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BRUNO GARCIA CAMPOS

**PEER EFFECTS AND TEACHER ABSENCES**

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Dissertação apresentada à Fundação Getulio Vargas – Escola de Economia, como requisito para obtenção do título de Mestre em Economia.

Área: Microeconomia Aplicada

Orientadora: Prof. Dra. Priscilla Tavares

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*To Mara and Adriana*

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## **Resumo**

A qualidade dos professores é de importância crítica para o desenvolvimento dos alunos. Além de treinamento prévio, experiência e metodologia pedagógica, a assiduidade dos professores exerce papel fundamental na aprendizagem. Neste trabalho, investigamos como o absenteísmo de professores é influenciado pelos seus colegas de trabalho. Mais especificamente, tentamos responder se há efeitos dos pares por trás do comportamento dos docentes. Recorremos a modelos de variáveis instrumentais para isolar o impacto causal de potenciais problemas de identificação, oriundos de formação endógena do quadro docente, e estimamos um impacto positivo e significativo da conduta dos colegas sob os professores focais. Adicionalmente, exploramos como professores sob diferentes regimes contratuais são afetados, e mostramos que os efeitos não são lineares – o que sugere a existência de uma alocação ótima de professores com vistas a minimizar o número de faltas. Além disso, mostramos que os professores exercem algum grau de discricionariedade ao faltar, e que é desse comportamento que derivam nossos resultados.

Palavras chave: Efeitos dos Pares, Economia Comportamental, Economia da Educação, Economia do Trabalho, Trabalho de Professores, Variáveis Instrumentais.

## **Abstract**

Teacher quality is of critical importance in student achievement. In addition to previous training, experience and teaching methodologies, teacher assiduity plays a pivotal role in pupils' development. In this paper, we investigate how teacher absences are influenced by their colleagues at work. More specifically, we try to answer if there are peer effects behind teachers' behavior. We resort to a model of instrumental variables to isolate the causal impact from potential identification problems arising from endogenous group formation and estimate a positive, significant peer effect of teacher absences on those of their colleagues. Additionally, we explore how teachers under different contract regimes are affected, and show peer effects are not linear – what suggests the existence of an optimal allocation of teachers that minimizes collective absences. Furthermore, we show teachers exert discretion on absences, and that this kind of absences are what mainly drives our results.

Key-words: Peer Effects, Behavior Economics, Education Economics, Labor Economics, Teachers Labor, Instrumental Variables.

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## 1 Introduction

Teacher quality is of critical importance in student achievement. In addition to previous training, experience and teaching methodologies, teacher assiduity plays a pivotal role in pupils' development. This discussion is especially relevant in developing countries, where human capital is greatly needed and teacher absence is disproportionately high – depriving children from instruction, and public coffers from resources. Chaudhury et. al (2006) report the combined results of unannounced visits in schools in six countries in Africa, South Asia and Latin America. Absence averaged 19 percent in their sample, with results ranging from 11, in Peru, to 27, in Uganda. They highlight also that among these countries absenteeism is generally higher in poorer regions. Benveniste, Marshall and Araujo (2008) document an absence rate of 16 percent in Cambodia, and that only 14 percent of absent teachers were replaced by a substitute<sup>1</sup>.

Duflo, Hanna and Ryan (2012) measure causal impact of teacher absence in students' development. From a pool of 120 informal one-teacher schools in rural India, 60 were randomly assigned to participate in a program that financially incentivized attendance. Teachers were given a camera that automatically recorded date and time, and were required to take daily pictures with students. Their salaries were a direct function of this attendance measure. The absence rate in treatment schools after a year was 22 percent, that was 21 percentage points lower than control schools'. That yielded a leap of 0.17 standard deviations in student test scores, who were also 40 percent more likely to be admitted in regular schools than those in control schools.

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<sup>1</sup> A brief survey of studies on teacher absence can be found in Patrinos (2013).

Schools in North Carolina are studied by Clotfelter, Ladd and Vigdor (2007), who find a smaller, but also negative, causal impact of 0.02 standard deviation originating from an increase of ten days of absence. They also point out that teacher absences are regressive, as less assiduous teachers are more likely to serve lower income students. The researchers argue that the larger impact found by Duflo et al. is attributable to the tremendous reduction in absenteeism, that also starts from a significantly higher level. In the U.S., teacher absence rate averages only five percent – the authors highlight that this is, however, higher than average sick leave in other industries.

It is hardly the case that teaching is that much more harming to human health, and that solely accounts for higher absence rates. Miller, Murnane and Willet (2008) theorize that a sizable portion of teacher absence is discretionary, as teachers who are required to report absences directly to their principal are less likely to miss classes, most absences take place on Monday and Friday and most medical absences last one or two days (in the U.S. a medical certificate of illness is required for three or more days in absence). The researchers estimate a causal impact of teacher absence in a school district in California is of a decrease of 0.03 standard deviations in students' math test scores, similar to Clotfelter's results.

A more thorough examination of teacher absences is given by Herrmann and Rockoff (2012). Their estimate of impact is 0.02 percent of a standard deviation for an increase in ten absences, whose causal interpretation is reinforced by the fact that absences prior to the exam date have a stronger impact than absences after. Their estimates reveal that students' loss is decreasing in absence duration – as the fixed costs of finding substitute teachers could be smoothed for longer periods of absence, or more productive substitutes

might be sought after for longer assignments –, and productivity loss associated with absenteeism is greater for more experienced teachers.

The issue of tackling absenteeism, however, is far from settled. In addition to the program evaluation by Duflo, Hanna and Ryan (2012), Banerjee and Duflo (2006) find mixed results in other efforts of enhancing teacher attendance in India and other developing countries, what suggests we need a better understand of the mechanisms behind absenteeism. It is mostly associated with both extrinsic and intrinsic factors, such as permissive leave policy, higher exposure to infectious diseases (carried by students), deficient school infrastructure, poor management-labor relations, stress of the job and demographic characteristics. In this research attempt, we investigate an intrinsic driver of teacher absenteeism.

In this paper, we investigate how teacher absences are influenced by their colleagues at work. More specifically, we try to answer if there are peer effects behind teachers' behavior. Manski (1993) first indicated that the main challenge in identification are simultaneous feedback between the focal individual and his peer group (the so called reflection problem) and unobserved variables that might be driving common behavior or behind group membership. The author demonstrates that the latter question is particularly detrimental to measure peer effects, and proposes that without prior information about group formation it is impossible to identify causation.

Several works tackled these questions by analyzing exogenous assignment to peer groups. Imberman, Kugler and Sacerdote (2012) exploit the migration naturally caused by hurricanes Katrina and Rita. The massive exodus of children fleeing the storms was interpreted as a natural experiment to better understand how peers' ability in math and reading impact individual test scores. Babcock, Bedard, Charness, Hartman, and Royer

(2015) study the effect of incentives in two separate randomized field experiments where participants were paid to study in a library in the first one, and exercise in a gym in the other. Social interaction effects were measured by allocating individuals either in a control group, an individual-incentive group or a team-incentive group (where individual reward was a function of the outcome of a team member). Carrell, Fullerton and West (2009) argue that peer effects pervade classroom interactions, and capitalize on a dataset of randomly assigned students who not only attend classes together, but are also required to spend most of their time with each other. Academic peer effects are measured in a much larger magnitude, and are more comparable to changing the entire group of peers. On the other hand, the results found by Carrell, Sacerdote and West (2013) discourage optimal group design and emphasize the importance of endogenous group formation. The researchers conduct a controlled experiment in which low-ability students are coupled with high-ability students. Previously estimated nonlinear peer effects suggested low-ability students should benefit, whereas high-ability students' outcome would not be inhibited. Surprisingly, the treatment effect is negative for low-ability students, as they ended up avoiding their more proficient peers.

In endogenously formed groups, peer effect identification is significantly more challenging. Rarely this problem is undoubtedly settled, and most studies only propose reasons why unobservables related to the outcome are not driving group membership. Bayer, Ross and Topa (2008) evaluate if the propensity to work together increase if individuals live nearby. The underlying assumption is that what drives individuals to choose a job position is not related to their choice of neighborhood. By showing that observed variables of each individual, such as education attainment, number of children in the household and race, are not highly correlated with the neighborhood average, the

authors argue that unobservable variables should follow the same pattern. Their claim is strengthened when they find similar results after estimating the same models with a restricted sample, in which only low-correlation neighbors are included. Mas and Moretti (2009) explore productivity spillovers among cashiers working at a supermarket chain, whose work shifts are not experimentally controlled, but arguably exogenous. The authors disclose that itineraries are set two weeks before any given shift, and the measured peer effects take place in a matter of minutes. To further their case, they implement empirical tests to confirm that there is no discretion by the management to assign more productive workers to busiest hours (being them predictable or not), and scheduling is unsystematic. Hensvik and Nilsson (2010) examine the influence co-workers exert in child-bearing decisions. The identification hypothesis of exogenous group formation is tested by re-estimating the same models with three placebo peer groups. The first one consists of workers in the same firm but not the same workplace, who are subject to the same firm-specific policies and shocks. The second group are people who will work together in the future, but whose (possible) peer effects are measured while they work separately – any unobserved variable behind both group membership and pregnancy decision should, however, be already at play. Finally, the third group is composed of siblings of actual peers, who likely share many unobserved characteristics but are not actual co-workers of focal subjects. The comparison of their baseline result with these placebo tests appeal to the plausibility of the identification hypothesis, as no significant peer effect is found under these alternative conditions.

In Sao Paulo State public schools teachers have a limited scope to choose where to work and, therefore, to choose their peers. We resort to a model of instrumental variables to isolate the causal impact from potential identification problems arising from endogenous

group formation and estimate a positive, significant peer effect of teacher absences on those of their colleagues. Additionally, we explore how teachers under different contract regimes are affected, and show peer effects are not linear – what suggests the existence of an optimal allocation of teachers that minimizes collective absences. Furthermore, we show teachers exert discretion on absences, and that this kind of absences are what mainly drives our results.

This paper is organized as follows. The next section describes the institutional background of Sao Paulo state public schools' rules outlining teachers' contracts. Section 3 presents the data and identification strategy and in section 4 we present our results. Finally, in section 5 we make final remarks and considerations.

## **2 Institutional background**

The São Paulo State Education Department is the largest educational system in Brazil, responsible for attending 3.6 million students in elementary education and high school. São Paulo State Government employs around 200 thousand teachers, by three different positions or contract category. Category 'A' refers to teachers that have been approved on an exam that enable them to work under a permanent contract with job stability. Category 'F' refers to teachers that work under a one year-temporary contract, renewable every year. Category 'P' refers to teachers that are occasionally hired to substitute absent ones for a short period of time (few days or weeks).

Leaves are, in general, long-term absences, such as maternity leave, health treatment, postgraduate studies, take on a public position etc. There is also a special type of leave (called *licença prêmio*) that consist on a sabbatical period of 90 Days, granted when teachers complete a period of five years of regular public service. In order to be entitled to these leave, they must first request authorization from the school director and the State Education Department, providing specific documentation (medical certificate, in the case of health leave or maternity leave and attestation of attendance, in the case of the sabbatical period). However, there are some types of short-term leave for various reasons (such as leave to deal with personal matters or to attend union meetings), which do not rely on specific documentation and whose granting is most associated with the principal's decision.

On the other hand, absences are temporary, short duration non-attendances. There are three quite frequent categories of absences. Medical absences are one-day absences for

attendance at medical appointments or examinations. Directors have the autonomy to require supporting documentation that later justifies the absence. Granted and justified absences (in Portuguese, *faltas abonadas e faltas justificadas*) are also absences from a day to which teachers are entitled by law and no documentation is required to request it. Every year, each teacher has the right to 6 granted absences (up to one per month) and 24 justified absences. Medical and granted absences do not imply salary discounts or interruptions in the count of service time for retirement, but are considered in the count of attendance and affects the count of service time for sabbatical period permission. The justified absences imply both salary discount and interruption in the count of service time.

Although all teachers are bounded by the same legal rules of attendance, there are different incentives to be absent for teachers of different categories. Category A teachers have job stability and are rarely dismissed for not being assiduous. According to legislation, teachers in this category may be dismissed just in case of being missing more than 30 consecutive days or more than 45 non-consecutive days per year, without justification. Excessive absences are also not the main reason for the dismissal of a Category F teacher (the rule is 15 consecutive days or 30 non-consecutive days). However, attendance is – along with qualification and career time – one of the criteria for hiring a teacher in the following year, as well as for their allocation in schools (*ceteris paribus*, assiduous teachers have priority of choice). In the case of Category A teachers, the priority of choice is based only on qualification and length of service, and assiduity has no influence at all.

Schools' principals in São Paulo consider the high rate of teacher absenteeism as the main managerial problem they have to handle with<sup>2</sup>. In fact, in a single school day about 12,000

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<sup>2</sup> Principals' Questionnaire, SARESP 2015.

effective teachers are absent from classrooms and by about 90 classroom hours are lost because there is no substitution<sup>3</sup>. The high number of absences among teachers may be related to occupational risk: manual activities and contact with many children and adolescents make teachers more susceptible to infections (Nechas, 1989). In addition, teachers often have voice-related problems (Rosenberg et al., 1999) and stress associated with work (Van Dick and Wagner 2001, Gasparini et al., 2005). However, in the literature there is evidence that a large part of teacher absences is discretionary. Miller (2008) shows, for example, that 64% of absences in US occur on days adjacent to "non-instructional" days (weekends and holidays), which correspond to 45% of school days. Between 2007 and 2010, in São Paulo, 60% of teachers lacked at least one day of the year and the average of short-term absences per teacher is about six school days per year. Two-third of these absences do not require documentation. About 50% of the teachers requested some type of medium or long-term license in this period.

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<sup>3</sup> DRHU, 2007-2010.

### **3 Data and identification strategy**

Our data consists in administrative records from the State of Sao Paulo Department of Education regarding teachers' yearly attendance from 2007 to 2010. That means we can observe the number of teachers' non-attendance, disaggregated by different modalities of absences and leaves. This allows us to discriminate between discretionary and non-discretionary absences.

On average, teachers are missing roughly 44 days – one fifth of a school year. Global mean is misleading, as teachers under distinct categories are related to different absence regimes. Category A teachers miss twice more classes than Category F teachers. This discrepancy is firstly due to different job assignments of Category A teachers – mostly at government related activities. Category A teachers invited to take part in government are withdrawn from their positions as teachers, whereas Category F in the same condition are mostly not assigned as teachers for a given year (see Table 1).

Other important source of absenteeism is teacher health condition. Health related leaves and medical absences (related to longer and shorter periods, respectively) account for 14 yearly absences, (one third of total absences). The share is also highly unequal among different teacher categories. Although Category F teacher are missing 11 days due to illness (less than Category A's 16), this number represent two thirds of their total absences. Most of this discrepancy possibly stems from the larger kinds of absences to which only Category A teachers are entitled (such as licença prêmio).

In order to attain study withdrawal, a teacher must provide a set of documents that prove his intent to study. Therefore, we consider training or study related withdrawal, along

with maternity leave, especially difficult to counterfeit and hardly influenced by peer effects. Most other kinds of absence have some level of discretion. The starkest example is medical absences, to which no proving document was required before 2009. We see a sharp decline of this kind of absences up from that year – unfortunately, the regime changed for all schools and we were unable to leverage on this discontinuity.

A unique teacher identifier enables us to track them in all schools they work every year. The database also contains socioeconomic and labor information such as age, gender, schooling, tenure, position (or contract category), work hours and base wage. Identifying contract category is important because, as we pointed out in previous section, teachers in different positions have different incentives for being assiduous. Our sample is composed by 282,550 observations: 81,907 (29%) elementary school teachers; 176,463 (62.5%) secondary or high school teachers; 36,098 (12.8%) principals and pedagogical coordinators. Almost 80% of teachers and managers are female, the average age and tenure are respectively 41 and 11 years. Category A and Category F teachers respond to 46% and 53% of all regular professors. Category P represents only 1% of teachers working in São Paulo School Department in this period (see Table 2).

In the peer effects literature, the linear-in-means model is the most commonly estimated one. The outcome  $y_{ist}$  (absences of focal teacher  $i$  in school  $s$  and year  $t$ ) is affected by their own attributes ( $x_{ist}$ ), some metric of their peers' characteristics ( $X_{-ist}$ ), usually the mean, and their peers' outcomes (absences of all other teachers in school  $s$  and year  $t$ :  $Y_{-ist}$ ):

$$y_{ist} = \beta_0 + \beta_1 \overline{Y_{-ist}} + \beta_2 x_{ist} + \beta_3 \overline{X_{-ist}} + \varepsilon_{ist}$$

According to Manski (1993),  $\beta_1$  captures how individual behavior is affected by the prevalent behavior in the group – the endogenous effect. Teachers' and peers' attributes such as schooling, age and experience can also be related with focal teachers' and peers' behavior. The parameters  $\beta_2$  account for the effect of individual's attributes on their own outcome and  $\beta_3$  represents the exogenous or contextual effect, that is the effect of exogenous group characteristics on individual behavior.

A crucial question in parameter identification is the problem of reflection, as first mentioned by Manski (1993). From a researcher's point of view, it's difficult to distinguish between the influence of the behavior of teacher  $j$  on teacher  $i$  and vice-versa. Other effect – the correlated effect – may arise from the fact that teachers in the same school could tend to have the same behavior because they have similar individual characteristics or because of sharing the same institutional environment and formal or informal rules.

The perfect experiment would be to induce exogenous random variation in absences in one teacher, and measure how other teachers respond. The case of studying teachers is further worsened because they have some freedom in choosing their own colleagues, and consequently adverse selection could be misinterpreted as peer effect. In spite of exogenous treatment and random group formation being not available, we can include teacher and school fixed effects in an effort to control for selection into peer groups. But this strategy cannot be enough to identify peer effects, i.e., controlling for the selection of teachers into peer groups is not the same as being able to separately identify endogenous and exogenous effects.

As pointed out by Bramoullé, Djebbari and Fortin (2009), endogenous and exogenous effects can be generally identified under network interaction. The reflection problem is a

potential threat to identification when a researcher tries to gauge *endogenous* peer effects, that is, how perceived behavior affects own behavior. *Exogenous* peer effects, however, should not be prone to reflection. As they are related to peers' outcomes, but not to the focal teachers', an instrumental variable approach is viable. In other words, if peer effects are at least partially associated with circumstances other than the behavior of interest, these circumstances provide a suitable instrument.

Our dataset enables unique identification of all teachers across schools, we can track those who work in two schools or more, and in which schools they teach in each year. For some teacher  $j$  that works in schools  $A$  and  $B$ , there is a teacher  $i$  who works only in school  $B$ . If teacher  $j$  is subject to *exogenous* peer effects in school  $A$ , and they promote his overall absence behavior, we can use these as instrument to measure the peer effect of teacher  $j$  on teacher  $i$ . As absence is correlated with gender, our instrument of choice is the proportion of women among peers of the focal teachers' colleagues in other schools (that is, the proportion of women in school  $A$  is the instrument for focal teacher  $i$ ).

To better understand how does peer effects in our context work, we employ a series of regression models that aim at different channels through which social interaction might be at play.

As teachers under distinct categories are subject to different incentives to be assiduous, we firstly investigate how strong peer effects are for teacher under different contract regimes. As mentioned above, Category A teachers face less penalties for missing classes as compared to Category F teachers. We therefore run the same regression models, restricting the sample to focal teachers under Category A and, separately, restricting to focal teachers under Category F.

It is possible that teachers in schools facing important personnel deficits behave differently. The information a teacher in a typically assiduous school receive when a colleague miss one day of work could be distinctly interpreted than that obtained in a school where absences are more the norm than exception. Furthermore, a principal could become more restrictive after a certain number of absences is achieved – if anything else, basic school functions could be undermined after a major part of its staff is missing. We test for these non-linearities by categorizing teachers' peers in quartiles, and estimating peer effects for each group. Teachers whose peers are in the fourth quartile (that is, whose peers miss many classes) should have a smaller peer effect if this hypothesis is to hold.

Finally, we resort to the richness of our dataset to evaluate if dissimilar kinds of absences are heterogeneously perceived by teachers. One channel through which social interaction might promote a certain behavior in the workplace is by spreading information of the outcome of that behavior. In the context of teacher absence, certain kinds of absence might provide more information about future sanctions in response to negligence than others. We argue that absences in which teachers exert more discretion should provide more information, as they are compatible to more severe punishment – and lack thereof should, accordingly, promote a focal teacher's absences who perceive it. Conversely, absences in which teachers have little or no room of discretion probably yield no penalties and consequently produces no additional information to observing teachers. An example of discretionary absence in Sao Paulo state public education system is medical absences, for which no document of validation was required up to 2009. On the other hand, withdrawals for studying or taking part in a training program were more closely verified and may be considered non-discretionary. Given our definitions of discretionary and non-discretionary absences, we look for potential effects of peers' discretionary absences on

focal teachers' discretionary absences. Conversely, we expect to find no relationship between focal teachers' non-discretionary absences and any type of their peers'.

## 4 Results

We first estimate a sequence of models that increase in complexity, in an attempt to more precisely measure the causal effect of peers' absences on focal teachers. For each model, we increment the set of covariates to assess possible omitted variable biases and better understand how endogenous and exogenous peer effects may interact. All models are specified in natural logarithms in both regressor and explanatory variables, to facilitate interpretation of coefficients as elasticities. The results are displayed in Table 3.

The simplest exercise already shows a positive relationship between focal teachers' absences and their peers'. The only control variables in this regression are year categorical variables, to capture potential trends over time. At this stage, it would be daring to understand this first estimate as a measure of causal impact, but it is safe to interpret correlations. We estimate a significant coefficient of 0.32. The result points to a strong, positive relationship between the outcome of focal teachers and their peers. The first correction we make is by including teacher-specific control variables. By doing so, the estimated coefficient slightly drops to 0.28, suggesting focal teachers' characteristics might be related to their peers' absences. We then include their peers' characteristics, and find a larger relationship of 0.37 between absences of focal teachers and their peers. The message here is both endogenous and exogenous peer effects are at play among Sao Paulo state schools' teachers, as peer characteristics are clearly related to focal teachers' absences.

As outlined above, the accuracy of the previous estimates might be compromised by the problems of reflection and self-selection. We try to curtail these issues by instrumenting

peers' absences with the outcomes of their colleagues from different schools. We argue that, other than through their common peers, there is no relationship between the absences of teachers from different schools. More formally, let the focal teacher  $i$  work in school  $A$ , and his peer  $j$  be the only teacher working in both school  $A$  and school  $B$ . In this setting, the focal teacher's absences  $y_{iA}$  is regressed on the explanatory variable of interest  $\overline{Y_{-iA}}$  (average absences in school  $A$  excluding teacher  $i$ ) and instrumented by  $\overline{Y_{-jB}}$  (average absences in school  $B$  excluding teacher  $j$ ). Consequently, the outcome of teacher  $i$  should not be affected by those of teachers who work in different schools, except from a second order reflection problem where the behavior of teacher  $i$  influences that of teachers in school  $B$  through teacher  $j$ . This is pivotal in ensuring that  $\overline{Y_{-jB}}$  is a suitable instrument. The models are estimated with our full sample, and with a restricted one that includes only focal teachers who work in a single school. The estimation with the restricted sample is simply to validate the full sample results, as it guarantees that there is no contact of focal teachers and his peers' colleagues in other workplaces.

Once the reflection problem is dealt with, peer effects become more evident and our estimate moves further into positive territory. We estimate a much larger impact in this specification (1.07 with full sample, 1.04 with restricted sample), firmly suggesting that reflection and self-selection are a critical issue in determining peer effects in our context. That is, a focal teacher observing his peers missing a day of work is expected to take close to a day off himself, being this an allowed absence or one disguised as some other type (medical absences, for example). This "tit-for-tat" approach to absence behavior is relatively intuitive, but raises concern nonetheless as the arrival of an especially lax teacher may significantly disrupt average attendance in a given school. The equally high, significant first stage estimates endorse the reliability of our IV strategy. It's also worth

mentioning that the results in full or restricted sample are barely different from each other, as most teachers work in only one school.

As Hoxby and Weingarth (2005) highlight, linear peer effects are hardly interesting. For policy implications, if peer effects are truly linear, there is few a policymaker could do in order to design an optimal combination of teachers, or best exploit the characteristics of social interaction. Should peer effects be linear, any reallocation of peers would have a zero net effect. The authors also point out that most works end up focusing on linear effects due to obstacles to identification, mostly residing on the limitations of the dataset. In our case, we have already demonstrated that there is significant peer effects in teacher absences with our linear models by way of instrumental variables. We do an additional exercise to better understand how the peer effects propagate along the distribution of absences. We rerun our full instrumental variables regression model with the same control variables used in the previous exercises, but the difference here is that we run independent regressions for each quartile of peers' absences distribution. The results in Table 4 clearly indicate that peer effects are de facto nonlinear: we estimate significant peer effects in all but the first quartile of the teacher spectrum. However close the estimates in the second and third quartiles may be (approximately one standard deviation), the difference from those to the impact on teachers in the fourth quartile is substantial. We speculate that in a school where most teachers are assiduous, an increment to the mean peer absence convey little information to a focal teacher – absences being so rare, it might be the case that an increment wasn't intentional and the focal teacher shouldn't be particularly incentivized to willfully miss a day of work. When we reach the other extreme, peer effects are also close to zero, but possibly because of a different reason. Once a certain level of absences

is reached, principals or even colleague teachers might look down harder on voluntary idleness and thus attenuate the perverse social effect on absences.

Another question that raises concern is the different regimes under which public teachers in Sao Paulo state may work. Although both teachers in Category A or F have work stability, a larger absence score of Category F teachers in a given year means they have less power to choose the school in which they will work in the following year. In this sense, it is expected that these teachers are more assiduous. We have shown in Table 1 that their mean average is indeed lower, and not only because they lack some of Category A teachers' benefits (such as granted absences). We have run our baseline model by restricting the sample for teacher categories A and F to evaluate if also their response to peer effects is distinct. The results presented in Table 5 show that Category F teachers respond considerably more than Category A teachers – the estimated responses are more than seven standard deviations apart. In spite of the higher absence rate among Category A teachers, average peer effects seems to be driven by a stronger response of teachers under the other modality. This result is puzzling, since incentives to attend to classes are supposedly much more compelling to Category F teachers, who risk having to change their workplace should they be not present for too many days.

In a final exercise, we investigate how different kinds of peers' absences distinctly affects focal teachers'. As explained above, should peer effects operate through an information channel – as means of teachers to anticipate how their bosses and colleagues might react to absences –, discretionarily missed classes should convey more information than non-discretionarily ones should. Therefore, we expect to see a stronger, positive impact on focal teachers who observe their peers willfully skipping classes. On the other hand, one would not expect any reaction to non-discretionary absences, or even a contrary response

– as focal teachers are expected to compensate students for peer teachers who are impeded to work.

Table 6 compares peer effects of distinct types of absences for all teachers, for different categories and along the peer distribution in the same fashion we did in the previous exercises. To facilitate comparison, we reproduced the previous results in the first row, labeled baseline models. In the second section of the table, we show that we could not significantly estimate any peer effects on focal teachers' non-discretionary absences, except for a very weak impact on teachers in the third quartile of peers distribution. As these absences arise from other reasons than peers' choice, it is expected that focal teachers' absences are not influenced by their colleagues' behavior.

However, when we consider focal teachers' discretionary absences, the figure is completely different. Regarding all peers' absences, the results are qualitatively similar to those of the baseline, unrestricted model, but magnitudes are lower. Focusing our attention on the impact of peers' non-discretionary absences, the estimate is significantly negative. This is in line with the flip side of social interaction among teachers: teachers who stay in school must compensate for their peers who are unintentionally elsewhere. In other words, given their colleagues are absent, focal teachers have less latitude to willingly avoid classes as duties in school, many of them fixed irrespective to the number of attending teachers, must be accomplished.

Finally, we find a positive response of peers' discretionary absences on focal teachers'. The estimated elasticity is 0.90, significant at 1%, meaning a proportional reaction of focal teachers to perceived peers' deliberate absences. Once again, we estimate a slightly higher elasticity for Category F teachers, what reinforces that these teachers are more sensitive to peer effects. Along the peer absence distribution, we estimate a somewhat

homogeneous impact. The strongest effect of peer absences on focal teachers in the first quartile is suggestive of a nonlinear impact potentially stemming from the same reason discussed above – the more peers are absent, the less room for additional missing teachers.

## 5 Conclusion

Teacher quality is of absolute importance in determining pupils' development, but it cannot be fully exploited if teachers are absent. We have shown in this paper that teachers exert at least some discretion in their assiduity profile and, more importantly, are influenced by their colleagues' behavior. Public teachers in Sao Paulo work under different contract regimes with a distinct set of benefits and obligations, and we estimate that the impact of peer effects is surprisingly larger on those who supposedly have more incentive to be present. We also show peer effects do not operate in a linear fashion, what suggests public administration should be able to optimally allocate teachers. In light of our results, preventing the formation of absence clusters should improve overall attendance.

To be fair, the administration is on the right path to reduce absenteeism. Few new teachers are hired under the most permissive contract, and assiduous teachers may choose first their workplace – what hopefully averts the formation of such absence clusters, but at least rightly incentivizes attendance. However, the high absence rate is definitely troubling, and suggest the matter is far from settled.

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## Appendix

### Tables

Table 1: Mean yearly days in absence, by teacher category

	All teachers	Category A	Category F
<i>Leave</i>			
Health treatment	13.2	15.1	9.8
Good attendance ( <i>licença prêmio</i> )	3.7	6.6	0.4
Personal matters	1.4	2.5	0.0
Maternity	1.3	1.4	1.0
<i>Withdrawal</i>			
Different job position	17.3	31.4	0.1
Syndicate related	0.1	0.2	0.1
Training and study related	0.1	0.1	0.0
<i>Absences</i>			
Granted	2.9	3.0	2.6
Justified	1.8	1.8	1.7
Medical	1.2	1.2	1.0
Unjustified	0.7	0.8	0.5
Blood donation	0.1	0.1	0.1
<b>Total</b>	<b>43.9</b>	<b>64.3</b>	<b>17.5</b>

*Source:* Administrative records, DRHU/SEE-SP 2007-2010

Table 2: Teachers characteristics by year

	2006	2007	2008	2009
<i>Teachers' role</i>				
Principal	16,311 7.0%	16,318 6.3%	17,023 7.0%	15,253 6.6%
Elementary school teacher	57,500 24.6%	70,627 27.4%	58,687 24.1%	55,589 24.2%
Middle school teacher	161,204 68.9%	174,983 67.9%	167,686 68.9%	160,265 69.8%
Education coordinator	6,932 3.0%	3,066 1.2%	12,020 4.9%	9,294 4.0%
<i>Teachers' gender</i>				
Women	186,187 79.6%	205,264 79.6%	190,541 78.3%	179,429 78.2%
Men	47,781 20.4%	52,605 20.4%	52,924 21.7%	50,084 21.8%
<i>Teachers' category</i>				
A	120,246 51.4%	120,263 46.6%	128,845 52.9%	122,253 53.3%
F	102,513 43.8%	128,121 49.7%	101,561 41.7%	97,431 42.5%
P	2,577 1.1%	2,333 0.9%	1,856 0.8%	1,444 0.6%
Not informed	9,940 4.2%	7,764 3.0%	12,060 5.0%	9,777 4.3%
<i>Teachers by number of schools in which they teach</i>				
One	191,724 81.9%	211,260 81.9%	196,821 80.8%	195,216 85.1%
Two	32,360 13.8%	34,548 13.4%	37,016 15.2%	29,400 12.8%
Three	7,662 3.3%	8,724 3.4%	7,806 3.2%	4,212 1.8%
Four or more	2,222 0.9%	3,337 1.3%	1,822 0.7%	685 0.3%
<b>Total</b>	<b>233,968</b>	<b>257,869</b>	<b>243,465</b>	<b>229,513</b>

Source: Administrative records, DRHU/SEE-SP 2007-2010

Notes: Teachers' role totals does not correspond to sum of rows because same teachers may take more than one role in the same school.

Table 3: Initial results and baseline model

	OLS			Instrumental variables	
	No covariates	Focal teachers' covariates	Focal teachers' and peers' covariates	Full sample	Restricted sample
Peer effect	0.32*** (.0038)	0.28*** (.0037)	0.37*** (.0039)	1.07*** (.0700)	1.04*** (.0733)
First stage				-0.55*** (.0106)	-0.56*** (.0114)

Notes: regressions' specification are log of focal teacher absences on log of peers' average absences. Standard errors in parentheses. One, two and three asterisks indicate significance at 10%, 5% and 1% levels respectively. Control variables are gender, age, experience, education attainment with an indicator for public education, teacher role (principal, elementary school teacher, middle school teacher or education coordinator), teacher category (A, F or P), compensation level, compensation step and weekly work hours.

Table 4: Heterogeneous impact models

	1st quartile	2nd quartile	3rd quartile	4th quartile
Peer effect	-18.84 (120.3268)	12.36*** (3.2913)	10.03*** (1.6621)	2.36*** (.2283)
First stage	0.00 (.0135)	-0.03*** (.0041)	-0.05*** (.0041)	-0.35*** (.0109)

Notes: Regressions' specification are log of focal teacher absences on log of peers' average absences. Standard errors in parentheses. One, two and three asterisks indicate significance at 10%, 5% and 1% levels respectively. Control variables are the same listed in Table 3.

Table 5: Peer effects by teacher category

	Total	Category A	Category F
Peer effect	1.07*** (.0700)	0.61*** (.1002)	1.37*** (.0945)
First stage	-0.55*** (.0106)	-0.54*** (.0142)	-0.55*** (.0161)

Notes: Regressions' specification are log of focal teacher absences on log of peers' average absences. Standard errors in parentheses. One, two and three asterisks indicate significance at 10%, 5% and 1% levels respectively. Control variables are the same listed in Table 3.

Table 6: Discretionary and non-discretionary absences' peer effects

	Total	Category A	Category F	1st quartile	2nd quartile	3rd quartile	4th quartile
<i>Baseline models: all absences of focal teachers</i>							
All peers' absences	1.07*** (.0700)	0.61*** (.1002)	1.37*** (.0945)	-18.84 (120.3268)	12.36*** (3.291)	10.03*** (1.662)	2.36*** (.2283)
<i>Focal teachers' non-discretionary absences</i>							
All peers' absences	0.00 (.0052)	0.00 (.0094)	0.00 (.0025)	2.33 (14.3881)	-0.11 (.2341)	0.24** (.1163)	0.02 (.0143)
Non-discretionary peers' absences	-0.19 (.2455)	-0.06 (.2026)	0.14 (.58)	-0.54 (.7348)	0.02 (.0426)	0.30* (.1696)	0.95 (1.9130)
Discretionary peers' absences	0.01 (.0127)	0.01 (.0219)	0.00 (.0061)	-0.07 (.0745)	-0.02 (.0360)	0.09** (.0427)	0.02 (.0138)
<i>Focal teachers' discretionary absences</i>							
All peers' absences	0.37*** (.0295)	0.27*** (.0403)	0.48*** (.0439)	-49.67 (302.9201)	6.17*** (1.5200)	3.18*** (.698)	0.80*** (.0904)
Non-discretionary peers' absences	-16.34** (7.14)	-5.80*** (1.93)	86.86 (220.2)	11.46 (9.410)	-1.13*** (.2412)	4.02*** (1.4603)	47.90 (86.700)
Discretionary peers' absences	0.90*** (.0698)	0.63*** (.0920)	1.18*** (.1083)	1.42*** (.3929)	0.95*** (.1894)	1.17*** (.2449)	0.77*** (.084)

Notes: Regressions' specification are log of focal teacher absences on log of peers' average absences. Standard errors in parentheses. One, two and three asterisks indicate significance at 10%, 5% and 1% levels respectively. Control variables are the same listed in Table 3.