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

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Abstract

We study how U.S. employees use paid 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 an administrative data set 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 between 0.38-0.45. Further, higher balances reduce the likelihood that teachers work sick, particularly during flu season.

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

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

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1 Introduction

Granting workers paid leave presents inherent tradeoffs for firms. 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., 2021; Schmutte and Skira, 2023). On the other hand, sick workers have lower marginal productivity and working sick ("presenteeism") may spread contagious diseases to coworkers and customers, possibly increasing future absences and decreasing customer demand (Barmby and Larguem, 2009; Adda, 2016; Pichler et al., 2021). Because employer costs for leave and employee productivity under presenteeism vary across firms, some employers will not offer sick pay unless mandated to do so (Maclean et al., 2021).

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. did pass 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 under the 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 fewer than 10 days per year (BLS, 2019), far less than allotments commonly seen in other OECD countries.[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 OECD 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)

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

[2] Some specific examples from the European Union: workers have access to 28 weeks per year at £75 per week in the UK, and 12 months over a three-year period at a minimum of €47.65 per day in France (Heymann et al., 2010). In Germany, workers can take 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).

leave is deducted when employees take paid time off work, and (iii) unused leave accumulates over time.[3] This scheme stands in stark contrast with the most common European schemes, the design of which resembles unemployment insurance (Hendren, 2017) and workers' compensation (Powell and Seabury, 2018) 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 the E.U. create different incentives for workers 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 the E.U. may not be informative for worker behavior in the U.S. The few existing sick leave papers using U.S. data do not focus on the role of institutional features such as leave balances, nor do they use administrative data to study daily leave taking behavior.[6]

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. Further, we study the implications for sick leave policy. We do this by leveraging the unique characteristics of a newly formed data set, which we compiled by merging several administrative sources. These data describe the daily labor supply of public school teachers in central Kentucky.[7] 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,

[3]These features are present in most proposed and passed leave mandates, such as the Healthy Families Act, the 14 state-level U.S. sick pay mandates, and the paid leave policies currently under consideration by the Biden Administration (National Partnership for Women and Families, 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), while 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-Castello, 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), coworkers (Hesselius et al., 2009), income taxes (Dale-Olsen, 2013), union membership (Goerke and Pannenberg, 2015), and unemployment (Nordberg and Røed, 2009).

[6]Examples include Gilleskie (1998, 2010); Stearns and White (2018); Chen and Meyerhoefer (2020); Callison and Pesko (2022); Maclean et al. (2021).

[7]By studying teachers, we contribute to a small literature in the U.S. (e.g., Ehrenberg et al., 1991; Belot and Webbink, 2010; Carlsson et al., 2015) and developing countries (e.g., Duflo et al., 2012) that focuses on how teacher absences impact student achievement, 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).

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. broadly and ubiquitous among U.S. public school teachers (National Center for Education Statistics, 2021).

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; however, we can observe events that shift the probability of illness and other events that 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) immediately before and after scheduled holidays, (ii) immediately following the Super Bowl, (iii) while the University of Kentucky men's basketball team is playing in the NCAA tournament, and (iv) during the fall and spring horse racing meets at Keeneland, an internationally renowned and very 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 of sick leave being used for leisure in the full sample. Leave use is *less* common immediately before or after holidays. The average teacher is *not* statistically more likely to use sick leave while Keeneland is in session, the Monday following the Super Bowl, or on days that the University of Kentucky men's basketball team is playing in the NCAA tournament. All else equal, teachers are most likely to use sick leave on Fridays, followed by Monday, which is a stylized finding in the economics of sick leave literature. However, we discuss below that this behavior does not necessarily imply that teachers are taking leave for leisure. Interestingly, we find that while Keeneland is in session, teachers are statistically more likely to use *personal* days, particularly on Fridays.[8] District

[8]There is also an increase in personal day use on Superbowl Monday and on days the University of Kentucky basketball team is playing in the NCAA tournament, but the former increase is not statistically significant and the latter is only significant for men.

policy allows using personal days for these occasions; in a sense, it is precisely what personal days are for.

These statistical tests for how leave use responds to an increased incidence of illness and utility from absence rely on administrative data at the daily level. To our knowledge, this paper is the first to use precise, leave-spell data on U.S. employees. With these tests, we contribute to the literature on 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. While we find null results for the effects of "temptation days" on sick leave use in the full sample, we do find evidence that sick leave use is statistically elevated in sub-populations of our data. Both male teachers and teachers with less than five years experience are 20 percent more likely to take a sick day when Keeneland is open. Teachers above the age of 40 are 16 percent more likely to take a sick day when the University of Kentucky is in the NCAA tournament. While these percentage effects seem large, they translate into a relatively small number of lost days per teacher per year.[9]

In our second exercise, we examine how employees' paid leave balances impact their leave use. Because workers accrue leave balances in U.S. sick leave schemes, there is much greater variation in the individual availability of paid leave than in European schemes. Some "low-balance" employees who use a lot of paid leave early in the academic year may run out, while experienced employees that have stock-piled leave may have an abundance at their disposal. Understanding the relationship between leave balance and leave use is important for policy makers deciding how much leave to grant employees, as well as rules regarding leave accumulation. We model the relationship between the balance and use by controlling for teacher and date fixed effects.

Our results show that as paid leave balances increase, so too does leave use: on average, a 10 percent increase in leave balance increases taking leave on any particular day by 4.5 percent. This relationship is strongest at the bottom of the leave-balance distribution, as teachers seek to avoid reaching a balance of zero, making additional leave unpaid.[10] A non-trivial share (about

[9]For male teachers, for example, the estimates for Keeneland imply that approximately 0.11 sick days are taken per teacher per year. Alternatively, one of nine teachers (on average) will use one sick day for Keeneland per year.

[10]If we exclude from our analysis teachers with leave balances under 5 to focus balance effects at the intensive

11 percent) of the leave observed in our data appears to be for child birth (e.g., long, uninterrupted spells taken by women under 40), though our data do not explicitly flag maternity leave. Because parental leave as structurally different than sick leave, both in aim and scope (e.g., Maya Rossin-Slater, 2018; Thomas, 2021; Danzer et al., 2022), we also estimate our model with these women removed from the sample and find a leave-balance elasticity of 0.38.

These results contribute to the literature on how individuals respond to institutional features of social insurance programs (Ruhm, 1998; Lalive et al., 2014; Deshpande, 2016; Campbell et al., 2019) and the literature on how leave generosity affects use. Because most research on sick leave is from Europe, the variation in generosity that is the focus of existing research is fundamentally different than ours. For example, De Paola et al. (2014) examines an Italian reform that reduced wage replacement rates from 100 to 80 percent for the first nine months of sick leave. Johansson and Palme (2002) examine a Swedish reform that cut replacement rates from 90 to 65 percent during the first three days of a spell. In one of the few studies on U.S. sick leave, Maclean et al. (2021) find that workers who gain sick leave through mandates take two additional sick days per year in the first two years.

Our third line of inquiry examines a potential implication of our first two results. Specifically, we provide evidence that (i) teachers use leave primarily for illness and not recreation and (ii) leave use increases with leave balance. While it is possible that teachers use leave for leisure in ways that we (the researchers) cannot measure, an alternative testable explanation of our first two findings is that teachers with low leave balances engage in presenteeism. Presenteeism is notoriously difficult to measure in administrative data because employees actually come to work and sickness is typically unobserved. Self-reports suffer from 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; Marie and Vall-Castello, 2023; Pichler et al., 2021).

Given this measurement challenge, we explore the relationship between leave balances and presenteeism in two ways. First, 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 then test whether sick leave spells are more likely to contain presenteeism events when leave bal-

margin, the estimated elasticity falls to 0.38.

ances are low. We find that lower leave balances increase presenteeism, and that this effect is strongest during flu season. Second, we exploit the fact that our data contain multiple teachers in the same school to test whether own-leave behavior rises when other teachers in the same school have low balances—the implication being that other, low-balance teachers engage in presenteeism, spreading illness. We find own-leave behavior indeed increases when the share of one's colleagues with a low balance increases. This finding not only corroborates the first finding that high balances prevent presenteeism, but provides evidence of spillover effects from presenteeism. These results contribute to literatures on the optimal design of social insurance (Chetty, 2008; Powell and Seabury, 2018), and how it relates to population health (Goodman-Bacon, 2018).

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 its employees. Despite bipartisan voter support for a national mandate (NORC, 2018; National Partnership for Women and Families, 2020), over the past two decades Congress could not pass the Healthy Families Act, the most recent iteration of which is 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.[11] Since 2009, 14 states, the District of Columbia, and dozens of large cities 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. Our results indicate that sick leave use increases when severe flu cases are more prevalent. While our results also indicate that some leave may be used for leisure, the magnitude of misuse is relatively small. We also document an important positive externality of paid leave; namely, that 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 how teachers use paid leave. The Online Data Appendix details the origi-

[11] Some federal policy options under discussion by the Biden Administration include "medical and family leave", which differs from the short-term sick leave schemes studied here (White House, 2021). Medical leave refers to "long-term sick leave" (or "temporary disability insurance", see Campbell et al. (2019)), whereas family leave primarily includes parental leave for childbirth.

nal 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.[12]

2. Daily administrative leave data provided by the Scott County School District (SCSD) in Kentucky.[13] The file contains the date, current leave balance, and type of leave taken on every school day during 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 admissions data from the universe of hospitals and ambulatory facilities in Scott County, as well as the seven counties bordering Scott County. 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.[14]

5. Event dates including dates that horse races take place at the Keeneland Race Course, Super Bowl Monday dates, and dates that the University of Kentucky's Men's basketball team plays in the NCAA tournament.

We refer to the final data file as the Kentucky School Teacher Leave Dataset (KSTLD). The KSTLD contains complete records of all school teachers employed by SCSD from school year 2010/2011 up to and including the school year 2017/2018.

Most important for our purposes, 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

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

[13] 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, comprised of eighteen schools, with approximately 9,500 enrolled students (https://www.greatschools.org/kentucky/georgetown/scott-county-school-district/) and 1,364 faculty and staff (https://www.scott.k12.ky.us/district_staff.aspx?action=search&location=0&department=0).

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

contains such detailed administrative records on daily leaving taking, along with the leave balance at the employee-day level.

The final KSTLD database is an unbalanced panel at the teacher-day level and has 790,615 observations from 982 unique teachers.

2.1 SCSD Teacher Demographics and School Characteristics

Table 1 collapses the KSTLD to the teacher-year level to illustrate teacher demographics and school characteristics that are fixed within a school year. 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, 23 percent in middle schools, and 24 percent in high schools.

Those in our sample are fairly representative of teachers nation-wide. Based on a 2016 survey of 40,000 public school teachers conducted by the National Center for Education Statistics, 77 percent of U.S. teachers are female, 80 percent are white, average experience is 14 years, and 57 percent have post-baccalaureate degrees (National Education Association, 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) for a full description. 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 have the flexibility to supplement this offer with additional sick and/or personal/emergency days.

In the SCSD, each teacher is credited with ten new sick days at the start of each school year. These personalized sick days are recorded on an individual account and can be taken for any medical reason, e.g., own sickness, child sickness, doctors appointments, check-ups, scheduled surgeries, maternity leave, etc.[15] Additionally, each teacher earns two emergency days and one personal day at the beginning of every school year. Both emergency and personal days may be requested for non-medical reasons, though the former tends to be used for last minute emergencies, while the latter can be used for any reason and are often scheduled in advance.

For all three types of leave, unused days roll over and increase teachers' *sick leave* balance in the following year. This sick leave balance grows without limit over the course of a teacher's career. Teachers can also donate days to one another.[16] Upon retirement, teachers are compensated for accumulated unused leave credit in two ways: (i) they receive a lump sum worth one third of the value of their unused days at their current wage rate and (ii) their annual retirement benefit increases in proportion to this lump sum. Additional details can be found in the Online Data Appendix, Section DA4.

2.3 Descriptive Statistics on Leave Use

Table 2 reports descriptive statistics from the KSTLD on leave use, duration, and balance, collapsed to the teacher-year level. Panel A shows that teachers take an average of 9 leave days per school year, approximately two-thirds of the 13 days of annual credit. The large 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; e.g., 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 (includes fractional and full days off). Divided by the number of work days,[17] this yields a leave rate of about 6 percent on a given school day. Five percent of teachers take no leave each academic year. 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.

[15] Kentucky runs no public Temporary Disability Insurance (TDI) or Family and Medical Leave (FML) program. Consequently, in addition to the rules outlined in this section, *The Family and Medical Leave Act of 1993 (FMLA)* applies. It provides up to 12 weeks of *unpaid* leave in case of pregnancy, own disease, or disease of a family member to employees (cf. Thomas, 2021). The law only applies to employees who work at least 1,250 hours annually in businesses with at least 50 employees but there are special rules for public teachers who are covered (D'Albies et al., 2021). In Section DA3.1 of the Online Data Appendix, we discuss the typical maternity experience of teachers in Kentucky.

[16] This is uncommon in the case of acute illness. Donations are more common when younger teachers with lower leave balances bear children.

[17] All school years contain 187 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.

Panel B of Table 2 shows the duration of leave spells. A spell is defined to begin on a full or fractional day off and it continues until there are two consecutive full days back to work. Only school days contribute to the spell; i.e., we exclude weekends and holidays from the tally. The large majority (79 percent) of spells contain a single day, while 17 percent of spells last 2 to 3 days. Only 3 percent of leave spells are 4 or more days. However, 24 percent of all leave days belong to a spell of 4 or more days (not shown).

Panel C of Table 2 reports that the mean balance entering a school year is 52. However, 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 at the teacher-year level. Roughly 67 percent of teacher-years start with 52 (or fewer) available leave days (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.[18] 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 right as few teachers gain leave over the course of the year.[19] The figure highlights that for many teachers, leave balances can be a binding constraint – 5.5 percent of teachers finish the year with exactly zero paid leave days remaining, while 16 percent of teachers finish with fewer than 5 days.

Finally, given the design of the sick leave scheme, one would expect leave balances to be increasing in experience. Figure 2 shows average leave balances entering the school year by teacher experience; Panel C of Table 2 reports related sample means. For those entering their first year of full-time teaching, the mean balance is 14, while the mean is 37 days for those with 5 to 10 years of experience, and 73 days for those with 15 to 20 years of experience.[20] There is variation both within and across experience categories; the experience-specific balance distributions display substantial overlap—at the teacher-year level, the experience-balance correlation coefficient is 0.53.

[18] 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 C of Table 2, minimums fall below 13 because we have included late-starting teachers in that table.

[19] One exception would be, for example, teachers who are gifted leave from a colleague.

[20] 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.

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 the local flu intensity, we measure total 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.[21] We measure admissions at the weekly level.

Figure 3 shows total weekly I&P admissions from July 2010 to July 2018. We observe the characteristic flu seasonality patterns, with spikes primarily from December to February, but with variation between years in the exact timing of the peak. The slightly increasing trend in the admit count is explained by both population growth and the fact that 2014/15 and 2017/18 were both high-infection years nation-wide.[22] Our regression models control for this time trend using year fixed effects.

Scheduled Breaks. Also included in the KSTLD are a number of calendar-event indicators, that is, variables that do not vary across teachers within the district on a particular day. 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 from school that lasts three or more days; this excludes 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, meaning a little over nine on average each school year. In the following section, we study whether teachers are using leave to extend these breaks.

[21] Bordering counties include Owen, Grant, Harrison, Bourbon, Fayette, Woodford, and Franklin. The total population count of these counties, plus Scott, is 530,000, which represents about 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.

[22] https://www.cdc.gov/flu/about/burden/past-seasons.html.

NCAA Tournament. We create a number of variables related to the timing of local and nationwide sporting events that may exogenously shift the probability of taking leave for recreational purposes. We emphasize that these events do not represent a comprehensive set of circumstances that could shift the utility of absence (e.g., we cannot observe birthdays of friends or relatives), but nevertheless are events that raise the appeal of taking a day off work.

The first sporting-event variable indicates days that the University of Kentucky's (UK) Men's Basketball team is playing in the NCAA tournament. UK basketball consistently ranks among the top NCAA basketball programs in attendance[23] and popularity,[24] and the dedication of NCAA basketball fanbases is never more evident than during the NCAA tournament (often called "March Madness"). In a 2014 survey of U.S. adults, eleven percent reported that they *would* call in sick to watch the NCAA tournament,[25] while BLS estimates the average absence rate nationwide is three percent.[26] First-round games are always played on a Thursday and Friday in mid-March. Third-round games are played on the following Thursday and Friday, while the championship game is played two Mondays later. First round games are scheduled throughout the day with many occurring during the work/school-day. UK made the tournament in all years of our sample period, except 2013. In total, this amounts to 13 days (7,327 teacher-day observations) where school was in session and UK Men's Basketball was playing in the NCAA tournament.

Super Bowl. The second sporting-event variable indicates that it is 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.[27] There are 6 instances of Super Bowl Monday occurring on a school day in our time-frame (3,382 teacher-day observations); February 3, 2014 (closed due to weather) and February 5, 2018 (scheduled closure) are the exceptions.

Horse Racing at Keeneland. The third variable indicates that a popular local horse-racing track is open. Located in Fayette County (home to the city of Lexington), which is just 20 minutes from the center of Scott County, Keeneland is an internationally renowned horse-racing

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

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

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

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

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

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); approximately 20 percent of the population of Scott County attended the 2014 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 of particular interest for our sample, because Keeneland is as much a social event as a sporting event, meaning females, who make up the majority of our sample, are just as likely to attend as males. The 'Super Bowl Monday' phenomenon, on the other hand, is more likely to be driven by males.

3 Empirical Analysis

Our empirical analysis aims to answer the following three questions, which were outlined in the introduction:

3.1 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 empirical specification is:

$$y_{it} = \beta_0 + ln(admits_w)\beta_1 + Z_t\beta_2 + X_{it}\beta_3 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it} \tag{1}$$

where the dependent variable y_{it} is a binary indicator for 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 on day t, though the data vary only at the weekly level w. In alternative specifications, we replace this variable with a series of vintile dummies $\Sigma_{k=2}^{20} V_{w,k}^{a}$ to allow for a more flexible relationship between the number of flu hospitalizations and teacher leave behavior. This indicator of contagious disease exposure varies in a plausibly exogenous fashion over time. We use it to test for whether individuals are more likely to use sick leave (or any other type of leave) in response to increased risk of illness and hypothesize a positive statistical relationship.

To investigate how teachers respond to events that shift the utility of absence, we include a vector of indicator variables, Z_t, for the (i) school days before and after holidays, (ii) school days Keeneland is open (plus an indicator for a Keeneland Friday), (iii) school days on which UK Basketball is playing in the NCAA tournament, and (iv) school days falling on the Monday after the Super Bowl. Again, these event indicators are plausibly exogenous as they are predetermined and unresponsive to employee leave taking. For instance, we are not aware of a year when any of these events was rescheduled due to high employee sickness or flu activity.

Equation (1) also includes day-of-week (DOW_t), month (δ_m), and year fixed effects γ_y. The model also controls 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 include controls 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 these specifications because it is endogenous; addressing this is the focus of Section 3.2.

Leave use in response to increased flu hospitalizations. Table 3 shows the results from estimation of Equation 1. Each column represents a separate OLS regression where the column header indicates the type of leave used as the dependent variable. As hypothesized, higher flu activity, as measured by the number of (log) admits at local hospitals, significantly increases the probability that teachers take leave. The overall effect (column 1) is clearly driven by sick leave use (column 2) as opposed to other leave types. The figures suggest that a 10 percent increase in local flu hospitalizations among the general population increases the probability that a teacher takes leave by roughly 0.09 percentage points (ppt). Given that the baseline leave rate is roughly six percent, this reflects a 1.5 percent increase in leave taking.

In the absence of localized high-frequency data on number of flu cases, we interpret this admission variable as an *ordinal* measure of local flu intensity, rather than a cardinal approximation for overall population flu rates. Increased prevalence in flu should lead to increased hospitalizations, but there is not a clear algebraic relationship between hospital rates in week t and the total number of cases among public school teachers in that area. First, hospitalization rates for influenza 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 are 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.

The relationship between flu hospitalizations and leave use may vary in intensity across the distribution of hospitalizations, particularly because increased hospitalizations may reflect increased overall prevalence or greater severity of a particular strain of influenza. To investigate this possibility, we re-estimate Equation 1 but replace the single continuous $ln(admits_t)$ variable with 19 binary ventile indicators, where the baseline category is flu hospitalizations in the lowest ventile.[28] In Figure 4, we plot the ventile coefficients when the dependent variable is any leave use. Over the entire 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 roughly 1.75ppt. The leave rate in the bottom ventile is 0.04; thus, flu season yields a 44 percent increase in leave taking behavior.

Leave use when the utility of absence increases. Returning to Table 3, the next set of regressors are thought to increase the likelihood of 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). We would interpret a higher incidence of leave taking on these days as using leave for leisure, as it would likely reflect teachers extending their vacations; however, we find the opposite. Teachers are significantly *less* likely to take sick, personal, or uncompensated leave around 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 can help alleviate friction in this particular principal agent problem. Note that teachers are often strictly forbidden from taking personal days preceding and/or following a holiday. In such instances,

[28] 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.

though sick and emergency days are not forbidden, the restriction may dissuade teachers from using non-personal leave around holidays, for fear that administrators suspect that the leave is truly personal in nature.

Rows 4 and 5 of Table 3 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) to (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 that 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; none-the-less, they are unwilling to use sick leave inappropriately in order to attend.

Finally, rows 6 and 7 test whether leave is more commonly taken on school days in which UK's Men's basketball team is playing in the NCAA tournament or on Super Bowl Monday. Neither of the events has a significant positive effect on any type of leave for the full sample. That said, 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 3 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 widely viewed by administrators and teachers that Friday is the least disruptive day for a teacher to take leave.[29] As a result, teachers reported to us that routine doctor's office and dental appointments, which teachers are allowed to use sick leave for, are "virtually always" scheduled on Fridays. The same is true for minor outpatient procedures, where teachers also benefit from having the weekend to recover. Many continuing education workshops for teachers also start on Fridays, requiring teachers to miss a day of work.

Regarding Mondays, several studies from different industries suggest that transitioning back to work after the weekend comes with psychological strain 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.[30] 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.

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., pre-planned doctors 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

[29] One reason is that teachers commonly 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 educational value of having a classroom teacher manage children during these events, as opposed to a substitute, is very 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).

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

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 the least amount of leave is taken in August, the first month of the school year, and June, the last month of the school year. Leave use is increasing in experience, which is consistent with teachers having access to a larger leave balance (explored in more detail in the following section). Though not shown, in an alternative specification we include school-specific fixed effects and find no evidence that teachers use more leave at the lower-income schools in the district, which contrasts with the findings of Boyd et al. (2005).

Robustness and Heterogeneity. Appendix Table A2 contains several robustness checks. Column (1) contains our main results for comparison; those from column (1) of Table 3, 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-A7, we explore heterogeneous effects across several observables. 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 for men. We cannot pin down a specific mechanism for this difference; however, as women generally provide a disproportionate share of care-giving to children (Ranji and Salganicoff, 2014) and elder family (Grigoryeva, 2017), it is plausible that female teachers take more sick leave during flu season because they are caring for others. Regarding leave for leisure, Keeneland has a statistically significant effect on sick leave use for men, but not for women. Finally, men are more likely to take any leave on days that UK's Men's basketball team is playing in the NCAA tournament. While 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 economics of sick leave literature (e.g., Ichino and Moretti, 2009), we also find that female teachers take more days off than male teachers at the mean, a difference of roughly 3.5 days annually.

Table A4 contains split sample results for teachers under and over the age of 40. The only notable difference between the samples is that older teachers are significantly more likely to use sick leave on days when UK's Men's basketball team is playing in the NCAA Tournament. The same significant effect can be seen for more experienced teachers in Table A5, which compares teachers with less than five years of experience to teachers with more than five years of experience. An additional difference between these subsamples is that inexperienced teachers commit the "rookie mistake" of calling in sick on a Keeneland Friday. Table A6 compares teachers with a Master's degree to those with a Bachelor's degree, and shows that aside from a stronger response to flu hospitalizations on the part of teachers with a Master's degree, the results are otherwise similar. Finally, in Table A7, teachers who are not observed in the data for all sample years are statistically most likely to use sick leave on Keeneland Fridays.

In summary, while there is evidence that sick leave is used for leisure among certain subsamples, the pattern is not sufficiently pronounced to lead to statistically significant results for the full sample. We acknowledge the possibility that leave is taken for leisure that we simply cannot detect (e.g., family occasions). Additionally, taking sick leave for some of the leisure events we examine (e.g., Keeneland) presents the probability of getting "caught" in a small community where reputation effects matter. However, we do observe statistically significant increases in leave use during flu season, consistent with the underlying motivations for providing leave.

3.2 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 beginning of each school year. Moreover, 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 the extent to which teachers' leave balances influence their leave taking behavior. As a larger leave balance clearly and unambiguously decreases the cost of taking time off, we hypothesize that leave use is increasing in the balance (i.e., a positive balance-use elasticity). However, *a priori*, this remains an empirical question, as is the question of whether the the relationship varies across the balance distribution.

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

$$y_{it} = \beta_0 + sinh^{-1}(Balance_{i,t-10})\beta_1 + X_{it}\beta_2 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it}. \quad (2)$$

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 work days prior to day t. We transform $Balance_{i,t-10}$, which takes the value of zero at times, using the inverse hyperbolic sine function as opposed to the natural log. Other variables are as previously defined.

This specification addresses several endogeneity concerns that would arise were a leave indicator regressed on current balance, $Balance_{i,t}$, alone. First, a teacher's balance is positively correlated with her age and experience. As teachers age, they may experience greater health challenges; thus, age and experience are among the controls in X_{it} to avoid two key 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 selection problem by including a teacher fixed effect, 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 work-days prior to the observation day to avoid the mechanical association between leave balance and leave taking that arises 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 for all teachers starting on the first day are increased 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.

Table 4 shows the main estimates of the balance-use elasticity. To illustrate how the previously described sources of bias affect these results, note how the estimand of interest changes as we move from left to right. The first column shows results from a naive regression that ignores the three endogeneity concerns above. The second column adds linear and quadratic age and experience controls, which have little impact on results. Note that the point estimates in columns (1) and (2) are negative and statistically significant, opposite our hypothesized sign.[31] Yet, both the selection and mechanical association concerns described above would lead the balance-use elasticity to be biased down. 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 that a 10 percent increase in a teachers leave balance increases leave taking by 0.27ppt. Compared to the baseline leave taking rate, this reflects a roughly 4.5 percent increase in the likelihood of taking leave on any given day, yielding an elasticity of 0.45.

Robustness and Heterogeneity. In Appendix Table A8, we present the results of sensitivity analysis to alternative assumptions about functional forms for leave balance as well as concerns about dynamic selection. Results do not substantively change when we include calendar-week fixed effects (column (2)); measure the leave balance in levels (column (3)); use the the natural log of the leave balance, plus 1 (column(4)); or limit the sample to teachers who are employed throughout the full eight year sample period (column (5)). The last of these tests alleviates dynamic selection concerns, or that teachers who plan to remain in the profession longer have a greater incentive to accumulate large balances.[32]

In Appendix Table A9, we study possible effect heterogeneity by gender, age, and experience. Elasticity estimates vary little across these observables.

Next, we test whether the balance elasticity varies at different points in the balance distribution, which is important for policy design. For example, if the balance-use elasticity operates entirely through the bottom of the balance distribution, then it 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

[31] Consistent with these findings, Appendix Figure A2 shows that the unconditional correlation between leave balance and use on any given day is negative.

[32] As is described in the Data Appendix, Section DA4.2, for teachers working in the district before July 1, 2008, only five years of service are required to be eligible for retirement benefits; thus, even teachers planning to leave the profession early have an incentive to accumulate days. After July 1, 2008, this threshold was increased to 10 years.

balance, which could be done, for example, by giving new employees larger starting balances. To this end, we repeat the ventile approach used in Section 3.1, dividing the balance distribution into twenty equal bins. Appendix Table A1 describes the leave-balance range in each ventile. The bins are represented by dummy variables and replace the continuous balance regressor of interest in Equation (3) as follows:

$$y_{it} = \beta_0 + \Sigma_{k=2}^{20} V_{i,t-10,k}^{b} \beta_{1,k} + X_{it}\beta_2 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it}. \quad (3)$$

Figure 5 plots the 19 ventile coefficients where the bin with the least balance days serves as baseline. We observe a strictly positive relationship between leave balance and leave use. It is noteworthy that the likelihood of taking leave jumps significantly 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 4 percentage points, a 64 percent increase over baseline. This finding is *not* a mechanical artifact of teachers being unable to take leave when their balance is zero. Recall that our dependent variable, any leave of any type, includes unpaid leave, which teachers are able to take when their balance is zero. For bins two through four (the fourth bin contains a maximum of 13 days, which is the total number of days allocated per school year), the likelihood remains almost constant, after which it increases 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 give 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 show that balance-use relationship is strongest at the bottom of the balance distribution. As such, Table A10 examines how the balance-use elasticity changes when we exclude observations with zero balance or a balance in the bottom ventile. The top panel of the table illustrates that dropping observations with zero balance (just over 1 percent of observations) yields very small changes in the estimated coefficients. In the bottom panel, we drop the 5 percent of observations with balance in the bottom ventile and the estimated balance-use elasticity decreases to 0.38. The panels also show that both results are robust to alternative assumptions on functional form (e.g., log, log plus one, and levels).

Childbirth, Leave Use, and Effects on Balance-Use Elasticity. Many of the teachers in our data are female and of childbearing age. For teachers giving birth during the school year, their typical sick leave is used to fund maternity-related absence as the leave system provides no separate paid maternity leave. As such, there are at least two reasons to consider excluding maternity leave when estimating the balance-use elasticity. First, pregnant teachers who intend to use their balance to fund their maternity leave exhibit some control over their leave-balance that raises additional endogeneity concerns. For example maternity leave can be anticipated and is often explicitly chosen, by choosing to become pregnant, allowing a teacher to stock-pile leave in preparation. Also, most recipients of leave donations 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 spells longer than 10 days, many of which are due to child-birth, are a threat to our identification strategy, because the mechanical relationship between balance and leave within spell still exists for these long spells.

We cannot directly observe pregnancy in our data. Instead, we code a leave event as "maternity" if the teacher is female, under age 40, and takes leave for at least 15 consecutive days. These leave spells account for 11.2 percent of all leave taken in our data; moreover, 146 of the 982 teachers in our sample (14.9 percent) ever take "maternity leave".[33] The timing of maternity leave is interesting. Figure 6 separates leave into "maternity" and "non-maternity." The vertical axis measures the share of each leave type taken in each month, excluding the summer months of June and July.[34] 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 non-maternity sick leave is most common in winter months (i.e., flu season), maternity leave is far more common surrounding the summer months. Clearly, if teachers can use the summer for maternity leave, they do not have to use large amounts of 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. Most interesting, maternity leave is more common in August and September than May. This pattern could be the product of teachers trying to time a summer delivery, but strategically erring on

[33] 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.

[34] Due to school cancellation for snow days, school was in session for some days in June in 2011, 2014, 2015 and 2018. This represents less than 1 percent of all observations; therefore, we consider June to be a summer month.

the side of a late, rather than early birth, as teachers receive 13 additional days of leave at the start of the school year.[35]

To estimate the balance-use elasticity without maternity leave, we re-estimate Equation 2, 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 leave stock-piling in preparation for maternity leave biases our results. Dropping these observations produces a coefficient on balance of .02 and the baseline leave rate for this sample is .053, or a balance use elasticity of 0.38.

In summary, we estimate a balance-use elasticity between 0.38 and 0.45. Moreover, we show that while leave use increases with balance throughout the balance distribution, use drops dramatically when the balance nears zero. This finding is intuitive, as leave use with a balance of zero results in with-holdings from a teacher's typical pay-check; that is, teachers are not paid for the days that they miss. Moreover, 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 3.1, finding that while some subsets of teachers may use leave for leisure, the practice is not strong or consistent enough to produce statistically significant effects for the full sample. An alternative explanation is that teachers use discretion in deciding whether to take leave *when sick*, which is why the next section asks, "Are larger leave balances helping teachers to avoid presenteeism behavior?"

3.3 Does a Larger Leave Balance Reduce Presenteeism Behavior?

Presenteeism, or working while sick, is notoriously difficult to measure. Neither administrative nor survey data typically contain information regarding how an employee "feels" while working. Further, when directly asking employees whether they went to work sick, response biases and framing effects 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 spill-overs.

To begin, we propose the following novel measure for presenteeism behavior using our

[35] Other research has documented that *all* births are more common in the summer, not just among teachers. For example, Darrow et al. (2009) show using birth records from Atlanta that birth rates were two to five percent higher than 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 any other month October-April.

daily administrative data: we flag instances where teachers briefly return to work in the midst of a leave spell. More specifically, consider a teacher who takes leave on day t, comes 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 a presenteeism event. The first relates to measurement error. All days categorized 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).[36] 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, the proposed definition of presenteeism literally 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 school-day level will result in estimates that are biased upwards (towards zero).

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

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

Based on whether or not the spell contains any working, we can then classify illness spells as containing presenteeism or not.[37] Column (1) of Table 5 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 in length, which represents half of the total amount of 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

[36] Using the example above, the individual may have been sick on day t and missed on $t+2$ for unrelated reasons, meaning there was no illness on day $t+1$. Also, a teacher may work every day through an illness, never taking time off.

[37] 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.

percent). Important for our analysis is that our definition of presenteeism 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 of at least three days. To do so, we estimate the following model:

$$Presenteeism_{it} = \beta_0 + \Sigma_{k=2}^{20} V_{i,t-10,k}^{b} \beta_{1,k} + Z_t \beta_2 + X_{it} \beta_3 + \delta_m + \gamma_y + \alpha_i + \epsilon_{it} \tag{4}$$

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 prior to the start of the spell in ventile indicators.[38] We plot regression coefficients, $\beta_{1,k}$, in Figure 7. Overall, 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, which contains a maximum balance of 24.5 days.

We expand on these findings by re-estimating the model both in times of high and low flu activity, as measured by $admit_t$. In particular, we estimate two models. 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 that represents "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 8 shows the results graphically, plotting the bin coefficients separately for times inside and outside of flu season. Outside flu seasons (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 it is that they 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

[38]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.

from zero after 7th 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 previously mentioned, we advise caution when interpreting these findings due to possible measurement error in our presenteeism measure. First, consider type-1 measurement error, or falsely assigning presenteeism when there is none. The flu season results are less likely to be driven by such 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. If anything, more leave credit should lead to more type-1 errors and thus *increase* the presenteeism rate. Under this scenario, our estimates would be lower bounds.

Second, the previous section shows that the balance-use elasticity is largest 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 mostly 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 to meet our definition of presenteeism. 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 the measurement error and distributional issues discussed above, we extend our exploration of presenteeism with a final statistical model that alters Equation 2 in two ways: (i) we replace school-type fixed effects with explicit school-specific fixed effects and (ii) we add 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 rises 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 3.2 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 are engaging in presenteeism. 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 such spillovers.

Our initial results are presented in column (1) of Table 6. As expected, leave use increases as the share of one's colleagues with a low balance increases, conditional on own leave balance and various other factors; the relationship is statistically significant at the five percent level. We believe that this finding is driven by 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 excludes teacher i), as well as the natural log of the number of flu admits at local medical facilities that week. Moreover, similar to the approach taken in Section 3.2, in column (3) we 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.

4 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 whom we observe for up to eight school years. The sick leave scheme faced by teachers in our sample resembles the scheme faced by most public employees in the United States, which includes 3.5 million public school teachers. Moreover, 14 U.S. states mandate similar schemes for the private sector and the Biden Administration has considered mandating paid leave access at the federal level (A Better Balance, 2022; White House, 2021). All these paid leave schemes grant workers paid leave credits on individual accounts, allow workers to take leave credits when deemed necessary (under some constraints), allow unused leave credit to accumulate over tenure with the employer, and (typically) compensate workers for unpaid leave upon retirement. Such schemes are uncommon outside the U.S.

Given the lack of research on employee behavior under these individualized leave-credit schemes, we first extensively describe sick leave use across workers and over time to lay the foundation for the following three main research questions: First, when and why do employees use leave under these schemes? In particular, do employees use sick leave as intended or for the purpose of leisure? Second, as their leave balance grows, how much more likely is it that employees take leave? Third, do high balances decrease the likelihood of working while ill?

Our findings suggest that employee use of sick leave for leisure is not widespread, but may occur among some subsets of teachers. Sick leave use increases significantly when environmental hazards increase, for instance, during flu season. Further, we find no evidence that teachers use sick leave to extend vacation periods. We find that a popular, local horse racing event increases the likelihood of taking Friday leave by 11%; however, this effect is driven mostly by *personal* leave, which is allowable under district rules. We do find elevated sick leave use during the horse racing event for male teachers and for those with less than five years of experience. Additionally, we find some evidence that older teachers call in sick during the NCAA Tournament, although the total effect on teacher absences is very small both because of the small coefficients and infrequency of these days. From the perspective of the policymaker, who at times must consider marginal increases or decreases in the generosity of this scheme, our results do not support arguments for less generosity on the basis of waste under the current scheme.[39]

Next, we provide clear evidence that a larger leave balance increases leave use, which is in line with economic theory. The balance-use elasticity is positive, between 0.38 and 0.45, and statistically different from zero along the entire balance distribution; moreover, we document that leave taking is most responsive to balance increases at the bottom of the balance distribution. This finding is consistent with workers avoiding unpaid leave. The likelihood of taking a sick day increases discontinuously when moving from having 0-5 days vs. having 5-13 days, and then increases at a relatively constant rate over the remainder of the balance distribution.

Finally, we use two statistical methods to show that large leave balances can protect against 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 measure of presenteeism using temporary returns to work in the midst of a series of absences. Using this measure, we show that a larger sick leave bal-

[39] A related debate in the Kentucky Legislator in 2018 served as motivation for 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).

ance reduces the probability of working sick, conditional on having an illness spell. What's more, this statistical link is most pronounced during the flu season, when the negative externality of presenteeism is strongest and measurement error concerns are weakest. Our second method shows that having a high share of coworkers with a low balance predicts own leave use, the implication being that one's coworkers engage in presenteeism. This finding corroborates and complements our finding that higher balances not only prevent presenteeism, but protect against the spread of contagious diseases.

Taken together, our study provides several parameter estimates that are crucial for sick leave policy design. The analysis that produced these estimates was made possible by two features of our data that, to our knowledge, are unique in the literature. Specifically, our empirical tests of whether leave is used as intended or for leisure requires a daily employee-level panel of leave behavior. This feature, plus knowledge of one's daily leave balance, is required for the estimation of the balance-use and balance-presenteeism elasticities.

Our collective findings suggest the potential for welfare improving adjustments to the design of the most popular U.S. sick leave scheme. We document (i) a strong decline in leave use when an employee's paid leave balance approaches zero and (ii) that 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. Policymakers might achieve this goal in a cost-effective way by offering employees more paid leave at the start of their careers, with fewer marginal credits earned over time.[40] As an example, consider the teachers in the school district we study. Were state or district administrators to offer first-time teachers a balance of, for example, 40 days, but reduce their flow of leave over their next 9 years of employment to 10 days (as opposed to 13), teachers would receive the same amount of leave credits by year 10 as in the current system. However, many fewer teachers would ever have a balance near zero. Such an adjustment to the leave-scheme would likely result in less presenteeism and reduced illness spread within schools as well as the larger community.[41]

[40]Currently, several states mandate that employees earn a minimum of 1 hour of paid leave per 30-40 hours of work. Policymakers could 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.

[41]Such a change would also ease the hardship of lost income during maternity for young teachers. That said, the teachers most likely to leave the profession early may also be the most likely to engage in moral hazard, taking advantage of the new program. For this reason, additional rules preventing employees from rapidly using all leave days prior to switching jobs or careers would likely be needed to prevent abuse.

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 all of 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 ways that affect sick leave usage. 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 reputations are important. Also, it may be easier to get "caught" using sick leave for leisure in a small community, which may serve as a deterrent. These results may or may not look different in a larger MSA. Third, most of the paid leave granted to teachers in our setting is specifically for sick days, not vacation. (Teachers are expected to take vacations during school breaks.) We consider this a positive feature of our setting, as decision makers face very clean tradeoffs; however, in some leave schemes employees are granted "paid time off banks" (PTO) to use for vacation or illness as they see fit and leave taking behavior may differ in these settings. Fourth, an instruction day in K-12 schools cannot be intertemporally displaced the way research, report writing, sales calls, or even most physical labor can. On school days, children in a classroom require instruction and supervision. Leave taking behavior (and responses) may substantively differ in occupations where five days of work 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

Notes: Observations are teacher-years (NT=4,580). There are 982 teachers, 293 of which are present in all 8 years. SD stands for "Standard Deviation."

Table 2: Kentucky Public School Teacher Data, Leave and Balance Variables

	Mean	SD	Min	Max
A. 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
B. Leave Duration				
Average spell length	1.54	2.88	1	132
Share of 1 day	0.79	0.41	0	1
Share of 2-3 days	0.17	0.38	0	1
Share of 4+ days	0.03	0.18	0	1
C. 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 for Panels A are teachers-years (NT=4,580). There are 982 teachers, 293 of which are present in all 8 years. Observations for Panel B are leave spells, of which there are 30,491 in the data. A leave spell is defined in Section 2.2. SD stands for "Standard Deviation."

Table 3: 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 (1) 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 4: 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 (2). Additional controls include indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, and annual salary.

Table 5: Distribution of Presenteeism Events

Spell Length	Frequency (1)	Percent of Spells (2)	Percent of Leave (3)	Percent Containing Presenteeism (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.

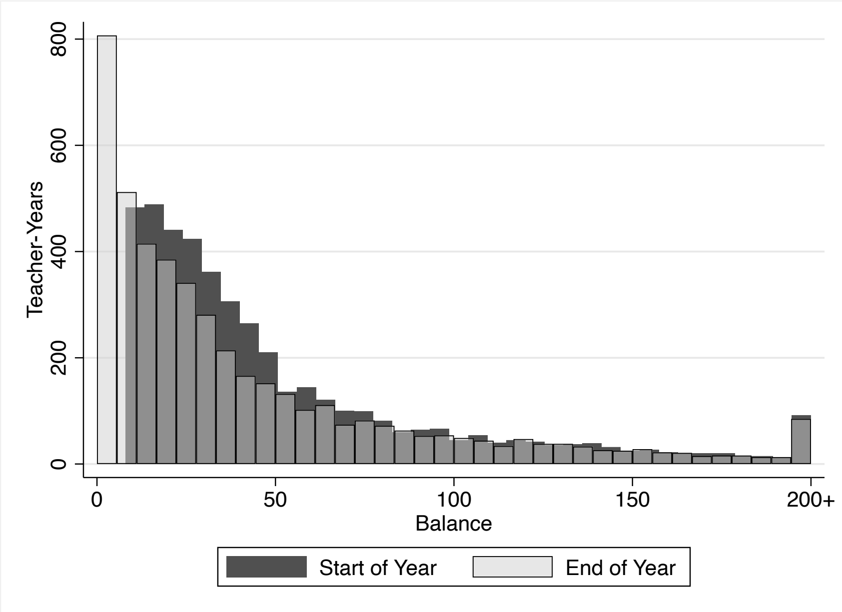
Table 6: Evidence of Presenteeism

	(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 (1)-(3) is one regression. Controls (not shown) and fixed effects are identical to those included in Equation (1), but school type fixed effects have been replaced by school fixed effects. In the third column, the share of teachers in the school with a balance less than 10 is measured with a 10-day lead.

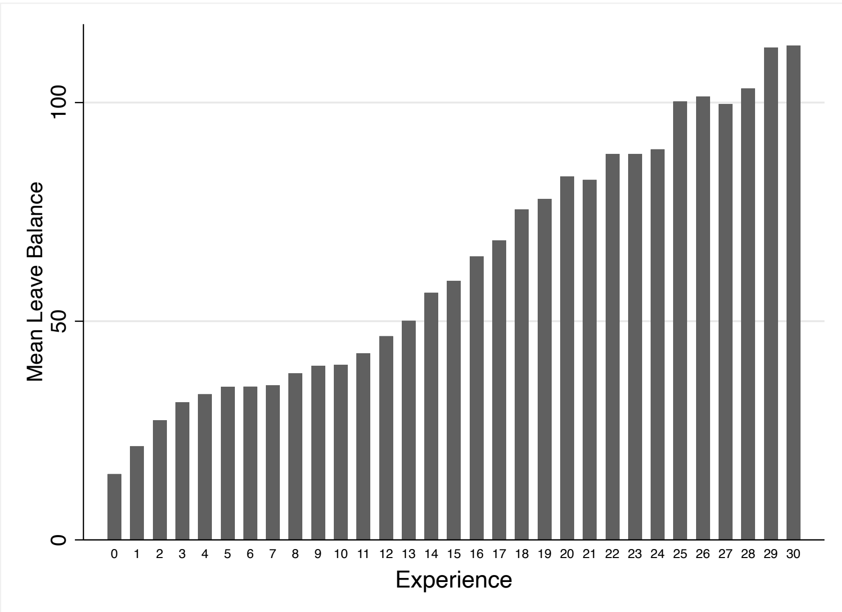
Figures

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



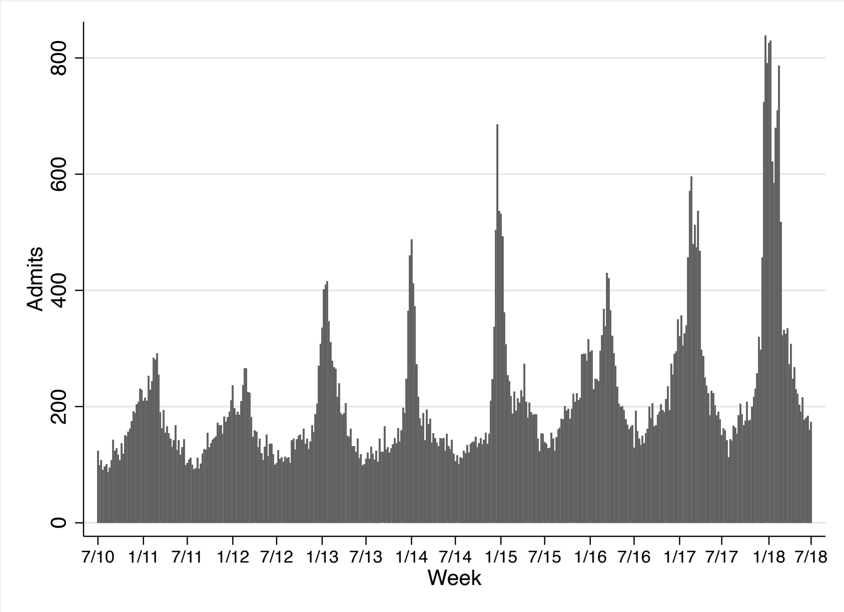
Notes: KPSTD data, aggregated to the teacher-year, yielding a total of 4,580 observations. Histograms of two variables are reported: (i) teacher balance on the first day of the school year and (ii) teacher leave balance on the last day of the school year.

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



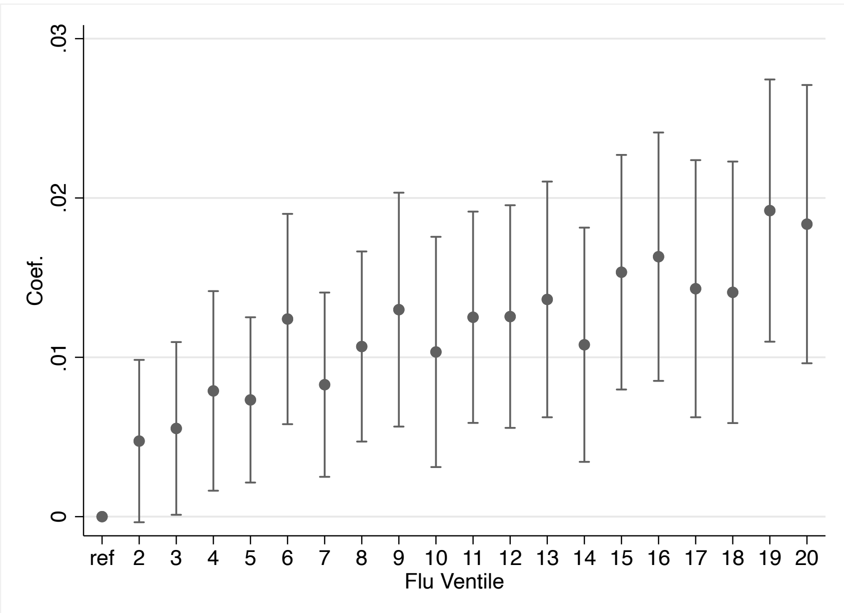
Notes: Data comes from the KSTLD. The bars measure mean leave balance at the start of the year for teachers of different experience levels.

Figure 3: Weekly F&P Patients from Scott and Bordering Counties



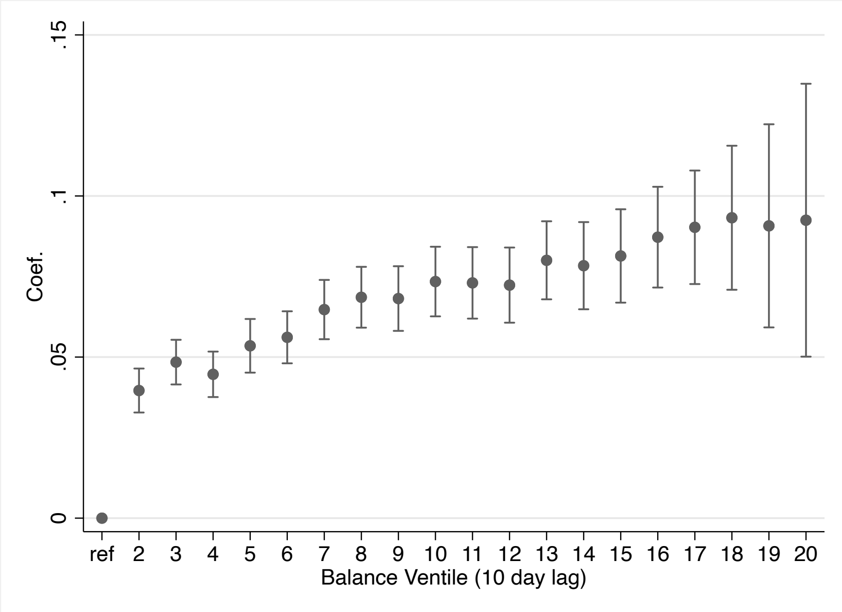
Notes: Cabinet for Health and Family Services in Kentucky, Health Facility and Services Data. Data are all hospital and ambulatory facility admissions with a condition code indicating Influenza or Pneumonia (ICD9 codes 480-488 for weeks 1/1/2000 - 9/30/2015 and ICD10 codes J09-J18 for weeks beyond 10/1/2015)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

Figure 4: Impact of Flu Hospitalization Ventile on Leave Probability



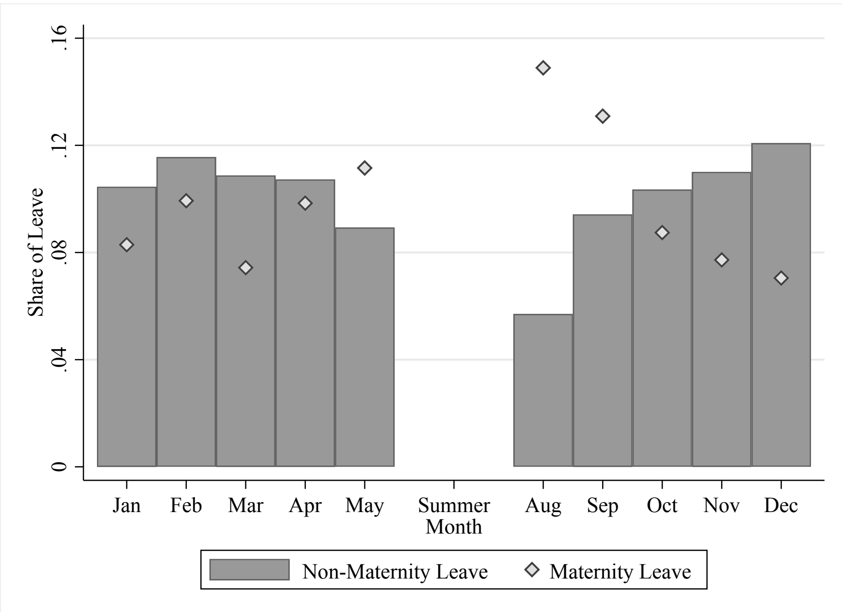
Notes: KPSTD data. Graph shows vintile coeffients $\Sigma_{k=2}^{20} V_{t,k}^{a}$ of a regression as in Equation 1, where $ln(admits_t)$ has been replaced by ventile indicators and the leftmost vintile (i.e., least amount of flu admits) is the baseline category. The dependent variable is any leave use, which has a sample mean of 0.0595.

Figure 5: Impact of Balance Ventile on Leave Probability



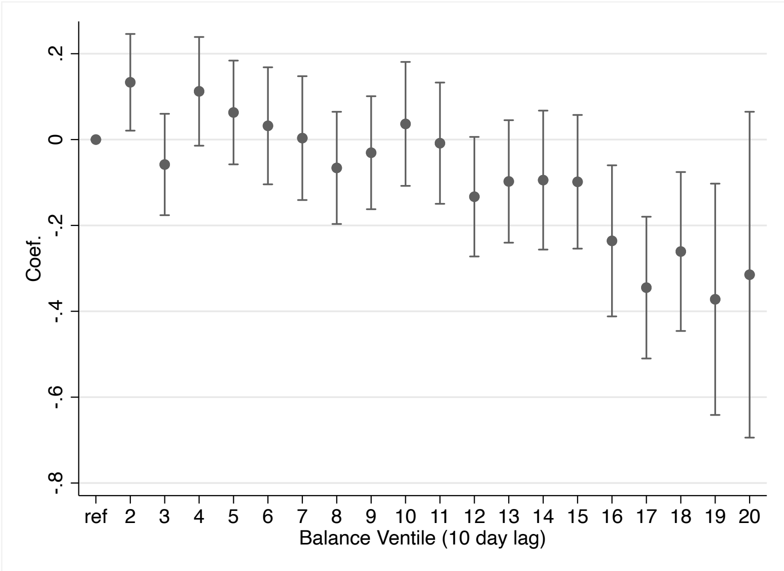
Notes: KPSTD data. Observations are teachers-days (NT=790,615). The graph shows 10-day lead leave-balance ventile coefficients and 95% confidence intervals. The dependent variable is whether any leave was taken on a particular day, the sample mean of which is 0.0595. The regression is as equation (3) 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 6: Maternity and Non-Maternity Leave Shares by Month



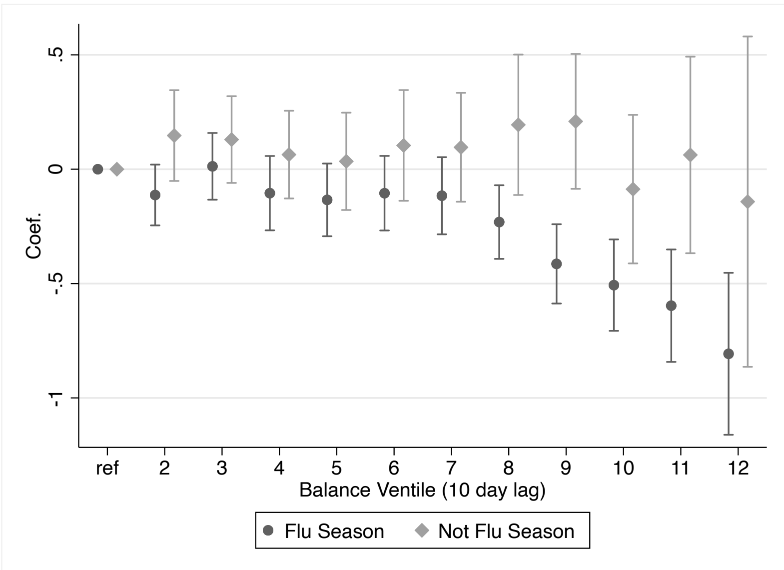
Notes: KPSTD data. Maternity leave is defined as leave taken by female teachers, who are under 40, during a leave spell lasting 15 consecutive days or longer. The vertical axis measures the share of all leave, for pregnancy and not, that occurs in each month. To account for the fact that some months 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 7: Impact of Balance Ventile on Presenteeism



Notes: KPSTD data, collapsed to the illness-spell level. The graph shows leave-balance ventile coefficients (from equation (4)) and 95% confidence intervals. The outcome variable is whether the spell contains a presenteeism event, see Table 5, 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 8: 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 (4) 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 5. 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

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). Tables shows mean number of sick day balance by ventile (columns [3]-[4]) as well as as 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 (1) 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 parenthesis are clustered at the teacher-level. Column (1) represents our main specification, column (1) from Table 3 (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 (1) 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 parenthesis 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 (1) 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 parenthesis 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 (1) 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 parenthesis are clustered at the teacher-level.

Table A6: 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 (1) 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 parenthesis are clustered at the teacher-level.

Table A7: 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 (1) 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 parenthesis are clustered at the teacher-level.

Table A8: Estimating the Balance-Use Elasticity: Robustness 1

	Full Sample - All Balances				
	(1)	(2)	(3)	(4)	(5)
$sinh^{-1}(\text{balance}_{i,t-10})$	0.027 ***	0.027 ***			0.023 ***
	(0.0018)	(0.0018)			(0.0023)
$\text{balance}_{i,t-10}/100$			0.061 ***		
			(0.015)		
$\ln(\text{balance}_{i,t-10} + 1)$				0.031 ***	
				(0.002)	
Month Fixed Effects	X		X	X	X
Week Fixed Effects		X			
Continuously Employed					X

Notes: KPSTD data. Observations are teachers-days (NT=740,235). Each column (1)-(5) is one regression as in Equation (2). The dependent variable in all columns is an indicator for any leave use, which has a sample mean of 0.0595 in all columns but the last, where it has a sample mean of 0.0607. Additional controls are day of the week indicators, teacher education, year indicators, experience, experience squared, age, age squared, school type (i.e., high school, middle school, elementary school), and annual salary. Column (1) is the baseline result; column (4) from Table 4. Column (2) replaces month fixed effects with calendar-week effects. Column (3) measures the leave balance in levels. Column (4) measures leave balance using a log-plus-one transformation. Column (5) limits the sample to teachers working continuously over our eight year sample (NT=370,730).

Table A9: Estimating the Balance-Use Elasticity: Heterogeneity

	Male	Female	Under 40	Over 40	0–7	Experience 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

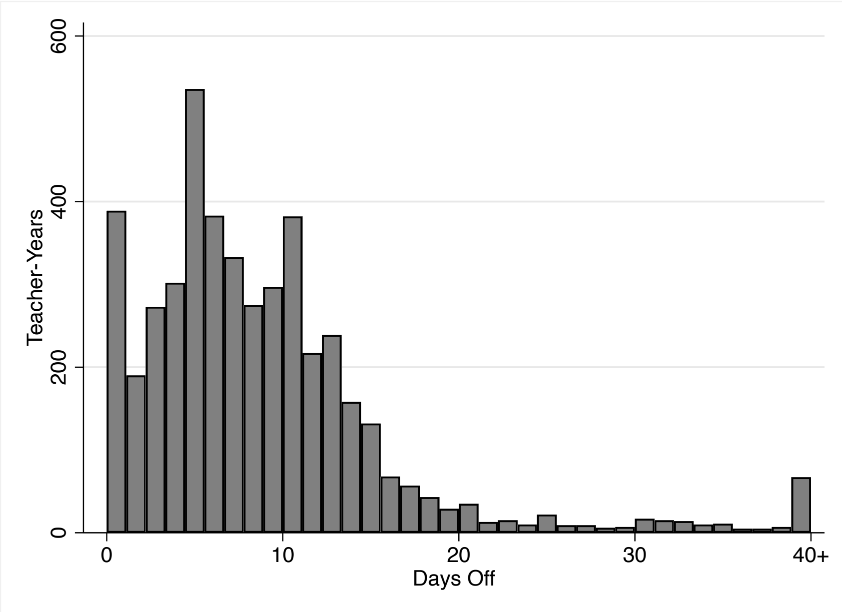
Notes: KPSTD data. Observations are teachers-days (NT=740,235). Each column is one OLS regression as in Equation (1) and also includes indicators for calendar year, school type (i.e., high school, middle school, elementary school), education, and annual salary (all not shown). The standard errors in parenthesis 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 2

	Zero balances excluded			
	(1)	(2)	(3)	(4)
$sinh^{-1}(\text{balance}_{i,t-10})$	0.026 ***			
	(0.0025)			
$\text{balance}_{i,t-10}/100$		0.050 ***		
		(0.016)		
$\ln(\text{balance}_{i,t-10} + 1)$			0.025 ***	
			(0.003)	
$\ln(\text{balance}_{i,t-10})$				0.028 ***
				(0.002)
Month Fixed Effects	X	X	X	X
	Lowest balance ventile excluded			
	(1)	(2)	(3)	(4)
$sinh^{-1}(\text{balance}_{i,t-10})$	0.023 ***			
	(0.004)			
$\text{balance}_{i,t-10}/100$		0.038 ***		
		(0.017)		
$\ln(\text{balance}_{i,t-10} + 1)$			0.024 ***	
			(0.004)	
$\ln(\text{balance}_{i,t-10})$				0.023 ***
				(0.004)
Month Fixed Effects	X	X	X	X

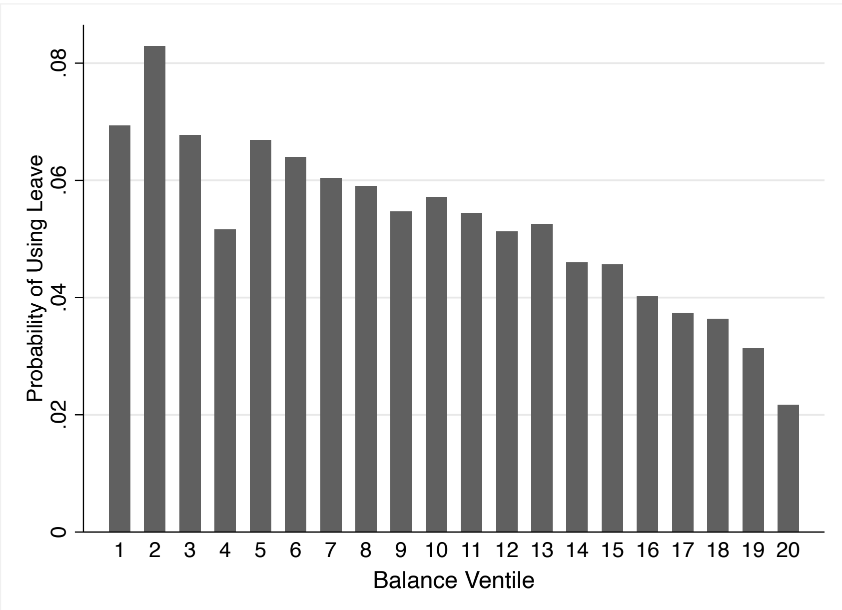
Notes: KPSTD data. Observations are teachers-days (731,012 when zero balances are excluded and 700,736 when the lowest balance ventile is excluded). Each column (1)-(4) is one regression as in Equation (2), where leave balance is measured differently in each. The dependent variable in all columns is an indicator for any leave use. Additional controls are day of the week indicators, teacher education, year indicators, experience, experience squared, age, age squared, school type (i.e., high school, middle school, elementary school), and annual salary. When zero balances are excluded, the dependent variable mean is 0.0617; when the lowest ventile is excluded, the mean is 0.0613. 4.

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: 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 Appendix – For Online Publication

DA1 Introduction

In this Data Appendix, we describe the construction of the Kentucky School Teacher Leave Dataset (KSTLD), which is the main data source for Cronin, Harris, and Ziebarth (2022). Moreover, we 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, comprised of sixteen 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 break, 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 extra compensation at their daily wage rate. For example, base compensation for a teacher with 5 years of experience and a masters degree is $47,526, plus $508.30 for two in service days.

There are several ways in which teachers and school administrators can earn more than this base pay. 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.

[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.

- 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, if they have 15 years of experience and a masters 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 Sick Leave Policy

The Kentucky Department of Education imposes the following rules on school districts regarding sick 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. Moreover, 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. Emergency/Personal days differ from sick days in that teachers must request permission from a supervisor to take an emergency/personal day, meaning they may be denied.[4] All unused paid leave days remaining at the end of an academic year are converted to sick days and banked for the following year; thus, most teachers, particularly experienced ones, have a stock of paid leave that is much larger than the 13 days granted at the start of each year. Teachers can choose to take unpaid leave, but only after depleting their stock.

Upon retirement, teachers are paid for any unused leave. We detail the exact relationship between leave stock and retirement compensation in Section DA4 below. For now, simply note that retirement pay is increasing almost linearly in accumulated stock at the time of retirement, up to a cap of 300 days.

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

[4] Since the 2016/17 school year, no distinction has been made between personal and emergency days; all are simply called personal days.

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. Retrospective school calendars were provided by the district, indicating whether 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 either 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

Administrators from the SCSD 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.
- A donation to 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 corresponding date that leave was received/deducted. For every employee, we see the available stock of sick leave *on one date only*.[5] 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.

[5]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 the 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 personal or emergency day, was denied, but took the day off none-the-less (for example, requesting to take a personal day on the Friday before Spring Break and being denied). Note both of these events represent absence from work; however, 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 training penalties and are, thus, dropped from the data.[6] 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 take. In both instances, if multiple unpaid leave days were taken, we assume they were taken consecutively.

[6]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.

Importantly, note that there are over 93,000 events in the raw paid leave file, but just 663 events in the dock day file; thus, true unpaid leave represents well under 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 and many of 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 over their careers as educators.[7] 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 academic-year specific variable 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 principle, guidance councilor, etc.).

DA2.3 Merge

The KCS merged the paid leave file described in DA2.1 with the KLDS. KLDS data contains 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 contained 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.

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

We eliminated anyone from the SC data that was not a "certified employee," which essentially includes full-time teachers, school administrators (e.g., principles, vice principles, deans, etc.), guidance councilors, psychologists, social workers, librarians, and 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 dropped 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 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 gatheres data from school districts on the first day of the school year. Thus, any teacher beginning the school year late is missing from the KLDS in that year; moreover, any teacher switching schools during the school year is only attached to the first school.[8] Second, young teachers often work as student teachers, teaching assistants, and teachers aids in the year prior to their first year of employment. During this pre-certified employment year, the future teachers bank any unused sick leave; however, 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, 52,695 leave events.

DA3 Special Events

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 working until the conclusion 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

[8] 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.

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, though 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 Maternity Leave

SCSD has no separate system of paid maternity leave.[9] In compliance with the FMLA, employees are entitled to 12 weeks of leave following the birth or adoption of the child. Employees are permitted to use up to 30 days of paid sick leave on the first thirty days of this period. More paid leave can be used if need is verified by a physician. Employees can further request that the superintendent allow them to take the remainder of the year as unpaid leave (this would register an exit code of 0d in the birth-year and an entry code of 1b in the following year); after which, requests must be made in one year increments.[10]

As maternity leave is treated no differently than an extended absence for an illness by the district, we cannot identify it explicitly in the data. Rather, maternity leave appears as consecutive days and weeks of paid leave. One way to get a sense of how much maternity may contribute to overall leave use in the data is to focus on long spells for women under the age of 40. Leave spells in excess of 15 days among this group make up roughly 12.3% of all leave in the data; there are 162 teacher with such a spell.

DA3.2 Partial Year Employment

Table DA1 shows that less than two percent of employees do not start on the first day of school in a given school year. Overwhelmingly, these teachers start within a month of the start of the school year. Most commonly, 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 (i.e., zero experience) teachers — 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 exiting 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.

[9] https://www.scott.k12.ky.us/docs/district/depts/38/16-17%20employeemanual.pdf

[10] In all instances of early exit due to what appears to be maternity, all leave is used prior to exit. Were a teacher to take the following year off due to maternity, the entry code upon re-entry would be 2a or 2b.

DA3.3 Job Transitions

There are four transitions that 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.[11]

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 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)

[11] 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.

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 anyone returning to work as a certified employee post-retirement from the sample.

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 3 inputs – years of service (Y), a multiplier (M), and annual income (I) – and is a very simple product:

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

This value then grows at a fixed 1.5% per year post-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.[12]

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

- 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, 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 start 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 that 5 years of experience *eventually* receives retirement benefits.[13] Once 27 years of service is reached, educators can retire with no 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%.

[13] 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.

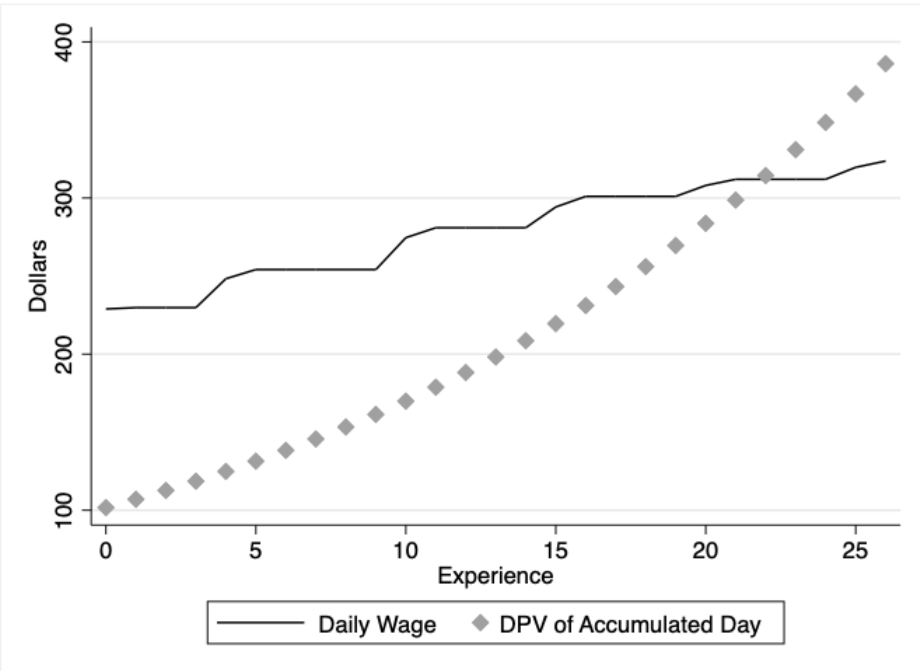
To illustrate, consider an individual who retires in 2019, after 27 years of service with a masters degree. This individual fully qualifies for retirement, so they face no penalty and their last 3 years of income are \$58,340, \$59,769, and \$60,529 (See Figure DA1) . They receive the lump-sum payment 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

Because paid sick days have financial value to 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 teachers 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.[14] In effect, one can think of this wage as being the benefit of the sick-leave policy to the teacher and cost to the district. The dotted line in Figure DA3 depicts 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. 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 costs 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 to teachers and the district are not equal until the teacher has 22 years of experience. To the extent that early career teachers are more likely to leave the profession before retirement, the dotted line would start closer to the origin and but have a steeper slope as the probability of remaining in the profession until retirement would increase with experience.

[14]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.