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Public work and private violence

Anders Kjelsrud & Kristin Vikan Sjurgard

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Public work and private violence

Anders Kjelsrud*and Kristin Vikan Sjurgard†

September 10, 2020

Abstract

Violence against women is persisting in many parts of the world. At the same time, there is a global trend of increased female labour force participation. In this paper we study the effect on intimate partner violence of a large public work program in India that explicitly encourages female participation (MGNREGA). Based on detailed administrative data, we show that the work program leads to more violence against women. We argue that the effect could be explained by a "male backlash" mechanism, where husbands exercise violence to regain power within marriage.

Key words: intimate partner violence, female employment, public work
JEL-codes: D19, J12, J16

*Department of Economics, University of Oslo, and Statistics Norway
†Department of Economics, University of Oslo
Corresponding author: Anders Kjelsrud, Department of Economics, University of Oslo, P.box 1095 Blindern, 0317 Oslo, Norway, E-mail: a.g.kjelsrud@econ.uio.no.
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1 Introduction

Violence against women and girls is a worldwide problem. In itself, violence is a stark human rights violation, but it also entails huge negative externalities in the form of preventing females from fully participating in society. Fearon and Hoeffler (2014) calculate that the cost of intimate partner violence is as high as 5 percent of GDP globally. The regional costs in much of Sub-Saharan Africa and South-Asia are likely to be much higher. Fortunately, eliminating violence against women is increasingly being recognised as an important development goal (UN, 2015), and we are gradually learning more about the factors triggering and preventing violence.

In this paper we study the effects on intimate partner violence of a large public work program in India, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). The work program guarantees all rural households 100 days of paid work each year, and it explicitly encourages female participation. Nearly half of total workdays are employed by females (Dasgupta and Sudarshan, 2011; Ravi and Engler, 2015), in sharp contrast to the otherwise low female labour market participation in India (Klasen and Pieters, 2015).

A priori, it is unclear what effect such a work program would have on domestic violence. On the one hand, MGNREGA provides a safety net of jobs, which could reduce violence caused by economic stress. On the other hand, it raises female employment in a way that could threaten established patriarchal norms, leading to more violence. The small empirical literature on MGNREGA and intimate partner violence is also inconclusive. Amaral *et al.* (2015) finds that the program leads to more violence against women, while Sarma (2019) documents that it dampens the effect of adverse rainfall shocks on violence.[1] Both papers are based on district-level MGNREGA data and police reported crimes. Our empirical analysis differs in two important ways. First, we make

[1]Field *et al.* (2019) study the effects on empowerment and domestic violence of depositing wages from MGNREGA directly into females' bank account.

use of finer geographical data on MGNREGA implementation, and second, we use survey data on domestic violence as opposed to data on reported crimes. This is an important advantage, as reported crimes are likely to be severally underreported. As an example, Palermo *et al.* (2014) explore more than 20 DHS surveys and show that only 7 per cent of females that reported abuse in the surveys had reported it to a formal source.

Our data on domestic violence is taken from the National Family and Health Survey (NFHS) from 2015-2016. This data includes GPS coordinates of survey clusters, which enable us to merge in administrative data on MGNREGA at the level of *blocks*—the second lowest administrative unit in India.[2] The NFHS asks every woman who reports an experience with violence *when* the first violent episode happened. We use this information to construct a time-series of violence onsets and use this as our main outcome variable (see Cools *et al.*, 2020). In the paper, we are thus studying whether MGNREGA affects the likelihood of husbands crossing the line and becoming violent towards their wives. That is, violence on the extensive margin.

We identify this effect using time-variation in the number of workers *within blocks* during the time period 2012 to 2015. The main threat to this approach is time-varying shocks at the block level, correlated with MGNREGA prevalence. One example could be negative income shocks that increase the demand for public work, and at the same time, cause more violence due to economic stress. Our key argument is that such shocks do not directly translate into more jobs. Extensive research show that implementation of the work program often is hindered by a number of hold-ups, and that the supply of jobs crucially depends on the will of local politicians and bureaucrats (Dutta *et al.*, 2014; Khosla, 2011; Maiorano, 2014). We therefore find it plausible that local year-to-year variation in MGNREGA is quasi-exogenous to factors determining the prevalence of intimate partner violence.

[2]We use the Census of India as an intermediator when doing this merge. The NFHS displaces the survey clusters by up to 5 kilometres to assure anonymity. Because of this, we do not merge our data on finer geographical levels than blocks.

We use night-time light to test whether our data is consistent with this. We first document a strong and negative relationship between economic activity (as measured by night-time light) and the number of job card applications. This is as expected, given that the demand for the relatively low-paid MGNREGA jobs is likely to be lower in economic upturns, and vice versa. We then test whether we find a similar relationship with the actual number of jobs provided. We do not. That is reassuring for our identification, as it suggests that local prevalence of the work program is driven by supply rather than demand.

Our main result is that MGNREGA leads to more intimate partner violence against women. In our preferred specification, we find that a 10 percent increase in the number of jobs raises the probability of violence by nearly 2 percent of the baseline. This result is robust to the inclusion of various time trends and time-varying controls, such as the amount of night-time light. Remember that our outcome variable captures onset of violence, but fails to capture the intensity of violence as well as the likelihood of repeated violence within a marriage. Thus, our estimated effect could in many ways be interpreted as a lower bound on the total effect.

Our paper is related to the rapidly growing literature on intimate partner violence and female labour market participation.[3] Theories point in both directions. In household bargaining models, improved labour market conditions for females relative to men typically raises their bargaining power by improving the outside option of marriage. This could reduce violence as the threat of divorce becomes more credible (Farmer and Tiefenthaler, 1997). However, in patriarchal societies like much of rural India, the threat of divorce is practically non-existent (Bhalotra *et al.*, 2018; Doyle and Aizer, 2018; Bulte and Lensink, 2019). Increased employment could in such circumstances lead to more, not less, violence. Consistent with the findings in our paper, Bhalotra *et al.* (2018) document a positive relationship between intimate partner violence and favourable labour market conditions for females, using a sample of 31

[3]See Kotsadam and Villanger (2020) for a nice overview of this literature.

low and middle income countries. Guarnieri and Rainer (2018) similarly find a positive relationship between female employment and intimate partner violence in Sub-Saharan Africa.

One hypothesis for why we see such patterns is that paid work empowers females and that husbands exercise violence to regain power within the marriage and to grab the extra resources (Eswaran and Malhotra, 2011; Krug *et al.*, 2002; Heath, 2014). Female employment could also lead to psychological stress by threatening male identity and causing status inconsistencies (Akerlof and Kranton, 2000; Bertrand *et al.*, 2015). This is argued to be especially likely if the man's breadwinner status is challenged (Hornung *et al.*, 1981; Jewkes, 2002; Macmillan and Gartner, 1999; Atkinson *et al.*, 2005; Angelucci, 2008).

Our findings are consistent with such a "male backlash" mechanism. First, we show that our estimated effect is driven by the number of female workers. In fact, when we condition on female employment we find a negative (but slightly insignificant) relationship between the number of male workers and violence. Second, we investigate heterogeneity of our estimates and show that the effect on violence only applies for areas with a low level of female labour force participation. We interpret these as areas with strong patriarchal norms against female employment (see also Vyas and Watts, 2009). This result is consistent with the findings of Heise and Kotsadam (2015), who find a stronger relationship between violence and female employment in countries where few women are working, and Tur-Prats (2017), who uses Spanish data to show that relatively better labour market conditions for females lead to more intimate partner violence, but only in areas with deep-rooted norms agains female employment.

The rest of the paper is organised as follows. In Section 2 we describe the relevant features of MGNREGA. In Section 3 we present our data and key variables, and in Section 4 we discuss our empirical approach. We present our findings in Section 5 and provide some concluding remarks in Section 6.

2 The Mahatma Gandhi National Rural Employment Guarantee Act

The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) of 2005 is a right-to-work act that legally guarantees all rural households in India 100 days of paid work, each year. The program was rolled out from 2006, and by 2008 it covered all parts of rural India. Typical work consists of manual tasks without particular skill requirements, such as water conservation, land development, and rural sanitation. To get employment through MGNREGA, households apply to the Gram Panchayats (the village council, India's lowest administrative unit), who verify the applications and hand out job cards to all eligible households. Job cards are valid for five years, and work seekers can submit a work application when needed. If work is not provided within 15 days, they are entitled to an unemployment allowance. The whole process, from applying for a job card to being employed, should not take more than one month.

MGNREGA has a strong gender dimension. Women are explicitly encouraged to partake, and nearly half of the allocated workdays are employed by women (Dasgupta and Sudarshan, 2011; Ravi and Engler, 2015). This is quite an achievement, given the otherwise low female labour force participation in India. Part of the high participation rate is assured through a one-third gender quota, but the work program also has some other features that are likely to be important, such as equal wages and short commute distances. Employment is provided within the block of residence, and if workers have to travel more than five kilometres from home they are entitled to a ten percent wage increase. There is, however, large variations in the proportion of female employees between states (Ehmke, 2016; Ravi and Engler, 2015), and where there is rationing of work, there also tend to be a lower share of women working (Dutta *et al.*, 2014).

MGNREGA builds on a principle of self-selection: every rural household that would like to work is legally entitled to do so. In practice, there is however a considerable unmet demand for employment (Dutta *et al.*, 2014; Maiorano, 2014; Ministry of Rural Development, Government of India, 2012). The supply of jobs varies greatly, even within small geographical areas, making supply of jobs an important determinant for who is employed (Gulzar and Pasquale, 2017). An estimated 19 percent of all households failed to get work in MGNREGA in 2009-2010, and many employees work less than desired, and less than the guaranteed 100 days (Imbert and Papp, 2015).

Some of the reason for this is that implementation depends on a rather complex structure of politicians and bureaucrats, spread over five levels of administration. MGNREGA is centrally funded, but administered at the village and block level. The Gram Panchayats monitor on-going projects and suggest plans for new ones. The block-level administrations have to approve these plans, and more generally, make sure that the supply of jobs matches demand within Gram Panchayats in the given block. On paper, politicians should play little or no role in the implementation. In reality, state-level politicians (MLAs) have both incentives and opportunity to influence the program implementation (Gulzar and Pasquale, 2017). Previous studies show that MLAs put pressure on local field officers to target certain blocks (Maiorano, 2014), and that they are able to manipulate the selection of works (Aiyar and Samji, 2009). There are also some evidence suggesting that Members of Parliament (MPs) are engaged in the local program implementation (Gupta and Mukhopadhyay, 2016; Kjelsrud *et al.*, 2020). In the end, the actual supply of jobs therefore depend on a combination of political will and administrative capacity.

3 Data and key variables

In this section we describe our data sources and how we construct our key variables.

3.1 Intimate partner violence

Our main data source is the National Family and Health Survey (NFHS) from 2015-2016. The survey was conducted on a sample of about 700,000 female respondents, all of them 15-49 years of age. A little more than 9 percent of these respondents were selected to the domestic violence module, which includes questions on the experiences of physical and sexual violence. Domestic violence is clearly a sensitive interview topic with a risk of underreporting. The NFHS interviewers are therefore trained to handle sensitive information and the guidelines for the module stress the absolute need for privacy and discretion. The data is collected using a modified version of the so-called Conflict Tactics Scale, which is found to be an advantageous method of recording domestic violence in surveys (Kishor, 2005).

The Conflict Tactics Scale is based on asking about different scenarios of violence, rather than a single yes/no question. Females are then considered to have experienced violence if they affirm to either one of the scenarios. The NFHS uses scenarios related to the following violent actions: i) *pushing*, ii) *twisting of an arm or pulling hair*, iii) *slapping*, iv) *punch with a fist or something that could hurt*, v) *kicking or dragging*, vi) *choking or burning*, vii) *attacking with a knife, gun or other weapon*, viii) *physically forced sexual intercourse*, ix) *physically forced other sexual acts* and x) *forced sexual acts through other threats.* About 31 percent of the female respondents state an experience with violence, using the above definition.

For women having experienced violence, the NFHS also asks *when* the first violent episode happened, in years after marriage. Since the survey includes information on date of marriage, we are able to construct a panel of women's first violent episode. We merge this panel with several other data sources, which are summarised in Table 1. The next subsection describes how we create the additional dataset.

Table 1: Overview of data sources

Variable	Source	Year	Level
• Intimate partner violence	NFHS	2015-2016	Individual
• Area characteristics and maps	Census of India	2001 and 2011	Block
• MGNREGA	MGNREGA Public Data Portal	2011-2012 to 2014-2015	Block
• Night-time light	Shrug/DMSP-OLS	2012-2013	Block
• Female labour force participation	Economic Census NSS Employment-Unemployment	2013 2011-2012	Block District
• Average expenditure and poverty	NSS Consumer expenditure	2011-2012	District
• GDP	Planning Commission	2011-2012 to 2014-2015	State

3.2 Creating a block-level dataset

The NFHS includes GPS coordinates of survey clusters that roughly corresponds to Gram Panchayats. The geocodes enable us to merge in other data using the Census of India as the link between the different sources.

The rural clusters in the NFHS are randomly displaced with up to 5 kilometres.[4] Because of this we aggregate all other data to Indian blocks. Note that we still risk that some of the NFHS clusters end up in wrong blocks due to the displacement. However, as the displacement is at random it should not introduce any particular bias in our estimation.

Census of India

We first combine the NFHS coordinates with a map over all 2001 Census villages from the InfoMap. From this we obtain 2001 village identifiers. We then link village codes to Census villages as of 2011 using the official correspondence

[4]In addition, a randomly selected 1 percent of the rural clusters are displaced by up to ten kilometres.

table. From this we obtain block identifiers as of 2011, which we use to merge in the other data.

In addition to serving as a link, the Census also provides useful information for our analysis. In particular, we extract data on village-level demographics and availability of public goods.

MGNREGA employment

We collect data on MGNREGA from the MGNREGA Public Data Portal. The data source has information on employment at the block level for the financial year 2011-2012 and onwards. We make use of data for the years 2011-2012 to 2014-2015, and extract the following information: the number of MGNREGA workers, the number of days worked by gender and the number of job card applications.[5]

The data includes names of blocks but does not have Census identification numbers. We therefore match the MGNREGA data with the Census based on block names and a combination of fuzzy matching and manual checking. In total, we are able to match more than 92 percent of the MGNREGA blocks to the Census (see Asher and Novosad, 2017; Gulzar and Pasquale, 2017; Kjelsrud *et al.*, 2020, for similar type of matching in the Indian context).

Night-time light

We get data on night-time light from the Shrug open data platform (Asher *et al.*, 2019). The light data in Shrug is aggregated to Indian villages based on the DMSP-OLS annual measures of night time luminosity, measured at 1/120 degree. We aggregate the data further to Indian blocks.

The DMSP-OLS light data spans the years 1994 to 2013, which is two years short of our study period. To deal with this, we linearly extrapolate the data to the years 2014 and 2015. Our light variable is therefore a trend-measure of

[5] Most of our other data are for calendar years. We match the financial year of 2011-2012 to the calendar year 2012, and so forth.

the amount of light at the block level.

Female labour force participation

We make use of two different data sources to derive estimates of female labour force participation.

The first source is the Economic Census of 2013, which provides a full enumerations of all non-farm establishments, including informal firms, service sector firms, and publicly-owned firms. It also includes information on the number of male and female workers. We use this to construct a measure of female labour force participation as the total number of female workers by blocks, divided by the total number of females (taken from the Indian Census).[6]

The second source is the Employment-Unemployment survey from 2011-2012, collected by the National Sample Survey (NSS). The NSS is a national representative household survey, usually collected every fifth year. The survey enables us to create a broader measure of labour force participation that also includes casual workers, self-employed and unemployed. We focus on married women in the age group 20 to 60 years, and rely on self-reported "principal activity", which refers to the status during the last year (Klasen and Pieters, 2015). The disadvantage with the NSS is that it does not provide GPS coordinates. The finest geographical identifier is districts. We therefore harmonise the district codes with the Census and merge the data to our other sources based on this.

Average consumer expenditure and poverty

The NSS consumer expenditure survey provides detailed information on household consumption and is the standard source to measure expenditure and poverty in India. We make use of the 2011-2012 survey to calculate district-level average per capita consumption and poverty. We measure poverty based

[6]We use the matching keys provided in the Shrug database (Asher *et al.*, 2019) to merge the Economic Census to the Census of India 2011.

on a simple headcount ratio and the official poverty lines that vary by Indian states (Government of India, 2013).

GDP by Indian states

Finally, we collect data on per capita net state domestic product for the financial years 2011-2012 to 2014-2015, from the Indian Planning Commission.

3.3 Sample restrictions and summary statistics

We apply several sample restrictions. Most importantly, we focus on women being no more than in their fifth year of marriage at the time of survey. There are two main reasons for this restriction.

First, the MGNREGA employment data spans the years 2012 to 2015 and the nature of the "first episode" variable implies that females enter the sample at the time of marriage and exit if they experience violence. This means that all females experiencing violence before 2012 are excluded from the sample. In Figure 1 we show a hazard plot, calculated as the number of females experiencing violence for the first time in a given marriage year, divided by the total number of females in the same marriage year without any earlier experience with violence. The figure shows that violence usually starts the first few years after marriage, and that it almost never starts more than ten years after marriage. The females that married many years ago, and that could have entered our estimation sample, would thus represent a very selected group of females from non-violent relationships.

Second, we are worried that women being married for a long time would forget episodes from early in the marriage and therefore misreport the timing of the first violent episode (see Cools *et al.*, 2020). The hazard rates in the figure support this suspicion, as women above their fifth marriage year tend to heap their reporting on 5, 10, 15, 20 and 25 years since marriage.

In addition to this, we remove women with inconsistent answers on the first violent episode and those stating that violence started before marriage. We also remove visitors and females that have moved to a new location after the first violent episode.

In total, our estimation sample consists of 11,482 marriage-years at risk, based on 4,834 married women from 2,257 blocks in 28 Indian states. In Table 2 we provide some key statistics from this estimation sample. The average number of MGNREGA workers fell steadily during our study period. In contrast, the number of job card applications was more or less stable—suggesting an increasing unmet demand for MGNREGA jobs. The female ratio, measured as the number of days worked by females over total numbers of days worked, rose somewhat from 2012 to 2015.

FIGURE 1: Risk of first violence, by years in marriage

The hazard rates show the number of women who experience violence for the first time in a given marriage year, divided by the number of women at risk that marriage year.

TABLE 2: Summary statistics, MGNREGA

	2012	2013	2014	2015
Log workers	9.122	9.048	8.957	8.659
Log card applications	9.857	9.831	9.783	9.738
Female ratio	0.384	0.387	0.406	0.418

4 Empirical framework

In this section we describe the empirical framework.

4.1 Baseline specification

Our empirical investigation is based on within-block variation in the number of MGNREGA jobs over time. We run the following baseline specification:

$$IPV_{ibt} = \beta_0 + \beta_1 \log MGNREGA_{bt} + \alpha_t t + \alpha_b + \alpha_m + \alpha_a + X'_{ib} + \epsilon_{ibt}, \quad (1)$$

where IPV_{ibt} denotes whether woman i from block b experienced intimate partner violence for the first time in year t. α_t is a common time trend, α_m denotes years-since-marriage fixed effects, while α_a denotes age-group fixed effects. X'_{ib} is a set of time-invariant individual characteristics (dummy variables for Hindu, Muslim, Christian and Buddhist). We use the number of workers as our main measure of local MGNREGA prevalence.[7] Our main coefficient of interest is β_1, which captures the relationship between the prevalence of MGNREGA and the likelihood of experiencing violence for the first time in a particular year.

Could we interpret this relationship casually? MGNREGA is a public work program built on the principle of self-selection. One might therefore worry that program participants are different than non-participants, also in their inclination to partner violence. It is important to stress that our setup does not use information on employment at the individual level—instead we explore the local prevalence of the work program. The main threat to our setup is unobserved *time-varying* shocks that are correlated with the prevalence of MGNREGA. One could for example imagine negative income shocks that both increase the demand for MGNREGA jobs and that trigger more violence. Our key argument is that such shocks do not directly translate into more

[7] As Gulzar and Pasquale (2017), we construct this variable as log(numbers of workers + 1). Our results are not very sensitive to this adjustment, as there are only a few blocks without a positive number of MGNREGA workers.

MGNREGA jobs. As mentioned in Section 2, extensive research shows that implementation often is hindered by a number of hold-ups, and that the supply of jobs crucially depends on the will of local politicians and bureaucrats. We therefore find it plausible that year-to-year changes in program implementation at the local level are quasi-exogenous to factors determining the prevalence of intimate partner violence. We explore this assumption further below.

4.2 Heterogeneity

We also investigate heterogeneity in the relationship between MGNREGA and violence. To do so, we run the following specification:

$$\begin{aligned} IPV_{ibt} = \beta_0 + \beta_1 \log MGNREGA_{bt} + \beta_2 (\log MGNREGA_{bt} \times Z_b) \\ + \alpha_t t + \alpha_b + \alpha_m + \alpha_a + X'_{ib} + \epsilon_{ibt}, \end{aligned} \tag{2}$$

where Z_b is a variable denoting some characteristic of block b, for which we test for heterogeneity in the relationship between MGNREGA and violence.[8] We use the following characteristics: female labour force participation (as measured by the Economic Census), total population, population share of Scheduled Castes (SCs) and Scheduled Tribes (STs), and availability of publicly provided goods and services.[9]

We also test for heterogeneity in terms of some district level characteristics, as this allows us to include a richer set of variables. We use the following variables: female labour force participation (as measured by the NSS), total population, population share of SCs and STs, availability of publicly provided goods and services, average per capita consumer expenditure and head count poverty rate.

[8] Note that the regression does not include Z_d in itself. This is because the variable would be absorbed by the block-level fixed effects.

[9] We construct the public goods variable based on village availability of the following goods and services: government primary schools, primary health center, electricity, tap water and paved roads. For each of these, we calculate the share of villages with access. We then calculate the average of the five shares for each block.

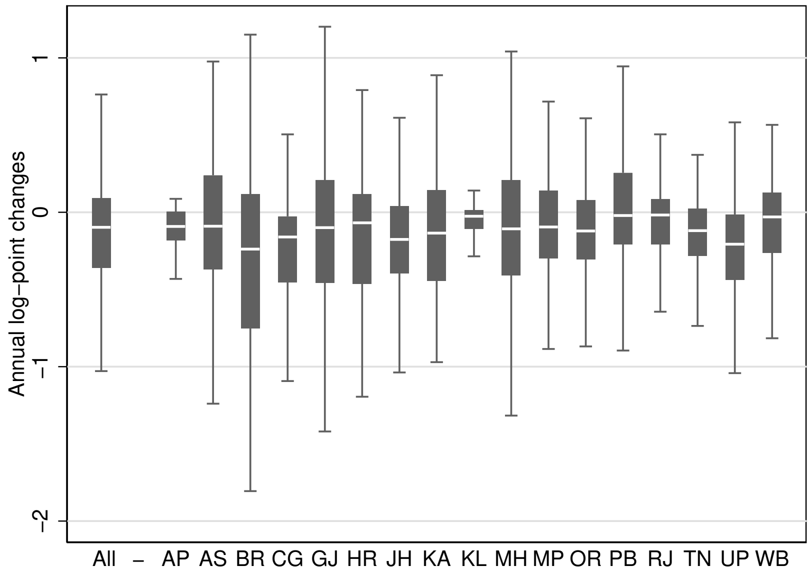
4.3 Assessing the empirical approach

Our identification relies on sufficient within-block time-variation in the number of MGNREGA jobs. Figure 2 is a whiskers plot, illustrating annual changes in the number of workers (in log-points). The first plot in the figure displays this for the full set of blocks in our estimation sample, while the rest of the figure displays whiskers plot by the major Indian states. As can be seen, there is quite substantial year-to-year variation in MGNREGA implementation. Our conjecture is that this within-block variation is driven primarily by supply of jobs, not local demand. We test whether our data is consistent with this conjecture using data on night-time light.

Night-time light has been shown to exhibit a reasonable correlation with economic activity in India (Prakash *et al.*, 2019). We therefore use our trend measure of night-time light as a proxy for activity at the block-level. We first regress the number of MGNREGA applications on log night-time light. Estimates are shown in the first two columns of Table 3. As can be seen, we find a strong and negative relationship between these variables, meaning that there are fewer job card applications when economic activity is higher. This is as expected, given that the objective of MGNREGA is to provide a safety-net of jobs. In economic upturns, the need for these relatively low-paid jobs is lower, and vice versa.

In the third and fourth columns, we use our main treatment variable, the number of MGNREGA workers, on the left-hand side. Reassuringly, the correlation with night-time is close to zero and far from being statistically significant.

Figure 2: Annual changes in the number of MGNREGA workers, log-points



The figure shows a whisker plot of annual log-point changes in the number of MGNREGA workers, based on the the 2257 blocks in our estimation sample. The vertical boxes denote the 25th (lower hinge) and the 75th percentile (upper hinge).

Table 3: Relationship between MGNREGA employment and night-time light

	Log Card applications		Log Persons worked	
	(1)	(2)	(3)	(4)
Log night-time light	-0.045***	-0.042***	-0.023	0.011
	(0.011)	(0.011)	(0.041)	(0.036)
Observations	6319	6319	6319	6319
Time trend	No	Yes	No	Yes

Robust standard errors clustered on blocks are shown in parentheses.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

5 Findings

In this section we present the empirical findings.

5.1 Main results

Our main results are presented in Table 4. In the first column we do not include any controls. The rest of the columns gradually include years-since-marriage fixed effects, age-group fixed effects, individual time-invariant controls and a common linear time trend. The inclusion of these variables barely change the MGNREGA-coefficient, which is positive and strongly significant. Our preferred estimate is shown in the last column and suggests that a 10 percent increase in the number of workers raises the probability of violence by 0.11 percentage point.

How large is this effect? One way of illustrating this is to compare it with the average yearly risk of violence in the estimation sample. Compared to this average, the estimated impact of a 10 percent increase in MGNREGA amounts to a 1.7 percent increase in violence.

Does the effect reflect female employment? Nearly half of the MGNREGA jobs are occupied by females, in sharp contrast to the Indian labour market in general. It is therefore reasonable to assume that most of the changes in employment due to the work program is driven by females (Azam, 2012). Still, in Table 5 we show more directly that our estimates are driven by variation in female employment. The MGNREGA Public Data Portal provides data on total workdays by gender. We use this to construct separate measures of MGNREGA prevalence for men and women. The estimates in the table clearly suggest that the effect on violence is driven by female employment. Although imprecisely estimated, the regression in fact suggests that male employment reduces violence against women. This result is consistent with other findings in the literature. For example, Bhalotra *et al.* (2018) find that beneficial female labour market conditions increase violence, while beneficial labour market conditions for males have the opposite effect.

As mentioned, the main threat to our estimation is unobserved time-varying shocks that are correlated with number of MGNREGA jobs. Below, we therefore investigate how sensitive our results are to alternative time trends, and to the inclusion of time varying controls.

Table 4: Impact of MGNREGA on intimate partner violence

	(1)	(2)	(3)	(4)	(5)
Log MGNREGA workers	0.013***	0.012***	0.013***	0.011***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	11482	11482	11482	11482	11482
Marriage length FEs	No	Yes	Yes	Yes	Yes
Age group FEs	No	No	Yes	Yes	Yes
Time trend	No	No	No	Yes	Yes
Individual controls	No	No	No	No	Yes

Robust standard errors clustered on blocks are shown in parentheses.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table 5: Impact of gender-specific MGNREGA on intimate partner violence

	(1)
Log MGNREGA workers females	0.016**
	(0.008)
Log MGNREGA workers males	-0.009
	(0.008)
Observations	11482

Robust standard errors clustered on blocks are shown in parentheses. The regression includes marriage length fixed effects, age-group fixed effects, individual time-invariant controls and a common linear time trend.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

5.2 Sensitivity to alternative trends and time-varying controls

In the first two columns of Table 6, we include a common time trend with polynomials of degree 2 and 3, respectively. In Columns (3) to (5) we add state-specific, district-specific and block-specific time trends. Finally, in the last two columns we include year fixed effects and year×state fixed effects, respectively. Overall, our estimated relationship between MGNREGA and intimate partner violence is robust to all of these more demanding time trends.

In Table 7, we test whether our results survive the inclusion of other time-varying controls. In the first column we add log job card applications. In the second column we add log night-time light, and in third column we add log annual GDP per capita at the state level. In the final column we add all three controls at once. The table reveals that our coefficient of main interest is unaffected by the inclusion of these variables.

Table 6: Impact of MGNREGA on intimate partner violence, using alternative time-trends

	Trend, degree 2 (1)	Trend, degree 3 (2)	State-specific trend (3)	District-specific trend (4)	Block-specific trend (5)	Year FEs (6)	Year× state FEs (7)
Log MGNREGA workers	0.008^{*} (0.004)	0.008^{**} (0.004)	0.013^{***} (0.004)	0.012^{**} (0.006)	0.018^{***} (0.007)	0.008^{**} (0.004)	0.010^{**} (0.005)
Observations	11482	11482	11482	11482	11482	11482	11482

Robust standard errors clustered on blocks are shown in parentheses. All regressions include marriage length fixed effects, age-group fixed effects and individual time-invariant controls.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table 7: Impact of MGNREGA on intimate partner violence, controlling for time-varying variables

	(1)	(2)	(3)	(4)
Log MGNREGA workers	0.011***	0.011***	0.012***	0.011***
	(0.004)	(0.004)	(0.004)	(0.004)
Log Job card applications	-0.001			0.005
	(0.016)			(0.016)
Log Night-time light		0.007		0.006
		(0.012)		(0.012)
Log GDP (state)			-0.106	-0.121
			(0.069)	(0.074)
Observations	11482	11220	11482	11220

Robust standard errors clustered on blocks are shown in parentheses. All regressions include marriage length fixed effects, age-group fixed effects, individual time-invariant controls and a common linear time trend.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent..

5.3 Heterogenous effects

In this section we investigate heterogeneity of the relationship between MGNREGA and intimate partner violence. We do this by estimating the specification from Equation (2). Results are presented in Table 8.

In the first column, we interact our main MGNREGA variable with female labour force participation, measured at the level of blocks. To easy interpretation we standardise labour force participation to mean zero and standard deviation one. The interaction coefficient is negative and statistically significant, meaning that the effect of MGNREGA on violence is smaller in areas with relatively high female labour force participation. In the second column we interact MGNREGA with a simple dummy variable, taking the value of unity for blocks with a below median female labour force participation rate. As can be seen, the estimated effect of employment on violence is primarily driven by these blocks.

In Columns (3) and (4), we run similar regressions using the NSS measure of female labour force participation at the level of districts. The estimates in the third column are similar to those in the first column, but less precisely estimated. The estimates in the fourth column suggest that the effect of employment on violence is driven entirely by districts with a female labour force participation below the median in the sample.

We interpret a low female participation rate as a proxy for strong norms against female working. Thus, the results in this section are consistent with a "male backlash" mechanism, where husbands turn to violence to regain power within the marriage.[10] The results are also in line with the findings of Heise and Kotsadam (2015), who document that the relationship between violence and female employment is stronger in countries where few women are working, and Tur-Prats (2017), who document that relatively better labour market conditions for females leads to more intimate partner violence in Spain, but only in areas

[10] See Pankaj and Tankha (2010) and Thapar-Björkert *et al.* (2019) for direct evidence of the effect of MGNREGA on female empowerment.

with deep-rooted norms agains female employment.

In the appendix, we test for heterogeneity in terms of the following additional characteristics, both at the level of blocks and district: total population, population share of SCs and STs, availability of public provided goods, average consumption expenditure (only district) and poverty rate (only district). We do not find a significant interaction coefficient for any of these variables.

Table 8: Heterogeneity of MGNREGA effect by female labour force participation (LFP)

	Economic Census (block)		NSS (district)	
	(1)	(2)	(3)	(4)
Log MGNREGA workers	0.010***	0.006	0.007	-0.003
	(0.004)	(0.005)	(0.005)	(0.009)
Log MGNREGA workers × Standardised female LFP	-0.006**		-0.006	
	(0.003)		(0.005)	
Log MGNREGA workers × Below median female LFP		0.011		0.017*
		(0.009)		(0.010)
Observations	10130	10130	11032	11032

Robust standard errors are shown in parentheses. The standard errors in Column (1) and (2) are clustered on blocks, while those in Column (3) and (4) are clustered on districts.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

6 Conclusion

The literature on domestic violence and female employment is largely inconclusive, both theoretically and empirically. One argument is that employment improves women's outside option of marriage, which might protect them from violence. Consistent with this, Aizer (2010) and Anderberg *et al.* (2016) find that favourable labour market conditions for females reduce domestic violence in the US and the UK, respectively. The outside-option-argument is however likely to be less relevant in patriarchal societies, like much of rural India, where the threat of divorce is practically non-existing. Female employment could in such societies lead to more violence by threatening male identity. Indeed, empirical studies from developing countries often identify a positive relationship between employment and intimate partner violence (Bhalotra *et al.*, 2018; Cools and Kotsadam, 2017; Luke and Munshi, 2011; Guarnieri and Rainer, 2018), but not always (Kotsadam and Villanger, 2020).

We add to this literature by studying the effect on intimate partner violence of the large public work program, MGNREGA. To do so, we combine detailed administrative data on employment with household survey data from rural India. Our main result is that more female employment leads to more violence. In our preferred specification, we find that a 10 percentage increase in the number of MGNREGA jobs raises the probability of violence against women by almost 2 percent of the baseline level. This estimate is derived using an outcome variable that only captures onsets of violence. Since it seems plausible that the work program also affects the frequency and intensity of violence, the estimate should be interpreted as a lower bound of the total effect on violence.

We also investigate heterogeneity of the relationship between violence and employment and find that it only applies in areas with low female labour force participation. This is consistent with other studies showing that the risk of violence is largest in societies where the norms against female employment is strongest (Vyas and Watts, 2009; Heise and Kotsadam, 2015; Tur-Prats, 2017).

A recurring suggestion for how to improve female empowerment is to facilitate work outside the household. Globally, there is also a clear tendency of increased female labour force participation (Heath and Jayachandran, 2016). Our results are important in this context, and they suggest that efforts to stimulate employment should be combined with other types of efforts, such as combating patriarchal gender norms.

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Appendix

In this appendix, we test for heterogenity in terms of additional block and district characteristics.

Table A1 presents regressions where we interact our MGNREGA variable with the following block-level characteristics: total population, share of SCs and STs and public goods availability. As before, we construct the interaction term in two different ways. In Columns (1), (3) and (5), we standardise the block-level variables to mean zero and standard deviation one before creating the interaction terms. In Columns (2), (4) and (6), we use simple binary variables taking the value of unity for values below the median in the sample. As can be seen from the table, we do not find a significant interaction coefficient in any of the regressions.

Table A2 presents similar regressions based on district-level characteristics. In addition to the three variables above, we construct interaction terms based on average consumption expenditure and poverty headcount rates. Again, we do not find a significant interaction coefficient in any of the regressions.

Table A1: Heterogeneity of MGNREGA effect by block-level characteristics

	Total population		Share SCs/STs		Public goods availability	
	(1)	(2)	(3)	(4)	(5)	(6)
Log MGNREGA workers	0.010***	0.009*	0.012**	0.009	0.011***	0.008
	(0.004)	(0.005)	(0.005)	(0.008)	(0.004)	(0.007)
Log MGNREGA workers × Standardised	0.002		0.002		0.000	
	(0.003)		(0.004)		(0.004)	
Log MGNREGA workers × Below median		0.005		0.001		0.003
		(0.007)		(0.009)		(0.008)
Observations	11482	11482	11482	11482	11482	11482

Robust standard errors clustered on blocks are shown in parentheses.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table A2: Heterogeneity of MGNREGA effect by district-level characteristics

	Total population		Share SCs/STs		Public goods availability		Average expenditure		Poverty rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log MGNREGA workers	0.010**	0.004	0.010***	0.004	0.010***	0.013***	0.010***	0.015***	0.010***	0.009*
	(0.004)	(0.008)	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Log MGNREGA workers × Standardised	-0.001		-0.000		0.002		0.002		0.002	
	(0.004)		(0.004)		(0.003)		(0.003)		(0.004)	
Log MGNREGA workers × Below median		0.009		0.009		-0.005		-0.009		0.004
		(0.008)		(0.008)		(0.007)		(0.008)		(0.007)
Observations	11482	11482	11482	11482	11377	11377	11032	11032	11032	11032

Robust standard errors clustered on districts are shown in parentheses.
*** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.