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

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ABSTRACT

This paper studies how U.S. employees use paid sick leave. The most common U.S. sick-leave schemes operate as individualized credit accounts---paid leave is earned over time and unused leave accumulates, producing an employee-specific "leave balance." We construct a unique administrative dataset containing the daily balance information and leave behavior of 982 public school teachers from 2010 to 2018. We have three main findings: First, we provide evidence of judicious sick-leave use---namely, teachers use more sick leave during higher flu activity---but no evidence of inappropriate use for the purposes of leisure. Second, we find that leave use is increasing in the leave balance with an average balance-use elasticity of 0.45. This relationship is strongest at the very bottom of the balance distribution. Third, we find that a higher leave balance reduces the likelihood that a teacher works sick ("presenteeism"), especially during flu season. Taken together, these results suggest that a simple alteration to the current sick-leave scheme could reduce the likelihood of presenteeism, thereby lowering infection risk in schools, with few adverse consequences.

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1 Introduction

Granting workers paid sick 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; Pichler and Ziebarth, 2017; Maclean et al., 2021). 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 and Ziebarth, 2017). 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; 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 2021, a quarter of all U.S. workers did not have access to any paid sick days, with the rate highest (37%) 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) 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 sick leave is vitally important for ongoing debates about

[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% wage replacement; wages are replaced at 70% for the next 72 weeks (Ziebarth and Karlsson, 2014).

[3] These features are present in most proposed and passed leave mandates, such as the Healthy Families Act, the 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, 2021; Findlay, 2021).

[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).

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. sick-leave scheme influence employee decision making. Further, we study the implications of those decisions 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 is *daily* information on every sick, personal, emergency, and unpaid day taken by *each* teacher from 2010 to 2018. The second is a daily account of each teachers' leave balance over the same eight school years.

We examine three aspects of how U.S. workers use their leave. First, we examine whether teachers use sick leave judiciously, or inappropriately for the purpose of 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 or the temptation for shirking. We therefore test whether events that alter the likelihood of illness or shirking alter the frequency of leave taking. As an exogenous shifter of the probability of illness, we use data on local flu hospitalizations at the weekly level as a proxy for exposure to flu activity. As exogenous shifters of the temptation to shirk, we use school days (i) immediately before and after scheduled holidays, (ii) immediately following the Super Bowl, (iii) taking place 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. Keeneland is an internationally renowned and very popular local racecourse.[8] 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 use their leave judiciously. Teachers are more likely to take sick days during flu season: a 10% increase in the severity of a local flu wave (measured by hospitalizations) leads to a 1.5% increase in leave taking. Conversely, we find little evidence

[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, 2020). 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 (2021); 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).

[8] Keeneland hosts races Wednesday-Sunday for three weeks each Fall and Spring. When Keeneland is racing, average daily attendance exceeds 15,000.

that teachers use leave inappropriately. Leave use is *not* more common immediately before or after holidays. Teachers are *not* 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.[9] Note, these statistical tests on appropriate vs. inappropriate leave use rely on administrative data like ours with daily spell data. Such data are very rarely available to researchers. We thus contribute to the literature on shirking 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 shirking 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 broadcasted at night during the Winter Olympics in Calgary.

Second, we examine how an employee's paid leave balance impacts her 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 fiscal 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. We also implement dynamic panel regression techniques, using the balance lead as an instrument for the contemporaneous balance.

Our results show that as paid leave balances increase, so too does leave use: on average, a 10% increase in one's leave balance leads to a 4.5% increase in the likelihood of taking leave on any particular day. We find that this relationship is strongest at the bottom of the leave-balance distribution.[10] 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), in addition to the literature on how leave generosity affects use. Because most research on sick leave generosity is from Europe, the variation in generosity that such research studies is fundamentally different. For example, De Paola et al. (2014) examines a reform in Italy that reduced wage replacement rates from 100-80% for the first nine months of sick leave. Johansson and Palme (2002) examine a Swedish reform prior to which workers had up to six days leave with no doctors note, and 29 days leave with a single note. Aside from structural differences in sick leave schemes, or cultural differences on leave taking, we expect worker behavior to differ in the U.S. due to basic diminishing marginal benefits from absence. In one of the few studies on U.S. sick leave, Maclean et al. (2021) find that workers who gain

[9] Interestingly, we find that while Keeneland is in session, teachers *are* statistically more likely to use *personal* days, particularly on Fridays. 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. Using personal days for these occasions is allowable under district policy; in a sense, it is precisely what personal days are for.

[10] All else equal, for teachers with paid leave balances of 5–13 days (13 days is the allotment for a single year) the likelihood of taking leave on any particular day is 64% higher than teachers with 0–5 days of paid leave available. Yet, teachers with much larger paid leave balances in excess of 92 days are just 47% more likely to take leave than teachers with 5–13 days available leave.

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, if evidence suggests that (i) teachers use leave primarily for illness and not recreation and (ii) leave use increases with leave balance, then are teachers with low balances more likely to exhibit 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, 2020; Pichler et al., 2021). 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 balances are low. We find that lower leave balances increase presenteeism, and that this effect is strongest during flu season. This finding suggests that higher leave balances help teachers avoid working while sick, potentially preventing the spread of illness within schools. As such, this result contributes to literature 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 has repeatedly failed to pass the Healthy Families Act (the most recent iteration of which is the 2021 House Bill 4575). 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] However, since 2009, 14 states, the District of Columbia, and dozens of large cities passed similarly designed regional mandates; see A Better Balance (2021) for an overview. While some of the resistance to universal leave guarantees is attributed to potential labor costs, wage and employment effects, and whether the locus of control should lie with the government or private sector, a substantial barrier to progress is employer trust of employees. In a survey of employers, the most common concerns regarding mandated sick leave centered around potential *abuse* of available leave and moral hazard (Smith and Kim, 2010). We contribute to this policy debate by providing evidence that public school teachers, one of the largest professions in the country, (i) use sick leave appropriately and (ii) are less likely to come to work sick with larger leave balances.

The next section details the institutional underpinnings and construction of our data set as well as some descriptive analysis. Section 3 contains our empirical analysis and results. Section

[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 which differs from sick leave in both, aim and scope (Rossin-Slater et al., 2013; Lalive et al., 2014; Dahl et al., 2016; Baum and Ruhm, 2016; Brenøe et al., 2020)

4 discusses limitations, summarizes, and recommends areas for future work.

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 original data files, merge methods, and sample selection criteria. In a first step, we combine the following:

1. A state-wide, annual longitudinal data file on all Kentucky school teachers, collected and maintained by the Kentucky Department of Education (KDE), containing demographic information, education, years of experience, school, and job title.[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 races take place at the Keeneland horse track, 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% 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% in middle schools, and 24% 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% of US teachers are female, 80% are white, average experience is 14 years, and 57% 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

[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. 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.

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."

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. Leave balances are allowed to grow 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, balance, and duration, 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% 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% on a given school day. Five percent of teachers take no leave each academic year. The total annual leave distribution 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.

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%) of spells contain a single day, while 17% of spells last 2 to 3 days. Only 3% of leave spells are 4 or more days. However, 24% of all leave days belong to a spell of 4 or more days (not shown).

Finally, Figure 1 shows average leave balances entering the school year by teacher expe-

[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.

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

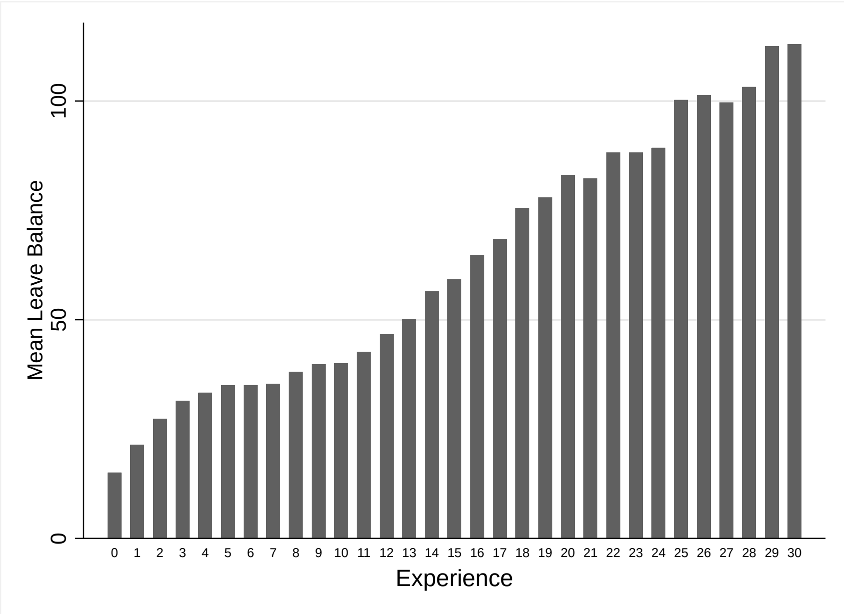
Notes: Observations for Panels A are teachers-years (NT=4,580). There are 982 teachers, 293 of which are present in all 8 years. Observations for Panel B are leave spells, of which there are 30,491 in the data. A leave spell is defined in Section 2.2. SD stands for "Standard Deviation."

rience. As expected, the leave balance is strictly increasing in experience. Reported in Panel C of Table 2 is the mean balance entering a school year (52), as well as balance by experience levels. 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.[18] There is variation both within and across experience categories; the experience-specific balance distributions display substantial overlap.[19]

[18] 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.

[19] At the teacher-year level, the experience-balance correlation coefficient is 0.53.

Figure 1: 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.

2.4 Supplemental Data

The KSTLD contains a number of variables thought to influence the likelihood of leave use.

Flu Activity. 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,[20] with an ICD 10 diagnosis code indicating Influenza or Pneumonia.[21] We measure admissions at the weekly level.

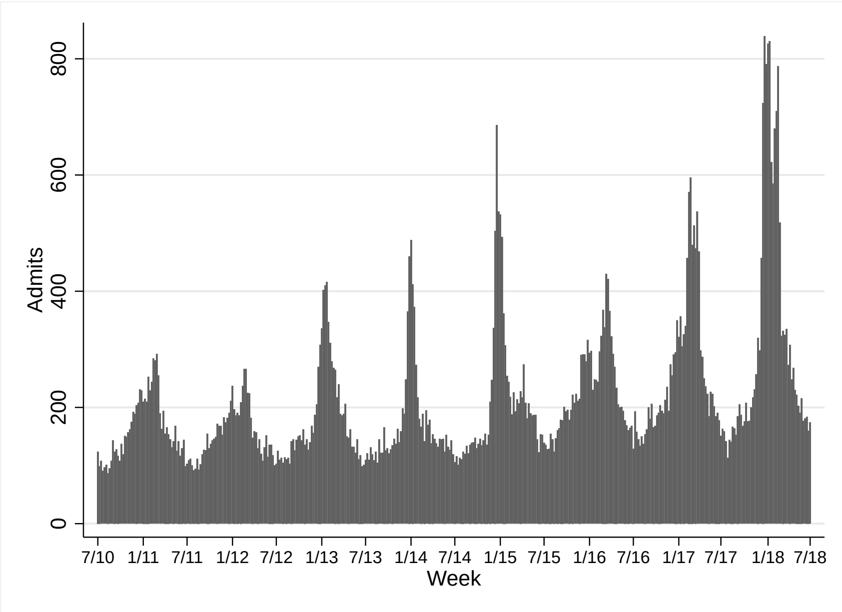
Figure 2 shows total weekly I&P admissions from July 2010 to July 2018. We observe the characteristic flu seasonality patterns, with spikes primarily from December to February, but with variation between years in the exact timing of the peak. Because of population growth, we also observe a slightly increasing trend in the admit count. The upward trend is also partly

[20] These include Owen, Grant, Harrison, Bourbon, Fayette, Woodford, and Franklin counties. The total population count of these counties is 530,000, which represents about 12% of the state's population.

[21] 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.

explained by 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.

Figure 2: 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.

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.[23] 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 leave taking around these breaks to test for possible shirking behavior.

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

[23] This excludes school cancelation due to weather.

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. 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[24] and popularity[25], 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 US adults, eleven percent reported that they *would* call in sick to watch the NCAA tournament.[26] BLS estimates the average absence rate nationwide is three percent on any given day.[27] 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% of the US workforce *plans* to miss work the Monday following the Super Bowl each year.[28] 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 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.

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

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

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

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

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

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 ($\sim$9% 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 just as much a social event as a sporting event. Whereas the 'Super Bowl Monday' phenomenon is likely predominantly driven by males rather than females, who make up the majority of our sample.

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 both judicious and inappropriate leave-taking. 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 severity of flu activity and teacher sick-leave behavior. This indicator of contagious disease exposure varies in a plausibly exogenous fashion over time. We use it to test for judicious leave-taking and hypothesize a positive statistical relationship.

To test for possible inappropriate leave-taking (shirking), 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 Super Bowl Monday. 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 are also able to 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.

Judicious Leave Use. Table 3 shows the results from 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% increase in local flu activity among the general population increases the probability that a teacher takes sick leave by roughly 0.09 percentage points (ppt). Given that the baseline leave rate is roughly six percent, this reflects a 1.5% increase in leave-taking.

The relationship between flu activity on leave use may vary in intensity across across the flu activity distribution. 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 activity in the lowest ventile.[29] Figure 3 shows the results when we plot the ventile coefficients. Over the entire flu activity distribution, we observe a strictly positive relationship, reinforcing that sick leave behavior increases incrementally with the environmental risk 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%

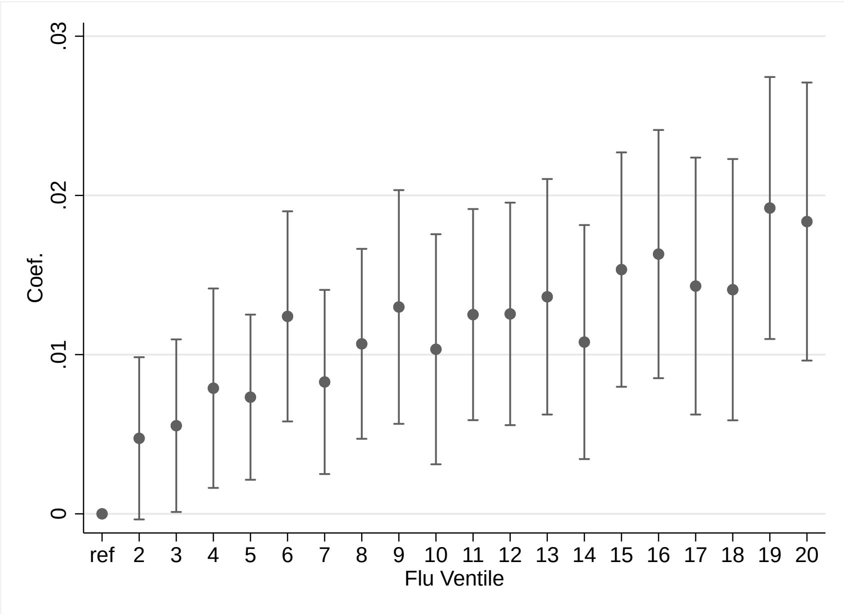
[29]Ventiles are defined across all school years, excluding days in which school is not in session. Appendix Table A1 contains the admit range within each ventile.

Table 3: Testing for Judicious and Inappropriate Leave-Taking

	Any	Sick	Emergency	Personal	Uncomp
Judicious Use					
ln(admits)	0.0094 ***	0.0094 ***	0.0009 **	-0.0009 **	0.0002
	(0.0023)	(0.0022)	(0.0004)	(0.0004)	(0.0003)
Shirking					
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)
$\times$ 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)
Other					
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)

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.

Figure 3: Impact of Flu Activity 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.

increase in leave-taking behavior.

Shirking. Returning to Table 3, the next several regressors are all thought to increase the likelihood of recreational leave-taking and, thus, serve as a test for shirking behavior. For example, 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 shirking, 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.[30] 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.

Rows 4 and 5 of Table 3 test whether leave is more commonly taken during the Keeneland Spring and Fall Meets. The first column suggests that Keeneland increases overall leave use, but the effect is only statistically different from zero on Fridays. On a typical non-Keenland

[30]Teachers are often strictly forbidden from taking personal days preceding and/or following a holiday. The superintendent can simply state that all personal days preceding Christmas Break, for example, will be denied. Though sick and emergency days are not forbidden, this restriction may dissuades teachers from using non-personal leave around holidays, for fear that administrators may suspect that the leave is truly personal in nature.

Friday, there is a 7.5% chance that a teacher takes leave. All else equal, Keeneland raises the likelihood of Friday leave by 0.82ppt (11%). Comparing columns (2) to (5), one can see that this result is driven almost entirely by the use of personal leave and that even on Keeneland Wednesdays and Thursdays, personal leave use is elevated by a statistically significant amount. Keeneland has no statistical effect on any other type of leave use. Importantly, using personal days in this manner is well within district rules; as such, we find no evidence that teachers are using paid leave inappropriately when Keeneland is in session.

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. That said, for both events, the observed increase in personal leave is closer to reaching statistical significance than the other leave types; p-values of 0.12 and 0.20, respectively. Again, using personal leave in this manner is well within district rules.

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 leave rate Wednesday is 0.053; thus, the coefficients suggest that all else equal leave use is 16% more common on Monday and 43% more common on Friday, than on Wednesday. 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 shirking or "leisure behavior" (Miller et al., 2008). Regarding Fridays, 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.[31] As a result, teachers reported to us that routine doctor's office 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

[31]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).

weekend to recover. Many continuing education workshops for teachers also start on Fridays, requiring teachers to miss a day of work.[32] 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 US and Canada, respectively, workers compensation injuries are most common on Mondays due to psychological strain. Consistent with this conclusion, Willich et al. (1994) shows that heart attacks among employees peak on Mondays. Unfortunately, we cannot observe the reason for a teacher's absence, but these explanations cast doubt on the interpretation of elevated Monday and Friday leave as "leisure behavior."

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).

Appendix Table A2 contains several robustness checks. Column (1) contains our main results for comparison; those from column (1) of Table 3. 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. Were leads and lags correlated with use, one might worry that flu admits simply capture seasonal patterns in leave use. Column (4) reports qualitatively similar results with admits measured in levels. Column (5) reports results for the sample of 283 teachers (50 percent of observations) who teach continuously over our eight year time frame. That results are similar suggests that dynamic selection in and out of teaching has little impact on our findings.

In Appendix Table A3, we explore heterogeneity in our effects across several observables. We find that women are more responsive to flu season than men. Men are more likely than women to take off on a Keeneland Wednesday or Thursday. UK NCAA tournament games

[32]A natural follow-up question is, "how common would these events need to be in order to eliminate the Friday effect?" 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 in order for us to argue that the high Friday leave rate does *not* imply shirking.

significantly increase the likelihood of leave for men, but not women. Although not shown, this result is driven entirely by personal leave use and *not* sick leave use. Consistent with 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. Keeneland Fridays are most popular among young teachers and teachers in their last year of teaching.

3.2 Does a Larger Leave Balance 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 relationship is possibly non-linear.

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 (full or partial) of any type was taken on day t. $Balance_{i,t-10}$ measures the sick leave balance 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. All 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

Table 4: Estimating the Balance-Use Elasticity

	(1)	(2)	(3)	(4)	(5)	(6)
ln(balance)	-0.012 ***	-0.013 ***	0.010 ***	0.027 ***	0.015 ***	0.027 ***
	(0.0007)	(0.0008)	(0.0017)	(0.0018)	(0.0012)	(0.0018)
Socio-demographic controls	X	X	X	X	X	X
Day of week fixed effects	X	X	X	X	X	X
Month, year fixed effects	X	X	X	X	X	X
Individual fixed effects			X	X	X	X
10 day lead				X	X	X
Drop spells > 10					X	
IV, 10 day lead						X

Notes: KPSTD data. Observations are teachers-days (NT=790,615). In columns (1)-(5), each column is one regression as in equation (2); the model in column (6) instruments the current leave balance with the balance ten days prior. The F-statistic for the first stage regression is 47.6. Additional controls include indicators for calendar year and month, school type (i.e., high school, middle school, elementary school), education, and annual salary.

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 $t+1$.

Table 4 shows the main estimates of the balance-use elasticity. To illustrate how the preceding 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; yet, both the selection and mechanical association concerns listed 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% 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% increase in the likelihood of taking leave on any given day, yielding an elasticity of 0.45.

The estimates in column (4) are consistent only if a ten school-day lead is sufficiently long to break the mechanical association between leave taking and leave balance that is created by sick spells. If sick spells longer than ten days lead the mechanical association to persist, then our estimates in column (4) should continue to be biased down. In column (5), we repeat our analysis while dropping all spells longer than ten days. As the point estimate does not increase in magnitude, we take this as evidence that the ten-day lead is sufficient. Moreover, note that the balance elasticity of leave taking decreases when spells of at least two weeks are excluded. If employers are concerned about workers using high leave balances to take time off on more marginal days, this elasticity is probably more relevant. Compared to the baseline leave-taking rate, the calculated elasticity in column (5) when long spells are excluded is only 0.3.

One interpretation of the specification in equation 2 is that it reflects a reduced-form relationship—the ten-day lead balance can be thought of as a plausible instrument for contemporaneous balance. In column (6), we report 2SLS estimates using the ten-day lead balance as a formal instrument. The estimate is identical to that in column (4). Instrument relevance is strong with an F-stat 47.6. The validity assumptions requires that the impact of the instrument solely operates through the instrumented variable; in our case, this is plausible as it is hard to think of a reason why the balance ten days ago would have a separate impact on leave-taking, other than through its correlations with the contemporaneous balance.

In Appendix Table A4, we present the results of our robustness analysis. Results do not change when we include calendar-week fixed effects (column (2)), measure the leave balance in levels (column (3)), or limit the sample to continuously employed teachers (column (4)). The last of these tests relaxes any concern about dynamic selection, or that teachers who plan to remain in the profession longer have a greater incentive to accumulate large balances. In Appendix Table A5, we study possible effect heterogeneity by gender, age, and experience. Elasticity estimates do not vary across these observables.

Next, we examine the relationship between a teacher's leave balance and leave-taking behavior using a more flexible functional form, 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 balance, which could be done, for example, by giving new employees larger starting balances.

To this end, we repeat the ventile approach above, dividing the balance distribution into twenty equal bins. Appendix Table A1 describes the leave-balance range in each vintile. The bins are represented by dummy variables and replace the continuous balance regressor of interest in equation (3) as follows:

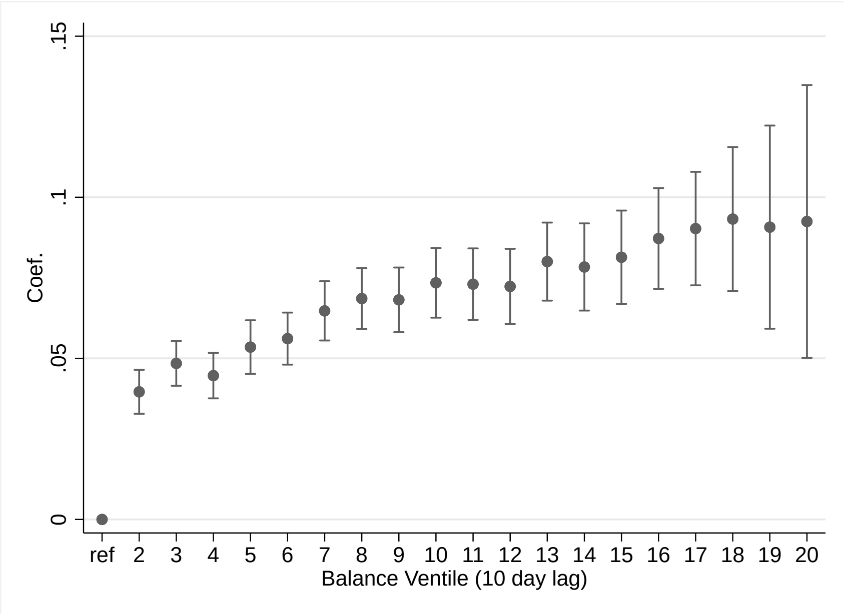
$$y_{it} = \beta_0 + \Sigma_{k=2}^{20} V_{i,t-10,k}^{b} \beta_{1,k} + X_{it}\beta_2 + DOW_t + \delta_m + \gamma_y + \alpha_i + \epsilon_{it}. \tag{3}$$

Figure 4 plots the 19 vintile coefficients where the bin with the least balance days serves as baseline. We observe a strictly positive relationship between leave balance and leave taking. 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). Specifically, the likelihood of taking leave increases by 4ppt, a 64% increase over baseline. 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% more likely to take leave on any give day than teachers in the baseline bin, and 47% more likely than teachers in bins two through four.

In summary, we estimate a balance-use elasticity of 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 teachers typical pay-check; that is, teachers are not paid for the days that they miss.

As the previous section finds little reason to suspect that teachers (mis)use this leave balance for leisure, a natural next question is, "Are larger leave balances helping teachers to avoid presenteeism behavior?"

Figure 4: 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 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

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.

We propose the following novel measure for presenteeism behavior using our 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, shows up at 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).[33] 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.[34] 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%) 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% of all spells), but do represent a sizable proportion of total leave taken (19%). 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% contain a presenteeism event.

Using this measure of presenteeism, we test whether increases 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:

[33] 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.

[34] 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.

Table 5: Distribution of Presenteeism Events

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

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

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

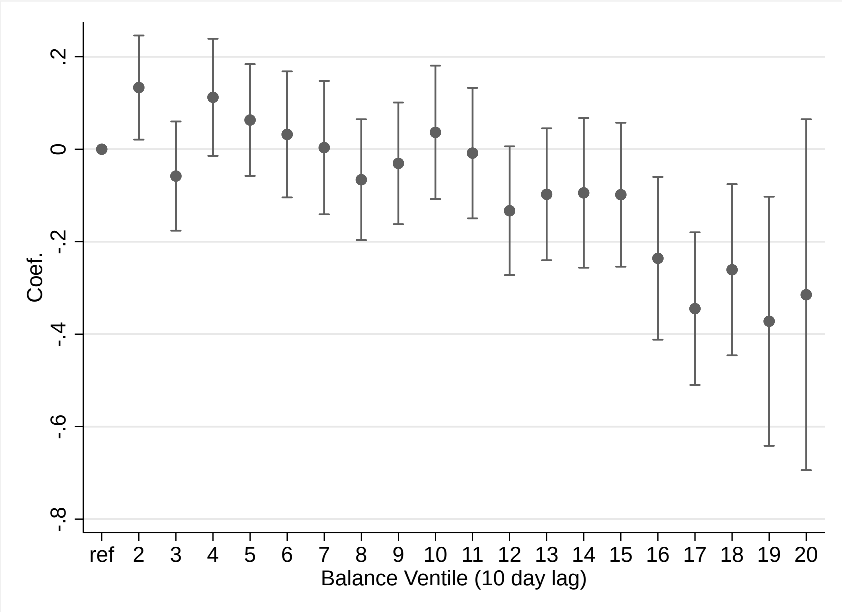
where our outcome is the binary measure of presenteeism described above. All other variables are defined as above and $\Sigma_{k=2}^{20} V_{i,t-10,k}^{b}$ measures the leave balance ten days prior to the start of the spell in ventile indicators.[35] We plot regression coefficients, $\beta_{1,k}$, in Figure 5. 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 "Non 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 bins to 12.

Figure 6 shows the results graphically, plotting the bin coefficients separately for times in-

[35] 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.

Figure 5: Impact of Balance Ventile on Presenteeism



Notes: KPSTD data, collapsed to the illness-spell level. There are 30,491 illness spells in the data. The graph shows leave-balance ventile coefficients and 95% confidence intervals. The outcome variable is whether the spell contains a presenteeism event, see Table 5. The regression runs equation (4) and 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.

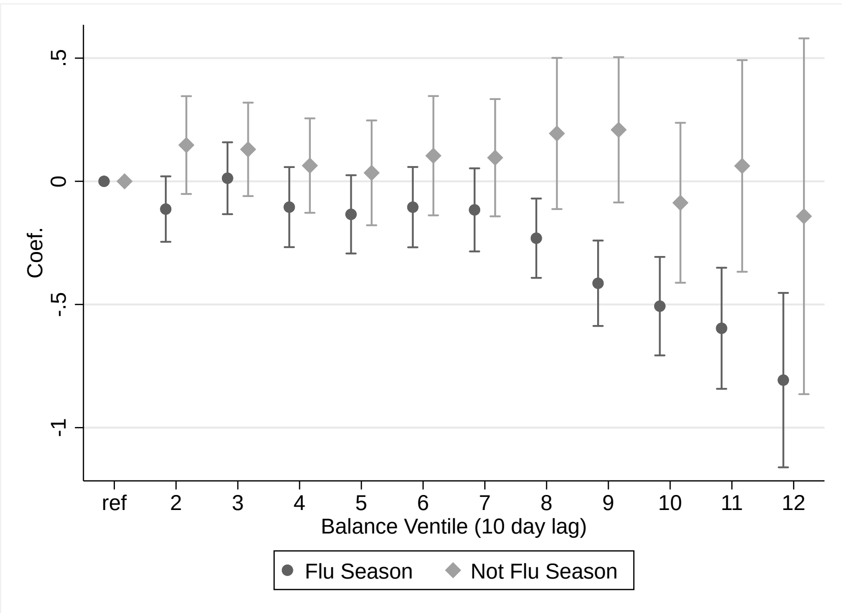
side and outside of flu season. Outside flu seasons (i.e., in the early fall or late spring), we see an almost perfectly flat relationship between presenteeism spells and having a higher leave balance. During flu seasons (i.e., mostly in January and February), we see a decrease in the coefficients as 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 coefficients become (and stay) significantly different from zero after 7th ventile, which contains a maximum of 30 days of leave.

There are several aspects of note when interpretating these results: First, these findings are of policy relevance because they show that high balances protect against presenteeism when the negative externality associated with presenteeism (i.e., illness spread) is greatest.

Second, one of the main empirical challenges when studying presenteeism is type-1 measurement error, or falsely assigning presenteeism when there is none. The flu season results are unlikely to be driven by type-1 errors. During this season, absences are more likely to be illness related than other times of the year, reducing type-1 measurement error. 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.

Third, the previous section shows that the balance-use elasticity was 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.

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



Notes: KPSTD data, collapsed to the illness-spell level. There are 30,491 illness spells in the data. 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.

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. Their sick-leave schemes resembles the schemes of most public employees in the United States. Moreover, 14 states mandated similar schemes for the private sector. Such schemes are also under discussion by the Biden Administration for implementation at the federal level (A Better Balance, 2021; White House, 2021). These paid leave schemes have in common that workers earn paid leave credits which accumulate on individual accounts, leave can be taken when deemed necessary, and unused leave time accumulates over tenure with the employer.

Given the lack of research on employee behavior under these individualized leave-credit schemes, we ask three main research questions: First, how do employees use leave under these schemes? In particular, do employees use sick leave judiciously or inappropriately for the purpose of leisure? Second, as their leave balance grows, how much more likely is it that employees take leave? Third, does a higher balance decrease the likelihood of working while ill?

Our findings suggest that employees use sick leave primarily as intended. Sick leave use increases significantly when environmental hazards increase, for instance, during flu season. Further, there is no evidence that sick leave is used 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 entirely by the use of personal leave, which is allowable under district rules. There is no evidence that teachers "fake sick" to attend this event, nor is there evidence that teachers use sick leave following the Super Bowl or during University of Kentucky Men's basketball NCAA tournament games. 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.[36]

Next, we provide clear evidence that access to a larger leave balance increases leave use, which is in line with economic theory. The balance-use elasticity is positive, on average 0.45,

[36] 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).

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 taking unpaid leave. The likelihood to take a sick day increases discontinuously when moving from having 0-5 days vs. having 5-13 days, and then increases at a fixed rate over the remainder of the balance distribution.

Finally, we show that large leave balances can protect against presenteeism behavior. Working sick is notoriously difficult to measure as it is typically unobserved, while self-reports are inherently unreliable. Nevertheless, the negative externality inherent in presenteeism (that is, working sick with a contagious illness can result in spread of diseases to coworkers and general public) makes it a crucial policy variable of interest. Relying on daily administrative sick-leave data — similar data may be collected by public agencies and private firms and used by researchers in the future — we 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 balance 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.

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 schemes. 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. Under the current credit-based schemes, policymakers could 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.[37] As an example,

[37]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

consider the teachers in the school district we study. Were state or district administrators to offer first-time teachers a balance of, for example, forty days, but reduce their flow of leave over their next nine years of employment to ten days (as opposed to thirteen), teachers would receive the same amount of leave credits by year ten 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.

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 incentives to shirk. Second, Scott County is not a large community, meaning reputations are important and could encourage judicious leave use. These results may or may not look different in a larger MSA. Third, the leave granted to teachers is specifically for sick days, not vacation. Teachers are expected to take vacation days on school breaks (including winter break and summer break). The fact that these days are specifically for use in the case of illness is a positive feature for our analysis as it makes it much cleaner. However, in some leave schemes employees are granted "paid time off banks"(PTO) to use for vacation or illness as they see fit. Leave taking behavior may differ in PTO schemes where sick days and vacation days are not separated. 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.

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have to be earned or repaid over time. Either way, additional rules preventing employees from rapidly using all leave days prior to switching jobs or careers would likely be needed to prevent abuse.

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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: Testing for Judicious and Inappropriate Leave-Taking: Robustness

	(1)	(2)	(3)	(4)	(5)
Judicious Use					
ln(admits)	0.0094 ***	0.0109 ***	0.0100 ***		0.0148 ***
	(0.0023)	(0.0025)	(0.0028)		(0.0033)
ln(admits$_{t-5}$)			0.0028		
			(0.0025)		
ln(admits$_{t+5}$)			-0.0013		
			(0.0026)		
admits/100				0.0024 ***	
				(0.0008)	
Shirking					
Holiday					
day prior	-0.0045 ***	-0.0032 **	-0.0032 **	-0.0034 **	-0.0027
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0019)
day following	-0.0092 ***	-0.0044 ***	-0.0044 ***	-0.0045 ***	-0.0055 ***
	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0017)
Keeneland	0.0020	0.0011	0.0011	0.0012	0.0021
	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0021)
$\times$ Friday	0.0062 ***	0.0059 ***	0.0059 ***	0.0060 ***	0.0035
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0028)
UK Basketball	0.0042	0.0039	0.0041	0.0038	0.0010
	(0.0029)	(0.0028)	(0.0028)	(0.0028)	(0.0039)
Super Bowl Monday	0.0048	0.0065	0.0066	0.0069	0.0034
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0066)
Other					
Day of the week					
Monday	0.0086 ***	0.0076 ***	0.0076 ***	0.0077 ***	0.0081 ***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0015)
Tuesday	0.0020 **	0.0013 *	0.0013 *	0.0013 *	0.0014
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0011)
Thursday	0.0038 ***	0.0038 ***	0.0038 ***	0.0038 ***	0.0042 ***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0011)
Friday	0.0229 ***	0.0226 ***	0.0226 ***	0.0226 ***	0.0219 ***
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0018)
Experience	0.0062 **	0.0062 **	0.0062 **	0.0062 **	-0.0010
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0070)
Age	0.0029	0.0027	0.0027	0.0027	0.0036
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0035)
Month Fixed Effects	X				
Week Fixed Effects		X	X	X	X
Observations	790,615	790,615	790,615	790,615	395,634

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 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. Column (5) restricts the sample to teachers remaining in the district for the full eight years.

Table A3: Testing for Judicious and Inappropriate Leave-Taking: Heterogeneity

	Male	Female	Under 40	Over 40	Middle Years	First Year	Last Year
Judicious Use							
ln(admits)	0.0022	0.0108 ***	0.0079 **	0.0113 ***	0.0104 ***	0.0081	0.0044
	(0.0035)	(0.0027)	(0.0034)	(0.0030)	(0.0026)	(0.0059)	(0.0139)
Shirking							
Holiday							
day prior	-0.0047	-0.0045 ***	-0.0034 *	-0.0060 ***	-0.0034 **	-0.0077 ***	-0.0068
	(0.0031)	(0.0015)	(0.0019)	(0.0019)	(0.0015)	(0.0026)	(0.0068)
day following	-0.0072 ***	-0.0096 ***	-0.0092 ***	-0.0093 ***	-0.0092 ***	-0.0098 ***	-0.0092
	(0.0020)	(0.0013)	(0.0013)	(0.0018)	(0.0013)	(0.0022)	(0.0061)
Keeneland	0.0086 ***	0.0008	0.0022	0.0019	0.0028 *	0.0001	-0.0046
	(0.0029)	(0.0016)	(0.0018)	(0.0023)	(0.0016)	(0.0028)	(0.0079)
× Friday	0.0061	0.0063 ***	0.0078 ***	0.0042	0.0051 **	0.0067	0.0254 *
	(0.0050)	(0.0023)	(0.0027)	(0.0032)	(0.0023)	(0.0042)	(0.0137)
UK Basketball	0.0154 **	0.0020	0.0030	0.0058	0.0035	0.0070	-0.0003
	(0.0068)	(0.0032)	(0.0037)	(0.0046)	(0.0033)	(0.0063)	(0.0171)
Superbowl Monday	0.0042	0.0049	0.0049	0.0046	0.0047	0.0017	0.0437
	(0.0105)	(0.0051)	(0.0063)	(0.0066)	(0.0051)	(0.0087)	(0.0375)
Other							
Day of the week							
Monday	0.0083 ***	0.0086 ***	0.0086 ***	0.0085 ***	0.0081 ***	0.0102 ***	0.0113 **
	(0.0018)	(0.0011)	(0.0012)	(0.0016)	(0.0011)	(0.0018)	(0.0054)
Tuesday	0.0017	0.0020 **	0.0024 ***	0.0013	0.0013	0.0049 ***	-0.0029
	(0.0016)	(0.0009)	(0.0009)	(0.0012)	(0.0009)	(0.0016)	(0.0042)
Thursday	0.0041 ***	0.0038 ***	0.0038 ***	0.0038 ***	0.0036 ***	0.0046 ***	0.0050
	(0.0015)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0015)	(0.0040)
Friday	0.0277 ***	0.0220 ***	0.0228 ***	0.0231 ***	0.0223 ***	0.0252 ***	0.0316 ***
	(0.0031)	(0.0014)	(0.0014)	(0.0021)	(0.0014)	(0.0020)	(0.0061)
Experience	0.0097 *	0.0058 **	0.0097 ***	0.0062	0.0061 *	0.0025 ***	0.0100 ***
Age	-0.0094	0.0044	0.0139 *	0.0011	0.0012	0.0008	-0.0118
Socio-demographics	X	X	X	X	X	X	X
Month, year fixed effects	X	X	X	X	X	X	X
Teacher fixed effects	X	X	X	X	X		
Observations	130,058	660,557	448,153	342,462	608,246	165,486	25,081

Notes: KPSTD data. Observations are teachers-days (NT=790,615). 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 A4: Estimating the Balance-Use Elasticity: Robustness

	(1)	(2)	(3)	(4)
$\ln(\text{balance}_{i,t-10})$	0.027 ***	0.027 ***		0.023 ***
	(0.0018)	(0.0018)		(0.0023)
$\text{balance}_{i,t-10}/100$			0.061 ***	
			(0.015)	
Month Fixed Effects	X		X	X
Week Fixed Effects		X		
Continuously Employed				X
Observations	740,235	740,235	740,235	370,730

Notes: KPSTD data. Observations are teachers-days. Each column (1)-(4) is one regression as in equation (2). 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) limits the sample to teachers working continuously over our eight year sample.

Table A5: Estimating the Balance-Use Elasticity: Heterogeneity

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

Notes: KPSTD data. Observations are teachers-days (NT=790,615). 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.