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# DOES MENSTRUATION EXPLAIN GENDER GAPS IN WORK ABSENTEEISM? 

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Does Menstruation Explain Gender Gaps in Work Absenteeism?
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#### Abstract

Ichino and Moretti (2009) find that menstruation may contribute to gender gaps in absenteeism and earnings, based on evidence that absences of young female Italian bank employees follow a 28-day cycle. We analyze absenteeism of teachers and find no evidence of increased female absenteeism on a 28 -day cycle. We also show that the evidence of 28 -day cycles in the Italian data is not robust to the correction of coding errors or small changes in specification. We show that five day workweeks can cause misleading group differences in absence hazards at multiples of 7, including 28 days.


Jonah E. Rockoff<br>Columbia University<br>Graduate School of Business<br>3022 Broadway \#603<br>New York, NY 10027-6903<br>and NBER<br>jonah.rockoff@columbia.edu<br>Mariesa A. Herrmann<br>International Affairs Building<br>Department of Economics<br>Columbia University<br>420 W 118th Street<br>New York, NY 10027<br>mariesah@gmail.com

A large literature in economics documents differences in earnings between men and women (see Goldin (1990), Blau and Kahn (2000)). In a recent paper, Ichino and Moretti (2009, hereafter IM) suggest that gender gaps in earnings can be partially explained by increased female absenteeism related to menstruation. While the higher rate of absenteeism among females is a well known fact (see Paringer (1983)), IM present new evidence on the role of menstruation using data from a large Italian bank, where they find women under the age of 45 exhibit a high rate of absences at 28-day intervals when compared with men under the age of 45 .

Standard explanations for the gender earnings gap include gender differences in preferences, gender differences in skills, and discrimination (Altonji and Blank (1999)). The notion that biological differences between men and women partially explain gender gaps in labor market outcomes is novel, provocative, and deserves scrutiny. Indeed, IM are careful to note that their "findings are based on data from only one firm and their external validity is unclear."

This paper provides several key pieces of evidence against the notion that menstruation is an important determinant of gender gaps in absences and earnings. First, we use data on New York City public school teachers to investigate whether female employees in a different institutional setting also exhibit high rates of absences at 28-day cycles. There are many reasons why we might expect New York City school teachers to respond differently to menstruation than Italian bank employees: Teachers are highly educated and may face higher financial and psychic costs of absence (e.g., because they care about student achievement), and Americans may face different cultural norms about work absence due to menstruation, or work absence more generally. Because of these differences, our setting provides an important test of whether IM's findings generalize to other groups of workers, which is crucial for understanding menstruation's overall role in the labor market. While we find that female teachers are absent more often than
their male colleagues, there is no evidence that young female teachers exhibit higher rates of absence at 28-day intervals than their same-aged male colleagues. This suggests that menstruation may not explain gender gaps in absenteeism, at least for a substantial segment of the female labor force in the U.S. ${ }^{2}$

Second, we revisit the study of absenteeism among Italian bank employees. ${ }^{3}$ We find that the estimates suggesting an impact of menstruation are sensitive to the correction of coding errors, small changes in specification, and allowing for serial correlation within individuals; corrected estimates do not provide strong evidence that the absences of female bank employees follow a 28 -day cycle.

Finally, we show that cycles of absences occur with high frequencies at distances that are multiples of 7 due to the five-day workweek. This can cause significant differences in the hazard rates of absences at multiples of 7 across groups with different absence frequencies, even when we have no a priori reason to expect cycles of absences at these particular distances between groups. For example, we find statistically significant differences at various multiples of 7 (including 28 days) between older and younger men, neither of whom experience menstruation. These patterns caution against interpreting 28-day cycles of absences as an effect of the menstrual cycle.

The rest of the paper proceeds as follows. We describe the New York City data in Section 2 and present graphical and regression analyses in Section 3. Section 4 contains our reanalysis of Italian bank data. In Section 5, we discuss whether 28-day cycles should be interpreted as an effect of menstruation. Section 6 concludes.

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## 2. New York City Data and Summary Statistics

New York is the largest school district in the United States and employs roughly 80,000 teachers annually to staff 1,500 schools. All teachers are employed full-time under the same collectively bargained contract and are paid based on a salary schedule that depends only on their years of experience and graduate education. Teachers earn ten days of paid absence for each year of work. Unused days roll over and teachers can accumulate up to 200 days of absence, but teachers cannot take more than ten undocumented days of paid absence per school year. If a doctor's note certifies that an absence was due to illness, then the absence will not count towards the annual cap. Teachers who resign or retire are paid $1 / 400^{\text {th }}$ of their salary for each of their accumulated unused absence days, so using "paid" absences entails a future financial cost.

We use data on all absences taken by all full-time public school teachers in New York City during the school years 1999-2000 through 2002-2003. We also use data on teacher characteristics (e.g., demographics, education, and experience) from employee payroll files, and data on extended leaves taken during this time period (e.g., sabbatical, maternity leave). ${ }^{4}$ We can distinguish absences taken for a number of special reasons (e.g., jury duty, military service, funeral, or religious holiday). These comprise 24 percent of absences and, to be more in line with the analysis of Italian bank data studied in Section 4, we remove them from the analysis. Absences taken for illness that are medically certified are also distinguishable, but illnesses that are not certified cannot be separated from absences taken for other personal business.

Summary statistics for the 71,998 female teachers and 27,777 male teachers in our data are shown in Table 1. Following IM, we excluded "all employees who took maternity leave at any point," as well as any teacher who took an extended leave of absence (i.e., medical,

[^1]sabbatical) during the school year or left their teaching position before the end of the school year. Note that this is a bit larger than the sample used to estimate hazard regressions because we can only conduct the analysis for teachers with at least one absence spell during the school year. As in IM, we separately examine younger (under 45) and older (45 and over) workers. This age cutoff is sensible for examining whether menstruation causes 28-day cycles of absence: women begin to experience menopause as they approach age 50, and there is a substantial increase in variation of menstrual cycles prior to menopause (Treloar et al. (1967)).

Teaching has historically been one of the most common female professions, and it is not surprising that we see a clear majority of women among both older and younger teachers (70 and 73 percent, respectively). Within age categories, teachers of both genders are similar in their average age and years of teaching experience, and females tend to be somewhat more likely to have a master's degree. Rates of absence are higher for younger women than young men ( 6.9 vs . 6.4 per year) and higher for older women than older men ( 7.3 vs. 7.0 per year). Thus, the stylized fact that women are absent more often than their male colleagues holds for our sample of public school teachers, although the gaps are wider in the Italian bank examined by IM. ${ }^{5}$ Consecutive days of absence are grouped into spells in our analysis, and we present the average annual number of spells of absence by gender and age category. ${ }^{6}$ While younger women have more individual days of absence than younger men, they have slightly fewer spells per year (4.9 vs. 5.1). Thus, compared to younger men, younger women have fewer but longer absence spells; 48 percent of younger women have absence spells that last more than one day, compared to 44 percent of younger men. On the other hand, older women have slightly more spells than older

[^2]men per year (5.0 vs. 4.9), and their spells are longer; 54 percent of older women have absence spells that last more than one day, compared to 46 percent of older men.

## 3. Are there 28-day Cycles in Absenteeism for Female Teachers?

Our analysis of absences among teachers closely follows IM's previous analysis of Italian bank data. We first look for graphical evidence that female absenteeism occurs at 28 -day cycles. We limit our sample to teachers under age 45 and calculate the distribution of days between the starts of consecutive absence spells for each gender, as well as the difference between the female and male distributions. IM find that the gender difference (female minus male) displays a positive spike at a distance of 28 days for Italian bank employees.

Figure 1, which plots these distributions for teachers at distances of 100 days or less, shows that the densities of the distributions for both men and women increase markedly for distances that are multiples of 7. This is due to the fact that schools are not open on weekends; conditional on the date of a prior absence, the probability that school is open 7 days later (or any multiple of 7 days later) is considerably higher than for distances that are not multiples of 7 . Similar peaks at multiples of 7 are found in the Italian bank data; most Italian banks are not open on weekends, though some open for a shortened business day on Saturday. ${ }^{7,8}$ More importantly, the increased mass at multiples of 7 amplifies the differences between the probability distributions at these points. The difference between female and male distributions is large and negative at multiples of 7 between 7 and 42 days and becomes positive and noisy when the probability distributions cross.

[^3]While Figure 1 shows that younger women are not more likely to have consecutive absences 28 days apart, it does not capture the degree to which non-consecutive absences occur at distances of 28-days; for example, in Figure 1, a teacher absent on the $1^{\text {st }}, 5^{\text {th }}$, and $29^{\text {th }}$ of January would be coded as having absences at distances of 4 and 24 days. To examine the importance of non-consecutive spells, we calculate the probability distributions of the distances between all pairs of absences by gender and age category. We plot the difference between female and male probability distributions for three age categories, under 45 years old (before menopause), 45 to 55 years old (during menopause), and over 55 years (after menopause), in Figure 2. While one might expect that the inclusion of all pairs of absences to reduce the effect of the five-day workweek, the spikes at multiples of 7 persist in this figure. In addition, the pattern of absences is relatively constant across age groups: males are more likely to have absences at distances below 40 , especially at multiples of 7 .

In addition to plotting the raw data, we generate Kaplan Meier estimates of hazard rates for absences, separately for men and women under 45 and 45 and over. These hazard rates (and the difference in hazards between genders) are shown in Figure 3 for distances less than 100 days. Again, males are more likely to have absences at distances below 40, particularly those that are evenly divisible by 7. Note that there does not appear to be a constant "7-day periodicity [that] differs between genders," as IM argue for Italian bank employees. The magnitudes of the spikes at 7-day multiples vary systematically for teachers under 45 , forming a $U$-shape with a peak at 35 days. For those 45 and older, the spikes are large and roughly constant from 7 to 35 , small and roughly constant from 42 to 56 , and dissipate at higher values.

For our more formal analysis, we begin with the Cox proportional hazard model shown by Equation 1, where $t$ indexes days from the start of the previous absence spell, $X_{i t}$ are
covariates, and $\Psi$ is a vector of coefficients. There are three main control variables: (1) an
indicator for whether the teacher is female $\left(F_{i}\right),(2)$ an interaction of the female indicator with an indicator for distances that are multiples of $7\left(S_{i t}\right)$, and (3) an interaction of female with an indicator for a distance of 28 days $\left(M_{i t}\right) . C_{i t}$ is a vector of controls for day of the week and teacher characteristics (i.e., age, experience, and possession of a master's degree).

$$
\text { (1) } h\left(t, X_{i t}, \Psi\right)=\lambda(t) \exp \left(\alpha+\beta F_{i t}+\delta S_{i t} F_{i}+\gamma M_{i t} F_{i}+\theta C_{i t}\right)
$$

IM explain that they include the interaction term $S_{i t} F_{i}$ to "allow for the possibility that the 7-day periodicity differs between genders." However, the Kaplan-Meier hazards (Figure 3) show that this specification does not fit the data well. Moreover, because the number of observations is decreasing in $t$, the identification of the coefficient $\delta$ is heavily weighted towards the femalemale difference at a distance of 7 days. The result is that the coefficient $\gamma$ is mostly identified as the difference between the female and male hazard rates at 28 days, above the difference between the hazard rates at 7 days. ${ }^{9}$ We therefore estimate specifications that include and exclude the interaction term. Because the distance between absence spells is likely to be correlated within teachers over time, we calculate standard errors that allow for clustering at the individual level.

In Table 2, we present results for teachers under 45 (Columns 1-3) and 45 and older (Columns 4-6). ${ }^{10}$ In Columns 1 and 4, we present specifications that include the interaction between female and distances that are multiples of 7. In Columns 2 and 5, we present

[^4]specifications that separately interact female with each multiple of 7 up to 70 days. ${ }^{11}$ For both age groups, Wald tests strongly reject the equality of the coefficients on the interactions of female with distances that are multiples of 7 other than 28 . The p -values of these tests are both less than 0.0001 , suggesting that gender differences in 7 -day periodicity are not constant. Thus, in Columns 3 and 6, we present a specification that excludes the interaction between female and multiples of 7; it seems that in both age groups, if anything, male teachers are more likely to have 28-day cycles than their female colleagues.

## 4. Re-analysis of Absenteeism in an Italian Bank

Ichino and Moretti analyze data covering the absences of employees in a large Italian bank over a period of three years, and we refer the reader to their paper for additional details on these data. The main piece of evidence that menstruation increases absenteeism among female bank employees is that the hazard rate of an absence spell increases 28 days after the start of a previous absence spell for females, relative to males, under the age of 45 . Using data and code generously provided to us by Ichino and Moretti, we replicate the results of these hazard regressions. Again, the main control variables are: (1) an indicator for whether the employee is female, (2) an interaction of the female indicator with an indicator for distances that are multiples of 7, and (3) an interaction of female with an indicator for a distance of 28 days.

In Column 1 of Table 3, we display the estimates for their most rigorous specification, which includes these three controls as well as controls for workers' characteristics (age, years of schooling, marital status, number of children, managerial occupation, and seniority) and the day of the week. The coefficient on female is significantly greater than one, in line with higher

[^5]female absence rates. More importantly, the coefficient on the interaction of female with a distance of 28 days is 1.15 and statistically significant with a t-statistic of 2.16.

However, there were several anomalies in the computer code used to estimate these regressions. First, when workers had multiple absence spells, their last absence spell was unintentionally dropped from the regression, rather than being coded as right censored. ${ }^{12}$ Second, the day of the week controls were coded as the day of the week on which the previous absence spell started, rather than the day of the week on day $t .^{13}$ Finally, employees were coded as having the same age as at the start of the three-year sample period, not their actual age. ${ }^{14}$

We present hazard regressions that sequentially correct these coding errors - right censoring, day of the week controls, and age. Column 2 of Table 3 shows that correcting the right censoring increases the overall hazard for women because men were more likely to have right-censored spells, which were dropped from the original regressions. Column 3 present results that also correct the day of the week controls. Controls for actual day of the week could potentially be important, since the probability of another spell occurring is nearly zero on Saturdays and Sundays, but this coding error turns out to be fairly innocuous. Since these explain a large portion of difference in hazards at multiples of 7, this correction increases the standard error on the interaction of female and multiple of 7 but does not change the coefficient on the interaction between female and 28 days.

[^6]Next, we correct the employees' age variable to reflect their actual ages, rather than their ages at the start of the sample period (Table 3, Column 4). This causes the coefficient on the interaction of female and 28 days to decline to 1.11 and its $t$-statistic to fall to 1.61. This correction also increases the coefficient on the interaction of female and multiple of 7 to 0.98 (from 0.96 ) and the corresponding t-statistic to -0.67 (from -1.50 ).

As mentioned above, the distance between absence spells is likely to be correlated within individuals, but IM treat all spells of absence as independent. While this is not an error in coding, we believe a more appropriate treatment of the data is to calculate standard errors allowing for clustering at the individual level. When we do so, the $t$-statistic on the interaction of female and 28 days falls to 1.49 (Table 3, Column 5).

It is interesting that the largest reduction in the coefficient on the interaction of female and 28 days occurs when we change the age coding. We believe that this is due to slight changes in the composition of the under 45 sample. Men who turned 45 in 1993 or 1994 are considerably more likely to have absences at distances of 7,14 , and 21 days, so including them in the under 45 regressions causes the interaction of female and multiple of 7 to be more negative, forcing the interaction of female and 28 to be more positive. In addition, there are a few women who turned 45 in 1993 or 1994 and had a fairly high number of spells at a distance of 28 days.

Another important issue in these hazard regressions is that the relatively high female hazard rate at 28 days may be driven by high male hazard rates at early multiples of 7. To examine this issue, we return to IM's original code, but add interactions between female and each multiple of 7, as we did with our sample of New York City teachers. These results are shown in Column 6 of Table 3. The Wald test rejects the equality of the interactions of female and multiples of 7 , excluding 28 , with a p-value below 0.0001 , suggesting that gender
differences in 7-day periodicity are not constant in this context. Men are more likely to have absence spells at distances of 7,14 , and 21 days, and the difference between females and males in the hazard at 28 days is relatively small (1.10) and statistically insignificant (t-statistic 1.47). In addition, the coefficients on the interactions between female and 63 and 70 days are positive, more precisely estimated, and of a greater magnitude than the coefficient on the interaction between female and 28 days, even though menstrual cycles are very unlikely to occur at 63 or 70 day intervals. ${ }^{15}$ Dropping the interaction between female and distances that are multiples of 7 (Column 7) leaves the coefficient on the interaction of female and 28 days unchanged (1.10) with at-statistic of 1.57. Correcting coding errors and allowing for serial correlation at the individual level (Column 8) leaves the coefficient on the interaction of female and 28 days unchanged (1.10) but reduces the t -statistic from 1.57 to 1.36 .

Correction of the age variable alters the sample of employees under age 45. To test the sensitivity of the results to sample composition, we also estimate hazard regressions using age cutoffs from 42 through 52. Panel A of Table 4 shows estimates using the specification from Column 5 of Table 3 (i.e., correcting errors but leaving the interaction of female with multiples of 7 days). The coefficient on the interaction of female and 28 days is only statistically significant when we use age cutoffs of 50 or 51 . The pattern of increasing statistical significance of the relative hazard for females at 28 days as we move to older samples does not support the conclusion that these absences are due to menstruation, because the medical evidence is quite clear that menstrual cycles show increasing variability as women approach menopause (Treloar

[^7]et al. (1967)). Moreover, if we drop the interaction of female with multiples of 7 (Panel B of Table 4), the interaction of female and 28 days is never significant, regardless of the age cutoff.

## 5. Is the Coefficient at 28 Days Evidence of a Menstrual Cycle Effect?

While our corrections reduce the point estimates and eliminate the statistical significance of the interaction between being female and distances at 28 days in the Italian bank data, the coefficients are still positive. Thus, one might still interpret them as providing some support for the link between menstruation and absenteeism. To further test this interpretation, we estimate hazard regressions that compare the absence patterns of two groups who do not experience menstruation: men under 45 and men 45 and older. Significant differences in the absence patterns of these groups at 28 days would cast doubt on the interpretation of 28-day cycles of absences as effects of menstruation. For these specifications, we include (1) an indicator variable for males age 45 and over, (2) interactions between this indicator variable and distances that are multiples of 7 from 7 through 70, and (3) the controls used in the previous hazard regressions (e.g., age, experience, day of the week controls, etc.). ${ }^{16}$

The results for male New York City teachers and male Italian bank employees are displayed in Table 5, Columns 1 and 2, respectively. Nearly all of the interactions between the indicator for older males and multiples of 7 are statistically significant, suggesting that large differences in absence patterns are frequently manifested at multiples of 7. Moreover, in the Italian bank data, the coefficient on the interaction between older males and 28 days is positive, statistically significant, and at least as large as the coefficient for women in Table 3. While the

[^8]interaction between older males and 28 days is not the largest of all the interaction terms in Column 2, we can think of no explanations for why older male employees in an Italian bank are much more likely to have 14-day cycles of absences than younger males, or why younger male teachers in New York City are more likely to have 42-day cycles of absences than older male teachers. These results suggest one should be very cautious about interpreting the coefficient on 28-day cycles of absences as evidence of an effect of menstruation.

## 6. Conclusion

A link between menstruation and workplace absenteeism among females provides a provocative and potentially important explanation for gender gaps in labor market outcomes. However, we find little evidence that females are more likely to be absent at 28-day cycles in a large dataset on public school teachers in New York City or in our re-analysis of the Italian bank data used by Ichino and Moretti. Moreover, the fact that the five-day workweek accentuates differences in absence hazards between groups at multiples of 7 suggests that 28-day cycles cannot necessarily be interpreted as an effect of menstruation, casting additional doubt on the strength of the link between female absenteeism and menstruation.

Nevertheless, the medical literature clearly documents that a small percentage of women may experience severe symptoms brought on by menstruation (e.g., premenstrual dysphoric disorder), and it is foolhardy to believe that these serious conditions would never cause a woman to miss a day of work. Yet if the effects of menstruation on female absenteeism are small, we doubt they will be accurately measured only with data on absences, especially because of the confounding day of the week effects. A more promising approach is that used by Oster and

Thornton (2009), who uncover a very small impact of menstruation on school attendance in Nepal using data on both the timing of menstruation and absences.

Finally, it is worth noting that labor laws and labor contracts which recognize the right of women to take a "feminine day" or "menstrual leave" once per month are common in Indonesia, Japan, South Korea, and Taiwan. Given the potential importance of labor institutions in mediating the relationship between menstruation and the labor market, more research is clearly needed on this topic.

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Table 1: Summary Statistics on NYC Teachers by Gender and Age Group

|  | Under Age 45 |  |  | Age 45 and Over |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Male | Female |  | Male | Female |
| Number of Observations | 39,444 | 111,453 |  | 37,538 | 95,287 |
| Number of Teachers | 15,811 | 43,732 |  | 11,966 | 28,266 |
| Age | 33.7 | 33.0 |  | 53.1 | 52.9 |
| Teaching Experience | 4.3 | 4.5 |  | 14.5 | 13.6 |
| Black | $22.7 \%$ | $23.8 \%$ |  | $15.7 \%$ | $20.4 \%$ |
| Hispanic | $16.4 \%$ | $17.2 \%$ |  | $8.6 \%$ | $10.2 \%$ |
| Masters Degree | $34.4 \%$ | $40.7 \%$ |  | $23.0 \%$ | $27.5 \%$ |
| Number of Days Absent | 6.43 | 6.93 |  | 7.01 | 7.31 |
| Number of Absence Spells | 5.12 | 4.93 |  | 4.91 | 4.97 |
| No Absences | $11.0 \%$ | $12.6 \%$ |  | $12.0 \%$ | $9.1 \%$ |
| Absence Spells Longer than 1 Day | $43.5 \%$ | $48.0 \%$ |  | $46.3 \%$ | $54.0 \%$ |

Note: The unit of observation is a teacher-year. Absences only includes absences for illness (certifed by a doctor's note or self-reported) and personal reasons.

Table 2: Hazard of an Absence Spell for Females Relative to Males on 7 Day Multiples

|  | Under 45 |  |  | 45 and Over |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | $\begin{gathered} \hline 0.99 \\ (-1.26) \end{gathered}$ | $\begin{gathered} 0.99 \\ (-1.26) \end{gathered}$ | $\begin{gathered} 0.98 \\ (-3.89) \end{gathered}$ | $\begin{gathered} 0.99 \\ (-2.34) \end{gathered}$ | $\begin{gathered} \hline 0.99 \\ (-2.34) \end{gathered}$ | $\begin{gathered} 0.97 \\ (-5.35) \end{gathered}$ |
| Female*28 Days | $\begin{gathered} 0.97 \\ (-1.79) \end{gathered}$ | $\begin{gathered} 0.89 \\ (-6.24) \end{gathered}$ | $\begin{gathered} 0.91 \\ (-5.52) \end{gathered}$ | $\begin{gathered} 0.98 \\ (-1.18) \end{gathered}$ | $\begin{gathered} 0.89 \\ (-6.28) \end{gathered}$ | $\begin{gathered} 0.90 \\ (-5.46) \end{gathered}$ |
| Female*Multiple of 7 Days | $\begin{gathered} 0.93 \\ (-9.72) \end{gathered}$ |  |  | $\begin{gathered} 0.91 \\ (-11.25) \end{gathered}$ |  |  |
| Female*7 Days |  | $\begin{gathered} 0.92 \\ (-4.18) \end{gathered}$ |  |  | $\begin{gathered} 0.84 \\ (-9.25) \end{gathered}$ |  |
| Female*14 Days |  | $\begin{gathered} 0.89 \\ (-6.63) \end{gathered}$ |  |  | $\begin{gathered} 0.87 \\ (-7.47) \end{gathered}$ |  |
| Female*21 Days |  | $\begin{gathered} 0.90 \\ (-6.24) \end{gathered}$ |  |  | $\begin{gathered} 0.89 \\ (-6.58) \end{gathered}$ |  |
| Female*35 Days |  | $\begin{gathered} 0.90 \\ (-5.80) \end{gathered}$ |  |  | $\begin{gathered} 0.90 \\ (-5.06) \end{gathered}$ |  |
| Female*42 Days |  | $\begin{gathered} 0.92 \\ (-3.95) \end{gathered}$ |  |  | $\begin{gathered} 0.96 \\ (-1.72) \end{gathered}$ |  |
| Female*49 Days |  | $\begin{gathered} 1.01 \\ (0.60) \end{gathered}$ |  |  | $\begin{gathered} 0.98 \\ (-0.82) \end{gathered}$ |  |
| Female*56 Days |  | $\begin{gathered} 0.98 \\ (-0.85) \end{gathered}$ |  |  | $\begin{gathered} 0.96 \\ (-1.39) \end{gathered}$ |  |
| Female*63 Days |  | $\begin{gathered} 1.00 \\ (0.06) \end{gathered}$ |  |  | $\begin{gathered} 1.03 \\ (0.84) \end{gathered}$ |  |
| Female*70 Days |  | $\begin{gathered} 0.98 \\ (-0.67) \end{gathered}$ |  |  | $\begin{gathered} 1.04 \\ (1.00) \\ \hline \end{gathered}$ |  |

Note: All specifications control for age, teaching experience, education (masters degree), and indicator variables for day of the week. Standard errors allow for clustering at the individual worker level, and t-statistics are shown in parentheses. A hazard ratio of 1 indicates no effect.

Table 3: Hazard of an Absence Spell for Females Relative to Males - Italian Bank Data, Under 45

|  | IM (2009) | Re-analysis of IM Data |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Female | $\begin{gathered} 1.39 \\ (35.94) \end{gathered}$ | $\begin{gathered} 1.46 \\ (41.55) \end{gathered}$ | $\begin{gathered} 1.46 \\ (41.37) \end{gathered}$ | $\begin{gathered} 1.47 \\ (41.44) \end{gathered}$ | $\begin{gathered} 1.47 \\ (20.26) \end{gathered}$ | $\begin{gathered} 1.39 \\ (35.94) \end{gathered}$ | $\begin{gathered} 1.38 \\ (37.34) \end{gathered}$ | $\begin{gathered} 1.47 \\ (19.51) \end{gathered}$ |
| Female*28 Days | $\begin{gathered} 1.15 \\ (2.16) \end{gathered}$ | $\begin{gathered} 1.16 \\ (2.18) \end{gathered}$ | $\begin{gathered} 1.16 \\ (2.18) \end{gathered}$ | $\begin{gathered} 1.11 \\ (1.61) \end{gathered}$ | $\begin{gathered} 1.11 \\ (1.49) \end{gathered}$ | $\begin{gathered} 1.10 \\ (1.47) \end{gathered}$ | $\begin{gathered} 1.10 \\ (1.57) \end{gathered}$ | $\begin{gathered} 1.10 \\ (1.36) \end{gathered}$ |
| Female*Multiple of 7 Days | $\begin{gathered} 0.95 \\ (-2.04) \end{gathered}$ | $\begin{gathered} 0.95 \\ (-1.93) \end{gathered}$ | $\begin{gathered} 0.96 \\ (-1.50) \end{gathered}$ | $\begin{gathered} 0.98 \\ (-0.67) \end{gathered}$ | $\begin{gathered} 0.98 \\ (-0.61) \end{gathered}$ |  |  |  |
| Female*7 Days |  |  |  |  |  | $\begin{gathered} 0.76 \\ (-4.16) \end{gathered}$ |  |  |
| Female*14 Days |  |  |  |  |  | $\begin{gathered} 0.90 \\ (-1.74) \end{gathered}$ |  |  |
| Female*21 Days |  |  |  |  |  | $\begin{gathered} 0.82 \\ (-3.21) \end{gathered}$ |  |  |
| Female*35 Days |  |  |  |  |  | $\begin{gathered} 0.96 \\ (-0.62) \end{gathered}$ |  |  |
| Female*42 Days |  |  |  |  |  | $\begin{gathered} 1.02 \\ (0.26) \end{gathered}$ |  |  |
| Female*49 Days |  |  |  |  |  | $\begin{gathered} 1.09 \\ (1.10) \end{gathered}$ |  |  |
| Female*56 Days |  |  |  |  |  | $\begin{gathered} 1.05 \\ (0.55) \end{gathered}$ |  |  |
| Female*63 Days |  |  |  |  |  | $\begin{gathered} 1.15 \\ (1.64) \end{gathered}$ |  |  |
| Female*70 Days |  |  |  |  |  | $\begin{gathered} 1.20 \\ (2.02) \end{gathered}$ |  |  |
| Corrections |  |  |  |  |  |  |  |  |
| Right Censoring |  | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |  |  | $\checkmark$ |
| Day of the Week |  |  | $\checkmark$ | $\checkmark$ | $\checkmark$ |  |  | $\checkmark$ |
| Age |  |  |  | $\checkmark$ | $\checkmark$ |  |  | $\checkmark$ |
| Clustered Standard Errors |  |  |  |  | $\checkmark$ |  |  | $\checkmark$ |

Note: The first column displays results from Ichino and Moretti (2009), Table 2. The remaining columns display results from hazard regressions that use the same Italian Bank data but differ in that issues of right censoring, day of the week coding, and age coding have been corrected, standard errors allow for clustering at the the individual worker level, or the interaction of female with multiples of seven has been replaced or omitted from the specification. All specifications control for age, years of schooling, marital status, number of children, managerial occupation, seniority, and dummies for each day of the week. T-statistics are shown in parentheses. A hazard ratio of 1 indicates no effect.

Table 4: Hazard of an Absence for Females Relative to Males - Italian Bank Data, Various Age Cut-offs

|  | Re-analysis of IM Data |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Panel A | Under 42 | Under 43 | Under 44 | Under 45 | Under 46 | Under 47 | Under 48 | Under 49 | Under 50 | Under 51 | Under 52 |
| Female | $\begin{gathered} 1.48 \\ (19.03) \end{gathered}$ | $\begin{gathered} 1.48 \\ (19.55) \end{gathered}$ | $\begin{gathered} 1.48 \\ (20.02) \end{gathered}$ | $\begin{gathered} 1.47 \\ (20.26) \end{gathered}$ | $\begin{gathered} 1.47 \\ (20.55) \end{gathered}$ | $\begin{gathered} 1.46 \\ (20.56) \end{gathered}$ | $\begin{gathered} 1.45 \\ (20.41) \end{gathered}$ | $\begin{gathered} 1.45 \\ (20.37) \end{gathered}$ | $\begin{gathered} 1.45 \\ (20.52) \end{gathered}$ | $\begin{gathered} 1.45 \\ (20.65) \end{gathered}$ | $\begin{gathered} 1.44 \\ (20.59) \end{gathered}$ |
| Female*28 Days | $\begin{gathered} 1.09 \\ (1.07) \end{gathered}$ | $\begin{gathered} 1.08 \\ (1.01) \end{gathered}$ | $\begin{gathered} 1.11 \\ (1.36) \end{gathered}$ | $\begin{gathered} 1.11 \\ (1.49) \end{gathered}$ | $\begin{gathered} 1.08 \\ (1.04) \end{gathered}$ | $\begin{gathered} 1.14 \\ (1.76) \end{gathered}$ | $\begin{gathered} 1.14 \\ (1.83) \end{gathered}$ | $\begin{gathered} 1.13 \\ (1.78) \end{gathered}$ | $\begin{gathered} 1.15 \\ (2.03) \end{gathered}$ | $\begin{gathered} 1.14 \\ (1.98) \end{gathered}$ | $\begin{gathered} 1.13 \\ (1.87) \end{gathered}$ |
| Female*Multiple of 7 Days | $\begin{gathered} 0.98 \\ (-0.59) \\ \hline \end{gathered}$ | $\begin{gathered} 0.98 \\ (-0.58) \\ \hline \end{gathered}$ | $\begin{gathered} 0.98 \\ (-0.61) \\ \hline \end{gathered}$ | $\begin{gathered} 0.98 \\ (-0.61) \\ \hline \end{gathered}$ | $\begin{gathered} 0.97 \\ (-1.18) \\ \hline \end{gathered}$ | $\begin{gathered} 0.95 \\ (-1.86) \\ \hline \end{gathered}$ | $\begin{gathered} 0.95 \\ (-1.71) \\ \hline \end{gathered}$ | $\begin{gathered} 0.96 \\ (-1.46) \\ \hline \end{gathered}$ | $\begin{gathered} 0.96 \\ (-1.58) \\ \hline \end{gathered}$ | $\begin{gathered} 0.96 \\ (-1.48) \\ \hline \end{gathered}$ | $\begin{gathered} 0.96 \\ (-1.58) \\ \hline \end{gathered}$ |
| Panel B | Under 42 | Under 43 | Under 44 | Under 45 | Under 46 | Under 47 | Under 48 | Under 49 | Under 50 | Under 51 | Under 52 |
| Female | $\begin{gathered} 1.48 \\ (18.32) \end{gathered}$ | $\begin{gathered} \hline 1.48 \\ (18.85) \end{gathered}$ | $\begin{gathered} \hline 1.48 \\ (19.30) \end{gathered}$ | $\begin{gathered} 1.47 \\ (19.51) \end{gathered}$ | $\begin{gathered} 1.46 \\ (19.68) \end{gathered}$ | $\begin{gathered} 1.45 \\ (19.59) \end{gathered}$ | $\begin{gathered} 1.44 \\ (19.48) \end{gathered}$ | $\begin{gathered} 1.44 \\ (19.46) \end{gathered}$ | $\begin{gathered} 1.44 \\ (19.57) \end{gathered}$ | $\begin{gathered} 1.44 \\ (19.71) \end{gathered}$ | $\begin{gathered} 1.43 \\ (19.62) \end{gathered}$ |
| Female*28 Days | $\begin{gathered} 1.07 \\ (0.93) \\ \hline \end{gathered}$ | $\begin{gathered} 1.06 \\ (0.86) \\ \hline \end{gathered}$ | $\begin{gathered} 1.09 \\ (1.21) \end{gathered}$ | $\begin{gathered} 1.10 \\ (1.36) \\ \hline \end{gathered}$ | $\begin{gathered} 1.05 \\ (0.68) \\ \hline \end{gathered}$ | $\begin{gathered} 1.09 \\ (1.20) \end{gathered}$ | $\begin{gathered} 1.09 \\ (1.32) \end{gathered}$ | $\begin{gathered} 1.09 \\ (1.36) \end{gathered}$ | $\begin{gathered} 1.11 \\ (1.57) \end{gathered}$ | $\begin{gathered} 1.11 \\ (1.56) \end{gathered}$ | $\begin{gathered} 1.09 \\ (1.41) \end{gathered}$ |

Note: Each column displays results from hazard regressions that use the Italian Bank data where issues of right censoring, day of the week coding, and age coding have been corrected and standard errors allow for clustering at the the individual worker level. In Panel B, the interaction of female with multiples of seven has been omitted from the specification. All specifications control for age, years of schooling, marital status, number of children, managerial occupation, seniority, and dummies for each day of the week. T-statistics are shown in parentheses. A hazard ratio of 1 indicates no effect.

Table 5: Hazard of an Absence Spell for Older vs. Younger Males

|  | NYC |  |
| :--- | :---: | :---: |
|  | Teachers | Italian Bank <br> Employees |
| Older Male | $(1)$ | $(2)$ |
| Older Male*28 Days | 0.92 | 0.93 |
|  | $(-7.03)$ | $(-2.62)$ |
| Older Male*7 Days | 1.03 | 1.16 |
|  | $(1.38)$ | $(2.12)$ |
| Older Male*14 Days | 1.38 | 1.38 |
|  | $(13.74)$ | $(13.75)$ |
| Older Male*21 Days | 1.10 | 1.38 |
|  | $(4.46)$ | $(4.55)$ |
| Older Male*35 Days | 1.05 | 1.13 |
|  | $(2.43)$ | $(1.84)$ |
| Older Male*42 Days | 0.95 | 1.12 |
|  | $(-2.15)$ | $(1.65)$ |
| Older Male*49 Days | 0.90 | 0.96 |
|  | $(-4.07)$ | $(-0.55)$ |
| Older Male*56 Days | 0.93 | 1.08 |
| Older Male*63 Days | $(-2.51)$ | $(0.95)$ |
|  | 0.92 | 0.99 |
| Older Male*70 Days | $(-2.44)$ | $(-0.08)$ |
|  | 0.94 | 1.27 |

Note: Specifications for NYC teachers control for age, teaching experience, education (masters degree), and indicator variables for each day of the week. Specifications for Italian bank employees control for age, years of schooling, marital status, number of children, managerial occupation, seniority, and indicator variables for each day of the week. Standard errors allow for clustering at the individual worker level. T-statistics are shown in parentheses. A hazard ratio of 1 indicates no effect.

Figure 1: Distribution of the Distance Between Consecutive Absence Spells


Notes: This figure displays the frequency distribution of the distance in days between consecutive absence episodes for male and female New York City teachers (using the y-axis on the left side), as well as the difference between the two distributions (using the $y$-axis on the right side).

Figure 2: Distribution of the Distance Between (All) Absence Spells, NYC Teachers


Figure 3: Kaplan-Meier Hazard Rates, by Gender and Age Group, NYC Teachers

Hazard Rates, Under 45


Female-Male Difference in Hazard Rates, Under 45


Hazard Rates, 45 and Over


Female-Male Difference in Hazard Rates, 45 and Over



[^0]:    ${ }^{2}$ In 2008, teaching in an elementary or middle school was the third most prevalent occupation for employed women in the United States, behind secretaries/administrative assistants and registered nurses; $3.5 \%$ of employed women worked as elementary or middle school teachers. (http://www.dol.gov/wb/stats/main.htm, accessed 5/16/2009)
    ${ }^{3}$ We thank Ichino and Moretti for generously sharing their data and computer code, as well as answering a number of our questions and discussing our findings.

[^1]:    ${ }^{4}$ Kane et al. (2008) and Herrmann and Rockoff (2010) provide more detail on these datasets.

[^2]:    ${ }^{5}$ In their data, female employees averaged roughly 13 absences per year compared to only 8 for males.
    ${ }^{6}$ We have connected absences that occur on consecutive workdays into spells into spells in order to closely follow IM's methodology.

[^3]:    ${ }^{7}$ Of absences spells in the Italian bank data, 0.26 percent began on Saturday or Sunday.
    ${ }^{8} \mathrm{IM}$ attribute the peaks at 7-day multiples to people taking absences on the same day of the week (e.g., a "Monday effect'". In practice, we find this is unimportant relative to effect of the five-day workweek.

[^4]:    ${ }^{9}$ If women were more likely to be absent on multiples of 7 for other reasons (e.g., weekly child care commitments), then the coefficient at 28 days would be biased upwards and the inclusion of an interaction between female and any multiple of 7 days would mitigate this bias. However, this control is only appropriate if the gender-specific hazard rate of absence at multiples of 7 is a constant. Because the control is heavily weighted towards the gender difference at a distance of 7 days, the inclusion of the interaction between female and any multiple of 7 can create a bias in favor of the menstrual cycle hypothesis if men are more likely to be absent 7 days apart.
    ${ }^{10}$ We report hazard ratios, with t-statistics in parentheses; a hazard ratio of 1 means no effect, while a hazard greater (less) than 1 indicates a positive (negative) effect.

[^5]:    ${ }^{11}$ This also follows Ichino and Moretti, whose multiple of 7 indicator only includes multiples of 7 for distances less than or equal to 70 .

[^6]:    ${ }^{12}$ For workers with a single absence spell, their spell was correctly treated as right censored. For all workers with multiple absences, their final spells were dropped from the regression.
    ${ }^{13}$ Suppose an absence spell started on a Monday and there were 30 days until the start of the next spell. IM's code would create 30 observations with hazard time running from 1 to 30 , but all of the observations would be coded as Mondays. We fix this, so that the observation at time $=2$ occurs on a Tuesday, time $=3$ occurs on a Wednesday, etc. This is potentially important because the hazard rate for an absence on the weekend is nearly zero.
    ${ }^{14}$ In a previous version of this paper, we also noted there are some adjacent spells in the Italian bank data that are separated by a distance of one. The distance between spells should never equal one because spells are formed from consecutive days of absence. Any adjacent spell that is separated by a distance of one from a previous spell should have been part of the previous spell. We do not correct this error in this version because its effect on the results is negligible.

[^7]:    ${ }^{15}$ We gauge the likelihood of menstrual cycles occurring at distances of 63 and 70 days using information from Chiazze et al. (1968), who collected data on onset of each menstrual cycle between January 1964 and December 1965 for a group of 2,316 (predominantly Catholic) American and Canadian women, each of whom were followed for a minimum of ten cycles. We use the probability distribution of cycle lengths reported in their study to estimate the probability that a woman has two (possibly non-consecutive) menstrual cycles at various distances. We estimate that the probability of cycles at distances of 28 days and 56 days are, respectively, 16 and 9 percent. In contrast, estimated probabilities of cycles at distances of 63 and 70 days are just 2.6 and 0.8 percent, respectively.

[^8]:    ${ }^{16}$ These regressions compare two different age ranges, rather than two genders of the same age range. We therefore also estimated specifications that allow for a separate age trend for males 45 and older and find very similar results to those reported here; when this additional age control is included the coefficient on older male decreases but the coefficients on the interactions between multiples of 7 and older male remain quite stable.

