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THE ANATOMY OF U.S. SICK LEAVE SCHEMES: EVIDENCE FROM PUBLIC SCHOOL TEACHERS

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ABSTRACT

We study how public school teachers use paid sick leave. Most U.S. sick leave schemes operate as individualized credit accounts – paid leave is earned and unused leave accumulates, producing an employee-specific leave balance. We construct a unique data set from administrative records containing the daily balances and leave behavior of 982 teachers from 2010- 2018. We find that sick leave use increases during flu season. We do not find evidence that the average teacher uses sick leave for leisure; however, there is evidence of such behavior among certain subsets of teachers (e.g., young, inexperienced teachers). Usage increases with leave balance; the elasticity is around 0.4. Further, higher balances reduce the likelihood that teachers work sick, particularly during flu season.

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1 Introduction

Granting workers paid leave presents inherent tradeoffs. On the one hand, there is a classic moral hazard problem as 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 between 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 do not have federal mandates to ensure universal employee access to paid sick leave (Raub et al., 2018). In 2020, the U.S. passed the Families First Coronavirus Response Act, the first federal sick leave mandate in U.S. history, which provided up to two weeks of emergency sick leave for COVID-related reasons (H.R.6201 - Families First Coronavirus Response Act, 2020). And yet, 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 percent of all U.S. workers did not have access to *any* paid sick days, with the rate highest (38 percent) in service industries (BLS, 2021). Among those with access to paid leave, the average private sector allotment is less than 10 days per year (BLS, 2019), much less than the allotments commonly seen in European countries, for example.[2]

In addition to substantial differences in leave-related regulation and generosity, the primary features of short-term sick leave schemes are fundamentally different in the U.S. than in most European countries. In the U.S., the following three features are nearly ubiquitous: (i) workers own individual paid leave accounts, whereby leave is earned through work performed, (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

[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 from the European Union: 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 percent 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 percent wage replacement; wages are replaced at 70 percent for the next 72 weeks (Ziebarth and Karlsson, 2014).

[3]These features are present in most proposed and passed leave mandates, such as the Healthy Families Act, the

leave upon retirement in an effort to prevent moral hazard. This scheme starkly contrasts with the most common European schemes, the design of which resembles unemployment insurance and workers' compensation in the U.S. – without individualized leave credits, but instead with replacement rates as a share of salary.

The structural differences in sick leave schemes between the U.S. and Europe create different employee incentives and may induce different behavioral responses.[4] Understanding how workers in the U.S. use their leave is vitally important 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, previous research on worker responses to changes in sick leave policies in Europe may not be informative for worker behavior in the U.S. The few existing studies on sick leave using U.S. 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).

The main contribution of this paper is to study how the institutional features of the typical U.S. paid leave scheme influence employee leave taking. To this end, we begin with a theoretical model of leave behavior, which helps us to characterize key tradeoffs created by the typical U.S. leave scheme. To empirically test several predictions of the model, we then utilize a newly formed data set, which we 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, job descriptions, and work experience, the data set contains two truly unique features among U.S. data sets. The first feature is *daily* information on every sick, personal, emergency, and unpaid day taken by *each* teacher from 2010 to 2018. The second feature 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 that is typical in the U.S. As we study the sick

14 state-level U.S. sick pay mandates, and the paid leave policies consideration by the Biden Administration in 2021 (NPWF, 2023; Findlay 2021; Healthy Families Act 2023).

[4]For example, though both schemes disincentivize leave taking, European workers generally face a penalty in the present (e.g., a lower pay check). In contrast, consequences for U.S. workers are typically realized in the future (e.g., 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 with 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), the role of 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 that focuses on how teacher absence affects student achievement (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., 2014a,b).

leave behavior of public school teachers in Kentucky, we believe that our findings have clear external validity for all 3.8 million public school teachers in the United States (NCES, 2021), as well as 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 U.S. 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 school days (i) before and after scheduled holidays, (ii) following the Super Bowl, (iii) while 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: a 10 percent increase in the severity of a local flu wave (measured by hospitalizations) leads to a 1.5 percent increase in leave taking. We find no conclusive evidence that sick leave is used for leisure in the full sample. To our knowledge, this paper is the first to use precise daily leave data on U.S. employees, which is needed for the statistical tests described above. We thus contribute to the literature on the determinants of leave taking behavior, such as the "Monday Effect" in workers' compensation, which refers to a spike in back injury and sprain claims on Mondays (Card and McCall, 1996; Campolieti and Hyatt, 2006). As another example, Skogman Thoursie (2004) implements a test very similar to ours; he uses Swedish administrative data to show that Swedish men are 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 such "temptation days" in some of our sub-group analysis, e.g., *male* teachers 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. Our results show that as balances increase, so too does the use of leave. On average, a 10 percent increase in leave balance results in a 4.5 percent increase in the probability of taking leave on any particular day. We show that this relationship is strongest at the bottom of the balance distribution, as teachers seek to avoid reaching a zero balance, making additional leave unpaid. Our balance-use elasticity estimate 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 elasticities are difficult to compare. The key reason is that an additional leave credit in the U.S. system carries value even for an employee that opts not to use it; the credit carries monetary value at retirement. A higher replacement rate only benefits employees who opt to take time away from work.

Third, we investigate if teachers with low leave balances exhibit presenteeism, or "working sick". Given that the first sets of results indicate that teachers (i) do not systematically use sick leave for leisure, and (ii) as teachers accrue higher balances they use more leave, presenteeism can explain the intersection of those 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 that 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 lower 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 lower leave balances increase presenteeism, 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 one's colleagues with a low balance increases, suggesting spillover effects from presenteeism.

Our findings provide important evidence for ongoing policy discussions concerning sick leave mandates in the U.S. As mentioned, the U.S. 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,

[7]Some federal policy options under discussion by 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-

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 contribute to this policy debate by documenting how leave is actually being used, at least in the public sector. Our results indicate that sick leave use increases when severe flu cases are more prevalent. Though leave may be used for leisure among some subgroups, the magnitude of misuse is relatively small. We also document an important positive externality of paid leave; namely, workers with larger sick leave balances are less likely to come to work while ill, reducing the spread of illness in the workplace.

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. In a first step, we combine the following:

1. A state-wide, annual longitudinal data file on all Kentucky school teachers, collected and maintained by the Kentucky Department of Education (KDE), containing demographic information, education, years of experience, school, and job title.[8]

2. Daily administrative leave data provided by the Scott County School District (SCSD) in Kentucky.[9] The file contains the date, current leave balance, and type of leave taken for every school day of the 2010/2011 school year through the 2017/2018 school year.

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, as well as the seven bordering counties. This information is drawn from Kentucky's Health Facilities and Services Data, which is collected and maintained by the Kentucky Cabinet for Health and Family Services.[10]

term sick leave" (or "temporary disability insurance", see Campbell et al. (2019)), while family leave primarily includes parental leave for childbirth.

[8]Information about the Kentucky Longitudinal Data System can be found here: https://kystats.ky.gov/About/History.

[9]Kentucky has a total of 172 school districts for its 120 counties. Scott County, located 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). SCSD is the 12th largest district in the state, composed of 18 schools, with approximately 9,500 students enrolled (https://www.greatschools.org/kentucky/georgetown/scott-county-school-district/) and 1,364 faculty and staff (https://www.scott.kyschools.us/).

[10]https://chfs.ky.gov/agencies/ohda/Pages/hfsd.aspx.

5. Event dates marking (i) when horse races take place at the Keeneland Race Course, (ii) Super Bowl Monday, and (iii) when the UKMBB team plays 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. Eighty-three percent are female and nearly 97 percent are white, non-Hispanic. Over 60 percent have a masters degree or more. Experience ranges 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 DA1); the average base salary is $50,770 per school year but has a standard deviation of $9,922. Half of all teachers work in elementary schools and 23 (24) percent in middle (high) schools.

SCSD teachers are fairly representative of teachers nation-wide. Based on a 2016 survey of 40,000 U.S. public school teachers, 77 percent are female, 80 percent are white, average experience is 14 years, and 57 percent have post-baccalaureate 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 DA1.3. 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, etc.[11] 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 tends to be used for last-minute emergencies, while the latter can be used for any reason and is 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 DA1.3). Finally, as is common for public school teachers throughout the U.S., 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.

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.[12] Upon retirement, teachers are compensated for unused leave in two ways: (i) they receive a lump sum worth one third of 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.[13] The retirement scheme is detailed in full in the Online Appendix, Section DA4. Importantly, if a teacher stops working in Kentucky public schools prior to retirement eligibility (i.e., aged 55 years or 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., 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).

[11] 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 to employees (cf. Thomas, 2020). In Section 4.2.3, we discuss the typical maternity experience of teachers in Kentucky.

[12] Teachers can also donate days to one another, though it is fairly rare – fewer than 2 percent of "spent" credits are donated. The rules governing leave donations are outlined in Appendix Section DA1.3.

[13] We show in Appendix Figure DA3 that, under some assumptions, the discounted present value of an unused sick day ranges between \$100 and \$400, depending on years of service. For more than 22 years of service, the discounted present value of an unused sick day exceeds the daily wage.

2.3 Descriptive Statistics on Leave Use

Panel C of Table 1 shows that teachers take an average of 9 leave days per school year, approximately two-thirds of the 13 days credited each year. The vast majority are sick days, on average 7.6 per year. Teachers average 0.7 personal and 0.6 emergency days per year. Teachers can take fractional days off. In 22 percent 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 (this includes fractional and full days off), which yields a daily leave rate of about 6 percent.[14] In each academic year, five percent of 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 percent of all teachers take more than 20 days of leave per year, which accounts for 22 percent of all leave use.

Panel D of Table 1 reports that the mean balance entering a school year is 52 days. There 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 percent of teacher-years start the year 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 school year.[15] Figure 1 also shows the histogram of leave balances *at the end* of the school year using light gray bars. One clearly observes a balance distribution that is shifted to the 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 percent of teachers finish the year with zero paid leave days remaining, while 16 percent finish with fewer than 5 days.

Finally, given the design of the sick leave scheme, one would expect leave balances to increase with experience. Figure 2 shows the average leave balance entering the school year by teacher experience; Panel D of Table 1 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 to 10 (15 to 20) years of experience.[16] There is variation both within and across experi-

[14] 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.

[15] Annual leave allotments for teachers starting after the first day of school are prorated. In Figure 1 we only include teachers starting on the first day of the school year. In panel D of Table 1, minimums fall below 13 because we have included late-starting teachers in that table.

[16] The mean balance entering 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 they transition to full-time status.

ence 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 a number of variables thought to influence the likelihood of leave use.

Hospital Admissions for Influenza. The first variable measures Influenza and Pneumonia (I&P) admissions from the Health Facility and Services Data, which is collected by the Kentucky Cabinet for Health and Family Services. To proxy for local flu intensity, we measure total weekly admissions to Kentucky hospitals (ED, 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 A2 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, federal and local holidays, etc. 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.

Sporting Events. We create several variables related to the timing of local and national sporting events that may exogenously shift the probability of taking leave for recreational purposes.

[17] Bordering counties include Owen, Grant, Harrison, Bourbon, Fayette, Woodford, and Franklin. The population of these counties, plus Scott, is 530,000; 12 percent of the state's population. Regarding diagnosis, we use ICD9 codes 480-488 for weeks 1/1/2000 - 9/30/2015 and ICD10 codes J09-J18 for weeks beyond 10/1/2015.

The first event variable indicates that a popular local horse racing track, Keeneland, is open. Located in Fayette County (home to the city of Lexington). Just 20 minutes from the center of Scott County, Keeneland is an internationally renowned horse-racing track that serves as a popular social event for central Kentuckians. Races are held Wednesday through Sunday during most weeks in October (Fall Meet) and April (Spring Meet), with daily attendance around 15,000. Scott County residents are particularly fond of Keeneland. According to Bollinger (2015), more Keeneland attendees come from Scott County than any other Kentucky county (besides Fayette). In 2014, approximately 20 percent 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 is in session (∼9 percent of the sample), roughly a third of which are Fridays, the most popular weekday to attend. This variable is particularly interesting for our sample because Keeneland is as much a social event as a sporting event, meaning its appeal reaches all demographics.

The second event variable indicates days that the University of Kentucky Men's Basketball (UKMBB) team is playing in the NCAA tournament. UKMBB consistently ranks among the top NCAA basketball programs in attendance[18] and popularity.[19] The dedication of NCAA basketball fanbases is never more evident than during the NCAA tournament (often called "March Madness"), which is the apex of the season. In a 2014 survey of U.S. adults, eleven percent reported that they *would* call in sick to watch the NCAA tournament,[20] while BLS estimates the average absence rate nationwide is three percent.[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 for 2013. This totals 13 days (7,327 teacher-day observations) when school was in session and UKMBB was playing in the NCAA tournament.

The third 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 roughly 10 percent of the U.S. 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 (closed due to weather) and February

[18] https://www.ncaa.com/news/basketball-men/article/2020-10-27/25-mens-college-basketball-teams-hi
[19] https://bleacherreport.com/articles/550473-the-duke-blue-devils-and-the-50-best-fan-bases-in-co
[20] https://retailmenot.mediaroom.com/2014-03-10-March-Madness-Brings-Madness-to-the-Workplace
[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/

5, 2018 (scheduled closure) are the exceptions.

3 Theoretical Model

We present a simple model of optimal leave use. We do not estimate this model, but rather, use it to highlight the tradeoffs faced by teachers operating under this leave scheme, to frame the empirical analysis that follows.

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 DA1). 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, 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 non-monetary cost, γ, caused by any stigma or monitoring costs imposed by the district.[23]

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 tradeoffs associated with leave taking, one needs to consider her optimal level of leave, d_1^*, in the first period alone.

[23] District administrators communicated to us that while taking unpaid leave is allowed, it is discouraged but for a small set of circumstances. Please see Appendix DA1.3 for additional context.

Using Bellman's equation, the period 1 value function can be written 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

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

In words, the discounted present value of leave decision d_1 has three components: One, contemporaneous utility, $U(\cdot_1)$. Two, discounted expected utility in period two, $\delta E[U \cdot_2]$, which is influenced by d_1 through b_2; i.e., more leave use in period one lowers the balance entering period two. In period one, the teacher does not know ϵ_2 and, therefore, can only calculate her *expected* utility. Upon learning ϵ_2 at the start of the following period, she knows that she will choose the optimal d_2^*. Three, 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. The value of retirement, V_R, assumes 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.[24]

The teacher chooses d_1 such that $\partial V_1 / \partial d_1 = 0$. Note that U is discontinuous and, therefore, not differentiable where $d_t = b_t$. As such, 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 $d_2 > b_2$.[25] 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 $Pr(\epsilon \leq a) = F(a)$.

[24] The rules governing retirement pay, including those determining how leave balances influence retirement pay can be found in Appendix Section DA4.

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

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

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

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

Equation (4) clearly illustrates the tradeoffs 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 taking leave today.

The first cost is BC', where $B = Pr(d_2 \leq b_2)$ and C is the discounted expected value of the choice d_2 when $d_2 \leq b_2$. In this circumstance, the teacher retires with accumulated leave and is, therefore, paid for that leave. Thus, BC' captures the first cost of taking leave, namely, that financial benefits in retirement are sacrificed (in expectation). In Appendix Section DA5, 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, meaning they receive 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 DA5 that d_1 only affects (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.

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.

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.

We ask in Section 4.1: *When and why do teachers take leave?* In particular, our analysis tests whether sick leave use responds to observable events that (i) raise the likelihood of illness and/or (ii) are recreational in nature. As it relates 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 like 'getting caught using a sick day for recreation' would lower α_R.

We ask in Section 4.2: *Do larger leave balances induce more leave taking?* The model is particularly helpful in understanding 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. As such, higher balances reduce *two* of the costs of taking leave today in Equation (4) – $(1 - B)D'$ and $B'(C - D)$ – each of which relate 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, we ask in Section 4.3: *Does a larger leave balance reduce presenteeism behavior?* As discussed above, illness in the model 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 suffering future utility losses associated with 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, potentially forcing teachers to work while sick.

4 Empirical Analysis

4.1 When and Why do Teachers Take Leave?

To answer this question, 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:

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

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 for 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.

We investigate how teachers respond to events that shift the utility of absence by including a vector of indicator variables, Z_t, for the school days (i) before and after holidays, (ii) Keeneland is open (plus an indicator for a Keeneland Friday), (iii) UK Men's Basketball (UKMBB) is playing in the NCAA tournament, and (iv) the Monday after the 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 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 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 OLS regression. The column header indicates the type of leave used as the dependent variable. As hypothesized, higher flu activity, measured by the number of (log) 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 other types of leave. The figures suggest that a 10 percent 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 six percent, this reflects a 1.5 percent increase in leave taking.[26]

To allow a more flexible relationship, we re-estimate 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.[27] In Appendix Figure A3, 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 behavior increases incrementally with the risk (or severity) of catching a contagious disease. If we define "flu season" arbitrarily using the top five ventiles, then compared to baseline, flu season increases the probability of taking leave by approximately 1.75 percentage points. The leave rate in the bottom ventile is 0.04; thus, flu season increases eave taking by 44 percent.

4.1.2 Leave Use in Response to Higher Utility from Absence

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

[26] 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 for the flu rates of the general population. An increased prevalence of flu should lead to increased 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.

[27] 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.

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 during Keeneland, but the effect is only statistically different from zero on Fridays. On a typical non-Keeneland Friday, there is a 7.5 percent chance that a teacher takes leave. All else equal, Keeneland raises the likelihood of Friday leave by 0.82 percentage points (11 percent). Comparing columns (2) through (5), the statistical significance of the Keenleand Friday effect on any leave use in column (1) is driven mainly by the use of personal leave, though sick leave accounts for approximately 1/3 of the magnitude of the effect. Even on Keeneland Wednesdays and Thursdays, personal leave use is elevated by a statistically significant amount. Keeneland has no statistical effect on sick leave use. In a sense, events like Keeneland are precisely the reason personal leave is allocated. Furthermore, note that the significant, positive impact of Keeneland on personal leave use validates our statistical test, as it proves that teachers do in fact value the event; nonetheless, they are unwilling to use sick leave inappropriately in order to attend.

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

The next several rows of Table 2 show how leave use varies by the 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 the highest likelihood of leave use on Monday and Friday. The average Wednesday leave rate is 0.053; all else equal, leave use is 16 percent more common on Monday and 43 percent more common on Friday. The Friday effect is statistically larger than the Monday effect at the one percent level.

Mondays and Fridays are the most popular days for leave among teachers nationwide (Frontline, 2017), which some have argued suggests "leisure behavior" (Miller et al., 2008). This may be the case; however, conversations with both district administrators and teachers have suggested 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.[28] As a result, teachers reported to us

[28]One reason is that teachers often create lesson plans in weekly blocks, with Fridays used primarily for review and testing, both of which a substitute teacher does more easily than introduce new material. Another reason is that students are the least focused on Fridays as they anticipate the weekend, which leads administrators to schedule non-traditional school activities (e.g., assemblies, pep rallies, band/choral concerts, etc.) on Fridays. Again, the marginal

that routine doctor's office and dental appointments, both acceptable justifications for sick leave use, are "virtually always" scheduled on Fridays. The same is true for minor outpatient procedures, where 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 U.S. and Canada, respectively, workers compensation injuries are most common on Mondays due to psychological strain.[29] 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 the weekends (O'Malley, 2013), there are numerous medical reasons for a rise in sick leave use on Mondays.[30]

These alternative explanations are compelling, but obviously cannot rule out the interpretation that heightened leave use around the weekend suggests leisure behavior. As such, another way to consider this data pattern is to calculate how common these alternative-explanation events need to be in order 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 percent fewer Fridays off (i.e., 0.77 fewer Fridays per year), then the Friday leave rate would be statistically indistinguishable from Wednesday, all else equal. In other words, the above events (e.g., preplanned doctor visits, professional development, etc.) need to explain 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 a "worst-case scenario," where there are no weekend injuries or 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 month of the school year, respectively. Leave use is increasing in experience, which is consistent with teachers having access to a larger leave balance (explored in more detail in Section 4.2).

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 days of the week (Redbooth, 2017).

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

[30] An attentive referee pointed out that it could also be the case that presenteeism, not shirking behavior, varies over the course of a week, with presenteeism being lowest on Mondays and Fridays.

4.1.3 Robustness and Heterogeneity.

Appendix Table A2 contains several robustness checks. Column (1) contains our main results for comparison; those from column (1) of Table 2, where "any leave" is the dependent variable. Shown in column (2), all estimates are robust to the use of calendar-week fixed effects. In 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, reinforcing 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.

Gender and kids. 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; however, since women generally provide a disproportionate share of caregiving to children (Ranji and Salganicoff, 2014) and elder family (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 teachers have children, are married, or where teachers live. Twelve of the 15 schools are located in the city center, the other three within 7 miles of it, suggesting that child care facilities are in close proximity. Regarding leave for leisure, Keeneland has a statistically significant effect on sick leave use for men, but not for women. Furthermore, men are more likely to take any leave on days that UKMBB is playing in the NCAA tournament. Although the statistical significance of that result is driven by personal leave, sick leave accounts for about one-third of the magnitude of the overall effect. Additionally, the "Friday effect" specific to sick leave is over 50 percent 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 the age of 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 is playing 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 teachers who are 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 degree to those with a Bachelor's. Aside from a stronger response to flu hospitalizations by teachers with a Master's degree, 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) and (ii) use more leave for leisure. We find evidence of neither. We also stratify the results by high school vs. elementary school teachers, as well as rural vs. urban elementary schools, and find no significant differences in leave use. All of these results are available upon request.

Leave Duration. Similar to the literature on the demand for health care that distinguishes between "discretionary" and "nondiscretionary" care (Finkelstein et al., 2013) and finds much smaller elasticities for inpatient care (Manning et al., 1987), the duration of sick leave proxies for different underlying health shocks (Ziebarth, 2013). Less severe illnesses require short-term sick leave, whereas severe illnesses require longer-term sick 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. As such, in Appendix Table A8, we re-estimate Equation (5) for two subsamples: (i) the top panel considers one-day spells only (i.e., all teacher days that are part of an illness spell that is 2 or more days are dropped) and (ii) the bottom panel only considers spells that are of 4 days or more (i.e., all teacher days that are part of an illness spell that is 1, 2, or 3 days are dropped).[31] The results show a statistically significant increase in the likelihood of using any leave when UKMBB is playing in the NCAA tournament and after the Super Bowl when looking at short spells, but not long spells. The Keeneland Friday, Monday, and Friday effects are also larger when considering short spells compared to long spells. That said, flu admissions are *also* predictive of sick leave use *only* in the short-spell sample. This is in part due to the fact that a nontrivial share of long spells are due to what looks like maternity (6%, see Section 4.2.3 for details on how we proxy for maternity). If we also drop maternity leave, the coefficient on flu admissions for the long-spell sample becomes statistically different from zero and matches the magnitude of the short-spell sample (not shown).

[31] See Section 4.3 to see how we define a leave spell and its length.

In summary, we find a statistically significant increase in leave use with greater flu activity, consistent with the underlying motivation for providing 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) presents the possibility of getting "caught" in a small community where reputations matter. Testing 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. Obvious policy questions are: Is this annual allotment of sick leave credit appropriate, too high, or too low? And, should there be limits on the accumulation of leave? This section aims to shed light on these questions by assessing how teachers' leave balances influence their leave-taking behavior. Our theoretical model in Section 3 suggests that leave use should increase as one's balance increases. Here, we test that prediction empirically.

4.2.1 Empirical Approach

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

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

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 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 avoids 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 nets out time-invariant unobservables, allowing the parameters to be identified off of within-teacher variation. Third, we measure the leave balance ten days before the observation day to avoid the mechanical association between one's leave balance and their 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, there are two remaining sources of variation in teachers' leave balances that identify our estimates. The first source 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, that force extended time away from school and, therefore, 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, one can 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 and statistically significant, opposite our hypothesized sign.[32] Yet, both the selection and mechanical association concerns described above would lead to a downward bias of the balance-use elasticity. In column (3), we control for selection by adding individual fixed effects, which causes the sign to flip to 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.

As the balance variable is transformed using the inverse hyperbolic sine 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 to suggest

[32]Consistent with these findings, Appendix Figure A4 shows that the unconditional correlation between leave balance and use on any given day is negative.

that a 10 percent increase in a teacher's leave balance increases leave taking by 0.27ppt. Compared to the baseline leave taking rate, this reflects a roughly 4.56 percent increase 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. 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, the balance-use elasticity operating entirely through the bottom of the balance distribution would suggest that when teachers run out of paid leave credit, they reduce 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 by giving new employees larger starting balances. To 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 3 plots the ventile coefficients. We observe a strictly positive relationship between leave balance and leave use. Notably, the likelihood of taking leave jumps substantially when moving from the baseline bin (0 to 5.5 days) to the second bin (5.5 to 9 days) – the likelihood of taking leave increases by four percentage points, a 64 percent increase 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 non-linearly when teachers hit a zero balance because unpaid leave operates under a distinct framework, which we discuss in detail in Appendix Section DA1.3. 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. Holding all else equal, these "high-balance" teachers are 148 percent more likely to take leave on any given day than teachers in the baseline bin, and 47 percent more likely than 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, the inverse hyperbolic sine function that we employ is nearly identical to the natural log function, which is the basis for interpreting our coefficients as elasticities, everywhere *except* near zero.[33] In light of these 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: (i) across all 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 inverse hyperbolic sine, but the difference diminishes as balances near zero are removed from the sample, and (iii) elasticities are smallest and most uniform when the bottom balance ventile is dropped.[34]

Childbirth and Maternity Leave. Many teachers in our data are female 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 estimating 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. Also, most leave donation recipients that we observe in the data are likely to have given birth (e.g., recipients tend to be young females 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.

[33] Recent research has explored potential pitfalls with (and alternative to) using the common "log plus 1" and inverse hyperbolic sine transformations of the dependent variable (Chen and Roth, 2024; Mullahy and Norton, 2024), but do not address situations like ours where an independent variable is transformed.

[34] Results are not shown, but we also confirmed that our main findings are robust to (i) including calendar week fixed effects and (ii) limit the sample to teachers who are employed throughout the full eight year sample period (i.e., there is no evidence of dynamic selection).

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 percent of all leave taken in our data; of the 982 teachers, 146 (14.9 percent) ever take maternity leave.[35] The timing of maternity leave appears somewhat strategic. Figure 4 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 was 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 that 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.[36]

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 stock-piling 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.

In summary, we estimate a balance-use elasticity between 0.38 and 0.45. Furthermore, we show that while leave use increases with balance throughout the balance distribution, leave use decreases dramatically when the balance nears zero. This finding is logical, as leave use with a balance of zero results in withholding pay from a teacher's typical pay-check; that is, teachers are not paid for the days that they miss. This finding suggests some discretion in leave use, or that leave is not entirely explained by exogenous illness shocks that are unlikely to be correlated with balance levels. We explored the idea of using leave for leisure in Section 4.1, finding that while

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

[36] 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 two to five percent higher than the trend in July, August, and September. Though maternity is measured imperfectly in our data, teachers are over 50 percent more likely to take maternity-like leave in August or September than in the months October to April.

some subsets of teachers may use leave for certain types of leisure, the practice is not strong or consistent enough to produce statistically significant effects for the full sample. That said, we cannot rule out the possibility that teachers use sick leave to engage in non-systematic leisure (i.e., leisure not correlated with the observable events we study) and that such behavior contributes to our positive balance elasticities.[37] Yet another plausible explanation is that teachers use discretion in deciding whether to take leave *when sick*, which is the topic of the next section.

4.3 Does a Larger Leave Balance Reduce Presenteeism Behavior?

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. As such, we take two approaches to studying presenteeism. The first approach attempts to measure presenteeism directly from the data. The second approach infers 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 where 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 taking leave on nearly situated 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).[38] 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. As such, a regression of presenteeism days on leave balance at the daily level will result in estimates that are biased upward (toward zero). We address this econometric issue by conducting our analysis at the illness-spell level. Consider the following proposition:

[37] Though not shown, we estimated 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.

[38] 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 no illness on day $t+1$. Similarly, presenteeism could involve working sick for a day, followed by consecutive days off – or – taking consecutive days off, then working while sick.

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) or not.[39] Column (1) of Table 4 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 percent 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 percent of spells in each spell-length grouping that contain a presenteeism event.

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

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 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 measure of presenteeism described 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.[40] We plot regression coefficients, $\beta_{1,k}$, in Figure 5. The figure suggests that across the balance distribution, higher balances reduce presenteeism; however, the reference ventile has relatively few presenteeism events, making many of the coefficients 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

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

[40] 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.

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. As such, we expand on the findings above by re-estimating the model both in times of high and low flu activity, as measured by $admit_t$. More precisely, we estimate the model on two distinct subsamples. The first limits the sample to spells where the total number of flu admits during the spell was above the sample median. This we define as “Flu Season.” All other spells are included in the second regression representing “Not Flu Season.” Results are robust to alternative cutoffs. As we are splitting a sample of just 3,045 illness spells, we also reduce our number of leave-balance bins to 12.

Figure 6 shows the results graphically, plotting the bin coefficients separately for times inside and outside flu season. Outside flu season (i.e., in the early fall or late spring), we see an almost perfectly flat relationship between presenteeism spells and having a higher leave balance. During flu season (i.e., mostly in January and February), we see a decrease in the coefficients as the balance grows. In other words, the larger a teacher’s leave balance, the less likely they are to call in sick, come back to work (for up to one day), and call in sick again – our measure of 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 when interpreting these findings due to possible measurement error in our presenteeism proxy. First, consider type-1 measurement error, or falsely assigning 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 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. As such, one may have expected 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 imperfect feature of 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, this presenteeism definition will miss more presenteeism (type-2 error) 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 is two-fold. 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 when own-leave balance declines, finding that own-leave use is positively associated with deficits in *other*-leave balances suggests that others may be engaged in presenteeism. Because such a finding could also be explained by peer effects, or a school with a culture of heavy leave use, we also replace the school-type fixed effects in Equation 6 with school-specific fixed effects. Second, policy makers (or school administrators) should seek to prevent presenteeism events only if negative externalities result; the most plausible of which are illness spillovers and poor teaching quality. As such, 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 5. As expected, the share of one's colleagues with a low balance is a significant, positive predictor of own-leave use, conditional on 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 for 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. Similar to the approach 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.[41]

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

5 Discussion and Conclusion

This paper is the first to study paid leave use by U.S. 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 deemed necessary (under some constraints), allows unused leave credit to accumulate over tenure with the employer, and compensates the workers for unpaid leave upon retirement. Such schemes are common in the U.S., and are nearly ubiquitous for U.S. public employees, but are less common elsewhere.

Our empirical work focuses on three key questions, which are motivated by a simple, theoretical model of leave use under the scheme just described. Our first question asks, *when and why do employees use leave under these schemes?* And, in particular, *do employees use sick leave as 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, to attend a popular local horse racing event, or to watch nationally televised sporting events. The local horse racing event does increase the 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 sub-groups 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 the generosity of a scheme, our results do not support arguments for less generosity based on waste under the current scheme.[42]

Our second question asks, *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 a workers desire to avoid unpaid leave. The likelihood of taking a sick day increases discontinuously when moving from having 0-5 days vs. having 5-13 days; then it increases at a relatively constant rate over the remainder of the balance distribution.

[42] 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 in 2019 (https://www.vox.com/identities/2019/11/6/20951459/kentucky-democrat-beshear-bevin-teachers).

Our final question asks, *do high balances decrease the likelihood of working while ill?* We use two statistical models to show that increasing leave balances can protect against such presenteeism behavior. The first method relies 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 using temporary returns to work in the midst of a series of absences. Using this measure, we show that a larger sick leave balance reduces the probability of working sick, conditional on having an illness spell. What is more, this statistical link is most pronounced during the flu season, when the negative externality of presenteeism is strongest and measurement error concerns are the weakest. Our second method shows that having a high share of coworkers with a low balance predicts own leave use, implying that one's 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 U.S. 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 behavior than those with low balances. Both findings suggest that keeping employees away from very low balances would reduce presenteeism behavior, making workplaces safer. Also note our finding that leave is rarely used inappropriately in the 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.[43] As an example, consider offering first-year teachers in the school district we study an initial a balance of 40 days, but reduce their flow of leave over their next 9 years of employment to 10 days (as opposed to 13). Under such a scheme, teachers would receive the same amount of leave credits by year 10 as in the current system, but many fewer teachers would ever have a balance near zero.[44]

Given the differences between the typical U.S. and European style sick leave scheme, ideally our results would illustrate under what circumstance each scheme was preferred from a welfare perspective. Unfortunately, such analysis is beyond the scope of this paper. To see why, first

[43]Outside of teaching, there are several states that currently mandate that employees earn a minimum of 1 hour of paid leave per 30-40 hours of work. Our conclusions here would suggest that policymakers should instead increase the initial accrual rate, followed by lower accrual rates over employees' tenure. Alternatively, policymakers could consider providing an upfront amount of paid leave credit that would have to be earned or repaid over time.

[44]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, further commitment to the monitoring described in Appendix Section DA1.3 may be needed to prevent employees from rapidly using all of their leave before switching jobs or careers.

recall that the typical European sick leave scheme resembles the design of unemployment insurance (UI) in the U.S.; that is, the schemes (i) specify a maximum number of coverage days per illness episode and (ii) reimburse employees for missed work days at a fraction of the salary. For example, a worker in such a scheme might face a 60 percent wage replacement rate, meaning that when she takes a day off, she sacrifices 40 percent of her daily wage. Compare this to a worker in the U.S. with a high balance of days; when such in individual misses work, she faces no immediate monetary cost and foregone retirement benefits are discounted. At the heart of any formal welfare analysis would be the question: *which of the two systems does a better job maximizing the likelihood that an ill employee stays home, while minimizing the likelihood that well employees come to work?* Because our data do not contain individual-level data on illness and because 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.[45]

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, U.S. style schemes disproportionately benefit healthy workers for several reasons. First, workers who take less than their full allotment of leave effectively receive a 100 percent 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 health 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 an important knowledge gap in understanding leave behavior under the most common U.S. 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 around the generalizability of these 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 not a large community, meaning (i) reputations maybe more important and (ii) the likelihood of getting "caught" using sick leave for leisure may be

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

greater than in a larger community; both factors may deter leave for leisure. Third, most 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 tradeoffs; however, in some leave schemes, workers receive "paid time off" (PTO) credits, which can be used for vacation *or* illness. Behavior may differ in these settings. Fourth, an instruction day in K-12 schools cannot easily be shifted intertemporally the way research, report writing, sales calls, or even most physical labor can. On school days, children in a classroom need instruction and supervision. Leave taking behavior (and responses) may differ in occupations where five days of labor can be, in a sense, compressed into four onerous working days.

Tables

Table 1: Kentucky Public School Teacher Data, Teacher Demographics

	Mean	SD	Min	Max
A. Socio-Demographics				
Age	39.4	10.2	21	74
Female	0.835	0.371	0	1
Race				
Hispanic	0.009	0.095	0	1
Black	0.020	0.140	0	1
Asian	0.004	0.066	0	1
Education				
Bachelor	0.386	0.487	0	1
Master	0.462	0.499	0	1
Rank 1 or above	0.152	0.359	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	50,770	9,922	3,095	83,220
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 of fewer days of leave taken	0.19	0.39	0	1
20+ days of 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 teachers-years (NT=4,580). There are 982 teachers, 293 of which 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 teachers-days (NT=790,615). Each column is one OLS regression as in Equation (5) and also 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 parenthesis are clustered at the teacher-level.

Table 3: Estimating the 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)
Socio-demographic 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 teachers-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: Distribution of Presenteeism Events

Spell Length	Frequency	Percent of Spells	Percent of Leave	Percent 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 upon which leave was 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.

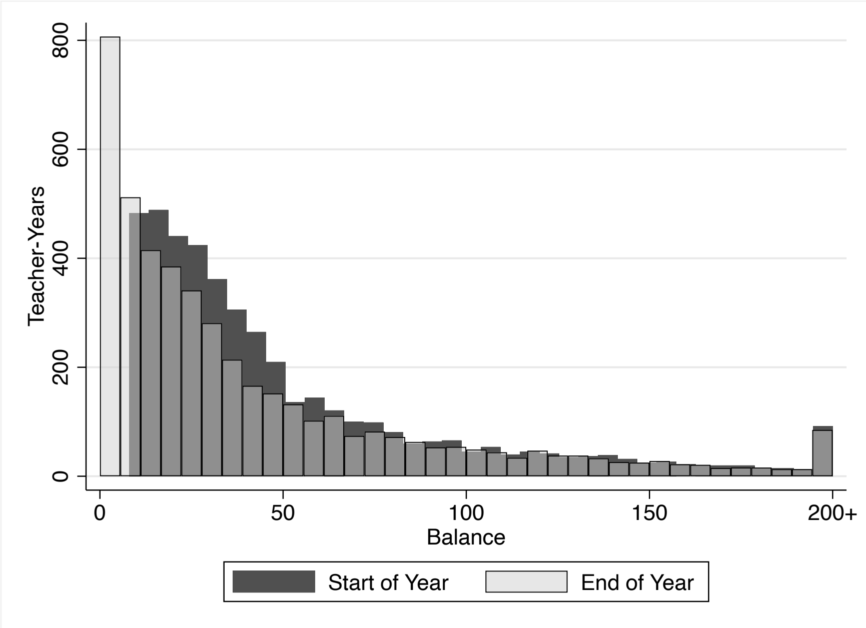
Table 5: Evidence of Presenteeism

	(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)
Socio-demographic 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 teachers-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.

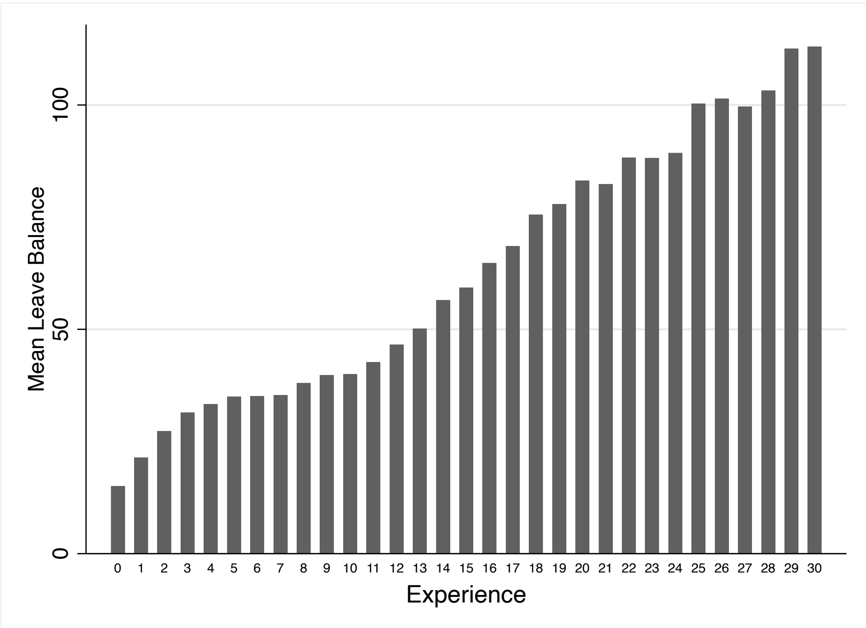
Figures

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



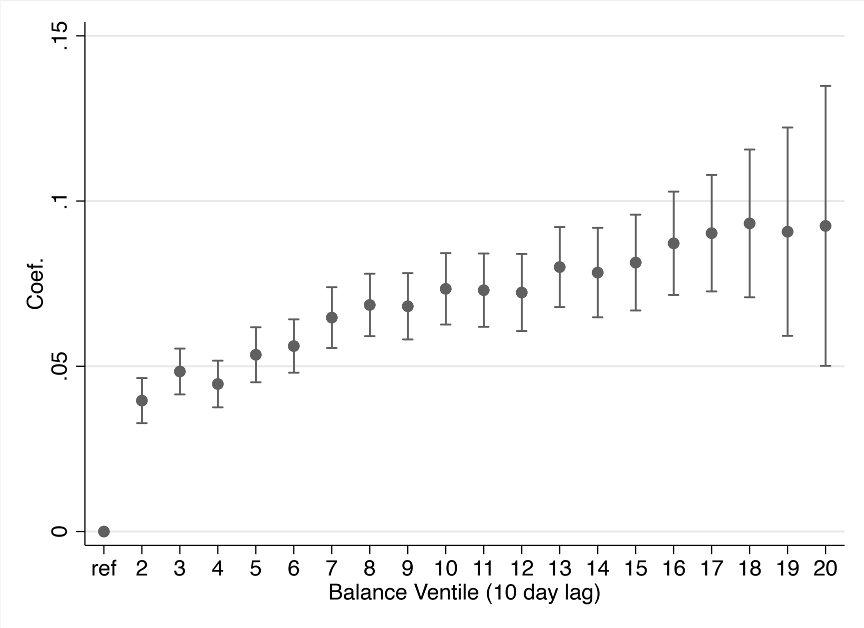
Notes: KPSTD data, aggregated to the teacher-year, yielding a total of 4,580 observations. Histograms of two variables are reported: (i) teacher balance on the first day of the school year and (ii) teacher leave balance on the last day of the school year.

Figure 2: Mean Balance at the Start of the School Year, by Experience



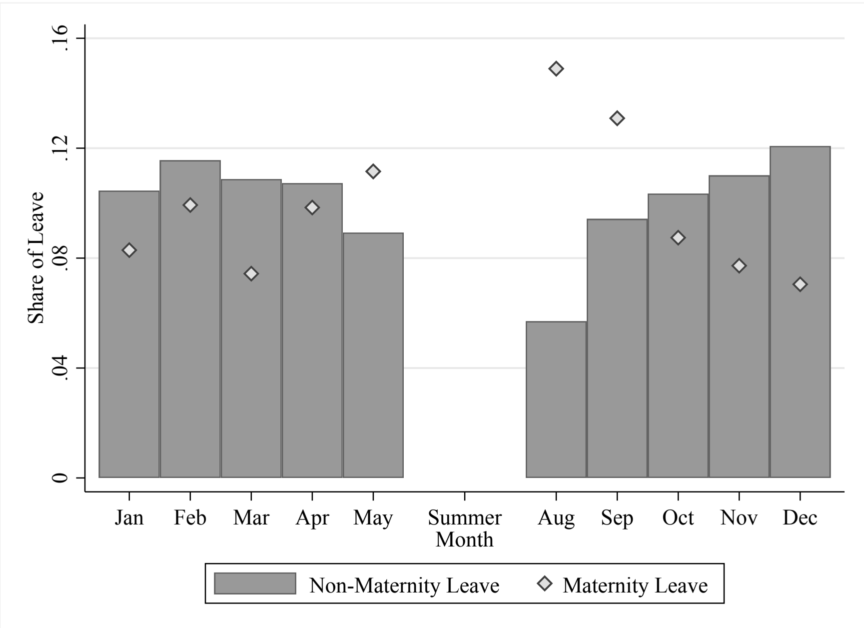
Notes: Data comes from the KSTLD. The bars measure mean leave balance at the start of the year for teachers of different experience levels.

Figure 3: Impact of Balance Ventile on Leave Probability



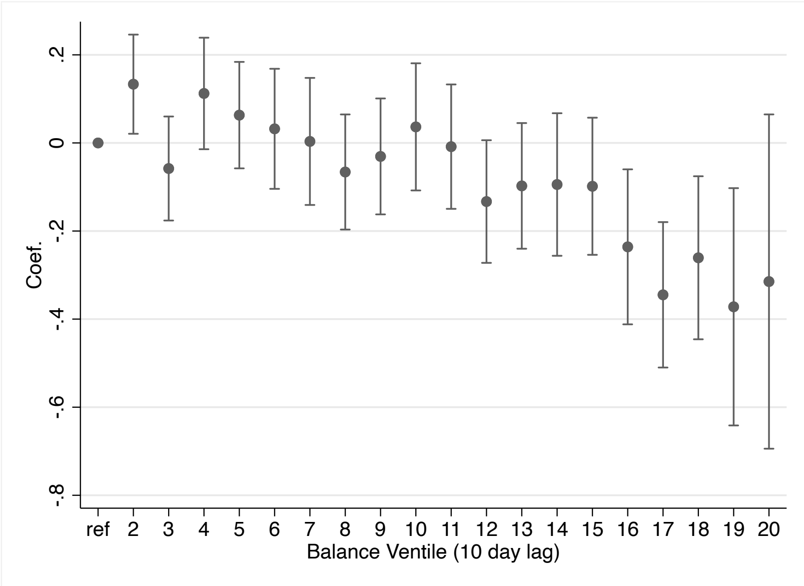
Notes: KPSTD data. Observations are teachers-days (NT=790,615). The graph shows 10-day lead leave-balance ventile coefficients and 95% confidence intervals. The dependent variable is whether any leave was taken on a particular day, the sample mean of which is 0.0595. The regression is as Equation (7)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

Figure 4: Maternity and Non-Maternity Leave Shares by Month



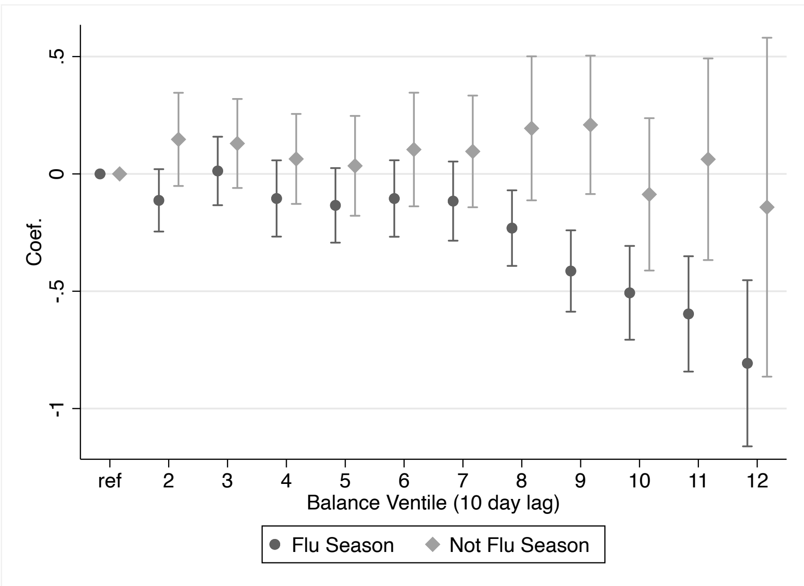
Notes: KPSTD data. Maternity leave is defined as leave taken by female teachers, who are under 40, during a leave spell lasting 15 consecutive days or longer. The vertical axis measures the share of all leave, for pregnancy and not, that occurs in each month. To account for the fact that some months 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 5: Impact of Balance Ventile on Presenteeism



Notes: KPSTD data, collapsed to the illness-spell level. The graph shows leave-balance ventile coefficients (from Equation (8)) and 95% confidence intervals. The outcome variable is whether the spell contains a presenteeism event, see Table 4, of which the sample mean is 52 percent. The regression controls for teacher education, age, experience, and salary, as well as year, month, and day-of-week indicators. The regression also includes a teacher fixed effect. Standard errors are clustered at the teacher-level.

Figure 6: Impact of Balance Ventile on Presenteeism By Flu Season



Notes: KPSTD data, collapsed to the illness-spell level. The graph shows ventile balance-presenteeism coefficients and 95% confidence intervals from two regressions as in Equation (8) by flu season. The first (represented by dark grey circles) studies illness spells starting during flu season, while the second (represented by light grey diamonds) studies spells outside of flu season. The outcome variable is whether the spell contains a presenteeism event, see Table 4. Both regressions control for teacher education, age, experience, and salary, as well as year, month, and day of week indicators. The regressions also include a teacher fixed effect. Standard errors are clustered at the teacher-level.

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Appendix Tables and Figures – For Online Publication

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 teachers-days (NT=790,615). The table shows the mean number of sick day balances by ventile (columns [3]-[4]) as well as the mean number of F&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 teachers-days (NT=790,615). Each column is one OLS regression as in Equation (5) and also includes teacher fixed effects, as well as 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 teachers-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, 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 teachers-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, 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 teachers-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, 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? In data for all eight years or not

	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)
$\times$ 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)
$\times$ 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 teachers-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, 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? Masters vs. Bachelors Degree

	Any	Sick	Emergency	Personal	Uncomp
			Bachelors 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
			Masters 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 teachers-days (NT=306,259 for teachers with a bachelors degree and 484,356 for teachers with a masters degree or more). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects, 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	1.0000	0.8275	0.0875	0.0815	0.0059
			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	0.9309	0.8331	0.0503	0.0346	0.0163

Notes: KPSTD data. Observations are teachers-days (NT=xxx in the top panel when only leave of short duration is considered or yyy when only leave of long duration is considered). Each column is one OLS regression as in Equation (5) and also includes individual fixed effects, 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: Estimating the Balance-Use Elasticity: Heterogeneity

	Male	Female	Under 40	Over 40	Experience 0–7	8–14	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

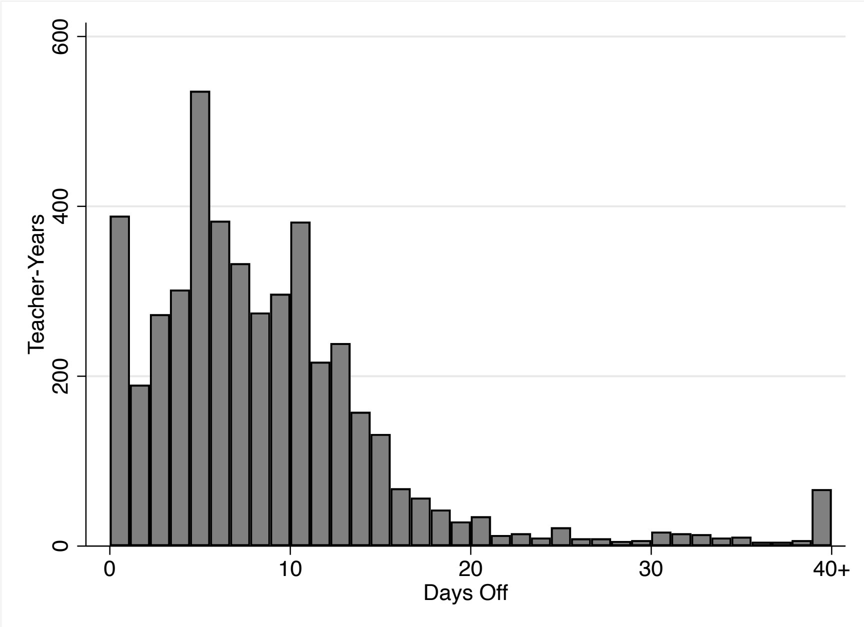
Notes: KPSTD data. Observations are teachers-days (NT=740,235). Each column is one OLS regression as in Equation (5) and also includes indicators for calendar year, school type (i.e., high school, middle school, elementary school), education, and annual salary (all not shown). The standard errors in 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: Estimating the Balance-Use Elasticity: Robustness

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

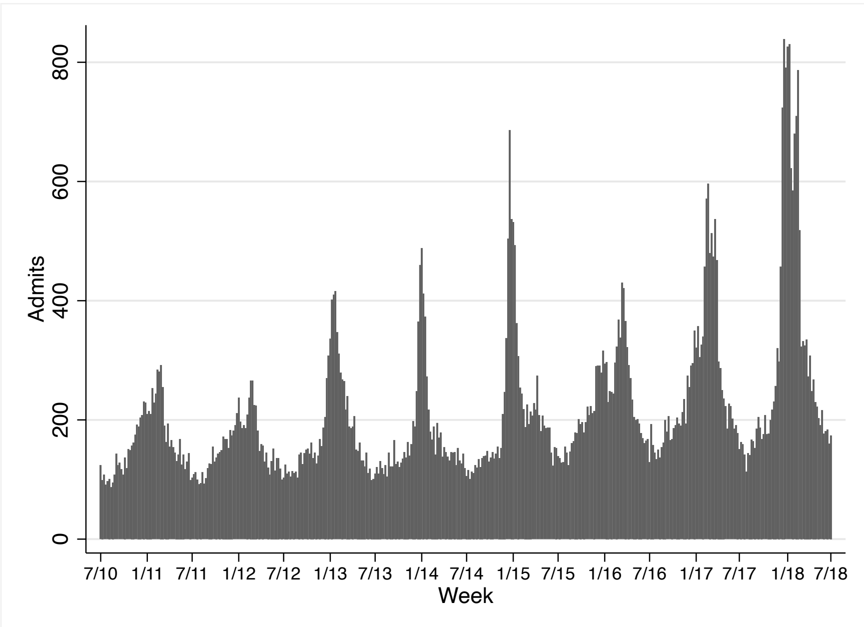
Notes: KPSTD data. Observations are teachers-days. Panel A uses all observations: 739,738. Panel B drops any observations where the ten-day lead balance is zero: 730,515. Panel C drops all observations where the ten-day lead balance is in the bottom ventile: 700,239. Each column (1)-(3) is one regression 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. Panel A, regression three includes an indicator for having a ten-day leave balance that is 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 percent 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).

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



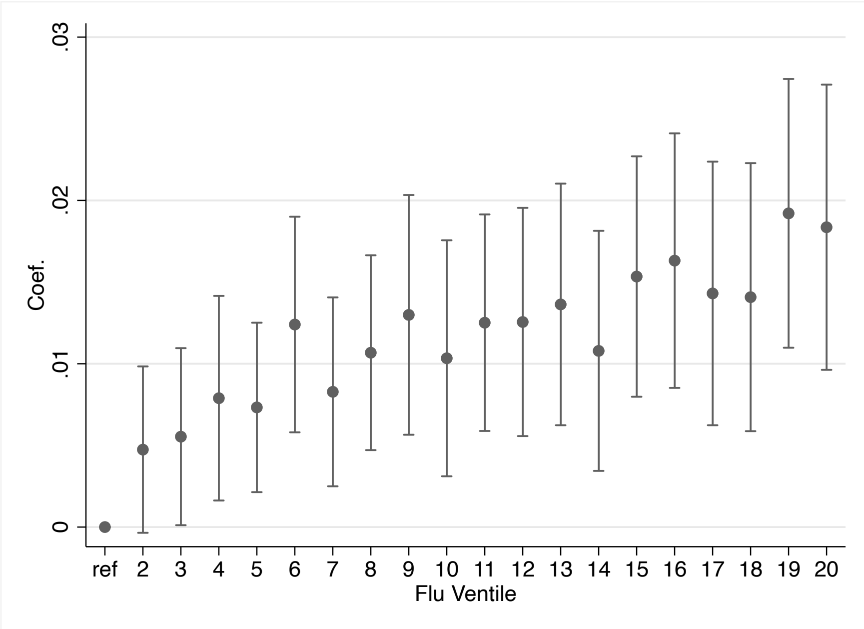
Notes: KPSTD data, aggregated to the teacher-year, yielding a total of 4,580 observations. The horizontal axis measures total days off (i.e., full or fractional) from all sources (i.e., sick, personal, emergency, or unpaid) over the school year.

Figure A2: Weekly I&P Patients from Scott and Bordering Counties



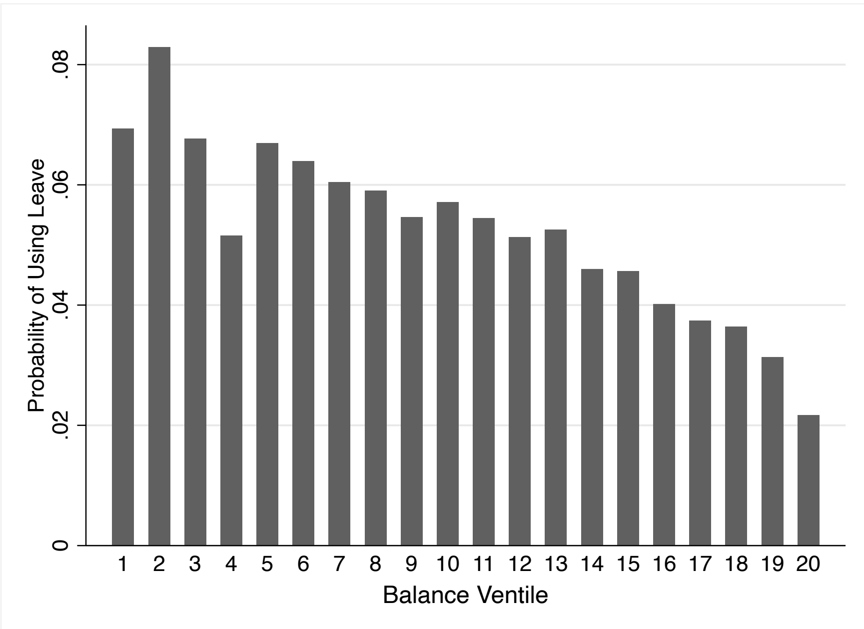
Notes: Cabinet for Health and Family Services in Kentucky, Health Facility and Services Data. Data are all hospital and ambulatory facility admissions with a condition code indicating Influenza or Pneumonia (ICD9 codes 480-488 for weeks 1/1/2000 - 9/30/2015 and ICD10 codes J09-J18 for weeks beyond 10/1/2015) for residents of Scott County and the seven bordering counties.

Figure A3: Impact of Flu Hospitalization Ventile on Leave Probability



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

Figure A4: Probability of Using Leave by Balance Ventile



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

Data and Policy Appendix – For Online Publication

DA1 Introduction

In this appendix, we describe the construction of the Kentucky School Teacher Leave Dataset (KSTLD), which is 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.

DA1.1 Scott County School District

Kentucky has a total of 172 school districts and 120 counties. Scott County, located 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, the Scott County Schools District (SCSD).[1] The 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 DA1 contains the 2018–2019 salary schedule. The salary schedule is tied to 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:

- Taking on additional paid roles that require out-of-school work, such as athletic team coaches, club leaders, choir directors, etc. These wage rates vary, but are tied to base pay – for example, the high school yearbook coordinator received 107% of their base salary.
- For administrators, such as principles and vice principles, 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 principle in our data works 230 days per year; thus,

[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

Figure DA1: 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 bachelors degree, Rank II a masters degree, Rank I is an additional teaching certificate earned post-masters degree, and Rank I-A is a PhD or EdD. Both Rank IV and V correspond to individuals who have not attained a bachelors degree, but have some college credit. Individuals can only be hired to full time teaching positions on a temporary basis (e.g., long term substitute teachers) without a bachelors degree.

if they have 15 years of experience and a master's degree, they earn a $15,000 bonus, plus $67,672.89 for their 230 days, rather than $55,609.46 for 189 days. Assistant principles and guidance councilors are similar but may work fewer days and earn smaller bonuses.

- School psychologists earn the base pay plus 8%

DA1.2 SCSD Leave Policy

The Kentucky Department of Education 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 towards the teachers last year of income when factoring in retirement (discussed below).

Like many districts, the SCSD grants teachers 13 days of paid leave per academic year: 10 sick days, 2 emergency days, and 1 personal day. We detail the rules governing the use of each type of leave below, 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 DA4.3 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.

DA1.3 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, which 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

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

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, etc.). 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 making a distinction 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 only to be denied if qualified substitute teachers are unavailable.[4] Note also that the superintendent, at times, strictly prohibits the use of personal leave; e.g., the day before Christmas break. 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 well 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 their full compensation.

Ex-ante, sick leave is never denied, but using sick leave for reasons other than those stated

[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

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 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 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.

The 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] This first is short-term, non-medical leave. An example is jury duty, which the district, by law, cannot deny. Another example is 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 result from a simple illness after a teacher has used all of her paid leave. Another common reason for such leave is that a teacher out on maternity runs out of sick days (though this generally results in a flood of donations, 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

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

[8] This would register 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 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

under FMLA rules, and the district treats it much like the maternity leave described above.[11]

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 drop their balance below 15. Second, a recipient of donated leave must suffer a "catastrophic loss" to his/her person, family, or property that will likely cause a 10+ consecutive work day absence. Third, the recipient must have exhausted all of his/her own paid leave. Fourth, donated leave that is not used consecutively as part of the original justification for the donation will be returned to the donor.

DA2 Original Data Sources and Merge

The Kentucky School Teacher Leave Dataset (KSTLD) is a record of individual employment activity for teachers in the SCSD on every calendar day between August 1, 2010 and June 29, 2018. The district provided retrospective school calendars, indicating whether the school was in session for 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 their leave activity. All teacher-level information is supplied by SCSD administrators or the Kentucky Department of Education (KDE). Below, we describe each original data source and the process used to merge and clean the two data files.

DA2.1 Scott County Data

The 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 in time 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.

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

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

- 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 that the employee's pay is docked, as well as the dollar amount. The following describe possible events:

- Taking unpaid leave, either because (i) the individual depleted their stock or (ii) the individual requested a paid personal day and it was denied, but the individual took the day off none-the-less (for example, requesting to take a personal day on the Friday before Spring Break and being 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. More specifically, 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 also 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 for docked pay. Second, the date provided for each event is the pay date upon which the teacher 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 from incomplete training and (2) impute the date of unpaid leave days (i.e., missed trainings are irrelevant for our purposes).

We make several assumptions. First, according to SCSD officials, all salary deductions for incomplete training are imposed on the last pay check of the school year, which occurs in the last week of June. Thus, all dock day events occurring on this pay check are assumed to be incomplete

[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.

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. As such, the assumptions discussed above are unlikely to have any significant impact on our findings.

DA2.2 State Data

While stock of sick leave and teacher activity are measured at the daily level, all 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 every individual that taught (at any time) in SCSD during the academic years 2010/11 to 2017/18, we receive a full history of their 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, etc.).

[14] Note that in doing this, we likely inadvertently drop some true unpaid leave that occurs in the last two weeks of school. As such, 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, administrative assistants, etc.

DA2.3 Merge

The KCS merged the paid leave file described in DA2.1 with the KLDS. The KLDS data contain first and last names, date of birth, as well as a state identification number (i.e., EPSBID), for 100% of observations. The paid leave file also contains first and last names and date of birth for 100% of observations, but EPSBID for just 40%. As such, observations were first merged by EPSBID, then by first and last name and date of birth.

We eliminated anyone from the SC data that was not a "certified employee," meaning we eliminated those who are not full-time teachers, school administrators (e.g., principles, vice principles, deans, etc.), guidance councilors, psychologists, social workers, librarians, or speech therapists. This leads to 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 only attached 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 pre-certified 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 evaluating 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]Note, this accounts for most of the non-matched and demographic only matched teachers discussed above. If an individual only teaches for one year and begins that year late, she may never enter the KLDS data.

DA3 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, it is useful to 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 current year's employment in relation to 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.
  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 Table DA1. We discuss special events related to this table in the following subsections.

Table DA1: 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.

DA3.1 Partial Year Employment

Table DA1 shows that less than two percent 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., entry code 0d), and the reason for late entry is that schools do not know their exact funding until enrollment has been determined. As such, 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 rational for late hires is the replacement of employees who leave mid-year. 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 that they accrue are pro-rated according to how much of the school year that they miss.

DA3.2 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 the SCSD is represented by B, are observable in our data. Importantly, so 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 moving 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.[17]

2. Employed in Kentucky district A or B in year t, takes a leave of absence (partial year, full year, or multiple years), then works in Kentucky district B or C in the future. All such transitions, where the 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 their sick leave balance with them when they return 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 exit Kentucky teaching (or vice-versa). Those simply exiting Kentucky teaching have an exit code beginning with "3." Those entering teaching in SCSD for

[17] Upon exiting SCSD for another Kentucky School district, unused sick days are always rolled forward to the following year. Most of the time, personal/emergency days are *not* rolled forward, as personal/emergency days vary by district. In the few instances that they are rolled forward, we see in the data that the employee eventually returns to SCSD, and is credited with these days.

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 retaining 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 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 which did not complete their final year (exit code "2d"). Table DA1 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.

DA4 Retirement

DA4.1 Retirement Formula

When KDE certified employees retire, they are paid monthly until they die by the state. The formula for an employee's annual retirement benefit has just three inputs – years of service (Y), 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 taking an unpaid year off to have a baby or carrying in 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.[18]

- The multiplier (M) is determined by one's years of service and date of entry into the profession, according to the following table:

Figure DA2: 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.

- 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.

DA4.2 Eligibility

KDE certified employees who begin 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 they reach 55. Importantly, note that they do not need to be working when they reach age 55 in order to earn benefits - e.g., an employee with 10 years of experience that 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.[19] Once 27 years of service is reached, educators can retire without penalty.

KDE certified employees who start 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%.

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

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

DA4.3 Role that Sick Leave Plays 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, this lump-sum transfer counts as income in the year received, which often influences annual income (I) in the Annual Retirement Income calculation above.[20]

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 they face no penalty and their last 3 years of income are $58,340, $59,769, and $60,529 (See Figure DA1) . They receive the lump sum payment for accrued sick days in the last year, when their daily wage rate is 60,529/187 $\approx$ $323. Thus, their first-year retirement income varies as follows with accrued sick leave:

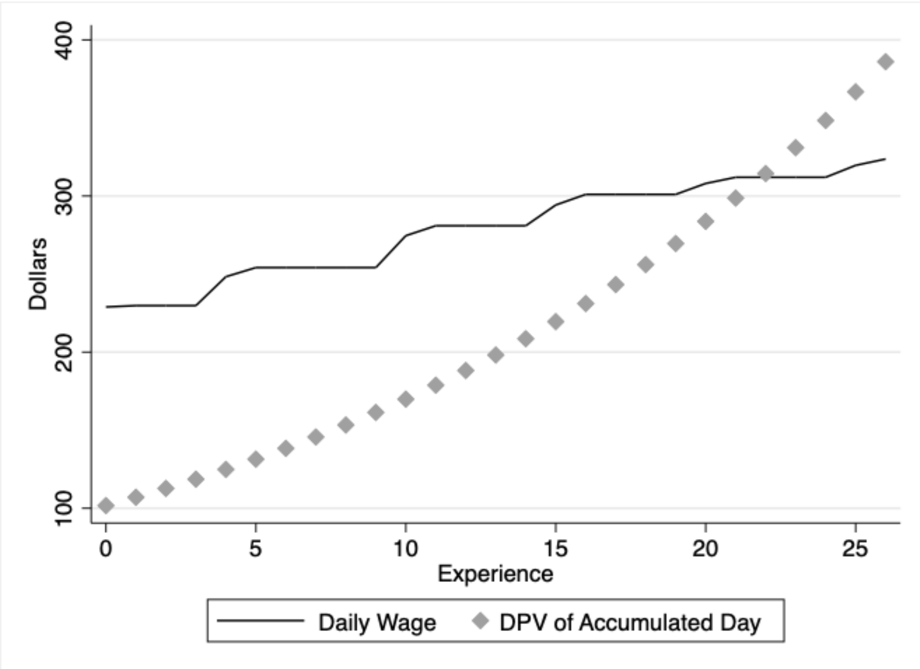
- 0 days:
  - Lump Sum = 323*0*.3 = $0
  - ARI = 27 * 0.025 * (58,340 + 59,769 + [60,529 + 0])/3 = $40,153.35
- 50 days:
  - Lump Sum = 323*50*.3 = $4,845
  - ARI: 27 * 0.025 * (58,340 + 59,769 + [60,529 + 4,845])/3 = $41,283.68
- 100 days:
  - Lump Sum = 323*100*.3 = $9,690
  - ARI: 27 * 0.025 * (58,340 + 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

[20] Note that teachers are only paid for this unused leave 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.

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 DA3 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, which is determined by the salary schedule in Figure DA1 and represented by the solid line in Figure DA3.[21] 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 DA3 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, and that future retirement 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 22 years of experience.

[21] 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.

Figure DA3: The 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 masters degree (see Figure DA1). 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 masters degree, death at age 85, exponential discounting at a 5% rate, and that future retirement wage increases exactly keep up with inflation.

DA5 Expressions from the Theoretical Model

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

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

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

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 one does NOT consume all of their leave tomorrow.

Taking partials with respect to C and D requires 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 second line uses the Envelope Theorem – i.e., when considering the effect of changes in d_1 to V_2 we need only to consider the direct effect on the objective function and not the indirect effect on d_2^*. To move from the second to third line, note that we are only integrating 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 only affect 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, 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 text, with one exception, $(2B-1)E$. This incentive/disincentive for consuming greater d_1 relates to small likelihood that $d_2^* = b_2$. Because this event is unlikely, the magnitude of $(2B-1)E$ should be small relative to the other four additive terms. We explain the intuition for $(2B-1)E$, none-the-less: Note that $B = Pr(d_2 \le b_2) \in (0,1)$; 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.