The Effects of Social Movements: Evidence from #MeToo

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Abstract

Social movements are associated with large changes in norms and behavior, but evidence on their causal effects is limited. We study the effect of the MeToo movement on a high stakes personal decision—reporting a sexual crime to the police. We construct a new dataset of sexual and non-sexual crimes in 24 OECD countries, covering 81 percent of the OECD population. We analyze the effect of the MeToo movement by employing a triple difference strategy over time, across countries, and between crime types. We find that the movement increased reporting of sexual crimes by 14 percent during its first three months. While the effect slightly declines over time, the movement had a strong effect even 15 months after it started. We use more detailed US data to show that despite the increase in crimes reported, the movement did not increase the number of sexual crimes cleared by the police. In contrast to a common criticism of the movement, we do not find evidence for substantial differences in the effect across racial and socioeconomic groups. Our results suggest that social movements can rapidly change high stakes personal decisions.

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1 Introduction

Societal changes are often associated with social movements advocating for changes in norms and behaviors. For example, the increase in women's labor force participation, the shift in attitudes towards LGBTQ individuals, and the increased concern for the environment all happened in conjunction with social movements advocating for these changes. Despite the importance of these changes and the common perception that social movements took part in bringing them about, it is difficult to establish if these movements are the drivers of change or if they are caused by changing norms. In this paper, we focus on the MeToo movement and estimate its effect on reporting sexual crime to the police.

We study the effects of the MeToo movement, which started on October 15, 2017, and was exceptionally effective in rapidly increasing awareness around sexual misconduct in many countries. Since the movement did not lead to major immediate changes in laws or government institutions, we can attribute the effects of the movement on behavior to changes in social norms. We focus on the effect on reporting sexual crimes to the police since underreporting of sexual crimes is a major social problem directly related to the goal of the MeToo movement—sharing one's story and breaking the stigma surrounding being a victim of sexual misconduct. In addition, reporting a sexual crime is a high stakes decision as it can come with substantial costs in terms of the victim's time, social stigma, the negative experience of reliving the trauma, and a risk of reprisals by the offender or a community shared by the victim and offender. Hence, using the number of crimes reported to the police as the outcome variable is setting a high standard for the types of behaviors that the MeToo movement might have changed.

We construct a data set on the number of crimes reported to the police by quarter in 24 OECD countries, covering 81% of the OECD population. We identify the effect of the MeToo movement using a triple difference strategy comparing countries with weak and strong MeToo movements, sexual and non-sexual crimes, and the pre and post periods. We find that the MeToo movement increased the number of reported crimes by 14% during the first three months of the movement.[1] While countries with strong MeToo movements are different from countries with weak movements, we show that the two sets of countries have similar pre-trends for the difference between sexual crime and non-sexual crime. Furthermore, we confirm the reliability of the result by performing placebo tests setting a fictional start date of the MeToo movement in each of the quarters between 2010-2017. The placebo tests show that our empirical strategy neither over rejects the null hypothesis nor frequently estimate effects of the

[1]The exact estimate of the effect is 14 log points, which is equal to a 15% increase. For simplicity, we describe the effects in log points as percentage changes throughout the paper, although this slightly understates the results.

magnitude that we find. To the best of our knowledge, this is the first rigorous evidence on the effects of the MeToo movement on reported sexual crimes.[2]

To measure the persistence of the effects, we focus on the countries with an initially strong MeToo movement and use a difference-in-difference strategy comparing sexual crime with all other crimes over time.[3] We find that among these countries, the effect of the movement declines from approximately 17% in the first quarter after the movement started to 10-13% in subsequent quarters. While the movement had its largest effect in the quarter immediately after it started, the results indicate that the change in norms caused by the movement is persistent, and that the movement still had a strong effect on behavior 15 months after it started.

The international data allows for the strongest identification strategy, but it lacks details on the crimes reported. To better understand the mechanisms underlying the effect of the MeToo movement, we use detailed incident-level data from the US at both the national and city level. The national data is collected from the FBI National Incident-Based Reporting System (NIBRS) and covers approximately 30% of the US population. The city data, which includes additional covariates and covers more crime categories, is collected from seven large US cities. Since the US lacks substantial geographic heterogeneity in the strength of the MeToo movement, we employ a difference-in-difference strategy comparing sexual crimes to all other crimes over time.

We find that the MeToo movement increased the number of sexual crimes reported in the US by 7% in the first three months after the movement started. The results are consistent in the FBI and city-level samples and robust to employing the matrix completion method (Athey et al., 2017), which uses more flexible patterns in the city-level data to create a counterfactual for the number of sexual crimes reported had there been no MeToo movement.

We present three main findings based on the US data. First, by focusing on crimes that were committed before the start of the MeToo movement, while still including crimes reported after the start of the movement, we show that our results are driven by an increase in the propensity to report sexual crimes and not by an increase in the incidence of sexual crimes. Second, the movement had a larger effect on crimes that were reported at least a month after they occurred. However, the effect on crimes which were immediately reported is also strong and statistically significant, implying that even if part of the effect of the movement is due to the reporting of a stock of old crimes, the movement also increased the

[2] Rotenberg and Cotter (2018) present descriptive statistics showing that sexual crimes reported increased in Canada after the MeToo movement started.

[3] We use this strategy instead of our main triple difference specification since the MeToo movement became more prominent over time in several of the countries where it was initially weak.

reporting of a flow of new crimes. Third, we do not find evidence for the claim, commonly made in media reports, that the MeToo movement mainly affected white women of high socioeconomic status. We investigate this question by combining the city data with data on neighborhood characteristics and do not find evidence that white, educated, or high-income neighborhoods were more likely to be affected by the movement. Furthermore, when disaggregating the increased reporting in the NIBRS data by the race of the victim, we find similar effects for black and white victims.

The results are related to three different streams of literature. First, we contribute to a debate, mostly concentrated among sociologists and political scientists, on whether social movements have any political influence (Burstein and Sausner, 2005). In a review of the topic, Amenta et al. (2010) state that "The disagreement on this basic issue is wide. Some ... hold that social movements are generally effective and account for most important political change. Others ... argue that social movements are rarely influential." Papers in this field often document a correlation between a movement's activity and an outcome, such as congressional attention (e.g., Baumgartner and Mahoney, 2005), but do not necessarily identify causal effects. A smaller literature focuses on the causal effects of political protest, a specific tactic often employed by social movements. This literature has shown that protests can mobilize people and change voting behaviors, but that violent protest may also cause a political backlash leading to less political support and subsequent electoral defeat (Madestam et al., 2013; Wasow, 2017).[4] We bridge these literatures by identifying the causal effect of an important social movement. An additional contribution of our paper is that we do not focus on political outcomes, which are typically studied, but rather show how a social movement can affect costly *personal* decisions. Studying the effects of social movements on such decisions is important since many social movements focus on changing norms and individual behavior and not only official policy. Personal decisions also often have large externalities (e.g., more equal sharing of non-market labor between men and women) and carry high stakes for the individual, which may make them more difficult to change than voting decisions, for example.

A second contribution to the literature is showing how norms can rapidly change. It is well established that social norms, and especially gender norms, have strong effects on behavior (e.g., Alesina et al., 2013; Bertrand et al., 2015; Charles et al., 2018). However, there is still limited understanding of how social norms change. Several studies have shown how popular culture can affect norms and behavior (e.g., Banerjee et al., 2019; Chong and Ferrara, 2009; Jensen and Oster, 2009; La Ferrara et al., 2012). There are also well-documented examples of how deceptive practices can lower trust towards certain

[4] Acemoglu et al. (2017) also show that street protests, but not twitter protests, can reduce the valuation of politically connected firms and may serve as a check on political rent-seeking overall.

institutions and change behavior (Alsan and Wanamaker, 2017; Martinez-Bravo and Stegmann, 2018). A recent literature based on theory, as well as information interventions, shows how multiple equilibria of social norms can exist when individuals do not express their personal beliefs publicly, and that social norms can "unravel" quickly when individuals start expressing those beliefs (Bursztyn et al., 2017, 2018; Sunstein, 2019). Cheng and Hsiaw (2019) applies a similar logic to the reporting of sexual misconduct and presents a model where the MeToo movement leads to a shift from a low reporting equilibrium to a high reporting equilibrium by raising awareness of misconduct. We contribute to this literature by demonstrating in an important real-world setting that norms can shift quickly and change important behaviors as awareness to a social issue rises.

This paper also contributes to the literature on reporting gender-based violence by showing that awareness-raising campaigns can have a large effect on the reporting of sexual crimes. Previous studies have shown that a high profile rape and murder case increased reporting of sexual crimes in India (Bhatnagar et al., 2019; McDougal et al., 2018), that an information treatment targeting social norms increased the reporting of violence towards women (Green et al., 2019), and that the election of female politicians increased the reporting of crimes towards women (Iyer et al., 2012). Public campaigns increasing awareness is a common strategy to increase reporting.[5] However, there is limited evidence on the effects of awareness-raising campaigns. The MeToo movement can be seen as a particularly successful awareness-raising campaign, and our results show that such campaigns can be effective in increasing the reporting of sexual crimes.

The rest of the paper is organized as follows. Section 2 describes the underreporting of sexual crime and the MeToo movement in more detail. Section 3 describes the international data, our identification strategy, and provides evidence for the effect of the movement. Section 4 describes the US data and provides results on mechanisms as well as heterogeneity in the effect of the movement. Section 5 interprets the overall results, and Section 6 concludes.

2 Background: Underreporting of Sexual Misconduct and the MeToo Movement

2.1 Reporting of sexual misconduct

Underreporting of sexual misconduct is a serious problem. In the US, only 33% of sexual crime victims stated that the crime had come to the knowledge of the police, compared to 46% of victims of other

[5] For example, the largest US-based anti-sexual violence organization RAINN spends 27% of its budget on educating the public.

violent crimes.[6] Underreporting decreases social welfare since it reduces the probability that perpetrators are held accountable. Thus it may increase the incidence of sexual misconduct because repeat offenders are not prevented from committing additional crimes, and future offenders are not deterred. Indeed, Green et al. (2019) and Iyer et al. (2012) provide suggestive evidence showing that increases in reporting reduce the incidence of gender-based violence.

Reporting a sexual crime to the police is a high stakes decision for the victim. The process of reporting the crime and attending hearings with detectives and prosecutors have monetary costs such as lost income, childcare, and travel costs (Morabito et al., 2019). Moreover, reporting a sexual crime forces the victim to relive the experience by giving detailed accounts of what happened at several points in the investigation process. Reporting is especially hurtful for victims who experience that their account of the event is not believed by law enforcement officials, which is a common experience in at least some parts of an investigation (Spohn and Tellis, 2012). Furthermore, reporting a crime may lead to reprisals by the offender or the community shared by the victim and the offender. Sexual crimes are often committed by offenders who are in the same social circle or workplace as the victim, reporting a crime may therefore lead to parts of the community defending the offender and turning against the victim. 17% of sexual crime victims who did not report the crime to the police cite fear of reprisals as a reason for not reporting the crime, while the same figure for victims of other violent crimes is 7%.[7]

In this paper we focus on reporting of sexual crimes to the police. However, the MeToo movement also highlighted cases of sexual misconduct which do not constitute a criminal offense (e.g., many cases of workplace sexual harassment), but still have negative welfare consequences (Hersch, 2011). Furthermore, a victim has a range of possible actions to take in response to sexual misconduct. Reporting to the police is probably one of the actions with the greatest consequences. It is therefore likely that if reports to the police increased, many other behaviors changed as well. Indeed, there have been anecdotal reports of increased traffic to the EEOC website and an increase in the number of calls to helpline centers following the MeToo movement.[8] Therefore, the effects we find on reporting crime to the police are probably a subset of the overall behavioral effects of the movement.

[6] Authors' calculations using 2011-2017 National Crime Victimization Survey microdata.

[7] Authors' calculations using 2011-2017 National Crime Victimization Survey microdata.

[8] Chiwaya, Nigel - New data on #MeToo's first year shows 'undeniable' impact. NBC News. Oct 11, 2018. Online: https://www.nbcnews.com/news/us-news/new-data-metoo-s-first-year-shows-undeniable-impact-n918821

2.2 The MeToo movement

The MeToo movement went viral on October 15, 2017, after the Harvey Weinstein sexual misconduct allegations, when a tweet by Alyssa Milano encouraged people who had been sexually harassed or assaulted to write "Me too" on social media.[9] The movement uncovered a large number of sexual misconduct cases, and within a year more than 200 high profile men had been ousted from their positions in the US alone.[10]

The MeToo movement provides a setting particularly well suited to the study of the effects of social movements on behavior for four reasons. First, the movement was very effective in drawing attention to sexual harassment and sexual misconduct. While the movement started in the US, its effect quickly spread to other countries. Figure 1 shows that in the OECD, mean Google search interest for MeToo and for sexual misconduct (sexual harassment and sexual assault) increased substantially immediately after the start of the MeToo movement. In the 15 months after the movement started, mean search interest in the OECD for sexual harassment and sexual assault was 99% higher than in the period from January 2010 to September 2017. In the US, approximately eight months after the movement started, 65% of social media users stated that some or a great deal of the content they seen in social media is about sexual harassment or assault.[11] Furthermore, people who do not use social media were also likely to encounter the movement. Appendix Figure A.1 shows that among four major US newspapers, coverage related to sexual assault and sexual harassment increased substantially after the movement started and remained much higher than average coverage before the movement started for at least nine months.

Second, there was large variation in the strength of the movement between countries, as shown in Figure 2. The OECD country in the 75th percentile in terms of MeToo search interest had a 651% larger interest in the MeToo movement in October 2017, compared to the country in the 25th percentile. This allows us to identify the causal effect of the MeToo movement by comparing changes across countries. Third, one of the main objectives of the MeToo movement, increasing reporting of sexual misconduct, is an outcome for which there is high-quality administrative data across many countries.

Fourth, while the MeToo movement had a big impact on the public discourse, it did not result in immediate widespread changes to laws or government institutions, allowing us to attribute the effect we find to changes in social norms. A report by the International Lawyers Network (2019) shows that

[9] The phrase "Me Too" was first used by Tarana Burke in 2006, but widespread usage only started after October 15, 2017.

[10] The New York Times - #MeToo Brought Down 201 Powerful Men. Nearly Half of Their Replacements Are Women. October 23, 2018. Available online: https://www.nytimes.com/interactive/2018/10/23/us/metoo-replacements.html

[11] Pew Research Center American Trends Panel Wave 35.

among the 11 OECD countries covered by the report, the US was the only country that made changes to laws governing sexual misconduct between the start of the MeToo movement and the end of 2018. This is not surprising given that passing legislation is a lengthy process, often taking more than a year. Even the earliest legislative changes in the US took effect in the second quarter of 2019 and therefore could not have directly influenced reporting in the short run.[12] We can, therefore, attribute the effect we find to changes in social norms, where norms are broadly defined to include the norms of victims, firms and government employees, such as police officers, but exclude any changes to laws or government policy.

Our ability to isolate social norms as a mechanism differs to studies of cases where laws and norms changed simultaneously. For example, following the high-profile rape and murder case in India, studied by McDougal et al. (2018) and Bhatnagar et al. (2019), major changes were made to both laws and police administration, making it impossible to disentangle the effects of changing social norms from the effects of changes in policy.

While the MeToo movement was very successful in raising awareness, it is by no means unique. In recent years, several social movements such as Black Lives Matter and March for Our Lives, have had similar success in raising awareness about their causes (Pew Research Center, 2018). Social media has enabled new social movements to raise awareness at a larger scale, within shorter time spans, and with almost no organizing structure.[13] However, little is known about the effects of these modern social movements that are often disconnected from party politics and do not use traditional organizing techniques such as strikes or publishing lists of demands.

3 Identifying the Effect of the Movement: Analysis of International Data

3.1 Data

3.1.1 Outcome: reported crimes

We build a data set with quarterly data on the number of crimes reported in 24 OECD countries representing 81% of the OECD population.[14] We include in our sample countries that have quarterly, or more frequent, data available, disaggregated by sexual crime and non-sexual crime. We collect data available from the

[12] An analysis of US laws conducted by USA Today one year after the start of the MeToo movement found that Congress passed no laws related to sexual harassment in the workplace since the movement started. While there was a slight uptick in state laws related to sexual misconduct, they were mostly limited in scope. Kelly, Cara, and Hegarty, Aaron - #MeToo was a culture shock. But changing laws will take more than a year. USA Today. October 4, 2018.

[13] Enikolopov et al. 2019 show how social media facilitated protests in Russia. There is also a literature on how different technologies enables the diffusion of social movements (e.g., Christensen and Garfias, 2018; García-Jimeno et al., 2018).

[14] See Table A.5 for a list of the countries and data sources.

start of 2010 until the end of 2018 and manually classify offense categories as sexual crimes or non-sexual crimes for each country. We define sexual crime as all forms of sexual assault and sexual harassment and define non-sexual crime as all other crime. When possible, we exclude crimes of sexual nature that were not the focus of the MeToo movement, such as incest, human trafficking, and pornography. For more details on crime classification and OECD data collection, see Appendixes A.1 and A.2, respectively.

3.1.2 Strength of the MeToo movement

We use monthly Google Trends data on search behavior from 2010-2018 to create a proxy for the strength of the MeToo movement in each OECD country.[15] The primary measure is based on the proportion of total Google searches for the "topic" of the MeToo movement. Google defines a search for a topic as any search query including a phrase directly linked to the topic in any language. Figure 1a shows the search interest in the topic of MeToo over time for the entire OECD. Figure 1b shows the interest in the topics of sexual harassment and sexual assault, which we use as an alternative measure for the strength of the movement. The figure demonstrates that the movement had a large effect on interest in sexual misconduct. Appendix A.3 provides more details on how the Google Trends data was processed.

We define *immediate interest* as the interest in the MeToo movement during October 2017, the month the MeToo movement started. In our main specification, we categorize a country as having a *strong* MeToo movement if the immediate interest is above the OECD median and a *weak* MeToo movement if the immediate interest is below the OECD median. Figure 2 shows the immediate interest for each OECD country, highlighting the countries for which we have crime data and indicating which of these countries we classify as having strong and weak MeToo movements. Appendix Figure A.2 confirms the validity of our primary measure for the strength of the MeToo movement by comparing it with survey data on the fraction of the population who has heard of the MeToo movement (YouGov, 2019). Even though the survey took place in February-March 2019 and our measure is based on data from October 2017, there is a strong correlation of 0.77 between the two measures.

3.2 Empirical strategy

Our main empirical strategy to measure the causal effect of the MeToo movement on sexual crime reported to the police is a triple difference strategy where we use the difference over time, across countries,

[15]Caputi et al. (2019) show that the MeToo movement affected Google search interest in the US.

and between sexual crimes and non-sexual crimes:

$$y_{itc} = \beta_1 Post_t \times StrongMeToo_c \times SexCrime_i + \beta_2 Post_t \times SexCrime_i + \beta_3 Post_t \times StrongMeToo_c + \beta_4 Post_t + \beta_{5,ic} Trend_t + \gamma_{i,c,q(t)} + \varepsilon_{itc} \quad (1)$$

- y_{itc} is the natural logarithm of the number of reported crimes of type i, in quarter t, in country c
- $Post_t$ is an indicator for Q4 2017, i.e. the quarter that the MeToo movement started
- $StrongMeToo_c$ in an indicator for whether country c had a strong MeToo movement
- $\beta_{5,ic} Trend_t$ controls for differential linear time trends by the full interaction of country and crime category
- $\gamma_{i,c,q(t)}$ controls for the full interaction of country, calendar quarter and crime category fixed effects

The regression is unweighted and uses standard errors that are clustered at the country by crime category level.[16]

Our identifying assumption is that without the MeToo movement, the difference between sexual crimes and non-sexual crimes would have changed in the same way from the pre to the post-period (after controlling for crime and country-specific seasonality and for differential linear time trends) in the countries with strong and weak MeToo movements. For an omitted variable to explain the results we find, it would have to have a non-linear change after October 2017, to affect the number of reported sexual crimes more than it affects reported non-sexual crimes, and to disproportionately affect countries where the MeToo movement was strong, as compared to countries where it was weak. While the strength of the MeToo movement is not random, we have no reason to believe it is correlated with an omitted variable affecting sexual crimes differentially in the post period.

In this section, we focus on the effects of the MeToo movement in the first quarter after it began when the difference in interest between countries with a strong movement and countries with a weak movement is the largest. In Section 5.1, we test if the effect is persistent over time.

[16] Standard errors clustered at the country level are smaller than the standard errors clustered at the country by crime level. Therefore, we choose the more conservative of the two standard errors.

3.3 Results

Table 1 shows that the MeToo movement caused an increase in sexual crimes reported in our sample of 24 OECD countries. Column (1) uses data only on sexual crimes to show a simple difference-in-difference estimator over time and between countries with strong and weak MeToo movements. Column (2) uses all 24 countries and shows a difference-in-difference over time and between sexual and non-sexual crime. While the two columns use different sources of variation, they both find statistically significant effects of 11-14%. Column (3) estimates the effect from Column (2) separately for countries with strong and weak MeToo movements. The effect on the entire sample is driven by the countries that had a strong MeToo movement. These countries had an effect of 17%, while the effect was only 3% among countries with weak MeToo movements. Finally, Column (4) shows the results from our main triple difference specification described in Equation 1. Here the coefficient of interest is that on $Post_t \times StrongMeToo_c \times SexCrime_i$ and we find an effect of 14%. Appendix Tables A.1 and A.2 show that the triple difference result from Column (4) is robust to using different measures of the strength of the MeToo movement but that using continuous measures yields less precisely estimated effects.[17]

In Columns (3) and (4) of Table 1, the coefficient on $Post_t \times StrongMeToo_c$ can be interpreted as a difference-in-difference estimate of the effect of the MeToo movement on non-sexual crimes, using variation between countries and time. Since we do not expect the MeToo movement to affect the number of non-sexual crime reported, this coefficient can be used as a placebo test. We estimate the coefficient to be very close to zero, which confirms that our estimate of the MeToo movement's effect is not influenced by differential trends in non-sexual crime reporting between countries with weak and strong movements.

We present the raw data used in our triple difference result visually in Figure 3. Sub-figure 3a shows the number of sexual crimes reported, indexed to be 100 in the third quarter of 2017, and averaged across the countries with strong and weak MeToo movements. To make the average numbers comparable over time, we have shortened the data series to the years 2013-2017 and excluded three countries for which we only have data for shorter time periods. The strong and weak MeToo movements have similar pre-trends. Even in this relatively short time span, a clear seasonality is observed, where the fourth quarter of each year tends to see a decrease in the number of sexual crime reports. This is true for both strong and weak MeToo movement countries until the fourth quarter of 2017 when the strong MeToo movement countries experience an increase in the number of reported sexual crime while the weak

[17] For example, Column (1) of Appendix Table A.2 shows that a one standard deviation increase in MeToo movement interest (equivalent to a move from the 38th to the 63rd percentile in our 24 country sample) is associated with a six percentage points larger effect on the number of sexual crimes reported.

MeToo movement countries experience the typical decline.

Sub-figure 3b shows that this differential increase in reported crimes for the countries with strong MeToo movements did not happen for non-sexual crimes. The figure also shows that the strong and weak MeToo movement countries may have somewhat different pre trends for non-sexual crimes. In our main specification, we control for linear time trends, and hence, these differential trends do not drive the effects as measured in Table 1. Furthermore, Sub-figure 3c shows that in the difference between the sexual and non-sexual crime indexes displayed in Sub-figures 3a and 3b, there are no differential pre-trends, while there is a substantial divergence between countries with strong and weak MeToo movements after the start of the MeToo movement.

3.4 Placebo tests

We conduct a set of placebo tests to further assure that MeToo movement is driving our result and not some other mechanism, such as non-linear differential trends between countries with strong MeToo movements compared to those with weak movements. Figure 4 presents placebo tests setting the start of the MeToo movement in each of the quarters from 2010 to 2017. We estimate the effect of these placebo MeToo movements using the triple difference specification from Equation 1, just as we do in our main specification in Column (4) of Table 1. Out of the 31 placebo tests, only two are significantly different from zero (one with a positive coefficient and one with a negative) at the 10% level, and only one of these two tests is significant at the 5% level, which is expected when running 31 placebo tests. If our specification over-rejected the null hypothesis, we would have expected to see more placebo tests rejecting the null hypothesis at both the 95% and 90% confidence levels. The actual effect of the MeToo movement (Q4 of 2017) has the second-largest coefficient among the 31 placebo tests.

4 Heterogeneity and Mechanisms: Analysis of US data

To study heterogeneity and mechanisms in the effects of the MeToo movement, we focus on the US since that is where the movement started and since rich incident-level data is available for the US.

4.1 Data

We use US data from two sources: the FBI National Incident-Based Reporting System (NIBRS) and more detailed crime data for seven large US cities. In contrast to the international data, both US datasets provide data at the incident-level and thus allow us to analyze mechanisms and heterogeneity of the effects of the MeToo movement.

4.1.1 National data: FBI NIBRS

Law enforcement agencies voluntarily report data on offenses as part of the FBI's Uniform Crime Reporting (UCR) Program. Agencies have been gradually shifting from reporting summary statistics of the most severe offenses to reporting incident-level data using the NIBRS for 52 specific crimes, defined as Group A offenses.[18] By 2017, more than 7,000 agencies covering approximately 30% of the US population reported data using the NIBRS program. In our main specification, we use 2010-2017 NIBRS data aggregated at the state by crime category level for each month. Similarly to the international analysis, we aggregate data into two main categories: Sexual crime and non-sexual crime. Since Group A offenses do not include sexual harassment, our estimates will measure the effect only on sexual assaults.

The main advantage of using NIBRS data is that the crime categories and the variables describing each incident are harmonized across law enforcement agencies. This allows us to test for heterogeneous effects by crime type, the characteristics of the victim and offender, and whether a case was cleared. Appendix A.4 provides more details on how the NIBRS data was processed.

4.1.2 City-level crime data

We collect incident-level data from seven large US cities with a combined population of 16 million: Denver, Kansas City, Los Angeles, Louisville, Nashville, New York City, and Seattle. Our sample consists only of cities that provide incident-level data on all crimes and provide both the date each crime occurred and the date it was reported, along with the crime's approximate location. The seven cities selected are the cities that met our inclusion criteria among the 50 largest US cities.

The city-level data is used to complement our analysis in four ways. First, information on the location of each incident allows us to analyze heterogeneity in the effect of the MeToo movement by neighborhood. Second, we use the detailed reporting and occurrence dates to analyze for heterogeneous effects according to whether the crime was immediately reported. Furthermore, by focusing on crimes that occurred before the start of the movement, we can isolate the effect of the propensity to report crime from a possible effect on crime incidence. Third, the data includes virtually all crimes reported

[18] For more details, see the 2019 National Incident-Based Reporting System User Manual. Available online: https://ucr.fbi.gov/nibrs/nibrs-user-manual

to the police, and not only the relatively severe offenses covered by NIBRS.[19] Specifically, this allows us to analyze the effect of the movement on sexual harassment, in addition to sexual assault. Finally, this dataset includes crime that occurred through the end of 2018 and thus allows us to analyze the persistence of any effect.

We aggregate crime into three main categories: sexual assault, sexual harassment, and non-sexual crime. We manually classify the crime categories for each city separately and exclude crimes that could be indirectly affected by the MeToo movement. In our main specification, we aggregate data at the city by crime category by month level. To estimate heterogeneity within cities, we define neighborhoods according to the police administrative areas (e.g., a police division or precinct) of each city and aggregate the data at the neighborhood by crime category by month level. We calculate the demographics of each neighborhood based on the 2016 American Community Survey 5-year estimates. Appendixes A.1, A.5, and A.6 provide more details on how crimes were classified, how the city data was processed and how the neighborhood-level data was processed.

4.2 Empirical strategy

We analyze US data using a difference-in-difference specification over time and by crime type. We do not use a triple difference strategy since we do not observe meaningful variation in the strength of the MeToo movement across different regions within the US, as seen in Figure A.3.[20] This is unsurprising as the national media covered the movement and the allegations related to it, and the movement generated substantial public discussion in social media, which is not limited to a specific media market. Indeed in a PEW survey from November-December 2017, 92% of Americans reported reading or hearing about recent allegations of sexual harassment and assault.[21]

We use the following regression for our primary specifications:

$$y_{itc} = \beta_1 SexCrime_i \times Post_t + \beta_2 Post_t + \beta_{3,ic} Trend_t + \gamma_{i,c,m(t)} + \varepsilon_{itc} \tag{2}$$

- y_{itc} is the inverse hyperbolic sine transformation of the number of reported crimes of type i, in

[19] There are several exceptions, such as cities excluding crimes related to child abuse cases or unfounded complaints.

[20] While the OECD country in the 75th percentile in terms of search interest had a 651% larger interest in the MeToo movement, compared to the country in the 25th percentile, the same figure for US states was only 47%. Furthermore, the variation between OECD countries was relatively stable over time with a correlation of 0.95 between interest in October 2017 and interest in November 2017, while the same correlation for US states was just 0.34. This figure indicates that a large part of the variation in interest between US states is probably due to noise and not actual differences in the strength of the MeToo movement.

[21] Pew Research Center, December 2017 Political Survey.

month t, in location (state or city) c. The inverse hyperbolic sine is used instead of a log transformation since there are months when no crime is recorded for a specific location and crime category

- $Post_t$ is an indicator for October 2017 and later
- $\beta_{3,ic}Trend_t$ controls for differential linear trends by the full interaction of location and crime category
- $\gamma_{i,c,m(t)}$ controls for the full interaction of location, calendar month and crime category fixed effects

The specification is similar to our triple difference specification described in Equation 1 with several differences. First, we aggregate the data at the monthly level, instead of the quarterly level. Second, we use robust standard errors. Since our main specification includes only two crime categories, we cannot cluster the standard errors at the crime category level (where the treatment occurs). Appendix Table A.3 uses the same specification, with a finer aggregation of crime categories, which allows us to cluster the standard errors at the crime category level, and shows that the point estimates and standard errors remain similar. In section 4.4, we show that the results are also robust to an estimation strategy using a finer aggregation of crime categories at the city level and bootstrapping the standard errors. A third difference is that we weight regressions by the average number of crimes that occurred in a location in the pre-period since we are interested in the effect of MeToo on the number of crimes reported and not in the effect of the movement on an average city or state.[22] An additional advantage of weighting the data is that the weights reduce the importance of the aggregation method in our estimates (e.g., whether we aggregate the data by state or county).

Our identifying assumption is that without the MeToo movement, the difference between sexual crime and non-sexual crime in the post-period would have been the same as the difference in the pre-period after controlling for crime by location-specific seasonality and crime by location time trends.

4.2.1 Heterogeneity by neighborhood demographics

We estimate heterogeneity by the neighborhood where the crime occurred using the following regression:

$$y_{itc} = \beta_1 SexCrime_i \times Post_t + \beta_2 Post_t + \beta_{3,ic} Trend_t + \beta_4 SexCrime_i \times Post_t \times Demog_c + \beta_5 SexCrime_i \times Demog_c + \beta_6 Post_t \times Demog_c + \beta_7 Demog_c + \beta_{8,ic} Trend_t + \gamma_{i,c,m(t)} + \varepsilon_{itc} \quad (3)$$

[22] The international analysis regressions in Section 3.4 are not weighted, since in this analysis the treatment occurs at the country level and we are interested in the average effect of the MeToo movement on different sets of countries.

The regression is based on our main specification with c not representing a neighborhood instead of a city/state and β_4 estimating heterogeneous effects by various neighborhood characteristics. Each demographic variable ($Demog_c$) is constant across time and is first subtracted by its weighted mean to keep the estimates for the effect of the MeToo movement consistent across specifications.

4.3 Results

Table 2 shows that the MeToo movement had a strong and statistically significant effect on crimes reported in both datasets, and demonstrates that the effect found is robust to using different samples (OECD, US states, US cities) with different sources of variation (triple difference, difference-in-difference). Based on NIBRS data, Column (1) shows that the MeToo movement increased the number of reported sexual assaults by 7% in the three months after the movement started. Column (2) shows that in our sample of large cities the effect on sexual assault and sexual harassment is approximately 10% and 21%, respectively. Since both effects are related to the MeToo movement, in Column (3), we aggregate sexual assault and sexual harassment into one category, labeled sexual crime, which we will focus on throughout the rest of the analysis. We find an effect of approximately 12% on reporting sexual crimes in our city sample. Column (4) repeats the analysis for all months through the end of 2018 and finds a similar effect. To ensure that the effect in one city is not driving the results, we run our main specification separately for each city. Appendix Table A.4 shows that the effect is positive for six of the seven cities in our sample and statistically significant for four of the seven cities.

4.3.1 Mechanisms: Disentangling the effect on reporting from the effect on crime incidence

One concern with our interpretation of the results is that the effect of the MeToo movement on the number of crimes reported could be driven by an increase in the incidence of crimes and not an increase in the propensity to report crimes. We find it unlikely that such a backlash effect is driving our results given that we are not aware of any anecdotal reports of increases in sexual crimes committed, while there is ample anecdotal evidence of an increase in the propensity to report crimes.[23] We can also rule out that an increase in crimes committed drives the increase in sexual crimes reported during the first three months of the MeToo movement by restricting our analysis to crimes that were committed before

[23]For example: At colleges (Binkley, Collin - MeToo inspires wave of old misconduct reports to colleges. PBS October 13, 2018); In the entertainment industry (Maddaus, Gene - Many Accused, None Prosecuted: Why #MeToo Hasn't Led to a Single Criminal Charge in L.A. Variety. September 25, 2019); Among congressional candidates (Godfrey, Elaine, Felton, Lena and Hosking, Taylor - The 25 Candidates for 2018 Sunk by #MeToo Allegations. The Atlantic. July 26, 2018)

the start of the MeToo movement.

Table 3 shows that the MeToo movement had a strong and statistically significant effect even on crimes that occurred *before* the movement started when incidence could not have been affected by the movement. In the regression, we isolate the effect on the propensity to report crime by including only crimes that were reported at least three months after they occurred and that were reported by December 2017 (i.e., occurred before October 2017). This analysis shows that an increase in incidence cannot explain the increase in reporting. However, the MeToo movement may have decreased the incidence of sexual crime, and in that case, the effects we estimate are lower bounds of the increase in the propensity to report.

4.3.2 Mechanism: Heterogeneous effects by report timing and crime type

Table 4 uses city-level data to show that while the MeToo movement had a stronger effect on crimes reported at least a month after they occurred, the movement also affected crimes which were immediately reported. For this analysis, we aggregate crime into three main categories: Sexual crimes reported more than a month after they occurred, Sexual crimes reported a month or less after they occurred, and non-sexual crimes, which is the reference category. Column (1) shows that the movement had an effect of 10% on crimes reported within 30 days, and an effect of 18% on crime reported more than 30 days after they occurred. The effect may be stronger for crimes that are not immediately reported since the movement affected a stock of old crimes. This explanation would predict that the effect on sexual crimes reported after a month would decline as the stock of old unreported crimes is exhausted. Columns (2) and (3) analyze the short and long-term effects of the movement separately and show that the effect on crimes reported more than a month after they occurred does not decline with time. This suggests that the movement had a persistent effect on a flow of cases which are not immediately reported. Alternatively, there may be a very large stock of unreported crimes, which is gradually affected by the MeToo movement.

We use the NIBRS data to test for heterogeneity by crime type. Column (1) of Table 5 splits the category of sexual crime according to the specific offense type and shows that the MeToo movement had a large effect on the number of rapes reported, the most severe sexual offense category, and on fondling cases. Column (2) and Column (3) analyze heterogeneity by whether any injury was reported and whether the victim knew the offender. While the differences between the crime types analyzed in the columns are not statistically significant, the results suggest that the marginal victim more likely to be affected by the movement is a victim who was not injured and who knew the offender. This result fits the narrative of the movement, which focused on cases where the victim knew the offender.

4.3.3 Heterogeneous effects by race and socioeconomic status

The MeToo movement has been criticized for focusing on white victims of high socioeconomic status and ignoring the experiences of working-class women and women of color (Onwuachi-Willig, 2018). To test whether the effect of the MeToo movement on reporting was stronger among whites and groups with high socioeconomic status, we estimate the heterogeneous effects of the movement by demographics of the victim, offender, and the location where the crime occurred. We do not find evidence for large heterogeneity along these dimensions.

We test for heterogeneous effects among victims by separating sexual assault into sub-categories according to the victim demographics.[24] Column (1) of Table 6 shows that the movement had a larger effect among female victims than among male victims, although the difference is not statistically significant. This is consistent with the general narrative of the MeToo movement, which tended to focus specifically on female victims of sexual crimes. Column (2) finds a similar effect on black and white victims, and we cannot reject a homogeneous effect across the victim's race.[25] Columns (4)-(5) repeat the analysis according to the offender's demographics. We cannot reject the hypothesis that the movement had a homogeneous effect across the offender's race.[26]

Table 7 shows that the MeToo movement did not have substantial heterogeneous effects by neighborhoods with different demographic profiles. The table estimates the effect of the MeToo movement using neighborhood-level data. Column (1) analyzes the effect of the movement based on our specification in Equation 2, and in Columns (2)-(6) we estimate heterogeneous effects according to each demographic variable separately, as described in Equation 3. We find no evidence for stronger effects in neighborhoods with higher income, a greater share of whites, or a greater share of college-educated individuals. In Column (7), we include all demographic variables in the same regression. The results are not clear-cut, but they still suggest that the movement did not affect mostly white neighborhoods with high socioeconomic status (e.g., when

[24] For example, when estimating heterogeneous effects by race, the treated categories are sexual assaults of black victims and sexual assaults of white victims, and the reference category is non-sexual crimes.

[25] The NIBRS also includes data on Hispanic ethnicity. We do not find a stronger effect of the movement on individuals who are not Hispanics or Latinos. We do not present the results by ethnicity since the ethnicity could not be identified for 28% of victims and 82% of offenders.

[26] We also test whether the movement had a differential effect on how the complaints are treated. We do not find evidence for heterogeneity in the effect of the movement on the number of cleared cases by the victim's race (not presented). For more details on clearance, see Section 4.3.4.

controlling for other covariates neighborhoods with more Hispanics were less likely to be affected, but neighborhoods with more blacks were more likely to be affected). Finally, in Column (8) we add a full interaction between city, post-period and crime category fixed effects, in order to exploit variation between neighborhoods *within* cities, instead of comparing all neighborhoods to each other. Adding these fixed effects does not qualitatively change our results.

To conclude, based on the analysis of victim, offender, and neighborhood demographics, we can reject the argument that the MeToo movement more strongly affected the reporting of whites or those with high socioeconomic status.

4.3.4 Effect on the number of cleared cases

The NIBRS data allows us to test not only whether crime reporting increased, but also whether the movement had an effect on the number of cases cleared by the police. A case is defined as cleared if a suspect is arrested, summoned to court or if the police have sufficient probable cause to arrest a suspect, but could not make an arrest for reasons outside their control.[27] Table 8 shows that increased reporting of cases which were *not* cleared is driving the entire MeToo effect on police reporting . The results only include the effects for cases reported in the three month period between October 2017 and December 2017 and should be cautiously interpreted as the effects might have changed over time. In Column (1), the effect is estimated by aggregating the data into three separate categories: Sexual crimes which were cleared, sexual crimes which were not cleared, and non-sexual crimes, and estimating the effect of the MeToo movement on both sexual crime categories, where non-sexual crime is the reference group. In Column (2), we test the robustness of this result using a slightly different specification: we aggregate the data at the state by month by crime category and whether a crime was cleared, and control for the full interaction of crime category and whether a crime was cleared. This allows us to control for any changes in the number of cleared cases after October 2017 that are not unique to sexual crimes. Using this specification, our coefficient of interest is the interaction of clearance, sexual crime, and the post-period. We indeed find a negative and significant effect that cancels out the effect of the movement on crimes reported.

One possible explanation for this result is that the MeToo movement affected mostly the type of cases where the probability of clearance is low. Indeed, as shown in Table 4, the MeToo movement had

[27] Reasons for not arresting and charging the offender in these cases include the death of the offender, the prosecutor declining prosecution for a reason other than lack of probable cause, the offender being in custody of another jurisdiction, the victim refusing to cooperate, and the offender being a juvenile.

a stronger effect on cases reported more than a month after they occurred. Based on cities that collect clearance data, the share of cases cleared in the pre-period (all months before October 2017) is lower for sexual assaults reported at least a month after they occurred.[28] However, the movement also had a strong effect on crimes reported within a month, which are far more common. Furthermore, even cases reported at least a month after they occurred, have a non-negligible clearance rate in the pre-period. Therefore, the increased reporting of old crimes only provides a partial explanation for why the number of cleared cases did not increase.

4.4 Robustness: Matrix completion method

Our difference-in-difference specification relies on the assumption that other crimes are a suitable control group for sexual crimes after controlling for crime and location-specific seasonality and differential linear time trends. In this section, we relax those assumptions, and instead of estimating an effect based on the standard difference-in-difference specification, we use the matrix completion method and show that the results are robust to the method used.

The matrix completion method (Athey et al., 2017) is used for panel data and is based on a matrix where each row is a unit and each column is a time period. The method attempts to predict the counterfactual outcome for treated units in the post-period. We use the method to create a counterfactual for the expected number of sexual crimes in the post periods, which would have been reported if there was no MeToo movement. The counterfactual matrix is created for all observations, and values are chosen to minimize the sum of squared differences between the actual outcomes and the predicted counterfactual outcomes for observations that were not affected by the movement (non-sexual crimes in all periods and sexual crimes in the pre-periods), with penalization according to the nuclear norm of the predicted matrix. Penalization is required to prevent overfitting, and the regularization parameter is selected through cross-validation. Finally, the average treatment effect is the weighted difference between the actual outcomes and counterfactual outcomes for the treated units in the post-periods. The main advantage of the matrix completion approach is that it is "*able to model more complex patterns in the data, while allowing the data (rather than the analyst) to indicate whether time-series patterns within units, or cross-sectional patterns within a period, or a more complex combination, are more useful for predicting counterfactual outcome*" (Athey, 2018).

[28] Anecdotal evidence also suggests that it was difficult to clear MeToo-related cases since they were reported long after they occurred. For example, see Maddaus, Gene - Many Accused, None Prosecuted: Why #MeToo Hasn't Led to a Single Criminal Charge in L.A. Variety. September 25, 2019

We use this method with our city-level data and define each unit as a crime category by city combination, and each time period as a month. We use the original crime categories defined for each city and do not aggregate crimes to broader categories.[29] We exclude categories for which there was at least one month with no crimes reported. All sexual assault or sexual harassment crimes that occurred on or after October 2017 are considered treated. In total, we have 43 treated groups and 440 control groups. We explicitly control for category and time fixed effects and do not add any additional controls. We weight each crime group by the number of reported crimes for that crime group in the pre-period.[30]

We find an average treatment effect of 0.16, significant at the 1% level using standard errors generated by bootstrapping. Note that even though the method aggregates units differently and uses different information to create the counterfactual, the results are similar to that of our primary specification in Table 2, Column (4). Figure 5a shows that the counterfactual created by the method fits the actual outcome well in the pre-period, and Figure 5b highlights that the treatment effect is relatively persistent.

5 Interpretation

5.1 Is the effect of the movement persistent?

Table 9 uses data from the countries with a strong MeToo movement to measure the persistence of the effect over time. For some of the countries where the MeToo movement was initially weak, such as South Korea and Japan, it gained traction and became stronger three to nine months after the start of the movement. Therefore, we do not use our triple difference empirical strategy to estimate the longer-term effects of the movement since including countries where the movement was initially weak but grew stronger in later periods would contaminate our counterfactual. Instead, we use the difference-in-difference specification and only focus on countries where we know that the movement started around October 2017. Column (1) shows that the average effect for the first five quarters after the movement started is estimated to be 12%. Column (2) shows that the effect is strongest in the first quarter after the start of the movement, at a 17% increase in reported sexual crimes. In the following four quarters, the effect declines to between 10% and 13%, but there is no pattern of continuous decline after the first quarter. The international data suggests that the effect of the MeToo movement is persistent and had a lasting

[29]For example, indecent exposure in Los Angeles is a row in the matrix and is considered treated for time periods (matrix columns) on or after October 2017. Simple assault in Nashville in an example for a row in the matrix which is untreated in all time periods.

[30]The method was estimated using the R package gsynth by Yiqing Xu and Licheng Liu. Available online: https://yiqingxu.org/software/gsynth/gsynth_examples.html

effect on behavior.

Table 10 focuses on the sample of US cities and shows that in the US, the effect of the movement was rather consistent. For all quarters, the estimated effect was between 11% and 14%. Columns (3)-(4) repeat the analysis by quarter only for crimes that were reported within a month after they occurred. While the effects are slightly smaller, the results are similar and continue to provide evidence that the effect of the movement was persistent.

Combined, the US and international data show that the MeToo movement had a positive effect on the reporting of sexual crimes even 15 months after the movement started.

5.2 Changes in awareness and beliefs

One possible explanation for how norms affected reporting is that the MeToo movement increased awareness of sexual misconduct, and as a result, victims were more willing to report sexual crimes. Table 11 uses survey data to show that awareness of sexual misconduct indeed increased in April-May 2018, compared to July 2016. We use data from the Views of the Electorate Research Survey since the survey asked a large panel of respondents the same set of questions before and after the movement started. An additional advantage of this survey is that the timing of the survey was not affected by the movement. Other topical surveys were more likely to ask questions related to sexual misconduct when the movement was discussed in the news, and therefore the salience of the movement could affect the respondents' answers.

Column (1) of Table 11 shows that agreement with the statement "*sexual harassment against women in the workplace is no longer a problem in the United States*" decreased by 0.14 standard deviations in 2018, compared to 2016. In column (2), we provide evidence for heterogeneous effects between men and women. While men's agreement with the statement decreased by 0.24 standard deviations, women's agreement decreased by only 0.05 standard deviation. We cannot reject a null effect on women, and the difference between the effect on men and women is statistically significant. In columns (3) and (4), we show that while awareness increased, agreement with "*women who complain about harassment often cause more problems than they solve*" did not change substantially between 2016 and 2018.

These results suggest that awareness of the problem of sexual misconduct may be an important channel affecting behavior. Interestingly, it seems that a general increase in awareness may have an effect, even when the awareness of women, who are much more likely to be victims, is not substantially affected. It is possible that when victims perceive that there is greater awareness of sexual misconduct, they believe it is less costly to report a crime. The results suggest that individual behavior can be affected by a change in the beliefs of other individuals, complementing experiments demonstrating that second-order beliefs can affect behavior (Bursztyn et al., 2018).

6 Conclusions

This study shows that the MeToo movement had a substantial, persistent effect on the propensity to report sexual crimes. This result is consistent across multiple samples and is robust across multiple estimation techniques (triple difference among OECD countries, difference-in-difference among US states and cities and matrix completion for US cities). Furthermore, the heterogeneity results provide additional evidence for the causal effect of the MeToo movement, in contrast to some other event that occurred around October 2017. The MeToo movement focused on female victims, and often on cases that occurred several months or years before they were discussed in the media. We find a strong significant effect among female victims and an especially strong effect among crimes that are reported at least a month after they occurred.

Focusing on the US allows us to understand better who was affected by the movement. The effect is strong and statistically significant for both sexual harassment and sexual assault. While the movement may have disproportionately focused on the experiences of white women (Onwuachi-Willig, 2018), its impacts in terms of reporting of sexual crimes to the police were felt across both white and black victims, offenders and neighborhoods. Furthermore, we do not find evidence that the movement disproportionately affected neighborhoods with higher incomes or more education. Overall, we can reject the argument that the MeToo movement had an effect mostly among whites or those with high socioeconomic status.

We estimate that in the first three months of the movement, 11,598 additional sexual crimes were reported in the 13 OECD countries with strong MeToo movements for which we have data, as a result of the MeToo movement.[31] 4,349 of these are sexual assaults in the US. This number is a lower bound for the total effect since the NIBRS only includes severe criminal offenses and the city-level data reveals that the MeToo movement had a stronger effect on reported sexual harassment cases. Furthermore, it is likely that the MeToo movement also led to changes in lower stakes decisions, such as reporting sexual misconduct by a colleague to an employer, talking to a friend about an experience of sexual misconduct,

[31] The estimation uses the difference-in-difference specification for each country separately and compares this to the number of predicted crimes reported if the MeToo movement had not taken place, based on the same regression. The calculation for the countries where we have partial police data (the US, the UK, Iceland, and Australia) is based on the assumption that the MeToo movement had the same effect on areas for which we obtained data as in other areas in the country.

or calling a helpline for victims of sexual misconduct.

One limitation of this study is that it is difficult to disentangle the effect of the MeToo movement on the incidence of crimes from its effect on the propensity to report crimes. We show that a change in incidence cannot explain the effect found and is unlikely to drive the results. However, it is possible that as a result of the movement, the incidence of sexual crimes decreased, and in that case, our primary estimates should be interpreted as lower bounds for the increase in the propensity to report sexual crimes, as they are reduced by a lower incidence of crime.

The findings imply that social movements can have large, long-lasting effects on social norms and, as a result, individuals make meaningful changes in their personal decisions. The action individuals take is costly and the effect occurs almost immediately. This suggests that awareness-raising campaigns can be effective in changing personal behavior.

The effects on social welfare in this setting are ambiguous. While typically reporting a crime to the police has a positive externality, since it can prevent other crimes from occurring, our analysis of the US data shows that the number of cases cleared did not increase, and thus reporting may not have prevented future crimes. More research is needed to understand why an increase in propensity to report crimes did not increase the number of cases cleared, and whether the propensity to report crime will decrease back to baseline levels as victims realize that increased reporting rates are not leading to more charges and arrests.

References

Acemoglu, D., T. A. Hassan, and A. Tahoun (2017). The power of the street: Evidence from Egypt's arab spring. *The Review of Financial Studies 31*(1), 1–42.

Alesina, A., P. Giuliano, and N. Nunn (2013). On the origins of gender roles: Women and the plough. *The Quarterly Journal of Economics 128*(2), 469–530.

Alsan, M. and M. Wanamaker (2017). Tuskegee and the health of black men. *The Quarterly Journal of Economics 133*(1), 407–455.

Amenta, E., N. Caren, E. Chiarello, and Y. Su (2010). The political consequences of social movements. *Annual Review of Sociology 36*, 287–307.

Athey, S. (2018). The impact of machine learning on economics. In *The Economics of Artificial Intelligence: An Agenda*.

Athey, S., M. Bayati, N. Doudchenko, G. Imbens, and K. Khosravi (2017). Matrix Completion Methods for Causal Panel Data Models. *Working Paper*, 1–49.

Banerjee, A., E. La Ferrara, and V. Orozco (2019). Entertainment, education and attitudes towards domestic violence. Working paper.

Baumgartner, F. R. and C. Mahoney (2005). Social movements, the rise of new issues, and the public agenda. *Routing the opposition: Social movements, public policy, and democracy*, 65–86.

Bertrand, M., E. Kamenica, and J. Pan (2015). Gender identity and relative income within households. *The Quarterly Journal of Economics 130*(2), 571–614.

Bhatnagar, A., A. Mathur, A. Munasib, and D. Roy (2019). Sparking the #MeToo revolution in India: The 'Nirbhaya' case in Delhi. Working paper, American Enterprise Institute.

Burstein, P. and S. Sausner (2005). The incidence and impact of policy-oriented collective action: competing views. In *Sociological Forum*, Volume 20, pp. 403–419. Springer.

Bursztyn, L., G. Egorov, and S. Fiorin (2017). From extreme to mainstream: How social norms unravel. Working paper, National Bureau of Economic Research.

Bursztyn, L., A. L. González, and D. Yanagizawa-Drott (2018). Misperceived social norms: Female labor force participation in Saudi Arabia. Working paper, National Bureau of Economic Research.

Caputi, T. L., A. L. Nobles, and J. W. Ayers (2019). Internet searches for sexual harassment and assault, reporting, and training since the #MeToo movement. *JAMA internal medicine 179*(2), 258–259.

Charles, K. K., J. Guryan, and J. Pan (2018). The effects of sexism on american women: The role of norms vs. discrimination. Working paper, National Bureau of Economic Research.

Cheng, I.-H. and A. Hsiaw (2019). Reporting sexual misconduct in the #MeToo era. Working paper.

Chong, A. and E. L. Ferrara (2009). Television and divorce: Evidence from Brazilian novelas. *Journal of the European Economic Association 7*(2-3), 458–468.

Christensen, D. and F. Garfias (2018). Can you hear me now? How communication technology affects protest and repression. *Quarterly journal of political science 13*(1), 89.

Enikolopov, R., A. Makarin, and M. Petrova (2019). Social media and protest participation: Evidence from Russia. Working paper, SSRN.

García-Jimeno, C., A. Iglesias, and P. Yildirim (2018). Women, rails and telegraphs: An empirical study of information diffusion and collective action. Working paper, National Bureau of Economic Research.

Green, D. P., A. Wilke, and J. Cooper (2019). Countering violence against women at scale: A mass media experiment in rural Uganda. Working paper, Colombia University.

Hersch, J. (2011). Compensating differentials for sexual harassment. *American Economic Review 101*(3), 630–34.

International Lawyers Network (2019). Sexual harassment in the workplace: What employers need to know. Report.

Iyer, L., A. Mani, P. Mishra, and P. Topalova (2012). The power of political voice: women's political representation and crime in India. *American Economic Journal: Applied Economics 4*(4), 165–193.

Jensen, R. and E. Oster (2009). The power of TV: Cable television and women's status in India. *The Quarterly Journal of Economics 124*(3), 1057–1094.

La Ferrara, E., A. Chong, and S. Duryea (2012). Soap operas and fertility: Evidence from Brazil. *American Economic Journal: Applied Economics 4*(4), 1–31.

Madestam, A., D. Shoag, S. Veuger, and D. Yanagizawa-Drott (2013). Do political protests matter? Evidence from the tea party movement. *The Quarterly Journal of Economics 128*(4), 1633–1685.

Martinez-Bravo, M. and A. Stegmann (2018). In vaccines we trust? The effects of the CIA's vaccine ruse on immunization in Pakistan. Working paper.

McDougal, L., S. Krumholz, N. Bhan, P. Bharadwaj, and A. Raj (2018). Releasing the tide: How has a shock to the acceptability of gender-based sexual violence affected rape reporting to police in India? *Journal of interpersonal violence*, 1–23.

Morabito, M. S., L. M. Williams, and A. Pattavina (2019). Decision making in sexual assault cases: Replication research on sexual violence case attrition in the US. Report, US Department of Justice, National Institute of Justice NCJ.

Onwuachi-Willig, A. (2018). What about #UsToo: The invisibility of race in the #MeToo movement. *Yale LJF 128*, 105.

Pew Research Center (2018). Activism in the social media age. Research report.

Rotenberg, C. and A. Cotter (2018). Police-reported sexual assaults in Canada before and after #MeToo, 2016 and 2017. *Juristat: Canadian Centre for Justice Statistics*, 1–27.

Spohn, C. and K. Tellis (2012). Policing and prosecuting sexual assault in Los Angeles city and county: A collaborative study in partnership with the Los Angeles Police Department, the Los Angeles County Sheriff's Department, and the Los Angeles County District Attorney's Office. Report, US Department of Justice, National Institute of Justice NCJ.

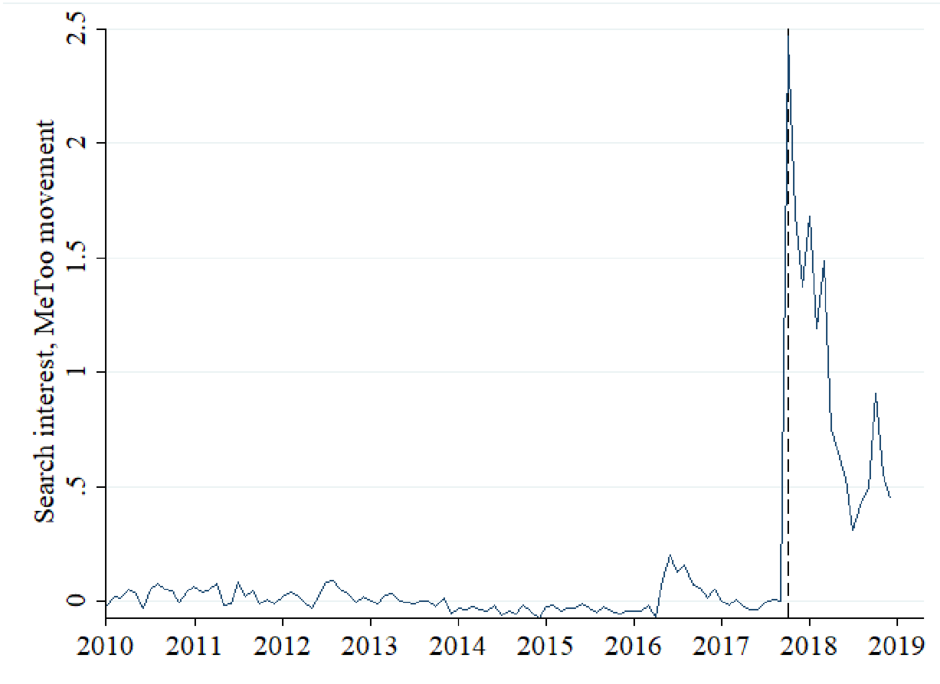
Sunstein, C. R. (2019). *How Change Happens*. MIT Press.

Wasow, O. (2017). Do protests matter? Evidence from the 1960s black insurgency. Working paper.

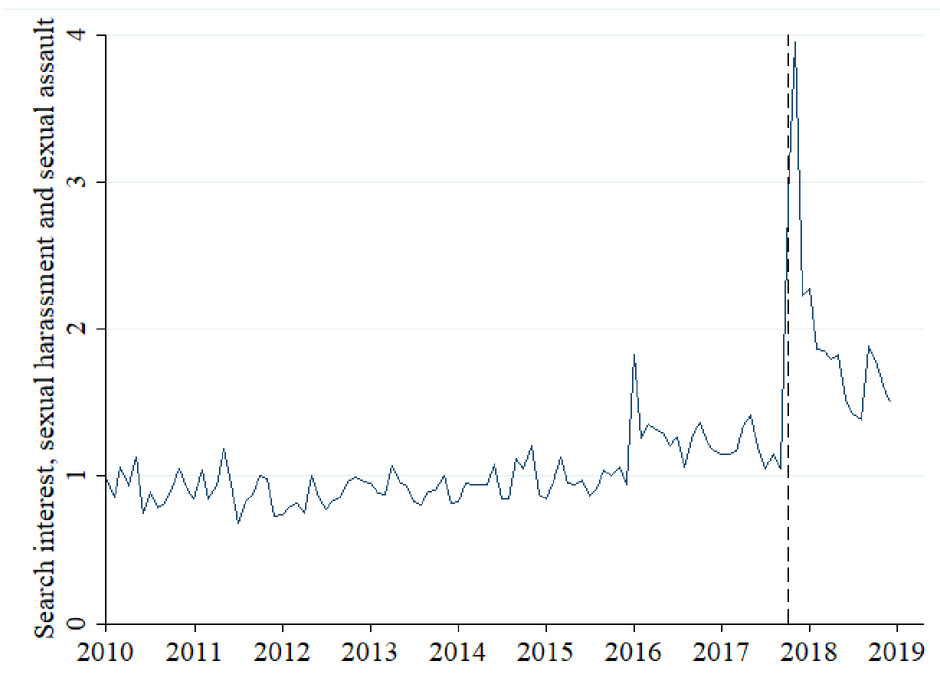
YouGov (2019). Metoo favourability. Survey results, YouGov-Cambridge Globalism Project.

Figure 1: Google search interest in the OECD

(a) OECD search interest in the topic of the MeToo movement

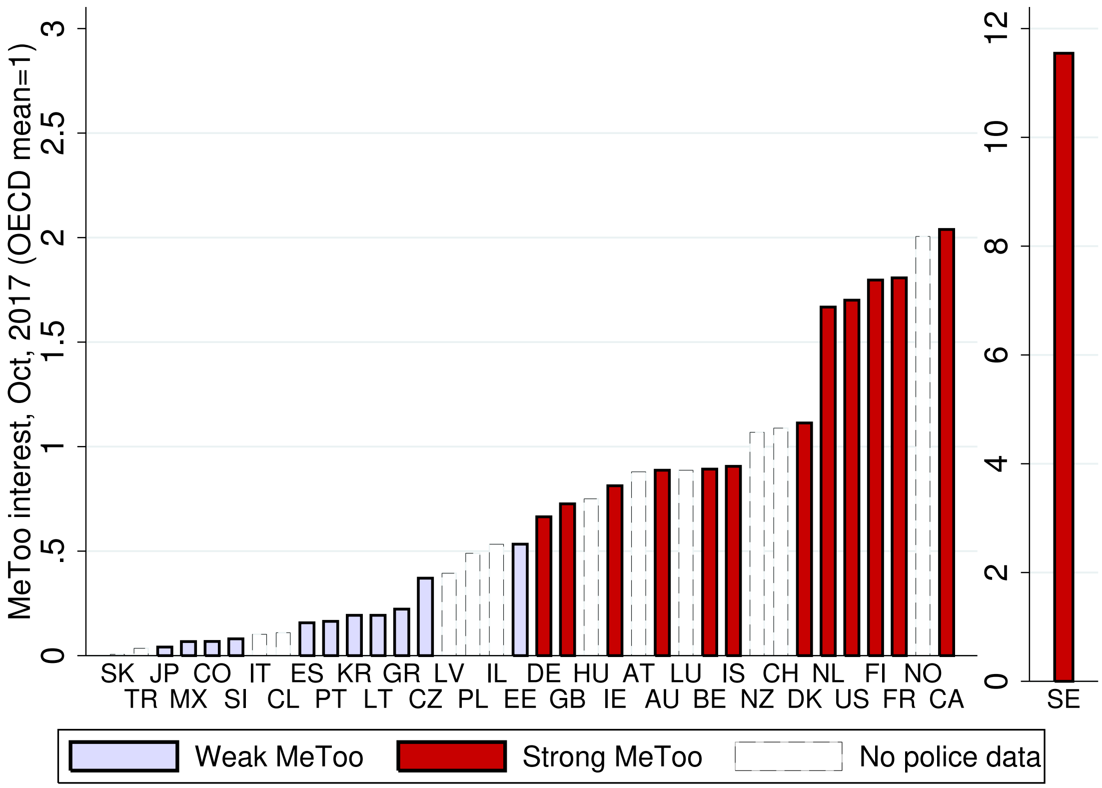


(b) OECD search interest in the topics of sexual harassment and sexual assault



The figures show the monthly time series for the OECD means of both measures of the strength of the MeToo movement from 2010 to 2018. Data is from Google Trends. The vertical dashed line represents the start of the MeToo movement (October 2017). Sub-figure (a) shows search interest in the topic of the MeToo movement. Mean pre-MeToo interest is subtracted from the time series for each country separately so that the pre-MeToo period has a mean of zero, the data is then normalized so that the post-MeToo OECD mean equals 1. Sub-figure (b) shows search interest in the topics of sexual harassment and sexual assault. The data is normalized so that the pre-MeToo mean equals 1 for each country.

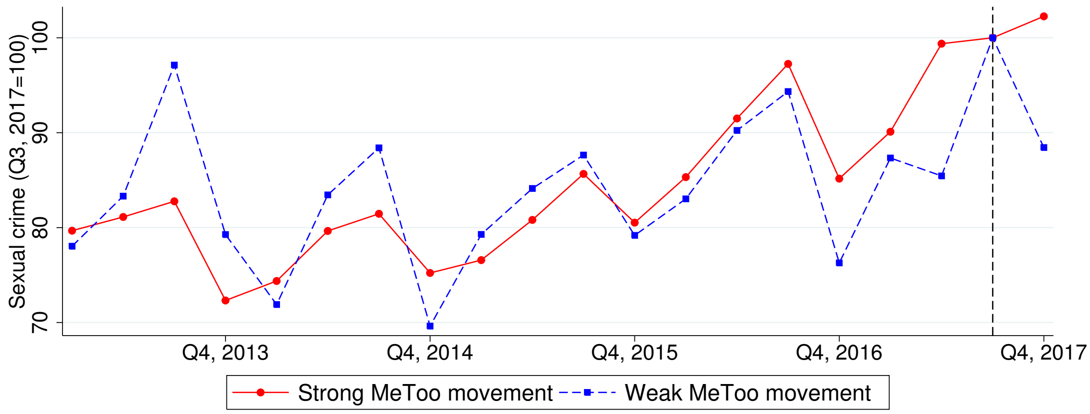
Figure 2: Immediate search interest in MeToo Movement



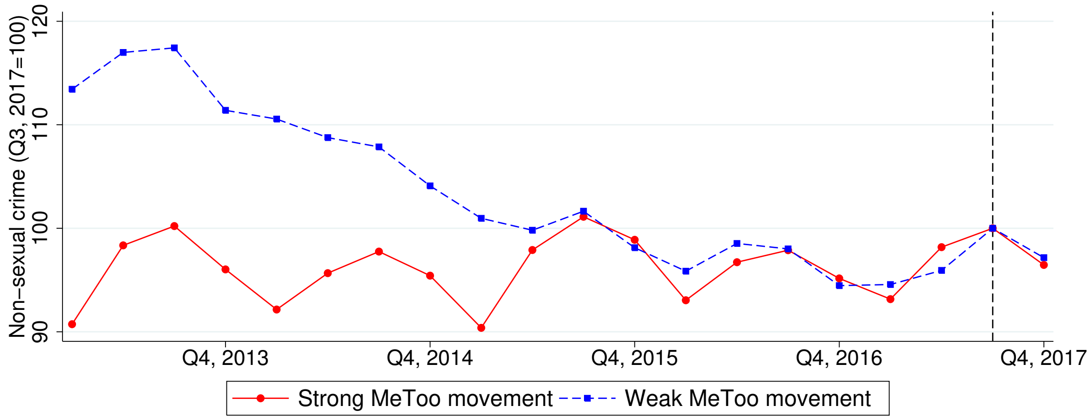
This figure shows the strength of the MeToo movement in OECD countries, based on Google Search interest in the topic of the MeToo movement during October 2017. The Weak MeToo group of countries have below-median interest, the Strong MeToo group of countries have above-median interest, and the rest of the countries are not included in our sample since we have not obtained access to their police data.

Figure 3: Crimes reported over time

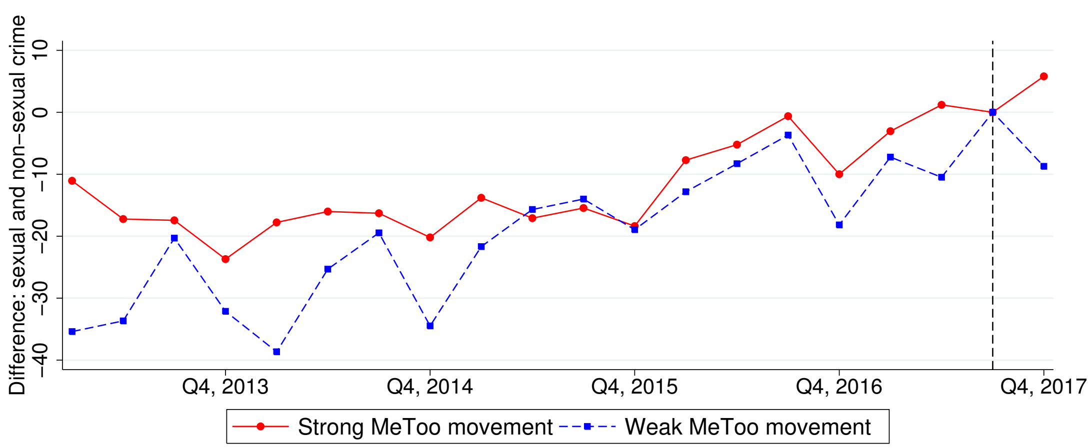
(a) Sexual crime reported in countries with strong vs. weak MeToo movements



(b) Non-sexual crime reported in countries with strong vs. weak MeToo movements

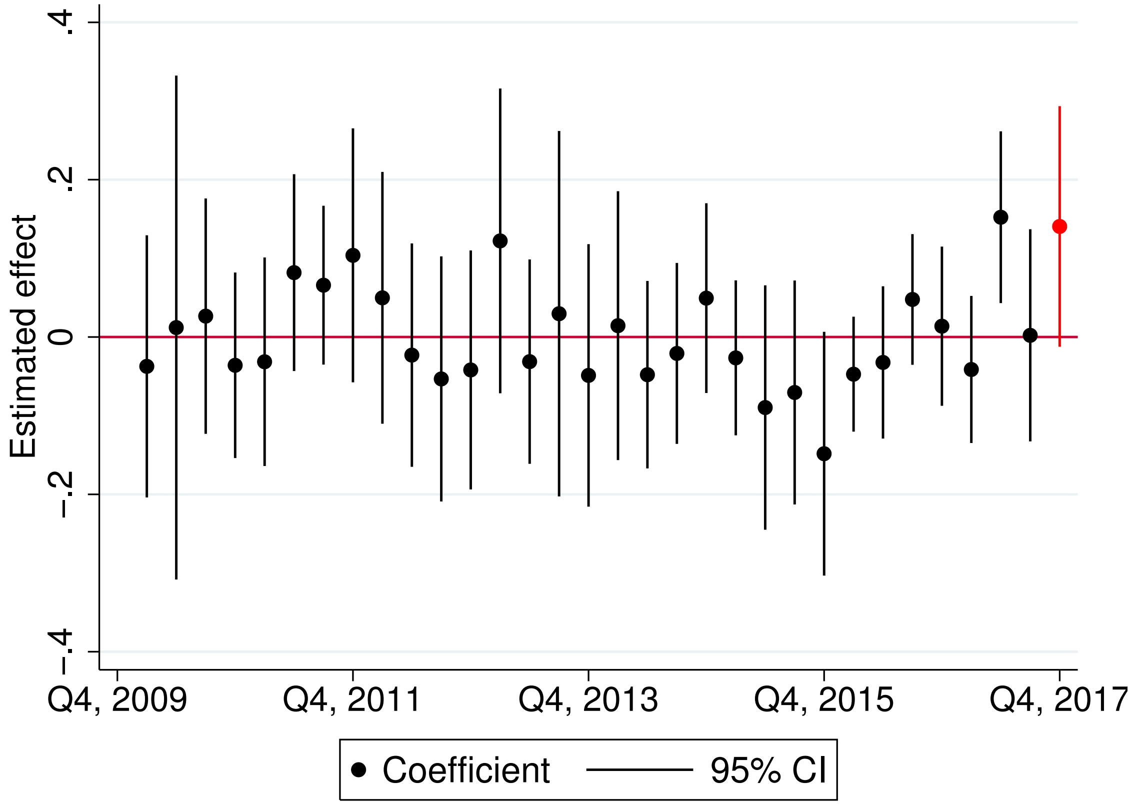


(c) Difference between sexual and non-sexual crime reported in countries with strong vs. weak MeToo movements



Figures (a) and (b) show the number of reported sexual crimes and the number of reported non-sexual crimes, both normalized to 100 in Q3, 2017 for each country, and averaged separately for the countries with strong and weak MeToo movements. Figure (c) shows the difference between the normalized number of sexual crimes and the normalized number of non-sexual crimes. The vertical dashed line represents the last quarter before the start of the MeToo movement, Q3, 2017. To make the observations comparable over time, Japan, Lithuania, and Mexico are excluded since data for these countries is not available for the entire 2013-2017 period.

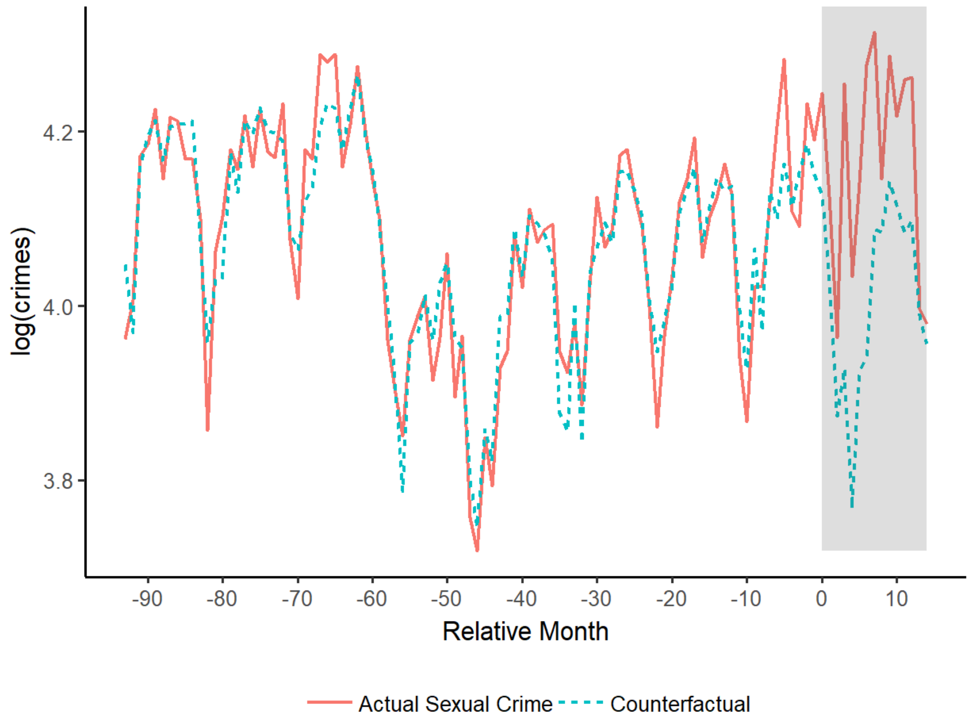
Figure 4: Placebo tests, setting the start date of the MeToo movement in each of the quarters from 2010 to 2017



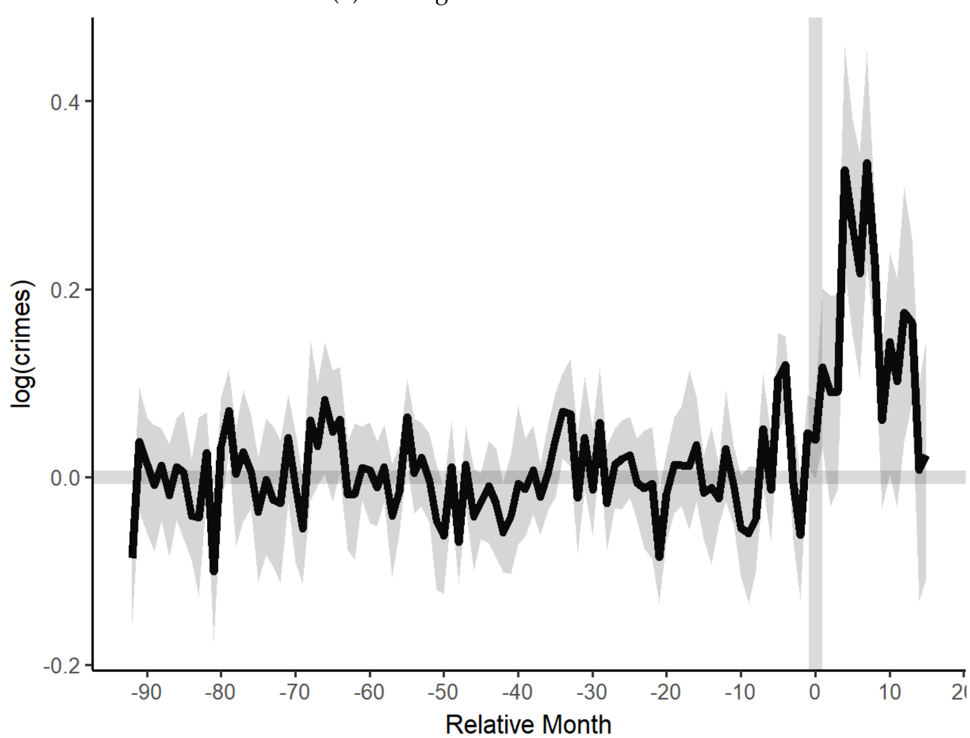
This figure shows the results from 31 placebo triple difference regressions (Q1 2010-Q3 2017) and our main triple difference result (Q4 2017). Each coefficient comes from a regression using the full 2010-2017 data set, but with a different quarter for when the placebo MeToo movement happened. The corresponding confidence intervals are constructed using standard errors clustered at the country by crime type level.

Figure 5: Matrix completion results

(a) Counterfactual versus actual outcomes



(b) Average treatment effect



Sub-Figure (a) shows the actual and counterfactual reported sexual crimes (in logs) based on the matrix completion method for our sample of US cities. The method is described in Section 4.4. Sub-Figure (b) presents the average treatment effect - the difference between the actual crimes and the counterfactual. Standard errors are bootstrapped.

Table 1: Effect of the MeToo movement during the first three months in 24 OECD countries

	ln(crimes)			
	(1)	(2)	(3)	(4)
Post * Strong MeToo	0.136*		-0.00462	-0.00462
	(0.0662)		(0.0423)	(0.0423)
Post * Sexual crime		0.109***		0.0306
		(0.0400)		(0.0633)
Post * Strong MeToo * Sexual crime			0.171***	0.141*
			(0.0457)	(0.0780)
Post * Weak MeToo * Sexual crime			0.0306	
			(0.0633)	
Observations	688	1,376	1,376	1,376
Country * Crime type * Lin. trend	X	X	X	X
Country * Crime type * Quarter	X	X	X	X
Post	X	X	X	X
Crime data used	Sexual crimes	All crimes	All crimes	All crimes

This table shows the effect of the MeToo movement on sexual crimes reported using data from 24 OECD countries for the period 2010 Q1-2017 Q4. Column (1) uses data on sexual crime only while Columns (2)-(4) uses data on both sexual and non-sexual crimes. A country is categorized as having a strong MeToo movement if search interest for the topic of the MeToo movement was above the OECD median in October 2017. Standard errors clustered at the country by crime level in parenthesis. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 2: Effect of the MeToo movement on sexual crime in the US

	ihs(crime)			
	(1)	(2)	(3)	(4)
Post * Sexual Assault	0.070***			
	(0.022)			
Post * Sexual Assault		0.101***		
		(0.037)		
Post * Sexual Harassment		0.213***		
		(0.056)		
Post * Sexual Crimes			0.125***	0.124***
			(0.035)	(0.021)
State * Crime Type * Time	X			
State * Crime Type * Month	X			
City * Crime Type * Time		X	X	X
City * Crime Type * Month		X	X	X
Post	X	X	X	X
Data	NIBRS	City	City	City
Final Month	Dec 2017	Dec 2017	Dec 2017	Dec 2018
Observations	6,654	1,800	1,200	1,368

This table shows the effect of the MeToo movement on sexual crimes reported based on NIBRS and city crime data. Regressions are weighted by the number of crimes that occurred in each state/city before the MeToo movement started. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 3: Incident - Effects on Crimes that Occurred Before the Movement Started

	ihs(crime)
Post * Sexual Crimes	0.194**
	(0.077)
City * Crime Type * Time	X
City * Crime Type * Month	X
Post	X
Final Month	Dec 2017
Crimes Included	3 Month <= Lag
Observations	1,179

This table shows the effect of the MeToo movement on sexual crimes, which were reported at least three months after they occurred. The table only includes crimes reported by December 2017. Therefore, all crimes included in this table occurred before the MeToo movement started. 2010-2017 city crime data. Regressions are weighted by the number of crimes in each city before the MeToo movement started. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 4: Effect by the lag between occurrence and reporting dates

	ihs(crime)		
	(1)	(2)	(3)
Post * Sexual Crimes, Lag<=30 Days	0.104***	0.112***	0.102***
	(0.022)	(0.038)	(0.024)
Post * Sexual Crimes, Lag>30 Days	0.172***	0.149**	0.173***
	(0.036)	(0.065)	(0.041)
City * Crime Type * Time	X	X	X
City * Crime Type * Month	X	X	X
Post	X	X	X
Treatment Dates	Oct 17-Dec 18	Oct 17-Dec 17	Jan 18-Dec 18
Observations	2,031	1,779	1,968

This table shows the effect of the MeToo movement on sexual crimes according to when the crime was reported. In all columns, the data is aggregated into three categories: Sexual crimes reported within 30 days, sexual crimes reported after more than 30 days, and non-sexual crimes. Non-sexual crimes is the reference category. Column (1) includes all data until the end of 2018, Column (2) focuses on the short-term effect and includes data until December 2017 and Column (3) excludes October 2017-December 2017. Regressions are weighted by the number of crimes that occurred in each city before the MeToo movement started. City crime data 2010-2018. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 5: Effect of the MeToo movement, by relationship and crime type

	ihs(crime)		
	(1)	(2)	(3)
Post * Fondling	0.103***		
	(0.026)		
Post * Rape	0.070***		
	(0.022)		
Post * Sodomy	−0.032		
	(0.045)		
Post * Statutory Rape	0.022		
	(0.056)		
Post * Sexual Assault, No Injury		0.078***	
		(0.022)	
Post * Sexual Assault, Injury		0.036	
		(0.028)	
Post * Sexual Assault, Knew Offender			0.074***
			(0.022)
Post * Sexual Assault, Stranger			0.053
			(0.044)
Difference		0.042	0.021
State * Crime Type * Time	X	X	X
State * Crime Type * Month	X	X	X
Post	X	X	X
Observations	16,125	9,675	9,675

This table shows the effect of the MeToo movement on different crime types. In each column, crimes are aggregated into different categories. The reference group for all columns is non-sexual crimes. In Column (1), the category "Sexual Assault With An Object" is excluded since approximately a third of state*months had zero crimes reported. Incidents related to multiple sexual offense crime categories are also excluded. In Column (2), cases where it is unknown if a victim was injured are excluded. In Column (3), cases where the relationship between the victim and offender was not reported or where the relationship is unknown are excluded. 2010-2017 NIBRS Data. Regressions are weighted by the number of crimes that occurred in each state before the MeToo movement started. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 6: Effect by victim and offender demographics

	ihs(crime)			
	(1)	(2)	(3)	(4)
Post * Sexual Assault, Victim Female	0.080***			
	(0.021)			
Post * Sexual Assault, Victim Male	0.037			
	(0.032)			
Post * Sexual Assault, Victim Black		0.056*		
		(0.032)		
Post * Sexual Assault, Victim White		0.075***		
		(0.021)		
Post * Sexual Assault, Offender Female			0.022	
			(0.059)	
Post * Sexual Assault, Offender Male			0.083***	
			(0.022)	
Post * Sexual Assault, Offender Black				0.081***
				(0.029)
Post * Sexual Assault, Offender White				0.082***
				(0.024)
Difference	0.044	-0.019	-0.061	-0.001
State * Crime Type * Time	X	X	X	X
State * Crime Type * Month	X	X	X	X
Post	X	X	X	X
Observations	9,675	9,675	9,675	9,675

This table shows the effect of the MeToo movement by victim and offender demographics. In each column, crimes are aggregated into different categories. The reference group for all columns is all non-sexual crimes. In Columns (1) and (3) crimes where the sex the victim or offender is unknown are excluded along with crimes with multiple victims or offenders. In Columns (2) and (4) Crime where the race of the victim or offender is unknown are excluded along with crimes with multiple victims or offenders. Crimes with a victim or offender of another race (e.g., Asian) are also excluded since they are relatively rare. 2010-2017 NIBRS Data. All regressions are weighted by the number of crimes that occurred in each state before the MeToo movement started. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 7: Effect by neighborhood

	ihs(crime)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post * Sexual Crimes	0.135***	0.137***	0.134***	0.135***	0.135***	0.135***	0.151***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.000)
Post * Sexual Crimes * Median Income (std. dev.)		0.016					0.098***	0.082***
		(0.013)					(0.027)	(0.030)
Post * Sexual Crimes * Share College Educ.			−0.014				−0.231	−0.530***
			(0.064)				(0.162)	(0.171)
Post * Sexual Crimes * Share Blacks				0.105*			0.286***	0.024
				(0.061)			(0.088)	(0.108)
Post * Sexual Crimes * Share Other Non-Whites					0.159*		0.478***	0.241*
					(0.081)		(0.111)	(0.141)
Post * Sexual Crimes * Share Hispanics						0.008	−0.143	−0.225**
						(0.057)	(0.098)	(0.112)
Weighted Mean of Demographic		58,622	0.341	0.23	0.284	0.298		
Neighborhood * Crime Type * Time	X	X	X	X	X	X	X	X
Neighborhood * Crime Type * Month	X	X	X	X	X	X	X	X
Post	X	X	X	X	X	X	X	X
City * Crime Type * Post								X
Observations	27,432	27,432	27,432	27,432	27,432	27,432	27,432	27,432

This table shows the effect of the MeToo movement based on neighborhood-level data and tests for heterogeneous effects by neighborhood demographics. 2010-2018 city crime data. All regressions are weighted by the number of crimes that occurred in each neighborhood before the MeToo movement started. All demographic variables are first subtracted by their weighted mean. Robust standard errors in parenthesis.
***p<0.01; **p<0.05; *p<0.1

Table 8: Effect of the MeToo movement by clearance

	ihs(crime)	
	(1)	(2)
Post * Sexual Assault, Not Cleared	0.114***	
	(0.022)	
Post * Sexual Assault, Cleared	−0.057*	
	(0.033)	
Post * Sexual Assault		0.219***
		(0.044)
Post * Sexual Assault * Cleared		−0.375***
		(0.063)
Difference	0.171***	
State * Crime Type * Time	X	X
State * Crime Type * Month	X	X
Post	X	X
Crime Type * Cleared		X
Observations	9,675	12,900
Note *	*p<0.1; **p<0.05; ***p<0.01	

This table shows the effect of the MeToo movement on sexual crimes which were cleared and sexual crimes which were not cleared. In Column (1), the crimes are aggregated to three separate crime categories: Sexual crimes which were cleared, sexual crimes which were not cleared and non-sexual crimes, which are the control group. In Column (2), we aggregate the data at the state by month by crime category and whether a crime was cleared, and control for the full interaction of crime category and whether a crime was cleared. 2010-2017 NIBRS data. Regressions are weighted by the number of crimes that occurred in each state before the MeToo movement started. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 9: Persistence of the effect in countries with a strong MeToo movement

	ln(crimes)	
	(1)	(2)
Post * Sexual crime	0.122***	
	(0.0321)	
2017 Q4 * Sexual crime		0.170***
		(0.0466)
2018 Q1 * Sexual crime		0.115***
		(0.0340)
2018 Q2 * Sexual crime		0.101**
		(0.0383)
2018 Q3 * Sexual crime		0.0992**
		(0.0396)
2018 Q4 * Sexual crime		0.130***
		(0.0428)
Observations	880	880
Post	X	
Country * Crime type * Lin. trend	X	X
Country * Crime type * Quarter	X	X
Q4 2017-Q4 2018 FE		X

This table shows the effect of the MeToo movement over time using data from the countries with a strong MeToo movement. Standard errors clustered at the country by crime level in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

Table 10: Persistence of the effect in US cities

	ihs(crime)			
	(1)	(2)	(3)	(4)
Post * Sexual Crimes	0.125***		0.104***	
	(0.021)		(0.022)	
2017 Q4 * Sexual Crimes		0.125***		0.113***
		(0.033)		(0.039)
2018 Q1 * Sexual Crimes		0.136**		0.081
		(0.065)		(0.067)
2018 Q2 * Sexual Crimes		0.106***		0.090**
		(0.038)		(0.037)
2018 Q3 * Sexual Crimes		0.138***		0.136***
		(0.035)		(0.035)
2018 Q4 * Sexual Crimes		0.115***		0.103**
		(0.038)		(0.041)
City * Crime Type * Time	X	X	X	X
City * Crime Type * Month	X	X	X	X
Post	X	X	X	X
Crimes	All	All	Reported Within 1 M	Reported Within 1 M
Observations	1,368	1,368	1,361	1,361

This table shows the effect of the MeToo movement on sexual crimes by quarter. Data is aggregated at the monthly city by crime category level. Each coefficient represents the effect on sexual crimes in a three month period. 2010-2018 city crime data. Regressions are weighted by the number of crimes that occurred in each city before the MeToo movement started. Column (1)-(2) include all crimes and columns (3)-(4) include only crimes that were reported up to 30 days after they occurred. Robust standard error in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table 11: Change in beliefs regarding sexual harassment

	Workplace sexual harassment no longer a problem		Accusers cause more problem than they solve	
	(1)	(2)	(3)	(4)
2018	-0.139^{***}		-0.010	
	(0.032)		(0.025)	
Women, 2018		-0.047		0.004
		(0.043)		(0.035)
Men, 2018		-0.238^{***}		-0.026
		(0.048)		(0.035)
Respondent FE	X	X	X	X
Observations	9,252	9,236	9,212	9,196

This table shows the change in beliefs regarding sexual harassment between 2016-2018. The data is the pooled 2016 and 2018 responses for the Views of the Electorate Research Survey. Columns (1) and (2) refer to respondents' agreement with: "Sexual harassment against women in the workplace is no longer a problem in the United States." Columns (3) and (4) refer to respondents' agreement with "Women who complain about harassment often cause more problems than they solve." The answers are coded between 0 (strongly disagree) and 3 (strongly agree) and then standardized. The results are similar when a binary coding of the response is used instead. All regressions control for respondent fixed effects. Robust standard error in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Appendix For Online Publication

A Processing Crime Data

A.1 Crime classification

For both the US and international data we classify each crime as belonging to one of the following categories: sexual assault, defined as a sexual crime that includes physical contact; sexual harassment, defined as a sexual crime that does not include physical contact (e.g. stalking or indecent exposure); non-sexual crimes and crimes which are not directly affected by the MeToo movement but could be indirectly related to it. Crimes indirectly related to the MeToo movement include crimes related to bestiality, bigamy, domestic assault, harassment where it is not clear if the harassment is of sexual nature, incest, pedophilia, pornography, prostitution, and registration of sexual offenders. We exclude these crimes from the analysis since spillovers from the MeToo movement can affect this group of crimes, and therefore, they are not a suitable control group. We also exclude from the analysis cases appearing in police records, which are not related to any specific crime (e.g., missing person investigation) and traffic tickets.

Throughout most of the analysis, we aggregate the sexual assault and sexual harassment crimes into one category, defined as sexual crime.

A.2 OECD crime data collection and processing

To collect high-frequency crime data from as many OECD countries as possible, we first downloaded the data available on the websites of the statistics agencies and the police. If no data was available online, we contacted both the main statistics agency as well as the national police requesting data on the number of crimes reported at a monthly or quarterly level. Finally, if these contacts did not yield the required data, we filed the equivalent of a Freedom of Information Act request or purchased data specifically aggregated for our project from the statistics agency. The effort has currently succeeded in collecting data from 24 OECD countries, but the data collection efforts are ongoing, and more data will be added to this dataset as more countries respond to our requests.

In Australia, Iceland, the United Kingdom, and the United States, high-frequency data on the number of crimes reported are not available for the whole country. For Australia we have data for New South Wales, Queensland, Victoria, and Western Australia, covering 88% of the population, but not for the Australian Capital Territory, Northern Territory, South Australia, and Tasmania. For Iceland, we have data for the Capital region, covering 63% of the population. For the United Kingdom, we have data for England, Northern Ireland and Wales, covering 92% of the population, but not Scotland. For the United States, we use the NIBRS data described in more detail in Appendix Section A.4.

The 24 countries in our data set are listed in Appendix Table A.5 together with the organizations providing the data, the time period covered as well as the percentage of the population covered by the police agencies providing the data.

A.3 Google search data processing

As our primary measure of the MeToo movement's strength, we use the search interest in the topic of the MeToo movement in October 2017. Our search interest data is scraped from google trends and contains monthly search interest figures for all of the OECD from 2010-2018.[32] To ensure that our primary measure of MeToo movement strength is not higher for countries that more frequently use search terms related to the MeToo movement, before these terms had been given the meaning they were given by the MeToo movement, we difference out the average search intensity for these terms from the period before the MeToo movement for each country, so that each country has an average interest of zero in the pre-period. Finally, to simplify the interpretation of this measure, we normalize the magnitude of the interest so that the average interest in the OECD is one in the post-period.

Google does not provide information on the phrases defined as being part of the MeToo movement topic. Therefore, we also create our own definition of the MeToo movement topic in all of the languages used in the OECD, for which we could find a phrase related to the MeToo movement. We restricted our measure to phrases with search interest in their country of origin of at least 1% of the search interest for "me too" in the US, these terms are: "me too", "balance ton porc", "moi aussi", "quella volta che" and "yo tambien" as well as these terms written without spaces.[33] In the relevant time period from October 2017 to December 2017 searches for these phrases has a 0.99 correlation with the MeToo movement topic defined by Google. We prefer to use the search for the MeToo movement topic instead of our list of exact

[32]For scraping, we used the R package gtrendsR written by Philippe Massicotte and Dirk Eddelbuettel.

[33]We exclude searches that contained the term "me too" along with the words "meghan", "trainor" or "song" since the song "Me too" by Meghan Trainor caused an increase in search interest around its release in May 2016.

phrases since it is more likely that the topic search will include searches for additional phrases related to the MeToo movement in other languages.

In Appendix Tables A.1 and A.2, we use an alternative measure of search interest based on searches related to the topics of sexual harassment and sexual assault. Again, the topics are defined by Google as all searches that include the concept of sexual harassment or sexual assault in any language. In contrast to searches for the MeToo topic, searches for the topics of sexual harassment and sexual assault have the same interpretation before and after the start of the MeToo movement. Therefore, we normalize the search interest so that the pre-MeToo period mean is one for each country.

A.4 NIBRS crime data processing

We classify NIBRS offenses as either sexual assault or non-sexual crimes. The sexual assault offenses are fondling, rape, sexual assault with an object, sodomy, and statutory rape. We exclude incest, human trafficking, and the pornography/obscene material crime categories. All other 43 offense types form the non-sexual crimes category. Domestic assault is not a separate offense type in the NIBRS dataset. To exclude domestic violence crimes which may have been affected by the MeToo movement, we exclude all aggravated assaults where the circumstances of the assault are defined in the NIBRS as a "lovers quarrel" and all assaults or aggravated assaults for which the relationship between the offender and victim is defined in the NIBRS as one of the following: victim was ex-spouse, victim was spouse, homosexual relationship, victim was boyfriend/girlfriend, victim was common-law spouse.

In the NIBRS data, an incident can include multiple crimes if they occurred in concert, at the same time and place. Since our classification of incidents depends on the type of offense committed, we define an incident as a sexual assault if one of the offenses which occurred as part of the incident is a sexual assault. Similarly, if the incident is not a sexual assault, we exclude it if one of the offenses which occurred as part of the incident should be excluded (e.g., if an incident includes both a pornography/obscene material offense and a weapon law violations offense, it will be excluded).

We aggregate the NIBRS data at a geographical area by crime category by month. When analyzing state-level data, we exclude state-years where there are months with fewer than 100 crimes reported in total.

A.5 City crime data processing

Data for each city was obtained separately from the city's open data website. For each city, we first categorize a crime as a sexual assault, sexual harassment, non-sexual crime, or a crime which should be excluded since it is indirectly related to the MeToo movement (as explained in Appendix Section A.1). If an observation is defined at the crime level and the data includes multiple crimes per incident, we then aggregate crimes at the incident level. The incident crime category is defined as the most severe crime of the crimes composing the incident, where we use the following hierarchy: Sexual assault, sexual harassment, excluded crimes, other crimes.[34]

In the city data, we define each month as spanning from the 15th day of the calendar month to the 14th day of the next calendar month. By defining months in this way, we can cleanly categorize each observation in the aggregated data as occurring before or after the start of the MeToo movement, since the movement started on October 15, 2017.[35]

A.6 Neighborhood level demographics

To determine the neighborhood where each crime occurs, we use the most coarse definition of police administrative areas available in the dataset. We use the most coarse definition (e.g., a police division instead of a police beat) to ensure that the number of crimes is positive for most observations. The jurisdictions are detailed in Appendix Table A.6. In the case of Nashville, the police precinct where the crime occurred is not reported in the city's crime dataset, and we identify the precinct based on the rounded coordinates of the crime's location.

We use the shapefiles for the police boundaries of each city to identify the geographical boundaries of each neighborhood. For most cities, we use the most recent shapefile available. For Seattle, where changes in the shapefiles are clearly defined, we use different shapefiles for different years and determine the boundaries of each police precinct according to the year when the crime occurred.

The demographics of each neighborhood are determined by spatially matching the neighborhood with census block groups. We calculate each neighborhood's demographics as the weighted average of

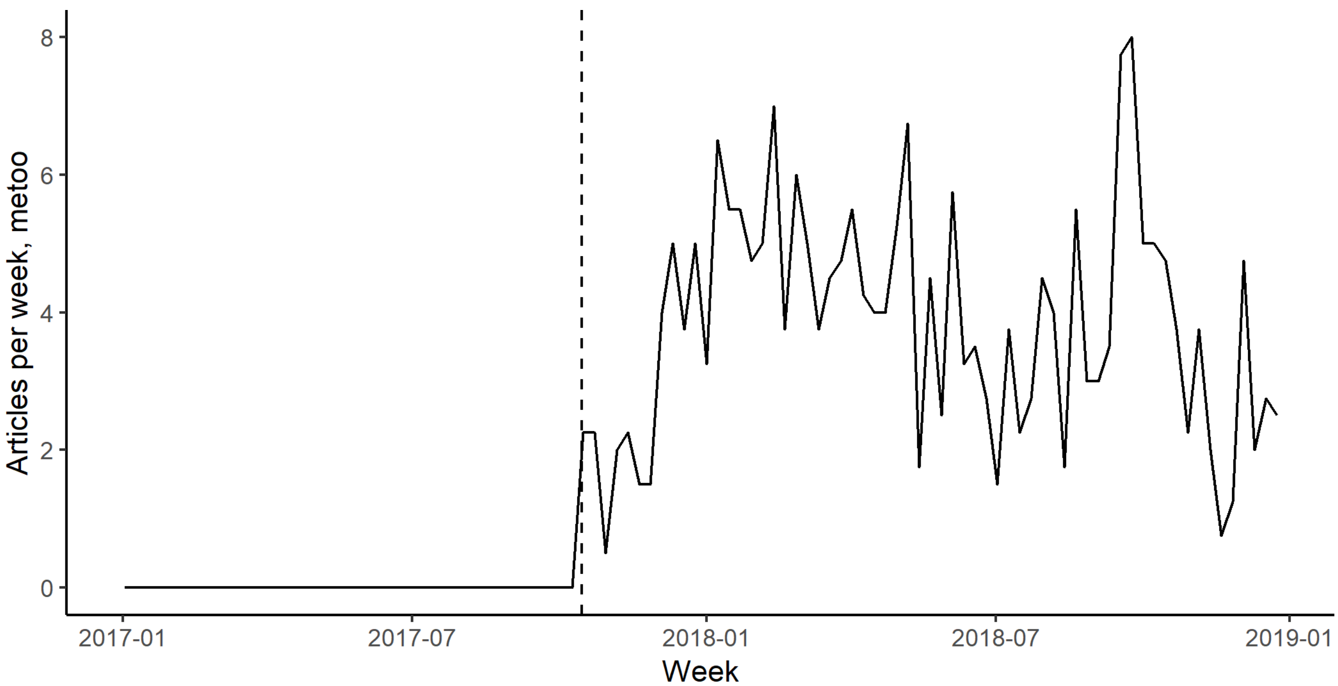
[34]Typically, multiple crimes which form an incident occur at the same date. However, in Kansas City, an incident (or a "case") can be continuously updated and appear multiple times in the dataset, for example, when the victim reports a crime and when the police has a suspect. In cases where an incident appears more than once in the dataset and includes at least one report from a victim, we include only the report of the victim. If an incident still has multiple observations, we include only one observation and define the date the incident was reported as the minimal date among all observations related to the incident. If crimes related to the incident occurred over multiple days, we define the date the incident occurred as NA.

[35]We do not use a similar definition when analyzing the international data or NIBRS data since most international data we collect is already aggregated at the month or quarter level, and since we want to keep the NIBRS results consistent with the international analysis.

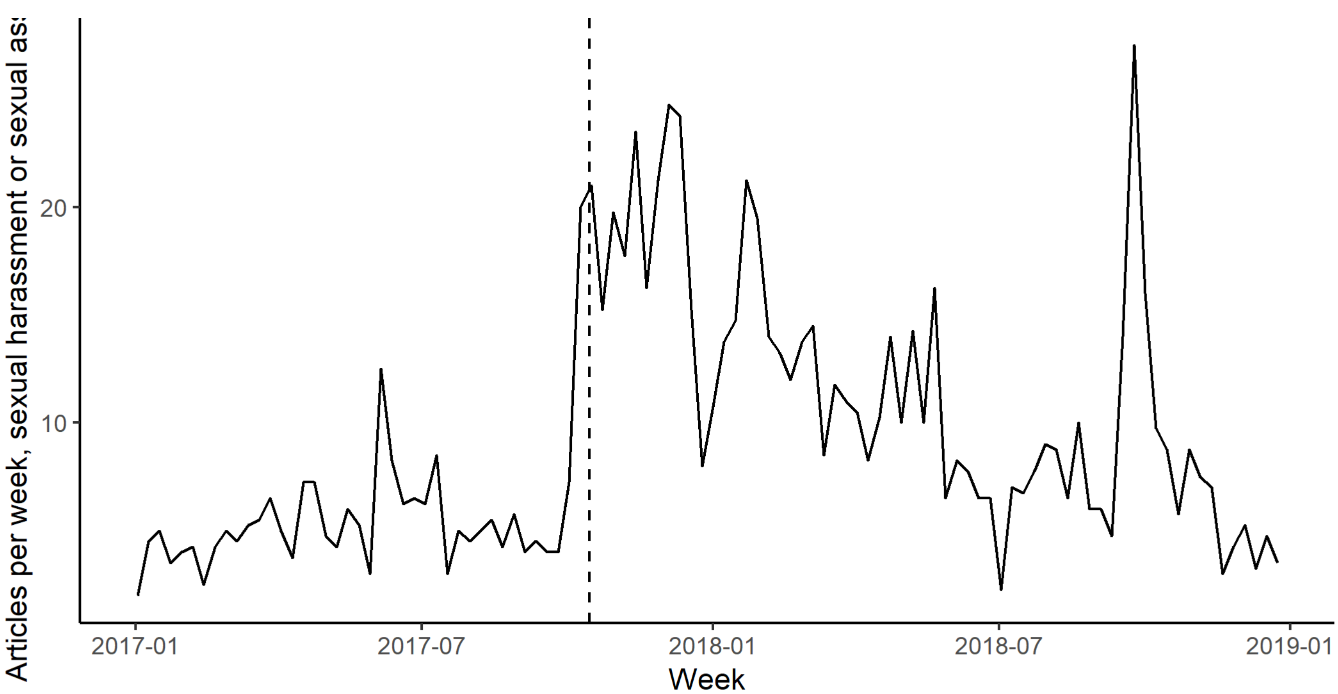
the covariates among overlapping block groups, where the weight of each block group is the population of the block group multiplied by the share of the block group's area overlapping with the neighborhood. The demographics for each block group are based on the American Community Survey 5-year 2016 estimates.

B Additional Figures and Tables

Figure A.1: Newspaper coverage



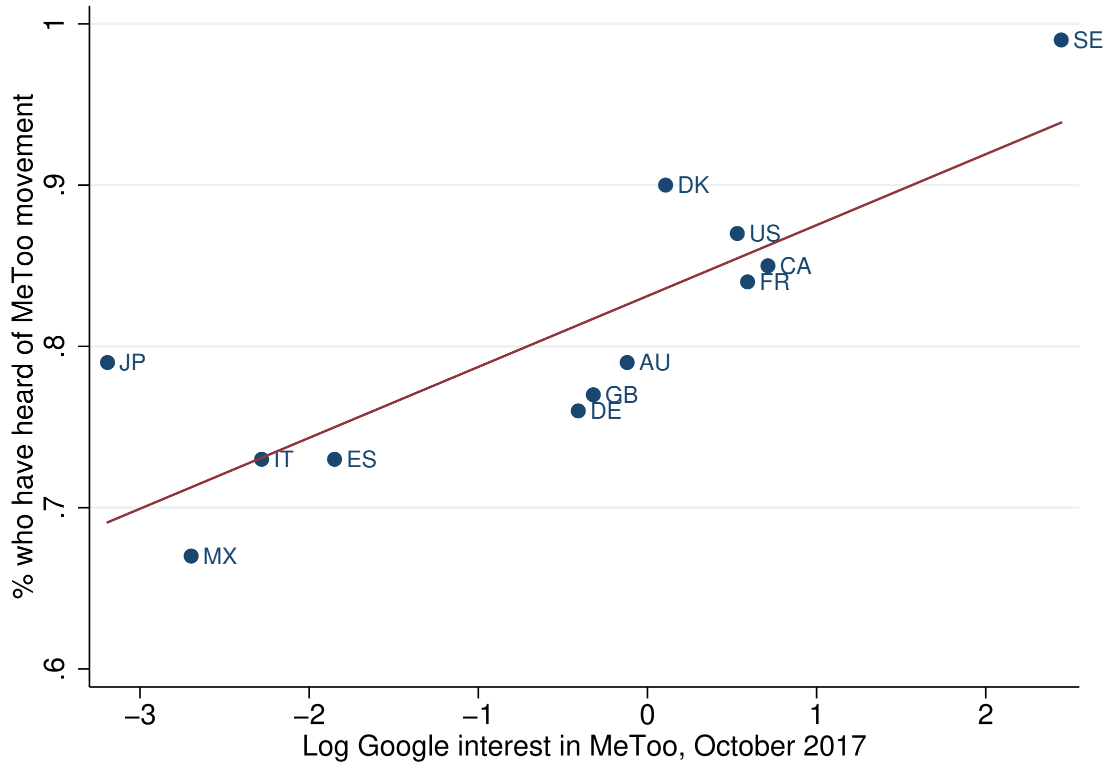
(a) Newspaper articles mentioning the term metoo



(b) Newspaper articles mentioning the terms sexual harassment or sexual assault

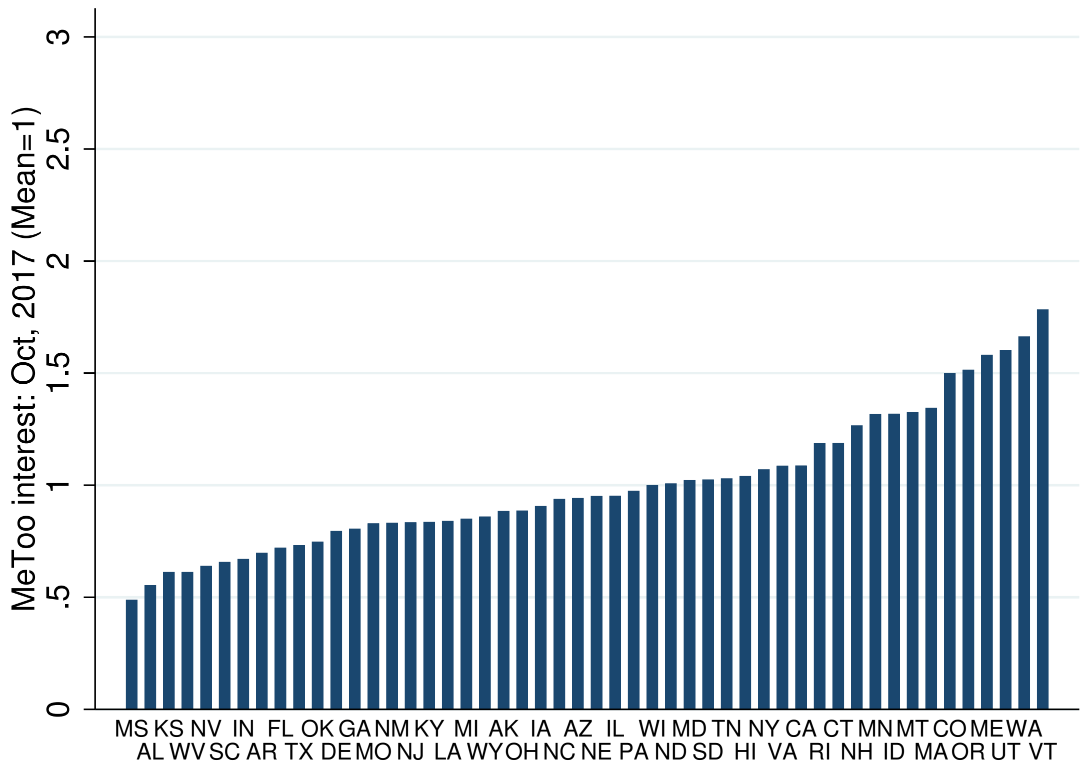
The first sub-figure show the average number of weekly articles mentioning the term "metoo" in the newspapers USA Today, New York Post, Denver Post, and Chicago Sun Times. The second sub-figure present the average number of weekly articles mentioning the terms "sexual assault" or "sexual harassment" (articles mentioning both terms are counted twice). The newspapers were chosen based on circulation and data availability. The number of articles is determined using the website newslibrary.com.

Figure A.2: Relationship between Google search interest and knowledge about MeToo movement



This figure shows the relationships between the log of google search interest for terms related to the MeToo movement in October 2017 and the fraction of respondents who had heard about the MeToo movement in a YouGov survey conducted from February to March in 2019 (YouGov, 2019). The data comes from the 12 OECD countries in our data that were included in the survey.

Figure A.3: Variation in MeToo interest across US states



This figure shows the strength of the MeToo movement in US states, based on Google Search interest in the topic of the MeToo movement during October 2017.

Table A.1: Robustness check: Q1 effects estimated using different binary measures of MeToo strength

	ln(crimes)			
	(1)	(2)	(3)	(4)
Post * Strong MeToo * Sexual crime	0.141*	0.134*	0.131*	0.0225
	(0.0780)	(0.0796)	(0.0778)	(0.0817)
Post * Sexual crime	0.0306	0.0343	0.0478	0.0962
	(0.0633)	(0.0624)	(0.0502)	(0.0643)
Observations	1,376	1,376	1,376	1,376
Country * Crime type * Lin. trend	X	X	X	X
Country * Crime type * Quarter	X	X	X	X
Post * Strong MeToo	X	X	X	X
Measure of MeToo Strength	Immediate search interest	Q1 search interest	Imme. increase SH/SA topic searches	Q1 Increase SH/SA topic searches

This table shows the robustness of our main specification to using different measures of the strength of the MeToo movement. All four columns use binary measures for whether a country is above or below the OECD median interest, but the underlying measure of interest differs between the columns. Column (1) uses our main measure, the immediate search interest for phrases directly related to the MeToo movement in October 2017. Column (2) uses search interest in phrases related to the MeToo movement from October 1, 2017 to December 31, 2017, the same period for which our main outcome variable is measured. Column (3) uses the increase in searches for the topics of Sexual Harassment (SH) and Sexual Assault (SA) during October 2017, after taking into account seasonality and linear trends. Column (4) uses the same measure as Column (3) but for the time period October-December, 2017. Data from our sample of 24 OECD countries for the period 2010-2017. Standard errors clustered at the country by crime level in parenthesis. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table A.2: Q1 effects estimated using continuous measures of MeToo strength

	ln(crimes)			
	(1)	(2)	(3)	(4)
Post * MeToo strength * Sexual crime	0.0620	0.0632	0.0551*	0.0417
	(0.0393)	(0.0514)	(0.0304)	(0.0348)
Post * Sexual crime	0.106**	0.107***	0.107***	0.107***
	(0.0398)	(0.0397)	(0.0391)	(0.0395)
Observations	1,376	1,376	1,376	1,376
Country * Crime type * Lin. trend	X	X	X	X
Country * Crime type * Quarter	X	X	X	X
Post * Strong MeToo	X	X	X	X
Measure of MeToo Strength	Log immediate search interest	Log Q1 search interest	Imme. increase SH/SA topic searches	Q1 increase SH/SA topic searches

This table shows the main result when using different continuous measures of the MeToo movement strength. To make coefficients comparable between columns, all measures of MeToo movement strength are recast as standard deviations away from the mean of our 24 country sample. Column (1) and (2) uses the standard deviations of the log of search interest in phrases directly related to the MeToo movement in any language. Column (3) and (4) uses the standard deviations of increase, after controlling for linear treads and seasonality, in the proportion of searches related to Sexual Harassment (SH) or Sexual Assault (SA) in any language. Data from 24 OECD countries for the period 2010-2017. Standard errors clustered at the country by crime level in parenthesis. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table A.3: MeToo effect, with crime aggregated by offense types

	ihs(crime)		
	(1)	(2)	(3)
Post * Sexual Assault	0.070***		
	(0.021)		
Post * Sexual Assault		0.080***	0.080***
		(0.018)	(0.031)
State * Crime Type * Time	X	X	X
State * Crime Type * Month	X	X	X
Post	X	X	X
Agg Crimes	Sexual/Other Crimes	NIBRS Categories	NIBRS Categories
S.E	Robust	Cluster by Crime Type	Cluster by Crime*State
Num of Clusters		21	735
Observations	6,450	67,725	67,725

This table shows the effect of the MeToo movement using different crime aggregation and inference methods. Column (1) is our main estimate where crimes are categorized as either sexual crimes or non-sexual crimes, and robust standard errors are used. In columns (2)-(3), crimes are aggregated according to the NIBRS offense types. Incidents that include multiple offense types are excluded. Column (2) clusters standard errors by crime category and column (3) clusters by the interaction of state and crime category. All regressions are weighted by the number of crimes that occurred in each state before the MeToo movement started.2010-2017 NIBRS data. ***p<0.01; **p<0.05; *p<0.1.

Table A.4: MeToo effect by city

	ihs(crime)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post * Sexual Crimes	0.184^{***}	0.053^{*}	0.157^{***}	0.035	0.267	-0.097	0.083^{*}
	(0.027)	(0.028)	(0.049)	(0.064)	(0.189)	(0.059)	(0.048)
Crime Type * Time	X	X	X	X	X	X	X
Crime Type * Month	X	X	X	X	X	X	X
Post	X	X	X	X	X	X	X
City	NYC	LA	Seattle	Denver	Nashville	Louisville	Kansas City
Observations	216	216	216	144	144	216	216

This table shows the effect of the MeToo movement on sexual crimes where the effect is calculated for each city separately. Robust standard error in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table A.5: Data sources for international data

Country	Data Providing Organization	Time period	Share of the population covered
Australia	New South Wales Bureau of Crime Statistics and Research, Queensland Police, Crime Statistics Agency of Victoria, and Western Australia Police	2010-2018	88%
Belgium	Federale politie	2010-2018	100%
Canada	Canadian Centre for Justice Statistics	2010-2018	100%
Czech republic	Policie České republiky	2010-2018	100%
Colombia	Policía Nacional	2010-2018	100%
Denmark	Danmarks Statistik	2010-2018	100%
Germany	Bundeskriminalamt	2012-2018	100%
Estonia	Politsei- ja Piirivalveamet	2010-2018	100%
Finland	Tilastokeskuksen	2010-2018	100%
France	Ministère de l'Intérieur	2010-2018	100%
Greece	Hellenic Statistical Authority (ELSTAT)	2010-2018	100%
Iceland	Lögreglan a höfudborgarsvaedinu	2013-2018	63%
Ireland	Central Statistics Office	2010-2018	100%
Japan	National Statistics Center	2015-2018	100%
Korea	Supreme prosecutors' office	2010-2018	100%
Lithuania	Informatikos ir Rysiu Departamentas	2012-2015 and 2017-2018	100%
Mexico	Instituto Nacional de Estadística y Geografía	2015-2018	100%
Netherlands	Korps Nationale Politie	2012-2018	100%
Portugal	Instituto Nacional de Estatística	2010-2018	100%
Slovenia	Statistični Urad	2010-2018	100%
Spain	Ministerio del Interior	2010-2018	100%
Sweden	Brottsförebyggande rådet	2010-2018	100%
United Kingdom	Home Office: Crime and Policing Analysis Unit and Open Data Northern Ireland	2010-2018	92%
United States	Federal Bureau of Investigation	2010-2018	30%

Table A.6: Definition of the neighborhood level by city

City	**Neighborhood Level**
Denver	Police District
Kansas City	Police Division
LA	Patrol Division
Louisville	Police Division
Nashville	MNPD Zone (Patrol Area)
New York City	Police Precinct
Seattle	Police Precinct