a PhD or EdD. Both Ranks IV and V correspond to individuals who have not attained a bachelor's degree but have some college credit. Individuals can only be hired to full-time teaching positions on a temporary basis (e.g., as long-term substitute teachers) without a bachelor's degree.

Figure A8: KDE Retirement Multiplier

Multipliers for Non-university			
Year of Service*	**Entry Prior to July 1, 2002**	**Entry on or after July 1, 2002**	**Entry on or after July 1, 2008**
1 – 10.0	2.5%	2%	1.7%
10.01 – 20.0	2.5%	2.5%	2%
20.01 – 26.0	2.5%	2.5%	2.3%
26.01 – 30.0	2.5%	2.5%	2.5%

* Years prior to 1983-84 are at 2 percent. For each new tier of service credit attained, all prior years convert to the new multiplier, up to 30 years of service. Any years in excess of 30 (and only those years) use a multiplier of 3 percent.

Figure A9: Immediate Costs and Discounted Future Benefits of a Sick Day



Notes: KPSTD data. The solid line simply measures the daily wage rate across the experience distribution for a teacher with a master's degree (see Figure A7). The dotted line measures the present value of a sick day upon retirement, discounted to the current year. To make this calculation, we assume retirement at age 55 with 27 years of service and a master's degree, death at age 85 and exponential discounting at a 5% rate and that future retirement wage increases exactly keep up with inflation.

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https://www.ssrn.com/link/ZEW-Ctr-Euro-Econ-Research.html
https://ideas.repec.org/s/zbw/zewdip.html

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