Work Disruption, Worker Health and Productivity: Evidence from Teaching

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Abstract

We use data from New York City to examine the impact of work disruptions and worker health on productivity in teaching, as measured by student achievement. Extended work disruptions due to leaves of absence and mid-year resignations have large negative effects on math and English achievement, roughly equivalent to moving from the 50th to the 30th percentile of the teacher quality distribution, or substituting a novice teacher for a teacher with four years of experience. Work disruptions due to daily absences also have significant negative effects, though to a smaller degree. Additionally, we use the timing of student tests to separately identify the impact of worker health, above and beyond any relationship it bears with work disruption. Specifically, we find student achievement is significantly lower when work disruptions caused by health shocks occur after students have already been tested. No effects are found for work disruptions that occur after exams for reasons other than health shocks.

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Recent estimates suggest that about two percent of work time in the U.S. is lost annually due to worker absence, the vast majority of which is caused by poor worker health (Bureau of Labor Statistics, 2008a). Worker absence can have important disruptive effects on production, as labor inputs are unlikely to be perfectly substitutable and contracts are unlikely to require workers to compensate employers fully if they are absent. However, few studies convincingly demonstrate the impact of work disruption on labor productivity.[1]

Moreover, many worker health shocks may not result in absence but still significantly reduce productivity. While a large body of literature examines the links between worker health and wages, earnings, labor force participation, and education (see Currie and Madrian (1999), Smith (1999), Currie (2009)), there has been far less work on the impact of worker health on worker productivity, particularly in developed countries such as the U.S.[2] While a literature in social psychology exists on the impact of health on productivity at work (dubbed "presenteeism"), these analyses use cross-sectional data and self-reported measures of productivity (e.g., Goetzel et al. (2004), Pauly et al. (2008)). Our study aims to begin to fill this gap through a careful analysis of the impact of work disruptions and worker health on the productivity of public school teachers.

In addition to being one of the largest occupations in the U.S., teaching is an attractive setting in which to study these issues. A substantial body of research documents a sizeable impact of teacher quality on students' academic achievement.[3] These studies have generally

[1] The only recent examples we have found are Krueger and Mas (2004) and Mas (2008), who present convincing evidence on the productivity impacts of work disruption caused by labor disputes at the tire manufacturer Bridgestone/Firestone and the construction equipment manufacturer Caterpillar.

[2] Strauss and Thomas (1998) cite several experimental studies from the 1970s on worker health and worker productivity among agricultural workers in developing countries.

[3] See, for example, Rockoff (2004), Rivkin et al. (2005), and Aaronson et al. (2008). While there is some debate regarding estimation of causal impacts of teachers on students (see Kane and Staiger (2008) and Rothstein (forthcoming)), our identifying assumptions—which concern variation within teachers—are much weaker than those needed to identify variation in instructional quality between teachers.

assumed teachers work continuously over the school year, but, in practice, nearly all teachers are absent at some point each year, and a significant fraction take extended periods of leave due to health shocks. A substitute teacher will be present in the classroom during periods of work disruption, but he or she may provide lower quality instruction. Finally, while lost work time due to absence is roughly the same for teachers as for all workers nationwide (Bureau of Labor Statistics, 2008b), there is evidence that school teachers show up to work despite health problems more frequently than workers in other occupations (Aronsson and Dallner (2000)).

In this paper, we use detailed panel data on teachers and students in New York City that contains precise information on the timing and causes of work disruptions in teaching. By disruption, we mean any period of time when a student's regularly assigned teacher is absent, either for a single day or for an extended period of time, or a teacher's departure during the school year. In order to separately identify the impacts of work disruption and worker health, we take advantage of the timing of student exams, which are taken several months prior to the end of the school year. Work disruptions that occur after students have taken their exams cannot have a causal effect on test scores via work disruption. However, disruptions due to serious health conditions are likely to bear a relationship with worker productivity prior to exams via correlation with prior health status. In contrast, work disruptions for reasons other than teacher health that occur after exams should have no impact on test scores.

A general concern in studies of the impact of teachers on students is that observable teacher characteristics are correlated with important omitted variables. For instance, teachers who are absent less often may also work harder outside of the classroom and be more effective in general. For this reason, we control for teacher fixed effects, thereby estimating the impact of work disruptions and health shocks by comparing teacher productivity across years among students assigned to the same teacher. Additionally, we control for a wide set of observable student characteristics, including students' prior achievement.

We find clear evidence that work disruptions in teaching have a negative and statistically significant impact on student achievement. We estimate that an extended work disruption prior to student exams causes student achievement to fall by 0.06 and 0.03 standard deviations in math and English, respectively. These effects are roughly equivalent to moving from the 50th to the 30th percentile of the teacher quality distribution, or substituting a novice teacher for a teacher with four years of experience.[4] We also estimate that an additional 10 teacher absences prior to student examinations reduce achievement by 0.014 and 0.007 standard deviations in math and English, respectively.[5]

We also find strong support for the importance of teacher health in determining productivity. Specifically, student achievement in math falls by 0.09 and 0.06 standard deviations, respectively, when teachers go on medical or maternity leave after the exam, and there is a significant negative relationship between student achievement and teacher absences after the exam for illnesses that are certified by a doctor. Extended disruptions and daily absences occurring after the exam for other reasons are not significantly related to student achievement, supporting the interpretation that teacher health issues have important causal impacts on student learning, above and beyond the effects of work disruption.

In Section 2 we describe the data and provide descriptive statistics, and in Section 3 we describe our methodology and present our empirical estimates. Section 4 concludes.

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[4] Estimates of the variation in teacher quality and returns to experience are based on an analysis of New York City data by Kane et al. (2008). Note that their analysis excludes teachers with an extended work disruption.

[5] A number of previous papers investigate the impact of teacher absence. Two recent studies (Miller et al. (2008), Clotfelter et al. (2009)) that use a teacher fixed effects approach find estimates similar to ours: 10 additional teacher absences reduce student achievement in math by 0.017 to 0.033 standard deviations. There is also a considerable literature on teacher absences in developing countries (e.g., Chaudhury et al. (2006), Duflo and Hanna (2005)).

2. Data and Descriptive Statistics

The New York City Department of Education (hereafter "the DOE") is the largest school district in the U.S. Importantly for our study, the DOE keeps careful records of the type, timing, and duration of teachers' absences, extended leaves, and departures from teaching. Our data come from several files. First, we have information on the complete "service history" of all full-time teachers employed during the school years 1999-2000 through 2004-2005. A teacher's service history file consists of a set of observations representing a period of time in the teacher's employment during which his/her work activity did not change. Most important for our analysis are variables for work status (e.g., active duty, retired, on maternity leave), and the start and end dates of each service period. We only observe service histories through May 2005 (when the file was created) and therefore limit our analysis to the school years 1999-2000 through 2003-2004.

We use work status codes to identify extended work disruptions, which we initially group into 11 categories: Maternity Leave, Child Care Leave, Medical Leave, Sick Family Member Leave, Personal Leave, Sabbatical, Resignation or Retirement, Involuntary Termination, Certification Termination, Death, and Other Leave.[6] "Other leaves" include events such as military deployment, teaching abroad, teaching in a charter school or university, or working for the teacher's union. Certification Termination refers to the termination of teachers who lacked the credentials to continue teaching. These occur primarily just prior to school year 2003-2004, when teachers in New York State were required to be certified (see Kane et al. (2008)).

Extended work disruptions can span school years and impact students when they end as well as when they begin. We therefore match each extended disruption to the years during which

[6] Although there are many work status codes, many represent variations on the same type (e.g., "Sabbatical-doctoral Study 1 Year" vs. "Sabbatical-doctoral Study 6 Months.") We classify sabbaticals for "restoration of health" as medical leaves. In about 10 percent of cases, one extended leave is followed immediately by one or more additional types of leave (e.g., maternity leave frequently turns into child care leave.) When this occurs, we aggregate them into a single leave of absence and use the category of the first initial leave to classify the entire sequence.

it began and ended. If the event began or ended in the middle of the school year, we consider it disruptive. We also link events that start in the summer months to teachers from the preceding school year so that we can test for any relationship between student achievement and these "non-disruptive" events.

Annual files on teacher absences (as opposed to extended disruptions) provide us with the date and reason for each absence. We group absences into three categories: Self-Treated Sickness / Personal Days, Certified Sickness / Injury, and Other Absences. The "Other" category includes conferences and other school related activities, death of a family member, funerals, jury duty, military service, attendance of a child's graduation, religious holiday, grace period, any unauthorized absence, and partial absences of at least half a day.[7] The most common type of absence is Self-Treated Sickness, and teachers are allowed to use up to 10 of these days per year. However, if a teacher presents proof of illness from a doctor, the absence is coded as Certified Sickness and does not count against the annual 10 day cap. Thus, teachers with serious health shocks may have a strong incentive to submit certification. Teachers are allowed to use three Self-Treated Sickness days for personal business (which are coded as Personal Days), but it is highly unlikely that teachers designate all days taken for personal business. Support for this notion can be found in tabulations of absence by the day of the week. As one might expect, 39.9 percent of absences for Certified Sickness or Injury take place on a Monday or Friday. In contrast, 47.4 percent of absences for Self-treated Sickness (and 51.2 percent of Personal Days) take place on these days. We therefore group Self-Treated Sickness and Personal Days together.

[7] "Grace period" applies to teachers who have exhausted their sick days and are therefore not paid for their absence. A grace period is capped at 30 days and typically applies to teachers who are absent prior to an extended leave (e.g., maternity). Absences that are consecutive to teaching disruptions are also counted as part of those disruptions. In addition to grace period absences prior to maternity leave, medical leaves are typically preceded by several days of absence where the teacher is certified to be sick.

We measure student achievement using data on test scores in math and English covering all students in New York City from 3rd to 8th grade in the school years 1998-1999 through 2003-2004. Because we use prior test scores as a control variable, our analysis focuses on students in grades 4 to 8 and the school years 1999-2000 to 2003-2004. In addition to test scores, our student data include information on student demographics: receipt of free and reduced price lunch, special education, and English Language Learner services. The data also contains information on student absences and school suspensions, and we use students' prior year values for these outcomes as control variables. Because many students receiving special education services in New York are taught in classrooms (or even schools) containing solely students with disabilities, and most of these students are tested using methods that differ dramatically from the standardized statewide exams, we limit our analysis to students in regular education classrooms, excluding classrooms where the portion of students receiving special education exceeded 25 percent. Because of potential coding errors, we also exclude classrooms with less than 7 or greater than 45 students.

Importantly, the student file also provides identifiers that can be used to link students with their reading and math teachers. Students in elementary grades (4, 5, and some 6th graders), typically have the same teacher for both subjects, while older students are taught by two different teachers. One shortcoming of our data is that it is limited to regular classroom teachers, and we do not have information on substitute teachers who fill in for those who go on leave.

Summary statistics on extended disruptions and similar events that are non-disruptive, by type, are shown in Table 1. Approximately 5,500 events of either type occur in our data, and about one fifth of these (1,134 events) are disruptive. The variation in the fraction of events that are disruptive gives us a sense of the ability of teachers and administrators to control the timing of different event types. For example, maternity and medical leaves—where we do not expect much control over timing—are disruptive 87 and 73 percent of the time, respectively. In contrast, resignation and retirement, sabbatical, and involuntary termination are disruptive roughly 10 percent of the time. Note that about three quarters of extended disruptions are in the categories of maternity leave, medical leave, and resignation/retirement.

For each type of extended disruption, we calculate the fraction that begin and/or end in the middle of the same school year and the number of instructional days the teacher misses due to the event. Overall, 34 percent of disruptive events begin and end in the same school year, while 48 percent begin in the middle of the year but end after the school year, and the remaining 17 percent are events that began before the school year but end sometime during the year. The average number of instructional days missed is 56, and the averages of individual types of events are quite similar, varying between roughly 40 and 70 days. The sole exception are disruptions for sabbatical (where teachers take one semester of leave), which averages 92 days but varies little—the 25th and 75th percentiles are 91 and 92 days, respectively. For all other types of events, there is considerable variation in the number of days missed within leave types, with 25th percentiles around 15 to 35 days and 75th percentiles around 60 to 100 days.

In order to examine the characteristics of teachers who experience extended disruptions, we use data from the payroll records which cover every full-time teacher on the DOE payroll at the end of September, November, and May of each school year 1999-2000 through 2003-2004. The payroll file includes teachers' gender, ethnicity, age, and type of certification, and information on each teacher's salary schedule and position, which are functions of teaching experience and graduate education.

These summary statistics are presented in Table 2.[8] For purposes of comparison, we also display the average characteristics of teachers who do not experience an extended work disruption. There are several interesting differences in the characteristics of teachers across types of events, some of which are not surprising. For example, 99 percent of teachers taking maternity leave and 97 percent taking child care leave are coded as female, relative to 78 percent for teachers with no disruptive event. Teachers taking maternity and child care leave also tend to be younger and have fewer years of teaching experience. In contrast, teachers taking sabbatical have much higher levels of experience (16 years on average, as opposed to 7 for teachers without any disruption event), and 100 percent of them have a masters degree (relative to 67 percent for teachers without no event). While it is not surprising that nearly all terminations for certification occur for teachers who have been coded as lacking certification, it is interesting that about three quarters of disruptive involuntary terminations occur for these teachers.

To examine whether extended work disruptions are more common for teachers who teach particular types of students, we calculate average student characteristics by type of disruption and compare them with averages for students whose teachers did not experience any extended disruption (Table 3). Overall, extended disruptions occur with similar frequency in schools serving different populations throughout New York City. However, there is noticeable variation in the characteristics of students when we look at individual disruption types. For example, black and Hispanic students comprise a relatively greater share of students in classrooms that

[8] For teachers with multiple events, we only consolidate events of the same type within the same year when calculating these statistics. For example, a teacher who goes on medical leave and (after returning briefly) goes on personal leave in the same year will generate two observations, as would a teacher on medical leave twice, but in different years. In contrast, only one observation is generated by a teacher who goes on medical leave twice in the same school year. Thus, the numbers of observations by leave/departure type in Table 2 are similar to Table 1 but not exactly the same.

experience a disruption due to involuntary termination than white or Asian students, compared to their shares in classrooms with no disruption events.

Summary statistics on annual absences by type and by whether or not the teacher experienced an extended disruption are shown in Table 4. Teachers who experience an extended work disruption during the year have slightly more absences on average than other teachers (10.0 vs. 9.4). This difference is driven mainly by absences for poor health that are certified by a medical professional. Prior literature on teacher absences (e.g., Clotfelter et al. (2009)) finds that rates of absence are higher in schools that serve relatively disadvantaged populations of students. We do not find a similar pattern among schools within New York City. In our matched student teacher data, students who receive free lunch have teachers who are absent 9.3 times per year on average, while the average for other students is 9.7 teacher absences per year.

3. Empirical Methods and Results

In our analysis, we examine the impacts of extended work disruptions separately from daily teacher absences. A typical disruptive event in our dataset covers roughly 60 instructional days, and should therefore have a much larger effect on student achievement than a day of absence. Whether these longer disruptions are more or less damaging to student achievement than isolated days of absence *on a per day basis* is an empirical question. For example, schools may find it difficult to find a single substitute to work full time for several weeks or months on short notice, and thus may cause additional disruption by filling this role with multiple individuals. On the other hand, the pool of substitutes available for long term assignments may be of higher quality, and schools may be willing to pay search costs needed to identify better candidates.

Our basic estimation specification takes the following form:

$$(1)\ Y_{it} = \beta_g X_{it} + \theta L_{it} + \delta A_{it} + \lambda W_{it} + \rho S_{it} + \pi_{gt} + \varepsilon_{it}$$

where Y_{it} is the math or reading score of student *i* in year *t*, L_{it} and A_{it} are, respectively, an indicator for an extended disruption and the number of daily absences taken by the teacher to whom the student is matched, X_{it} is a vector of student characteristics, W_{it} is a vector of teacher characteristics, S_{it} is a vector of school characteristics, and π_{gt} is a grade-year fixed effect.[9]

Estimates of Equation 1 for math and English exams are shown in Columns 1 and 4 of Table 5. Students whose teacher has a disruptive event have 0.060 and 0.036 standard deviations lower achievement in math and English, respectively, on average. Additionally, student achievement is estimated to fall by 0.0018 and 0.0010 standard deviations in math and English, respectively, for each additional day of absence taken by their teacher. Of course, one potential explanation for these results is that disruptions and absences are more likely to occur with teachers that provide lower quality instruction, and that the disruption itself is not significantly detrimental. If this selection is related to time-invariant dimensions of teacher quality, then the addition of teacher fixed effects will remove this potential source of bias. Estimates with teacher fixed effects are smaller but still statistically significant.[10] Students' math and English achievement are 0.047 and 0.018 standard deviations lower, respectively, in years when an extended work disruption occurs, relative to other years for the same teacher. When teachers

[9] Student characteristics include a cubic polynomial in prior year math score, a cubic polynomial in prior year reading score, gender, race and ethnicity, free/reduced price lunch, special education, English Language Learner, and the number of absences and suspensions for the student in the previous year. We also interact all of these variables with the student's grade level. Teacher characteristics include teaching experience, type of certification, and possession of a graduate degree. School characteristics include school level averages of student characteristics.
[10] We have also estimated specifications that control for teacher-by-school fixed effects and find very similar results in both magnitude and statistical significance.

takes more (than their average) absences, math and English achievement are estimated to be 0.0013 and 0.0007 standard deviations lower, respectively, for each additional absence taken.[11]

The effect of a work disruption is likely to vary depending on its timing. As stated above, disruptions that occur after exams have been taken cannot have a direct causal impact on student test scores. In Columns 3 and 6, we present specifications that allow the coefficients on extended work disruptions to differ depending on whether the disruption began: before the school year started, during the school year but before the students' exam, and during the school year but after the students' exam. We also add an indicator for extended leaves and departures from teaching that began in the summer following the school year and are therefore non-disruptive. In math, the coefficients on extended disruptions beginning before the school year or after the school year are both small and statistically insignificant. However, the estimated effect of disruptions starting within the year and before the exam is large (-0.058) and statistically significant. Extended disruptions starting after the exam are negatively related to student achievement and the coefficient (-.030) is marginally significant (p-value 0.15). In English, the coefficient on disruptions starting during the year but before the exam (-.034) is also statistically significant, while the coefficient on disruptions after the exam is positive and statistically insignificant.

Interestingly, the coefficients on absences that occur both before and after the exam are statistically significant (Columns 3 and 6 of Table 5). The coefficients on absences occurring before the exam are somewhat larger (-0.0014 and -0.0007 in math and English) than for those

[11] It is useful is to note that the coefficient estimates on extended disruptions—which, on average, last 60 days—are less than 60 times the estimated coefficients on daily absences. This is in line with the view that unexpected absences are more detrimental than those known in advance. If a worker calls in sick one hour before the start of the work day, there may be little time for employers to find a highly qualified substitute. In contrast, if an employer knows that a worker will be going on leave for two months, more attention can be placed on the selection and training of a replacement.

occurring after the exam (-.0010 and -.0006). Nevertheless, these results suggest either a role for teacher health shocks or another form of selection bias that is not avoided by the use of teacher fixed effects.

As stated above, one reason why an extended work disruption or absence occurring after an exam may be negatively associated with student test scores is that they are caused by worker health shocks that lowered productivity prior to the exams. In order to examine this explanation, we allow for heterogeneity across four types of extended disruptions: (1) maternity leave, (2) medical leave, (3) retirement or resignation and (4) all other types of events. While grouping all other events together ignores some substantial differences (e.g., sick family member leave vs. sabbatical), none of the remaining categories of extended disruption occur with sufficient frequency for us to reasonably expect to estimate a precise effect if we examine them separately. For simplicity, we present results of specifications that limit attention to disruptions that start within the school year and include teacher fixed effects.[12]

The results of this analysis (shown in Table 6) provide support for the worker health explanation. For both math and English, the estimated impacts of disruptions prior to the exam are always negative, though the effects for maternity and medical leaves (relative to other types of extended disruptions) are smaller in math and slightly larger (or at least more precisely estimated) in English. Generally, these estimates do not suggest a great amount of heterogeneity across types of disruptions that occur prior to student exams. In contrast, the negative effect of extended disruptions that started after the exam on math achievement presented in Table 5 seems to be driven entirely by medical and maternity leaves, consistent with the notion that worker health shocks affect productivity above and beyond the work disruption channel. Students

[12] In other specifications—available upon request—we do not find any significant impacts of extended disruptions starting before or after the school year when we allow effects to differ by type. However, in line with the results in Table 5, the point estimates are all negative for disruption events that start before the school year.

whose teacher goes on medical (maternity) leave after the exam score 0.094 (0.063) standard deviations lower in math on average than similar students with the same teacher in other years. In contrast, the estimated effect for resignation or retirement after the exam is positive and insignificant and the estimate for other types of extended work disruptions events after the exam is small, negative and statistically insignificant. For English, none of the coefficients on extended disruptions occurring after the exam are statistically significant, and, notably, the only negative coefficient is for medical leaves (-.020 standard deviations).

We further explore the worker health explanation by allowing the impact of daily teacher absences to depend on the cause for the absence. As mentioned above, we separate absences into three types: Self-Treated Sickness / Personal Days, Certified Sickness / Injury, and Other Absences. Self-Treated Sick and Personal Days are taken at the behest of the teacher, and may be due to sickness or other unexpected events but may also reflect teachers taking additional vacation time during the school year. Absences where the teacher has been certified as sick or injured are highly likely to reflect real health problems, and, like the disruption estimates, we might reasonably expect instructional quality prior to the exam might be lower for teachers who are absent with health problems after the exam takes place.

The results of these estimates are shown in Table 7, and largely confirm our findings for extended disruptions.[13] In math, all three types of absences occurring before the exam have significant negative coefficients. In English, absences occurring before the exam for all types of absences are negatively related to student achievement; the estimate of Self Treated Sickness / Personal Days is marginally significant (p-value 0.11) and the estimate for Certified Sickness /

[13] We use the same specification as shown in Columns 2 and 4 of Table 6, except absences are broken out by both timing and type. We do not present the disruption coefficients, but they are nearly identical to those presented in Table 6.

Injury is significant at conventional levels. However, in both subjects, the only significant coefficient for absences that occur after the exam is for Certified Sickness / Injury.

Overall, we believe these results support the idea that work disruptions and worker health have a causal negative impact on productivity in teaching. Of course, without an exogenous source of work disruption we cannot completely rule out all possible alternative explanations. Nevertheless, our use of within-teacher variation and the timing of student exams should do much to avoid most likely sources of bias.

Finally, it is potentially important that all of these results presented above constrain the effect of disruptions and absences to be the same across different types of students and teachers. In order to investigate the plausibility of this restriction, we have estimated two additional specifications, the results of which are available upon request. Motivated by the idea that high achieving students may have greater resources outside the classroom that insulate them from variation in teacher productivity, we allow work disruptions to have different effects on students with prior test scores below and above the citywide median. We find similar negative impacts of both extended disruptions and daily absences on both sets of students. The other hypothesis we test is that that work disruptions may be less harmful for students taught by experienced teachers. For example, new teachers may have few lessons planned in advance and may provide little guidance to substitute teachers. However, we did not find any evidence of heterogeneity in a specification that tested for different effects among teachers with no experience or one that tested for different effects among teachers with less than three years of experience.[14]

[14] One additional hypothesis we test is whether the effects of teacher health might be driven by a relationship with student absences. This relationship could be causal (i.e., teacher illness leads to student illness, which lowers achievement) or spurious (i.e., student illness leads to lower achievement and higher teacher illness), but either case would be important for the interpretation of our results. However, including current student absences as a control variable in our regression has almost no impact on our coefficient estimates, although these absences are negatively related to student achievement.

4. Conclusion

Few existing studies credibly estimate the impact of work disruption or worker health on productivity. Using extremely detailed data from New York City on the timing and cause of work disruptions in teaching, we present evidence that both work disruption and worker health are economically important determinants of teacher productivity. We take advantage of the panel structure of our data and the timing of student exams to support the notion that the effects we estimate are causal.

Our findings also have implications for the larger literature on estimating the impacts of teachers on student outcomes. Researchers have documented considerable variance in student learning within teachers over time in addition to stable variance in quality across teachers. While part of this within-teacher variance is likely a result of test measurement error and other idiosyncratic "noise" (e.g., a dog barking outside on the day of the test), there is a significant role for teacher health in explaining variation in teacher performance over time. Also, our results suggest that, in addition to being absent more often, teachers provide lower quality instruction in years when they experience health shocks. Therefore, in studies of the impact of teacher absences on student achievement, the use of a teacher fixed effects strategy may produce biased results when researchers only observe teachers' total number of absences for the year. Future work on this issue should focus on strategies to isolate exogenous variation in absences.

Extended work disruptions in teaching are rare—occurring in roughly 2.5 percent of classrooms per year in New York City—but our results suggest that they have appreciable negative effects on student achievement. Thus, there may be an important role for policies that help stabilize instructional quality when these disruptions arise. For example, individual schools may spend few resources in preparation for extended disruptions due to the rarity of these events.

However, at more aggregate levels of administration, the frequency of extended disruptions is more steady and predictable, perhaps making the maintenance of a staff of professional "replacement teachers" more cost effective. Another policy that may mitigate the effects of extended disruptions is the institution of a common curriculum across schools, making it easier for well trained substitutes to teach effectively.

Economists have done a considerable amount of research on the impact of financial incentives on worker absence, including several studies that focus on teachers.[15] Our estimates suggest that teachers provide lower quality instruction when they work during periods of illness. Thus, the impact of absence reduction polices on teacher productivity will depend crucially on how the elasticity of absences with respect to price varies across absences with different causes. While it is reasonable to think that teachers' benefits from absence (and their reservation price) would be high when they are in poor health, this is ultimately an empirical question.

[15] See, for example, Winkler (1980), Jacobson (1989), Ehrenberg et al. (1991), Barmby et al. (1991), Brown and Sessions (1996), Lindeboom and Kerkhofs (2000), Duflo and Hanna (2005), and Clotfelter et al. (2009).

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Table 1: Summary Statistics on Disruption Events for Teachers Matched with Student Achievement Data

Type of Event	Frequency: All Events	Frequency: Disruptive Events	Fraction of Disruptive Events that… Both Start and End in Year	Fraction of Disruptive Events that… Start But Not End in Year	Fraction of Disruptive Events that… Start Before But End in Year	School Days Missed (Zeros Excluded): Mean	School Days Missed (Zeros Excluded): 25th Pctile	School Days Missed (Zeros Excluded): Median	School Days Missed (Zeros Excluded): 75th Pctile
Maternity Leave	399	347	57.3%	37.2%	5.5%	57	37	52	71
Child Care Leave	370	112	43.7%	40.2%	16.1%	65	39	58	82
Medical Leave	279	204	41.7%	50.0%	8.3%	66	38	61	89
Personal Leave	391	29	17.2%	20.7%	62.1%	64	30	50	95
Sick Family Member Leave	54	30	63.3%	30.0%	6.7%	41	20	36	57
Other Leave	156	19	21.1%	42.1%	36.8%	60	22	61	86
Sabbatical	285	25	0.0%	100.0%	0.0%	92	91	92	92
Resignation or Retirement	2827	286	8.0%	72.0%	19.9%	65	29	66	97
Involuntary Termination	577	58	8.6%	5.2%	86.2%	51	20	45	76
Termination, Certification	101	19	5.3%	47.4%	47.4%	45	13	35	73
Death	11	5	0.0%	100.0%	0.0%	47	32	43	62
All Events	5450	1134	34.4%	48.2%	17.4%	62	34	55	87

Note: Statistics on school days missed are calculated using only disruptive events.

Table 2: Summary Statistics on Teachers by Type of Disruption Event

	No Disruption Event	Type of Disruption Event: All Types	Maternity Leave	Child Care Leave	Medical Leave	Sick Family Leave	Death	Personal Leave	Other Leave	Sabb-atical	Resignation or Retirement	Involuntary Termination	Termination, Certification
Number of Observations	46347	1128	347	112	204	30	5	29	20	25	283	19	58
Age	39.25	36.97	31.86	33.13	42.49	40.27	45.60	33.68	40.20	50.32	38.85	41.42	37.16
Female	78%	84%	99%	97%	84%	77%	60%	93%	55%	72%	68%	47%	71%
Black	27%	30%	29%	16%	27%	30%	20%	17%	35%	24%	27%	42%	53%
Hispanic	13%	12%	13%	15%	8%	3%	20%	14%	25%	4%	10%	42%	22%
Asian	3%	3%	3%	3%	2%	3%	0%	7%	5%	0%	3%	0%	3%
Teach for America	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	2%
Teaching Fellow	5%	5%	4%	2%	2%	3%	0%	7%	5%	0%	9%	11%	0%
Ever Uncertified	26%	35%	34%	21%	33%	37%	40%	17%	20%	0%	37%	74%	88%
Masters Degree	67%	61%	63%	84%	63%	63%	60%	55%	65%	100%	54%	37%	26%
Teaching Experience	6.79	5.66	3.98	5.10	8.59	7.20	7.40	2.79	7.35	15.84	5.32	5.42	3.60

Note: Number of Observations correspond to the number of teachers by year that take any type of leave

Table 3: Summary Statistics on Student Characteristics by Type of Disruption Event

	No Disruption Event	Type of Disruption Event: All Types	Maternity Leave	Child Care Leave	Medical Leave	Sick Family Leave	Death	Personal Leave	Other Leave	Sabb- atical	Resignation or Retirement	Involuntary Termination	Termination, Certification
# of Observations	46,347	1,128	347	112	204	30	5	29	20	25	283	19	58
Black	36%	40%	38%	32%	46%	41%	40%	31%	23%	30%	42%	45%	55%
Hispanic	38%	38%	38%	38%	35%	34%	30%	30%	52%	37%	42%	51%	34%
White	14%	12%	14%	17%	10%	13%	21%	29%	17%	19%	8%	1%	8%
Asian	12%	10%	10%	13%	9%	12%	9%	10%	8%	14%	8%	3%	3%
Female	49%	50%	49%	49%	50%	51%	58%	53%	50%	52%	49%	53%	50%
Free/Reduced Price Lunch	84%	85%	84%	80%	88%	91%	83%	76%	81%	81%	88%	89%	84%
English Language Learner	6%	6%	5%	3%	6%	2%	3%	10%	22%	5%	6%	18%	9%

Note: Displayed are the characteristics of students matched with their math or English Language Arts teachers and included in our regression analysis, averaged across students whose teacher in either subject had a particular type of disruption event.

Table 4: Absence Frequency by Presence of Extended Work Disruption

	No Extended Disruption	Any Extended Disruption
Number of Observations	46,347	1,128
Total Absences	9.416	9.980
By Type of Absence:		
Self-Treated Sick / Personal	4.895	4.355
Certified Sick / Injured	2.631	4.543
Conference/School Activities	1.048	0.357
Funeral / Death in Family	0.338	0.254
Jury Duty/Military Service	0.290	0.193
Graduation	0.102	0.034
Religious Holiday	0.086	0.088
Grace Period	0.019	0.143
Unauthorized	0.004	0.011
Late More than Half Day	0.003	0.002

Note: Number of Observations corresponds to the number of teachers by year that are matched with student level data in 4th to 8th grade, from the school years 1999-2000 through 2003-04.

Table 5: Baseline Results on Work Disruptions and Teacher Productivity

	Math		
	(1)	(2)	(3)
Extended Work Disruption	-0.0603*	-0.0471*	
	(0.0059)	(0.0081)	
Extended Work Disruption Starting…			
…Before the Start of School Year			0.0012
			(0.0208)
….Before Student Exams			-0.0577*
			(0.0102)
….After Student Exams			-0.0295
			(0.0203)
Non-Disruptive Event (After Year Ends)			-0.0019
			(0.0043)
Total Daily Absences	-0.0018*	-0.0013*	
	(0.0001)	(0.0002)	
Total Daily Absences Prior to Exam			-0.0014*
			(0.0002)
Total Daily Absences After Exam			-0.0010*
			(0.0003)
Teacher Fixed Effects		√	√
R-squared	0.673	0.704	0.704
Number of Observations	1267869	1267869	1267869
	English		
	(4)	(5)	(6)
Extended Work Disruption	-0.0357*	-0.0179*	
	(0.0060)	(0.0080)	
Extended Work Disruption Starting…			
…Before the Start of School Year			-0.0159
			(0.0164)
….Before Student Exams			-0.0335*
			(0.0106)
….After Student Exams			0.0188
			(0.0177)
Non-Disruptive Event (After Year Ends)			-0.0003
			(0.0051)
Total Daily Absences	-0.0010*	-0.0007*	
	(0.0002)	(0.0002)	
Total Daily Absences Prior to Exam			-0.0007*
			(0.0002)
Total Daily Absences After Exam			-0.0006*
			(0.0003)
Teacher Fixed Effects		√	√
R-squared	0.633	0.659	0.659
Number of Observations	1169717	1169717	1169717

Note: All specifications control for student characteristics, teacher experience, school characteristics, and a grade-year fixed effect. Specifications without teacher fixed effects also control for time-invariant teacher characteristics. For more information, see the text. Standard errors (in parentheses) are clustered by school. + significant at 10% * significant at 5%

Table 6: Heterogeneity by Timing and Cause of Extended Work Disruptions

	Math	English
Extended Disruption Before Exam Due To…		
Maternity Leave	-0.0443*	-0.0312*
	(0.0143)	(0.0159)
Medical Leave	-0.0379	-0.0428*
	(0.0240)	(0.0195)
Resignation, Retirement, or Termination	-0.1003*	-0.0305
	(0.0211)	(0.0310)
Other Type of Leave	-0.0813*	-0.0272
	(0.0217)	(0.0250)
Extended Disruption After Exam Due To…		
Maternity Leave	-0.0629+	0.0332
	(0.0336)	(0.0238)
Medical Leave	-0.0941*	-0.0201
	(0.0419)	(0.0315)
Resignation, Retirement, or Termination	0.0242	0.0280
	(0.0363)	(0.0481)
Other Type of Leave	-0.0126	0.0259
	(0.0375)	(0.0346)
Total Daily Absences Prior to Exam	-0.0014*	-0.0006*
	(0.0002)	(0.0002)
Total Daily Absences After Exam	-0.0010*	-0.0006*
	(0.0003)	(0.0003)
R-squared	0.704	0.659
Number of Observations	1,267,869	1,169,717

Note: These specifications control for student characteristics, teacher experience, school characteristics, teacher fixed effects, and a grade-year fixed effect. For more information, see the text. Standard errors (in parentheses) are clustered by school. + significant at 10% * significant at 5%

Table 7: Heterogeneity by Timing and Cause of Daily Absences

	Math	English
Total Daily Absences Prior to Exam		
...Self Treated Sickness / Personal Days	-0.0032*	-0.0011
	(0.0006)	(0.0007)
….Certified Sickness / Injury	-0.0012*	-0.0006*
	(0.0002)	(0.0002)
….Other Types of Absence	-0.0015*	-0.0004
	(0.0005)	(0.0006)
Total Daily Absences After Exam Due to…		
...Self Treated Sickness / Personal Days	-0.0003	0.0003
	(0.0009)	(0.0008)
….Certified Sickness / Injury	-0.0015*	-0.0006*
	(0.0004)	(0.0003)
….Other Types of Absence	0.0007	-0.0012
	(0.0008)	(0.0008)
R-squared	0.704	0.659
Number of Observations	1,267,869	1,169,717

Note: These specifications control for student characteristics, teacher experience, school characteristics, the four types of disruptive events which start during the school year, before and after the exam, teacher fixed effects, and a grade-year fixed effect. For more information, see the text. Standard errors (in parentheses) are clustered by school. + significant at 10% * significant at 5%