Employment, Intimate Partner Violence, and Women's Empowerment in Colombia

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1 Introduction

An influential view dating back fifty years is that female labor force participation follows a U-shape with economic development (Goldin (1994); Boserup (2007)). At low levels of development, women participate in self-employment and home based production activities. As development, and consequently income increases, the marginal consumption a household can enjoy by having a second earner offers diminishing benefits, thus reducing the need for women labor force participation. Working outside of the house has implications for intra-household dynamics, especially those between a husband and wife. Because of the dynamics between intra-household dynamics and intimate partner violence (IPV), the question arises- do both female labor force participation and incidence of IPV follow the same inverted U-shaped pattern? And does the relationship between labor force participation and IPV change when women's empowerment is factored in? In this study, we examine the relationship between time in labor force, and domestic violence and women's empowerment.

The effects of labor force participation on domestic violence are mixed, and studies have found that these effects vary based on a woman's initial bargaining power. Heath (2014) finds that working outside the house initially increases the likelihood that a woman is exposed to domestic violence, when a woman has lower initial bargaining power. Similarly, theoretical household bargaining models have shown that a woman's access to economic opportunities can either decrease or increase violence, depending on her initial level of bargaining power and empowerment (Tauchen et al. (1991);Eswaran & Malhotra (2011)). Though these studies discuss empowerment and bargaining power, they do not clearly establish how this relationship works further than controlling for empowerment and heterogeneity.

Literature on empowerment and labor force participation has shown that paid employment outside of home increases women's empowerment Anderson & Eswaran (2009). Heath & Mobarak (2015) find that exposure to the garment sector in Bangladesh is associated with delayed marriage and childbirth. This is consistent with Jensen's (2012) findings from rural India that women exposed to a job recruiting intervention were less likely to get married or have children, and instead choose to enter the labor market or stay school longer. However, these studies leave out the dynamic of intimate partner violence in their analyses.

As a woman continues to work, the initial increase in domestic violence then interacts with the increase in empowerment due to the outside working options. At this point, an interesting dynamic between domestic violence, and women's increasing bargaining power comes into play. This relationship between the three variables is not clearly understood in the literature. Given these gaps in knowledge, I attempt to answer how labor force participation affects incidence of domestic violence, and the role of women's empowerment in this dynamic. It is possible that labor force participation has differential impacts on women's empowerment, which in turn impacts domestic violence. I use both heterogeneous treatment effects model and mediation analysis to show that participating in the labor force affects incidence of domestic violence through impact on women's empowerment.

Studying IPV comes with several hurdles. First, the data collected on IPV is limited and incomplete since it is prone to under-reporting due to the stigma attached, fear of safety, and desirability bias. Additionally, panel data are rare because following the same household overtime is difficult and expensive. We create a unique community level panel dataset which has a large sample and allows us to control for unobserved heterogeneity at the community level. Our panel is comprised of the Demographic and Health Surveys (DHS) from the years 2000, 2005, 2010, and 2015. I aggregate the incidence of domestic violence, employment, empowerment, and the control variables at the enumeration area level area. The dataset contains 945 enumeration areas.

This paper has three main contributions to the literature on intimate partner violence, women's labor force participation, and empowerment. First, though previous studies have looked at one, or at most two, of the three variables, this paper analyzes this three way relationship directly. Second, I create a dataset that has four panel rounds with data on all the three variables which gives a rich sample to make the estimations demanded by the analyses. Lastly, in our knowledge, this is the first attempt to applying the methodology of causal mediation to analyzing the role of empowerment in intimate partner violence.

Intimate partner violence has socio-cultural differences in the way the abuser and victim are perceived, and risk factors among others (Fischbach & Herbert (1997)). IPV also has different implications in developing countries compared to developed countries. Colombia has some the highest prevalence of physical IPV in Latin America (Kishor & Johnson (2004)), and thus lends itself for the right setting for this study. Though previous studies have looked at risk factors leading to physical IPV (Flake & Forste (2006)) while others have studied the determinants of women's empowerment (Eswaran & Malhotra (2011)), not much has been done in understanding the inter-play of labor force participation, women's empowerment, and IPV.

The rest of the paper is structured as follows. In the second section, I explain the empirical strategy used, then I explain the data and methods, the results follow in section four, and section five concludes.

2 Theoretical Model

I compare the two models for analyzing the relationship between labor force participation and domestic violence - the naive heterogeneous treatment effect model and the causal mediation model.

In the naive model, empowerment is added as a control variable in the regression estimation. Previous literature leads us to believe that employment has differential effects on domestic violence depending on the levels of empowerment of the women. By allowing the intercept to differ heterogeneously by empowerment levels, we can test the heterogeneous treatment effects of employment and empowerment. In this model, our coefficient of interest is the coefficient on employment (the treatment variable), and coefficient on the interaction term between employment and empowerment. For the rest of the paper, the effect of employment (treatment) on domestic violence (outcome) is referred to as the *"direct effect"* which is also explained in the causal mediation analyses.

To understand the causal mediation model, we look at Figure 1. The purpose of the causal mediation model is to disintegrate the total effect of employment into the direct effect (effect of treatment on outcome) and indirect effect (effect of mediator on outcome). The

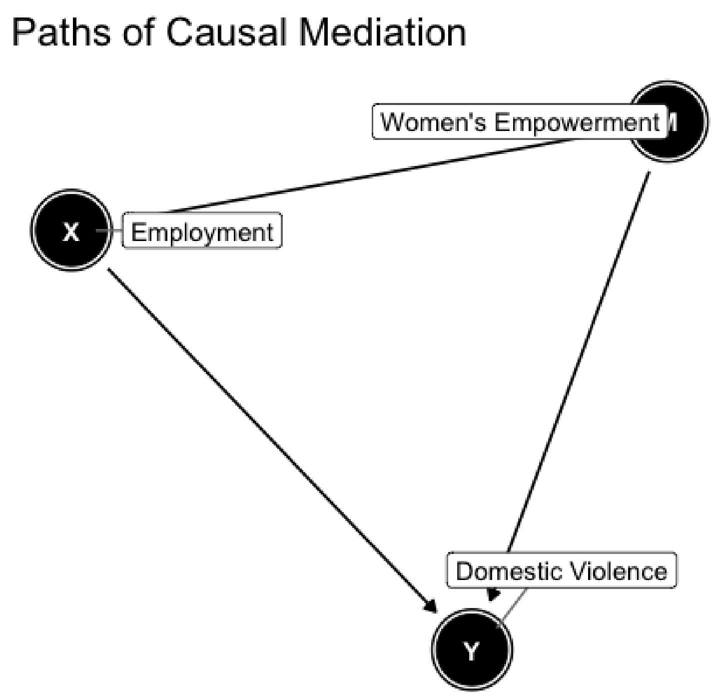

Figure 1: The effect of employment on incidence of domestic violence mediated through women's empowerment

relationship between employment and domestic violence is mediated through the effect of the mediator on employment. The arrow from X to Y estimates the direct effect of employment. In the next step, causal mediation estimates the effect of employment on the mediator. Lastly, these two effects are used to calculate the part of the total effect of employment mediated through empowerment, or the indirect effect.

3 Empirical strategy

3.1 Data and Methods

I use panel data at the enumeration area level from the Demographic and Health Surveys (DHS) from Columbia. The panel nature of the dataset offers an opportunity to capture most of the unobserved heterogeneity apart from the time and enumeration area effects. 4 panels also allow for enough variation in the outcome, treatment, and the mediating variables. The dataset includes 4 panels for the years 2000, 2005, 2010, and 2015 and has 940 enumeration area levels. The dataset comes from surveys conducted with all eligible women of ages 13-49 years in sampled households. I restrict the sample to only women who are heads of households (female headed households) or spouses of heads of households. I do this to restrict the sample to include only one woman per household and satisfy the no-interaction among observations assumption to make asymptotically consistent causal mediation estimates.

Similar to other cross-sectional analyses for IPV, I classify the physical according to the severity of the violence (Kishor & Johnson (2004)). I classify the physical violence into four categories. First, less severe violence, which has indicators for the following variables from the questionnaire: "being hit with the hand," "being hit with an object," "being pushed or shaken". Second, severe violence, which includes "being, dragged or kicked", "being strangled or burnt", "being threatened by gun/knife or other weapon". Third, sexual violence, which includes "being physically forced into unwanted sex", and "being forced into other unwanted sexual acts". Lastly, I have an indicator for any violence which is indicated by one or more of the above three categories.

For the employment variable, I use whether the woman is *Currently Employed* which refers to women who are in the paid labor force. Additionally, I have two individual-level control variables which are characteristics that could be associated with both incidence of domestic violence, and participation in the labor force. I use education, age, and children born as control variables for the women. As with other variables, I average these variables over the enumeration area level to use with the dynamic panel estimation.

For women's empowerment, I include decision making variables such as decisions for respondent's health care, large household purchases, daily household needs, visits to family and friends, and food cooked. For these decision making variables, I code responses such as "respondent alone" to indicate a higher level of empowerment. I also use decision making variables for using contraception, and for desire for more children. For contraception use, "mainly respondent" indicates higher empowerment, and for desire for children, a higher empowerment is indicated by both partners wanting the same desired number of children.

We estimate a model measuring the effects of participating in the labor force on domestic violence. The variation in labor force participation is used to identify the effects of employment on incidence of domestic violence.

To measure the effect of labor force participation on incidence of domestic violence, I estimate a fixed effects model as follows. For an enumeration area v in year t: I estimate a fixed effects model as follows. For an enumeration v in year t:

$$AnyDvr_{vt} = \beta_1 LFPR_{vt} + \alpha X_{vt} + \lambda_t + \epsilon_{vt} \tag{1}$$

Where the dependent variable $AnyDVR_{vt}$ is the average number of women in an enumeration area v in year t who reported facing any domestic violence $LFPR_{vt}$ is the independent variable of interest which is equal to the average number of women who participate in the labor force in an enumeration area v in the time period t; X_{vt} is the vector of cluster level controls which include average number of years of education, average age, and average number of children for an enumeration area v in the time period t; and λ_t measures the gender-specific time-trends within an enumeration area.

Then, I also estimate a model using the squared labor force participation as an explanatory variable. For an enumeration area v in year t:

$$AnyDvr_{vt} = \beta_1 LFPR_{vt} + \beta_2 LFPRsq_{vt} + \alpha X_{vt} + \lambda_t + \epsilon_{vt} \tag{2}$$

Where the other variables are same as mentioned in equation (1), and $LFPRsq_{vt}$ is the squared labor force variable for cluster v at time period t

Lastly, I include women's empowerment as a control and interact it with employment to estimate equation (2) as the main model to test heterogeneity:

$$\begin{aligned} AnyDvr_{vt} = {} & \beta_1 LFPR_{vt} + \beta_2 LFPRsq_{vt} + \beta_3 WEI_{vt} + \beta_4 LFPR_{vt} * WEI_{vt} + \\ & \alpha X_{vt} + \lambda_t + \epsilon_{vt} \end{aligned} \tag{3}$$

The other variables in equation 3 are the same. Equation 3 uses women's empowerment index as a control. In other words, the variable *WEI* helps understand heterogeneous effects of empowerment on incidence of domestic violence.

First, we test the hypothesis that being employed has a significant effect on the incidence of domestic violence. For the second hypothesis, we test for the inverted U-shaped pattern. This relationship is the direction of the coefficient on labor force participation squared. Lastly, we test if labor force participation has a significant effect on domestic violence after controlling for women's empowerment, and the heterogeneous effects of women's empowerment.

3.2 Mediation Analysis

I follow Imai et al. (2011) approach to apply the method of causal mediation by placing a causal mediation analysis within the counterfactual framework of causal inference to formally define causal mediation effects. I am interested in the mediating effect of labor force participation on incidence of domestic violence, in which the mediating variable is women's empowerment.

Thus, the hypothesis is that participating in the labor force reduces the incidence of domestic violence by increasing the level of empowerment for women. I use M_i to denote the observed level of women's empowerment which takes two potential values, $M_i(1)$ or $M_i(0)$, and only one of the two is observed, that is, $M_i = M_i(T_i)$. For a person who is employed ($T_i = 1$), we observe $M_i(1)$ but not $M_i(0)$.

Next, we look at potential outcomes. Before, the potential outcomes are only a function of the treatment, but in causal mediation, potential outcomes depend on both the treatment and on the mediator. We denote $Y_i(t, m)$ as the potential outcome for individual i with treatment and mediator variables equal t and m, respectively. As before, only one of the multiple potential outcomes are observed, where the observed outcome Y_i equals $Y_t(T_i M_i$. Additionally, by restricting the sample to one woman per household, the assumption of no interference is satisfied- the potential mediator values for each unit do not depend on the treatment status of other units, and the potential outcomes of each unit also do not depend on the treatment status and the mediator value of the other units. In other words, the empowerment levels of one woman do not determine the employment status of other women in the sample, and the incidence of domestic violence for one woman does not depend on the empowerment or employment status of any other women.

The Causal Mediation Effect (or indirect effects) as:

$$CME_i(t) = Y_i(t, M_i(1)) - Y_i(t, M_i(0)), \tag{4}$$

for $t = 0, 1$. Thus, the causal mediation effect represents the indirect effect of the treatment (being employed) on the outcome (incidence of domestic violence) through the mediating variable (women's empowerment) (Pearl et al. (2009); Robins et al. (2003), Robins & Greenland (1992)). Note that if the treatment has no effect on the mediator, i.e. $M_i(1) = M_i(0)$, then the causal mediation effect is zero. In my dataset, the mediator is continuous, but the continuous nature of empowerment does not change the interpretation of the mediation analyses.

The direct effect of the treatment is:

$$DME_i(t) = Y_i(1, M_i(t)) - Y_i(0, M_i(t)) \tag{5}$$

The $DME_i(1)$ represents the direct effect of employment on individual i's incidence of domestic violence, holding the level of empowerment constant under labor force participation.

3.2.1 Sequential Ignorability Assumption

The key assumption of sequential ignorability allows us to make valid inference about the causal mediation effects. Imai et al. (2010) define this assumption. Let X_i be a vector of the observed pre-treatment confounders for unit i where X is the range of values that X_i can take on. Here, X_i includes for each unemployed individual the pre-treatment level of domestic violence as well as demographic characteristics such as education, age, and wealth index. The assumption can be formally expressed as: Assumption 1 (Sequential Ignorability; Imai et al. (2010)): We assume that the following two statements of conditional independence hold:

$$Y_i(t', m), M_i(t) \perp\!\!\!\perp T_i | X_i = x, \tag{6}$$

$$Y_i(t', m) \perp\!\!\!\perp M_i(t) | T_i = t, X_i = x \tag{7}$$

where $0 < Pr(T_i = t | X_i = x)$ and $0 < p(M_i(t) = m | T_i = t, X_i = x)$ for $t = 0, 1$ and all $x \in X$ and $m \in M$.

Assumption 1 is called sequential ignorability because two ignorability assumptions are made sequentially. First, given the observed confounders, the treatment assignment (of employment) is ignorable, i.e. statistically independent of both the potential outcomes (incidence of domestic violence) and potential mediator (empowerment). This condition is satisfied by the panel nature of the dataset, as well as the fixed effects model, controlling for which makes the treatment as randomly assigned.

The second part of assumption 1 is made conditional on the observed value of the ignorable treatment and the observed pre-treatment confounders. It is usually the case that randomizing the mediator is not possible, since empowerment is not randomly assigned in the dataset. The ignorability of the mediator implies that among those women who share the same treatment status and the same pre-treatment characteristics, the mediator can be regarded as if it were randomized. As mentioned earlier, it is always possible that there might be unobserved variables such as inherent ability, motivation, will-power, and argument making skills that confound the relationship between outcome incidence of domestic violence and the mediator empowerment even after conditioning on the observed treatment status and the observed covariates. Additionally, the covariates conditioned on must be pretreatment variables. In the absence of additional assumptions, we cannot condition on posttreatment confounders even if such variables are observed (e.g. Avin, Shpister, & Pearl, 2005). However, this assumption is referred to as nonrefutable because it is not possible to directly test this from the observed data (Manski (2009)). Imai et al. (2010) develop a set of sensitivity analyses that allow us to quantify the degree to which my empirical findings are robust to a potential violation of the sequential ignorability assumption.

Imai et al. (2011) prove that under sequential ignorability and the no-interaction assumption, the estimates based on product of coefficients method are asymptotically consistent of the causal mediation effect as long as the linearity assumption holds. The product of coefficients method is estimated as the following set of linear equations:

$$Y_i = \alpha_1 + \beta_1 T_i + \eta_1 X_i + \epsilon_{i1} \tag{8}$$

$$M_i = \alpha_2 + \beta_2 T_i + \eta_2 X_i + \epsilon_{i2} \tag{9}$$

$$Y_i = \alpha_3 + \beta_3 T_i + \gamma M_i + \eta_3 X_i + \epsilon_{i3} \tag{10}$$

This approach is similar to the one described by Preacher & Selig (2012). In general, their approach calls for a two step procedure for estimating the effect of labor force participation on domestic violence via potential mediating variable (i.e., the indirect effect) and the effect of labor force participation on domestic violence conditional on potential mediating variables (i.e., the direct effect). The product of the coefficients $\hat{\beta}_2\hat{\gamma}$ is an estimated second-stage mediation effect (MacKinnon et al. (2002); Preacher & Selig (2012)), also known as the indirect effect. The differences of the coefficient methods yields the numerically identical estimate by computing $\hat{\beta}_1 - \hat{\beta}_3$ in this linear case (MacKinnon et al. (2002)). Since $\hat{\beta}_1 = \hat{\beta}_2\hat{\gamma} + \hat{\beta}_3$ and $\beta_1 = \beta_2\gamma + \beta_3$ always holds, equation 8 is redundant given equations 9 and 10.

The sequential ignorability assumption is reasoned in the context of social experiments by Heckman & Pinto (2015) where they state that in order for mediation analysis to be causally interpreted, we need an assumption of independence between labor force participation (i.e., treatment status) and the potential mediator (i.e., women's empowerment) with respect to domestic violence conditional on observed covariates. In this paper, I support this assumption in two ways- I use unobservable selection and coefficient stability tests of Oster (2017) to test if coefficients on mediators change based on the inclusion of observable controls; if they do not, then Oster (2019) argues that coefficient estimates would be unlikely to change with the inclusion of unobservable variables.

4 Results

Table 2 reports the results from equations (1), (2), and (3). In column 1, employment has a significant positive effect on the incidence of domestic violence. In column 2, the effect of working increasing almost twice. The coefficient on the squared labor force participation is negative and significant indicating that employment increases domestic violence at a decreasing rate. This is preliminary evidence for the inverted U-shaped relationship between employment and incidence of domestic violence. In column 3, both employment and women's empowerment are significantly positively correlated with incidence of domestic violence.

I explain the results from the mediation analysis in three parts. First, I discuss the results from the first stage (equation 8) i.e, the effect of participating in the labor force on the mediating variable (women's empowerment). Second, I discuss the results from the second stage regression (equation 9) i.e., the effect of being in the labor force on incidence of domestic violence, conditional on the level of empowerment. Lastly, I discuss the indirect and direct effects of the causal mediation analysis.

4.1 CMA: First-stage

Table 3 in the Appendix reports the results of employment on women's empowerment, estimated in equation 8. An increase in employment is associated with a 1.67 units increase in women's empowerment. The coefficient on the squared employment variable is negative, suggesting that employment affects empowerment at a decreasing rate.

I use the coefficient on employment, β_2 to estimate the indirect effect in the next subsections.

4.2 CMA: Second-stage

The second stage mediation analysis (Preacher & Selig (2012)) estimates a model similar to equation 1, except that the second stage is conditional on the mediator (equation 9). β_3 is the direct effect of the treatment (employment) on incidence of domestic violence. The effect on the mediating variable (β_3) is the second-stage mediating effect which needs to be multiplied with the first stage mediating effect to calculate the indirect effect which is discussed in the next sub-section. I incorporate the dynamic panel structure for the estimation of the second-stage mediating effects, by using enumeration area level fixed-effects, as well as the time trends.

Table 4 in the Appendix shows the second-stage mediating effects. The direct effect, β_3 is big, and statistically significant at the 10% level even after conditioning on the mediating variables. I will apply Oster's coefficient stability tests to check whether these coefficients are robust to the stability tests Oster (2019).

4.3 Direct and indirect effects

We reject the null that employment has no direct effect on domestic violence. The direct effect of labor force on domestic violence is significant even after controlling for the mediating variable, estimated by β_3 in equation 9. In Table 1, we can see that a one percent increase in employment is associated with a TEN percent decrease in the incidence of domestic violence.

The direct effects with or without the mediating variable controls go in the same direction and have similar magnitudes.

I follow Preacher & Selig (2012)) to calculate 95% confidence intervals for the indirect effect of employment on domestic violence using Monte Carlo simulations of 20,000 replications. I use the coefficients and standard errors from Tables 3 and 4 in the Appendix to calculate the indirect effect, $\hat{\beta}_2\hat{\gamma}$, which is 0.0513. After running the Monte Carlo simulations on this effect, the 95% confidence interval is reported in Table 1. We can see that zero is not included in the interval, and thus conclude a small but statistically significant mediating effect of women's empowerment on incidence of domestic violence. The histogram of the simulations is reported in Figure 2 in the Appendix.

This significant mediating effect suggests that employment affects incidence of domestic violence through it's effect on empowerment. The existence of this mediating effect helps explore the dynamics between these three variables. If an increase in employment has an effect on empowerment, which then leads to a change in the incidence of domestic violence, the mediating effect is significant, which is indeed what I find.

5 Conclusion

In this paper, I aim to understand the relationship between employment, IPV, and women's empowerment. I use a dynamic panel model to identify the treatment (employment). Then, I set up a causal mediation model to see how much of the treatment effects, if at all, are mediated through the treatment's impact on women's empowerment.

Table 1: 95 % Confidence Intervals for Total Indirect Effect of Employment on Domestic Violence as Mediated by Women's Empowerment

	95 % Confidence Interval for Total Indirect Effect ($\beta_2\gamma$)	
Method	*Lower Limit*	*Upper Limit*
Monte Carlo	0.03331	0.07179

One advantage of using the causal mediation analyses to understand the dynamics of employment, incidence of domestic, and women's empowerment is the estimation of the indirect effect. If empowerment is only used as a control (equation 3), we can understand heterogeneous treatment effects, which is how the treatment differential affects women with similar levels of empowerment. However, the indirect effect gives a more clear picture of the effect of employment that is explained by the changes in mediator. i.e., given the same level of employment, how does a change in empowerment affect the incidence of domestic violence.

I find positive relationship between employment and incidence of domestic violence, which is similar to results found by other studies (Heath (2014), Friedemann-Sánchez & Lovatón (2012)). I also do find that a higher level of empowerment is correlated with a lower level of domestic violence. This indicates that the level of empowerment gained by being employed outside the house is still not enough to make a woman walk away from an abusive relationship with a partner. This finding has important policy implications in that the focus should not be only an increase in women's empowerment, because we are still lacking some other factors which affect incidence of domestic violence (factors such as social norms could play some role in explaining this). I find evidence that women's empowerment mediates a significant amount of the total effects of employment on incidence of domestic violence. My results show that even though empowerment mediation is statistically significant, it's economic significance is not very high. This has similar implications to there being other factors not levels of empowerment that determine whether a woman continues being in an abusive relationship. Additionally, I find preliminary evidence for the inverted U-shaped relationship between employment and incidence of IPV.

Future studies looking into this relationship for other countries using other data will help make stronger case for this mediation analysis. Additionally, a more experimental approach which can help randomly assign employment can identify the model to arrive at causal estimations for testing the relationship between employment and incidence of domestic violence. Even if that is done, it is important to note that randomly assigning empowerment will still be difficult and thus mediation results should be interpreted with immense caution.

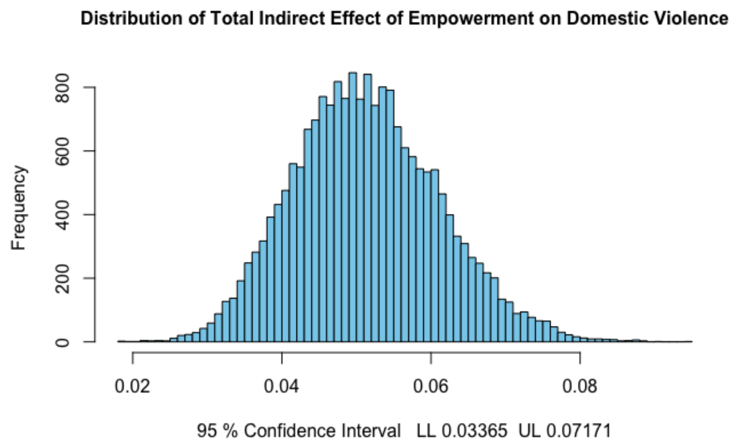

Figure 2: Simulation with 20000 replications

6 Appendix

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Table 2: Panel model with enumeration area fixed effects, and time trends

	Dependent variable:				
	anyDVR				
	(1)	(2)	(3)	(4)	(5)
LFPR	0.107***	0.250***	0.200***	0.149**	0.113
	(0.019)	(0.056)	(0.056)	(0.071)	(0.193)
LFPRsq		−0.136***	−0.110**	−0.124**	−0.090
		(0.051)	(0.050)	(0.051)	(0.179)
avgWEI			0.040***	0.030***	0.028**
			(0.005)	(0.010)	(0.013)
educ	−0.009***	−0.008***	−0.009***	−0.009***	−0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
age	−0.005***	−0.005***	−0.005***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ch	0.010*	0.011*	0.014**	0.014**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

Table 3: Causal Mediation results

	Dependent variable:	
	avgWEI	anyDVR
	(1)	(2)
LFPR	1.292^{***}	0.200^{***}
	(0.185)	(0.056)
LFPRsq	-0.716^{***}	-0.110^{**}
	(0.166)	(0.050)
avgWEI		0.040^{***}
		(0.005)
educ	0.030^{***}	-0.009^{***}
	(0.006)	(0.002)
age	0.017^{***}	-0.005^{***}
	(0.004)	(0.001)
ch	-0.070^{***}	0.014^{**}
	(0.018)	(0.006)

Table 4: Causal mediation model- First stage regression

	Dependent variable:
	avgWEI
LFPR	1.292***
	(0.185)
LFPRsq	−0.716***
	(0.166)
educ	0.030***
	(0.006)
age	0.017***
	(0.004)
ch	−0.070***
	(0.018)
Observations	3,596
R^2	0.089
Adjusted R^2	0.087

Table 5: Causal mediation model- Second stage regression

	Dependent variable:
	anyDVR
LFPR	0.200^{***}
	(0.056)
LFPRsq	-0.110^{**}
	(0.050)
avgWEI	0.040^{***}
	(0.005)
educ	-0.009^{***}
	(0.002)
age	-0.005^{***}
	(0.001)
ch	0.014^{**}
	(0.006)

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