The Effects of Social Movements: Evidence from #MeToo

Ro'ee Levy and Martin Mattsson*

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Abstract

Social movements are associated with large societal changes, but evidence on their causal effects is limited. We study the effect of the MeToo movement on a high-stakes decision—reporting a sexual crime to the police. We construct a new dataset of sexual and non-sexual crimes reported in 30 OECD countries, covering 88% 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. The movement increased reporting of sexual crimes by 10% during its first six months. The effect is persistent and lasts at least 15 months. Because we find a strong effect on reporting before any major changes to laws or policy took place, we attribute the effect to a change in social norms or information. Using more detailed US data, we show that the movement also increased arrests for sexual crimes in the long run. In contrast to a common criticism of the movement, we do not find evidence for large differences in the effect across racial and socioeconomic groups. Our results suggest that social movements can rapidly change high-stakes personal decisions.

^{*}Levy: Massachusetts Institute of Technology, roeelevy@mit.edu. Mattsson: Yale University, martin.mattsson@yale.edu. We thank Olle Folke, Eduardo Fraga, Sahana Ghosh, Joni Hersch, Dean Karlan, Sarah Khan, Costas Meghir, Mushfiq Mobarak, Johanna Rickne, Joseph Shapiro, Ebonya Washington, Jaya Wen, David Yanagizawa-Drott, Mor Zoran and numerous seminar participants for helpful comments and suggestions. We also thank Calvin Jahnke for excellent research assistance. Funding for this project was provided by the Department of Economics at Yale University, the Tobin Center for Economic Policy and Y-RISE.

1 Introduction

Societal changes are often associated with movements advocating for new norms and behaviors. For example, the increase in women's labor force participation, the shift in attitudes toward 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, it is difficult to establish if these movements are the drivers of change or if they are caused by external factors that would have led to societal changes regardless of the movements. In this paper, we focus on the MeToo movement and estimate its effect on reporting sexual crime to the police.

The MeToo movement started on October 15, 2017 and was exceptionally effective in rapidly increasing awareness around sexual misconduct. We show that the movement substantially increased search interest in and news coverage of sexual misconduct. While the movement spread internationally, there was large variation in its strength across countries. We exploit the variation in the strength of the movement, along with the fact that it started almost instantly, to identify its causal effect.

We focus on reporting sexual crimes because 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 the risk of reprisals. Hence, using the number of crimes reported to the police as the outcome variable is a high bar for the types of behaviors that the MeToo movement might have changed.

We construct a dataset on the number of crimes reported to the police by quarter in 30 OECD countries, covering 88% 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 classify countries as having a strong or weak MeToo movement based on Google search interest for terms related to the MeToo movement. We find that the MeToo movement increased the number of reported sexual crimes by 10% during the first six months of the movement. 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.

¹The estimate of the effect is 10 log points, which equals a 11% increase. For simplicity, we describe the effects in log points as percentage changes throughout the paper, although this slightly understates the magnitude of the results.

We confirm the reliability of the result by performing placebo tests where we estimate the effects of fictional MeToo movements set in each of the six-month periods from the second quarter of 2010 to the third quarter of 2017 (Q2 2010-Q3 2017). The effect we find is larger than all the placebo estimates. We also show that the result is robust to various specifications and alternative measures of the strength of the MeToo movement. While the point estimates are similar, our power is limited and the standard errors increase in some of the robustness tests. We also find an effect when employing the matrix completion method (Athey et al., 2017), which uses more flexible patterns in the data to create a counterfactual for the number of sexual crimes reported had there been no MeToo movement. Furthermore, the result is similar when instrumenting the strength of the MeToo movement with the share of the population speaking English.

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.² We find that the movement had a persistent effect, and estimate a strong effect on reporting at least 15 months after it started.

The international dataset 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 US national dataset is collected from the FBI National Incident-Based Reporting System (NIBRS) and covers approximately 30% of the US population. The city dataset, which includes additional covariates and covers more crime categories, is collected from seven large US cities. The US lacks substantial geographic heterogeneity in the strength of the MeToo movement; therefore 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 assaults reported in the US by 8% in the first six months after the movement started, and the effect is stronger in the city dataset which also includes sexual harassment.

We present three additional findings based on the US data. First, the movement had a larger effect on crimes that were reported at least a month after they occurred. However, the effect on crimes that 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 reporting of the flow of new crimes. Second, 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.

²We 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.

However, we do find that the movement has a stronger effect among female victims and in counties with a smaller share of Trump voters. Third, we show that in the long run, the movement also led to an increase in the number of arrests made for sexual crimes, suggesting that reporting led to positive externalities.

We discuss several possible mechanisms explaining the increase in reporting. A potential interpretation of the results is that the MeToo movement increased the *incidence* of sexual crimes. 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 an increase in the incidence of sexual crimes cannot explain the effect we find, and therefore, we conclude that the movement increased the propensity to report crime. The MeToo movement did not lead to major immediate changes in laws or government institutions and therefore legal changes could not be driving the increase in reporting. The mechanism that we have the strongest evidence for is a change in social norms and information. Awareness of the problem of sexual misconduct increased after the MeToo movement started, suggesting that awareness may have led to additional reporting.

The results are related to three different streams of literature. First, we contribute to a long debate among social 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 "[t]he 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, 2020). 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 or individual behavior and not only official policy. Personal decisions also often 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 that 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 toward certain institutions and change behavior (Alsan and Wanamaker, 2017; Martinez-Bravo and Stegmann, 2018). A recent literature based on theory, as well as information interventions, argues that social norms can "unravel" when individuals start expressing their personal beliefs (Bursztyn et al., 2017, 2018; Sunstein, 2019). 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 the election of female politicians increased the reporting of crimes toward women (Iyer et al., 2012), that an information treatment targeting social norms increased the reporting of violence toward women (Green et al., 2019), and that a high-profile rape and murder case increased reporting of sexual crimes in India (Bhatnagar et al., 2019; McDougal et al., 2018), potentially due to changes in police administration. Public campaigns increasing awareness is a common strategy to increase reporting.³ However, there is limited evidence on the effects of such campaigns. The MeToo movement can be seen as a particularly successful attempt to raise awareness. To the best of our knowledge, this is the first rigorous evidence on the effects of the MeToo movement on reported sexual crimes and thus demonstrates that increasing awareness can be effective in increasing the reporting of sexual crimes.⁴

The rest of the paper is organized as follows. Section 2 discusses the underreporting of sexual crime and describes 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 heterogeneity as well as the effect on arrests. Section 5 provides evidence on which mechanisms the effect operated through and interprets the overall results, and Section 6 concludes.

³For example, the largest US-based anti-sexual violence organization RAINN spends 27% of its budget on educating the public.

⁴Rotenberg and Cotter (2018) present descriptive statistics showing that sexual crimes reported increased in Canada after the MeToo movement started.

2 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 is known to the police, compared to 46% of victims of other violent crimes.⁵ Underreporting decreases social welfare by reducing 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 and attending hearings has monetary costs such as lost income, childcare, and travel costs (Morabito et al., 2019). Moreover, reporting a sexual crime forces the victim to repetitively relive the experience by giving detailed accounts of the crime. Reporting is especially hurtful for victims whose account of the event is not believed by law enforcement officials (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. According to National Crime Victimization Survey Data, 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%.

In this paper, we focus on reporting sexual crimes to the police. However, the MeToo movement also highlighted cases of sexual misconduct that do not constitute a criminal offense but still have negative welfare consequences, such as cases of workplace sexual harassment (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, other lower-stakes behaviors changed as well. Indeed, there have been anecdotal reports of an increase in the number of calls to helpline centers following the MeToo movement. Therefore, the effects we find on reporting crime to the police are probably a subset of the overall behavioral effects of the movement.

⁵Authors' calculations using 2011-2017 National Crime Victimization Survey microdata.

⁶Chiwaya, 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.⁷ 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.⁸

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 year following the start of the movement, search interest in sexual misconduct among OECD countries increased by 95% compared to January 2010-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 see on social media is about sexual harassment or assault. 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 the 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. This allows us to attribute the short-run effect we find to changes in social norms, where norms are broadly defined to include the norms of victims, firms, and

⁷The phrase "Me Too" was first used by Tarana Burke in 2006, but widespread usage only started after October 15, 2017.

⁸The 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

⁹Pew Research Center American Trends Panel Wave 35.

government employees, such as police officers, but exclude any changes to laws or government 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. 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 dataset with quarterly data on the number of crimes reported in 30 OECD countries representing 88% of the OECD population. We include in our sample countries that have quarterly, or more frequent, data available, disaggregated by sexual crimes and non-sexual crimes. For 24 of the countries, the time period that a crime is counted in is based on the date the crime was reported to the police, for the remaining countries it is based on when the crime occurred or some combination of the two. We separately obtain data available from the start of 2010 until the end of 2018 for each country. We harmonize the data by manually classifying offense categories as sexual crimes or non-sexual crimes for each country. We define sexual crimes as all forms of sexual assault and sexual harassment and define non-sexual crimes as all other crimes. 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.

¹⁰Enikolopov et al. (2019) show how social media facilitated protests in Russia. Acemoglu et al. (2017) 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. There is also a literature on how different technologies enable the diffusion of social movements (e.g., Christensen and Garfias, 2018; García-Jimeno et al., 2018).

¹¹See Appendix Table A.5 for a list of the countries and data sources.

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. 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. While Google search interest is an imperfect measure of the MeToo movement's strength, it provides a consistent measure of the movement's strength among a majority of the population, as Google is the dominant search engine in all of the countries in our data. 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 of 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 that 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 0.69 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, and between sexual crimes and non-sexual crimes:

$$y_{itc} = \beta_1 Post_t \times StrongMeToo_c \times SexCrime_i + \beta_2 Post_t \times SexCrime_i +$$

$$\beta_3 Post_t \times StrongMeToo_c + \beta_4 Post_t + \beta_{5,ic} Trend_t + \gamma_{i,c,g(t)} + \varepsilon_{itc}$$

$$(1)$$

• y_{itc} is the natural logarithm of the number of reported crimes of type i, in quarter t, in country c

¹²Caputi et al. (2019) show that the MeToo movement affected Google search interest in the US.

¹³In October 2017 among the countries in our sample, the mean of Google's market share of searches was 90%, while the minimum was 66%. Authors' own calculations using data from gs.statcounter.com.

- Post_t is an indicator for Q4 2017 (when the MeToo movement started) and later quarters
- $StrongMeToo_c$ is 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 because that is where the MeToo movement varies. ¹⁴ 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-period 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, it would have to have a non-linear change after October 2017 that affects the number of reported sexual crimes more than it affects reported non-sexual crimes among 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.

3.2.1 Time Frame of Analysis

In Section 3.3, we focus on the effects of the MeToo movement in the short run, defined as the first six months of the MeToo movement. In Section 3.4, we test if the effect is persistent over time. There are two main reasons for separating out the short-run effects. First, the first six months is the time period when there exists a substantial difference in interest between countries with a strong movement and countries with a weak movement. Therefore, this is the only period in which we can employ our triple-difference empirical strategy. Appendix Figure A.3 shows the convergence of interest over time between the countries that we classify as having strong and weak MeToo movements. Second, during the initial six-month period there were, to the best of our knowledge, no changes to laws governing sexual crimes in any of the countries in our sample. After the initial six-month period, some laws concerning sexual crime changed in at least three countries, probably as a result of the MeToo movement. Therefore, in the first six months, we can interpret the effect as being driven by a change in social norms or information.

¹⁴The standard errors clustered at the country level are smaller so choosing to cluster the standard errors at the country-by-crime category level is more conservative.

3.3 Results

Table 1 shows that the MeToo movement increased the reporting of sexual crimes. Column (1) uses data only on sexual crimes to show a difference-in-difference estimator over time and between countries with strong and weak MeToo movements. Column (2) uses all 30 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% and 7%, respectively. It is not surprising that Column (2) finds a smaller effect than Column (1) since it estimates the average effect for countries with both strong and weak MeToo movements. Column (3) estimates the effect from Column (2) separately for countries with strong and weak movements and shows that the effect is driven by the countries that had a strong MeToo movement. These countries had an effect of 12%, while the effect was only 2% 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 10%, statistically significant at the 10% level. Note, that in this column, countries with weak MeToo movements serve as a control group. If the MeToo movement had some effect in these countries, the estimate is a lower bound for the total effect of the movement.

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 over time. Since we do not expect the MeToo movement to affect the number of non-sexual crimes reported, this coefficient can be used as a placebo test. We estimate the coefficient to be 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.

To illustrate the triple-difference estimator, we present the raw data visually in Figure 3. Sub-figure 3a shows the number of sexual crimes reported, indexed to be 100 in Q3 2017, and averaged across the countries with strong and weak MeToo movements. A clear seasonality is observed in the time lines, where the fourth quarter of each year tends to see a decrease in the number of sexual crimes reported. This is true for both strong and weak MeToo movement countries until Q4 2017, when the number of reported sexual crimes stays flat in the countries with a the strong MeToo movement, while the countries

¹⁵To make the average numbers more comparable over time, we shorten the data series to start in 2012, since we lack data for many countries before 2012.

with a weak movement experience the typical decline. In Q1 2018, the number of reported sexual crimes in countries with strong and weak MeToo movements continues to diverge. 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 figures also shows that the strong and weak MeToo movement countries may have somewhat different pre-trends for sexual and 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 there are no differential pre-trends in the difference between the sexual and non-sexual crime indexes displayed in Sub-figures 3a and 3b, , while there is a substantial divergence between countries with strong and weak MeToo movements after the start of the MeToo movement.

Using a continuous estimate of the strength of the MeToo movement, we estimate the elasticity of crimes reported to the national interest in the MeToo movement. Replacing the *StrongMeToo_c* term in Equation 1 with the inverse hyperbolic sine transformation (IHS) of the immediate search interest in the MeToo movement provides an estimate of the effect of an IHS point increase on the log of reported sexual crimes.¹⁶ This regression yields an estimate of 0.05. However, this estimate is not statistically significant and it should be interpreted with caution because Google searches for the MeToo topic is a noisy proxy for the underlying interest in the MeToo movement and thus the estimate probably suffers from attenuation bias.¹⁷

3.4 Persistence of the Effect over Time

Was the effect of the MeToo movement driven by a short-term increase in the salience of exposing sexual crime or did the movement change the underlying social norms leading to a lasting effect on behavior? To estimate the long-term effects, we cannot use the triple-difference estimator, because in some of the countries where a MeToo movement was initially weak, it gained traction and became stronger after October 2017, as shown in Appendix Figure A.3. This means that when measuring long-term effects, our counterfactual will become contaminated in later periods. We use two alternative strategies instead. First, we use the difference-in-difference specification over time and by crime type and focus only on countries where we know that the movement started in October 2017. Second, in Appendix Section B.1,

¹⁶We use the IHS transformation instead of the natural logarithm since for one country the estimated interest is negative, but very close to zero.

¹⁷When instrumenting the interest in the MeToo movement using the fraction of the population that speaks English, the point estimate increases substantially, suggesting attenuation bias is affecting the estimate. For a more detailed description of the instrumental variable approach see Section 3.6.

we exploit the gradual spread of the movement and allow the MeToo movement to start at different time periods in different countries to estimate the effect over time. Using both methods we find that the movement's effect was persistent.

Table 2 uses data from the countries with a strong MeToo movement to measure the persistence of the effect over time. Column (1) shows that the average effect for the first five quarters after the movement started is estimated to be 10%. Column (2) shows that the effect is relatively stable until the end of our data, 15 months after the movement started. The effect stays between 8% and 12%, and there is not a pattern of a continuous change in the effect over time.

3.5 Placebo Tests

We conduct a set of placebo tests to further assure that the 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 every second quarter from Q2 2010 to Q4 2017 and then measuring the effect over six-month periods. 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. Of the 15 placebo tests, only one is statistically significant at the 10% level. The actual effect of the MeToo movement (Q4 of 2017) has a larger absolute coefficient than any of the 15 placebo tests.

3.6 Robustness Checks

Table 3 shows that our primary triple-difference estimator is robust to using different time periods, alternative regression specifications, alternative empirical strategies, and to most alternative definitions for the strength of the movement. Row (1) repeats the main estimate from Column (4) of Table 1. Row (2) shows the effect of the MeToo movement during its first quarter by restricting the sample to end in Q4 2017. Note that the first two weeks of this quarter could not have been affected by the movement and therefore this result probably underestimates the effect of the movement. Row (3) shows the effect of the MeToo movement during the first three quarters of the movement. All the effects range from 6% to 10%.

Rows (4)-(6) estimate the effect with different measures of the strength of the MeToo movement. Row

¹⁸We set the start date in every second period to avoid having two adjacent estimates using overlapping data and thereby introducing a mechanical autocorrelation. When estimating the placebo effect for every quarter, we still find that only one placebo test has a statistically significant effect at the 10% level and that the actual effect of the MeToo movement has a larger absolute coefficient than any of the 31 placebo tests.

(4) shows that the result is robust to using Google searches for the MeToo topic between October 2017 and March 2018, the same period for which we measure the number of reported crimes. Row (5) uses the sum of the Google search interest in the topics of sexual assault and sexual harassment.¹⁹ Using this noisier measure of MeToo strength produces a smaller estimate. Row (6) uses a survey measure of the fraction of the population that has heard of the MeToo movement in February-March 2019 (YouGov, 2019). The analysis is conducted for the 12 countries in our sample where the survey was conducted. This analysis yields a point estimate similar to our main estimate.

Row (7) shows the result of a regression weighted by the population of each country.²⁰ Using these weights changes the interpretation of the estimate from the average effect of the MeToo movement on the number of sexual crimes reported in countries that had a strong MeToo movement to the average effect of the MeToo movement on the population in the countries that had strong MeToo movements. This effect is estimated to be 12% and is more precisely estimated than our main estimate since we put more weight on countries with a large population that on average have a more stable quarter-to-quarter number of crimes reported. While most of our data is based on the date crimes were reported to the police, some of the data is based on the date crimes occurred. This may bias the results as crimes that occurred before the start of the MeToo movement could also be affected by the movement. Row (8) shows the results of our main specification including only data based on the date a crime was reported and confirms that differences in this reporting practice do not drive the results.

To ensure that our specification of the outcome variable is not driving the result, Row (9) shows the result when using the number of crimes reported as an outcome variable, whereas our main specification uses the log of crimes reported. We normalize the number of crimes reported to average one in the year before the start of the MeToo movement in each country by crime type category. The estimated effect is an 11% increase over the baseline year (Q4 2016 - Q3 2017). Row (10) shows the result is robust to using a negative binomial regression with the count data of crimes reported as the outcome variable.

Row (11) analyzes the data using the matrix completion method which creates a counterfactual for the number of sexual crimes that would have occurred in countries that had a strong MeToo movement, based on flexible patterns in the data.²¹ Despite using a very different empirical strategy the estimated

¹⁹Since there was a meaningful interest in these topics even before the start of the MeToo movement, we use the increase in search interest at the start of the MeToo movement after controlling for linear trends and monthly fixed effects in each country separately. This allows us to parse out pre-MeToo levels of interest, linear trends, or seasonality, which are not indicative of the strength of the MeToo movement.

²⁰We use UN population data for 2015 from the 2017 revision of World Population Prospects.

²¹Each row in the matrix is a crime*country category and each column in a year-quarter (for example a control category may be damage to property in Ireland and a treated category may be sexual harassment in Iceland). For more details on the method

effect is qualitatively similar to our main estimate. A potential problem with our main specification is that reverse causality could bias the results if an increase in sexual crime reporting increased the interest in the MeToo movement and thus affected the classification of strong and weak movements. To rule out such a mechanism we instrument having a strong MeToo movement with the fraction of the population speaking English.²² Since an increase in reported sexual crimes could not have affected the fraction of the population speaking English, this estimate should not suffer from reverse causality bias. Row (12) shows that our main result is robust to using this two-stage least squares regression.²³

4 Heterogeneity and Effect on Arrests: 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 because 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.

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.²⁴ 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 2010-2018 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. Group A offenses do not include sexual harassment, therefore our estimates measure the effect only on sexual assaults.

see Section 4.4).

 $^{^{22}}$ We use two variables based on Ethnologue data: the share of the population speaking English as a first language and the fraction of the population speaking English. We instrument the interactions of $Post \times Sexual\ Crime \times Strong\ MeToo$ and $Post \times Strong\ MeToo$ with the the same interactions, where Strong MeToo is replaced with each English speaking measure. See Appendix Section A.4 for a description of the data on English usage.

²³The Kleibergen-Paap Wald test statistic is 32.

²⁴For more details, see the 2019 National Incident-Based Reporting System User Manual. Available online: https://ucr.fbi.gov/nibrs/nibrs-user-manual

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 an arrest was made. Appendix A.5 provides more details on how the NIBRS data was processed.

4.1.2 Incident-Level Data from Cities

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 data is used to complement our analysis in three 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 heterogeneous effects according to whether the crime was immediately reported. Third, the data includes virtually all crimes reported to the police, and not only the relatively severe offenses covered by NIBRS.²⁵ Specifically, this allows us to analyze the effect of the movement on sexual harassment, in addition to sexual assault.

We aggregate the incident-level crime data 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. Appendix A.6 provides more details on how the city 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, as we do not observe meaningful variation in the strength of the MeToo movement across different regions within the US, as seen in Appendix Figure A.4.²⁶ This is

²⁵There are several exceptions, such as cities excluding crimes related to child abuse cases or unfounded complaints.

²⁶While 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. The low correlation 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.

unsurprising as the national media covered the movement and the allegations related to it. Furthermore, 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.²⁷

We use the following regression as our primary specification:

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

- y_{itc} is the inverse hyperbolic sine transformation of the number of reported crimes of type i, in month t, in location (state or city) c. The inverse hyperbolic sine is used instead of a log transformation because 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. For each location, we exclude months when no crimes were reported. 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.6 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.²⁸ An additional advantage of weighting the data is that the weights reduce

²⁷Pew Research Center, December 2017 Political Survey.

²⁸The international analysis regressions in Section 3.5 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 importance of the aggregation method in our estimates (e.g., whether we aggregate the data by state or county).

4.2.1 Heterogeneity by Demographics

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

$$y_{itc} = \beta_1 SexCrime_i \times Post_t + \beta_2 Post_t + \beta_3 SexCrime_i \times Post_t \times Demog_c +$$

$$\beta_4 SexCrime_i \times Demog_c + \beta_5 Post_t \times Demog_c + \beta_6 Demog_c + \beta_{7,ic} Trend_t + \gamma_{i,c,m(t)} + \varepsilon_{itc}$$

$$(3)$$

The regression is based on Equation 2 with c now representing a county instead of a city/state and β_3 estimating heterogeneous effects by the demographics of the county. Each demographic variable $(Demog_c)$ is constant across time and its weighted mean is subtracted to keep β_1 , the estimates for the effect of the MeToo movement, consistent across specifications. Data on county-level income, education, race, and ethnicity is based on the American Community Survey 5-year 2016 estimates. The share of Trump voters in each county is based on the MIT Election Data and Science Lab (2018). We exclude counties with a population of less than 10,000 and county-years where the police agencies reporting data cover less than 85% of the population.

4.3 Results

Table 4 shows that the MeToo movement had a strong and statistically significant effect on crimes reported based on both the NIBRS and the city datasets. Column (1) uses NIBRS data to show that the MeToo movement increased the number of reported sexual assaults in the US by 8% in the six months after the movement started. This effect may be smaller than our primary specification based on the international data because the NIBRS dataset includes mostly severe crimes. Column (2) shows that in our sample of large cities, the effects on sexual assault and sexual harassment are approximately 11% and 15%, respectively. As 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 13% on sexual crimes reported in our city sample. 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.7 shows that the effect is positive for six of the seven cities in our sample and statistically significant for four of the seven cities.

Appendix Table A.8 shows that the effect of the movement was persistent in the US and does not decline over time, both based on FBI data and on our sample of cities. One concern with estimating long-run effects is that they can potentially be affected by depletion in the stock of old crimes, and not due to a change in the effect on the propensity to report crime. The city data allows us to mitigate this concern by focusing only on the flow of crimes that were reported within a month after they occurred. Column (5) shows that the results are similar when focusing only on new crimes reported.

4.3.1 Heterogeneous Effects by Report Timing and Crime Type

Table 5 tests for heterogeneity by crime type. Column (1) 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) shows that the movement had a stronger effect on offenses where the victim was not physically injured. In Column (3) we do not find substantial heterogeneity by whether the victim knew the offender.

Table 6 uses city 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 22% on crime reported more than 30 days after they occurred. The total effect on all crimes (shown in Column (3) of Table 4) is similar to the effect on crimes reported within 30 days since only 20% of crimes are reported more than a month after they occur. Column (2) presents the results for the next nine months and shows a declining effect on crimes reported with a lag. This suggests that some of the short-term effect could be due to a stock of old crimes that was exhausted. However, even in the 7-15 months after the movement started, there is a large effect on crimes reported at least a month after they occurred. This long-term effect on crimes reported with a lag could be explained by either a persistent effect on a flow of cases which are not immediately reported or a very large stock of unreported crimes, which is gradually affected by the MeToo movement.

4.3.2 Heterogeneous Effects by Gender, Race, Socioeconomic Status and Political Ideology

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).

Based on the analysis of victim, offender, county, and neighborhood demographics, we find that the effect was larger for female victims, male offenders, and politically liberal counties. However, we do not find evidence that the MeToo movement mostly affected the reporting of whites or those with high socioeconomic status.

We test for heterogeneous effects among victims by separating sexual assault into sub-categories according to the victim demographics.²⁹ Column (1) of Table 7 shows that the movement had a larger effect on female victims than among male victims. 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.³⁰ Column (4) repeats the analysis according to the offender's demographics and points to a similar effect among black and white offenders.

Table 8 shows that the MeToo movement mostly did not have large heterogeneity in the effect between counties with different demographic profiles, relative to the total effect of the movement. In Column (1) we show the effect of the movement based on our specification in Equation 2, and in Columns (2)-(7) we estimate heterogeneous effects according to each demographic variable as described in Equation 3. Some of the coefficients are statistically significant, but the magnitude of most of the effects is small. While counties with a larger share of college graduates are associated with a slightly larger effect, the difference in the expected effect on reporting between a county in the 75th percentile of the share of individuals with a college education and a county in the 25th percentile is only expected to be 2 percentage points, compared to the average effect of 9%. ³¹ One exception to the relatively homogeneous effects we find is that the MeToo movement had a smaller effect in counties with a larger share of Trump voters. The difference in expected reporting between a county in the 25th percentile of Trump voters and county in the 75th percentile is 7 percentage points. We emphasize that these estimates are not intended to capture causal effects, but rather to describe which types of counties are associated with a larger increase in reporting sexual crimes during the MeToo movement. Appendix B.2 exploits the more detailed city data to analyze heterogeneity at the neighborhood-level. We do not find substantial heterogeneity by neighborhood demographics.

²⁹For 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.

³⁰The 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.

³¹Just like the rest of the US analysis, the average effects and the percentiles are weighted by the mean number of crimes in the pre-period.

4.3.3 Effect on Arrests

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 arrests made by the police. The FBI defines an arrest as a case where a suspect is taken into custody based on a warrant or a previously submitted report, arrested on view (without a warrant), or summoned to court.

Table 9 shows that the movement increased the number of arrests in sexual assault cases, but that this increase is smaller than the effect on reporting. In Column (1), the short-run effect is estimated by aggregating the data into three separate categories: sexual crimes where an arrest was made, sexual crimes where no arrest was made, and non-sexual crimes, which is the control group. In the short run, we find no effects on arrests. One concern with this specification is that the null effect could be explained by a decrease in the arrest rate over time for all crimes. Columns (2) and (3) show that the results are robust to using a slightly different specification: we run the regression separately only on crimes where an arrest was made and crimes where no arrest was made so that the control group for each group of sexual crimes is the non-sexual crimes in the same arrest category. Columns (4)-(6) repeat the analysis for the long-run effect over 15 months. In this period, the MeToo movement increased the number of arrests substantially, albeit the increase is still smaller than the effect on the number of crimes cleared.³²

Why did the MeToo movement not lead to a larger increase in the number of arrests? One possible explanation is that the movement affected mostly the type of cases where the probability of arrest is low. Indeed, as shown in Table 6, the MeToo movement had a stronger effect on cases reported more than a month after they occurred.³³ However, the movement also had a strong effect on crimes reported within a month, which are far more common. Therefore, the increased reporting of old crimes cannot explain the disproportionately smaller effect on arrests.³⁴

In Appendix Table A.10, we test whether other observables associated with the crimes affected by the

³²In Appendix Table A.9 we estimate the effect on cases cleared by the police. A case is cleared if it is associated with an arrest or if the police have sufficient probable cause to arrest a suspect but could not make an arrest for reasons outside their control, including the victim refusing to cooperate, the prosecutor declining prosecution for a reason other than lack of probable cause, the offender being in the custody of another jurisdiction, and the offender being a juvenile. The effects on clearances are similar to the effects on arrests.

³³Anecdotal evidence 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

³⁴Based on cities that collect arrest data (Kansas City, LA, and Nashville), the share of cases resulting in an arrest in the pre-period is 6% for sexual assaults reported at least a month after they occurred, compared to 14% for sexual assaults reported within a month. However, this gap is not large enough to explain the small effect on the number of arrests. We regress whether an arrest was made on the interaction of crimes and the post-period and find that the MeToo movement had a small negative effect on the arrest *rate*, at least in the short run. To test whether this is explained by increased reporting of crimes that were reported at least a month after they occurred, we control for the lag between the occurrence of the crime and its reporting date. The effect stays almost exactly the same when controlling for the lag.

movement could explain the arrest rate. We focus on the police agency where the crime occurred, the type of crime, the age, race, and sex of the victim, whether the victim was injured, the weapon used, the relationship between the victim and offender, and the type of location where the crime occurred. These covariates do not seem to explain the decrease in the arrest rate. However, there could be unobservables associated with crimes affected by the MeToo movement that are correlated with the likelihood of arresting an offender.

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).

We use this method with our city 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.³⁵ 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 39 treated groups and 399 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.³⁶

We find an average treatment effect over six months of 18% and a long-run 15-month effect of 16%. Both effects are significant at the 1% level using standard errors generated by bootstrapping. Appendix Figure A.5a shows that the counterfactual created by the method fits the actual outcome well in the pre-period, and Appendix Figure A.5b highlights that the treatment effect is relatively persistent.

5 Mechanisms and Interpretation

How did the MeToo movement increase the reporting of sexual crimes? In this section, we show that neither an increase in the incidence of sexual crime occurrence nor changes in legislation are likely to be driving the results. We provide evidence that beliefs regarding sexual misconduct changed after the start of the movement. Specifically, increased awareness of the extent of the problem of sexual misconduct may have led to the effect on reporting.

5.1 Changes in the Incidence of Sexual Crimes

The effect of the MeToo movement on the number of crimes reported could be driven by an increase in the incidence of crimes (a "backlash effect") and not an increase in the propensity to report crimes. We rule out that an increase in incidence is driving the entire increase in reporting by restricting our analysis to crimes that were committed *before* the start of the MeToo movement and thus their incidence could not have been affected by the movement. Table 10 uses the data from US cities and includes only crimes that were reported at least three months after they occurred and that were reported by December 2017 (i.e., occurred before the start of the movement in October 2017). The table shows that the MeToo movement had a strong and statistically significant effect on the reporting of crimes that occurred before the movement started. This evidence complements anecdotal reports of an increase in the propensity

³⁵For 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.

³⁶The method was estimated using the R package gsynth by Yiqing Xu and Licheng Liu. Available online: https://yiqingxu.org/software/gsynth/gsynth_examples.html

to report sexual crimes.³⁷ Furthermore, we are not aware of any anecdotal reports suggesting that the number of sexual crimes committed increased as a result of the MeToo movement.

5.2 Changes to Laws and Government Policy

The MeToo movement could also affect reporting by changing the laws governing sexual crimes, for example, due to an expansion of the behavior classified as illegal. We find evidence against this mechanism, at least in the short term. A report by the International Lawyers Network (2019) shows that among the 11 OECD countries covered by the report, no country made changes to laws governing sexual misconduct between the start of the MeToo movement and the end of Q1 2018, while some introduced legal changes after this date.³⁸ The lack of legal changes in the immediate aftermath of the MeToo movement is not surprising given that passing legislation is a lengthy process, often taking more than a year.³⁹

Furthermore, data from two US cities and one federal agency suggests that there were no substantial funding increases related to sexual crimes right after the start of the MeToo movement.⁴⁰

5.3 Changes in Awareness and Beliefs

Table 11 uses survey data to show that awareness of sexual misconduct increased after the movement started. 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 start of the movement: in July 2016 and April-May 2018. In contrast to most recent surveys focusing on issues raised by the MeToo movement, the timing of the survey was not affected by the movement. Column (1) shows that agreement with the statement "sexual harassment against women in the workplace is no longer a problem in the United States"

³⁷For 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)

³⁸To the best of our knowledge only three countries in our data, Iceland, Sweden and the US, changed major laws with respect to sexual crimes between October 2017 and the end of 2018. In Iceland and the US, the earliest changes took effect in Q2 2018 and in Sweden the change took effect in the Q3 2018. Therefore, these changes could not have directly influenced reporting in the first six months of the movement.

³⁹An 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.

⁴⁰We are in the process of collecting budget data for police units specializing in sexual crime and currently have data from two (Seattle and Kansas City) out of the seven US police departments in our city sample and on the total amounts of grants given by the United States Office on Violence Against Women (OVW). The data ranges from 2014 to 2018. The average budget increase in 2018, the first year in which the MeToo movement could have affected budgets, was 3.8% for the police departments and 3.5% for OVW. This can be compared to a 2.6% average increase in the total police department budgets between 2017 and 2018.

decreased by 0.14 standard deviations in 2018, compared to 2016. Other surveys also provide evidence for increased awareness. In a Washington Post-ABC poll in January 2018, 72% of respondents stated that sexual harassment of women in the workplace is a serious problem, compared to 47% in November 2011.

Awareness can affect behavior by decreasing the stigma associated with reporting (Bursztyn et al., 2017), by allowing individuals to coordinate and provide corroborating evidence (Cheng and Hsiaw, 2019), or by aggregating information and encouraging people to report as a form of protest if they learn that sexual assault is a large social problem (Battaglini et al., 2020). Since awareness affects reporting and is affected by it, an initial increase in awareness may lead to a tipping point that further increase reporting and awareness substantially.⁴¹

We cannot identify the exact mechanism through which awareness affects reporting, but we can explore the mechanisms further using the survey data. Column (2) of Table 11 provides evidence for heterogeneous effects in awareness between men and women. While men's agreement with the statement that sexual harassment is no longer a major problem decreased by 0.24 standard deviations, women's agreement decreased by only 0.05 standard deviation and is not statistically different from zero. 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. 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). Second-order beliefs may have affected reporting if they changed victims' expectations regarding the response to reporting a sexual crime, either of the police or the wider community. In columns (3) and (4), we show that while awareness increased, agreement with the statement "women who complain about harassment often cause more problems than they solve" did not change substantially between 2016 and 2018. This suggests that reporting can increase even when the average stereotype associated with reporting does not substantially change.

6 Conclusions

This study shows that the MeToo movement had a substantial, persistent effect on the propensity to report sexual crimes to the police. This result is consistent across multiple samples and is robust across

⁴¹A similar tipping point may have occurred around 2002 for clergy sexual abuse scandals (Bottan and Perez-Truglia, 2015).

multiple estimation techniques. Focusing on the US allows us to analyze 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 of high socioeconomic status, it increased the reporting of sexual crimes to the police for both white and black victims, offenders, and counties, as well as in counties with both high and low socioeconomic status.

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.

We estimate that the MeToo movement increased the number of sexual crimes reported by 25,870 in the first six months after the movement started. In the first 15 months, 66,658 crimes were reported as a result of the movement. Out of these crimes, 33,542 were sexual assaults reported in the US, and we find that the movement led to 4,174 arrests in the US.⁴² The effect found in the US is equivalent to closing 25% of the gap between the reporting of sexual crimes and other violent crimes observed in the National Crime Victimization Survey.

While the effect on the number of arrests is smaller than the effect on the number of reports, it is still an important channel through which reporting can have positive externalities. Increased arrests may deter offenders from committing future crimes, and if the arrests lead to convictions, they may also decrease the number of sexual crimes further by preventing potential repeat offenders from committing more crimes. Furthermore, even when a report does not lead to an arrest, it may lead to other disciplinary action, for example in a workplace or a university.

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, if the incidence of sexual crimes decreased as a result of the movement, 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.

⁴²We use the difference-in-difference specification to estimate an effect of the MeToo movement for each country separately and compare the actual number of reported sexual crimes with the predicted number of reported sexual crimes if the MeToo movement had not taken place. The calculation for the countries where we have partial police data (the US, the UK, and Australia) is based on the assumption that the MeToo movement had the same effect per-capita on areas for which we obtained data as in other areas in the country.

The findings show that social movements can have large, long-lasting effects on social norms, influencing individuals to make meaningful changes in their personal decisions. This effect may occur almost immediately and can change high stakes individual action.

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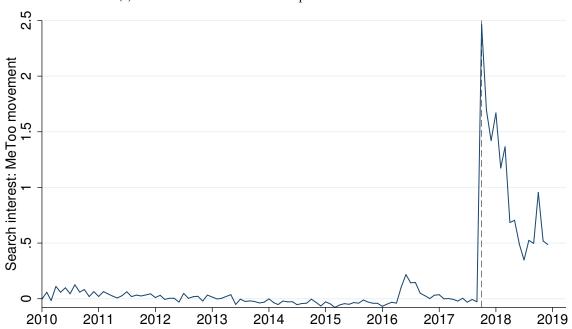
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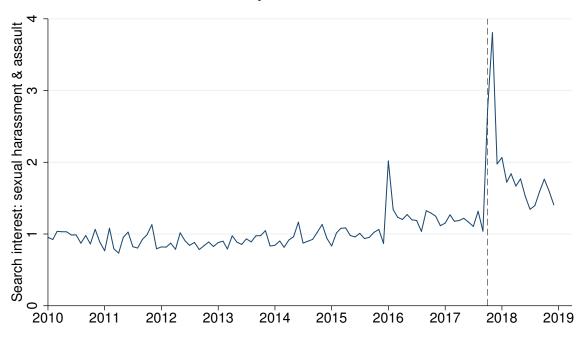
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Figure 1: Google Search Interest in the OECD

(a) OECD Search Interest in the Topic of the MeToo Movement



(b) OECD Search Interest in the Topics of Sexual Harassment and Sexual Assault



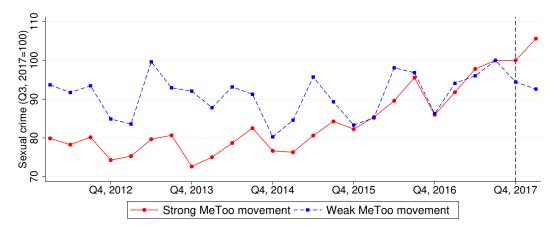
The figures show the monthly time series for the OECD means of both measures of the strength of the MeToo movement from 2010 to 2018. Data is from Google Trends. The vertical dashed line represents the start of the MeToo movement (October 2017). Sub-figure (a) shows search interest in the topic of the 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 variable 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 variable is normalized so that the pre-MeToo mean equals 1 for each country.

Figure 2: Immediate Search Interest in the MeToo Movement

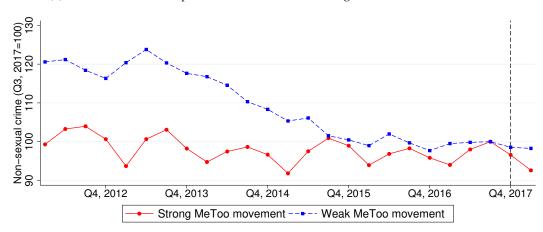
This figure shows the strength of the MeToo movement in OECD countries based on Google Search interest in the topic of the MeToo movement during October 2017. The Weak MeToo group of countries have below-median interest, the Strong MeToo group of countries have above-median interest, and the rest of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

Figure 3: Crimes Reported over Time

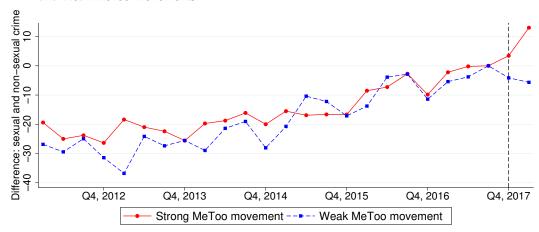
(a) Sexual Crime Reported in Countries with Strong and Weak MeToo Movements



(b) Non-Sexual Crime Reported in Countries with Strong and Weak MeToo Movements

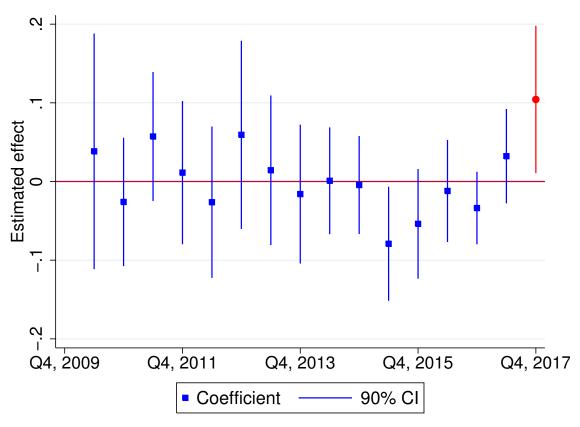


(c) Difference Between Sexual and Non-Sexual Crime Reported in Countries with Strong and Weak MeToo Movements



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 start of the MeToo movement, Q4, 2017. Data include all 30 countries in our sample. For four countries data is available for only part of the period, see Appendix Table A.5 for details.

Figure 4: Placebo Tests, Setting the Start Date of the MeToo Movement in Every Second Quarter from Q2 2010 to Q4 2017



This figure shows the results from 15 placebo triple-difference regressions (Q2 2010-Q2 2017) and our main triple-difference result (Q4 2017, shown in red). Each coefficient comes from a regression using the full Q1 2010 - Q1 2018 dataset, but with a different six-month period for when the placebo MeToo movement happened. The corresponding confidence intervals are constructed using standard errors clustered at the country by crime type level.

Table 1: Effect of the MeToo Movement During the First Six Months in 30 OECD Countries

	ln(crime)			
	(1)	(2)	(3)	(4)
Post * Strong MeToo	0.114**		0.009	0.009
	(0.048)		(0.031)	(0.031)
Post * Sexual crime		0.072**		0.019
		(0.030)		(0.044)
Post * Strong MeToo * Sexual crime			0.123***	0.104*
-			(0.036)	(0.057)
Post * Weak MeToo * Sexual crime			0.019	
			(0.044)	
Country * Crime type * Lin. trend	X	X	X	Х
Country * Crime type * Quarter	X	X	X	X
Post	X	X	X	X
Crime data used	Sexual crimes	All crimes	All crimes	All crimes
Final quarter	Q1 2018	Q1 2018	Q1 2018	Q1 2018
Observations	904	1,808	1,808	1,808
Clusters	30	60	60	60

This table shows the effect of the MeToo movement on sexual crimes reported using data from 30 OECD countries for the period from Q1 2010 to Q1 2018. 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: Persistence of the Effect in Countries with a Strong MeToo Movement

	ln(crime)		
	(1)	(2)	
Post * Sexual crime	0.104***		
	(0.035)		
2017 Q4 * Sexual crime		0.121***	
		(0.033)	
2018 Q1 * Sexual crime		0.122**	
		(0.051)	
2018 Q2 * Sexual crime		0.083**	
		(0.037)	
2018 Q3 * Sexual crime		0.087**	
		(0.037)	
2018 Q4 * Sexual crime		0.108**	
		(0.043)	
Country * Crime type * Lin. trend	X	X	
Country * Crime type * Quarter	Χ	X	
Post	X		
Q4 2017-Q4 2018 FE		X	
Final quarter	Q4 2018	Q4 2018	
Observations	1,012	1,012	
Clusters	30	30	

This table shows the effect of the MeToo movement over time using data from the 15 OECD countries with a strong MeToo movement in October 2017. Standard errors clustered at the country by crime level in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

Table 3: Robustness Checks

(1)	Preferred specification	0.104*
		(0.057)
Leng	gth of short-term period:	
(2)	3 month effect	0.060
		(0.063)
(3)	9 month effect	0.095*
		(0.055)
Diffe	erent measures of MeToo strength:	
(4)	6m MeToo search interest	0.102*
		(0.060)
(5)	SA/SH immediate search interest	0.037
		(0.059)
(6)	% heard of MeToo movement	0.095
		(0.080)
Alte	rnative specifications:	
(7)	Weighted by country population	0.119**
		(0.052)
(8)	Only data based on date crimes were reported	0.119*
		(0.065)
(9)	Outcome variable: Normalized number of crimes	0.112*
		(0.057)
(10)	Negative binomial regression	0.118**
		(0.048)
Alte	rnative empirical strategies:	
(11)	Matrix completion method	0.165***
		(0.03)
(12)	2SLS: Fraction Eng. speakers as IV	0.096
		(0.071)

This table shows robustness checks for our main triple-difference estimate. Row (1) repeats the main estimate from Column (4) of Table 1. Rows (2)-(3) use different periods over which the effect is measured. Rows (4)-(6) use different measures of the strength of the MeToo movement. Row (7) shows the result of our main specification weighted for the countries population. Row (8) only includes data from the 24 countries basing their statistics on the date the crimes were reported to the police. Row (9) uses the normalized number of crimes as the outcome variable. Crimes are normalized to be one on average for each country by crime type group, in the year leading up to the start of the MeToo movement. Row (10) shows the result of a negative binomial regression using the count data of crimes reported as the outcome variable. Row (11) shows the result of using the matrix completion method. Row (12) shows the result of a two-stage least squares regression where having a strong MeToo movement is instrumented for by the fraction of English speakers. All rows except Rows (6) and (8) use data from 30 OECD countries. Row (6) uses data from the 12 OECD countries surveyed in the 2019 YouGov survey. Standard errors clustered at the country by crime level are in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

Table 4: Effect of the MeToo Movement on Sexual Crimes in the US

		ihs(crime)	
	(1)	(2)	(3)
Post * Sexual Assault	0.081*** (0.015)		
Post * Sexual Assault		0.112*** (0.036)	
Post * Sexual Harassment		0.148*** (0.055)	
Post * Sexual Crimes			0.129*** (0.036)
State * Crime Type * Lin. Trend	Χ		
State * Crime Type * Month	Χ		
City * Crime Type * Lin. Trend		Χ	Χ
City * Crime Type * Month		Χ	X
Post	Χ	Χ	X
Data	NIBRS	City	City
Final Month	Mar 2018	Mar 2018	Mar 2018
Observations	6,654	1,863	1,242

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 5: Effect of the MeToo Movement by Relationship and Crime Type

	ihs(c	rime)	
	(1)	(2)	(3)
Post * Fondling	0.111***		
Ü	(0.019)		
Post * Rape	0.093***		
•	(0.017)		
Post * Sodomy	-0.024		
·	(0.031)		
Post * Statutory Rape	0.027		
7	(0.042)		
Post * Sexual Assault, No Injury		0.093***	
		(0.016)	
Post * Sexual Assault, Injury		0.028	
, ,		(0.022)	
Post * Sexual Assault, Knew Offender			0.089**
			(0.016)
Post * Sexual Assault, Stranger			0.104**
Ç			(0.035)
Difference		0.065***	-0.015
State * Crime Type * Lin. Trend	Х	Х	Х
State * Crime Type * Month	X	X	Χ
Post	X	X	X
Final Month	Mar 18	Mar 18	Mar 18
Observations	16,635	9,981	9,981

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. 2010-2018 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 of the MeToo Movement by the Lag Between the Occurrence and Reporting Dates

	(1)	(2)
Post * Sexual Crimes, Lag<=30 Days	0.095**	0.111***
	(0.038)	(0.023)
Post * Sexual Crimes, Lag>30 Days	0.215***	0.135***
, 0	(0.049)	(0.048)
City * Crime Type * Lin. Trend	X	X
City * Crime Type * Month	Χ	X
Post	Χ	Χ
Treatment Dates	Oct 17-Mar 18	Apr 18-Dec 18
Observations	1,842	1,905

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) focuses on the primary main short-term effect and includes data until March 2018 and Column (2) excludes October 2017-March 2018. 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 7: Effect of the MeToo Movement by Victim and Offender Demographics

		ihs(c	rime)	
	(1)	(2)	(3)	(4)
Post * Sexual Assault, Victim Female	0.091***			
	(0.016)			
Post * Sexual Assault, Victim Male	0.033			
	(0.024)			
Post * Sexual Assault, Victim Black		0.077***		
		(0.024)		
Post * Sexual Assault, Victim White		0.082***		
		(0.016)		
Post * Sexual Assault, Offender Female			0.015	
			(0.042)	
Post * Sexual Assault, Offender Male			0.098***	
			(0.016)	
Post * Sexual Assault, Offender Black				0.095***
				(0.022)
Post * Sexual Assault, Offender White				0.092***
				(0.017)
Difference	0.058**	-0.005	-0.083*	0.003
State * Crime Type * Lin. Trend	Χ	Χ	Χ	Χ
State * Crime Type * Month	Χ	Χ	Χ	X
Post	Χ	Χ	Χ	X
Final Month	Mar 18	Mar 18	Mar 18	Mar 18
Observations	9,981	9,981	9,981	9,981

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 of the victim or the offender is unknown are excluded along with crimes with multiple victims or offenders. In Columns (2) and (4), crimes with a single white or black victim or offender are included. 2010-2018 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 8: Effect of the MeToo Movement by County Demographics

Post * Sexual Assault (0.0)	(1)	(2)	(3)	(4)	(5)	(9)	(7
Post * Seviial Assault * Med Income (etd. dev.)	0.088***	0.088***	0.088***	0.088***	0.088***	0.088***	0.088***
		0.013 (0.009)					
Post * Sexual Assault * % College			0.127 (0.098)				
Post * Sexual Assault * % Blacks (Compared to Whites)				0.071 (0.075)			
Post * Sexual Assault * % Other Race (Compared to Whites)					0.557***		
Post * Sexual Assault * % Hispanics						0.309***	
Post * Sexual Assault * % Vote Trump							-0.266*** (0.071)
Interquartile Range of Demographic Diff. in Effect * 75th-25th Pct.		1.207	0.132	0.194	0.054	0.062 0.019	0.265
pue	 ×	× ×	× ×	××	××	××	×
County * Crime Type * Month Post	< ×	< ×	< ×	< ×	< ×	< ×	< ×
* Democraphic	< ×	< ×	×	×	< ×	< ×	×
	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18

This table shows the effect of the MeToo movement based on county-level data and tests for heterogeneous effects by county demographics. 2010-2018 NIBRS data. All regressions are weighted by the number of crimes that occurred in each county 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 9: Effect of the MeToo Movement on Arrests

			ihs(c	ihs(crime)		
	(1)	(2)	(3)	(4)	(5)	(9)
Post* Sexual Assault, No Arrest	0.095***			0.105*** (0.011)		
Post * Sexual Assault, Arrest	-0.008 (0.026)			0.052***		
Post* Sexual Assault		0.014 (0.027)	0.091***		0.071***	0.107*** (0.011)
Difference	0.103***			0.053***		
State * Crime Type * Lin. Trend	×	×	×	×	×	×
State * Crime Type * Month	×	×	×	×	×	×
Post	×	×	×	×	×	×
Final Month	Mar 18	Mar 18	Mar 18	Dec 18	Dec 18	Dec 18
Crimes	All	Arrest	No Arrest	All	Arrest	No Arrest
Observations	9.981	6.654	6.654	10.899	7.266	7.266

This table shows the effect of the MeToo movement on sexual crimes by whether an arrest was made. A case is defined to have an arrest if a suspect is taken into custody based on a warrant or previously submitted report, arrested on view without a warrant or summoned to was made are included and columns (3) and (6) include only crimes where no arrest was made. Columns (1)-(3) focus on the short-run effect court. In Column (1) and (4), the crimes are aggregated to three separate crime categories: sexual crimes where an arrest was made, sexual crimes where no arrest was made, and non-sexual crimes, which are the control group. In Column (2) and (5), only crimes where an arrest and columns (4)-(6) focus on the long-run effect. 2010-2018 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 10: Effect on Crimes that Occurred Before the MeToo Movement Started

	ihs(crime)
Post * Sexual Crimes	0.194**
	(0.077)
City * Crime Type * Lin. Trend	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 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)	
April-May 2018	-0.136*** (0.032)		-0.010 (0.025)		
Women, 2018		-0.047 (0.042)		0.004 (0.034)	
Men, 2018		-0.234*** (0.047)		-0.026 (0.035)	
Respondent FE Observations	X 9,252	X 9,236	X 9,212	X 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 Data Processing

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, crime against children, 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 that 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.

To quality control our international data, we crosschecked our data for the 19 EU countries in our sample with the 2017 Eurostat data on sexual violence. To avoid correlation between the two datasets driven by the population size of the countries, we compared the sexual crimes per population of 100,000. Reassuringly, the correlation in the number of sexual crimes per population of 100,000 is 0.96. The average percentage difference between the numbers in the two datasets is -1% showing that there is

no systematic difference in the level of the numbers and corroborating that the data we collected is in line with EU estimates. Finally, the average absolute percentage difference between the numbers in the two datasets is 24% showing that for most estimates the two numbers are similar in magnitude. The difference could be explained by the fact that we excluded specific sexual crimes that did not seem directly related to the MeToo movement (such as crimes against children) and since we include crimes that can appear outside the sexual assault category, such as stalking.

In Australia, 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 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.5.

The 30 countries in our dataset 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.

For most countries in the data, the quarter that a crime is counted in is based on the date the crime was reported. For four countries, Belgium, Colombia, Germany, and Iceland crimes are counted in the quarter when they occurred. For the UK and US, some of the crimes are counted in the quarter they were reported while other crimes are counted in the quarter they occurred. For Switzerland, the crime is counted in the quarter information about the case was transmitted to the Federal Statistical Office, which for the vast majority of crimes is in the same quarter as the crime is reported to the police. Only one of the countries not providing data based on the date the crimes were reported is a country classified as having a weak MeToo movement. Therefore, the small effect of the MeToo movement in countries with weak movements cannot be explained by the data from these countries being based on the date of occurrence as opposed to the date of reporting.

⁴³In the US, crime data for many agencies is also available through the UCR Summary Report System. We do not use that dataset since the definition for rape has changed in 2013 and agencies are gradually changing their reports based on the new definition. Furthermore, this system only collects data on the most severe crimes and therefore it does not include data on sexual assaults besides rapes.

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 2010-2018.⁴⁴ 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. In October 2017, searches for these phrases has a 0.997 correlation with the MeToo movement topic defined by Google across countries. We prefer to use the search for the MeToo movement topic instead of our list of exact 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 Tables A.1 and 3, 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.

⁴⁴For scraping, we used the R package gtrendsR written by Philippe Massicotte and Dirk Eddelbuettel. The data was scraped on December 18, 2019.

⁴⁵We 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.

A.4 Fraction of English Speakers Data Processing

We use data on the fraction of English speakers from the 23rd edition of the Ethnologue Global Dataset. The data contains estimates for the population using English as their first language, the population using English but for whom English is not a native language and the total population. We divide the population using English as a first language by the population to get the fraction of first-language English users. We take the sum of the population using English as a first language and the population using English as a non-native language and divide it by the total population to get the fraction of the population who uses English.

For five countries (Chile, Colombia, France, Slovenia, and Slovakia) we do not have an estimate for the number of first-language English users. We impute the fraction using Enlish as their first language using the median fraction of first-language English users for the country's region (South America, Western Europe, Southern Europe, and Eastern Europe). For Japan, there is no estimate for the fraction of non-native English users in the Ethnologue data. Instead, we use an estimate of 5% provided in communications with Ethnologue and confirmed in a report from Mitsue-Links.⁴⁶

A.5 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

⁴⁶https://www.mitsue.co.jp/english/global_ux/blog/201709/14_1700.html

material offense and a weapon law violations offense, it will be excluded).

When analyzing state-level data, we exclude state-years where there are months with fewer than 100 crimes reported in total.

A.6 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 that 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 include 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.⁴⁷

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, 2017.⁴⁸

B Additional Analysis

B.1 Allowing for Different MeToo Start Dates in Each Country

In addition to the strategy described in Section 3.4, we also use the variation in the start dates of the movement to estimate the effect of the movement over time. We restrict the sample of countries to countries that at some time before the end of 2018 had a MeToo movement and use the following regression:

$$y_{itc} = \beta_1 MeToo_{ct} \times SexCrime_i + \beta_2 MeToo_{ct} + \beta_{3,ic} Trend_t + \gamma_{i,c,q(t)} + \varepsilon_{itc}$$
(4)

⁴⁷Typically, 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 updates, 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 an incident is associated with crimes that occurred over multiple days, we define the date the incident occurred as NA.

⁴⁸We 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.

where $MeToo_{ct}$ takes a value of one if the MeToo movement in country c started before or in the first month of quarter t and $MeToo_{ct}$ equals one-third or two-thirds if the movement started in the second or third month of quarter t, respectively. The other terms of the equation are defined in the same way as in Equation 1.

We use two different strategies for estimating the start of the MeToo movement in each country. First, we define the start of the movement as the first month when Google search interest in the MeToo topic was higher than the OECD median in October 2017. Under this classification, all the countries that were classified as having had strong MeToo movements in the analysis in Section 3.3 have MeToo movements starting in October 2017, but additional countries have MeToo movements starting after October 2017. Our second criterion is based on search interest for the sexual harassment and sexual assault topics. We classify the start of a MeToo movement as the first month, in or after October 2017, that had the highest search interest for the sexual harassment and sexual assault topics since 2010. Appendix Table A.2 shows the start dates of the MeToo movement for each country according to both criteria. Note that both these specifications have potential reverse causality problems since an increase in sexual crimes reported to the police could affect searches for the topics of the MeToo movement, sexual harassment, and sexual assault. Due to this problem, we see this analysis as supplemental to our main analysis.

Table A.1 shows the results of our analysis using different start dates of the MeToo movement. Columns (1) and (2) use the start date based on searches for the MeToo topic, and Columns (3) and (4) use the start date based on sexual harassment and sexual assault topic searches. Column (1) reports an overall effect of the MeToo movement of 12%. Column (2) splits these estimates by the number of quarters since the start of the MeToo movement and shows that the effect is stable over time with all of the point estimates for each of the quarters since the start of the MeToo movement being between 9% and 13%.⁴⁹ The results of Column (3)-(4) are slightly smaller but qualitatively similar.

B.2 Neighborhood-Level Heterogeneity

In this section, we analyze heterogeneous effect of the MeToo movement by neighborhood demographics in the sample of seven large US cities. 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

⁴⁹In Columns (2) and (4), the dummy variables take the value of either one or zero, regardless of when in a quarter the MeToo movement started.

for most observations. The jurisdictions are detailed in Appendix Table A.3. 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.

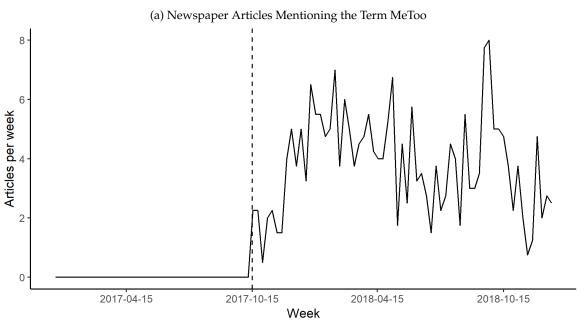
We use the shapefiles for the police boundaries of each city to identify the geographical boundaries of each neighborhood. For most cities, we use the most recent shapefile available. For Seattle, where changes in the shapefiles are clearly defined, we use different shapefiles for different years and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

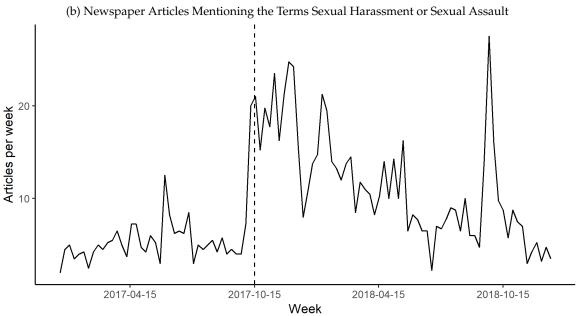
The demographics of each neighborhood are determined by spatially matching the neighborhood with census block groups. We calculate each neighborhood's demographics as the weighted average of the demographic covariates among overlapping block groups, where the weight of each block group is the population 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.

Table A.4 does not find evidence for strong heterogeneity by the neighborhood demographics. While some of the point estimates are consistent with a stronger movement among higher-income and college-educated neighborhoods, the estimated heterogeneity is relatively small. For example, the difference in the expected effect on reporting between a neighborhood in the 75th percentile of the share of individuals with a college education and a neighborhood in the 25th percentile is only expected to be 3 percentage points, compared to the average effect of 13%. Similarly, the difference between neighborhoods in the 75% and 25% percentile in the median income, the share of blacks, the share of Asians and other races, and the share of Hispanics, is 5, 2, 1, and -5 percentage points, respectively.

C Additional Figures and Tables

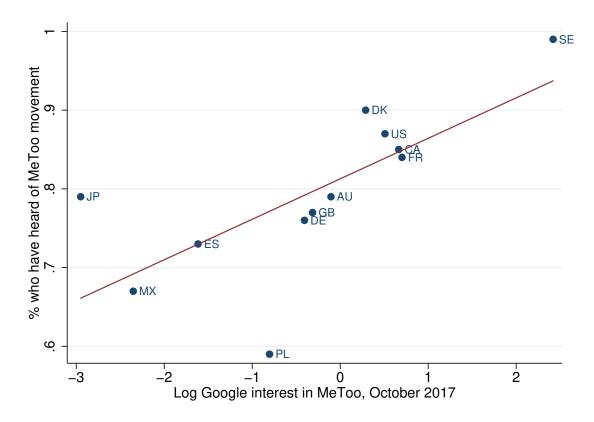
Figure A.1: Newspaper Coverage





The first sub-figure shows the weekly average number of articles mentioning the term "metoo" in the newspapers USA Today, New York Post, Denver Post, and Chicago Sun-Times. The second sub-figure presents the weekly average number of articles mentioning the terms "sexual assault" or "sexual harassment" (articles mentioning both terms are counted twice). The vertical dashed line represents the start of the MeToo movement (October 2017). The newspapers were chosen based on circulation and data availability. The number of articles is determined using the website newslibrary.com.

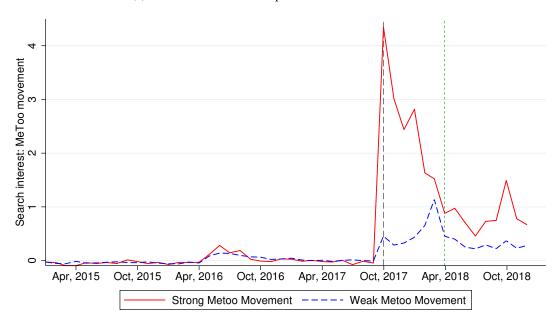
Figure A.2: Relationship Between Google Search Interest and Knowledge about the MeToo Movement



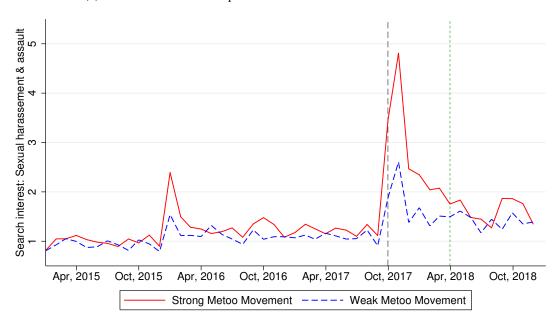
This figure shows the relationships between the log of Google search interest for terms related to the MeToo movement in October 2017 and the fraction of respondents who had heard about the MeToo movement in a YouGov survey conducted in February-March 2019 (YouGov, 2019).

Figure A.3: Search Interest by the Strength of the MeToo Movement

(a) Search Interest in the Topic of the MeToo Movement

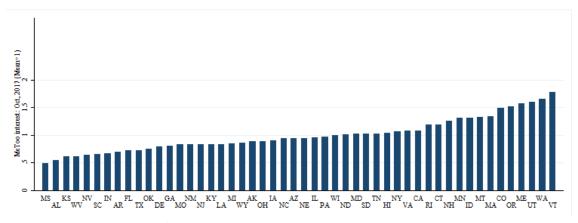


(b) Search interest in the Topics of Sexual Harassment and Sexual Assault



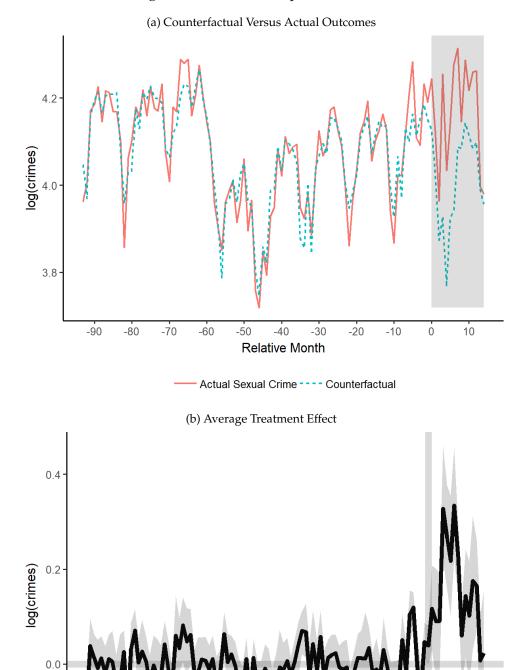
The figures show monthly search interest for OECD countries with strong and weak MeToo movements. Countries are classified as weak or strong by search interest in the MeToo topic in October 2017. Data is from Google Trends. The first vertical line represents the start of the MeToo movement, the second vertical line represents the end of the six month period we use to measure short-term effects. 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 A.4: 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.

Figure A.5: Matrix Completion Results



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.

-40

Relative Month

-30

-20

-10

10

2

-50

-0.2

-90

-80

-70

-60

Table A.1: Effect of the MeToo Movement, Using Different MeToo Start Dates

		ln(cri	ime)	
	(1)	(2)	(3)	(4)
Post MeToo start * Sexual Crime	0.094**		0.081**	
	(0.035)		(0.030)	
Quarter of MeToo start * Sexual Crime		0.080*		0.057*
		(0.045)		(0.029)
1Q after MeToo start * Sexual Crime		0.107**		0.056
		(0.049)		(0.045)
2Q after MeToo start * Sexual Crime		0.103**		0.045
		(0.041)		(0.043)
3Q after MeToo start * Sexual Crime		0.081**		0.108***
		(0.037)		(0.030)
4Q after MeToo start * Sexual Crime		0.092**		0.133***
		(0.044)		(0.039)
Country * Crime type * Lin. trend	X	X	Χ	X
Country * Crime type * Quarter	X	X	X	X
Post MeToo start	X		X	
Quarters since MeToo start FE		X		X
Final quarter	Q4 2018	Q4 2018	Q4 2018	Q4 2018
Sample	MeToo only	MeToo only	MeToo only	MeToo only
Observations	1,204	1,204	1,300	1,300
Clusters	36	36	40	40
MeToo start indicator	MeToo sea	rch interest	SH/SA sear	rch interest

This table shows the effect of the MeToo movement using different start dates of the MeToo movement in each country. In Columns (1) and (2) a start of the MeToo movement is the first month when searches for the MeToo movement topic was higher than the OECD median for October 2017. In Columns (3) and (4) a start of the MeToo movement is the first month, from October 2017 onward, when searches for the sexual harassment and sexual assault topics were the highest since 2010 in that country. Data from 30 OECD countries from 2010 to 2018. Standard errors clustered at the country by crime level in parenthesis. ***p<0.01, **p<0.05, *p<0.1.

Table A.2: MeToo Movement Start Date by Country

Country	Start date using search interest in	Start date using search interest in sexual	
	MeToo topic	harassment and sexual assault topics	
Australia	October 2017	November 2017	
Belgium	October 2017	October 2017 No strong MeToo movement	
Canada	October 2017	October 2017 October, 2017	
Chile	No strong MeToo movement	November 2017	
Colombia	No strong MeToo movement	April 2018	
Czech republic	November 2017	November 2017 No strong MeToo movement	
Denmark	October 2017	October 2017 October 2017	
Estonia	No strong MeToo movement		
Finland	October 2017	ctober 2017 October 2017	
France	October 2017	October 2017 October 2017	
Greece	No strong MeToo movement	<u> </u>	
Germany	October 2017	No strong MeToo movement	
Iceland	October 2017 No strong MeToo movement		
Ireland			
Israel	No strong MeToo movement	November 2017	
Japan	No strong MeToo movement	April 2018	
Korea	February 2018	•	
Lithuania	March 2018		
Mexico	No strong MeToo movement	November 2017	
Netherlands	October 2017	l 0	
New Zealand	October 2017 October 2017		
Poland			
Portugal	No strong MeToo movement	October 2017	
Slovakia	No strong MeToo movement	No strong MeToo movement	
Slovenia	No strong MeToo movement	December 2018	
Switzerland	O		
Spain	No strong MeToo movement November 2017		
Sweden	October 2017	October 2017	
United	October 2017	October 2017	
Kingdom			
United States	October 2017	October 2017	

Table A.3: Definition of the Neighborhood Used 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

Table A.4: Effect of the MeToo Movement by Neighborhood

			ihs(c	ihs(crime)		
	(1)	(2)	(3)	(4)	(5)	(9)
Post * Sexual Crimes	0.128***	0.135***	0.128***	0.129***	0.129***	0.128***
Post * Sexual Crimes * Med. Income (std. dev.)		0.045**				
Post * Sexual Crimes * % College			0.147			
Post * Sexual Crimes * % Blacks (Compared to Whites)				0.064 (0.093)		
Post * Sexual Crimes * % Other Race (Compared to Whites)					0.042 (0.132)	
Post * Sexual Crimes * % Hispanics						-0.148^{*} (0.087)
Interquartile Range of Demographic Diff. in Effect * 75th-25th Pct.		1.123	0.235	0.295	0.275	0.368
Neighborhood * Crime Type * Lin. Trend	×	×	×	×	×	×
Neighborhood * Crime Type * Month	×	×	×	×	×	×
Post	×	×	×	×	×	×
Post * Democraphic	×	×	×	×	×	×
Final Month	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18
Observations	25,056	25,056	25,056	25,056	25,056	25,056

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 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	2010-2018	88%
	and Research, Queensland Police, Crime		
	Statistics Agency of Victoria, and Western Australia Police		
Belgium	Federale politie	2010-2018	100%
Canada	Canadian Centre for Justice Statistics	2010-2018	100%
Chile	Policía de Investigaciones	2010-2018	100%
Colombia	Policía Nacional	2010-2018	100%
Czech republic	Policie České republiky	2010-2018	100%
Denmark	Danmarks Statistik	2010-2018	100%
Estonia	Politsei- ja Piirivalveamet	2010-2018	100%
Finland	Tilastokeskuksen	2010-2018	100%
France	Ministère de l'Intérieur	2010-2018	100%
Germany	Bundeskriminalamt	2012-2018	100%
Greece	Hellenic Statistical Authority (ELSTAT)	2010-2018	100%
Iceland	Ríkislögreglustjóri	2010-2018	100%
Ireland	Central Statistics Office	2010-2018	100%
Israel	Central Bureau of Statistics	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%
New Zealand	New Zealand Police	Q3 2014-2018	100%
Poland	Wydział ds. Parlamentarnych i Informacji Publicznej	2010-2018	100%
Portugal	Instituto Nacional de Estatística	2010-2018	100%
Slovakia	Statisticky Urad	2010-2018	100%
Slovenia	Statistični Urad	2010-2018	100%
Switzerland	Bundesamt für Statistik	2010-2018	100%
Spain	Ministerio del Interior	2010-2018	100%
Sweden	Brottsförebyggande rådet	2010-2018	100%
United	Home Office: Crime and Policing Analysis	2010-2018	92%
Kingdom	Unit and Open Data Northern Ireland		
United States	Federal Bureau of Investigation	2010-2018	30%

Table A.6: Effect of the MeToo Movement in the US with Crime Aggregated by Offense Types

		ihs(crime)	
	(1)	(2)	(3)
Post * Sexual Assault	0.081*** (0.015)		
Post * Sexual Assault		0.096***	0.096***
		(0.018)	(0.027)
State * Crime Type * Lin. Trend	Χ	X	Χ
State * Crime Type * Month	X	X	X
Post	X	X	X
Agg Crimes	Sexual/Other	NIBRS Categories	NIBRS Categories
S.E	Robust	Cluster by	Cluster by
		Crime Type	Crime*State
Num of Clusters		21	735
Final Month	Mar 18	Mar 18	Mar 18
Observations	6,654	69,867	69,867

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. 2010-2018 NIBRS data. ***p<0.01; **p<0.05; *p<0.1.

Table A.7: Effect of the MeToo Movement by City

				ihs(crime)	me)		
	(1)	(2)	(3)	(4)	(5)	(9)	(2)
Post * Sexual Crimes	0.144^{***}	0.085***	0.189**	0.083	0.401	-0.074	0.093
	(0.041)	(0.032)	(0.074)	(0.075)	(0.307)	(0.082)	(0.065)
Crime Type * Time	×	×	×	×	×	×	×
Crime Type * Month	×	×	×	×	×	×	×
Post	×	×	×	×	×	×	×
Final Month	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18
City	NYC	LA	Seattle	Denver	Nashville	Louisville	Kansas City
Observations	198	198	198	126	126	198	198

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.8: Persistence of the Effect in the US

			ihs(crim	e)	
	(1)	(2)	(3)	(4)	(5)
Post * Sexual Crimes	0.100***		0.125***		
	(0.011)		(0.021)		
2017 Q4 * Sexual Crimes		0.070***		0.125^{***}	0.113***
		(0.017)		(0.033)	(0.039)
2018 Q1 * Sexual Crimes		0.093***		0.136**	0.081
		(0.020)		(0.065)	(0.067)
2018 Q2 * Sexual Crimes		0.101***		0.107***	0.090**
		(0.018)		(0.038)	(0.037)
2018 Q3 * Sexual Crimes		0.106^{***}		0.138^{***}	0.136***
		(0.020)		(0.035)	(0.035)
2018 Q4 * Sexual Crimes		0.137***		0.115***	0.102**
		(0.026)		(0.038)	(0.041)
Location * Crime Type * Lin. Trend	X	X	X	X	Χ
Location * Crime Type * Month	X	Χ	X	Χ	X
Post	Χ	Χ	Χ	Χ	X
Data	NIBRS	NIBRS	Cities	Cities	Cities
Crimes	All	All	All	All	Reported
					Within 1 M
Observations	7,266	7,266	1,368	1,368	1,361

This table shows the effect of the MeToo movement on sexual crimes by quarter. Data is aggregated at the monthly state/city by crime category level. Columns (1) and (2) are based on 2010-2018 NIBRS data. Columns (3)-(5) are based on the sample of US cities. Columns (1) and (3) report the long-run effects until December 2018. Columns (2), (4), (5) report the effect by quarter. Column (5) includes only crimes that were reported within 30 days of their occurrence. Regressions are weighted by the number of crimes that occurred in each city before the MeToo movement started. Robust standard error in parenthesis. ***p<0.01; **p<0.05; *p<0.1

Table A.9: Effect of the MeToo Movement on Clearance

			ihs(cr	ihs(crime)		
	(1)	(2)	(3)	(4)	(5)	(9)
Post * Sexual Assault, Not Cleared	0.106***			0.112*** (0.011)		
Post * Sexual Assault, Cleared	0.011 (0.024)			0.065***		
Post * Sexual Assault		0.025 (0.025)	0.103*** (0.017)		0.068***	0.115***
Difference	0.096***			0.047***		
State * Crime Type * Lin. Trend	×	×	×	×	×	×
State * Crime Type * Month	×	×	×	×	×	×
Post	×	×	×	×	×	×
Final Month	Mar 18	Mar 18	Mar 18	Dec 18	Dec 18	Dec 18
Crimes	All	Cleared	Not Cleared	All	Cleared	Not Cleared
Observations	9,981	6,654	6,654	10,899	7,266	7,266

or if the police have sufficient probable cause to arrest a suspect but could not make an arrest for reasons outside their control including the to three separate crime categories: Sexual crimes that were cleared, sexual crimes that were not cleared, and non-sexual crimes, which are that were not cleared. Columns (1)-(3) focus on the short-run effect and columns (4)-(6) focus on the long-run effect. 2010-2018 NIBRS data. Regressions are weighted by the number of crimes that occurred in each state before the MeToo movement started. Robust standard errors in This table shows the effect of the MeToo movement on sexual crimes by whether a case was cleared. A case is cleared if it has an arrest (a the offender being in the custody of another jurisdiction, and the offender being a juvenile. In Column (1) and (4), the crimes are aggregated control group. In Columns (2) and (5), only crimes where the case was cleared are included and columns (3) and (6) include only crimes suspect is taken into custody based on a warrant or previously submitted report, arrested on view without a warrant or summoned to court), victim refusing to cooperate, the death of the offender, the prosecutor declining prosecution for a reason other than lack of probable cause, oarenthesis. ***p<0.01; **p<0.05; *p<0.1

Table A.10: Effect of Crime Covariates on Changes in the Sexual Assault Arrest Rate

	(1)	(2)	(3)				(7)	(8)	(6)
Post	-0.008*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)	*	*	*	* *	-0.008*** (0.002)	-0.007*** (0.002)
Agency		×							×
Injury			×						×
Location				×					×
Relationship					×				×
Type						×			×
Weapon							×		×
Victim								×	×
Cal Month	×	×	×	×	×	×	×	×	×
Trend	×	×	×	×	×	×	×	×	×
Final Month	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18	Mar 18
Observations	625,172	625,172	625,172	625,172	625,172	625,172	625,172	625,172	625,172

All columns control for a linear trend and calendar fixed effects. Column (1) shows that the arrest rate for sexual assault decreased in the post-period. Column (2)-(9) control for additional covariates. Column (2) control for agency fixed effects. Column (3) controls for whether the incidence results in an injury. Column (4) controls for the location type (residence, outside residence, unknown or multiple locations). Column (5) controls for the relationship between the victim and the offender (offender known to the victim, the offender is a stranger, unknown This table shows the association between the post-period and arrests related to sexual assault when controlling for incident details. Each observation is a sexual assault crime reported between Jan 2010 and March 2018 and the outcome is whether the report resulted in an arrest. relationship or missing data). Column (7) controls for the type of sexual assault and whether the incident is associated with multiple offenses. Column (8) controls for the victim's race, sex, and age group. Column (9) controls for all the covariates. Robust standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.1