Evaluating a Women Empowerment Policy: Effects on Domestic Violence and Decision-Making among Women in India

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Executive Summary

This study evaluates the impact of the SABLA program, a women's empowerment initiative in India, on domestic violence and women's decision-making autonomy. Implemented in select districts in 2011, SABLA aimed to enhance women's social and economic standing through education, vocational training, and support networks. Using data from the National Family Health Survey (NFHS) - Round Four (2015-16) and advanced statistical methods, this research assesses the program's effectiveness and highlights areas for improvement. Previous studies have reported mixed effects of empowerment programs like SABLA. While such initiatives often reduce domestic violence by fostering communication, confidence, and life skills among women, they may inadvertently exacerbate household conflicts in settings where traditional gender roles are deeply entrenched. By analyzing SABLA's impact on financial, healthcare, and social decision-making autonomy, this study offers valuable insights into the nuanced effects of empowerment policies, providing important lessons for the design of future initiatives.

A key strength of this analysis lies in its methodological approach, which combines the traditional Difference-in-Differences (DiD) framework with the more advanced Double Machine Learning (DML) approach to evaluate SABLA's impact. While the DiD framework provides a straightforward interpretation of policy effects, the DML approach captures more complex, non-linear relationships in the data, offering a deeper understanding of the program's outcomes. The findings reveal a nuanced picture of SABLA's effects. On one hand, both the DiD and DML models provide evidence that women exposed to the program were less likely to report acts of physical or emotional violence, likely driven by increased awareness and access to resources provided by the initiative. On the other hand, the DML results diverge notably from the DiD findings on decision-making autonomy, which is a central focus of this research. While the DiD model suggests modest improvements in financial decision-making, the DML model identifies reductions in both financial and social autonomy, such as freedom to visit family or travel alone. These discrepancies may result from the DML model's ability to capture non-linearities and complex covariate interactions that the DiD framework might overlook, or they could reflect unobserved factors such as regional disparities, cultural norms, or household bargaining dynamics.

Overall, the findings underscore both the promise and challenges of women empowerment programs like SABLA. Mixed results suggest that cultural norms, household dynamics, and regional disparities may shape the program's reception and implementation, potentially limiting its ability to empower women uniformly. This study offers valuable insights for the development and evaluation of women-centric policies, emphasizing the importance of aligning program objectives with the diverse needs of targeted populations. By adopting robust evaluation methods and tailoring interventions to regional and cultural contexts, policymakers can enhance the effectiveness of empowerment programs and achieve more sustainable improvements in women's autonomy and well-being.

1 Introduction

Empowering women and reducing gender-based violence are critical global challenges, particularly in developing countries like India (Chatterjee and Poddar, 2024), where structural inequalities and cultural norms often constrain women's autonomy. This paper evaluates the Rajiv Gandhi Scheme for Empowerment of Adolescent Girls, commonly known as SABLA, a multidimensional women empowerment program launched in India in 2010. The program aimed to enhance adolescent girls' social and economic standing by providing supplementary nutrition, reproductive health education, life skills training, and increased access to public services. While the program's objectives did not explicitly target domestic violence or women's decision-making autonomy, its multifaceted approach has the potential to influence these outcomes indirectly by improving women's health, education, and economic opportunities.

In my earlier work, Muraly (2022), I replicated the findings of Chatterjee and Poddar (2020) and conducted a preliminary analysis of SABLA's impact on intimate partner violence and women's attitudes towards domestic violence using a Difference-in-Differences (DiD) approach. This analysis utilized data from the National Family Health Survey (NFHS) – Round Four, conducted in 2015-2016, which includes information on domestic violence and decision-making autonomy among ever-married women. The identification strategy leveraged geographical variation in SABLA's roll-out across 205 districts and cohort variation based on women's eligibility defined by age criteria. While the DiD approach provided initial evidence of the program's success in reducing certain forms of domestic violence, it left several questions unanswered about its broader impacts on decision-making autonomy and the underlying mechanisms driving these outcomes. Building on this foundational analysis, my current research incorporates the Double Machine Learning (DML) model within the DiD framework to address these gaps. The DML approach offers a more flexible and robust methodology, utilizing machine learning tools to capture non-linear relationships and interactions between covariates and policy treatment effects. By complementing the traditional econometric framework, this research aims to provide a more nuanced understanding of SABLA's effects, particularly in areas where conventional methods may overlook complexity and heterogeneity in treatment impacts.

The findings from this study reveal notable differences between the DiD and DML results, highlighting the trade-offs and strengths of each econometric model. Both frameworks provide evidence that SABLA reduced the likelihood of women experiencing acts of physical and emotional violence, likely reflecting the program's success in increasing awareness and access to resources. However, the results diverge in their assessment of decision-making autonomy. While the DiD model suggests modest improvements in financial autonomy, the DML analysis shows reductions in both financial and social autonomy, such as freedom to spend on household purchases or visit family. These discrepancies may stem from the DML model's ability to capture complex interactions and heterogeneity in treatment effects that the DiD framework might overlook. For instance, regional disparities, household bargaining dynamics, and deeply rooted cultural norms could play a role in shaping the program's varied impact on autonomy-related outcomes. Furthermore, the mixed results in women's autonomy, as revealed by the DML model, may provide insights into the insignificant impact observed on certain dimensions of domestic violence. While the SABLA program appears to have enhanced autonomy in specific areas, such as decision-making over contraception, reductions in financial and social autonomy could have offset these gains, thereby mitigating the overall effect on domestic violence. These findings indicate that changes in household bargaining dynamics or unexpected behavioral reactions to the policy may have created counteracting forces, diminishing the program's overall effectiveness in reducing domestic violence.

The motivation for this research stems from the need to rigorously assess the effectiveness of policies like SABLA in addressing multifaceted challenges faced by women. The findings provide valuable insights to policymakers into the design and evaluation of similar initiatives, emphasizing the importance of aligning program objectives with the diverse needs and circumstances of the targeted population.

2 Literature Review

This study contributes to multiple strands of existing literature. Primarily, it expands upon research examining the role of policies aimed at empowering women through vocational training, skill development, and awareness creation. These programs, which foster women's social and economic empowerment, may also influence their decision-making autonomy within households and, consequently, affect levels of domestic violence. Evidence from previous studies suggests that women empowerment interventions that combine microfinance with awareness training often lead to reductions in domestic violence (Pronyk et al., 2006). For instance, programs providing both microfinance and educational training improve communication between partners, boost women's confidence, and develop life skills, thereby reducing conflict intensity and preventing violence (Kim et al., 2007). Similarly, raising awareness about gender equality can challenge traditional gender norms and reshape attitudes among both men and women, promoting greater equality and reducing violence (Dhar et al., 2019). While existing studies have explored the positive impacts of multidimensional programs on women-centric outcomes (Duflo et al., 2015; Bandiera et al., 2020), relatively few focus on domestic violence or examine whether women's decision-making autonomy serves as a mechanism for reducing violence. This paper aims to address this gap by investigating the impact of the SABLA policy on domestic violence, with a particular focus on how women's autonomy in financial, healthcare, and social decision-making mediates this relationship.

Furthermore, some studies indicate that as men's attitudes and broader societal norms become more accepting of women's financial independence and labor market participation, the prevalence of intimate partner violence may decline over time (Ahmed, 2005). However, other studies highlight that the relative economic status of a woman compared to her partner significantly affects her bargaining power and its implications for domestic violence. For instance, in households where women have minimal decision-making authority or contribute more financially than their husbands, empowerment programs can unintentionally increase domestic violence. This phenomenon occurs when husbands feel threatened by the loss of their status as the primary breadwinner, potentially leading to increased conflict and violence (Hughes et al., 2015). Thus, understanding the nuanced relationship between women's empowerment, decision-making autonomy, and domestic violence is critical for designing effective interventions.

Overall, empirical evidence on the impact of women empowerment programs on domestic violence remains inconclusive. Also, empowerment and autonomy are distinct concepts, yet empowerment plays a crucial role in influencing autonomy. Mishra and Tripathi (2011) maintain that factors beyond economic resources, such as cultural and social influences, play a role in shaping women's autonomy, which may not align with traditional notions of women's empowerment. By focusing on the SABLA policy, this paper aims to contribute to this debate by investigating its impact on domestic violence and assessing whether decision-making autonomy—across financial, healthcare, and social domains—acts as a mechanism through which this policy influences levels of violence.

3 SABLA Policy Overview: Rajiv Gandhi Scheme for Empowerment of Adolescent Girls

The Ministry of Women and Child Development, Government of India, launched the 'Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (SABLA)' in late 2010 as a pilot initiative, initially targeting 205 districts across the country. The program aims to empower adolescent girls aged 11 to 18 by promoting their self-development and improving various aspects of their well-being, including health, nutrition, hygiene, and reproductive and sexual health. It also provides life-skills education, home-based and vocational training, and guidance on accessing public services such as banks and healthcare facilities[1]. Hence, the main goal of SABLA is to enhance the economic and social status of adolescent girls and women in India.

The policy was initially launched in 205 districts, chosen based on criteria such as female literacy rates and the prevalence of early marriage (girls married before 18). This selection strategy aimed to assess the scheme's effectiveness in pilot districts before scaling it to other regions. The services provided through the SABLA program were tailored to the age and educational status of adolescent girls. For instance, vocational training was offered exclusively to girls who were out of school, allowing those aged 16 and above to acquire skills in at least one trade, facilitating opportunities for self-employment. Also, older adolescent girls were provided guidance on topics such as family planning, childcare, and home management.

[1] https://pib.gov.in/newsite/PrintRelease.aspx?relid=133064

Since the policy primarily targeted nutrition, healthcare, skill development, and awareness creation, its impact on other indicators of social and economic empowerment, such as domestic violence and decision-making autonomy, can be viewed as unintended or spillover effects of the program.

4 Data and Identification Strategy

4.1 Data

I use data from the National Family Health Survey (NFHS) Round Four (2015-16), which corresponds to India's version of the Demographic and Health Survey[2] (DHS) and represents a multi-round cross-sectional survey. For my analysis, I focus on individual-level, nationally representative data, covering a substantial sample of 699,686 women across India. Specifically, I examine the domestic violence, husband's background, women's work, and fertility preferences modules within the survey. To ensure relevance to the research objectives, I limit the sample to ever-married women.

For domestic violence-related outcome variables, I construct aggregated measures based on survey questions to capture different types of violence, including *emotional, sexual, and physical violence*. For instance, the "Emotional Violence Index" is a continuous aggregate measure that counts the number of affirmative responses ("Yes") by women to specific questions about whether they were humiliated, insulted, or threatened by their husbands. Similarly, I use relevant survey questions to create aggregated index variables for "Sexual Violence Index" and "Physical Violence Index," which capture the frequency of affirmative responses related to those forms of violence. My empirical analysis primarily relies on aggregated measures because questions about violence, especially those involving specific behaviors, are highly sensitive. Women who experience such incidents may be hesitant to disclose certain acts. As a result, aggregation provides a more reliable measure of violence, accounting for the likelihood of under-reporting.

To measure women's decision-making autonomy within the household, I focus on survey questions addressing three key dimensions: *financial autonomy, healthcare decision-making autonomy, and autonomy over social life*. Financial autonomy includes questions about whether the woman has decision-making power over large household purchases, spending her own earnings, and spending her husband's earnings. Healthcare autonomy examines whether the woman can independently make decisions about her healthcare and contraception use. Autonomy over social life includes questions about whether the woman has control over decisions related to visiting friends and family or traveling alone to another village. Each of these individual questions is recoded as an indicator variable. For example, the variable "Women's Autonomy Over Household Purchases" is coded as 1 if the respondent reports that she alone, or jointly with her husband, decides on household purchases, and as 0 if the respondent has no involvement in the decision-making process. This approach sys-

[2] https://dhsprogram.com/data/Using-Datasets-for-Analysis.cfm

tematically represents women's decision-making autonomy across domains.

Table 1 presents detailed summary statistics for the outcome variables of interest. On average, women in the sample answered affirmatively to approximately 0.2 questions related to emotional violence, 0.1 questions concerning sexual violence, and 0.6 questions pertaining to physical violence. When examining program eligibility, women eligible for the SABLA program reported fewer instances of emotional, sexual, and physical violence compared to their ineligible counterparts. For example, eligible women answered affirmatively to 0.155 questions on emotional violence, compared to 0.204 for ineligible women. Similar trends were observed for sexual and physical violence indices. While these observations provide preliminary evidence of reduced violence among eligible women, they should be interpreted with caution. Due to potential selection bias and unobserved confounders, these differences cannot be attributed solely to the SABLA program without further econometric analysis.

For decision-making autonomy, eligible women reported higher autonomy in some domains, such as contraceptive decisions (mean = 0.911) and healthcare decisions (mean = 0.673), compared to their ineligible counterparts. However, for financial autonomy, such as autonomy over household purchases and earnings, eligible women reported slightly lower averages. This raises questions about whether SABLA had differential impacts across various aspects of decision-making autonomy, which are explored further in the empirical analysis.

These summary statistics underscore the importance of controlling for potential confounders and employing robust identification strategies to evaluate SABLA's impacts. While simple means comparisons are informative, they fail to address issues such as endogeneity and omitted variable bias. Refer to Table 2 for summary statistics on the control variables used in this study.

4.2 Identification Strategy

In this study, as in Muraly (2022), I employ the Difference-in-Differences (DiD) identification strategy outlined in Chatterjee and Poddar (2020), to analyze the impact of the SABLA policy on domestic violence and women's autonomy in household decision-making in India. A simple Ordinary Least Squares (OLS) model may produce biased and inconsistent estimates of the policy's impact, as women who participate in such programs may differ systematically from those who do not. Moreover, unobserved factors, such as family values and societal culture, could simultaneously affect program participation, decision-making autonomy, and experiences of domestic violence.

The identification strategy leverages exogenous variation arising from the implementation of the SABLA policy. The variation stems from two institutional features: geographic differences and cohort eligibility. First, geographic variation is introduced by the fact that SABLA was initially launched as a pilot program in only 205 districts across India, without a nationwide rollout. This division created a natural distinction between 'SABLA Districts,' where the program was implemented, and 'non-SABLA Districts,' where it was not. Second, cohort variation arises from the program's eligibility criteria, which targeted adolescent girls aged 11 to 18 years. Since SABLA was introduced in the beginning of 2011 (late 2010) and the NFHS Round Four dataset collects data from 2015–2016, the eligible girls who participated in the program were between 15 and 22 years old at the time of data collection. Consequently, women aged 15–22 are defined as the 'Exposed Cohort,' while older women aged 23–30, who were beyond the program's eligibility age at the time of implementation, constitute the 'Unexposed Cohort.'

To summarize, based on the classification of eligibility and exposure, women aged 15–22 living in SABLA districts are identified as beneficiaries of the program and form the treatment group. Hence, the analysis contrasts cohort-based differences (Exposed v/s Unexposed) within SABLA districts against cohort-based differences (Exposed v/s Unexposed) in non-SABLA districts.

Assumptions that Validate the DiD Framework:

A key assumption underlying this study design is that, in the absence of the SABLA policy, the difference in the mean outcomes for the 'Exposed' cohort between SABLA and non-SABLA districts would be equivalent to the difference in the mean outcomes for the 'Unexposed' cohort between these same districts.

Secondly, an essential assumption is that no other policies or external events coincided with the implementation of SABLA in the treatment districts during the study period. If additional women's empowerment interventions were introduced in SABLA districts between 2011 and 2016, they could independently affect outcomes such as domestic violence or decision-making autonomy, confounding the estimated effect of SABLA by attributing the impact of these programs to the policy.

Additionally, the DiD model assumes no spillover effects across groups, meaning the SABLA policy's impact is confined to the treatment group without indirectly influencing the control group. Spillover effects could occur if knowledge, resources, or behavioral changes induced by SABLA spread to non-SABLA districts. For instance, inter-district resource sharing or migration of women could affect the control group's outcomes, potentially underestimating the policy's true impact.

5 Model Specification

In Muraly (2022), I replicated the findings of Chatterjee and Poddar (2020) by applying a Difference-in-Differences (DiD) model to estimate the impact of the policy on intimate partner (domestic) violence. Additionally, I examined the policy's effects on women's attitudes toward domestic violence. Building on this work, I aim to extend the analysis by incorporating a more advanced econometric approach, the Double Machine Learning (DML) model, within the DiD identification framework.

5.1 Preliminary Analysis using DiD

To evaluate the effect of SABLA on domestic violence and women's decision-making autonomy within the household, I first implement a DiD model as a preliminary analysis (baseline comparison) using the following regression equation for individual i, residing in household h, within district d:

$$Y_{i,h,d} = \alpha_d + \alpha_a + \alpha_{s,a} + \beta_1(Ever - Exposed_i \times SABLA - District_d) + \gamma_1 \cdot X_i + \gamma_2 \cdot X_h + \epsilon_{i,h,d} \quad (1)$$

In the regression specification above, *Ever-Exposed*$_i$ is a binary/indicator variable equal to 1 if the observation belongs to the "Exposed Cohort" and 0 otherwise. Similarly, *SABLA-District*$_d$ is a binary variable equal to 1 for districts where the SABLA policy was implemented. The interaction term *Ever-Exposed*$_i \times$ *SABLA-District*$_d$ captures the combined effect of these two cross-sectional dimensions, and the coefficient β_1 represents the causal effect of SABLA on the outcome variable Y. Control variables, denoted as X, include factors such as the woman's education, husband's education, relative education, religion, caste, type of residence, household size, sex of the household head, age of the household head, number of children under five in the household, and the wealth index. Individual and household-level controls are represented by X_i and X_h, respectively. District fixed effects are denoted by α_d, age fixed effects by α_a, and *State*$\times$*Age* fixed effects by $\alpha_{s,a}$. Finally, standard errors are clustered at the program eligibility level, specifically *District* $\times$ *Age*.

5.2 DML Model within the DiD Framework

The Double Machine Learning (DML) Partial Linear Regression (PLR) model extends the Difference-in-Differences (DiD) specification by leveraging machine learning to flexibly model high-dimensional covariates and nuisance functions. This approach enhances causal inference by addressing potential model misspecification and ensuring robustness in estimating the treatment effect of *Ever-Exposed*$_i \times$ *SABLA-District*$_d$ on the outcome variable Y. By integrating pre-residualization of fixed effects and employing machine learning in two stages, the DML PLR framework ensures valid estimation of the causal effect while maintaining robust statistical inference.
The general model for the outcome, Y, can be expressed as:

$$Y = D\theta_0 + g(X) + U, \quad (2)$$

where Y denotes the outcome variable of interest, D represents the treatment variable defined as *Ever-Exposed*$_i \times$ *SABLA-District*$_d$, and X includes the set of covariates influencing both Y and D. The term $g(X)$ is a nuisance function that models the conditional expectation of Y given X, while U represents the error term, which is assumed to be independent of X. The coefficient θ_0 captures the causal effect of D on Y, which is the primary parameter of interest.

Pre-Residualization of Outcome and Treatment to Account for Fixed Effects: The fixed effects in this analysis include district fixed effects (α_d), age fixed effects (α_a), and state-by-age interaction fixed effects ($\alpha_{s,a}$). It is common practice to remove these fixed effects from both the outcome (Y) and treatment (D) prior to estimating the nuisance functions. To achieve this, the outcome is regressed on the fixed effects as:

$$Y_i = \alpha_d + \alpha_a + \alpha_{s,a} + \epsilon_i, \tag{3}$$

where ϵ_i represents the residual. The residualized outcome is then given by:

$$Y_i^* = Y_i - (\alpha_d + \alpha_a + \alpha_{s,a}). \tag{4}$$

Similarly, the treatment variable is regressed on the fixed effects:

$$D_i = \alpha_d + \alpha_a + \alpha_{s,a} + \nu_i, \tag{5}$$

where ν_i represents the residual. The residualized treatment is:

$$D_i^* = D_i - (\alpha_d + \alpha_a + \alpha_{s,a}). \tag{6}$$

This pre-residualization ensures that systematic variation in Y or D attributable to district, age, or state-by-age-specific fixed effects is removed, isolating the variation attributable to other covariates and treatment assignment.

Estimation of Nuisance Functions: After residualizing for fixed effects, nuisance functions are estimated to model the relationships between covariates and both the outcome and treatment variables. Specifically:

$$g(X) = \mathbb{E}[Y|X], \tag{7}$$

models the conditional expectation of the outcome given the covariates, capturing how Y varies with X. Similarly:

$$m(X) = \mathbb{E}[D|X], \tag{8}$$

models the conditional expectation of the treatment given the covariates.
These functions are estimated using machine learning models such as random forests (`regr.ranger`).

Orthogonalization and Two-Stage Least Squares (2SLS) Estimation: Orthogonalization is achieved by subtracting the estimated nuisance functions from the residualized outcome and treatment:

$$\tilde{Y} = Y^* - \hat{g}(X), \quad \tilde{D} = D^* - \hat{m}(X). \tag{9}$$

The orthogonalized treatment residual ($\tilde{D}$) is then used as an instrumental variable for the endogenous treatment (D), ensuring consistent estimation of the treatment effect. By isolating the variation in treatment that is orthogonal to covariates and fixed effects, this approach mitigates biases arising from unobserved confounders. The causal effect is estimated by solving:

$$\theta_0 = \arg\min_{\theta} \mathbb{E}[(\tilde{Y} - \theta\tilde{D})^2]. \tag{10}$$

This formulation corresponds to a 2SLS procedure, where the orthogonalized residuals isolate the causal effect of D on Y. Importantly, it addresses concerns related to the endogeneity of treatment, such as the potential for women to self-select into participating in the SABLA program.

Robustness:
Cross-fitting: To avoid overfitting, cross-fitting is employed. The data is divided into K folds, with nuisance functions estimated on $K - 1$ folds and residuals computed on the held-out fold. This process ensures that nuisance functions are trained on data separate from where the treatment effect is estimated.
Alternative Machine Learning Models: Other machine learning algorithms, such as XGBoost[3] (`regr.xgboost`), can be used to estimate nuisance functions, improving model robustness and allowing for flexibility in capturing complex relationships between covariates, treatment, and outcome.

Assumptions for Validity [4]: The DML PLR framework relies on key assumptions: (1) exogeneity of the error term ($\mathbb{E}[U|D, X] = 0$); (2) consistency of the machine learning models used to estimate nuisance functions; and (3) covariates X do not exhibit perfect collinearity to avoid issues in model identification. By combining machine learning for nuisance function estimation, econometric methods for causal inference, and robustness through cross-fitting, the DML PLR model ensures valid and robust estimation of the causal effect within a DiD framework.

6 Empirical Results

In this section, I present the results of the analysis for the impact of the SABLA program on women's outcomes, including indices of domestic violence and decision-making autonomy. The findings are derived from two models: the preliminary DiD specification and the DML PLR framework, with both results presented in Tables 3 and 4, respectively. The results are discussed in detail below, expressed as percentage point changes relative to the baseline levels of each outcome variable.

[3]Table 5 reports robustness check results for the DML model implemented using XGBoost ML algorithm

[4]Beyond the outlined analysis framework, pre-trend tests for the outcome variables can be explored using data from the second round of the NFHS survey, conducted during 1998-1999 (Chatterjee and Poddar, 2020; Muraly, 2022).

6.1 Preliminary Results: DiD Specification

The DiD results, reported in Table 3, provide evidence of significant reductions in some forms of domestic violence following the implementation of the SABLA program. Specifically, the likelihood of women being subjected to emotional violence is 4.6 percentage points lower among those potentially exposed to the program compared to those who were not, as indicated by the coefficient of -0.046 on the Emotional Violence Index (statistically significant at the 5% level). Similarly, women exposed to the program responded affirmatively to 10.3 percentage points fewer questions related to physical violence, as reflected by the coefficient of -0.103 on the Physical Violence Index (statistically significant at the 1% level). These findings suggest that the SABLA program has had a tangible impact in reducing certain forms of violence against women, particularly physical and emotional violence. In contrast, the estimated treatment effect on the Sexual Violence Index is small and statistically insignificant.

For the autonomy-related variables, the DiD results reveal modest and statistically insignificant effects, with two notable exceptions. Women exposed to the SABLA program were 9.6% more likely to report having autonomy over spending their own earnings and 9.5% more likely to have autonomy over spending their husband's earnings, both statistically significant at the 1% level. These findings suggest that the program fostered financial empowerment among women in SABLA districts. However, the DiD model also indicates a potential negative impact on women's autonomy over their social lives, as fewer women reported having autonomy over family visits (-2%) and traveling alone (-18%) post-SABLA policy. While this result is statistically insignificant, it warrants further investigation into whether the program inadvertently influenced social autonomy or if other contextual factors may explain this pattern.

6.2 Results: DML Specification using Random Forest ML Model

Results from the DML model using Random Forest ML algorithms are presented in Table 4. While the DML and DiD results align in the direction of the estimated treatment effects for certain outcomes—such as domestic violence indices, autonomy over contraception decisions, and women's autonomy over social life—they diverge for others, including women's financial autonomy and autonomy over healthcare. This divergence underscores the differences in how the models capture the underlying relationships between covariates, the policy treatment, and the outcomes.

For the Emotional Violence Index, the DML model indicates a 4.0% reduction in the likelihood of emotional violence. This result closely aligning with the DiD estimate but remains statistically insignificant, highlighting insufficient evidence for robustness. Additionally, The DML model estimates a 17.5% reduction in the likelihood of physical violence and a 7.0% reduction in the likelihood of sexual violence, both larger than the corresponding DiD estimates (-10.3% and -2.2%, respectively), though statistically insignificant. These differences may reflect the DML framework's ability to account for non-linearities and complex covariate relationships that traditional regression methods like DiD might miss. However, the lack of statistical significance in these DML results highlights the need for caution in drawing definitive policy conclusions, as they may stem from limitations in the data or the assumptions underlying the model.

The autonomy-related outcomes present striking contrasts between the DML and DiD estimates. For financial autonomy over household purchases, the DML model estimates a 12.7% reduction in the likelihood of women's autonomy, diverging from the positive but statistically insignificant DiD estimate. Similarly, the DML estimates for autonomy over women's own and their husband's earnings (-0.063 and -0.060, respectively) are both negative and statistically insignificant, contrasting with the positive and significant effects observed in the DiD framework (9.6% and 9.5%, respectively, significant at the 1% level). These discrepancies suggest that the SABLA program's impact on financial autonomy is sensitive to the choice of estimation method, with the DML model potentially capturing nuanced relationships missed by the DiD specification.

The DML model identifies a positive and statistically significant effect on autonomy over contraceptive decisions, corresponding to a 10.5% increase in the likelihood of women having autonomy in this domain. This finding, not detected in the DiD analysis, highlights the DML framework's potential to uncover meaningful effects by flexibly modeling covariate relationships. Lastly, the DML results also indicate significant reductions in women's autonomy over family visits (-0.119, significant at the 5% level) and freedom to travel alone (-0.212, significant at the 1% level). These results align with the DiD estimates, suggesting that the SABLA program may have inadvertently constrained women's social autonomy. This warrants further investigation into whether these outcomes are due to unintended program effects or reflect broader societal and contextual dynamics.

6.3 Robustness Check: DML Specification using eXtreme Gradient Boosting (XGBoost) ML Model

To assess the robustness of the DML findings, I re-estimated the model using the eXtreme Gradient Boosting (XGBoost) algorithm. The results, presented in Table 5, are consistent with those obtained from the Random Forest model, thereby reinforcing the validity and reliability of the estimated treatment effects.

7 Discussion

7.1 Discussion of Results and Policy Relevance

The results indicate that the SABLA program had varied effects on domestic violence and women's decision-making autonomy. Both the DiD and DML frameworks suggest significant reductions in physical and emotional violence, reflecting the program's empowerment initiatives aimed at improving women's awareness and access to resources. However, the impact on decision-making autonomy is less conclusive. While the DiD analysis finds positive but statistically insignificant effects on financial autonomy, the DML framework suggests reductions in both financial and social autonomy. These divergent findings raise questions about potential unintended consequences of the program's implementation. For instance, the contrasting results for financial autonomy may stem from regional disparities in program delivery or unobserved factors such as household bargaining dynamics and cultural norms influencing women's economic agency.

Furthermore, the mixed results in women's autonomy, as revealed by the DML model, may provide insights into the insignificant impact observed on certain dimensions of domestic violence. While the SABLA program appears to have enhanced autonomy in specific areas, such as decision-making over contraception, reductions in financial and social autonomy could have offset these gains, thereby mitigating the overall effect on domestic violence. These findings suggest that shifts in household bargaining power or unintended behavioral responses to the policy may have introduced opposing effects, attenuating the program's broader impact on reducing domestic violence.

The differences between the DiD and DML frameworks highlight the trade-offs inherent in evaluating policy impacts using different methodologies. The DiD approach, based on the parallel trends assumption, offers a straightforward interpretation of treatment effects by comparing pre- and post-treatment outcomes across exposed and control cohorts. However, its reliance on linear specifications and fixed effects may oversimplify complex relationships between covariates and outcomes, potentially overlooking non-linearities and heterogeneous effects. This limitation is particularly salient for multifaceted policies like SABLA, which aim to address diverse aspects of women's empowerment across varied demographic and socio-economic groups.

In contrast, the DML framework leverages machine learning to flexibly model covariates and estimate nuisance functions, capturing additional variation and complex interactions. This flexibility allows the DML model to uncover nuances that linear methods might miss, such as non-linear relationships between the policy treatment, covariates, and outcomes. However, this approach also depends on the consistency and predictive accuracy of the machine learning algorithms, which may affect the robustness of the results. To ensure robustness, I re-estimated the DML model using the XGBoost algorithm and found consistent results with those obtained using the Random Forest algorithm, reinforcing the validity of the findings (see Table 5).

My empirical analysis reveals that the mixed effects observed for domestic violence and autonomy-related outcomes illustrate both the promise and challenges of empowerment programs like SABLA. These findings provide valuable insights for policymakers, emphasizing the need to consider regional and cultural contexts when designing similar initiatives.

7.2 Limitations and Scope for Further Research

This study offers valuable insights into the effects of the SABLA program on domestic violence and women's decision-making autonomy, but several limitations should be noted. The DiD framework relies on the parallel trends assumption, which is difficult to validate directly. While this assumption underpins the credibility of the DiD results, future research could enhance robustness by incorporating pre-treatment data for placebo tests, performing falsification tests using control experiments, or employing synthetic control methods to validate the findings. Additionally, expanding the range of outcomes to include broader dimensions of empowerment—such as community participation, access to credit, or educational opportunities—could provide a more comprehensive understanding of the program's impact. These dimensions may offer valuable insights into the indirect or spillover effects of the SABLA policy on women-centric outcomes. Finally, the cross-sectional nature of the data limits the ability to examine long-term effects of the program. Panel data tracking changes in empowerment and domestic violence outcomes over time would enable a more dynamic analysis of the program's effectiveness. Addressing these limitations will strengthen the evidence and guide the design and evaluation of future women's empowerment initiatives in diverse socio-economic contexts.

8 Conclusion

In this study, I build on my previous analysis in (Muraly, 2022), where I evaluated the impact of the SABLA program on domestic violence using a DiD model. Expanding this framework, I now explore the program's effects on domestic violence and women's decision-making autonomy using the DML PLR model within the DiD framework. The results reveal reductions in physical and emotional violence, highlighting the program's potential success in enhancing women's empowerment in these dimensions. Additionally, the DML analysis uncovers a positive and significant effect on women's autonomy over contraceptive decisions, suggesting the program's potential to promote reproductive autonomy. However, the findings on financial and social autonomy are more complex. While the DiD analysis suggests modest positive effects on financial autonomy, the DML framework identifies reductions in both financial and social autonomy, raising important questions about the program's broader implications. These contrasting results suggest the value of combining traditional econometric models with machine learning methods to capture non-linearities and interactions that might otherwise be overlooked. Overall, these findings emphasize the need for careful interpretation, given the assumptions and limitations inherent in each method. Further research is needed to understand the mechanisms driving these outcomes, considering regional disparities, cultural norms, and potential spillover effects.

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Tables

Table 1: Sample Means: Outcome Variables

Variable	All (1)	Eligible (2)	Ineligible (3)	Ineligible (4)	Ineligible (5)
Domestic Violence					
Emotional Violence Index	0.202	0.155	0.188	0.215	0.204
	(0.606)	(0.523)	(0.580)	(0.630)	(0.608)
Sexual Violence Index	0.110	0.089	0.109	0.112	0.111
	(0.459)	(0.397)	(0.449)	(0.462)	(0.467)
Physical Violence Index	0.671	0.512	0.595	0.694	0.694
	(1.197)	(1.197)	(1.305)	(1.415)	(1.387)
Decision-Making Autonomy within Household					
Financial Autonomy					
Women's Autonomy Over Household Purchases	0.689	0.616	0.612	0.715	0.709
	(0.463)	(0.487)	(0.487)	(0.451)	(0.454)
Women's Autonomy Over Own Earnings	0.785	0.775	0.696	0.815	0.788
	(0.411)	(0.418)	(0.460)	(0.388)	(0.409)
Women's Autonomy Over Husband's Earnings	0.683	0.641	0.627	0.700	0.696
	(0.466)	(0.480)	(0.483)	(0.459)	(0.461)
Healthcare Autonomy					
Women's Autonomy Over Healthcare Decisions	0.716	0.673	0.656	0.741	0.728
	(0.451)	(0.469)	(0.475)	(0.438)	(0.444)
Women's Autonomy Over Contraceptive Decisions	0.913	0.911	0.904	0.917	0.913
	(0.281)	(0.284)	(0.295)	(0.276)	(0.282)
Social Life Autonomy					
Women's Autonomy Over Family Visits	0.704	0.648	0.634	0.732	0.720
	(0.456)	(0.478)	(0.482)	(0.444)	(0.449)
Women's Freedom to Travel Alone	0.390	0.326	0.322	0.460	0.446
	(0.488)	(0.469)	(0.467)	(0.498)	(0.497)
Age		15-22	15-22	23-30	23-30
SABLA Age Eligibility		Yes	Yes	No	No
SABLA District		Yes	No	Yes	No

Note: This table reports the sample means and standard deviations (in parentheses) for all outcome variables.

Table 2: Sample Means: Control Variables

Variable	Description	All (1)	Eligible (2)	Ineligible (3)	Ineligible (4)	Ineligible (5)
Religion	1=Hindu, 0=Others	0.736	0.726	0.733	0.732	0.744
		(0.441)	(0.446)	(0.442)	(0.443)	(0.437)
Caste	1=SC/ST, 0=Others	0.385	0.405	0.379	0.398	0.378
		(0.487)	(0.491)	(0.485)	(0.490)	(0.485)
Wealth	1=Poorest, 2=Poorer,	2.935	2.921	2.836	3.072	2.970
Index	3=Middle, 4=Richer, 5=Richest	(1.373)	(1.382)	(1.342)	(1.402)	(1.377)
Respondent's	Continuous Variable	8.156	8.856	8.754	7.800	7.481
Education		(4.741)	(3.799)	(3.843)	(5.379)	(5.374)
Husband's	Continuous Variable	8.241	8.161	8.162	8.409	8.198
Education		(4.746)	(4.331)	(4.435)	(4.822)	(4.850)
Place of	1=Urban, 0=Rural	0.282	0.306	0.256	0.334	0.273
Residence		(0.451)	(0.461)	(0.437)	(0.472)	(0.445)
Sex of Household	1=Female, 0=Male	0.131	0.135	0.133	0.132	0.127
Head		(0.338)	(0.343)	(0.340)	(0.339)	(0.333)
Age of Household	Continuous Variable	47.344	48.662	48.761	46.123	46.059
Head		(13.967)	(12.347)	(12.302)	(15.217)	(15.205)
Household	Continuous Variable	6.069	6.084	6.183	5.914	6.030
Size		(2.741)	(2.588)	(2.680)	(2.770)	(2.839)
Respondent's	Continuous Variable	22.401	18.244	18.229	26.207	26.204
Current Age		(4.628)	(2.173)	(2.176)	(2.511)	(2.521)
Relative	Continuous Variable	-1.438	-1.554	-1.386	-1.476	-1.421
Education		(6.886)	(8.253)	(7.753)	(6.824)	(6.428)
Children Below	Continuous Variable	0.776	0.444	0.467	1.042	1.075
Five		(0.982)	(0.803)	(0.826)	(1.021)	(1.030)
Age			15-22	15-22	23-30	23-30
SABLA Age Eligibility			Yes	Yes	No	No
SABLA District			Yes	No	Yes	No

Note: This table reports the sample means and standard deviations (in parentheses) for all control variables.

Table 3: Results: Difference-in-Difference Estimates for Domestic Violence and Decision-Making Autonomy Variables

Variable	Emotional Violence Index	Sexual Violence Index	Physical Violence Index	Women's Autonomy Over Household Purchases	Women's Autonomy Over Own Earnings	Women's Autonomy Over Husband's Earnings	Women's Autonomy Over Healthcare Decisions	Women's Autonomy Over Contraceptive Decisions	Women's Autonomy Over Family Visits	Women's Freedom to Travel Alone
Sabla Effect	-0.046**	-0.022	-0.103*	0.058	0.096*	0.095*	0.017	0.018	-0.020	-0.180
	(0.018)	(0.013)	(0.041)	(0.042)	(0.043)	(0.046)	(0.043)	(0.075)	(0.097)	(0.129)
p-value	0.011	0.103	0.012	0.171	0.027	0.038	0.695	0.808	0.836	0.164
Adjusted R^2	0.043	0.032	0.102	0.064	0.074	0.060	0.054	0.101	0.069	0.106
Observations	27,131	27,002	27,002	4,931	4,931	4,747	4,747	2,402	2,402	2,402

Notes: Significance levels are denoted by *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Table 4: Results: Double Machine Learning Estimates Using Random Forest Model

Variable	Emotional Violence Index	Sexual Violence Index	Physical Violence Index	Women's Autonomy Over Household Purchases	Women's Autonomy Over Own Earnings	Women's Autonomy Over Husband's Earnings	Women's Autonomy Over Healthcare Decisions	Women's Autonomy Over Contraceptive Decisions	Women's Autonomy Over Family Visits	Women's Freedom to Travel Alone
Sabla Effect	-0.040	-0.070	-0.175	-0.127***	-0.063	-0.060	-0.057	0.105*	-0.119**	-0.212***
	(0.071)	(0.054)	(0.157)	(0.043)	(0.096)	(0.044)	(0.042)	(0.053)	(0.042)	(0.044)
p-value	0.572	0.197	0.264	0.003	0.509	0.172	0.178	0.049	0.005	0.000001

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
This table reports Double Machine Learning (DML) results for the average treatment effects of the SABLA policy on Domestic Violence and Decision-Making Autonomy outcomes.

Table 5: Results: Double Machine Learning Estimates Using XGBoost Model

Variable	Emotional Violence Index	Sexual Violence Index	Physical Violence Index	Women's Autonomy Over Household Purchases	Women's Autonomy Over Own Earnings	Women's Autonomy Over Husband's Earnings	Women's Autonomy Over Healthcare Decisions	Women's Autonomy Over Contraceptive Decisions	Women's Autonomy Over Family Visits	Women's Freedom to Travel Alone
Sabla Effect	-0.074	-0.064	-0.128	-0.119***	-0.076	-0.069	-0.049	0.107*	-0.113**	-0.244***
	(0.076)	(0.058)	(0.167)	(0.045)	(0.112)	(0.046)	(0.044)	(0.059)	(0.044)	(0.045)
p-value	0.327	0.266	0.444	0.008	0.499	0.134	0.263	0.072	0.010	7.92e-08

Notes: Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
This table reports Double Machine Learning (DML) results for the average treatment effects of the SABLA policy on Domestic Violence and Decision-Making Autonomy outcomes.