Bolstering the Boys Club? The Gendered Effects of #MeToo and Nondisclosure Agreements on Workplace Social Capital in the United States

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Abstract: The #MeToo movement sparked changes in the social structures of workplaces as well as in legislation. In this paper, I use American Time Use Survey data alongside Google Trends and legislative data to examine the intersectional impact of #MeToo on workers' time spent socializing with bosses, coworkers, and clients. I find that in the aftermath of #MeToo, men, and White men in particular, spent more time in these social interactions, while there were no statistically significant changes for women. I then consider the role of state-level legislation responding to #MeToo: namely, new laws banning nondisclosure agreements (NDAs) that prevent employees from discussing workplace harassment or discrimination. Using staggered difference-in-difference estimations, I show that such legislation did not have a discernable impact on the amount of time working women or men spent socializing with bosses, coworkers, and clients. These results raise questions about how workplace 'Boys Club' behavior interacts differently with social movements and with legal frameworks.

Keywords: time use; #MeToo; social capital; gender equality

I. INTRODUCTION

Tarana Burke first coined the phrase "me too" in 2006 to draw attention to the pervasiveness of sexual abuse, especially among low-income women of color. The hashtag "#MeToo" went viral on Twitter in 2017, with many pointing to actress and activist Alyssa Milano's related tweet (Pflum, 2018). There has been a good deal of scholarship on the ways in which the #MeToo movement in 2017 replicated many intersectional power dynamics, particularly with the attention of the #MeToo movement focusing on White women in relatively privileged economic positions (Zarkov and Davis 2018; Fileborn and Loney-Howes 2019; Leung and Williams 2019; Trott 2021). Scholars have also noted that the #MeToo movement's impact was overstated, and would not have gained much traction had it not been for the work many feminist activists and workers had been undertaking in their own organizations and industries (Hansson et al 2024; Alvinius and Holmberg 2019).

Keeping these dynamics of intersectionality and groundwork in mind, one must simultaneously balance the fact that the 2017 iteration of the #MeToo movement brought issues of workplace

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sexual harassment to the fore of public consciousness (Noetzel et al 2023). As a result, there was a great deal of public debate and backlash surrounding the movement and narratives of sexual misconduct in the workplace. One dimension through which backlash was felt was through the avoidance of women the workplace.

In December 2018, Bloomberg Business published a piece titled, 'Wall Street Rule for the #MeToo Era: Avoid Women at All Cost': the article introduced strategies that more than 30 men in the financial district of Wall Street in New York adopted in the '#MeToo era' (Maaranen and Tienara 2020). However, this sentiment extended beyond Wall Street: according to broader survey results and qualitative case studies, many men responded to the #MeToo movement with feelings of victimhood, less willingness to work alone with a woman, and a desire to promote men's rights (Atwater et al 2021; Lisnek et al 2022; Maricort and Burrell 2022; Barron et al 2024; Ayanian et al 2024).[2]

Yet, as Atwater et al (2021, p. 310) put it, "Being fearful of women and deciding to exclude them at work does not provide positive, healthy steps forward in the wake of #MeToo." Avoidant behavior also harms women's ability to accumulate important workplace social capital that may provide useful benefits to their careers.

In addition to behavioral and social responses in the workplace, there were many legal and legislative responses to the #MeToo movement (Tippett 2018; Mininger 2019; Brake 2019; Fox 2020). One dimension of these responses was in limiting the power of nondisclosure agreements (NDAs) to squash sexual harassment reporting. Historically, NDAs have been used to protect firms' proprietary information or trade secrets, but now, NDAs are also commonly used to protect reputational interests, including discussions of sexual misconduct (Weston 2021). Indeed, recent empirical scholarship has suggested that NDAs have artificially propped up the reputations of many businesses along several dimensions of workplace culture (Sockin et al 2024; Hrdy and Seaman 2023).

[2] Other scholarship did not find such strong evidence of backlash, but rather found many were simply dismissive of accusations of sexual assault (Szekeres et al 2020).

Given these legal and social responses to #MeToo, the empirical research question posed in this paper is as follows: Did the #MeToo movement and subsequent state-level changes in NDAs laws affect the amount of time working women and men spend with their bosses, coworkers, and clients?

To answer this question, I use American Time Use Survey data alongside Google Trends and legislative data to examine the intersectional impact of #MeToo on workers' time spent socializing with bosses, coworkers, and clients. To preview my results, I find that in the aftermath of #MeToo, men, and White men in particular, spent more time in these social interactions, while there were no statistically significant changes for women. I then consider the role of state-level laws banning nondisclosure agreements (NDAs) that prevent employees from discussing workplace harassment or discrimination. Using staggered difference-in-difference estimations, I show that such legislation did not have a discernable impact on the amount of time working women or men spent socializing with bosses, coworkers, and clients. These empirical results raise questions about how 'Boys Club' behavior interacts differently with social movements and with legal frameworks.

This paper makes two main contributions. First, this work is among the first to offer a large-scale quantitative analysis of effects of #MeToo on social capital accumulating interactions in the United States. Several scholars have examined the effects of the #MeToo movement in legal contexts or though qualitative case studies, but this work uses nationally representative data to aggregate across industries, occupations, and geographies within the United States. Further, few have made use of nationally representative quantitative data to consider the effect of NDAs on labor generally (Sockin et al 2024; Balasubramanian et al 2024), and, to my knowledge, none have done so in relation to new laws limiting inclusions of sexual misconduct in NDAs.

Second, this paper offers a novel quantitative measure of workplace social capital. In many quantitative studies, participation in associations, religious groups, and clubs is used as a proxy to measure social capital, and others have used instruments like the World Values Survey to measure dimensions of trust or degrees of shared norms (van Staveren 2002). However, this

work considers a particular dimension workplace social capital: time spent socializing with one's boss, coworkers, or clients. Indeed, while the aforementioned measures of social capital capture important dimensions, the measure used herein, inspired by feminist economists use of time-use surveys (Esquivel 2011; Esquivel 2010), provides a more focused look at what goes on in the context of paid work and social networking. I discuss the specific measures I use to capture time spent socializing with one's boss, coworkers, or clients in subsequent sections.

Ultimately, the goal of this work is to equip feminist activists in their understanding of how social movements can affect social capital accumulation, and to offer policymakers a closer look at the impact of gender-related legislation on lived work experiences.

II. MOTIVATION: SOCIAL CAPITAL & THE IMPORTANCE OF SOCIAL TIME SPENT WITH BOSSES, COWORKERS, AND CLIENTS

Research across several different occupations and industries has shown the importance of social capital and connectedness in career climbing. Much of this research has also shown women, and especially women of color, often have less access to such capital (Broadbridge 2010; Fry 2021; Jabbar et al 2022).

Social capital, as articulated by Bourdieu (1986, 2010), are informal social networks used to provide access to relationships that lead to opportunities. These opportunities can include work experience, employment, promotion, and mentorship, among others. Indeed, because of the centrality of opportunity in social capital, the conceptualization of social capital as a resource often runs parallel to the analysis of other resources, like labor or financial resources (van Staveren 2002). Access to social capital typically requires some type of group membership, and the privileges of social capital groups are sometimes reproduced through exclusion of others, often on the basis of race, class, and gender (Bezanson 2006; Ross-Smith and Huppatz 2010; Bridges et al 2022).

Because social capital often offers a great deal of opportunities, inequitable access to the resource results in inequitable outcomes. In other words, exclusion from social networks is often

costly in one's career. Additionally, research from health scholars has also shown a lack of connectedness, even in one's work-life, has detrimental effects on health and wellbeing (Birmingham et al 2024; Breetzke and Wild 2022; Holt-Lunstad 2018). And among small business owners and micro-enterprises, social capital is especially important in success, and even more so for women (Tata and Prasad 2008; Sappleton 2009).

Not only has research suggested that women on average have less access to career-benefiting social capital (including in mentorship (Kay and Wallace 2009; McDonald and Day 2010; Gaddis 2012)), but scholars have suggested women have access to different types of social capital. Addis and Joxhe (2017), for instance, explain that, in Italy, women often having closer networks with family while men's networks are primarily with non-related individuals. They also point out how women face 'structures of constraint' as Folbre (1994) labels it: patriarchy's attribution of childrearing as women's activities limits their opportunities to diversify their social networks. Indeed, research from Munch et al (1997) has previously shown having a child has a statistically significant effect on women's network size, but not men's.

Still, several researchers have examined how women's social networks, and therefore career ladders, can be improved. For example, Kumra and Vinnicombe (2010) show that women in their United Kingdom-based sample feel a need to impress those above them in management to accumulate social capital, and that this is done in a defensive way: ensuring that one is seen as ambitious, likable and available and is dispelling any the negative stereotypes that attached to their gender. Similarly, other work has shown that, especially in industries dominated by men, women can eventually be included in social networks (thereby accruing social capital) by displaying various forms of cultural capital, which often includes assimilation in language, behavior, norms and values (Bourdieu 2010; Bridges et al 2022).

The #MeToo movement brought women's experiences with workplace sexual harassment to the fore, which may have disrupted many women's assimilation strategies in their workplace, thereby affecting their access to social capital. Given the literature's suggestion that many men avoided women during the onset of the #MeToo movement, the costs for women's social capital accumulation may have been detrimental. Additionally, motivations to bolster men's rights may have also meant bolstering men's social capital networks (i.e. bolstering 'Boys Clubs'). While

this paper does not explain the effect of bolstering 'Boys Clubs' had on women, or indeed, men of color, it documents whether this was indeed a widespread trend.

III. DATA

A. ATUS Data

I use data from the American Time Use Survey (ATUS), ranging from 2002 to 2023 (Flood et al. 2022).[3] ATUS is a nationally representative survey of how people in the United States spend their time. From each sampled household, one person age 15 or older is randomly selected to report how they spent the twenty-four-hour period the previous day. ATUS uses conversational interviewing, which allows respondents to report activities in their own words, then ATUS coders classify each reported activity into standardized activity categories. ATUS also collects demographic information from the respondent their household members and is linked to a respondents' Current Populations Survey (CPS) data, collected two to five months prior to the ATUS interview. I restrict my sample to employed (including self-employed) respondents aged 18 and older.

To proxy for social capital accumulation opportunities, I capture the amount of time individuals spend socializing with their boss, coworkers, and clients. To do this, I construct a measure which aggregates minutes spent per day on any of the following activities, as coded by the ATUS: attending social events with bosses or coworkers; talking with clients or coworkers at a social event; eating or drinking with bosses, clients, coworkers, or customers; attending sporting events with bosses; playing golf with clients; or working out work clients. This aggregated measure I now call 'social time' spent with bosses, coworkers, or clients. Figure 1 illustrates average minutes per day spent on these activities across the employed sample from 2003 to 2023, disaggregated by gender. Notice that, for most years, women spent less time in these activities

[3] Note that ATUS data on gender and race presents several challenges. The survey simply asks individuals whether they are male or female, which disregards distinctions between sex and gender. Further, the survey has several options for race but offers little by way of sample sizes for mixed-race respondents and lumps together many forms of race based identity, including indigenous groups. I move forward with the analyses acknowledging these weaknesses.

compared to men, with some exception in 2016. Also note that up until 2016, trends for men and women followed similar patterns.[4]

{Figure 1 about here}

B. Data Capturing the #MeToo Movement

In order to better understand when the #MeToo movement became viral, I make use of Google Trends data. As articulated by Choi and Varian (2012), Google Trends provides a time series index of the volume of queries users enter into Google's search engine in a given geographic area. The index ranges from 0 to 100: it is calculated as the total query volume for the given search term within a particular region divided by the total number of queries in that region during the period being examined. Therefore, the maximum query share in the time period specified is 100, and the query share at the initial date being examined is normalized to zero. In other words, a value of 100 is the peak popularity for the term, a value of 50 means that the term is half as popular, and so on.

Applying the search term "#MeToo" and restricting the geographic unit to the United States and the time period from January 2004 to September 2024, Google Trends provided the data presented in Figure 2.[5] The hashtag search term was its most popular in October 2017, and became viral very quickly, with September's index score at 0 and October's at 100. The term continued to be searched through September 2024 but plateaued in popularity by around July 2019.

{Figure 2 about here}

Additionally, however, it is important to note that even though Tarana Burke introduced the phrase "me too" in 2006, the hashtag "#MeToo" did not gain popularity until 2017. To better capture Burke's initial movement, I also pull the Google trends data for "me too" (as opposed to

[4] It is also worth noting that, overall, social time spent with bosses, coworkers, or clients trends downward. While this raises important questions about the role of social connectedness in organizations and careers, I leave these questions for another study, as it is outside the gendered focus of this paper.
[5] These data were collected in September 2024.

"#MeToo") over the same geography and time period. These data are presented in Figure 3. Note the surge in popularity of the phrase "me too" in late 2006, which coincides with Burke's initiation of the movement, as well as the peak popularity of the search term in October 2017.

{Figure 3 about here}

I use this data first to simply identify a moment in which #MeToo came most fervently into public awareness: October 2017. In my baseline model, which I describe in the next section, I construct a binary variable that identifies the 'before' and 'after' of the widest sweeping moment in the #MeToo movement: where the value is equal to 0 before October 2017 and equal to 1 during and after October 2017. In subsequent models, however, I also use the Google Trends indices for both the "#MeToo" and "me too" search terms to illustrate how changes in social time spent with bosses, clients, and coworkers relate to the popularity of Google searches related to the movements. This second approach better captures Burke's 2006 work and compares it to the 'hashtag' era of the movement taking place in late 2017. This may be especially important for the ATUS sample of working women of color, as Burke's movement began with a specific focus on this group.

C. State-Level Variation in Nondisclosure Agreement Laws

Concerns over NDAs are not reserved exclusively for Hollywood entertainers and white-collar workers: remarkably, over half of United States workers are now bound by NDAs (Balasubramanian, Starr, and Yamaguchi 2022). There has been a great deal of legal debate on the role of NDAs in protecting victims of sexual misconduct. Many suggest that use of NDAs to protect firms and individuals from accusations of sexual misconduct silence women's voices and make it difficult for perpetrators to be identified (Pagan 2021). These criticisms have come from both legal scholars (Villain 2023; Weston 2021; Prasad 2018) as well as popular figures (Spooner 2019). However, others have suggested that NDAs may come with some advantages for victims, including greater likelihood of compensation, swifter ends to a painful ordeal, and greater privacy (Rondeau 2019). Despite such debates among legal scholars, economists and organizational studies scholars have not considered how NDA provisions facilitate the flow of

social capital, particularly for women, who are more frequently the victims of workplace sexual misconduct. To better understand how changing laws around NDAs may have affected workplace behavior, I make use of state-level variation in NDA legislation in the wake of #MeToo.

In October 2023, the National Women's Law Center published a brief which documents state workplace anti-harassment laws enacted since #MeToo went viral. Since 2017, many states revised their laws on nondisclosure agreements to include stipulations around sexual harassment and assault. While the specifics vary from state to state, most of those which enacted the legislation were specific in prohibiting nondisclosure agreements that keep employees from discussing workplace-related sexual harassment or assault. Some also included stipulations which also prohibited NDAs that keep employees from discussing workplace discrimination.

Using the National Women's Law Center (2023), I compile a list of states which passed such legislation and the years in which they were passed. These are illustrated in Figure 4.

{Figure 4 about here}

Note that Illinois, Arizona, and Louisiana are excluded from the data as they enacted legislation on NDAs that was related, but not quite the same as those in the aforementioned states. To avoid confounding the results, I therefore exclude them from the sample in NDA related models. Also note that in December of 2022, President Biden signed federal legislation which applied these laws to NDAs across the country, regardless of state. Because this study makes use of state-level variations in NDA legislation, any state-level law changes in years *after* Biden's national legislation are not particularly useful for this study: federal legislation confounds the 'control' group in the quasi-experimental design described in the subsequent section, therefore, 2023 ATUS data is dropped from models which focus on NDA laws.

IV. EMPIRICAL METHOD

In my first empirical question, I ask: did #MeToo influence working women's and men's social time spent with bosses, coworkers, or clients? The #MeToo movement created an exogenous shock to the U.S. workforce. Therefore, to identify the impact of the #MeToo movement on working women's and men's social time spent with bosses, coworkers, or clients, I estimate the following baseline ordinary least squares (OLS) difference model.

$$SocialTime_{i,s,t} = \beta_0 + \beta_1 MeToo_t + \beta_2 X_i + \alpha_s + \lambda_t + \epsilon \quad (1)$$

Where *SocialTime* represents the number of minutes per day a working individual spends in social time with their boss, clients, or coworkers. *MeToo* is equal to 1 if the time period of the respondent's interview is during or after October 2017 and equal to 0 if before. The coefficient β_1 is the difference estimator which measures the effect of #MeToo movement on the social time workers spend with their boss, clients, or coworkers. The vector X includes a variety of individual level controls which literature suggests might influence time spent socializing at work. Namely, the vector includes the respondent's race, whether or not they identified themselves as Hispanic, their age, their household size, whether they were married, whether they had a child under the age of 5 in their household, whether they were a veteran, and their highest level of education. The vector also includes work-related controls: their main occupation and industry, the average share of women in their industry (constructed via ATUS sample responses over the sample time period), their usual number of hours worked per week, whether they had multiple jobs, whether their job(s) were covered by unions, and whether they worked in public institutions, private institutions, or were self-employed. The variable λ_t represents several time-based controls, including whether the respondent was interviewed on a holiday as well as the day of the week, month, and year in which the respondent was interviewed. The notation α_s represents state-level dummies that are included in the model. Summary statistics for the measures used in the model are included in Table 1.

{Table 1 about here}

I estimate the model separately for working women and for working men. Feminist econometricians emphasize the importance of running separate models on different demographic

groups, rather than, for instance just including dummy variables or interaction terms for gender (Sigle-Rushton 2014; Scott and Siltanen 2017; Small forthcoming). In this context, the separate models approach allows for an investigation of how the mix of explanatory factors changes across men and women, who face different barriers, opportunities, and expectations in paid work and time. In other words, separate models do not force covariates (like occupation or industry) to have the same relationship with social time across genders, but rather, allows for a fuller exploration of women's and men's unique work experiences. A separate models approach also allows for a direct comparison of the models' explanatory power across genders. This model is the simple baseline model from which I will build upon during robustness checks detailed in later sections of this paper.

My second empirical research question asks: did state-level changes in NDA legislation influence working women's and men's social time spent with bosses, coworkers, or clients? To answer this question, I begin by estimating a typical two-way fixed effects model that exploits variation in adoption of NDA laws between states and over time. The estimated model is of the following form:

$$SocialTime_{i,s,t} = \beta_1 NDALaw_{s,t} + \beta_2 X_i + \alpha_s + \lambda_t + \epsilon \quad (2)$$

Where the terms are the same as before, but now term β_1 is the coefficient of interest and $NDALaw_{i,s,t}$ is a dummy variable equal to one if a respondent lived in a state with a law that prevented NDAs from limiting discussions of sexual misconduct and equal to zero otherwise. This means that in the model, I consider a state "treated" ($NDALaw_{i,s,t} = 1$) if workers are operating under updated NDA laws. Again, consistent with feminist econometrician suggestions, I estimate this model separately for women and men. Recall that Biden's federal legislation, which was signed in December 2022, bans the use of NDAs to silence victims from speaking out about sexual misconduct. Therefore, in these models, I drop 2023 data from the analysis.

Because the sample includes states that are never treated alongside states that change from untreated to treated at different points in the time, the typical two-way fixed effects estimator could be biased (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon 2021). Causal

interpretation of the two-way fixed effects estimator requires not only parallel pre-trends, but also that the policy effects on the treated groups be constant across cohorts and over time (Goodman-Bacon 2021). This is fairly unlikely in my case, given Figure 4.

Recent literature has suggested a staggered difference-in-difference (DID) models for instances in which the same policies are implemented across different (staggered) periods of time (Callaway and Sant'Anna 2021; Freedman et al 2023). Because the enactment dates for state legislation barring NDAs from including sexual misconduct vary from 2018 to 2023, the staggered DID model may indeed be more appropriate in this case. Therefore, I also make use of Callaway and Sant'Anna's (2021) staggered difference-in-difference estimator, which Backer et al (2022) have shown offers less bias than other approaches to staggered DID. I also estimate an augmented version of Callaway and Sant'Anna's (2021) staggered difference-in-difference estimator, which includes all the covariates noted formerly in vector X_i aside from the occupation and industry controls which, like the Poisson estimates, overfit the model.

V. RESULTS

A. Baseline Estimates on the Impact of #MeToo

Results from estimating Equation 1 separately for the sample of working women and working men are illustrated in Table 2, Column (I). Among working women, the coefficient on the binary variable indication of pre- and post-#MeToo (October 2017) is not statistically significant. This implies that, all else constant, the #MeToo movement did not have a statistically significant relationship with the amount of time women spent with their bosses, coworkers, and clients. Notably, the model suggests that the largest positive contributors to such social time for women are their education (those with bachelor's degrees or higher spending more social time compared to those with less than high school education), the amount of time they spend at work, and whether they work in local government. Measures of race, ethnicity, and household formation status (e.g. children, marriage) do little to explain the amount of time women spend with their bosses, coworkers, and clients. From the perspective of intersectional feminists concerned about racism and care work burdens, this is perhaps a welcome finding.

On the other hand, referring to Table 2, Column (I), one can see that the #MeToo movement had a positive effect on the amount of time working men spent with their bosses, coworkers, and clients. Namely, after the October 2017 start of the #MeToo movement, men spent about 1.05 more minutes per day in these social interactions than they did before #MeToo. This result is markedly different from that in the model applied to working women.

Other covariates in the model for men tell a concerning story: men who indicated they were Black, Asian, or American Indian, Alaskan Native, Hawaiian, or Pacific Islander were less likely than their White counterparts to be spending social time with their bosses, coworkers, and clients. The largest gap is among Asian men, who on average spent around 23 fewer seconds per day in these interactions than their White counterparts.[6] Also in the covariates among the men's model, one can see that veterans spent less time in these social interactions relative to non-veteran counterparts. And, like in the working women's model, men with higher levels of education spent more social time with bosses, coworkers, and clients.

{Table 2 about here}

B. Robustness Checks

I next offer several robustness checks to support the validity of this model. First, many scholars have shown that the COVID-19 pandemic had substantial impacts not only on the amount of time workers spent in their workplaces, but also on their employment, income, and care responsibilities (Holder et al 2021; Collins et al 2021; Bahn et al 2020). Therefore, a reader concerned about these issues may wish to remove the COVID-era years entirely from the sample. As one can see illustrated in Column (II) of Table 2, I re-estimate the models just using data from 2003 to 2019. The same narrative holds for both samples of working men and women.

Based on the Google trends data, several additional interests and concerns arise. First, understanding how workers' social time was influenced by the ebbs and flows of the #MeToo

[6] Calculated as (-0.386) × (60 seconds) = 23.16 seconds.

movement's popularity cannot be accomplished with the simple binary measure used in the previous models. Second, one may wish to better understand not just the impact of the #MeToo movement that went viral in October 2017, but also the "me too" movement started by Tarana Burke in 2006. To better capture the impact of Burke's initial efforts, I re-estimate the same model but now use the Google trends popularity index for "Me Too", as shown in Figure 2, as the main variable of interest rather than the binary #MeToo variable used in the previous model. As shown in the first rows of Column (IV) in Table 3, among working women, a 1 unit increase in the "me too" Google trends popularity index correspondents with a 0.31 minute (18.4 second) decrease in social time spent with bosses, clients, and coworkers per day, all else constant. There was no statistically significant effect on men's social time using the "Me Too" Google trends index.

However, in the first few rows of Column (V) in Table 3, one can see that using the Google trends popularity index for the hashtag (as shown in Figure 3) does have a statistically significant relationship with men's time spent with bosses, coworkers, and clients. Namely, a one unit increase in the "#MeToo" Google trend popularity index increases men's social time by about 2.9 minutes per day on average. The Column (V) #MeToo Google trends model applied to women does not show a statistically significant relationship with women's time spent socializing with bosses, coworkers, and clients.

{Table 3 about here}

Given Burke's movement was initially focused on sexual harassment faced by low-income women of color, one may have reason to suspect the movement would have heterogenous effects across race and ethnicity in addition to gender. To better understand the intersectional dimensions of the movement's impact on work-based social time, I re-estimate the baseline model (as well as the two Google trends models) interacting the measure for the #MeToo movement with the ATUS measure for race. Equation 3 illustrates the functional form of this model:

$$SocialTime_{i,s,t} = \beta_0 + \beta_1 MeToo_t + \beta_2 Race_i + \beta_3 (Race_i \times MeToo_t) + \beta_4 X_i + \alpha_s + \lambda_t + \epsilon_{i,s,t} \quad (3)$$

In this case, β_3 is the coefficient of interest, because it shows whether the movement had statistically different effects for workers of color in terms of their social time. Results from this model are shown in the bottom portion of Table 3. Column (III) makes use of the binary #MeToo measure, while Column (IV) and (V) use Google trends data ("me too" and "#MeToo" respectively). Ultimately, none of the models show statistically significant coefficients on the interaction terms. In other words, there is no evidence the movement had substantially different effects on women or men of color relative to their White counterparts.

Finally, while time-use diaries in ATUS naturally have a large proportion of zeros for time spent on specific types of activities, previous research using time-diary data finds OLS models yield unbiased estimates, but estimates from tobit and two-part models are often bias (Stewart 2013). Muchomba and Kaushal (2022) explain that this may be because the zeros in time-use data arise not from censoring, but from a short reference period (namely, just one day in the case of ATUS). Still, to assuage concerns frequent zeros for minutes spent socializing with bosses, coworkers, and clients, I estimate a Poisson model that includes most of the same variables as those detailed in Equation 1. However, including industry and occupation controls in the Poisson model overfits (perfectly predicts) the models such that they do not converge (Silva and Tenreyro 2011). Therefore, these two measures are not included in the Poisson estimates presented in Table 4 and should be interpreted with caution as they do not account for occupational and industry-based differences.

{Table 4 about here}

Results from the upper-half of Table 4 (baseline formulation) show the Poisson models' estimation using the basic formulation without race-based interaction terms. The bottom portion of Table 4 shows the Poisson models' estimations using race-based interaction terms (interaction term formulation). Ultimately, no matter the measure of the #MeToo movement (either the binary #MeToo measure shown in Column (VI), the "me too" Google trends measure shown in Column (VII), or the "#MeToo" Google trends measure shown in Column (VIII)), it had a positive effect on men's time spent socializing with their bosses, coworkers, and clients.

Unlike the OLS model, the Poisson models suggests that the #MeToo movement (as measured by the "#MeToo" Google trends index or binary indicator) had a negative impact on women's time spent socializing with bosses, coworkers and clients. For example, using the coefficient detailed in upper half of Column (VI), it seems that after the #MeToo movement went viral in October 2017, women spent on average 18.4 minutes less per day socializing with their bosses, coworkers, and clients.

Based on results from the Poisson models that included interaction terms with workers' races, it looks like the #MeToo movement resulted in even further decreased social time for both women and men who identified as American Indian, Alaskan Native, Hawaiian, or Pacific Islander as well as those who identified as more than one race. It is especially important to note this result holds among men, implying that the boys club bolstering in response to the #MeToo movement may not have been extended to men in these racial groups. However, recall that all Poisson models presented in Table 4 should be interpreted with caution as they do not account for occupational and industry-based differences, which are especially pronounced along lines of both race and gender thanks to pre-labor market discrimination and occupational crowding (Darity et al 2022; Alonso-Villar and Del Río 2023; Small et al 2023).

C. The Impact of NDA Legislation

Table 5 illustrates the baseline results of the two-way fixed effects model as well as the Callaway and Sant'Anna (2021) staggered DID models (both typical and augmented). Results from the two-way fixed effects model suggest that state-level law changes disallowing sexual misconduct discussion be included in NDAs was associated with a slight decrease in time spent socializing with bosses, clients, and coworkers for both men and women. However, the more robust Callaway and Sant'Anna (2021) staggered DID estimators indicate there is no statistically significant relationship between such laws and social time spent with bosses, coworkers, or clients for men nor women. Lagging the treatment variable also does not produce statistically significant effects in any of the staggered difference-in-difference models.

{Table 5 about here}

It is possible that these insignificance results are due to the fact that not all workers are covered by NDAs. Unfortunately, ATUS data nor its linked Current Population Survey data ask workers whether they have signed NDAs related to their employment. Luckily, Balasubramanian et al (2024) recently used PayScale data from 2017 to estimate the share of workers in broad occupational and industry categories who have NDAs. I construct new variables to which I apply the occupational and industry shares provided by Balasubramanian et al (2024) to my ATUS data.

To illustrate: Balasubramanian et al (2024) found that 46.1 percent of workers in the construction industry in 2017 indicated they were covered by an NDA, so for every respondent in my data who indicated they worked in the construction industry for their main job, I assign a value of 46.1 percent for their imputed share with NDA by industry variable. Similarly for occupation: Balasubramanian et al (2024) found that 72.8 percent of workers in computer and mathematical science occupations were covered by an NDA in 2017, so for each ATUS respondent in my sample who indicated their main occupation was a computer and mathematical science occupation, I assign a value of 72.8 percent for their imputed share with NDA by occupation variable. While this is certainly a flawed and imperfect measure, it provides some rough estimates of the likelihood an individual worker has signed an NDA based on their occupation and industry. Table 6 illustrates these average imputed shares of workers with NDAs by occupation and industry, disaggregated by gender.

{Table 6 about here}

I then create a new categorical variable that is equal to one if the respondent is in an occupation *and* industry with more than 50 percent reporting NDA usage according to Balasubramanian et al (2024). Table 6 also includes the share of women and men who are categorized as such. Notably, using this method, about 66 percent of working women in the sample are categorized as highly likely to have an NDA as opposed to 44 percent of men.[7] Table 7 illustrates the mean number of

[7] More research should be done to investigate these gendered dimensions of NDA usage, as it may have consequences for women's labor power in addition to their ability to speak out about workplace sexual misconduct.

minutes per day workers spend socializing with their bosses, clients, and coworkers, disaggregated by both gender and whether they are categorized as highly likely to have an NDA. Working men in both occupations and industries with more than 50 percent of workers indicating they signed an NDA have the highest number of minutes spent in social time per day, at around 0.83.

{Table 7 about here}

Given these data on NDA exposure, I then re-estimate the baseline two-way fixed effect model as well as the Callaway and Sant'Anna (2021) staggered DID models restricting the samples to those categorized as highly likely to have an NDA. These results are presented in the bottom portion of Table 5. Results from the baseline two-way fixed effects model suggests that women with a high likelihood of having an NDA spent less social time with bosses, coworkers, and clients as a result of the NDA legislative changes, but there is no statistically significant effect for the analogous sample of men. Once again, the Callaway and Sant'Anna (2021) staggered DID models produce no statistically significant results on the treatment variable.

VI. DISCUSSION & CONCLUSION

Given the Callaway and Sant'Anna (2021) staggered DID is less likely to be bias than the two-way fixed effects model, one cannot say with any degree of statistical certainty that NDA law changes affected men's nor women's time spent socializing with bosses, coworkers, or clients. This is perhaps not surprising: scholars have indeed suggested NDA laws often fall short of creating positive change for working-class women and women of color, who make up a disproportionally large share of workers in industries like waitresses, hotel housekeepers, and factory workers, who face sexual abuse and harassment at especially high rates (Faludi et al 2020). Still, this 'null' result is worthwhile for policymakers and activists: it shows that the NDA laws potentially did very little damage to social capital accumulation opportunities for women, while the same cannot be said of the gendered dynamics resulting from the #MeToo movement more broadly.

Results from the econometric models focusing on the #MeToo movement illustrate that it had a powerful impact on the amount of time workers spend socializing with their bosses, coworkers,

and clients. Namely, after the #MeToo hashtag became viral in October 2017, men engaged in this social time more than before, while there is no evidence to suggest women were afforded the same increased access to social capital accumulation opportunities.

However, results from the regression models suggest this increase among men was only about a minute per day. Is this particularly substantial? Yes, these numbers are small, but they also represent just *one* day. Imagine multiplying the baseline coefficients by 5 days per week, then again by 52 weeks per year. This means the approximately 1 additional minute men spent with bosses, coworkers, and clients per day after #MeToo could accumulate to, on average, 4.3 more hours per year. One could imagine this as, say, one additional lunch per quarter. While there is little literature to suggest the exact amount of time one needs to spend in these interactions to gain meaningful social capital, it is difficult to imagine an additional lunch per quarter has no bearing on one's career.

Ultimately, improvements in men's time spent in social interactions with bosses, coworkers, and clients without corresponding increases for women suggest dynamics which bolster 'Boys Clubs.' And, given the models' estimated coefficients on race, these are more likely White Boys Clubs, which comes with a host of concerns for intersectional equity in organizations.

Though the momentum and positive change brought on by #MeToo cannot be denied, backlash and 'Boys Club' dynamics can also not be ignored. Revamping NDA laws, luckily, does not seem to have an especially negative affect on gendered workplace dynamics. This raises questions about how organizations should respond both to legal changes, but also to cultural movements.

Recent work by Bridges et al (2022) has suggested that social capital can be shared and transferred among women, even in industries dominated by men, to improve their career prospects. Indeed, the temptation to lean into 'Girls Clubs' is powerful, yet replicating the systems of exclusion brought on by 'Boys Clubs' does not seem to be a long-term solution, nor does it address questions of exclusion along dimensions of race, which were illustrated herein, as well as other intersectional dimensions such as class or disability. Indeed, feminist scholars have

criticized neoliberal ‘Girl Boss’ feminism along these and other dimensions (Miller et al 2018; Alexandersson and Kalonaityte 2021).

So what is the solution: how can men be encouraged to include women in work-related social interactions? And is that a worthwhile venture? Research from economists has suggested that firm managers which favor socially connected workers often do so at the firm’s detriment, whereas those which prioritize otherwise high-ability workers do not (Bandiera et al 2009). If operationalizing along such clubs is to the detriment of organizations, it is possible their power dissipates. Yet eliminating work-related socializing altogether also raises questions about the kind of work that is developing. Namely, would such work be anti-feminist in other ways? Ultimately, while it provides few answers, this study offers an opportunity to consider these questions in light of issues of gender and racial equality and the impact of legislation and social movements on social capital accumulation.

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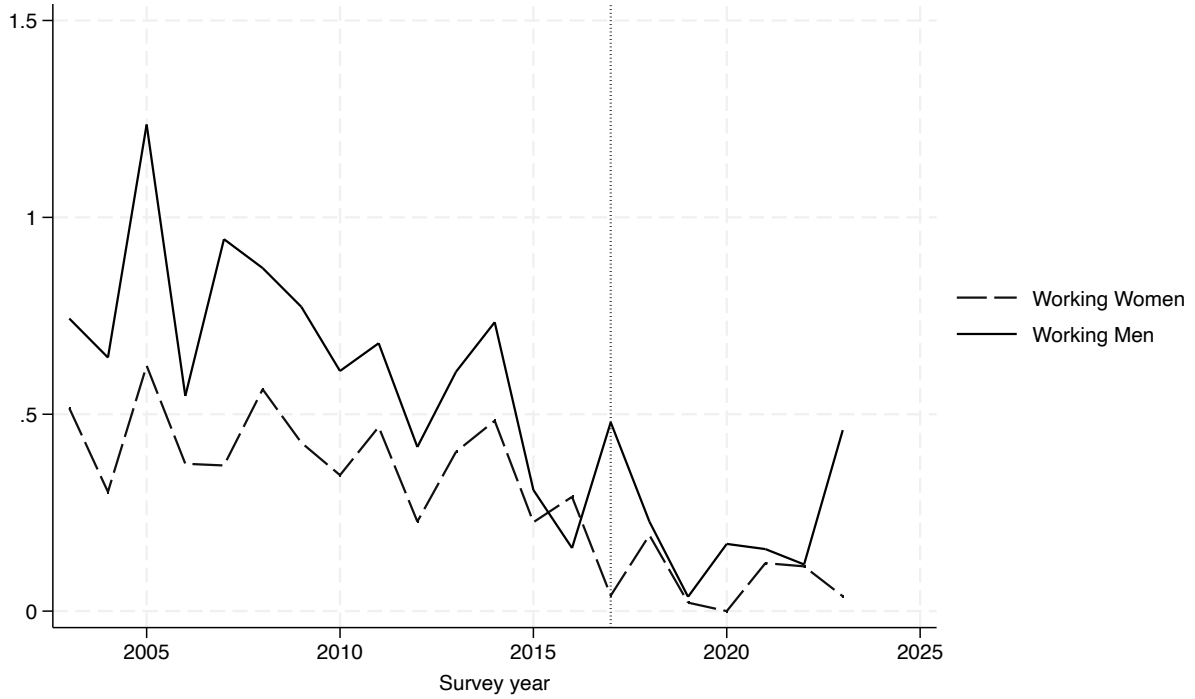
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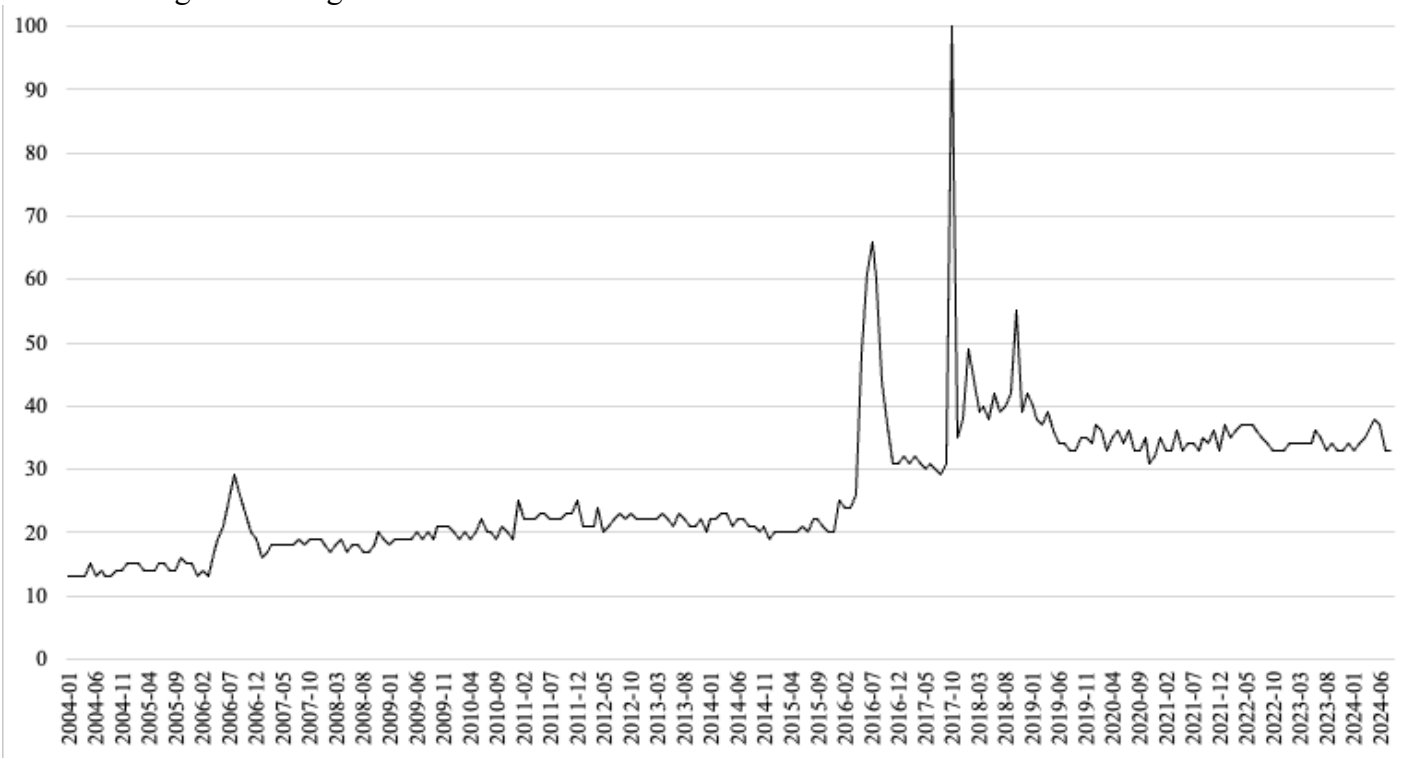
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Figure 1. Annual Average Minutes Per Day Spent in Social Time with Bosses, Clients, or Coworkers



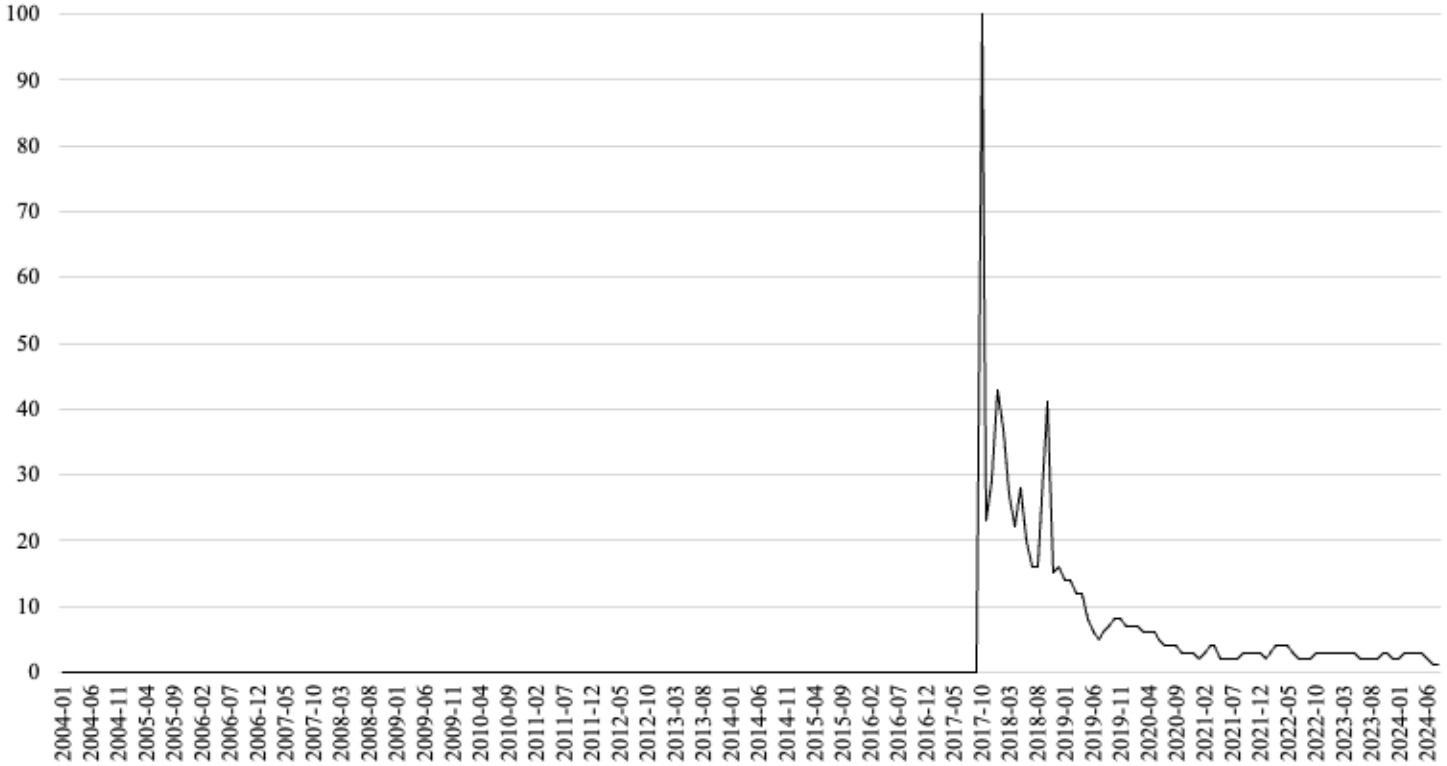
Note: Data from the American Time Use Survey, sample restricted to employed workers over the age of 18. This figure reflects a measure which aggregates minutes spent per day on any of the following activities: attending social events with bosses or coworkers; talking with clients or coworkers at a social event; eating or drinking with bosses, clients, coworkers, or customers; attending sporting events with bosses; playing golf with clients; or working out work clients.

Figure 2. Google Trends Index Data for the Search Term “Me Too” in the United States



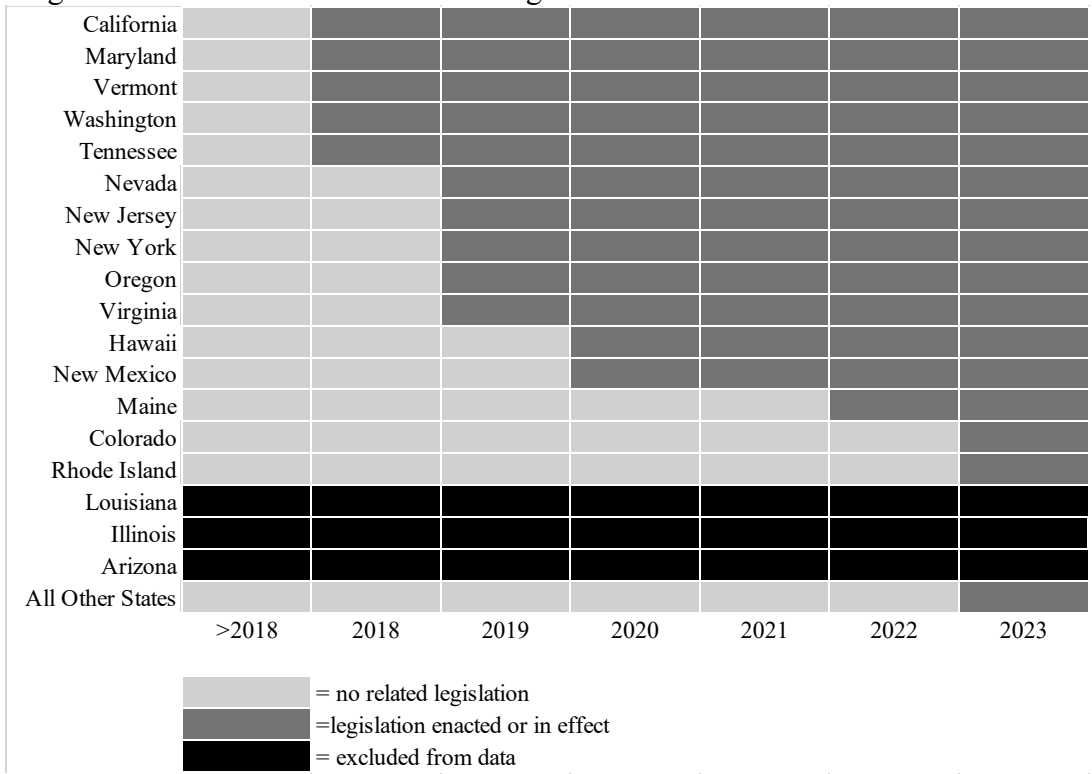
Note: Google Trends provides a time series index of the volume of queries users enter into Google’s search engine in a given geographic area. The index is calculated as the total query volume for the given search term within a particular region divided by the total number of queries in that region during the period being examined. Therefore, the maximum query share in the time period specified is 100, and the query share at the initial date being examined is normalized to zero. These data were pulled in September 2024 and span from January 1 2004 to August 2024.

Figure 3. Google Trends Index Data for the Search Term "#MeToo" in the United States



Note: Google Trends provides a time series index of the volume of queries users enter into Google's search engine in a given geographic area. The index is calculated as the total query volume for the given search term within a particular region divided by the total number of queries in that region during the period being examined. Therefore, the maximum query share in the time period specified is 100, and the query share at the initial date being examined is normalized to zero. These data were pulled in September 2024 and span from January 1 2004 to August 2024.

Figure 4. When States Enacted New Legislation on NDAs and Sexual Misconduct



Note: Readers should reference the National Women's Law Center (2023) brief for details on each law, though the following is a list of states and years in which such legislation was enacted: California, enacted in 2018; Colorado, enacted in 2023; Hawaii, enacted in 2020; Maine, enacted in 2022; Maryland, enacted in 2018; Nevada, enacted in 2019; New Jersey, enacted in 2019; New Mexico, enacted in 2020; New York, enacted in 2019; Oregon, enacted in 2019; Rhode Island, enacted in 2023; Tennessee, enacted in 2019; Vermont, enacted in 2018; Virginia, enacted in 2019; Washington, enacted in 2018. Illinois, Arizona, and Louisiana are excluded from the data as they enacted legislation on NDAs that was related, but not quite the same as those in the aforementioned states. All observations from 2023 are also dropped given federal legislative changes in December 2022.

Table 1. Summary Statistics from American Time Use Survey Data, 2003 to 2023

	Sample of Working Women		Sample of Working Men	
	Mean/Share	Standard Deviation	Mean/Share	Standard Deviation
Minutes Spent in Social Time with Bosses, Clients, or Coworkers	0.309	7.092	0.538	9.440
Race				
White	0.792	0.406	0.832	0.374
Black	0.146	0.353	0.100	0.300
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	0.009	0.096	0.009	0.094
Asian	0.040	0.195	0.047	0.211
More than one race	0.013	0.111	0.013	0.112
Hispanic	0.126	0.332	0.151	0.358
Age	43.445	12.870	42.929	12.511
Household Size	2.780	1.412	2.957	1.515
Married	0.500	0.500	0.612	0.487
Has Young Child in Household	0.185	0.389	0.218	0.413
Veteran	0.017	0.129	0.127	0.334
Education				
Less than High School Diploma	0.051	0.221	0.076	0.266
High School Diploma	0.218	0.413	0.244	0.429
Some College	0.181	0.385	0.169	0.374
Associate's Degree	0.121	0.327	0.099	0.298
Bachelor's Degree	0.260	0.439	0.255	0.436
Masters, Doctorate, or Professional Degree	0.168	0.374	0.158	0.365
Has Multiple Jobs	0.095	0.293	0.091	0.287
Share of Women in Industry (Main Job)	0.591	0.178	0.430	0.188
Usual Hours Worked per Week	36.771	13.395	42.267	14.081
Covered by a Union	0.140	0.347	0.148	0.355
Type of Employer				
Federal Government	0.031	0.174	0.037	0.189
State Government	0.072	0.259	0.049	0.216
Local Government	0.118	0.323	0.074	0.262
Private, For Profit	0.659	0.474	0.775	0.418
Private, Nonprofit	0.111	0.314	0.054	0.226
Self-Employed, Unincorporated	0.002	0.044	0.003	0.058
Self-Employed, Incorporated	0.005	0.073	0.007	0.085
Working Without Pay	0.000	0.012	0.000	0.009
n	63,803		60,217	

Note: Additional covariates not shown in this table include respondents' main occupation and industry, state of residence, whether the respondent was interviewed on a holiday, day of the week, month, and year in which the respondent was interviewed.

Table 2. Baseline Estimate of Equation 1 and Re-Estimation with Restricted Years

	(I) 2003-2023		(II) 2003 to 2019	
Dependent variable: Minutes Spent in Social Time with Bosses, Clients, or Coworkers	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men
#MeToo (=1 if during or after October 2017)	-0.051	1.051***	-0.049	1.038***
	(0.073)	(0.445)	(0.087)	0.110)
Race (reference group= White)				
Black	0.049	-0.252***	0.075	-0.249**
	(0.088)	(0.139)	(0.100)	(0.098)
Hawaiian, or Pacific Islander	0.147	-0.311*	0.198	-0.367*
	(0.229)	(0.417)	(0.259)	(0.203)
Asian	0.001	-0.386***	0.003	-0.482***
	(0.147)	(0.198)	(0.173)	(0.122)
More than one race	-0.329	0.251	-0.372	0.321
	(0.204)	(0.351)	(0.236)	(0.525)
Hispanic	-0.043	-0.077	-0.069	-0.068
	(0.077)	(0.128)	(0.091)	(0.118)
Share of Women in Industry (Main Job)	1.862	-15.351	2.097	-18.122
	(2.219)	(176.686)	(2.585)	(12.475)
Usual Hours Worked	0.009***	0.006	0.009***	0.008
	(0.002)	(0.003)	(0.002)	(0.005)
Age	-0.003	0.005	-0.004	0.007
	(0.002)	(0.004)	(0.003)	(0.005)
Has Multiple Jobs	0.208	0.218	0.247	0.149
	(0.155)	(0.139)	(0.177)	(0.133)
Household Size	-0.011	0.023	-0.022	0.017
	(0.033)	(0.033)	(0.036)	(0.045)
Married	-0.035	-0.049	-0.036	-0.025
	(0.083)	(0.103)	(0.094)	(0.133)
Has Young Child in Household	-0.061	0.068	-0.061	0.120
	(0.065)	(0.111)	(0.073)	(0.142)
Covered by a Union	0.024	0.002	-0.004	0.001
	(0.127)	(0.128)	(0.139)	(0.077)
Veteran	-0.068	-0.237**	-0.053	-0.236**
	(0.175)	(0.124)	(0.203)	(0.110)
Education (reference group= Less than HS diploma)				
High School Diploma	0.085	0.163	0.066	0.165
	(0.090)	(0.173)	(0.099)	(0.119)
Some College	0.068	0.238**	0.039	0.239**
	(0.071)	(0.187)	(0.078)	(0.104)
Associate's Degree	0.137	-0.058	0.082	-0.068
	(0.108)	(0.208)	(0.112)	(0.079)
Bachelor's Degree	0.354***	0.388***	0.353	0.387**
	(0.072)	(0.196)	(0.081)	(0.149)
Masters, Doctorate, or Professional Degree	0.397***	0.607***	0.422	0.692***
	(0.128)	(0.223)	(0.148)	(0.179)
Type of Employer (reference group= Federal Government)				
State Government	0.267	-0.119	0.313	-0.121
	(0.193)	(0.343)	(0.226)	(0.368)
Local Government	0.270*	-0.126	0.291	-0.192
	(0.149)	(0.345)	(0.173)	(0.341)
Private, For Profit	0.203	-0.167	0.214	-0.222
	(0.173)	(0.325)	(0.196)	(0.422)
Private, Nonprofit	0.262	0.139	0.261	0.199
	(0.199)	(0.375)	(0.231)	(0.339)
Self-Employed, Unincorporated	2.821	-0.333	3.529	-0.403
	(3.367)	(0.741)	(4.264)	(0.795)
Self-Employed, Incorporated	0.414	-0.123	0.475	-0.115
	(0.457)	(0.566)	(0.549)	(0.655)
Working Without Pay	-0.081	-0.606	-0.110	-0.797
	(0.418)	(4.267)	(0.547)	(1.631)
n	63,803	60,217	55,542	51,785
R-squared	0.019	0.017	0.021	0.019

Note: Additional covariates not shown in this table include respondents' main occupation and industry, state of residence, whether the respondent was interviewed on a holiday, and day of the week, month, and year in which the respondent was interviewed. * indicates $p < 10\%$, ** indicates $p < 5\%$, *** indicates $p < 1\%$. Robust standard errors shown in parentheses and clustered at the year level.

Table 3. Robustness Checks with Various Measures of the Me Too Movement and Race-Based Interaction Terms

	(III) Baseline Binary Measure		(IV) "Me Too" Google Trends Data		(V) "#MeToo" Google Trends Data	
Dependent variable: Minutes Spent in Social Time with Bosses, Clients, or Coworkers	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men
Baseline Formulation						
#MeToo (=1 if during or after October 2017)	-0.051	1.051***				
	(0.073)	(0.445)				
"Me Too" Popularity Index			-0.307*	2.739		
			(0.177)	(1.702)		
"#MeToo" Popularity Index					-0.276	2.857***
					(0.197)	(0.197)
n	63,803	60,217	58,113	55, 035	58,113	55, 035
R-squared	0.019	0.017	0.021	0.018	0.021	0.018
Interaction Term Formulation						
Me Too measure	-0.041	1.005***	-0.287	2.757	-0.352	3.171***
	(0.068)	(0.089)	(0.205)	(1.970)	(0.228)	(0.888)
Race (reference group= White)						
Black	0.045	-0.313***	-0.006	-0.242	-0.020	-0.203*
	(0.102)	(0.089)	(0.179)	(0.426)	(0.080)	(0.107)
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	0.208	-0.345	0.309	-0.169	0.179	-0.206
	(0.289)	(0.212)	(0.515)	(0.564)	(0.269)	(0.101)
Asian	0.077	-0.471***	0.134	-0.389	-0.028	-0.316**
	(0.210)	(0.113)	(0.459)	(0.409)	(0.168)	(0.137)
More than one race	-0.399	0.372	-0.499	1.059	-0.339	0.435
	(0.255)	(0.584)	(0.534)	(1.295)	(0.246)	(0.518)
(Race) × (Me Too measure)						
Black	0.017	0.279	0.002	0.043	0.574	-1.129
	(0.159)	(0.217)	(0.581)	(1.641)	(0.503)	(2.214)
American Indian, Alaskan Native, Hawaiian, or Pacific Islander	-0.256	0.146	-0.569	-0.401	-0.557	-2.686
	(0.335)	(0.322)	(1.267)	(1.866)	(0.958)	(1.959)
Asian	-0.266	0.272	-0.729	0.082	-0.921	-1.739
	(0.256)	(0.211)	(1.362)	(1.644)	(0.931)	(1.723)
More than one race	0.298	-0.460	0.765	-2.777	1.162	-3.488
	(0.279)	(0.584)	(1.382)	(3.394)	(0.902)	(2.933)
n	63,803	60,217	58,113	55, 035	58,113	55, 035
R-squared	0.019	0.017	0.021	0.018	0.021	0.018

Note: Google Trends are not available for 2003, so 2003 ATUS data are not included for the models presented in columns (IV) and (V) (these just include 2004-2023 ATUS data). Additional covariates not shown in this table include those detailed in Table 2 as well as respondents' main occupation and industry, state of residence, whether the respondent was interviewed on a holiday, and day of the week, month, and year in which the respondent was interviewed. * indicates $p < 10\%$, ** indicates $p < 5\%$, *** indicates $p < 1\%$. Robust standard errors shown in parentheses and clustered at the year level.

Table 4. Poisson Model Robustness Checks with Various Measures of the Me Too Movement and Race-Based Interaction Terms

		(VI) Baseline Binary Measure		(VII) "Me Too" Google Trends Data		(VIII) "#MeToo" Google Trends Data	
	Dependent variable: Minutes Spent in Social Time with Bosses, Clients, or Coworkers	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men
Baseline Formulation	#MeToo (=1 if during or after October 2017)	-18.392***	1.317***				
		(1.049)	(0.186)				
	"Me Too" Popularity Index			-0.939	3.381***		
				(1.161)	(0.741)		
	"#MeToo" Popularity Index					-5.374***	2.647***
						(1.563)	(0.409)
	n	63,803	60,217	58,113	55, 035	58,113	55, 035
	Pseudo R-squared	0.144	0.133	0.153	0.150	0.155	0.151
Interaction Term Formulation	Me Too measure	-19.752***	1.321***	-0.954	3.471***	-8.087***	2.721***
		(1.073)	(0.179)	(1.314)	(0.743)	(2.054)	(0.418)
	Race (reference group= White)						
	Black	0.057	-0.845***	-0.118	-0.424	-0.127	-0.826***
		(0.269)	(0.205)	(0.689)	(0.558)	(0.282)	(0.247)
	American Indian, Alaskan Native, Hawaiian, or Pacific Islander	0.263	-1.041	0.602	1.386	0.302	-0.893
		(0.536)	(0.984)	(1.169)	(1.688)	(0.532)	(0.981)
	Asian	-0.164	-1.475***	-0.301	-1.012*	-0.298	-1.213***
		(0.368)	(0.438)	(0.939)	(0.564)	(0.399)	(0.418)
	More than one race	-1.039	0.439	0.019	0.952	-1.162	0.551
		(1.145)	(0.584)	(1.795)	(1.092)	(1.223)	(0.584)
	(Race) × (Me Too measure)						
	Black	0.6064	-0.015	0.252	-1.875	5.524***	-0.522
		(0.807)	(1.043)	(0.304)	(2.931)	(1.382)	(1.537)
	American Indian, Alaskan Native, Hawaiian, or Pacific Islander	-18.235***	-16.007***	-1.994	-12.363*	-701.092***	-720.953***
		(0.931)	(1.037)	(4.210)	(6.429)	(54.670)	(59.818)
	Asian	-0.923	0.543	-0.277	-1.205	-22.389**	-5.661
		(0.911)	(0.801)	(3.754)	(2.125)	(10.719)	(4.511)
	More than one race	-17.548***	-16.549***	-6.154	-2.518	-748.602***	-857.066***
		(1.264)	(0.780)	(6.340)	(3.255)	(77.851)	(52.470)
	n	63,803	60,217	58,113	55, 035	58,113	55, 035
	Pseudo R-squared	0.144	0.133	0.153	0.150	0.155	0.151

Note: Google Trends are not available for 2003, so 2003 ATUS data are not included for the models presented in columns (IV) and (V) (these just include 2004-2023 ATUS data). Additional covariates not shown in this table include those detailed in Table 2 as well as respondents' state of residence, whether the respondent was interviewed on a holiday, and day of the week, month, and year in which the respondent was interviewed. * indicates p < 10%, ** indicates p < 5%, *** indicates p < 1%. Robust standard errors shown in parentheses and clustered at the year level.

Table 5. Effect of NDA Legislation on Social Time: Two-Way Fixed Effects Models and CS Staggered DID

			(IX) Baseline Two-Way Fixed Effects Model		(X) Callaway & Sant'Anna (2021) Staggered DID		(XI) Augmented Callaway & Sant'Anna (2021) Staggered DID	
		Dependent variable: Minutes Spent in Social Time with Bosses, Clients, or Coworkers	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men	Sample of Working Women	Sample of Working Men
Full Sample		State-Level NDA Legislation Changes	-0.219*	-0.163*	0.066	-0.993	0.116	-2.372
			(0.121)	(0.094)	(0.076)	(1.222)	(0.097)	(2.538)
		n	57,144	53,876	57,144	53,876	57,144	53,876
High Likelihood of NDA Sample		State-Level NDA Legislation Changes	-0.316*	-0.035	-0.122	-3.504	-0.129	-0.656
			(0.173)	(0.266)	(0.094)	(3.508)	(0.089)	(0.941)
		n	29,011	20,391	29,011	20,391	29,011	20,391

Note: Data is from ATUS 2003-2022; treatment variable data are detailed in Figure 4. The 'High Likelihood of NDA' sample includes individuals who were in an occupation *and* industry with more than 50% reporting NDA usage according to Balasubramanian et al (2024). In the baseline two-way fixed effects model, covariates not shown in this table include those detailed in Table 2 as well as respondents' main occupation and industry, state of residence, whether the respondent was interviewed on a holiday, and day of the week, month, and year in which the respondent was interviewed. In the augmented Callaway and Sant'Anna (2021) staggered DID model, covariates not shown in this table include those detailed in Table 2 as well as respondents' state of residence, whether the respondent was interviewed on a holiday, and day of the week, month, and year in which the respondent was interviewed. * indicates $p < 10\%$, ** indicates $p < 5\%$, *** indicates $p < 1\%$. Robust standard errors shown in parentheses and clustered at the year level.

Table 6. Descriptive Statistics: Imputed Estimates of NDA Exposure by Occupation, Industry, and Gender

	Sample of Working Women		Sample of Working Men	
	Share	Standard Deviation	Share	Standard Deviation
Imputed Share with NDA by Industry	0.567	0.074	0.565	7.884
Imputed Share with NDA by Occupation	0.555	0.068	0.528	0.100
Categorized as Highly Likely to Have NDA	0.662	0.473	0.444	0.497
n	43,809		45,973	

Note: Imputed shares are estimated using Balasubramanian et al (2024) and mapping onto ATUS respondents' occupations and industries. Respondents are categorized as highly likely to have an NDA if both their occupation and industry had more that 50 percent of individuals reporting they signed an NDA according to Balasubramanian et al (2024). Data include the ATUS sample of working men and women from 2002 to 2022.

Table 7. Descriptive Statistics: Minutes Spent in Social Time by Disaggregated by Likelihood of NDA Categories

Categorized as Highly Likely to Have NDA:

	Sample of Working Women		Sample of Working Men	
	Mean	Standard Deviation	Mean	Standard Deviation
Minutes Spent in Social Time with Bosses, Clients, or Coworkers	0.320	6.882	0.831	11.670
n	29,011		20,391	

Not Categorized as Highly Likely to Have NDA:

	Sample of Working Women		Sample of Working Men	
	Mean	Standard Deviation	Mean	Standard Deviation
Minutes Spent in Social Time with Bosses, Clients, or Coworkers	0.259	7.230	0.312	7.539
n	14,798		25,582	

Note: Respondents are categorized as highly likely to have an NDA if both their occupation and industry had more that 50 percent of individuals reporting they signed an NDA according to Balasubramanian et al (2024). Data include the ATUS sample of working men and women from 2002 to 2022.