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Education, Social Norms, and the Marriage Penalty

Evidence from South Asia

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Abstract

A growing literature attributes gender inequality in labor market outcomes in part to the reduction in female labor supply after childbirth, the child penalty. However, if social norms constrain married women's activities outside the home, then marriage can independently reduce employment, even in the absence childbearing. Given the correlation in timing between childbirth and marriage, conventional estimates of child penalties will conflate these two effects. The paper studies the marriage penalty in South Asia, a context featuring conservative gender norms and low female labor force participation. The study introduces a split-sample, pseudo-panel approach that allows for the separation of marriage and child penalties even in the absence of individual-level panel data. Marriage reduces women's labor force participation in South Asia by 12 percentage points, whereas the marginal penalty of childbearing is small. Consistent with the central roles of both opportunity costs and social norms, the marriage penalty is smaller among cohorts with higher education and less conservative gender attitudes.

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Education, social norms, and the marriage penalty: Evidence from South Asia

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1 Introduction

In nearly every country in the world, women participate in the labor force at a lower rate than men. The persistence of the traditional specialization of women in the home and men in the marketplace is one of the most consistent empirical facts in the social sciences. Much of this gap arises from the costs of child-rearing, which are disproportionately borne by women. In Asia, women spend around 5 times as much as men on household tasks (Van der Gaag et al., 2019). The sharp decline in the labor market outcomes of women relative to men around the birth of the first child – the so-called "child penalty" – is a central driver of gender inequality in the labor markets across the world (Kleven et al., 2019).

However, childbearing typically occurs concurrently with other key events of family formation, in particular marriage. Conventional estimates of the child penalty often ignore that, even in the absence of children, the act of marriage confers new responsibilities and social norms that may constrain a woman's labor supply. These marital constraints – the "marriage penalty" – may be conflated with childbearing constraints in a typical child penalty estimation, given the correlation in time between these two events.

In settings where gender roles are deeply entrenched (Jayachandran, 2020), married but childless women may be already confined to domestic responsibilities even where they are not yet constrained by the burdens of childcare. This marriage penalty may in part explain the mixed evidence globally on the impact of access to childcare on women's labor supply (Evans et al., 2021). In South Asia in particular – a region known for both conservative gender norms and low female labor force participation – the experimental evidence in favor of childcare access is weak (Nandi et al., 2020; Richardson et al., 2018), suggesting childcare responsibilities are not the main constraint to female employment. Similarly, Abraham et al. (2021) find no evidence of child penalties in India. This evidence points to the primacy of marriage over child penalties in settings where gender norms are strict.

Still, much like the child penalty, the marriage penalty may have diverse causes. Is a marriage penalty evidence of conservative social norms that proscribe married women's physical mobility and work outside the home? Or is it, instead, a reflection of the optimal household specialization between men and women, given limited outside options for women in the labor market, as in Becker (1993). In the context of South Asia, this paper answers two questions: (i) how can the marriage penalty be separated from the child penalty in the absence of individual-level panel data, and (ii) what drives the marriage penalty in South Asia. Does it represent optimal labor supply or a misallocation of talent?

To answer these questions, we use multiple rounds of the nationally representative Demographic and Health Surveys (DHS) from four South Asian countries – Bangladesh, India, Maldives, and Nepal. Separately estimating child and marriage penalties presents several challenges. First, since the timing of these major life events is endogenous, naive comparisons in the labor market outcomes between married and unmarried women or parents and the childless are contaminated by omitted variables. Recent work on child penalties has used event-study methods to solve this identification problem (Kleven et al., 2021, 2019, 2024).

However, even if a design exploits sharp changes in labor supply around marriage or childbirth for identification, these two events are correlated in time for a given individual. As such, estimates of the marriage penalty are obscured by the presence of children, and estimates of the child penalty are likewise capturing at least in part a marriage penalty. One solution is to use individual-level panel data, where a woman's employment status is observed before and after both marriage and childbirth. Here, event-study techniques readily apply, augmenting standard specifications with timing indicators for both events simultaneously, with marriage and childbirth coefficients separately identified by variation across women in the timing gap between these two events (Kleven et al., 2023).

However, access to such rich panel data is rare, particularly in developing country settings. We propose a method that allows for the separation of the marriage penalty from the child penalty in repeated cross-sectional data. Following Kleven et al. (2023), we generate pseudo-panels by matching women surveyed in the year of their marriage with younger unmarried women and older married women to construct pre- and post-marriage counterfactual employment trends. Our contribution is to restrict the pool of potential post-marriage matches to women without children (the "no child" sample) in order to isolate the marriage penalty from the child penalty. We then re-run this matching procedure on the unrestricted sample of women where children may be present (the "ignore child" sample). Comparing these two quantities yields the relative magnitude of marriage penalty alone and the combined marriage and child penalty.

We find that South Asian women reduce their labor force participation by 12 percentage points (p.p.) following marriage, even before childbearing. Among women with children, this rises just 4 p.p to 16 p.p. As such, 75 percent of the combined family formation penalty is driven by marriage itself, rather than the burden of childbearing, at least in the first five years of marriage. The largest effects are observed in India, while more muted effects are observed in Nepal, where the majority of the combined penalty is driven by children. Dynamic event-study estimates reveal flat trends in employment status leading up to the marriage date, and sharp drops in employment in the first year of marriage. These trends lend additional support to the notion that these estimates represent the causal effect of marriage. Men, in contrast, enjoy a marriage premium. This premium does not depend on the presence of children, consistent with the existing literature showing no child penalties for men (Kleven et al., 2023).

The marriage penalty may represent an optimal solution to a joint household maximization problem. If women have limited outside options in the labor market relative to their husbands, then specialization in home-based tasks might be economically efficient, even without children. However, the value of women's home production is greatly diminished without children, suggesting a role for social norms in driving the marriage penalty, particularly those that constrain women's mobility outside the home (Anukriti et al., 2020). To adjudicate these hypotheses, we use heterogeneity analyses to test the sources of the marriage penalty. Despite the fact that gender norms are more progressive in urban areas in South Asia (Asher et al., n.d.), we find no significant difference between urban and rural marriage penalties. This may in part reflect the nature of urban labor markets, where employment opportunities are concentrated *outside* the home, adding additional constraints to women's participation in the context of conservative gender attitudes (Jalota and Ho, 2024).

We then turn to testing the impact of education and social norms on marriage penalties in South Asia by interacting our post-marriage indicator with these characteristics. We find that educated women have much smaller marriage penalties, with post-secondary education erasing nearly half the baseline marriage penalty. At the same time, educated husbands exert a quantitatively similar effect. Because of positive assortative mating, spousal education levels are highly correlated, necessitating the inclusion of both interactions in a single regression. In this model, the wife's education remains significant while the coefficient on the husband's education falls to zero.

Interpreting these results through the lens of our hypotheses, we argue that a woman's education affects *both* household gender norms and her outside employment options. In contrast, her husband's education affects household norms, but does not directly affect her employment prospects. This suggests that outside options at least in part play a role in determining the marriage penalty. Finally, we directly test the role of gender attitudes by interacting the marriage indicator with DHS measures of household gender attitudes. We find strong evidence that women in households with more liberal gender norms experience smaller marriage penalties. The effects of education and social norms appear to be independent, suggesting that both opportunity costs and social norms play a role in driving the marriage penalty.

We contribute to the large and growing literature on gender inequality. The specialization of women in the home and men in the marketplace relates to women's real or perceived comparative advantage in the home (Becker, 1973). Under specialization, women invest in home specific human capital, while men invest in market specific human capital, raising wages. Empirically, married men have substantially higher wages than unmarried men, even after controlling for human capital and job characteristics (Hersch and Stratton, 2000), suggesting that specialization through marriage makes men more productive. Our evidence on men is consistent with this literature. Nevertheless, despite substantial attention to gender inequality in recent years, there is limited causal evidence about the impact of marriage on women's labor market outcomes. This paper begins to fill that gap.

Despite rising women's human capital and narrowing gender gaps in education across the world, female labor force participation remains low in many parts of the world, including South Asia. One potential explanation for low female labor force participation is gender norms, which can generate spousal disagreement over the provision of the household public good (Bertrand et al., 2016; Fernandez et al., 2004). Child penalties have been documented in high and lower income settings with magnitudes ranging from 12 to 38 percent (Kleven, 2022; Kleven et al., 2019, 2023). However, it can plausibly be argued that women have a comparative advantage in childcare relative to their husbands. We show that even before childbirth, marriage itself might already affect female labor force participation in settings with deeply entrenched gender norms. Our work provides some of the first evidence on the magnitudes of marriage penalties, rather than child penalties, and proposes a method for distinguishing between the two in cross-sectional data. We also directly link marriage penalties to skill levels, outside options, and social norms.

The remainder of the paper is organized as follows. Section 2 provides an overview of the data and empirical strategy. Section 3 presents our findings, followed by an exploration of the determinants of the marriage penalty for women in Section 4. Section 5 concludes with policy implications.

2 Data and Empirical Strategy

2.1 Data

We use data from the Demographic and Health Survey (DHS) from Bangladesh, India, Maldives, and Nepal in the analysis (Table A1).[1] The surveys were conducted approximately every 5 years starting in the 1990s. These nationally representative surveys form a repeated cross section of reproductive age women between the ages of 15 and 45. The more recent surveys also include data on the men in the households, so there are fewer rounds of data for men. The final sample covers 1,780,854 women and 389,313 men residing in around 650,000 households in all level 1 administrative areas of the 4 countries.

The surveys include age, education, urban residence, employment status, and marital status. For women, the surveys include age at cohabitation, which we use as the age at marriage, and birth history, which includes the timing of the first birth. Importantly, these surveys contain complete household rosters with data on employment status for *both* married and unmarried women, which will be essential to the pseudo-panel approach below.

[1] Other countries in South Asia are excluded because the DHS data lack sufficient information on employment status for both married and unmarried women.

More recent rounds of the DHS also include questions on decision making and attitude toward domestic violence. The decision making questions include whether or not women are involved in decisions on their own health care, purchases, and visits to family. The decision making index is the sum of all the decision making items in which the woman is involved individually or jointly. A higher index suggests higher decision making power for women. The questions on attitude toward domestic violence include whether it would be justified for a husband to beat his wife if she goes out without telling her husband, neglects the children, argues with her husband, refuses sex, and burns the food. The index for the attitude toward domestic violence is the sum of all the items with which the woman agrees. A higher index suggests a higher acceptance of domestic violence.

2.2 Empirical strategy

2.2.1 Estimation

We use an event study approach based on sharp changes in women's labor market outcomes observed around the time of marriage, $t = 0$, for individuals at age a observed in calendar year y. Ideally, the estimation uses individual-level panel data, in which case relative time indicators for marriage and childbirth can be included simultaneously, along with individual and year fixed effects, in a single event-study regression where labor market participation is the outcome Kleven et al. (2023).

However, in the absence of such data, following Kleven (2022), cross sectional data can be used to create pseudo-panel data. For married individuals, we observe the age of marriage, and therefore their location the post-marriage event space, $t \geq 0$. For unmarried individuals, we cannot observe their timing of marriage, and therefore only observe that they are in the pre-marriage event space, $t < 0$, but not their precise location in this space. The pseudo-panel approach matches married women to unmarried women with the same demographic characteristics to form a pre-marriage counterfactual estimate of the outcome, transforming the cross sectional data into a pseudo-panel across the pre and post-marriage event spaces.

Specifically, woman i is observed in the year of her marriage $t = 0$ in calendar year y at age a, with demographic characteristics X_i. She is matched to a surrogate observation in the pre-marriage period, an unmarried woman j observed in year $y-n$ with age $a-n$ and the same observed characteristics $X_i = X_j$. Then, for each n up to 5, the matches at $t-n$ are used to construct the pre-marriage counterfactual at that period. To maximize the sample, we match on a parsimonious set of characteristics, including the level of education and rural or urban residence.

A similar procedure is then applied to women k in the post marriage event space, who are observed in y at $t+n$ for n from 1 to 5. For these post-marriage matches, we additionally require that the age at marriage is the same as index woman i. Accordingly, a pseudo-panel is constructed for woman i to generate counterfactual employment levels for 5 years before and after marriage. Furthermore, woman i represents all of the women with X_i observed at $t = 0$ in y, who enter her cohort as "reference women" and are matched with the same counterfactual women j and k. Well call these groups, indexed c, "marriage cohorts."

These marriage cohorts are then collapsed at the event year-cohort level to obtain average labor market outcomes for each cohort for five years pre and post marriage, as well as cohort characteristics. The procedure is then repeated on the sample of men. A marriage cohort c, then, is a three-element vector, defined by an age of marriage, a rural-urban indicator, and an education level. Within each cohort, age a and birth year (birth cohort) b vary with event-time t by construction, given that the pre and post marriage components of the marriage cohorts are formed using ages relative to the reference woman.

For marriage cohort c at event time t, we estimate the following regression specification separately for each gender g:

$$Y^g_{ct} = \alpha^g + \beta^g D_{ct} + \delta^g_a + \gamma^g_b + \nu^g_{it} \tag{1}$$

Where Y^g_{ct} is the outcome of interest, the cohort average employment status. D_{ct} is an indicator for post-marriage event periods, and β^g is the estimate of the marriage penalty or premium. In our main estimates, we present D_{ct} as a collapsed indicator for all post-marriage event periods, giving the event time-averaged treatment effect. However, we also present event-study specifications where we include leads and lags of the event year ($t-5$ up to $t+5$), allowing for dynamic pre and post marriage trends in employment.

In a marriage single cohort, the pre and post marriage indicators are collinear with age and/or birth cohort fixed effects δ_a, and γ_b since the marriage cohort matches were selected by their age relative to the reference woman. However, when many marriage cohorts are stacked within a given survey round, then age fixed effects can be included in the regression, since age of marriage varies across marriage cohorts. That is, within a given age there is still variation across marriage cohorts in the location in event-time.

However, age and birth cohort remain collinear for all marriage cohorts in a given survey round (country-year). However, when multiple survey rounds per country are stacked, birth cohort fixed effects γ_b^g can be included as well as the age effects. Alternatively, to take into account multiple surveys across countries, country and survey year fixed effects could also be included. Note, however, that in cross-country pooled sample, country-year, age, and birth cohort fixed effects are collinear, and so including any two of these three yields equivalent estimates.[2]

The sample size in each country varies, so the analysis is weighted by marriage cohort size so that it is representative at the individual level, and provides identical coefficient estimates to estimation on the microdata in a "stacked" model. Standard errors are clustered at the marriage cohort level.

We also consider several heterogeneity analyses to investigate the mechanisms underlying the marriage penalty. To explore the role of urban residence, the same analysis as in equation 1 is conducted on the urban and rural samples separately. To explore the role of education, the analysis includes an interaction term between women's higher education and the post-marriage indicator. A separate regression is run to analyze the role of husband's education by including an interaction term between husband's higher education and the post-marriage indicator. Higher education (or husband's higher education) takes the value one if women (or their husbands) have more than secondary education. Finally, we explore the role of social norms similarly, interacting the post-marriage indicator with a marriage cohort-averaged gender attitudes index.

[2]In practice, we include birth-cohort and country-year fixed effects.

2.2.2 Identification of the marriage penalty

Marriage and childbirth are correlated in time across individuals. A naive pseudo-panel event-study regression would likely conflate these two effects, particularly as the share of women with children rises with t. We therefore propose a split-sample approach to separate the marriage penalty from the child penalty. The first case, the "no child sample", restricts the sample to women and men without children 5 years after marriage to explore gender norms. The second case, "the ignore child sample", matches women and men in the post marriage event space without considering the presence of children. This case combines the marriage and child penalties (or premium).

Our analysis relies on two identification assumptions to interpret β as the causal effect of marriage on employment. First, the precise timing of marriage must be uncorrelated with other shocks that plausibly influence labor supply. Our split sample approach, by construction, rules out childbirth as such a confounder. However, other confounders, such as relocation in the context of patrilocality, might also be correlated with marriage.

Our split-sample approach also generates a second identification assumption: that the women in the “no child” sample are not diferentially selected in their propensity to work. This assumption is more challenging to satisfy. Specifically, women who remain childless up to $t = 5$, particularly in a context of strong patriarchal norms, are likely to be those with a higher unobserved propensity to work. As such, this introduces a time-varying bias in the estimates, since this problem becomes increasingly severe as t rises: married women without children many years after marriage are particularly selected. However, since these women likely have a higher unobserved propensity to work, the results as we move toward the end of the event window probably represent a lower bound on the true marriage penalty.

2.2.3 Summary statistics

Table A2 presents marriage cohort-level summary statistics for the women in the no child and ignore child samples. About 20 percent of women in the sample are working. The average age of the cohort is 20 at the time of survey, almost 40 percent reside in urban areas, almost a third have more than secondary education. The average age at marriage is 21 and women marry men who are on average 3 years older than them. On average, women participate in 0.3 decisions out of a maximum of 5. Women agree to an average of 0.2 statements out of 5 on when it would be justified for a man to beat his wife. These characteristics are similar across the two samples.

Table A3 presents the summary statistics for the men in each sample. The size of the male sample is 75 to 80 percent of the female sample, since women of childbearing age are over-sampled in the DHS. About 53 percent of the men in the sample are working. The average age of the cohort is 21, a year older than the women's average age. About a quarter of men have more than secondary education, slightly lower than the women's share.

3 Results

3.1 Main results

The results of the main marriage penalty estimation are in Table 1. The model collapses the yearly event study indicators into pre- and post-marriage periods, with the full set of birth cohort and country-year fixed effects. The post-marriage treatment indicator is then interacted with a binary variable indicating whether the cohorts exclude women with children (the "no child sample") or allow for childbirth (the "ignore child sample").

Panel A shows the results for women across the region (column 1) and then the four constituent countries (columns 2-5). On average, marriage reduces labor force participation by 11.7 percentage points across South Asia among childless women in the five years after marriage. Among our sample countries, the penalty is largest in India, at 12.1 p.p., and lowest in Maldives, at 2.3 p.p., where it is not significant.

Across the region, the marginal effect of allowing for childbearing in the regression specification is small. Whereas the marriage penalty among all women is 15.7 p.p., the marriage penalty for childless women is 11.7 p.p., suggesting that childbearing explains just 25 percent of the aggregate family formation penalty. However, the gaps between the ignore child and no child samples vary widely. They are smallest in India and Bangladesh – the large countries that dominate the aggregate sample – where the total penalty and the marriage-only penalty are quantitatively similar, and widest in Nepal and Maldives. As expected, the estimates for the "ignore child" sample are larger than the no child sample for all countries. Still, the relatively small gap in these estimates implies that the reduction in female labor force participation around the time of marriage is driven specifically by employment restrictions placed on married women – likely due to social norms – rather than their childcare burdens.

In contrast, men enjoy a marriage premium in South Asia. Table 1, Panel B, shows the estimates for the men's sample. The estimated premium for men ranges from 13.2 to 17 p.p., with an aggregate effect size of 12.8 p.p. These impacts are consistent with the extensive literature on the marriage earnings premium in the US (Hersch and Stratton, 2000). As with women, the difference in the estimates between the no-child and ignore-child samples is small. Taken together, the findings in Table 1 demonstrate a marriage penalty for women and marriage premium for men in South Asia. These effects are driven primarily by the act of marriage itself, rather than the time and financial costs associated with childrearing.

3.2 Event-studies

Figure 1 plots event-study coefficients on indicators for leads and lags of the marriage year, relative to $t = -1$, by country. The pre-marriage event coefficients are all precisely estimated zeroes across each country, suggesting no trends in married women's labor force participation leading up to marriage, and no evidence of anticipation effects. The reduction in labor force participation kicks in immediately in all countries, with a $t = 0$ reduction in the no-child sample ranging from 7.3 to 13.2 p.p. across the region (dynamic point estimates are available in Table A4 and Table A5). As expected, the no-child dynamic estimates in Figure 1 are almost always above the ignore child sample estimates. Still, the confidence intervals typically overlap, and the magnitudes in the differences are very small for all countries except Maldives.

Lower labor force participation among married women without children persists up to 5 years after marriage in India and Maldives. In contrast, female employment rates appear to revert back to pre-marriage levels by $t = 5$ in the no-child sample for Bangladesh and Nepal. Still, it is important to recall that the event-study estimates in the no-child sample are likely affected by time-varying selection bias. In particular, the pool of eligible women gets increasingly selected as time passes, since the set of married women with no children at $t = 5$ are likely to have the highest propensity to participate in the labor market, even after matching on our set of observables. As such, we are increasingly likely to underestimate the true dynamic marriage penalty effects as t increases. Employment declines are more persistent for the ignore child sample, where this problem does not exist.[3] Lastly, in addition to this potential source of bias, the effects become less precisely estimated as t rises, since the pool of possible matches shrinks.

Figure 2 shows the dynamic male marriage employment premium, relative to $t = 0$. As with women, the pre-trends for each country are flat, indicating no change in employment status in anticipation of marriage. After marriage, male employment jumps by 12.8 to 17.6 p.p. across South Asia (dynamic point estimates are available in Table A6 and Table A7). The male marriage premium is sustained throughout the 5-year window and does not vary substantially over time.

4 Determinants of the marriage penalty

In this section, we explore some possible determinants of the marriage penalty in employment for South Asian women. We test whether marriage penalties are lower (i) in urban areas, (ii) for better-educated couples, and (iii) for couples with more liberal gender attitudes. To test these hypotheses, we interact fixed marriage cohort-specific characteristics with the post-marriage indicator to estimate heterogeneous responses of employment to marriage.

4.1 Urban-rural

Urban areas, with dynamic, service-oriented economies, may present with more and higher-earning employment opportunities (Petrongolo and Ronchi, 2020). Better job prospects imply a larger opportunity cost of keeping women out of labor market. Furthermore, evidence suggests urban areas in South Asia also have less conservative

[3]This could of course also be due to a more persistent child penalty as well. We cannot separately identify these two effects.

gender norms across a variety of measures (Asher et al., n.d.). Given fewer constraints to work and more attractive employment prospects, it would be reasonable to conclude that female marriage penalties may be smaller in urban areas. At the same time, women's baseline employment levels are significantly lower in urban than rural South Asia for a variety of reasons (Klasen and Pieters, 2015), including income effects, sectoral composition, and the predominance of outside-the-home work arrangements. Therefore, the relative size of the marriage penalty in rural and urban areas is theoretically ambiguous.

Table 2 tests this question empirically by splitting the sample between urban and rural cohorts and re-estimating the same regressions as in Table 1, Panel A. Across the region (column 1), the pure marriage penalty is 10.4 p.p. in rural areas, and 13.1 p.p. in urban areas, a 2.7 p.p. difference that is both economically small and statistically insignificant. Larger gaps emerge at the country level in Maldives and Nepal, with minimal rural-urban gaps in Bangladesh and India.

4.2 Education

Education interacts with other human capital domains and affects a range of labor market outcomes (Heath and Jayachandran, 2016). Education is likely to be a critical determinant of marriage penalty for two reasons. First, positive returns to female education in South Asia (Psacharopoulos and Patrinos, 2018) imply that more educated wives have a greater opportunity cost of non-participation. Second, education levels are correlated with more liberal gender attitudes, improving women's bargaining power and loosening constraints to the employment and mobility of married women.

These mechanisms are not necessarily straightforward to tease out, since a woman's education affects her outside options, social attitudes, and bargaining power. However, her husband's education should not directly affect her labor market opportunities, and instead should instead more directly affect the household adherence to social norms that are hostile to women working outside of the home. In this section, we test the response of the marriage penalty to both husbands' and wives' education levels by interacting both of these quantities with the post-marriage indicator. For simplicity, we measure education levels as a binary indicator for whether the wife or husband has attained any post-secondary education.[4]

Table 3 begins by including the interaction with the woman's higher education indicator in the no child sample (Panel A) and the ignore child sample (Panel B). Women with education levels beyond secondary school are significantly less affected by the marriage penalty on average in South Asia (column 1). Indeed, the marriage penalty is 12.9 p.p. for women without higher education, and just 7 p.p. for women with post-secondary schooling, a difference that is significant at the 1% level. Furthermore, this effect holds for three of the four South Asian countries, excluding Maldives, comprising the vast majority of the sample. Similar effects obtain in Panel B, though somewhat stronger in Maldives and Nepal. In aggregate, however, higher education offsets 46% of the pure child penalty, but only 37% of the combined marriage and child penalty. This suggests that the child penalty component is driven, in part, by childcare burdens, which can't necessarily be overcome by education.

Husbands' higher education may also help mitigate a women's marriage penalty by liberalizing household norms around women's work. At the same time, more educated men earn more, strengthening the pull of the income effect that draws married women out of the labor market. Table 4 tests the role of husband's education by interacting the post-marriage indicator with the cohort share of husbands with higher education. Remarkably, the magnitudes are almost identical to the results in Table 3. Cohorts with more educated husbands have significantly smaller marriage penalties, though here the effects are more concentrated in India.

However, the regressions in Tables 3 and 4 ignore a critical source of omitted variable bias. In particular, the marriage market in South Asia, as in other contexts, is characterized by high levels of positive assortative mating, where women with more education tend to marry men with more education (Becker, 1993). Indeed, about 70 percent of women with more than secondary schooling are married to men with the same level of education. As such, the educational attainment of wives is highly correlated with that of their husbands', suggesting that neither analysis alone appropriately accounts for these correlations. Estimating the independent effects is important, since wives' education

[4]The latter of these is the marriage cohort averaged share of women married to husbands with post-secondary education.

affects both her labor market returns and household norms, while husband's education mostly affects the latter and not the former. Including interactions with education levels for both husbands and wives in the same regression allows us to not only estimate independent effects, but to some extent separate between the mechanisms of opportunity cost and household gender norms.

Table 5 contains the results of a model containing interactions between the post-marriage indicator and both the husband and wife's education. In the region-wide sample (column 1) of Panel A, the wife's education increases in magnitude relative to Table 3. After accounting for the male education interaction, a woman's attainment of post-secondary education offsets 75% of the baseline marriage employment penalty. The coefficient on the interaction with husband's education is -0.052, suggesting that in cohorts where the men are highly educated, the marriage penalty is 5.2 p.p. *larger*. However, this coefficient is not significantly different from zero in the regional sample or in any of the individual countries. In the largest two countries – Bangladesh and India – the female education interaction remains positive and significant. Similar results obtain for the combined marriage and child penalty sample in Panel B, where the male education interaction is insignificant in all models, and the female education interaction is significant in 3 out of 4 countries.

These results suggest that a woman's opportunity cost of not working may matter more than her husband's gender attitudes in determining the marriage penalty. However, it is important to note that the male education effect can theoretically go in both directions, that is, income effects push the coefficient downward, so that even the results in Table 5 do not rule out the importance of gender norms. In the next section, we use direct measures of gender attitudes in the household to test for the role of social norms.

4.3 Gender attitudes

Women's labor supply in South Asia is constrained by household norms around female employment (Heath et al., 2024; Jayachandran, 2021; Bussolo et al., 2024). In conservative contexts, working outside the home, even without the burden of childcare, violates social norms that control women's mobility. These norms bind more strongly when women are married and become subject to pressure from the husband and his family (Anukriti et al., 2020). This dynamic may in part explain the prevalence of a marriage penalty in South Asia. If so, we should expect to see larger marriage penalties among marriage cohorts with more restrictive gender attitudes on average.

To test the role of gender attitudes, we would ideally use survey measures eliciting the husband's approval of women working outside of the home. However, the DHS does not contain survey questions on men's attitudes specifically around the labor market participation of their wives. Instead, the DHS contains information on other gender attitudes, including with respect to domestic violence, as well as measures of household decisionmaking roles. Using the DHS women's module, we compute two measures of gender attitudes: (i) the average agreement in the cohort with five survey questions featuring scenarios under which domestic violence toward a might could be "justified," and (ii) the average agreement in the cohort with five questions around decisionmaking on household income, expenditures, and child-rearing. For the "attitudes toward violence" index, larger numbers indicate a larger share of female respondents in the cohort agreed with justifications for wife-beating, while for the "decisionmaking" index, larger numbers indicate that the wife participates in more household decisions. These are highly imperfect proxies for the husband's gender attitudes toward work, since they are taken from wives' responses and do not directly concern work. Still, they may capture meaningful variation across marriage cohorts in the permissiveness of gender attitudes. For each of these variables, we collapse the average responses at the marriage cohort-event time level and then take the mean within marriage cohorts to get a marriage cohort-specific, time-invariant measure of gender attitudes.

Table 6 and Table 7 contain the results for decisionmaking and domestic violence, respectively. In the all South Asia sample, the marriage penalty when the woman has no decisionmaking agency is 13.9 p.p. However, as agency rises, the penalty falls. A one standard deviation increase in decisionmaking power reduces the by 5.1 p.p. The positive effect of decisionmaking power obtains for all countries in Panel A of Table 6, though the estimate is not always significant and often noisier in the country-level specifications. Similar, though slightly weaker, results obtain in Panel B for the combined family formation penalty. This is likely because child penalties are driven by other factors, for example, access to affordable childcare, that do not influence marriage penalties and are potentially unrelated to social norms.

The results for violence in Table 7, Panel A go in the same direction, though are not significant in the full sample. On average, among households where women do not agree with any domestic violence justifications, the marriage penalty is 11.3 p.p., rising by 3.5 p.p. for every additional justification agreed with. However, these effects are driven almost exclusively by India, and Nepal, which are significant at the 10 percent level, with null effects for the other countries. Similar results obtain for the combined marriage and child penalty in Panel B, again driven by India.

The preceding analysis does not separate the effects of education and social attitudes, which are likely to be highly correlated, at least within countries. Table A8 includes interactions between the post-marriage indicator and *both* the female higher education dummy and the cohort decisionmaking index. Column 1 of both Panels A and B, the regional specification, reveals that both interaction terms remain strong and significant, and nearly unchanged in magnitude from the single-interaction specifications. This suggests independent effects of outside options and household constraints in shaping the marriage penalty. Finally, Figure 3 summarizes all of the heterogeneous effects tested in Section 4, emphasizing the roles of female educational attainment and social norms in shaping the marriage penalty.

5 Conclusion

Recent studies have shown how child penalties affect women's labor market outcomes. However, a marriage penalty may emerge even before childrearing, either because of optimal household task specialization or social norms that prevent married women from working outside the home. In the context of South Asia, We show that the marriage penalty for women is substantially larger than the child penalty. This suggests that it is not the burdens of childrearing, per se, that inhibit female labor force participation in South Asia. Instead, low female labor supply in the region emerges after marriage and before children. This result reconciles mixed findings in the literature on access to childcare, since access is not the binding constraint to participation in South Asia.

We also explore the drivers of marriage penalties for women in South Asia in order to test whether such outcomes are a natural result of optimal household specialization, or are driven by conservative gender norms that constrain the labor supply of married women. Our findings are consistent with both explanations. We find that a woman's education – and not that of her husband – substantially reduces the marriage penalty. Since greater female education has the potential to both change gender norms *and* improve women's opportunities in the labor market, it is hard to disentangle these two mechanisms with this test alone. Still, we note that husband's education, which should affect household norms but not women's labor market outcomes, does not affect the marriage penalty. Regardless of the mechanism, the results clearly show that increasing education for women has the potential to mitigate the marriage penalty, potentially helping them realize their labor market potential.

Finally, we test for gender norms as a driver of the marriage penalty, and therefore a source of potential labor market misallocation in South Asia. Norms around household gender roles, as measured by women's decisionmaking power and attitudes toward domestic violence, are highly predictive of the extent of marriage penalties across South Asia. In addition, when both norms and female education are included as mechanisms, they remain strong independent predictors of the marriage penalty, suggesting that both labor market opportunities and social norms play a role in driving the marriage penalty. Policies that promote gender equality within the household and a shift in social norms may also have the potential to mitigate women's marriage penalty.

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Tables

Table 1: Marriage penalties and premiums

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: Women					
Post-marriage × No child sample	-0.117***	-0.0890***	-0.121***	-0.120**	-0.0229
	(0.005)	(0.014)	(0.006)	(0.044)	(0.017)
Post-marriage × Ignore child sample	-0.157***	-0.107***	-0.162***	-0.240***	-0.0755***
	(0.004)	(0.013)	(0.006)	(0.041)	(0.015)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	19987	3875	10734	1018	4350
R-squared	0.536	0.337	0.496	0.565	0.366
Panel B: Men					
Post-marriage × No child sample	0.128***	0.170***	0.130***	0.174***	0.132***
	(0.015)	(0.037)	(0.019)	(0.041)	(0.028)
Post-marriage × Ignore child sample	0.117***	0.166***	0.116***	0.108**	0.155***
	(0.010)	(0.032)	(0.013)	(0.040)	(0.022)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16328	2400	10036	721	3155
R-squared	0.611	0.307	0.631	0.698	0.499

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Marriage penalty by urban-rural residence

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: Rural					
Post-marriage × No child sample	-0.104***	-0.084***	-0.108***	-0.0543	-0.0334
	(0.005)	(0.014)	(0.007)	(0.053)	(0.019)
Post-marriage × Ignore child sample	-0.134***	-0.087***	-0.138***	-0.206***	-0.110***
	(0.005)	(0.013)	(0.006)	(0.052)	(0.017)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10845	2075	5770	655	2331
R-squared	0.588	0.482	0.489	0.627	0.341
Panel B: Urban					
Post-marriage × No child sample	-0.131***	-0.0804**	-0.136***	-0.134	-0.072***
	(0.008)	(0.025)	(0.011)	(0.075)	(0.019)
Post-marriage × Ignore child sample	-0.192***	-0.134***	-0.198***	-0.191**	-0.110***
	(0.007)	(0.023)	(0.010)	(0.070)	(0.017)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9137	1794	4957	357	2016
R-squared	0.595	0.233	0.594	0.513	0.536

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Marriage penalty by women's education

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: No child sample					
Post-marriage	-0.129***	-0.158***	-0.170***	-0.032	-0.058***
	(0.009)	(0.022)	(0.010)	(0.050)	(0.021)
Post-marriage × Higher education	0.059***	0.065**	0.064***	-0.033	0.067*
	(0.015)	(0.030)	(0.018)	(0.085)	(0.039)
No. of obs.	8922	1712	4847	440	1916
R-squared	0.263	0.154	0.17	0.174	0.131
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Ignore child sample					
Post-marriage	-0.167***	-0.165***	-0.198***	-0.228***	-0.112***
	(0.007)	(0.018)	(0.008)	(0.047)	(0.018)
Post-marriage × Higher education	0.061***	0.078***	0.040***	0.126*	0.082**
	(0.012)	(0.022)	(0.014)	(0.075)	(0.034)
No. of obs.	11065	2163	5887	578	2434
R-squared	0.275	0.151	0.198	0.187	0.099
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. Women's education is an indicator variable for any post-secondary education. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Marriage penalty by husband's education

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: No child sample					
Post-marriage	-0.129***	-0.144***	-0.175***	-0.107*	-0.053**
	(0.010)	(0.023)	(0.012)	(0.062)	(0.023)
Post-marriage × Husband higher education	0.066***	0.037	0.092***	0.093	0.036
	(0.019)	(0.035)	(0.025)	(0.116)	(0.044)
No. of obs.	7848	1712	3779	434	1916
R-squared	0.277	0.152	0.164	0.174	0.132
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Ignore child sample					
Post-marriage	-0.168***	-0.158***	-0.210***	-0.281***	-0.102***
	(0.008)	(0.019)	(0.009)	(0.051)	(0.020)
Post-marriage × Husband higher education	0.061***	0.060**	0.064***	0.184*	0.024
	(0.016)	(0.025)	(0.019)	(0.094)	(0.038)
No. of obs.	9583	2163	4413	570	2434
R-squared	0.296	0.149	0.211	0.188	0.103
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. Husband education is the share of women in the pseudo-cohort whose husband has any post-secondary education. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Marriage penalty by education

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: No child sample					
Post-marriage	-0.146***	-0.153***	-0.178***	-0.073	-0.058**
	(0.013)	(0.023)	(0.012)	(0.061)	(0.022)
Post-marriage × Higher education	0.111***	0.089*	0.086***	-0.104	0.08
	(0.029)	(0.047)	(0.026)	(0.100)	(0.055)
Post-marriage × Husband higher education	-0.052	-0.038	0.016	0.15	-0.024
	(0.042)	(0.053)	(0.036)	(0.130)	(0.062)
No. of obs.	7848	1712	3779	434	1916
R-squared	0.552	0.156	0.168	0.178	0.135
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Ignore child sample					
Post-marriage	-0.186***	-0.165***	-0.214***	-0.262***	-0.108***
	(0.01)	(0.02)	(0.01)	(0.05)	(0.02)
Post-marriage × Higher education	0.075***	0.083**	0.071***	0.065	0.124***
	(0.02)	(0.04)	(0.02)	(0.09)	(0.05)
Post-marriage × Husband higher education	-0.025	-0.008	0.004	0.134	-0.068
	(0.02)	(0.04)	(0.03)	(0.11)	(0.05)
No. of obs.	9583	2163	4413	570	2434
R-squared	0.608	0.152	0.215	0.2	0.106
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. Husband education is the share of women in the pseudo-cohort whose husband has any post-secondary education. Women's education is an indicator variable for any post-secondary education. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Marriage penalty by decisionmaking

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: No child sample					
Post-marriage	-0.139***	-0.180***	-0.131***	-0.234**	-0.084*
	(0.013)	(0.039)	(0.015)	(0.117)	(0.050)
Post-marriage × Decisionmaking	0.060***	0.047**	0.023	0.064	0.086
	(0.012)	(0.019)	(0.024)	(0.073)	(0.064)
No. of obs.	8812	1712	4847	440	1805
R-squared	0.524	0.327	0.490	0.558	0.413
Panel B: Ignore child sample					
Post-marriage	-0.176***	-0.188***	-0.155***	-0.208*	-0.152***
	(0.008)	(0.026)	(0.009)	(0.122)	(0.039)
Post-marriage × Decisionmaking	0.045***	0.041***	-0.041**	-0.026	0.066*
	(0.008)	(0.012)	(0.016)	(0.067)	(0.037)
No. of obs.	10884	2163	5887	578	2249
R-squared	0.564	0.353	0.530	0.576	0.422

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. All models include birth cohort and country-by-year fixed effects. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. Decision making is measured as the sum of indicator variables for 5 DHS questions on whether the respondent is involved in decision making individually or jointly, averaged by cohort, with larger values indicating greater decision making involvement. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Marriage penalty by attitudes toward domestic violence

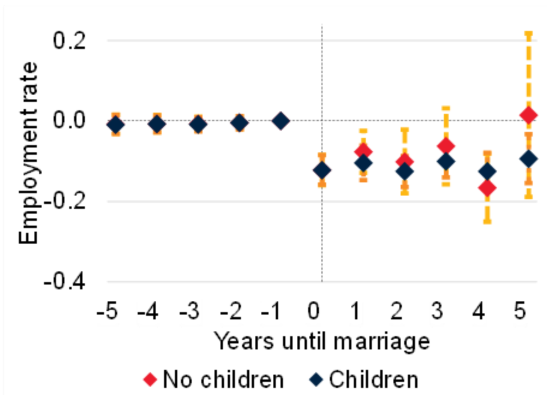
Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: No child sample					
Post-marriage	-0.113***	-0.101***	-0.115***	-0.156***	-0.007
	(0.012)	(0.023)	(0.013)	(0.046)	(0.030)
Post-marriage × Attitude towards violence	-0.035	0.029	-0.049*	0.143	-0.146*
	(0.022)	(0.053)	(0.025)	(0.101)	(0.079)
No. of obs.	8812	1712	4847	440	1805
R-squared	0.525	0.326	0.489	0.566	0.380
Panel B: Ignore child sample					
Post-marriage	-0.148***	-0.101***	-0.151***	-0.257***	-0.083***
	(0.008)	(0.014)	(0.008)	(0.046)	(0.018)
Post-marriage × Attitude towards violence	-0.059***	-0.038	-0.075***	0.095	-0.045
	(0.015)	(0.030)	(0.017)	(0.068)	(0.050)
No. of obs.	10884	2163	5887	578	2249
R-squared	0.568	0.357	0.536	0.594	0.376

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. All models include birth cohort and country-by-year fixed effects. SAR - SOuth Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. Attitude toward violence is measured as the sum of agreement indicator variables for 5 DHS questions on the acceptability of domestic violence, averaged by cohort, with larger values indicating greater agreement. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

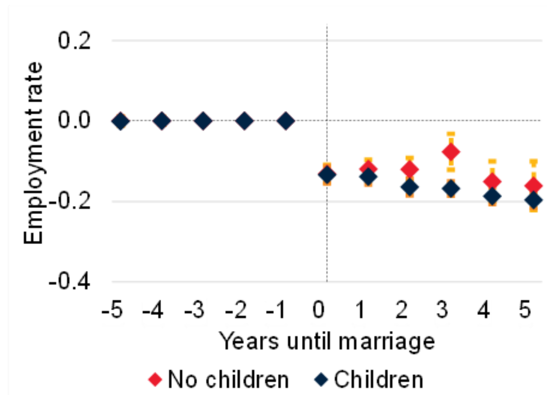
Figures

Figure 1: Event-study: women

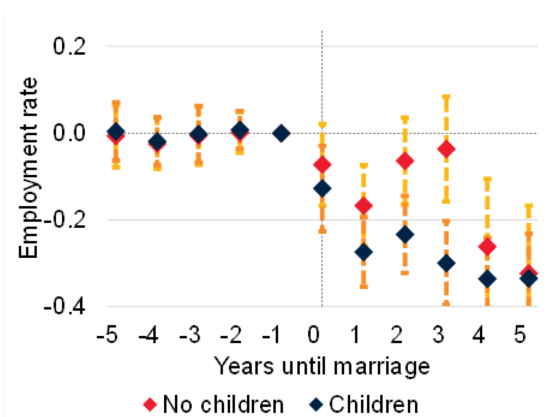
(a) Bangladesh



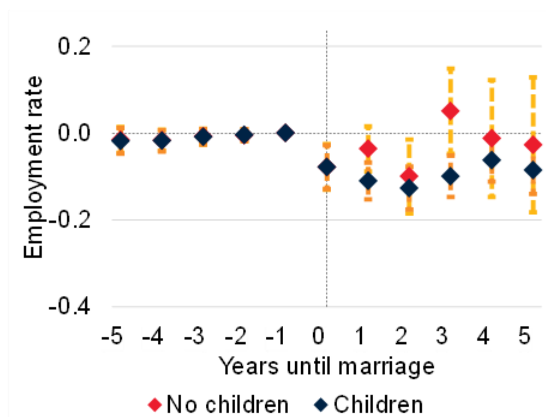
(b) India



(c) Maldives

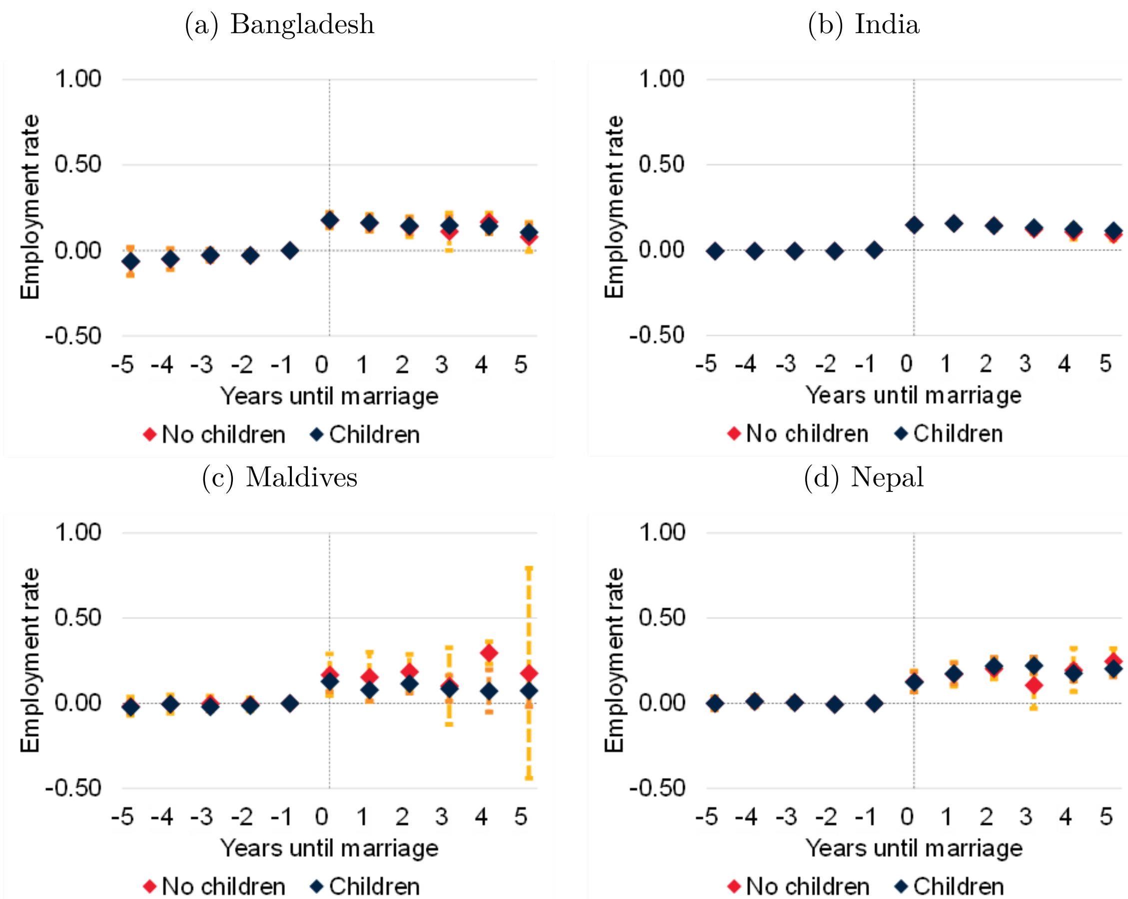


(d) Nepal



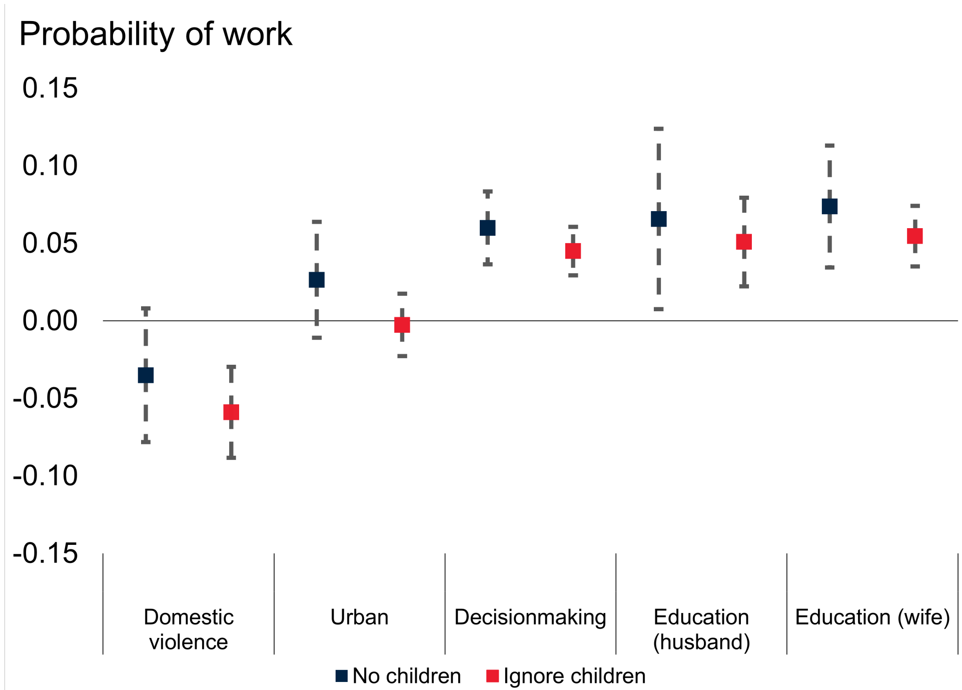
Note: Figure shows coefficient estimates and 95% confidence intervals from country-wise event-study marriage penalty regressions for the sample of female cohorts. Standard errors are clustered at the cohort level. 'Children' is the 'ignore child' sample.

Figure 2: Event-study: men



Note: Figure shows coefficient estimates and 95% confidence intervals from country-wise event-study marriage penalty regressions for the sample of male cohorts. Standard errors are clustered at the cohort level. 'Children' is the 'ignore child' sample.

Figure 3: Heterogeneous effects



Note: Figure shows interaction coefficient estimates and 95% confidence intervals obtained by estimating the baseline marriage penalty regression specification, interacting the post-marriage indicator with a given cohort characteristic, separately for the no child and ignore child samples. Domestic violence is measured as the sum of agreement indicator variables for 5 DHS questions on the acceptability of domestic violence, averaged by cohort. Decisionmaking is measured as the sum of indicator variables for 5 DHS questions on whether the female respondent is involved in decision making individually or jointly, averaged by cohort. Husband education is the share of women in the cohort whose husband has any post-secondary education. Women's education is an indicator variable for any post-secondary education for the cohort.

A Appendix

Table A1: DHS datasets used in the analysis

Country	Women	Sample size	Men	Sample size
Bangladesh	1993	11863	1993	8157
	1999	13527	1999	9028
	2004	15338	2004	20030
	2007	13769	2007	8183
	2014	20336	2014	6790
	2017	24439	2017	27602
India	1993	84558		
	1998	84862		
	2005	118514	2005	73465
	2015	670738	2015	110478
	2019	692985	2019	100275
Maldives	2009	6558	2009	1645
	2016	7074	2016	4132
Nepal	1996	903		
	2001	909	2001	2208
	2006	2970	2006	4333
	2011	3832	2011	4080
	2016	3607	2016	4043
	2022	4072	2022	4864

Note: List of DHS surveys used in the analysis. The Bangladesh DHS samples ever married women. To match women to surrogate observations in the pre-marriage event space, the household roster is used. To construct a sample of men, the household roster is used. Married men in the household roster are matched to their wives in the ever married women dataset. These men are then matched to surrogate observations in the pre-marriage event space using the household roster.

Table A2: Summary statistics: Women

Panel A. No child sample	Mean	SD	Obs
Working	0.195	0.129	8,922
Birth year	1,996.929	4.731	9,984
Age	19.512	3.626	9,984
Urban	0.377	0.485	9,984
Less than primary education	0.030	0.148	8,897
Primary education	0.018	0.100	8,897
Secondary education	0.125	0.143	8,897
More than secondary education	0.276	0.447	8,897
Decision making index	0.314	0.312	9,874
Attitude toward domestic violence index	0.187	0.191	9,874
Age gap with partner	3.051	1.545	4,859
Age at marriage	21.220583	3.098413	4535

Panel B. Ignore child sample	Mean	SD	Obs
Working	0.194	0.124	11,065
Birth year	1,996.881	4.781	11,944
Age	19.555	3.680	11,944
Urban	0.377	0.485	11,944
Less than primary education	0.031	0.149	10,776
Primary education	0.018	0.100	10,776
Secondary education	0.125	0.142	10,776
More than secondary education	0.276	0.447	10,776
Decision making index	0.330	0.336	11,763
Attitude toward domestic violence index	0.188	0.192	11,763
Age gap with partner	3.062	1.507	6,760
Age at marriage	21.274	3.178	6,228

Note: Data on cohorts of women from Bangladesh, India, Maldives, Nepal DHS. Decision making index based on the sum of decisions in which women are involved individually or jointly. Attitude toward domestic violence index based on the sum of statements respondents believe violence is justified.

Table A3: Summary statistics: Men

Panel A. No child sample		Mean	SD	Obs
Working	0.530	0.261	7,540	
Birth year	1,993.742	6.138	7,540	
Age	20.958	4.251	7,540	
Urban	0.379	0.485	7,540	
Less than primary education	0.033	0.148	6,481	
Primary education	0.021	0.101	6,481	
Secondary education	0.130	0.138	6,481	
More than secondary education	0.234	0.424	6,481	
Panel B. Ignore child sample	Mean	SD	Obs	
Working	0.541	0.265	8,792	
Birth year	1,993.519	6.277	8,792	
Age	21.155	4.394	8,792	
Urban	0.373	0.484	8,792	
Less than primary education	0.035	0.154	7,446	
Primary education	0.021	0.103	7,446	
Secondary education	0.128	0.137	7,446	
More than secondary education	0.232	0.422	7,446	

Note: Data on cohorts of men from Bangladesh, India, Maldives, Nepal DHS.

Table A4: Marriage penalty: event-study estimates for female no child sample

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
$t-5$	-0.000683	-0.00800	-0.000182	-0.00683	-0.0161
	(0.00330)	(0.0116)	(0.00430)	(0.0332)	(0.0121)
$t-4$	-0.000277	-0.00687	0.000381	-0.0241	-0.0164
	(0.00329)	(0.0113)	(0.00430)	(0.0322)	(0.0118)
$t-3$	-0.0000353	-0.00693	0.000414	-0.00564	-0.00826
	(0.00331)	(0.0112)	(0.00432)	(0.0322)	(0.0116)
$t-2$	0.000232	-0.00425	0.000485	0.00132	-0.00489
	(0.00338)	(0.0114)	(0.00441)	(0.0325)	(0.0116)
$t=0$	-0.125***	-0.122***	-0.132***	-0.0732	-0.0782*
	(0.0132)	(0.0296)	(0.0178)	(0.0630)	(0.0335)
$t+1$	-0.115***	-0.0768**	-0.119***	-0.167**	-0.0364
	(0.0105)	(0.0290)	(0.0140)	(0.0625)	(0.0315)
$t+2$	-0.117***	-0.101**	-0.121***	-0.0642	-0.100**
	(0.0110)	(0.0318)	(0.0145)	(0.0626)	(0.0385)
$t+3$	-0.0725***	-0.0626	-0.0766***	-0.0367	0.0505
	(0.0117)	(0.0340)	(0.0153)	(0.0679)	(0.0425)
$t+4$	-0.149***	-0.166***	-0.151***	-0.262***	-0.0127
	(0.0124)	(0.0402)	(0.0163)	(0.0767)	(0.0435)
$t+5$	-0.159***	0.0146	-0.162***	-0.323***	-0.0273
	(0.0129)	(0.0479)	(0.0168)	(0.0782)	(0.0569)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.534	0.351	0.496	0.598	0.394
Observations	8922	1711	4847	439	1914

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. $t=0$ is the time of marriage, $t-i$ is the pre-marriage space, $t+i$ is the post-marriage space. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Marriage penalty: event-study estimates for female ignore child sample

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
$t-5$	-0.000793	-0.00900	-0.000332	0.00382	-0.0181
	(0.00273)	(0.00983)	(0.00357)	(0.0271)	(0.0107)
$t-4$	-0.000411	-0.00728	0.000232	-0.0187	-0.0180
	(0.00272)	(0.00961)	(0.00356)	(0.0266)	(0.0104)
$t-3$	-0.000219	-0.00864	0.000276	-0.00243	-0.00911
	(0.00274)	(0.00957)	(0.00358)	(0.0268)	(0.0102)
$t-2$	0.0000293	-0.00442	0.000254	0.00718	-0.00483
	(0.00280)	(0.00975)	(0.00366)	(0.0270)	(0.0102)
$t=0$	-0.127***	-0.122***	-0.134***	-0.128*	-0.0786**
	(0.0109)	(0.0250)	(0.0147)	(0.0511)	(0.0294)
$t+1$	-0.136***	-0.104***	-0.139***	-0.274***	-0.110***
	(0.00866)	(0.0243)	(0.0115)	(0.0502)	(0.0272)
$t+2$	-0.161***	-0.126***	-0.164***	-0.234***	-0.127***
	(0.00885)	(0.0252)	(0.0117)	(0.0498)	(0.0297)
$t+3$	-0.164***	-0.0999***	-0.168***	-0.299***	-0.0997**
	(0.00902)	(0.0259)	(0.0119)	(0.0525)	(0.0303)
$t+4$	-0.181***	-0.125***	-0.187***	-0.336***	-0.0631*
	(0.00907)	(0.0276)	(0.0120)	(0.0539)	(0.0294)
$t+5$	-0.191***	-0.0939***	-0.197***	-0.335***	-0.0857**
	(0.00921)	(0.0283)	(0.0122)	(0.0553)	(0.0326)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.574	0.372	0.540	0.606	0.387
Observations	11064	2161	5886	577	2432

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. $t = 0$ is the time of marriage, $t - i$ is the pre-marriage space, $t + i$ is the post-marriage space. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Marriage premium: event-study estimates for male no child sample

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
$t-5$	-0.0088	-0.0642	-0.0071	-0.0192	-0.0013
	(0.006)	(0.025)	(0.008)	(0.026)	(0.015)
$t-4$	-0.0074	-0.0512	-0.0072	-0.0057	0.0106
	(0.006)	(0.025)	(0.008)	(0.025)	(0.015)
$t-3$	-0.006	-0.0281	-0.006	-0.0025	0.0034
	(0.006)	(0.025)	(0.008)	(0.025)	(0.014)
$t-2$	-0.0068	-0.03	-0.0058	-0.0073	-0.0069
	(0.006)	(0.026)	(0.008)	(0.025)	(0.014)
$t=0$	0.138***	0.176*	0.147***	0.167**	0.128**
	(0.028)	(0.083)	(0.038)	(0.063)	(0.039)
$t+1$	0.153***	0.161*	0.156***	0.154	0.171**
	(0.026)	(0.077)	(0.033)	(0.100)	(0.054)
$t+2$	0.139***	0.139	0.142**	0.184	0.204**
	(0.034)	(0.086)	(0.043)	(0.120)	(0.079)
$t+3$	0.109*	0.11	0.121*	0.101	0.106
	(0.044)	(0.093)	(0.057)	(0.156)	(0.117)
$t+4$	0.110*	0.168	0.106	0.296	0.195
	(0.054)	(0.109)	(0.071)	(0.183)	(0.117)
$t+5$	0.0814	0.0787	0.0911	0.176	0.247
	(0.059)	(0.128)	(0.077)	(0.320)	(0.158)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.627	0.314	0.651	0.547	0.515
Observations	7537	1055	4649	408	1410

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. $t=0$ is the time of marriage, $t-i$ is the pre-marriage space, $t+i$ is the post-marriage space. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: Marriage premium: event-study estimates for male ignore child sample

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
$t-5$	-0.0086	-0.0632	-0.0068	-0.0237	-0.0011
	(0.006)	(0.022)	(0.007)	(0.016)	(0.014)
$t-4$	-0.007	-0.0503	-0.0067	-0.0059	0.0103
	(0.006)	(0.022)	(0.007)	(0.016)	(0.013)
$t-3$	-0.0061	-0.0268	-0.006	-0.0201	0.00362
	(0.006)	(0.022)	(0.007)	(0.016)	(0.013)
$t-2$	-0.0067	-0.0294	-0.0057	-0.0133	-0.007
	(0.006)	(0.023)	(0.007)	(0.017)	(0.013)
$t=0$	0.139***	0.178*	0.147***	0.129***	0.125***
	(0.026)	(0.072)	(0.035)	(0.039)	(0.035)
$t+1$	0.154***	0.162*	0.156***	0.0787	0.174***
	(0.021)	(0.066)	(0.027)	(0.046)	(0.043)
$t+2$	0.142***	0.145*	0.141***	0.115**	0.219***
	(0.021)	(0.068)	(0.026)	(0.042)	(0.047)
$t+3$	0.131***	0.147*	0.131***	0.0865	0.222***
	(0.021)	(0.067)	(0.027)	(0.047)	(0.047)
$t+4$	0.120***	0.142*	0.122***	0.0718	0.175***
	(0.022)	(0.064)	(0.027)	(0.049)	(0.048)
$t+5$	0.110***	0.107	0.112***	0.0746	0.204***
	(0.022)	(0.068)	(0.027)	(0.051)	(0.050)
Birth Cohort FE	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.644	0.338	0.665	0.824	0.542
Observations	8790	1341	5386	310	1743

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. $t = 0$ is the time of marriage, $t - i$ is the pre-marriage space, $t + i$ is the post-marriage space. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Marriage penalty by decisionmaking and education

Dependent variable	Working				
Sample	SAR	BGD	IND	MDV	NPL
	(1)	(2)	(3)	(4)	(5)
Panel A: No child sample					
Post-marriage	-0.171***	-0.192***	-0.165***	-0.219*	-0.108**
	(0.013)	(0.041)	(0.016)	(0.120)	(0.049)
Post-marriage × Higher education	0.072***	-0.049	0.077***	0.006	0.106***
	(0.020)	(0.033)	(0.021)	(0.066)	(0.040)
Post-marriage × Decisionmaking	0.060***	0.056***	0.030	0.061	0.071
	(0.013)	(0.019)	(0.025)	(0.074)	(0.063)
No. of obs.	8812	1712	4847	440	1805
R-squared	0.545	0.337	0.512	0.563	0.427
Panel B: Ignore child sample					
Post-marriage	-0.203***	-0.198***	-0.184***	-0.241*	-0.167***
	(0.009)	(0.027)	(0.010)	(0.134)	(0.039)
Post-marriage × Higher education	0.053***	0.023	0.055***	0.103	0.125***
	(0.010)	(0.023)	(0.011)	(0.072)	(0.029)
Post-marriage × Decisionmaking	0.047***	0.036***	-0.028*	-0.016	0.041
	(0.008)	(0.013)	(0.017)	(0.070)	(0.036)
No. of obs.	10884	2163	5887	578	2249
R-squared	0.585	0.360	0.554	0.586	0.438

Note: Standard errors in parentheses clustered at the cohort level. All estimates weighted by cohort size. All models include birth cohort and country-by-year fixed effects. SAR - South Asia Region, BGD - Bangladesh, IND - India, MDV - Maldives, NPL - Nepal. No child sample refers matching post-marriage observations in the sample without children. Ignore child sample refers matching post-marriage observations in the full sample. Cohort FE refer to birth cohort. Women's education is an indicator variable for any post-secondary education. Decision making is measured as the sum of indicator variables for 5 DHS questions on whether the respondent is involved in decision making individually or jointly, averaged by cohort, with larger values indicating greater decision making involvement. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.