Sick Pay Generosity, Sick Leave Behavior, and Contagious Diseases: Spillovers and Infections in Public Schools

Abstract

This paper makes use of unique administrative data on daily attendance and sick leave behavior of 982 Kentucky school teachers from 2010 to 2018. All teachers work under a standard U.S. teacher sick pay scheme that provides ten new sick days per school year. Unused sick days roll over to the next school year. To study the economic incentives imposed by this sick pay scheme, we link these administrative data to CDC data on flu activity at the state-week level. Exploiting variation in the timing and strength of flu activity along with within-teacher variation in sick day balance, we first show that teachers are 0.3% more likely to take a sick day when flu activity increases by 10% or 1 confirmed ILI case per 1000 patients. Next, we show that teachers are more likely to take a sick day when their personal sick day balance is higher—we estimate this elasticity at 0.5 during the flu season and at 0.3 outside the flu season. Next, we study the link between the number of available sick days and presenteeism (‘working sick’) behavior. Finally, we provide evidence for peer and group spillover effects in sick leave behavior. All findings together provide evidence that a more generous sick leave policy incentivizes teachers to call in sick, especially during times of high flu activity.

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

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

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1 Introduction

The United States is only one of three OECD countries that does not guarantee universal access to paid sick leave for all employees (Heymann et al., 2010). Over the past decade, however, twelve states and dozens of cities have passed bills that mandate access to paid sick leave for all or the majority of employees. In addition, the former Obama administration mandated that all federal employees as well as all contractors of the federal government must provide sick leave to their employees. Moreover, many public employees at the state or district level, such as public school teachers, have access to paid sick leave.

A key question in this timely and policy-relevant debate is how to optimally design such a social insurance system (cf. Chetty and Finkelstein, 2013; Lalive et al., 2015; Hendren, 2017; Johnston and Mas, 2018). One crucial element is to embed economic incentives to trade-off shirking and presenteeism behavior. That is, overly generous sick leave schemes will encourage healthy employees to shirk and call in sick when they would actually be able to work and be productive. On the other hand, a significant share of Americans work sick and, when contagious, spread diseases (Susser and Ziebarth, 2016; Stearns and White, 2018). U.S. states that mandated sick pay saw a significant decrease in influenza-like illness rates (Pichler and Ziebarth, 2017; Pichler et al., 2019). Moreover, a rich strand of research has documented that the sick leave labor supply elasticity is significantly different from zero. In other words: when employees gain access to sick leave, or when sick leave systems become more generous, they will call in sick significantly more often (De Paola et al., 2014; Ziebarth and Karlsson, 2014; Fevang et al., 2014, 2017; Pichler and Ziebarth, 2020).

While the much older European sick pay schemes rather resemble unemployment insurance schemes, U.S. sick pay schemes are typically individualized sick leave credit accounts where employees earn and accumulate sick leave hours through work and where unused days carrying over to the next year, similar to medical savings accounts (Pauly et al., 1995; Keeler et al., 1996; Schreyögg, 2004). Moreover, sick pay schemes for public school teachers often factor accumulated and unused sick days into retirement pensions. When local governments design such teacher sick pay schemes, they have to additionally weigh the fiscal long-term impact of

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higher pensions against the risk of spreading diseases within schools and providing education to minors. For example, in Illinois 70% of all retired teachers receive higher pensions as a result of unused sick days—the total costs just for these unused sick days accumulate to over one billion over a decade and contribute to the pressure on the state budget (Dabrowski and Klingner, 2017).

While economists have studied the educational impact of teacher absences, teacher strikes or snow days (Lavy, 2009; Belot and Webbink, 2010; Taylor and Tyler, 2012; Opper, 2019), to our knowledge, this paper is the first to study the economic incentives of public teacher sick pay schemes. To study their impact on individual teacher sick leave behavior as well as within-school spillovers to colleagues, we use administrative data at the daily level for 982 Kentucky school teachers from 2010 to 2018.

At the beginning of each school year, the sick pay scheme provides every full-time teacher with a balance of ten sick days, two personal, and one emergency day. We observe, at a daily level, when teachers take sick days and for what reason. Because we can identify schools, we are able to identify within-school, between colleague peer “spillover” effects in sick leave behavior. Such spillovers could either be a result of presenteeism behavior and infections, or peer effects that are unrelated to contagious diseases. Workplace peer effects in natural settings are extremely rare to observe at high resolution, simply because data that identify co-workers along with daily productivity measures are rarely available. (A notable exception is Mas and Moretti (2009) who use high-frequency data from a U.S. supermarket chain and provides evidence for positive productivity peer effects, attributed to social pressure.)

We enrich our administrative data with information on public holidays, school vacations, snow days, and, most importantly, official data from the Centers for Disease Control (CDC) on flu activity on the weekly level over nine years (Centers for Disease Control and Prevention, 2019). The flu data provide us with objective doctor-certified influenza-like illness (ILI) rates and allow us to exploit plausibly exogenous variation in flu activity. Because we rely on teacher panel data and as we observe the sick day balance of each teacher on each day over our period of observation, we additionally exploit within-teacher variation in the number of available sick days.

Our findings show that teachers are significantly more likely to call in sick during times of high flu activity. The probability to take a sick day increases by 0.3% when flu activity increases by 10% or 1 confirmed ILI case per 1000 patients. This finding yields first evidence that teachers
take sick days as intended when they carry contagious diseases (or when the risk of contracting them is highly elevated).

Moreover, in line with our priors, when their sick day balance is high, teachers are more willing to call in sick. Most importantly, this “balance-utilization elasticity” is significantly larger during the flu season than outside the flu season. Outside the flu season and conditional on rich seasonal, vacation, day-of-week as well as individual fixed effects, roughly five more sick days increase the likelihood to take a sick day by 2.6%. During the flu season, the relationship is almost twice as large. The balance-absenteeism elasticity provides evidence that teachers are more likely to take their sick days when the risk of contracting infectious diseases is high.

Next, we study the link between the available sick leave balance at the beginning of the school year and the likelihood that a teacher engages in presenteeism behavior, that is, works sick. As working sick is typically unobserved by researchers, one contribution of this paper is to leverage our high-frequency administrative data and provide novel measures of presenteeism behavior.

In the final part of the paper, we aggregate the data at the school-week level and study infection spillover effects within schools.

One policy implication of these findings is that, especially when flu activity is high, schools should provide teachers who have few available sick days with extra sick days to minimize presenteeism behavior among teachers and infections in schools.

The next section provides a brief overview of the different literatures related to this paper. Section 3 describes in detail our administrative school teacher data and the various additional data sources that we link to these data. Section 4 discusses the institutional details. Section 5 discusses our empirical approach and Section 6 presents our findings. Section 7 concludes.

2 Literature

At the most general level, this paper contributes to the economic literature on how to optimally design social insurance programs or mandate them (cf. Chetty, 2006, 2008; Chetty and Finkelstein, 2013; Hendren, 2017). For example, a rich literature on permanent work disability has studied the labor supply effects of marginally rejected disability insurance applicants, which
happen to be between 15 and 30 percentage points more likely to work when being denied benefits (Bound, 1989; Chen and van der Klaauw, 2008; von Wachter et al., 2011; Maestas et al., 2013; French and Song, 2014; Kostol and Mogstad, 2014). Other papers empirically identifies important spillover effects and externalities within social insurance schemes (Dahl et al., 2014).

At the most narrow level, this paper contributes to the relatively small but growing literature on U.S. sick leave. Only a few U.S.-based papers study the causal effects of gaining access to paid sick leave, however.\(^1\) One notable exception that pre-dates the current literature is Gilleskie (1998) who exploits 1987 MEPS data to structurally model work absence behavior and simulates the effects of alternative policies. According to Gilleskie (1998), about a quarter of all male employees would not take sick leave when ill. Susser and Ziebarth (2016) use the representative 2011 American Time Use Survey Leave Supplement to estimate that, in a given week of the year, two percent of U.S. employees—mostly low-income female employees—would work sick. In almost half of all cases, the reasons indicated for such presenteeism behavior were directly related to a lack of sick leave coverage. In line with this finding, Pichler and Ziebarth (2017) and Stearns and White (2018) provide empirical evidence that the recently implemented U.S. sick pay mandates have reduced presenteeism behavior and influenza-like-illness rates. The World Health Organization estimates that, worldwide, seasonal influenza is responsible for 3 to 5 million cases of severe illnesses and up to 650 thousand respiratory deaths per year (World Health Organization, 2019). A growing body of economic research studies how infections relate to human behavior, their socio-economic determinants, and the effectiveness of public policies (Ward, 2014; Adda, 2016; Schwandt, 2017; Carpenter and Lawler, 2019).

Also exploiting variation in the implementation of sick pay mandates, Pichler and Ziebarth (2020) use administrative data from the National Compensation Survey and the years 2010 to 2017 to show that mandates increase coverage rates by 13 percentage points and that employees who gain access to pay sick leave take two additional sick days per year.\(^2\) This finding is in line with unpublished work based on survey data (Ahn and Yelowitz, 2016; Callison and

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\(^1\)In addition to the causal effects literature, studies outside of economics investigate important correlations. DeRigne et al. (2016) report that employees without access to paid sick leave are more likely to forgo medical care. Peipins et al. (2012) find that, compared to employees with access to sick pay, those without access to sick pay are less likely to undergo mammographies, pap tests, and endoscopies at recommended intervals.

\(^2\) Colla et al. (2014) find that, in San Francisco, 73% of all firms offered sick pay voluntarily before the mandate in 2006, and that this share had increased to 91% by 2009. Hall et al. (2018) report that 30% of a representative set of employees in New York City were unaware of their recently enacted sick leave rights.

The European literature on sick leave is much older and richer: Consistent with recent findings from the U.S., one general conclusion is that employees take more sick days when sick leave becomes more generous, and vice versa (Johansson and Palme, 2005; Ziebarth and Karlsson, 2010, 2014; De Paola et al., 2014; Dale-Olsen, 2014; Fevang et al., 2014). Other papers on sick leave investigate the role of probation periods (Ichino and Riphahn, 2005), culture (Ichino and Maggi, 2000), gender (Ichino and Moretti, 2009; Gilleskie, 2010; Herrmann and Rockoff, 2012), income taxes (Dale-Olsen, 2013), union membership (Goerke and Pannenberg, 2015), and unemployment (Nordberg and Røed, 2009; Pichler, 2015). There is also research on the impact of sick leave on earnings (Sandy and Elliott, 2005; Markussen, 2012).

In addition to the discussed literatures, this paper also contributes to the rich literature on school production functions and teacher productivity (cf. Chetty et al., 2014). For example, Jackson and Bruegmann (2009) use elementary school teacher data and find that teachers’ students have better educational outcomes when their colleague is a more effective teacher. In a field experiment in India, Duflo et al. (2012) find that teacher monitoring by cameras and tying their salaries to attendance reduced their absence rate by 21 percentage points. And Jacob (2013) uses data on public school teachers in Chicago and finds that annual teacher absences decreased by 10% after dismissal protection was lowered—mostly due a change in teacher composition.

Finally, this paper contributes to the literature on social networks, social behavior, and peer effects (Becker, 1974; Charness and Rabin, 2002; Bénabou and Tirole, 2006; Gächter et al., 2013); and, in particular, peer effects at the workplace and in education systems.³ For example, Sacerdote (2001) exploits random college roommate assignment and finds strong evidence for peer effects in educational outcomes. Calvó-Armengol et al. (2009) develop a peer-effect equilib-

³The peer effects literature using lab or field experiments is richer. For example, Falk and Ichino (2006) ask participants to fill in letters into envelopes, where some pairs worked alone and others with a second participant in the same room. The find a higher productivity in the pair treatment; low productivity workers were more sensitive to their peer’s influence.
rium model and find—using friendship data from U.S. Add Health—statistically positive peer effect correlations in school performance. On the other hand, using social insurance data from the Munich metropolitan area, Cornelissen et al. (2017) find only small peer effects in wages. Exploiting the unexpected death of academic superstar scientists in the life sciences, Azoulay et al. (2010) find strong evidence for causally related decreases in colleagues’ publication productivity, whereas Waldinger (2012) and Guryan et al. (2009) find no evidence for peer effects in academic departments in Nazi Germany and in golf tournaments, respectively.

### 3 Data

This section describes the different data sources and how we merged them together. We also discuss the most important variables, how we cleaned and imputed missing values, and provide summary statistics.

#### 3.1 Kentucky Public School Teacher Data

Our main dataset is a unique administrative dataset from one county in Kentucky, henceforth called Kentucky Public School Teacher Data (KPSTD). It contains complete records of all school teachers employed by the counties or the state from school year 2010/2011 up to and including school year 2017/2018. That is, the database contains demographics, the hiring date of each teacher, her number of years working as a teacher in the state, the current salary, the job description and classification code, the base salary and the number of days worked for that base salary, and all bonus payments. Most important for our purposes, the database contains detailed information on when exactly teachers took sick, personal or emergency leave days and also provides us with the sick day balance of each teacher at every point in time. We also observe when teachers retire, die or switch jobs.

In a first step, we converted the data from the teacher-event level to the teacher-day level over all eight school years. Because we observe a total of 982 unique teachers and have an unbalanced panel with essentially no missings, our final sample has 1,014,997 teacher-workday observations.
Main variables of interest

Our main variables of interest stem from the administrative information related to absence spells. Specifically, we observe how many leave days teachers requested on a given day, and how many and which days specifically, they were on leave. (Note that teachers can also take partial days off, that is, half a day or a quarter day.) Moreover, we observe whether the day off was officially classified as a sick day, a personal day or an emergency day. In addition, we see the individual balance of unused days of paid leave at every single workday when the teacher was employed. Also, it should be noted that, while we precisely observe paid sick days taken (and paid leave in general), we can only approximate the number of unpaid leave days taken.

Panel C of Table A1 shows the summary statistic of our main variables of interest. As seen, the average Running balance is 46 days implying that teachers have accumulated on average 47 paid leave days over their tenure. However, this balance varies substantially from -41 to 348 days, depending on the seniority level and the annual leave days taken.

Over all workdays during the school year, teachers take sick days on 3.4% of them; they take each, personal and emergency days, on 0.3% of all work days. The longest recorded sickness spell counted 43 work days, but in most cases only involves a few days.

Next, we construct measures of presenteeism behavior. One structural challenge in research on presenteeism is the inherent difficulty to observe and identify presenteeism behavior, as workers appear to be healthy (as they work) but are, in fact, not. Self-reports on weather respondents went to work sick are useful but suffer from survey methodological challenges as respondents are framed (Schwarz, 1999; Johns and Miraglia, 2015). One contribution of this research is to use administrative data and observed employee behavior at the daily level to

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4 That is, we do not observe sick days during school vacations over the summer outside of the teaching schedule, on weekends or on national holidays.

5 Unpaid leave is a rare event. In case of prolonged illness, teachers usually use up their paid leave days and then stop working for the district as Kentucky runs no Temporary Disability Insurance (TDI) program or medical leave system. We observe XX teachers first taking their remaining sick leave days and then quitting jobs before the end of the semester. Moreover, we have information on “dock days”, but do not know the exact reason and the exact dates for those dock days (339 dock day cases over eight school years or 0.03%). We classify dock days as unpaid leave days by randomly assigning them among all possible workdays that lie between the indicated dock day incidence.

6 Negative balances appear because XXX.

7 Note that our data include the number of days requested on the first day of the leave spell as indicated by the records (up to 19, not shown). If the sickness duration was not foreseeable, it is indicated as several subsequent spells which we sum over to generate Total sickness spell (weekdays only).
generate presenteeism measures. Specifically, we define that a teacher engages in presenteeism behavior when she is at least partially observed working today but entirely called in sick yesterday and will entirely call in sick tomorrow. Although being an imperfect measure as it underestimates true presenteeism behavior, we believe that this Presenteeism outcome measure reliably identifies teachers who go to work sick with high statistical precision. As seen, according to this definition, on 0.8% of all work days teachers went to work sick; in total, these are 8120 presenteeim events.

Because our data include school identifiers, we create a variable that indicates the number of co-teachers in the same school who (i) were sick on a given work day (Peers sick, 1.5 on average and between 0 and 12.5), (ii) were to work sick on a given work day (Peers presenteeism, 0.3 on average and between 0 and 5). By aggregating at the school level and summing over all teachers in a given school, we also generate the rates of co-teachers who were sick (3.4%) or engaged in presenteeism behavior (0.8%) on a given day (Presenteeism rate and Sickness rate, respectively).

As mentioned, we also observe when teachers received donation from other teachers or donated leave days (each 0.1% of all days). Lastly, every time teachers earn days (for example, at the beginning of the school year or in case of donations), it is recorded in our data as a separate event.

Other Variables

Panel A and B of Table A1 show the summary statistics of the remaining variables from the KPSTD data. As seen, 83% of all teachers are women and only 1 and 2% Hispanic and black, respectively. Less than 0.5% are Asian. The average age is 40 but varies from 21 to 75 years.

The large majority of all teachers, 83% are classroom teachers; the other job categories indicate whether the person is the Dean of students (1.1%), a Gifted & Talented Instructor (0.7%), a Guidance Counselor (2.2%), a School Psychologist (1.6%) or a Preschool Classroom Instructor (1.9%), just to name a few. Ninety-eight percent of all teachers are full-time employed. The average annual base salary is $50,831; we also observe payments from other sources.
3.2 CDC Influenza Surveillance Report

Our secondary data source is the Weekly U.S. Influenza Surveillance Report (ISR) produced by the Centers for Disease Control and Prevention (2019). The CDC publishes the weekly ISRs to inform the public about current influenza activity in the United States. Participating providers in each state submit their official statistics about the number of outpatient visits for influenza-like-illness (ILI) and number of laboratory confirmed influenza tests to the CDC, whose Influenza Division then prepares and publishes the weekly statistics and reports. We export the weekly ILI activity for Kentucky from October 2010 to June 2018. Because influenza-associated hospitalizations and mortality only measure a fraction and the most severe cases of overall influenza activity, we focus on ILI outpatient visits. The main advantage of these data is that they are a comprehensive measure of influenza activity. We normalize the number of medically attested ILI cases by the number of total patients seen for any reason among participating outpatient healthcare providers as reported by the states.

As shown in Panel D of Table A1, between 5 and 40 participating outpatient healthcare providers have provided data in a given week in Kentucky; these providers had between 1,034 and 27,934 patients in a given week and reported between 1 and 1277 confirmed ILI cases (Centers for Disease Control and Prevention, 2019). When normalizing, we count 10 ILI cases per 1000 patients. Due to the seasonality in influenza activity, the mean of ILI Cases per 1000 Patients varies from 0 to 123 cases per 1000 patients.

3.3 Additional Data

In addition to KPSTD and the ISR data, we manually collect and merge in information on school vacations, national holidays, and school closures, for example due to snow days or weather related events. Panel D of Table A1 shows that 82% of all days were school days, whereas 1% were “non-traditional” days, and 3.5% weather-related cancellations.

Because it has been well documented that sick leave behavior varies over the business cycle (Pichler, 2015), we also collect (seasonally adjusted) data on the state-level unemployment rate by month of the year as reported by the Bureau of Labor Statistics (2019). In Kentucky over our time period, the unemployment rate varied between 4 and 10% (Panel E of Table A1).

8ILI are when the patient presented with a fever (temperature of 100°F or greater) and a cough and/or sore throat—and with no other known cause of illness other than influenza.
9ISR data prior to October 2010 are not available in a consistently collected format.
Figure 1: Distribution of ILI Cases per 1000 Patients

Notes: Own calculation, own illustration. Figure 1a shows a simple histogram of ILI Cases per 1000 Patients, whereas Figure 2b plots ILI Cases per 1000 Patients relative to the week before the peak of the flu season, which is indicated through the vertical solid line.

4 Institutional Background

This section briefly discusses the institutional regulations of the Kentucky public school teacher paid leave system. The scheme is very similar to paid leave schemes for public teachers throughout the United States (cf. National Council on Teacher Quality, 2012). It should be
noted that Kentucky runs no public Temporary Disability (TDI) Insurance 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.\textsuperscript{10}

\section*{4.1 Paid (Sick) Leave Scheme for Kentucky School Teachers}

While each public school district can determine specifics of its sick leave policy, the state of Kentucky provides a general framework and standard which can be found in \textit{Kentucky Legislative Research Commission} (2019). For example, teachers have the right to earn a minimum of ten sick days per school year; districts must allow teachers to accumulate unused sick days without limit.

In the county that we focus on, each teacher earns ten sick days per school year. These personalized sick days are recorded on an individual account and can be taken in case of sickness. Unused days accumulate and roll over to the next school and calendar year. When taken, the sick days are fully paid. In addition, at the beginning of every school year, each teacher earns three personal and emergency days, which can be taken in case of an emergency or for personal use. If these days are not used by the end of the school year, they convert to accumulated sick days and increase the individual sick day balance.

When teachers switch schools within the state of Kentucky but between Kentucky counties, the sick leave balance is transferable. We observe such cases in our data. However, when teachers transfer from another state, their balance is usually not transferable. The same is true when teachers switch between the private sector and public sector teacher jobs.\textsuperscript{11}

Teachers can also take partial sick or personal days, for example, when a sickness kicks in after noon or when the own child becomes sick and has to be picked up at kindergarten. We observe in our dataset whether partial sick days were taken. Also note that teachers have the possibility to donate sick days to other teachers with a low balance. We observe these donations in our data and who donates as well as who is receiving the donation.

\textsuperscript{10}In principal, 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 (Cornell Law School, 2019).

\textsuperscript{11}We observe $X$ case of within-state transfers of teachers and $x$ cases where teachers transferred from other states or the private sector and their sick day balance was transferable.
4.2 Unused Sick Days and Retirement

Teachers who do not use their sick and personal days will have a higher retirement pension. The reason is that, upon retirement, teachers will receive 30% of their unused sick days, given their current daily wage, as a lump sum payment. The amount of unused sick pays that factor into this lump sum payment, however, is capped at 300 unused days.\footnote{This holds for teachers who entered the school district after June 30, 2008. For teachers who entered earlier, there is no cap. In our data, XXX teachers entered before June 30, 2008.}

In addition, because the 30% lump sum payment increase teachers’ income in the last year before retirement, it increases retirement pensions. Specifically, the annual retirement income ($R_i$) is the product of income ($I_i$), years of service ($S_i$) and a multiplier ($M_i$): $R_i = I_i \times S_i \times M_i$. The multiplier is essentially 2.5% for every year of service, slightly higher for teachers with more than 30 years of service and slightly lower for teachers with less than 10 years of service and teachers who entered the district after June 30, 2008.\footnote{Specifically, if someone exceeds 30 years of service, she gets 2.5% for the first 30 years and 3% for each year thereafter. That is, after 40 years of service $I_i \times S_i$ would be $30 \times 0.025 + 10 \times 0.03 = 1.05$.}

The income ($I_i$) is the average income in the three highest earning years of service for those who retire after the age of 55 and have at least 27 years of service (which is basically everyone). Because this calculation uses nominal income and because income increases in age and years of service, the highest paying service years are usually the final years before retirement, especially when 30% of unused sick days are added in.

As a back-of-the-envelope example, the daily gross wage for the teachers in our sample is about $400. A third of that amount, $120, will be payed out as a lump sum at retirement when a sick day is unused. Moreover, these $120 will be factored into the calculation for retirement benefits which is a function of the average income over the past three years. With 30 years of service, we get $120/3 \times 30 \times 0.025 = $30 higher gross pension per unused sick day until death.

However, a teacher is only eligible to receive a pension without penalties after 27 years of service or at age 60. After a minimum of 10 years of service one can retire from age 55 but each year under the age of 60 will be penalized with a 6% discount.\footnote{The latter is true for teachers who entered after June 30, 2008. For teachers who entered before, the minimum years of service are 5 years and the discount is 5%.
Figure 2: Illustration of Kentucky Teacher Retirement Scheme

![Graph showing first year retirement income and maximum retirement income by starting age and experience.]

Notes: Own calculation, own illustration.

Figure 2 illustrates pensions in the first year of retirement (Figure 2a) as well as the maximum pension (Figure 2b) by starting age and years of service. (Note that these pension schemes hold for teachers who entered before July 1, 2008 which is the large majority in our sample.) As seen in Figure 2, the amount of the first and also the maximum pension linearly increases in the number of service years and is higher, the earlier the starting age. For example, a teacher who started at the age of 50 solely has to work for 5 years to be eligible for a very small pension. By contrast, a teacher who started at the age of 22 is only eligible after 27 years of service, which could be as early as age 49 (Figure 2a).

5 Empirical Approach

5.1 Relationship between Flu Activity and Sick Leave Behavior

To provide evidence on how flu activity affects the likelihood of taking a sick day, in a first step, we estimate the following binned regression:

\[ y_{it} = \alpha + \kappa_j \sum_{j=1}^{9} Flu_{ij} + \gamma_k \sum_{k=11}^{20} Flu_{ik} + \theta Z_t + \delta_i + \zeta_i + \epsilon_{it} \]  

(1)

where \( y_{it} \) stands for our main outcome variable, whether teacher \( i \) took a paid sick day on day \( t \). The main regressors of interest are bins that cut the continuous ILI Cases per 1000
Patients measure in week-of-year \( w \) into 20 equally sized vintiles. We omit the tenth bin and use it as reference category and plot the other 19 coefficients of interest, \( \sum_{j=1}^{9} Flu_w + \sum_{k=11}^{20} Flu_w. \)

\( \delta_t \) is a vector of time controls and contains day-of-week, month and year fixed effects. These control for seasonalities and differences across years in flu activity. Moreover, we control for individual teacher fixed effects \( \xi_i \). Finally, we include a vector of controls that vary at the daily level, \( Z_t \), and indicate, for example, non-traditional days, snow days as well as the opening and closing days of the semester. Our standard model clusters standard errors, \( \epsilon_{it} \), at the flu activity level.

In a second step, we collapse the flu activity vintiles again to one continuous indicator, \( Flu_w \). We also add time-variant individual-level control variables, \( X_{it} \), as listed in Panels A and B of Table A1, and run the following regression model:

\[
y_{it} = \alpha + \phi Flu_w + \rho X_{it} + \theta Z_t + \delta_i + \xi_i + \epsilon_{it}
\]

### 5.2 Relationship between Sick Day Balance and Sick Leave Behavior

To provide evidence on how sick pay generosity affects the likelihood to take a sick day, similar to above, we estimate the following binned regression. We run these models separately for time periods with high and low flu activity:

\[
y_{it} = \alpha + \kappa_j \sum_{j=2}^{20} Balance_{i(t-5)} + \theta Z_t + \delta_i + \xi_i + \epsilon_{it}
\]

where all variables are defined as in Equation (1) except for the main regressors of interest, which are now ventile bins of the sick day balance five work days before at the individual-level. Here, we use the lowest vintile as the reference category and and plot the other 19 coefficients of interest, \( \sum_{j=2}^{20} Balance_{i(t-5)} \).

In a second step, again, as above, we collapse the vintiles to one continuous regressor indicating the sick day balance of the previous week, \( Balance_{i(t-5)} \). As seen, the model also controls for time-variant individual-level control variables, \( X_{it} \).
\[ y_{it} = \alpha + \phi Balance_{i(t-5)} + \rho X_{it} + \theta Z_{i} + \delta_{i} + \xi_{i} + \epsilon_{it} \] (4)

In a second step, we run the same models as in Equations (3) and (4), but use Presenteeism as outcome variable.

5.3 Presenteeism and Infection Spillovers at the School Level

Finally, as we can identify peers at the workplace within schools, we provide evidence on peer presenteeism behavior and related infections at the school level. To do so, we aggregate the data at the school-week level and leverage our two variables Presenteeism rate and Sickness rate, indicating the weekly share of teachers who went to work sick and the weekly share of teachers who called in sick. Then, we estimate a regression with the Presenteeism rate in leads and lags of ten weeks.

\[ Y_{sw} = \alpha + \kappa_j \sum_{j=-10}^{10} \text{Presenteeism}_{sw} + \gamma_k \sum_{k=+1}^{10} \text{Presenteeism}_{sw} + \theta Z_{sw} + \delta_{y} + \xi_{s} + \epsilon_{sw} \] (5)

where \( Y_{sw} \) stands for the share of sick teachers in school \( s \) during week \( w \). The main regressors of interest are the ten leads and then ten lags of the continuous Presenteeism rate in week-of-year \( w \) in school \( s \). \( \xi_{s} \) controls for school fixed effects, \( \delta_{y} \) controls for year fixed effects, and \( Z_{sw} \), indicates whether the week contained any unusual school days, like opening or closing days. As before, we also run simple models with one single continuous regressor Presenteeism_{sw}.

5.4 Identification Assumptions

The models in Equations (1) and (2) elicit the causal impact of flu activity on teachers’ sick leave behavior, as long as the variation in weekly flu activity is not correlated with the error term and the outcome variable through unobservables. Also, an individual teacher’s sick leave behavior should not have a statistically relevant impact on the flu rate in the state. A priori, there is no
reason to believe that either of these two conditions would be violated, especially because the models include rich sets of teacher fixed effects as well as seasonal fixed effects.

These rich fixed effects are also very helpful in Equations (3) and (4) to ensure that, for example, time-invariant individual-level unobservables, such as preferences for work or a general inclination to call in sick, are netted out. Recall that the sick leave balance, our main regressor in these models, is a clearly deterministic function of teachers’ seniority levels as well as the time within the school year and previous sick leave behavior. As we condition on rich sets of observables such as the type of job, occupation, age and experience of teacher, we control for the main deterministic driving forces of the sick day balance, along with the general inclination to take a sick day through teacher fixed effects. Moreover, because we always link the sick day balance of the previous workweek to sick leave behavior in the current workweek, we can exclude that reverse causality could be an issue.

Finally, when we aggregate the data up to the school-week level and control for school and year fixed effects, we test for general statistical links between the school’s presenteeism rate and its sickness rate in subsequent weeks of the year. Here, we do not claim to identify causal effects in a strict statistical sense, as it is well possible that third unobserved factors are correlated with both, the presenteeism rate today and the sickness rate in subsequent weeks. However, we will argue that the statistical pattern are consistent with infection rate spillovers through peer effects at the workplace.

6 Results

The results section follows the structure of the previous section. First, we will provide evidence on how variation in flu activity in a given week of the year affects the probability to take a sick day among public school teachers in Kentucky. Next, we will provide evidence on the relevance of available sick days for the decision to call in sick or go to work sick. Finally, we will aggregate the data at the school-week level to provide evidence on how workplace cultures may induce peer effects and intertemporal spillovers, such as higher sickness rates after elevated presenteeism rates at the workplace.
6.1 Relationship between Flu Activity and Sick Leave Behavior

Our very first step is to nonparametrically plot the association between flu activity and sickness rates at the weekly level. Figure 3 plots *ILI Cases per 1000 Patients* on the x-axis and the share of sick days among all teachers in the KPSTD. The scatter dots are overlaid with a kernel smoothing plot, where the grey area depicts the 95% confidence interval.

![Figure 3: ILI Cases per 1000 Patients and Sick Days Taken](image)

Notes: Own calculation, own illustration. The x-axis shows the number of ILI cases per 1000 Patients and the y-axis shows the share of sick days taken in the same week of the year. The smoothed dotted line shows a nonparametric kernel-weighted local polynomial cubic regression, where the grey area depicts the 95% confidence interval.

As seen, the statistical association is highly nonlinear. Between 0 and about 20 ILI cases per 1000 patients, we observe a clear, albeit noisy, increase in the sickness rate from about 2 to 3%. Then, the sickness rate decreases before it increases again up to an ILI rate of 50. Values about 50 are very rare but the ones that we observe rather show a negative statistical link with the sick leave rate in a cross-sectional perspective. Note that, although providing a first glance, Figure
is purely descriptive and does not net out seasonal or teacher-specific factors that could be correlated with both, the sickness and ILI rate.

To net such factors out, we estimate the regression model in Equation (1) at the teacher-workday level. Here we control for seasonal and teacher fixed effects as well as job-specific factors and time-variant controls at the school and teacher level. Figure 4 then plots the 20 flu severity vintile coefficients, where vintile 10—the median—is the reference category. The x-axis shows the vintiles and the y-axis the probability to take a sick day.

Left to the median, the point estimates and their confidence intervals largely include the zero line indicating no clear statistical link between flu activity and sick leave behavior. However, right to vintile 10—indicating ILI rates above 4.3 positive cases per 1000 patients—we observe positive, statistically significant, and upward trending coefficient estimates.

Figure 4: ILI Cases per 1000 Patients and Sick Days Taken II

Notes: Own calculation, own illustration. The figure plots the coefficients of a linear regression of the probability to take a sick day (dependent variable) on the flu severity vintiles, controlling for age, gender, job attributes, week-of-year, year and individual fixed effects as in Equation (1).

In a next step, we collapse the binned ILI rate vintiles to one continuous indicator and estimate a model like in Equation (2). Table 1 shows the results, where each column represents one regression model and sets of controls are added from the leftmost to the rightmost column. The model solely uses variation in the logarithm of the continuous ILI rate as the main regressor.
Table 1: Impact of Flu Activity on Likelihood to Take Sick Day

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<td>0.0010**</td>
<td>0.0010**</td>
<td>0.0010**</td>
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<td>(0.0004)</td>
<td>(0.0004)</td>
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* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the teacher level.

Data are at the teacher-workday level. The descriptive statistics are in the Appendix (Table A1). Each column represents one model as in Equation (1), estimated by OLS. The dependent variable indicates whether the teacher called in sick on a given school day, see Section 3.

of interest. Hence, the point estimates indicate the \((\phi/100)\) change in the sickness probability when flu activity increases by 1%.

The point estimates from Table 1 let us conclude: First, the link between flu activity and sick leave is significant at the 5% level in all four models. Second, while controlling for snow days and other non-traditional school days increases the point estimates slightly, overall, the estimates are very robust to controlling for time-varying teacher-specific characteristics. Third, the point estimates suggest that a 10% increase in flu activity (1 additional confirmed ILI case per 1000 patients) increases the probability to take a sick day by 0.0001 percentage points or 0.3% relative to the mean of 0.034 (Figure A1). In other words, when the flu activity doubles, which is regularly the case as illustrated by the long right tail in Figure 1—for example, when
moving from vintile 10 to vintile 14 in Figure 4, it triggers about 28 additional sick days among the 982 teachers in our dataset. (As a comparison moving from the median flu activity to vintile is a tenfold increase equal to an individual-level increase in the likelihood to take a sick day by 30%.) We interpret this statistical link as evidence that teachers take sick days as intended, namely more so, the higher the flu activity and the higher the risk of infecting others.

Finally, the day-of-week regressors in Table 1 show that, over the course of a workweek, the likelihood to call in sick follows a U-shaped pattern: it is significantly lower on Tuesdays, Wednesdays and Thursdays as compared to Mondays and Fridays. Note that this pattern has been well documented in the literature and does not necessarily imply shirking behavior (Card and McCall, 1996).

6.2 Relationship between Sick Day Balance and Sick Leave Behavior

Next, we test for the importance of the individual sick day balance for teachers’ inclination to call in sick. In other words, we ask ourselves how much the generosity of the sick pay scheme matters for the decision to work sick or call in sick. In Europe, where sick pay schemes have the design of unemployment insurance schemes, studies have estimated a labor supply elasticity of around one with respect to the replacement rate (cf. Ziebarth and Karlsson, 2014; Böckerman et al., 2018). U.S. based studies find that employees take more sick days when they gain access to sick leave coverage (Callison and Pesko, 2017; Maclean et al., 2020). However, to our knowledge, this paper is the first to test for the relationship between individual sick leave balances and sick leave behavior on the intensive margin.

In a first step, as above, we run a binned regression as in Equation (3) separately for weeks with high and low flu activity, respectively. Figure 5 then plots the two sets of vintile coefficient estimates $\kappa_j$ with $\sum_{j=2}^{20}$ along with 95% confidence intervals. We observe the following:

First, during and outside the flu season, there is a clear and positive link between the number of available sick days in a teacher’s sick leave account and her likelihood to call in sick in the subsequent work week. Relative to the lowest sick day balance vintile, which ranges up to 3 available sick days, this probability increases particularly between vintiles two (5.4 sick days on average) and four (11.4 sick days).

Second, during the flu season, this relationship is much stronger over almost the entire sick day balance distribution. This finding shows that teachers are significantly more likely to call in
Notes: The figure plots the coefficients of a linear regression of the probability to take a sick day (dependent variable) on the individual-level sick day balance vintiles of the previous week, controlling for age, gender, job attributes, week-of-year, year and individual fixed effects as in Equation (3). The models are separately estimated for weeks with high and low ILI activity rates.

sick when the spread of infections is high and precaution to infect others or be infected is very much desired from a public health perspective. As expected, the “sick leave balance—sick leave behavior” link matters more for teachers in the left tail of the sick day balance distribution; that is, for those with very few sick days.

Third, outside the flu season, the balance-behavior elasticity also increases in the right tail of the balance distribution (which is not the case during the flu season). In other words, for high balance vintiles, sick leave behavior inside and outside the flu season converges as seen in Figure 5. For a balance of more than 66 sick days in vintile 16, sick leave behavior become indistinguishable between times of high and low flu activity. This may hint at possible moral hazard effects among teachers with very high accumulated balances and is in line with the institutional fact that unused sick days become worthless for retirement beyond the cap of 300 total days (see Section 4).
Table 2: Impact of Sick Day Balance on Likelihood to Take Sick Day, by Flu Season

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<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
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<td>Log Sick Day Balance Last Week</td>
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<td>0.0088***</td>
<td>0.0089***</td>
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<td>(0.0014)</td>
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<td>(0.0014)</td>
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<td>Individual FE</td>
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<td>X</td>
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<td>DoW, Month, Year FE</td>
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<td>Vacation, Holiday, Snowday etc.</td>
<td>X</td>
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* p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the teacher level. The descriptive statistics are in the Appendix (Table A1). Each column represents one model as in equation (4), estimated by OLS separately for weeks without (Columns [1] to [4]) and with flu activity (Columns [5] to [8]). The main variable of interest is the logarithm of the number of available sick days five work days ago.
Table 2 shows regression point estimates mirroring what we see in Figure 5. We collapsed the balance vintiles to one main continuous regressor of interest and run models like in Equation (4). Each column stands for one model where the first four columns estimate effects for low flu activity times and the last four columns estimate effects for high flu activity times. Covariates are added from column (1) to (4) and (5) to (8).

The findings show, first of all, again very robust point estimates that do not change a lot when adding control variables. Second, all eight estimates are highly significant. Third, in line with Figure 5, the point estimates for flu season weeks are twice as large in size as the point estimates for weeks outside the flu season. While, during the flu season, an increase in the sick day balance by 10% (about one day relative to the mean of 9.8 days) increases the probability to take a sick day by 0.16 percentage points or 4.7%, it only increases the probability to take a sick day by 0.09 percentage points or 2.6% outside the flu season.

In a next step, we examine the importance of the individual sick day balance for teachers’ inclination to go to work sick and engage in ‘presenteeism behavior.’ Presenteeism behavior is highly undesirable from a public health perspective and contributes to the spread of contagious diseases. The CDC provides guidance for preventing the spread of seasonal flu at the workplace and urges workers with flu symptoms to call in sick and avoid human contact other than with health care workers. Moreover, they recommend to stay at home for at least 24 hours after the fever is gone (Centers for Disease Control and Prevention, 2020a,b).

As discussed in Section 3.1, it is one contribution of this paper to measure presenteeism based on daily administrative attendance data. Methodologically, we first run a regression of our presenteeism measure on sick leave balance vintiles, controlling for rich sets of teacher characteristics and fixed effects as shown in Equation (3). As above, we run these regressions separately for weeks with high and low flu activity. After that, we collapse the sick leave balance vintiles and use solely one continuous sick day balance variable as regressor of interest.

To be conducted until conference.

6.3 Evidence on Within-School Spillovers and Teacher Presenteeism

In the final part of the empirical analysis, we intend to provide evidence on peer spillover effects at the workplace. As our data are powerful enough to not only record daily attendance
and sick leave behavior but also identify schools and thus peers at the workplace, we collapse the data at the school-week level and obtain 5,705 observations for 17 different schools.

Figure 6: Variation in Presenteeism Rate across Schools

Notes: Own calculation, own illustration. The figure plots the average sick day balance at the school-week level by schools.
Figure 7: Variation in Sickness Rates across Schools

Notes: Own calculation, own illustration. The figure plots the average sick day balance at the school-week level by schools.
7 Conclusion

To the best of our knowledge, this paper is the first to study the economic incentives of public school teacher sick leave programs in the United States. We rely on unique administrative daily work absence and presence data of 982 Kentucky school teachers over 9 school years, which we link to officially reported flu rates at the state-week level. These data allow us to generate precise work attendance, sick leave and presenteeism indicators that we observe at the individual level. Moreover, because we can identify schools we are able to identify peers at the workplace and test whether workplace cultures of working sick have intertemporal consequences through higher infection rates which we indirectly identify.

Our basic findings show, first, that higher flu activity increases the likelihood that teachers call in sick. Although this finding does not exclude the possibility that teachers shirk, it is consistent with the notion that teachers take sick days as intended, namely at higher statistical rates when the exogenous risk of infections increases.

Second, we test for the relevance of available sick days in the individualized sick day credit accounts for the decision to call in sick or go to work sick. Our findings elicit statistically significant balance-absenteeism and balance-presenteeism elasticities. Specifically, conditional on rich teacher fixed effects, seasonal fixed effects and teacher as well as school characteristics, XXX To be conducted until conference.

Third, we identify peers at the workplace and aggregate the data at the week-school level. This allows us to show that XXX To be conducted until conference.

Overall, our findings imply that mechanisms to provide teachers with low sick day balances with additional sick days would reduce the risk for those teachers of working sick and their peers to be infected. Naturally, and also supported by our data, such tools would be even more effective during flu seasons and when the risk of spreading diseases is particularly high. Relevant future extensions of our work could test for the role of sick children and their parents’ sick pay coverage as a driving force for the spread of infectious diseases in school settings. The impact on schooling outcomes would also be natural and highly policy relevant extensions.
References


DeRigne, L., P. Stoddard-Dare, and L. Quinn (2016). Workers without paid sick leave less likely to take time off for illness or injury compared to those with paid sick leave. *Health Affairs* **35**(3), 520–527.


### A. Socio-Demographics

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### C. Sick Leave and Paid Leave

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### D. Flu Activity

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<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>ILI outpatient cases</td>
<td>136.82</td>
<td>226.57</td>
<td>1</td>
<td>1277</td>
<td>1,014,997</td>
</tr>
<tr>
<td>Number providers</td>
<td>17.523</td>
<td>8.5513</td>
<td>5</td>
<td>40</td>
<td>1,014,997</td>
</tr>
<tr>
<td>Total patients</td>
<td>16,283</td>
<td>6,455</td>
<td>1,034</td>
<td>27,934</td>
<td>1,014,997</td>
</tr>
<tr>
<td>ILI cases per 1000 patients</td>
<td>9.84</td>
<td>19.34</td>
<td>0.04</td>
<td>122.93</td>
<td>1,014,997</td>
</tr>
</tbody>
</table>

### D. School Days

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weather Cancellation</td>
<td>0.0351</td>
<td>0.1841</td>
<td>0</td>
<td>1</td>
<td>1,014,997</td>
</tr>
<tr>
<td>Opening day</td>
<td>0.0023</td>
<td>0.0479</td>
<td>0</td>
<td>1</td>
<td>1,014,997</td>
</tr>
<tr>
<td>Closing day</td>
<td>0.004</td>
<td>0.0629</td>
<td>0</td>
<td>1</td>
<td>1,014,997</td>
</tr>
<tr>
<td>School Day indicator</td>
<td>0.8153</td>
<td>0.3881</td>
<td>0</td>
<td>1</td>
<td>1,014,997</td>
</tr>
<tr>
<td>Non-traditional</td>
<td>0.0071</td>
<td>0.0843</td>
<td>0</td>
<td>1</td>
<td>1,014,997</td>
</tr>
</tbody>
</table>

### E. Other external data

<table>
<thead>
<tr>
<th></th>
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<th>SD</th>
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<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seasonal adj. unemployment</td>
<td>6.6162</td>
<td>1.7987</td>
<td>4</td>
<td>10</td>
<td>1,014,997</td>
</tr>
</tbody>
</table>

Authors’ calculations and illustration. Data sources are the Kentucky Public School Teacher Data linked to information from the CDC Weekly Influenza Surveillance Report, and the Bureau of Labor Statistics (2019). Data are at the weekday-teacher level and exclude weekends and days outside the school year. Classroom teacher indicates a classroom or ‘exceptional child instructor.’ School day indicates a regular school day, whereas Opening day and Closing day indicate the beginning and end of a semester and Non-traditional an irregular school day. Weather Cancellation indicates canceled school days due to weather. See Section 3 for a detailed discussion of the variables.