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Intergenerational transmission of teen childbearing in Latin America

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Using DHS data for six Latin American countries, we estimate the relation between a mother's teenage childbearing status and that of her daughter. Restricting the estimating sample to mother-daughter matches in the data leads to a large negative selection bias in the estimated effect because missing matches are non-random and affected by the teen childbearing status of mothers and daughters. We deal with this selection bias by developing a Maximum Likelihood estimation using all available data, including incomplete mother-daughter pairs, and allowing missing observations to be endogenous. Our results show that being the daughter of a teen mother increases the chances of being a teen mother between 8.7 and 26.2 percentage points (between 61 and 172%). We conclude that the prevalence of such high intergenerational transmission is at the core of persistent high teenage childbearing rates in Latin America and suggests alternative public policy fixes.

KEYWORDS

teen childbearing, teen pregnancy, teen motherhood, intergenerational transmission, non-ignorable missingness, DHS data, reproductive health in Latin America.

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Transmisión intergeneracional de la maternidad adolescente en América Latina

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Utilizando datos de las Encuestas Demográficas y de Salud (DHS, por sus siglas en inglés) para seis países Latinoamericanos, estimamos la relación entre la condición de maternidad adolescente de una madre y de su hija. Restringir la estimación de la muestra a los emparejamientos madre-hija en los datos conduce a un gran sesgo de selección negativo en el efecto estimado, dado que los emparejamientos faltantes no son aleatorios y están afectados por la condición de maternidad adolescente de madres e hijas. Abordamos este sesgo de selección desarrollando una estimación por máxima verosimilitud usando todos los datos disponibles, incluyendo pares incompletos madre-hija, y permitiendo a las observaciones faltantes ser endógenas. Nuestros resultados evidencian que ser hija de una madre adolescente aumenta la probabilidad de ser una madre adolescente entre 8.7 y 26.2 puntos porcentuales (entre 61 % y 172 %). Concluimos que la prevalencia de tan alta transmisión intergeneracional está en el centro de las elevadas tasas de persistencia de maternidad adolescente en América Latina y que ello sugiere medidas alternativas de política pública.

KEYWORDS

maternidad adolescente, embarazo adolescente, transmisión intergeneracional, datos faltantes no ignorables, Encuestas Demográficas y de Salud, salud reproductiva en América Latina.

1 | INTRODUCTION

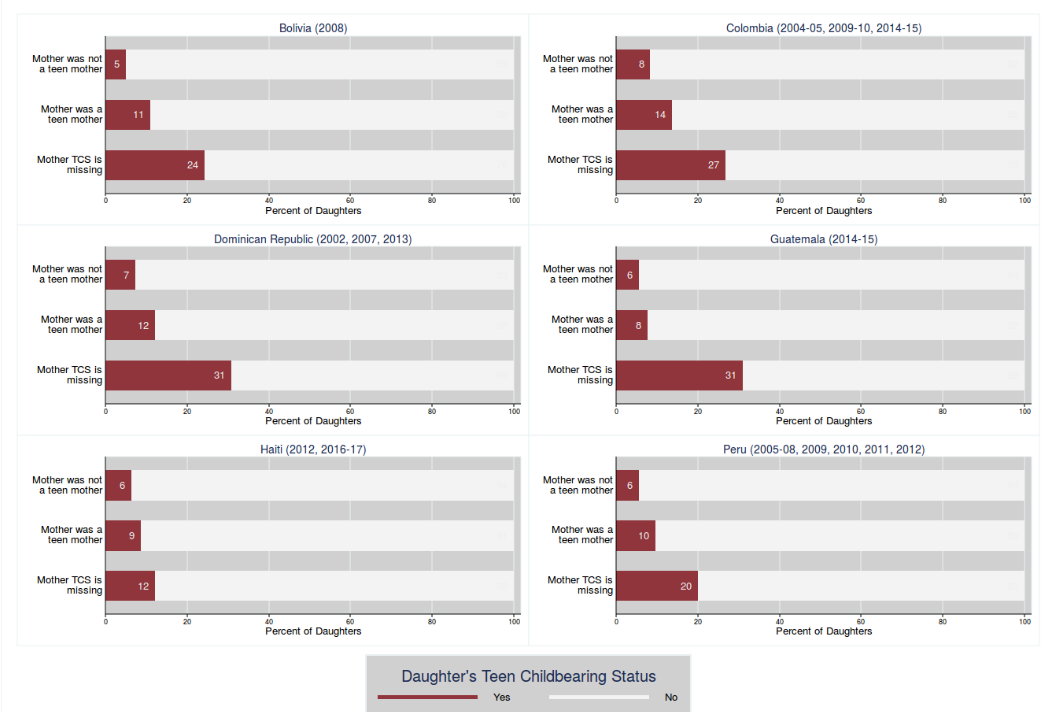
The Latin America and the Caribbean region has the second highest rate of adolescent fertility in the world, only second to Sub-Saharan Africa. In 2010-2015, for example, the region had 66.5 births per 1000 girls aged 15-19, compared to only 30.0 in the US and 11.3 in Canada (Caffe et al. 2016). More strikingly, these high rates of teen childbearing have persisted for decades, resulting in increasing gaps vis-à-vis the rest of the world. Understanding whether and to what extent such persistence originates within the family is critical to designing effective policies. If teen childbearing is transmitted from mothers to daughters, preventive efforts should target those teenagers at greater risk, i.e., the daughters of teen mothers. Hence, the identification of the target population warrants efforts to obtain a correct measure of the intergenerational transmission of teen childbearing.

In many countries, including Latin American countries, the only available databases to measure teen childbearing status, TCS, of both mothers and daughters are household surveys or census data. Matching all mothers and daughters in such data, however, can be tricky as mothers and daughters do not always live in the same household. Teen childbearing increases the probability of marriage/cohabitation and the abandonment of the parental home, and, ultimately, the proportion of mother-daughter matches. Consider, for example, a typical household survey where information is gathered only for individuals living in the household. Teenage daughters who no longer live with their parents usually appear as household heads or their spouses and information on their mothers is missing. Similarly, the daughter information is also missing in households of interviewed mothers whose daughters have already left their parents home. Therefore, these two groups of women are not present when analysis is carried out using matched mother-daughter pairs, i.e., the pairs of mothers and daughters living in the same household.

We show that restricting the estimation sample to matched mother-daughter pairs results in a sizable downward co-residential bias, between 68 and 91%, of the transmission of teenage childbearing from mothers to their daughters. In other words, unmatched pairs are endogenous to TCS and, therefore, non-ignorable. We also contribute to the literature by developing an empirical approach in the spirit of Ramalho and Smith (2013) that delivers unbiased estimation. Using our methodology with a sample of six Latin American countries, we estimate very large effects of having a teen mother on the probability of teen childbearing, between 8.7 and 26.2 percentage points (or between 61 and 172%). These results show that inertia within the family is an important driver of persistence of teen childbearing.

We use Demographic and Health Survey data (DHS) for the following countries: Bolivia, Colombia, Dominican Republic, Guatemala, Haiti and Peru. Our population of interest are teenage women, age 15 to 18 years old, and their mothers. A first look at matched mother-daughter pairs in the DHS data, as shown in Figure 1, reveals that daughters of teen mothers have a two to six percentage points higher probability of teen childbearing compared to daughters of adult mothers.[1] The figure also shows that daughters of mothers with missing TCS—that is, daughters who are unmatched to their mothers—are close to three times more likely to be teen mothers. This strongly suggests that missing mother-daughter matches are endogenous to the process of teen childbearing. Excluding them from the estimation sample may not be a cause of concern when they represent a small percentage of observations. In our sample, however, half of the observations are unmatched, i.e., they have either information on the daughter or on her mother, but not both. Estimating the mother-daughter TCS link with only mother-daughter matches is therefore likely to suffer from a large co-residential bias.

[1] Throughout the paper, we classify a mother as a teen mother if the eldest of her live births was born when she was a teenager.



Source: Own elaboration from Demographic Health Surveys.

FIGURE 1 Daughter's Teen Chidbearing Status by her Mother's. *Notes:* Own elaboration using birth histories from sample *Standard Demographic Health Surveys* (DHS). These are: (i) Bolivia: 2008; (ii) Colombia: 2004-05, 2009-10 and 2014-15; (iii) Dominican Republic: 2002, 2007, and 2013; (iv) Guatemala: 2014-15; (v) Haiti: 2012, 2016-17; and Peru: 2005-08, 2009, 2010, 2011, and 2012.

We deal with this bias by means of a Maximum Likelihood procedure that uses all available data, including unmatched daughters and unmatched mothers, and allows the missing process to depend on the TCS of both daughters and mothers. Essentially, we start with a simple binary probit model where the daughter's TCS depends on her mother's TCS (and other characteristics). We add a non-parametric model of the conditional missing process to this simple probit. There are three possible situations: We either observe the daughter, her mother or both. We construct two binary observability indicators, one for the daughter and another for the mother, which take value 1 whenever the daughter or mother is observed, and zero otherwise. The likelihood is then defined over the four binary variables conditional on all other characteristics. We ensure the identification of the parameters of the model by placing exclusion restrictions in the conditional missing process as in Ramalho and Smith (2013). In our case, the exclusion restrictions imply that any observed correlation between the observability indicators and the controls occur only through the direct effect of the latter on the daughter's and mother's TCS. We argue that these restrictions are valid in our context within each country and are much weaker than those implied when discarding the unmatched mother-daughter pairs. Nonetheless, as a robustness check, we relax such restrictions by estimating the model for different subsamples within each country.

We perform several extensions. We first expand our specification to check whether certain characteristics of the daughter may mediate the estimated mother-daughter inertia in TCS. We include controls for completion of primary education, submissive gender role in sexual relationships, knowledge of contraceptive health, and ideal number of children.

Adding these controls has little or no effect on the estimated average marginal effects of the mother TCS.

We then estimate our model on different subsamples defined according to the daughter's age and the household's wealth. The purpose of this analysis is twofold. On the one hand, it relaxes the assumptions made on the conditional missing process. Estimating the model on different subsamples weakens the set of exclusion restrictions by letting the missing process to also depend directly on the variables defining the subsamples. On the other hand, it allows the effect of the mother TCS to be heterogeneous. The main conclusions remain valid, i.e., the average marginal effect of the mother TCS on the daughter's probability of teen motherhood is large, very statistically significant and discarding the unmatched pairs always results in large negative biases in all countries and subsamples.

Lastly, we estimate a similar model for early sexual initiation and find congruent results. Having a mother who had an early initiation to sex increases the probability of having sex before 16 between 15.6 and 28.7 percentage points (on average 83.1%) and the probability of having sex before 19 between 22.1 and 31.0 percentage points (on average 88.7%).

We conclude that sexual behavior, either early initiation of sexual activity or its consequences in the form of teen childbearing, is prone to high levels of intergenerational inertia from mothers to daughters in the six Latin American countries studied.

Our focus on correctly measuring the mother-daughter association in teen childbearing stands comparable to the emphasis on obtaining unbiased estimates of the intergenerational transmission elasticity of permanent income (IGE). Such emphasis was motivated because the IGE is key to describing the dynamics of inequality in societies (see reviews by Solon, 1999, Black and Devereux, 2011, Jäntti and Jenkins, 2015, and Stuhler et al., 2018).[2] The literature on intergenerational transmission of income is also relevant because teen childbearing may be both a consequence and a cause of the persistence of poverty. Indeed, Latin America is not only affected by high rates of teen childbearing but also has higher intergenerational transmission of income than other regions in the world (**?**, **?**, and **?**). However, whereas the intergenerational transmission of income (and poverty) depends on many factors and is complicated to break (**?**), the transmission of risky behaviors, such as teen childbearing, affects a more circumscript population and may have different and easier fixes. Eventually, solving the latter should contribute to solving the former.

Within the broader literature on the intergenerational transmission of family characteristics, fertility patterns have received relatively little attention (Black and Devereux 2011, **?**). Some studies found evidence of mother-daughter transmission of teenage childbearing using survey data for the US and the UK (e.g., Card 1981, Kahn and Anderson 1992, **?**, and Francesconi 2008).[3]

Any study based on a cross-sectional survey may suffer from co-residential bias. Surveys, such as the US National Survey of Family Growth (NSFG), ask respondents for the age of their mother at first childbirth (see, for example Kahn and Anderson 1992). Such questionnaires avoid the need to construct mother-daughter pairs but they rely on the completeness and accuracy of the retrospective information provided by the child.[4] Longitudinal surveys

[2]The main measurement challenges faced by the intergenerational transmission literature were caused by data unavailability and measurement error.

[3]Francesconi (2008), for example, using survey data for the UK, explores differences across sisters in mother's age at birth to account for family characteristics. This selection comes at a cost, a relatively small number of observations, only 814 pairs from 524 households. The author acknowledges that 34% of the observations could not be matched with a sibling and were discarded. Notice that his definition of teen mothers differs from ours: all women in his sample are daughters of teen mothers according to our definition. His results are therefore not directly comparable to ours. He finds that being born to a teen mother at time of birth increases the probability of being a teen mother by 2.7 percentage points or 135%.

[4]The information on the mother's age at first birth may suffer from non-ignorable missing answers and non-

such as the *National Longitudinal Survey of Youth* (NLSY) or the *Panel Survey of Income Dynamics* (PSID) (used, for example, in Haveman et al. 2008), in which the children of the original respondents are followed regardless of their residence are alternatives to cross-sectional surveys. However,they are usually subject to attrition (especially long-term outcomes), which, again, is likely affected by teen childbearing.[5] Another alternative, administrative data (such as the one used in Aizer et al. (2020) for Norway), is mainly available in countries where teen childbearing has very low incidence.[6] In the absence of any of these three alternatives, our methodology delivers unbiased measures of intergenerational transmission of teen childbearing from household surveys or census data. This is particularly useful when we aim to make international comparisons using a common household survey such has the DHS.[7]

Our paper also relates to the literatures on the determinants and consequences of being a teen mother. Regarding the latter, recent studies conclude that differences in labor and education outcomes between teen mothers and their peers arise mostly due to selection into teen motherhood and that causal effects of teen childbearing on education and wages, although negative, are relatively modest (Ashcraft et al. 2013, Hotz et al. 2005, Fletcher and Wolfe 2009). These conclusions, however, were drawn from studies using contemporaneous US and European data, countries where teen pregnancy rates are relatively low, contraception is widespread, abortion is legal under general conditions, and public programs attend to teen mothers and their babies. Should we expect these results to apply to Latin American countries, where abortion is either very restricted or banned altogether (Guttmacher Institute 2018), there is no easy access to contraception, and no public safety net? Historical evidence for the period 1940-1968 in the US shows that, under similar conditions to those in contemporaneous Latin America, teenage childbearing had large negative effects on teen mothers (Lang and Weinstein 2015). Some studies using Mexican and Chilean data also find similar strong negative results (e.g. Arceo-Gómez and Campos-Vazquez 2014, Kruger and Berthelon 2012).[8,9]

classical measurement error because children of teen mothers are: (i) less likely to live with their natural parents by age 14 due to high divorce rates among teen mothers (e.g., **?**); (ii) are more likely to live with alternative guardians (Card 1981; **?**). For example, in Kahn and Anderson (1992)'s sample, only 52.8% of black and 79.6% of white respondents lived with their natural parents at the age of 14.

[5]There are also smaller longitudinal datasets that follow mothers and children over long periods. **?**, for example, describes such a dataset composed of married mothers who gave birth in July 1961 in the city of Detroit. Although attrition is relatively low considering the long period (15% of mothers and 18% of children), the small sample size (427 daughters) and other limitations of the data limit the generalization of results.

[6]Aizer et al. (2020) uses variance in sister's age at first birth collected from Norwegian administrative data to establish that those children whose mother was a teenager are 3 percentage points or 32% more likely to become teen mothers. Because their study needs data on three generations, they too have missing records, although the exact proportion is not reported. Previous studies using administrative data for Sweden also show that mother's age at first birth (relative to the average in the year) correlates positively with daughter's age at first birth (**?**) but results from the two studies are not easily comparable.

[7]Micro-level census data for countries in Latin America also suffer from a co-residential bias since only children living in the household are surveyed. Moreover, since birth histories are not usually part of the census questionnaires, it is not possible to establish whether mothers were teenagers at first birth. To our knowledge, for the six countries in our sample the only longitudinal data available that seems suitable to study the intergenerational transmission of teen childbearing is the ELCA data for Colombia (from the Spanish acronym "Encuesta Longitudinal Colombiana").

[8]On the contrary, Azevedo et al. (2012b), which also uses Mexican data but identifies the effect of childbearing using miscarriages as a natural experiment, finds non-negative and even positive results, which are in line with other results studies using the methodology on US data (e.g., Hotz et al. 2005).

[9]Related studies find that being born to a teen mother has negative effects on behaviors that increase the likelihood of teen pregnancy, such as early sexual activity and risky sexual behavior (Levine et al. 2001). Moreover, the medical literature has extensively documented negative health outcomes for the mother (e.g. labor complications) and the child (e.g. low birth weight) related to teen labor (e.g. **?**, **?**, **?**, Azevedo et al.

The literature on the determinants of teen pregnancy has identified multiple causes, from the distribution of parental income during childhood and adolescence to compulsory education (e.g. Carneiro et al. 2021; Chetty et al. 2011; Black et al. 2008; and An et al., 1993). In contrast to the literature on the consequences of childbearing, the literature on the determinants does include plenty of studies from Latin America.[10] These studies reveal mostly associations between poverty, poor family structure, poor family background, low educational inputs, low aspirational objectives, low sexual literacy, poor neighborhood, high levels of violence, and teen pregnancy and childbearing status.

The remainder of this paper is structured as follows. We present the data in Section 2, the econometric model and the empirical strategy in Section 3, and the main results in Section 4. Section discusses extensions and Section 6 concludes. Appendix A presents additional tables and results.

2 | DATA

We use comparable individual-level data from the standard *Demographic and Health Survey* (DHS) for six Latin American countries: Bolivia, Colombia, Dominican Republic (DR), Guatemala, Haiti, and Peru. DHS are nationally-representative household surveys comprising independent cross-sections conducted at about every five years. An important feature of the DHS is that all women in the household aged between 15 and 49 answer a specific questionnaire that provides, among other items, birth information—such as the birth date—for all of their live births. Therefore, it is possible to compute TCS for both mothers and daughters participating in the survey.

Our population of interest is teenage women aged 15 to 18 and their mothers. Unique household and individual identifiers permit the matching of teenage daughters to their mothers aged 49 or younger living in the same household. However, some interviewed daughters cannot be matched with their mothers because either (i) their mothers are older than 49 or deceased[11], or (ii) they live in a different household. Similarly, some interviewed mothers cannot be matched to their teenage daughters because (i) the daughter was not interviewed (exceptional), or (ii) she does not live with her mother.[12]

2.1 | Early and sample DHS

Our empirical strategy does not require the imputation of daughter's or mother's characteristics for the unmatched pairs. Nonetheless, as we show in Section 3.2, we exploit external information on the joint distribution of women's TCS, age, and education to facilitate sample identification. For simplicity, we denote these proportions as *Teen Childbearing Rates,* TCR. We need TCR for all mothers in matched and unmatched mother-daughter pairs. For mothers in matched pairs, we know their TCS, age, and education. For non-interviewed mothers,

(2012a)). Although the amount of medical evidence seems to indicate an effect, causality is often not formally established.

[10]Recent studies based on Latin American countries include Estrada et al. (2021), Aguia-Rojas et al. (2020), Alzate et al. (2020), Drewry and Garcés-Palacio (2020), Tsaneva and Gunes (2020), Dongarwar and Salihu (2019), Millán (2019), Mohr et al. (2019), Neal et al. (2018), and Alzate (2014).

[11]Girls up to age 14 are asked whether their mother is alive. Only 2.37% of girls aged 14 answered that their mother was not alive.

[12]The proportion of women aged 25-49 who had a daughter who died in adolescence is only 0.32%. We observe neither the daughter's cause of death nor her TCS. Given the Maternal Mortality rate (**?**) and observed teen pregnancy rates in these countries, we could expect at most 0.03% of observations in our sample where the daughter is missing because she died during pregnancy. Hence, for simplicity, we consider only women whose teenage daughters are alive.

we consider all potential combinations of TCS, age, and education with a limitation: in the case of age we assume they are between 27 and 64 years old because women younger than 27 and older than 64 are unlikely to have teen daughters. Lacking an external source of a long and homogeneous series of TCR, we compute them using DHS data. To do so, we classify all available DHS between those that we use to estimate the model—the "sample" surveys—and those that can only be used in the computation of TCR—the "early" surveys.

TABLE 1 Available Standard Demographic Health Surveys

Country	Early DHS	Sample DHS
Bolivia	1989, 1993-94 1998, 2003-04	2008
Colombia	1986, 1990 1995, 2000	2004-05, 2009-10, 2014-15
Dominican Republic	1986, 1991, 1996, 1999	2002, 2007, 2013
Guatemala	1987, 1995 1998-99	2014-15
Haiti	1994-95, 2000 2005-06	2012, 2016-17
Peru	1986, 1991-92, 1996 2000, 2003-04(*)	2005-08, 2009, 2010 2011, 2012

Notes: All available DHSs for the selected countries. Notation "YYY1-Y2" indicates that the survey was conducted in all years from YYY1 to YYY2. For each country, we distinguish early Demographic Health Surveys (DHSs) (under the heading "Early DHS") from later DHSs (under the heading "Sample DHS"). Sample surveys make up our estimation sample. Early surveys comprise all available DHSs prior to the first sample DHS. For each sample DHS we compute cohort-specific TPRs using all available DHSs but that one.
(*) Peru 2003-04 cannot be included in the Sample DHS because it is not possible to match mothers with their daughters.

To illustrate how we distinguish early from sample surveys, consider the case of Colombia, a country that participates in 1986 (wave I), in 1990, and, then subsequently every five years until 2015. The oldest women in Colombia for whom we have birth history information are those interviewed in 1986 who are, at the time, 49 years old (i.e., born in 1937). Those women are 64 years old in 2001. Therefore, the first sample DHS for Colombia is 2005 because it is the first survey for which we have average TCR by age for all women aged 27 to 64. We cannot use the 2000 Colombian DHS because we would need TCR for women aged 64, i.e., TCR for the birth cohort of 1936.[13]

The six countries that we use are those with enough early surveys to compute TCR for sample surveys. In Table 1 we summarize all available DHS for each of the six countries, distinguishing sample surveys that form the estimation sample from early surveys that are not included in the estimation sample. To ensure that TCR are external information in each specific sample DHS, we calculate TCR for each sample DHS using all the other DHS available. For example, for the Colombia 2005 sample, we compute TCR with all other DHS, including not only Colombia's early DHS but also Colombia 2010 and 2015.

2.2 | Estimation Sample

In Table 2, DHS samples sizes include all matched and unmatched pairs of mothers and their teenage daughters. The number of observations refers to the total number of mother-daughter pairs by country and wave. These totals vary mostly by country and are fairly stable by year. Overall, our sample consists of 65,008 observations. Mother-daughter matches (reported as percentage under the heading "Both observed (%)") represent on average 50.28% of the observations and, with the exceptions of Haiti and Dominican Republic 2002, they vary little across countries (ranging from 46.02% to 56.57%). Pairs where the mother is not interviewed are also common, on average 45.69% of all pairs, with four DHS where it is the most common situation. Lastly, although the proportion of pairs in which the daughter is not interviewed is residual, ranging from 1.11% in Haiti 2016-17 to 6.87% in Dominican Republic 2002, we include them in our estimation sample.

Each DHS provides demographic characteristics for every member of the household—such as age, gender, and education—and basic information on the characteristics of the household—such as household size, a wealth index, and whether the household is located in a rural or urban area. In addition, the DHS contains information to compute teen childbearing status of interviewed mothers and daughters and detailed information on i) sexual behavior, such as age at first sexual intercourse; ii) personal beliefs regarding gender roles in sexual relations; iii) knowledge of contraceptive health, such as fertility status along the menstrual cycle; and iv) fertility preferences such as the ideal number of children.

Our main dependent variable is a dummy for the TCS of the daughter which takes value one if the teenager is pregnant or already a mother. (As a robustness check, we also consider dummies for having had sex before 16 and before 19 years old as dependent variables.) The equivalent variable for the mother are used in the models as the factor of interest. Other covariates include year of interview dummies, dummies for the mother's and daughter's age, a dummy variable that takes value 1 when the mother's household is located in a rural area, a dummy variable for mother's household size larger than 6, a dummy that takes value 1 if the parents' household belongs to the two poorest quintiles of the country's population based on a continuous wealth measure produced by the DHS, a dummy for whether the daughter is the firstborn, and a dummy for whether the mother's education is at most primary. In an extended specification we add daughter's characteristics that are arguably endogenous such as whether the daughter completed primary education, knowledge of fertility along the menstrual cycle, ideal number of children, and whether the daughter shows a submissive role in sexual relationships.

[13]If we were to use external information from other sources (such as official statistics on age-specific fertility rates), the estimation sample would be even more constrained as these statistics start in the 1970s at the earliest and, in most cases, they are not available by education.

TABLE 2 Sample DHSs: Sizes and missing observations

	Number of observations	Both observed (%)	Mother missing (%)	Daughter missing (%)
Bolivia 2008	2,982	46.38	50.34	3.29
Colombia 2004-05	6,101	51.60	43.62	4.79
Colombia 2009-10	7,906	54.91	41.17	3.92
Colombia 2014-15	5,716	50.59	44.16	5.25
Dominican Republic 2002	4,149	41.31	51.82	6.87
Dominican Republic 2007	5,112	46.19	48.92	4.89
Dominican Republic 2013	1,532	46.02	48.96	5.03
Guatemala 2014-15	4,845	56.57	40.72	2.70
Haiti 2012	2,886	36.56	61.92	1.52
Haiti 2016-17	2,789	39.30	59.59	1.11
Peru 2005-08	5,771	53.13	42.87	4.00
Peru 2009	3,992	55.69	41.31	3.01
Peru 2010	3,776	52.60	43.67	3.73
Peru 2011	3,654	53.75	42.36	3.89
Peru 2012	3,797	52.88	42.56	4.56
All sample DHSs	65,008	50.28	45.69	4.04

Notes: DHS samples include all matched and unmatched pairs of mothers and their teenage daughters aged 15 to 18. "Number of observations" refers to the total number of pairs by country and wave. The proportion of pairs of mothers, aged 19 to 49, and their teenage daughters who are both interviewed is shown under the heading "Both observed (%)". Column "Mothers missing (%)" shows the percentage of mother-daughter pairs where the mother is not interviewed and, hence, cannot be matched to her daughter. Column "Daughters missing (%)" shows the percentage of mother-daughter pairs where the daughter is not interviewed.

Information on terminations.

Abortion is either very restricted or banned altogether in all six countries during the sample periods.[14] Research has shown that women that undertake an abortion are of higher socioeconomic status than other pregnant women (Fletcher and Wolfe 2009; Ashcraft et al. 2013). Hence, high abortion rates could compromise the representativeness of our data. In the DHS women are only asked whether they ever had a pregnancy that terminated in a miscarriage, abortion, or still birth. Thus, we can neither differentiate between abortion and the other reasons for terminations nor count the actual number of terminations per woman. (Nevertheless, we find it unlikely that the average number of terminations during teenage

[14] Abortion is prohibited altogether (no explicit legal exception) for Dominican Republic and Haiti (all years), and Colombia 2005. It is allowed: (*i*) only to save the life of the mother in Guatemala; (*ii*) to save the life of the mother and preserve physical health in Bolivia and Peru; (*iii*) to save the life of the mother and preserve physical and mental health in Colombia 2010 and 2015; and (*iv*) in exceptional circumstances such as in case of rape or incest in Bolivia and Colombia 2010 and 2015.

years differs much from the proportion of teenagers with at least one termination.) In Panel A of Table A.1 we show that the percentage of women that had at least one termination before age 19 is between 1.7% and 5.0% (between 2.1% and 6.2% among women who were sexually active). As a percentage of pregnant women, the proportion of women with at least one termination ranges from 7.4% and 14.4%.[15] Lang and Weinstein (2015) consider that in their US sample for the years 1948-1968, the percent of miscarriages among teens was around 6% and the percentage of abortions was not higher than 3%. Based on these figures, they discard the possibility that abortion rates bias their estimates. Our termination rates lead us to think that abortion rates in our sample are not higher than those reported in Lang and Weinstein (2015) and, hence, should not seriously bias our estimates.

3 | THE ECONOMETRIC MODEL

3.1 | Non-ignorable missing observations

In Figure 1 we gave graphical evidence of non-ignorable missingness. It shows that daughters who are not matched to their mothers are close to three times more likely to be teen mothers. Additional evidence of non-ignorable missingness is provided in Table 3. Pooling all countries together, we use all pairs for which we have the daughter's information and show differences in means in some of the daughter's characteristics between matched and unmatched pairs. The differences are statistically significant in most cases, hardly surprising given the number of observations. In some variables, they are revealingly sizable. The largest of the differences, reported in the first line, confirms what we have already mentioned: the probability of TCS in unmatched pairs is almost three times higher than in matched pairs. We also find sizable differences in the identity of the household head and whether the daughter is married. Finally, other variables with sizable differences relate to the sexual behavior of the daughter: if she has had sexual relations, the number of sexual partners, if she uses contraceptive methods, and, finally, her ideal number of children. Arguably, all these differences are expressions of the same process behind the differences in TCS. In contrast, the mean differences observed in all other variables are much smaller. In summary, differences between matched and unmatched pairs are sizable in variables related to the event of becoming a mother at a young age.

Estimation using only matched pairs when the missing process is not random results in sample selection bias. We avoid this bias by developing a Maximum Likelihood (ML) procedure in the spirit of the GMM approach first proposed by Ramalho and Smith (2013). Our ML procedure involves using all observations and permits the missing process to be endogenous. The procedure also allows us to test whether we can ignore the unmatched pairs when estimating the model, which we refer to as a test of Ignorability. As we mentioned in section 2.1, we improve the identification of the model by imposing restrictions on the parameters exploiting external information on TCR.[16]

[15] In our sample of teenage daughters, those who report having had a termination in the past are either mothers or currently pregnant. Hence, there is no difference between teen childbearing and teen pregnancy status. Although there is a legitimate concern regarding under-reporting of illegal abortions, there are reasons to think that this problem is minor in our sample: (i) As women are only asked about ever having had a termination, they can safely conceal an illegal abortion in their answers; (ii) termination rates during adolescence reported by women aged 23—shown in Panel A in Table A.1—are comparable with miscarriage rates reported elsewhere (Lang and Weinstein 2015, Lang and Nuevo-Chiquero 2012), (iii) among sexually active women, they are lower during adolescence (PANEL A, sixth row, in Table A.1) than after adolescence (PANEL B), suggesting that these terminations are mostly miscarriages; finally (iv) we checked that the presence of adults during the interview did not affect the rate of reported terminations.

[16] Our methodological procedure is closest to Carro, Machado and Mora (2021), which estimates a mother-

TABLE 3 Mean tests of daughter characteristics by mother observability

	Mother observed	Mother missing	Difference	Std.Err.	p-value
TCS	0.09	0.24	-0.15	0.003	0.000
Age	16.31	16.61	-0.30	0.009	0.000
Years of education	8.74	8.03	0.71	0.020	0.000
Firstborn	0.31	0.18	0.12	0.004	0.000
Rural	0.37	0.39	-0.02	0.004	0.000
Household size 7+	0.31	0.27	0.04	0.004	0.000
Wealth index (1 to 5)	2.81	2.73	0.08	0.011	0.000
Parent is household head	0.94	0.43	0.51	0.003	0.000
Other relative is household head	0.06	0.23	-0.18	0.003	0.000
Married	0.05	0.07	-0.02	0.003	0.000
Ever had sex	0.23	0.44	-0.20	0.004	0.000
No menarche	0.01	0.01	0.00	0.001	0.842
Knows contraceptive method	0.93	0.94	-0.01	0.002	0.000
Uses contraception	0.08	0.15	-0.08	0.003	0.000
Fertility knowledge	0.19	0.18	0.01	0.003	0.000
Condom ok if STD	0.96	0.94	0.01	0.003	0.000
No sex ok if adultery	0.94	0.91	0.02	0.002	0.000
Beating by partner ok	0.08	0.12	-0.03	0.003	0.000
Ideal no. of children	2.15	2.25	-0.09	0.008	0.000
No. of sex partners	0.37	0.69	-0.32	0.009	0.000

Notes: Means tests are two-tail t-tests on the equality of means allowing for unequal variances.

3.2 | The likelihood function

We define $y_i = 1$ if daughter i is a teen mother and $y_i = 0$ otherwise. We model y_i as dependent on her mother's TCS, y_i^m. We assume the following discrete choice linear specification:

$$y_i = \mathbf{1}\{\alpha y_i^m + x_i\beta + x_i^m\beta^m + z_i\gamma + \epsilon_i > 0\}. \quad (1)$$

Control vectors x_i, x_i^m, and z_i are discrete. Vector x_i includes variables that are missing when the daughter is not interviewed. Similarly, x_i^m includes variables that are missing when the mother is not interviewed. Some controls may be always observable. We denote these controls by vector z_i.

The aim is to estimate parameter vector $\theta \equiv \{\alpha, \beta, \beta^m, \gamma\}$ where:

$$\Pr\{y_i | y_i^m, x_i, x_i^m, z_i\} = F(y_i, y_i^m, x_i, x_i^m, z_i; \theta) \quad (2)$$

daughter transmission model of female labor force participation using historical data. In their model, only the labor participation variables for the daughter and the mother can be missing. In contrast, in our model when the TCS of the daughter (mother) is not observed, we allow all her (her mothers') characteristics to be missing. This feature makes our approach more relevant for other applications where missing information stems from non-interviewed subjects.

Assuming normality for error ϵ, we have the conditional probit model:

$$F\left(y_i, y_i^m, x_i, x_i^m, z_i; \theta\right) \equiv \begin{cases} \Phi\left(\alpha y_i^m + x_i\beta + x_i^m\beta^m + z_i\gamma\right) & \text{if } y_i = 1 \\ 1 - \Phi\left(\alpha y_i^m + x_i\beta + x_i^m\beta^m + z_i\gamma\right) & \text{otherwise} \end{cases} \tag{3}$$

Let us define a binary indicator I_i, which takes value 1 if the daughter is interviewed and 0 otherwise. Similarly, let I_i^m take value 1 if the mother is interviewed and 0 otherwise. For an observation with non-missing information, the joint probability of non-missingness, i.e., $I_i = I_i^m = 1$, and the vector variables $\left\{y_i, y_i^m, x_i, x_i^m, z_i\right\}$ is:

$$\begin{aligned} \Pr\left\{I_i = I_i^m = 1, y_i, y_i^m, x_i, x_i^m, z_i\right\} = \; & \Pr\left\{I_i = I_i^m = 1 \left| y_i, y_i^m, x_i, x_i^m, z_i\right.\right\} \times \\ & F\left(y_i, y_i^m, x_i, x_i^m, z_i; \theta\right) \times \Pr\left\{y_i^m, x_i, x_i^m, z_i\right\}. \end{aligned} \tag{4}$$

There are two situations in which a given observation may have missing information: when the mother's information is missing but the daughter's is not and when the daughter's information is missing but the mother's is not. Consider the second case. The joint probability for observation $\left\{I_i = 0, I_i^m = 1, y_i^m, x_i^m, z_i\right\}$ decomposes into several event probabilities:

$$\begin{aligned} \Pr\left\{I_i = 0, I_i^m = 1, y_i^m, x_i^m, z_i\right\} = & \sum_{\{y,x\}} \Pr\{I_i = 0, I_i^m = 1, y_i = y, y_i^m, x_i = x, x_i^m, z_i\} \\ = & \sum_{\{y,x\}} [\Pr\{I_i = 0, I_i^m = 1 \left| y, y_i^m, x, x_i^m, z_i\right.\} \times \\ & \quad F\left(y, y_i^m, x, x_i^m, z_i; \theta\right) \times \Pr\{y_i^m, x, x_i^m, z_i\}]. \end{aligned} \tag{5}$$

The treatment of the first case, i.e., when the mother's information is missing but the daughter's is not, is similar:

$$\Pr\left\{I_i = 1, I_i^m = 0, y_i, x_i, z_i\right\} = \sum_{\{y^m, x^m\}} \Pr\{I_i = 1, I_i^m = 0, y_i, y_i^m = y^m, x_i, x_i^m = x^m, z_i\} \tag{6}$$

$$= \sum_{\{y^m, x^m\}} [\Pr\{I_i = 1, I_i^m = 0 \left| y_i, y^m, x_i, x^m, z_i\right.\} \times \tag{7}$$

$$F\left(y_i, y^m, x_i, x^m, z_i; \theta\right) \times \Pr\{y^m, x_i, x^m, z_i\}]. \tag{8}$$

We ensure the identification of θ by restricting the conditional missing process (Ramalho and Smith, 2013). In our case, we make the following assumption:

Assumption 1 *Observability of the mother and the daughter information,* I_i *and* I_i^m*, is conditionally independent of* x_i*,* x_i^m*, and* z_i*; i.e.,*

$$\Pr\{I_i, I_i^m \left| y_i, y_i^m, x_i, x_i^m, z_i\right.\} = \Pr\{I_i, I_i^m \left| y_i, y_i^m\right.\}. \tag{9}$$

Although Assumption 1 allows for a flexible non-parametric specification of the missing process, it relies on exclusion restrictions. These exclusion restrictions imply that the observed correlations between $\left\{I_i, I_i^m\right\}$ and $\left\{x_i, x_i^m, z_i\right\}$ occur only through the direct effect of the latter on y_i and y_i^m. A less restrictive assumption would allow the missing process to depend on an additional subset of the controls. However, Assumption 1 is relatively parsimonious, deals with non-ignorable missingness, and helps avoiding sample identification problems.[17] Crucially, several reasons justify it in our application. First, as Figure 1 shows, unmatched daughters are much more likely to be teen mothers than matched daughters. This suggests that motherhood in adolescence decreases the probability of a mother-daughter match. Hence, it seems necessary to allow the missing process to depend on the daughter's TCS, i.e., y_i.

Second, it is likely that the mother's TCS also affects the probability of the mother-daughter match, although the direction of the effect is unclear. On the one hand, children of teenage mothers are often raised by grandparents or other relatives (Card 1981; **?**). Hence, a mother who was a teen mother might decrease the probability of a match. On the other hand, at least two other factors, which correlate with y_i^m, affect the probability of a match: adverse economic conditions (because they might discourage the daughter leaving the parental home) and age of the mother (as teen mothers are more likely to be younger than 49 and therefore interviewed). Hence, it also seems necessary to allow the missing process to depend on the mother's TCS, i.e., y_i^m. By conditioning the probability on y_i and y_i^m jointly, we also allow for interaction effects in how they affect the likelihood of a match.

Third, as shown in Table 3, differences between matched and unmatched pairs are only sizable in variables related to the event of becoming a mother at a young age. Hence, in the interest of keeping the model tractable, excluding additional variables from the conditional probability of a match seems reasonable. As a robustness check, to weaken Assumption 1, we also estimate the model for subsamples based on the values of z_i in section 5.

Let $H_{y_i y_i^m}^{I_i I_i^m} \equiv \Pr\left\{I_i, I_i^m \,|y_i, y_i^m\right\}$, with I_i, I_i^m, y_i, and $y_i^m \in \{0,1\}$, and $\Pi_{y_i^m, x_i, x_i^m, z_i} \equiv \Pr\left\{y_i^m, x_i, x_i^m, z_i\right\}$, where $\Pi_{y_i^m, x_i, x_i^m, z_i} \in [0,1)$. For observations with information for mother and daughter, Assumption 1 implies that:

$$\Pr\{I_i = I_i^m = 1, y_i, y_i^m, x_i, x_i^m, z_i\} = H_{y_i y_i^m}^{11} F\{y_i, y_i^m, x_i, x_i^m, z_i; \theta\} \Pi_{y_i^m, x_i, x_i^m, z_i}. \tag{10}$$

When only the daughter's information is observed, the joint probability is:

$$\begin{aligned} \Pr\{I_i = 1, I_i^m = 0, y_i, x_i, z_i\} &= \sum_{y^m, x^m} \left(H_{y_i y^m}^{10} F\{y_i, y^m, x_i, x^m, z_i; \theta\} \Pi_{y^m, x_i, x^m, z_i} \right) \\ &= \sum_{y^m} \left(H_{y_i y^m}^{10} \sum_{x^m} \left(F\{y_i, y^m, x_i, x^m, z_i; \theta\} \Pi_{y^m, x_i, x^m, z_i} \right) \right) \end{aligned} \tag{11}$$

where $F\{y_i, y^m, x_i, x^m; \theta\}$ and Π_{y^m, x_i, x^m, z_i} are evaluated at values y_i, x_i, and z_i and all potential combinations of running values y^m and x^m. Finally, the joint probability of an observation without daughter's information is:

$$\Pr\{I_i = 0, I_i^m = 1, y_i^m, x_i^m, z_i\} = \sum_{y} \left(H_{y y_i^m}^{01} \sum_{x} \left(F\{y, y_i^m, x, x_i^m, z_i; \theta\} \Pi_{y_i^m, x, x_i^m, z_i} \right) \right) \tag{12}$$

The model parameters are: (*i*) probit model parameters θ; (*ii*) conditional missing process parameters $\left\{H_{y y^m}^{I I^m}\right\}$; and (*iii*) marginal probabilities $\{\Pi_{y^m, x, x^m, z}\}$. The conditional likelihood

[17] Specifically, when allowing the conditional probability $\Pr\left\{I_i, I_i^m \,|y_i, y_i^m, x_i, x_i^m, z_i\right\}$ to additionally depend—non-parametrically—on a subset of $\left(x_i, x_i^m, z_i\right)$, each additional discrete variable at least doubles the number of parameters related to the missing process.

$\mathcal{L}_i$ for any given observation i is:

$$\begin{aligned}\mathcal{L}_i = \quad & \left(H^{11}_{y_i y_i^m} F\left\{y_i, y_i^m, x_i, x_i^m, z_i; \theta\right\} \Pi_{y_i^m, x_i, x_i^m, z_i}\right)^{I_i I_i^m} \times \\ & \left(\sum_{y^m}\left(H^{10}_{y_i y^m} \sum_{x^m}\left(F\{y_i, y^m, x_i, x^m, z_i; \theta\} \Pi_{y^m, x_i, x^m, z_i}\right)\right)\right)^{I_i (1-I_i^m)} \times \\ & \left(\sum_{y}\left(H^{01}_{y y_i^m} \sum_{x}\left(F\left\{y, y_i^m, x, x_i^m, z_i; \theta\right\} \Pi_{y_i^m, x, x_i^m, z_i}\right)\right)\right)^{(1-I_i) I_i^m}.\end{aligned} \tag{13}$$

The log-likelihood function results from the sum of the log of $\mathcal{L}_i$, $\log(\mathcal{L}) = \sum_{i=1}^{N} \log(\mathcal{L}_i)$ and is maximized subject to the following constraints:

$$\begin{aligned} H^{II^m}_{yy^m}, \Pi_{y^m,x,x^m,z} \in [0,1) \ \text{ for all } I, I^m, y, y^m, x, x^m, z \\ \sum_{I,I^m} H^{II^m}_{yy^m} = 1 \text{ for all } y, y^m \\ \sum_{y^m,x,x^m,z} \Pi_{y^m,x,x^m,z} = 1 \end{aligned} \tag{14}$$

Maximum Likelihood estimation will yield consistent and asymptotically efficient estimates of θ. The number of parameters in $\Pi_{y^m,x,x^m,z}$ grows exponentially with the number of controls and rapidly becomes computationally intractable. In our application, we reduce the number of parameters in $\Pi_{y^m,x,x^m,z} = \Pi_{y^m,x^m|x,z}\Pi_{x,z}$ by assuming that $\Pi_{y^m,x^m|x,z} = \Pi_{y^m,x^m|z}$, i.e., mother characteristics are predetermined with respect to those of the daughter. We further reduce the number of parameters by assuming that $\Pi_{y^m,x^m|z} = \Pi_{y^m,v(x^m)|w(z)}$ where $v \subseteq x^m$ and $w \subseteq z$, i.e., the joint probability of y^m and x^m conditional on z only varies along a subset of x^m and a subset of z. For example, in our application for each country, v includes dummies for the age and the education of the mother and w includes survey time dummies and, therefore the dimension of $\Pi_{y^m,v(x^m)|w(z)}$ does not increase with the number of controls. Finally, we improve sample identification with the use of external information on $\Pi_{y^m,v(x^m)|w(z)}$—referred to as TCR in Section 2.1.

4 | MAIN RESULTS

Table 4 shows country-specific estimates of Equation (3) under ignorability, i.e, using only observations from matched mother-daughter pairs. In this basic specification, besides the mother's TCS, we include survey year dummies and a small set of exogenous dummy variables: age of the daughter to account for the effect of time and right censoring; a dummy for whether the mother is 45 or older; and, a dummy for rural residence. All significant coefficients have the expected sign and direction, i.e., the mother TCS status ($y^m = 1$), older age of the daughter, and rural residence are associated with higher probability of being a teen mother. We also show the average marginal effect (AME) of y^m for each country. All AMEs are positive and statistically significant. Their magnitudes imply that being a daughter of a teen mother increases her chances of being a teen mother herself between 2.4 to 5.2 percentage points, or between 35 and 69 percent. These AME are of similar magnitude as the implicit AME obtained from comparing the first and second bars (when the mother TCS is not missing) for each country in Figure 1.

TABLE 4 Probit estimates under ignorability. Matched mother-daughter pairs only.

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
y^m	0.403***	0.306***	0.297***	0.201**	0.204**	0.268***
	(0.109)	(0.036)	(0.054)	(0.079)	(0.089)	(0.038)
Mother 45+	0.069	0.009	0.058	0.008	0.093	-0.022
	(0.119)	(0.042)	(0.067)	(0.091)	(0.092)	(0.044)
Age = 16	0.361**	0.314***	0.375***	0.384***	0.295*	0.317***
	(0.171)	(0.054)	(0.084)	(0.132)	(0.156)	(0.059)
Age = 17	0.687***	0.670***	0.667***	0.756***	0.821***	0.655***
	(0.165)	(0.052)	(0.082)	(0.127)	(0.145)	(0.057)
Age = 18	0.817***	0.981***	1.023***	1.009***	1.137***	0.973***
	(0.170)	(0.052)	(0.081)	(0.127)	(0.142)	(0.058)
Rural	0.638***	0.180***	0.069	0.185**	0.068	0.253***
	(0.109)	(0.038)	(0.054)	(0.081)	(0.091)	(0.038)
AME(y^m)	0.051***	0.052***	0.046***	0.024**	0.025**	0.034***
	(0.014)	(0.006)	(0.008)	(0.009)	(0.011)	(0.005)
$\overline{y}$	0.074	0.106	0.094	0.066	0.072	0.072
No.obs	1383	10381	4780	2741	2151	11247

Notes: *** p<0.01, ** p<0.05, * p<0.1. Estimation sample obtained from matched mother-daughter pairs from sample DHSs as described in Table 1. Dependent variable is daughter's TCS. All models include survey dummies. Standard errors in parenthesis. Variable y^m is the dummy for the mother's teen childbearing status. Mother 45+ is a dummy variable for mother 45 and older. Age = 16-Age = 18 are age dummies (reference category is age 15). Rural takes value 1 when the household is located in a rural area. AME(y^m) is the estimated Average Marginal Effect of y^m. $\overline{y}$ is the average value of the daughter's teen childbearing status in the estimating sample.

We carry out ML estimation of (13) subject to (14) with the same specification as the probit under ignorability. Table 5 shows the results. Relative to results under ignorability, the number of observations is close to double as we now also include unmatched pairs in the estimation. The average TCS of the daughter, $\overline{y}$, is also larger because unmatched daughters are more likely to be teen mothers, as shown in Figure 1. Turning our attention to the coefficient estimates, those related to y^m and to Mother 45+ are much larger, and both increase significantly the probability of being a teen mother. Also, being a daughter of a teen mother increases the changes of being a teen mother from 10.1 percentage points in Peru to 26.2 percentage points in Dominican Republic. Comparing these AME estimates to those of Table 4, they are between 2.5 to 7.9 times larger. Under the header 'Ignorability tests', we report likelihood ratio tests for the null hypothesis that $H^{1,1}_{yy^m} = \Pr(I = 1, I^m = 1 | y, y^m)$ are invariant to y^m and y. We strongly reject the null in all countries, which shows that unmatched pairs are not ignorable. We conclude that ignoring the missing observations leads to a substantial negative selection bias in AMEs of the mother TCS.

TABLE 5 Non-ignorable ML estimates. Full Estimation Sample

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
y^m	1.198***	0.562***	1.171***	1.369***	1.152***	0.560***
	(0.204)	(0.045)	(0.057)	(0.080)	(0.150)	(0.052)
Mother 45+	0.742***	0.317***	0.821***	1.223***	0.451***	0.396***
	(0.103)	(0.040)	(0.049)	(0.060)	(0.081)	(0.043)
Age = 16	0.371***	0.401***	0.351***	0.349***	0.378***	0.372***
	(0.117)	(0.038)	(0.054)	(0.090)	(0.104)	(0.042)
Age = 17	0.823***	0.791***	0.803***	0.866***	0.861***	0.825***
	(0.110)	(0.037)	(0.051)	(0.085)	(0.099)	(0.040)
Age = 18	1.113***	1.140***	1.115***	1.070***	1.293***	1.157***
	(0.111)	(0.036)	(0.052)	(0.084)	(0.098)	(0.040)
Rural	0.774***	0.529***	0.267***	-0.028	-0.090	0.428***
	(0.108)	(0.035)	(0.049)	(0.068)	(0.081)	(0.038)
AME(y^m)	0.218***	0.128***	0.262***	0.190***	0.194***	0.101***
	(0.020)	(0.006)	(0.006)	(0.006)	(0.010)	(0.006)
Ignorability test	199.830	4426.646	2670.480	3323.589	174.805	5075.481
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\overline{y}$	0.162	0.178	0.208	0.168	0.102	0.129
N. obs.	2982	19723	10793	4845	5675	20990

Notes: *** p<0.01, ** p<0.05, * p<0.1. Maximum Likelihood estimates of (13) subject to (14). Estimation sample obtained from all mother-daughter pairs (matched and unmatched) from sample DHSs as described in Table 1. Dependent variable is daughter's TCS. All models include survey dummies. Standard errors in parenthesis. Variable y^m is the dummy for the mother's teen childbearing status. Mother 45+ is a dummy variable for mother 45 and older. Age = 16, Age = 17, and Age = 18 are age of the daughter dummies (reference category is age 15). Rural takes value 1 when the mother's household is located in a rural area. Vector x^m includes Mother 45+ and Rural—$v(x^m)$ is Mother 45+. Vector z includes age of the daughter dummies and the survey year dummies, the latter being $w(z)$. Vector x is empty. AME(y^m) is the estimated Average Marginal Effect of y^m. Ignorability tests are likelihood ratio tests for the null hypothesis that conditional probabilities $\Pr(I = 1, I^m = 1 | y, y^m)$ are invariant to mother and daughter *TCS*, y^m and y, respectively, their p-values are in parenthesis. $\overline{y}$ is the average value of the daughter's teen childbearing status in the estimating sample.

Because mothers' TCS may be correlated with relevant omitted variables, we enrich our basic specification by including more mother characteristics as controls in our estimation: (*i*) a dummy for whether the mother has no more than primary education (At most primary); (*ii*) a dummy for whether the mother's household size has at least seven members (Household size); (*iii*) a dummy for whether the mother's household belongs to the two poorest quintiles in the country (Poor); (*iv*) and a dummy that indicates that the mother's eldest child is the teenage daughter (Firstborn). Results under the Likelihood Approach are shown in Table 6.

TABLE 6 Non-ignorable ML estimates. Full Estimation Sample. Additional controls

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
y^m	1.409***	0.495***	1.159***	1.472***	1.074***	0.531***
	(0.119)	(0.050)	(0.059)	(0.081)	(0.091)	(0.057)
Mother 45+	0.732***	0.283***	0.672***	1.280***	0.430***	0.344***
	(0.110)	(0.046)	(0.055)	(0.063)	(0.086)	(0.050)
At most primary	0.133	0.017	0.398***	0.193	0.385***	-0.095*
	(0.143)	(0.040)	(0.063)	(0.122)	(0.134)	(0.050)
Age = 16	0.357***	0.408***	0.371***	0.325***	0.369***	0.371***
	(0.121)	(0.039)	(0.056)	(0.092)	(0.104)	(0.043)
Age = 17	0.818***	0.792***	0.819***	0.851***	0.845***	0.827***
	(0.114)	(0.037)	(0.053)	(0.087)	(0.098)	(0.041)
Age = 18	1.065***	1.123***	1.131***	1.036***	1.264***	1.140***
	(0.117)	(0.037)	(0.054)	(0.087)	(0.096)	(0.040)
Rural	0.139	0.146***	0.113**	-0.063	-0.134	0.056
	(0.161)	(0.048)	(0.052)	(0.073)	(0.110)	(0.062)
Household size	0.252**	0.633***	0.606***	0.123*	0.165**	0.606***
	(0.106)	(0.037)	(0.050)	(0.070)	(0.084)	(0.039)
Poor	0.648***	0.169***	0.061	0.123*	0.101	0.352***
	(0.160)	(0.047)	(0.055)	(0.074)	(0.106)	(0.069)
Firstborn	0.628***	0.285***	0.586***	0.419***	0.280***	0.359***
	(0.118)	(0.042)	(0.052)	(0.077)	(0.096)	(0.049)
N.obs	2982	19723	10793	4845	5675	20990
AME(y^m)	0.262***	0.108***	0.240***	0.197***	0.176***	0.087***
	(0.011)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
$\overline{y}$	0.162	0.178	0.208	0.168	0.102	0.129
AME under	0.043***	0.035***	0.022**	0.018*	0.020*	0.020***
ignorability	(0.014)	(0.006)	(0.009)	(0.010)	(0.011)	(0.005)

Notes: *** p$<$0.01, ** p$<$0.05, * p$<$0.1. Dependent variable is daughter's TCS. All models include survey dummies. Standard errors in parenthesis. Variable y^m is the dummy for the mother's teen chilbearing status. Mother 45+ is a dummy variable for mother 45 and older. At most primary is a dummy variable that takes value 1 if the mother has no more than primary education. Age = 16, Age =17, and Age = 18 are age dummies (reference category is age 15). Rural takes value 1 when the mother's household is located in a rural area. Household size takes value one when the mother's household has at least seven members. Poor takes value 1 if the mother's household belongs to the two poorest quintiles in the country based on a continuous wealth measure produced by the *DHS*. Dummy variable Firstborn, obtained from the mother's birth history data, indicates that the mother's eldest child is the teenage daughter. Vector x^m includes Mother 45+, Rural, At most primary, Household size, Poor, and Firstborn—$\nu(x^m)$ is Mother 45+ and At most primary. Vector z includes age of the daughter dummies and the survey year dummies, the latter being $w(z)$. Vector x is empty. AME(y^m) is the estimated Average Marginal Effect of y^m. $\overline{y}$ is the average value of y in the estimating sample. AME under ignorability stands for the average marginal effect of y^m using the probit estimates under ignorability for the same variable specification.

Generally, all additional controls significantly increase the probability of teen motherhood. Regarding the AMEs, including the additional controls only slightly changes the results. In four out of the six countries AMEs are now slightly lower than with the basic specification shown in Table 5. However, in all countries, the new AMEs are still very large and statistically significant—specially when compared to the AMEs obtained under ignorability (reported in the bottom line of Table 6). They range from 8.7 percentage points in Peru to 26.2 percentage points in Bolivia. Relative to the average probability of teen motherhood, ratios range from 60.7 percent in Colombia to 172.5 percent in Haiti.

Table 7 reports ML estimates of the probability of having a mother-daughter match, i.e., $H^{1,1}_{yy^m}$, as well as the Ignorability test. The estimates vary considerably by y and y^m and we can strongly reject the null hypothesis of ignorability in all countries, as in the basic specification. In all but one case, conditional on the value of y^m, the probability of a match decreases when daughters are teen mothers. Regarding the marginal effect of the mother's TCS on the probability of a match, results are mixed. Conditional on $y = 0$, the mother being a teen mother increases the probability of the match in all countries. However, if $y = 1$, then only for Colombia and Peru is the marginal effect of y^m again positive. These results suggest that, as discussed in Section 3.2, several factors correlated with y^m affect the probability of the match.

TABLE 7 Missing process estimates & ignorability tests. Full Estimation Sample

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
$\Pr(I = 1, I^m = 1 \mid y = 0, y^m = 0)$	0.394	0.457	0.377	0.477	0.316	0.455
$\Pr(I = 1, I^m = 1 \mid y = 0, y^m = 1)$	0.952	0.935	0.879	0.951	0.681	0.923
$\Pr(I = 1, I^m = 1 \mid y = 1, y^m = 0)$	0.272	0.233	0.275	0.403	0.368	0.238
$\Pr(I = 1, I^m = 1 \mid y = 1, y^m = 1)$	0.192	0.443	0.179	0.174	0.200	0.425
Ignorability tests	1437.687	4702.846	2681.797	3431.309	1043.114	8478.349
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: ML estimates for the probabilities of the missing process using the non-ignorable ML estimates with additional controls reported in Table 6. Ignorability tests are likelihood ratio tests for the null hypothesis that conditional probabilities $\Pr(I = 1, I^m = 1 \mid y, y^m)$ are invariant to mother and daughter *TCS*, y^m and y, respectively, their p-values are in parenthesis.

5 | EXTENSIONS AND ROBUSTNESS CHECKS

5.1 | Potentially endogenous controls

One might suspect that the results presented so far are biased upward by the absence of sufficient controls for the daughter's characteristics. We only include the age of the daughter,[18] which is exogenous. Other variables, such as her education or attitudes and beliefs about sex, are likely simultaneous to her TCS and, consequently, endogenous. However, it would be interesting to study to what extent the inclusion of these potentially endogenous characteristics captures most of the AME. The interpretation of the results would be problematic, but it would establish a minimum AME and could suggest the existence of channels through which the effect of the mother takes place.

[18] Firstborn, although a characteristic of the daughter, is drawn from the birth history of mothers and is, therefore, only observed when the mother is observed.

TABLE 8 The role of potentially endogenous controls. Non-ignorable ML estimates

Panel A: At most primary

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
$\widehat{\beta}_{\text{At most primary}}$	0.887***	0.927***	1.019***	0.515***	0.722***	0.840***
	(0.082)	(0.034)	(0.039)	(0.062)	(0.061)	(0.035)
AME(y^m)	0.217***	0.114***	0.202***	0.189***	0.148***	0.096***
	(0.009)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)

Panel B: Submissive gender role

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
$\widehat{\beta}_{\text{Submissive gender role}}$	0.141	-0.005	-0.129**	-0.010	0.056	-0.187***
	(0.111)	(0.053)	(0.064)	(0.069)	(0.070)	(0.051)
AME(y^m)	0.263***	0.134***	0.241***	0.202***	0.186***	0.105***
	(0.010)	(0.006)	(0.005)	(0.006)	(0.007)	(0.005)

Panel C: Fertility knowledge

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
$\widehat{\beta}_{\text{Fertility knowledge}}$	-0.008	-0.088***	0.006	-0.033	0.041	-0.092***
	(0.082)	(0.029)	(0.068)	(0.079)	(0.074)	(0.033)
AME(y^m)	0.263***	0.133***	0.240***	0.201***	0.176***	0.104***
	(0.011)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)

Panel D: x = Fertility preferences

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
$\widehat{\beta}_{\text{Fertility preferences}}$	0.076	0.074	0.188***	0.088	-0.100	0.081
	(0.133)	(0.064)	(0.052)	(0.067)	(0.075)	(0.057)
AME(y^m)	0.261***	0.134***	0.240***	0.202***	0.174***	0.103***
	(0.011)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)

Panel E: Results in Table 6

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
AME(y^m)	0.262***	0.108***	0.240***	0.197***	0.176***	0.087***
	(0.011)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parenthesis. All models use the same specification as in Table 6 adding one additional dummy variable as x. “At most primary” takes value one if the daughter has obtained at most primary education. “Submissive gender role” takes value one if the daughter agrees with "the partner having a sexually transmitted disease is no reason to use a condom" or "the partner having a sexual affair with another individual is no reason to refuse sex", or both. “Fertility knowledge” takes value one if the daughter correctly states the moment during the menstrual cycle in which a woman is likely most fertile. “Fertility preferences” takes value one if the daughter declares her ideal number of children to be larger than 2. $\widehat{\beta}_x$ reports the ML estimate of the parameter associated to x. AME(y^m) is the estimated Average Marginal Effect of y^m.

In Table 8, we present the results obtained with the Likelihood Approach when adding four characteristics of the daughter, one at a time. They are the following: (*i*) At most primary takes value one if the daughter has obtained, at most, primary education and zero otherwise; (*ii*) Submissive gender role takes value one if the daughter agrees with "the partner having a sexually transmitted disease is no reason to use a condom" or "the partner having a sexual affair with another individual is no reason to refuse sex", or both; (*iii*) Fertility knowledge takes value one if the daughter correctly states the moment during the menstrual cycle in which a woman is likely most fertile and zero otherwise; and (*iv*) Fertility preferences takes value one if the daughter declares her ideal number of children to be larger than 2 and zero otherwise.

Adding these controls has little or no effect on the AME. Regarding the estimation with At most primary, although its coefficient ($\widehat{\beta}_{\text{At most primary}}$ in Panel A of Table 8) is positive and very significant in all countries, the AME only slightly decreases in Bolivia, DR, and Haiti. For the estimations with the other new controls, the AME only slightly changes (increases) for Colombia and Peru.

5.2 | Heterogeneity

In this section, we estimate the model using different subsamples defined by the age of the daughter and the wealth of the household. Our motivation for this exercise is twofold. First, the assumption on the missing process, Assumption 1, although reasonable is restrictive. Estimating the model on different subsamples is equivalent to relaxing it by allowing the missing process to also be conditionally dependent on the daughter's age or the household's wealth. Second, the effect of the mother, i.e., the parameter α, may be heterogeneous. One way to assess this heterogeneity is by estimating the model on different subsamples and comparing the estimated α's.[19] The estimation by country presented in Section 4 was already motivated by these same concerns.

5.2.1 | Age of the daughter

In the estimations presented thus far, we allow the age of the daughter to affect the probability of being a teen mother, i.e., it enters as a set of dummies in 3. However, we assume it affects neither the missing process directly nor the mother's effect. Results in Section 4 show that the probability of teen motherhood increases significantly with the daughter's age. Given its range, from 15 to 18 years old, this result is not surprising. The psychological development, the duration of compulsory education, and society's perceptions suggest that an 18-year-old daughter is most likely past adolescence while younger daughters are not. Moreover, adulthood starts at 18 in all countries in our data. Consequently, one would expect 18-year-old daughters to have a lower probability of living with their mothers and to experience a different effect of their mothers' TCS on their own probability of motherhood. In other words, age is likely to affect both the missing process and the effect of the mother's TCS.

We always observe the age of the daughter because, when the daughter's information is missing, we can retrieve it from the mothers' birth histories. Consequently, we can partition the sample by daughter's age. We present two estimates for each country: one for 18-year-old daughters and another for younger daughters. In Table 9 we show the results for the two age subsamples.

[19] Even when the estimated α's are similar, the AMEs may differ, as other characteristics—x, x^m and z—also vary by subsample.

TABLE 9 Non-ignorable ML estimates. Subsamples by age.

	Bolivia		Colombia		DR		Guatemala		Haiti		Peru	
	15-17	18	15-17	15-17	18	15-17	18	15-17	18	15-17	15-17	18
y^m	0.745**	1.477***	0.399***	0.792***	1.254***	1.105***	1.618***	1.167***	1.363***	1.864***	0.419***	0.887***
	(0.296)	(0.192)	(0.074)	(0.070)	(0.074)	(0.100)	(0.107)	(0.127)	(0.207)	(0.190)	(0.087)	(0.074)
	[0.17,1.32]	[1.10,1.85]	[0.26,0.54]	[0.65,0.93]	[1.11,1.40]	[0.91,1.30]	[1.41,1.83]	[0.92,1.42]	[0.96,1.77]	[1.49,2.24]	[0.25,0.59]	[0.74,1.03]
AME(y^m)	0.115***	0.354***	0.074***	0.260***	0.221***	0.345***	0.171***	0.279***	0.163***	0.537***	0.057***	0.263***
	(0.025)	(0.020)	(0.009)	(0.011)	(0.007)	(0.013)	(0.007)	(0.015)	(0.009)	(0.014)	(0.008)	(0.011)
	[0.07,0.16]	[0.31,0.39]	[0.06,0.09]	[0.24,0.28]	[0.21,0.23]	[0.32,0.37]	[0.16,0.18]	[0.25,0.31]	[0.15,0.18]	[0.51,0.56]	[0.04,0.07]	[0.24,0.28]
AME under	0.035**	0.069*	0.031***	0.050***	0.018**	0.045	0.023**	-0.012	0.012	0.040	0.021***	0.014
ignorability	(0.015)	(0.039)	(0.006)	(0.019)	(0.008)	(0.027)	(0.010)	(0.031)	(0.011)	(0.039)	(0.005)	(0.017)
	[0.01,0.06]	[-0.01,0.15]	[0.02,0.04]	[0.01,0.09]	[0.00,0.03]	[-0.01,0.10]	[0.00,0.04]	[-0.07,0.05]	[-0.01,0.03]	[-0.04,0.12]	[0.01,0.03]	[-0.02,0.05]
$\bar{y}$	0.126	0.273	0.132	0.327	0.160	0.363	0.128	0.296	0.067	0.214	0.094	0.254
N.obs.	2258	724	14993	4730	8252	2541	3699	1146	4307	1368	16400	4590

Notes: *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is daughter's TCS. Standard errors in parenthesis. 95 percent confidence intervals in brackets. "15-17" refers to the subsample of daughters aged between 15 and 17. "18" refers to the subsample of daughters aged 18. All models include survey dummies, a dummy variable for mother 45 and older, a dummy variable that takes value 1 if the mother has no more than primary education, a dummy that takes value 1 when the household is located in a rural area, a dummy variable for parents households with at least seven members, and a dummy variable that indicates whether the daughter is the eldest child of the mother. For the 15-17 subsamples age dummies of the daughter are also included. Variable y^m is the dummy for the mother's teen chilbearing status. AME(y^m) is the estimated Average Marginal Effect of y^m. $\bar{y}$ is the average value of y in the estimating sample.

Although the AMEs for the whole sample fall within the interval obtained with the estimates from the two subsamples, they are closer to those in the 15- to 17-year-old subsample, possibly because this subsample is bigger. The estimated AMEs for the 18-year-old daughters are between 1.6 and 4.6 times larger than the estimates for the 15- to 17-year-old daughters. However, because there is a higher percentage of mothers among the 18-year-old daughters (on average 4.8 times higher), the AMEs are lower relative to $\bar{y}$. Another difference with respect to previous results is the magnitude of the Ignorability bias. For the 18-year-olds the bias is 134.7% (268.3%) higher than that obtained with the overall sample (15-17 year-old subsample). The larger biases are due to the higher percentage of unmatched mother-daughter pairs among the 18-year-old daughters since, compared to younger daughters, they are less likely to live with their mothers and more likely to be mothers themselves.[20]

Regarding the estimation of the missing process parameters (results available upon request), the pattern found for the younger subsample is identical to that found in the whole sample. This pattern is broadly replicated for the 18-year-old subsample, the only difference being that when the daughter is a teen mother, the effect of the mother's TCS reduces the probability of matching for all countries except Bolivia.

Overall, although results are sensitive to age, the main conclusions remain valid for both age groups: the AMEs are large, statistically significant, and the ignorability bias is still sizable, especially for the 18-year-old daughters.

5.2.2 | Wealth

The probability of observing a matched pair may also be affected by the socioeconomic conditions of the mothers' household, conditional on y and y^m. For example, in a poorer family, the daughter may lack the financial support to become independent, making the mother-daughter match more likely. Alternatively, one of the two women may be forced to migrate in search of a job, resulting in an unmatched pair. The direction in which wealth affects the missing process, if it does at all, is therefore an empirical question. Just as age, wealth may also affect the level of inertia, i.e., the parameter α. The data show that poor households tend to locate in neighborhoods with a high incidence of TCS. Suppose teen mothers are more likely to transmit TCS to their daughters if they live in neighborhoods with high TCS incidence than otherwise. A teen mother living in a high TCS neighborhood would more likely result in a (1,1) pair, i.e., teen childbearing for both daughter and mother, while a teen mother living in a low TCS neighborhood would more likely result in a (0,1) pair. The former situation would lead to more inertia among the poor while the latter to less inertia among the non-poor. Other configurations are possible, as we will see.

Ideally, we want to stratify the sample by the level of wealth in the household where the daughter grew up and estimate the model in these different subsamples. Contrary to age of the daughter, which was a variable z in our model, the wealth of the household where the daughter grew up is not observed and, therefore, cannot be used to partition the sample. In the case of a mother-daughter match, we observe the wealth of the current household, not necessarily the household where the daughter grew up. However, when the mother's information is missing, we observe only the wealth of the daughter's household, and if the daughter is married or cohabits with her partner, she does not live in the home where she grew up.[21]

[20]The proportion of 18-year-old daughters who are matched with their mothers is, on average, only 39%, compared to 49% in the whole sample and 51% in the 15- to 17-year-old subsample.

[21]When the daughter is missing, we use the current wealth of the mother, implicitly assuming that the mother did not move to a household different from the one where she lived with her daughter.

TABLE 10 Non-ignorable ML estimates. Poor vs. Rich. Additional controls

	Bolivia		Colombia		DR		Guatemala		Haiti		Peru	
	Poor	Rich	Poor	Rich	Poor	Rich	Poor	Rich	Poor	Rich	Poor	Rich
y^m	1.263***	1.121***	0.167***	1.059***	0.842***	0.669***	1.259***	1.606***	1.017***	1.351***	0.227***	1.101***
	(0.153)	(0.325)	(0.064)	(0.072)	(0.072)	(0.191)	(0.103)	(0.093)	(0.209)	(0.206)	(0.076)	(0.069)
	[0.96,1.56]	[0.48,1.76]	[0.04,0.29]	[0.92,1.20]	[0.70,0.98]	[0.29,1.04]	[1.06,1.46]	[1.42,1.79]	[0.61,1.43]	[0.95,1.76]	[0.08,0.38]	[0.97,1.24]
AME(y^m)	0.301***	0.151***	0.040***	0.184***	0.207***	0.101***	0.195***	0.189***	0.168***	0.190***	0.042***	0.143***
	(0.015)	(0.025)	(0.008)	(0.009)	(0.008)	(0.016)	(0.009)	(0.008)	(0.015)	(0.010)	(0.008)	(0.006)
	[0.27,0.33]	[0.10,0.20]	[0.02,0.06]	[0.17,0.20]	[0.19,0.22]	[0.07,0.13]	[0.18,0.21]	[0.17,0.20]	[0.14,0.20]	[0.17,0.21]	[0.03,0.06]	[0.13,0.15]
AME under	0.109***	0.016	0.035***	0.035***	0.024	0.018*	0.023	0.014	0.011	0.029*	0.026***	0.016***
Ignorability	(0.034)	(0.014)	(0.009)	(0.008)	(0.015)	(0.010)	(0.017)	(0.011)	(0.018)	(0.015)	(0.009)	(0.006)
	[0.04,0.18]	[-0.01,0.04]	[0.02,0.05]	[0.02,0.05]	[-0.01,0.05]	[-0.00,0.04]	[-0.01,0.06]	[-0.01,0.04]	[-0.02,0.05]	[-0.00,0.06]	[0.01,0.04]	[0.00,0.03]
$\bar{y}$	0.255	0.113	0.232	0.116	0.301	0.126	0.222	0.132	0.122	0.088	0.183	0.086
N.obs.	1041	1941	10533	9190	5065	5728	1973	2872	2437	3238	9349	11641

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dependent variable is daughter's TCS. Standard errors in parenthesis. 95 percent confidence intervals in brackets. "Poor" refers to the subsample of households belonging to the two poorest quintiles of the country's population based on a continuous wealth measure produced by the *DHS*. "Rich" refers to the remaining subsample of households. All models include survey and age dummies, a dummy variable for mother 45 and older, a dummy variable that takes value 1 if the mother has no more than primary education, a dummy that takes value 1 when the household is located in a rural area, a dummy variable for parents households with at least seven members, and a dummy variable that indicates whether the daughter is the eldest child of the mother. Variable y^m is the dummy for the mother's teen chilbearing status. AME(y^m) is the estimated Average Marginal Effect of y^m. $\bar{y}$ is the average value of y in the estimating sample.

Despite this caveat, and because we believe results are interesting nonetheless, we use the wealth of the household where the daughter or her mother currently lives, i.e., the variable *Poor*, to stratify the sample into lower and upper socioeconomic groups. *Poor* households have wealth levels within the first two quintiles of the country's distribution and non-poor households within the last three quintiles. *Poor* correctly stratifies the sample when a daughter who leaves a poor home goes to another poor home and when a daughter who leaves a non-poor home goes to another non-poor home. Hence, we should interpret results with caution.[22]

Table 10 reports results by country and wealth (non-poor is denoted as "rich" in the table). As expected, the incidence of teen childbearing, $\overline{y}$, is in all countries higher among poorer households. Although the coefficients associated with y^m, i.e., α, differ by wealth, their confidence intervals overlap for Bolivia, DR, Guatemala, and Haiti. In Colombia and Peru, they are much larger for rich households, reflecting that mothers' TCS has a larger effect on their daughters' probability of motherhood among the richer households. Given the lower incidence of TCS among the richer group, the larger estimate for α is likely driven by a relative higher percentage of (0,0) outcomes among the rich compared to the other possible outcomes. Dissimilarities in AMEs between poor and non-poor households arise not only from differences in the coefficients associated with y^m but also from average differences of all the other variables. That is why the differences in AME by wealth are significant in four of the six countries. For Bolivia, DR, and Guatemala, the AME is larger in the poor than in the non-poor sample. The opposite happens in Colombia, Haiti, and Peru.

Regarding the missing process, teen childbearing of the daughter decreases the probability of a match except in Haiti. Among the richer subsamples, teen childbearing of the mother always increases the probability of a match when the daughter is not a teen mother and decreases it when the daughter is a teen mother. Among the poor subsamples, teen childbearing of the mother increases the probability of a match except in Haiti.

Although the magnitudes of the estimated alphas and AMEs may be sensitive to wealth, the main conclusions drawn in Section 4 remain valid: (i) the AME is always positive, large, and statistically significant in all countries and wealth groups, and (ii) the bias is large in all the subsamples, except for the poor households in Colombia, where results under Ignorability are similar.

5.3 | Early Initiation to Sex

In this section, we use our ML approach to estimate a similar model but with a different, although related, dependent variable. The aim is to estimate the effect of a mother's sexual behavior during adolescence on the probability that her teenage daughter(s) had already had sex. Accordingly, the dependent variable y takes value one if the daughter reports to have had sex and zero otherwise and y^m takes value 1 if her mother had sex for the first time during adolescence, and zero otherwise. Assumption 1, is still valid as early sexual initiation is closely related to TCS.

[22] We have done the same exercise defining non-poor households as those in the 3rd and 4th quintile and the results, available upon request, are similar.

TABLE 11 Sexual behavior: Ever had sex. Non-ignorable ML estimates.

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
y^m	1.101***	0.957***	0.939***	1.954***	0.756***	1.095***
	(0.216)	(0.032)	(0.106)	(0.094)	(0.148)	(0.041)
Mother 45+	0.577***	0.225***	0.349***	1.334***	0.208***	0.359***
	(0.101)	(0.031)	(0.057)	(0.054)	(0.067)	(0.034)
At most primary	-0.001	-0.133***	0.179***	0.112	0.182**	-0.191***
	(0.114)	(0.028)	(0.052)	(0.092)	(0.084)	(0.034)
Age = 16	0.364***	0.482***	0.410***	0.306***	0.415***	0.446***
	(0.094)	(0.029)	(0.045)	(0.076)	(0.058)	(0.034)
Age = 17	0.778***	0.906***	0.855***	0.651***	0.840***	0.906***
	(0.091)	(0.029)	(0.044)	(0.074)	(0.058)	(0.034)
Age = 18	1.101***	1.311***	1.163***	0.892***	1.329***	1.303***
	(0.094)	(0.030)	(0.046)	(0.075)	(0.060)	(0.034)
Rural	0.318**	0.128***	0.085*	-0.113*	-0.206***	0.130***
	(0.135)	(0.033)	(0.047)	(0.059)	(0.078)	(0.039)
Household size	0.417***	0.306***	0.566***	-0.148***	-0.013	0.443***
	(0.092)	(0.028)	(0.046)	(0.057)	(0.060)	(0.030)
Poor	0.401***	0.004	0.099**	0.106*	-0.082	0.240***
	(0.134)	(0.031)	(0.051)	(0.061)	(0.078)	(0.041)
Firstborn	0.338***	0.209***	0.471***	0.361***	0.186***	0.356***
	(0.103)	(0.027)	(0.048)	(0.063)	(0.071)	(0.032)
N.obs	2929	19663	10548	4807	5650	20985
AME(y^m)	0.243***	0.310***	0.248***	0.266***	0.221***	0.238***
	(0.019)	(0.005)	(0.012)	(0.005)	(0.015)	(0.004)
$\bar{y}$	0.269	0.441	0.341	0.254	0.350	0.244
AME under	0.085***	0.153***	0.075***	0.077***	0.080***	0.077***
ignorability	(0.023)	(0.010)	(0.014)	(0.016)	(0.023)	(0.008)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable y is a dummy variable that takes value one if the daughter reports to have had sex and zero otherwise. All models include survey dummies. Standard errors in parenthesis. Variable y^m takes value one if the mother reports to have had sex before age 19 and zero otherwise. Mother 45+ is a dummy variable for mother 45 and older. At most primary is a dummy variable that takes value 1 if the mother has no more than primary education. Age = 16-Age = 18 are age dummies (reference category is age 15). Rural takes value 1 when the household is located in a rural area. Household size is a dummy variable for parents households with at least seven members. Poor takes value 1 if the parents' household belongs to the two poorest quintiles of the country's population based on a continuous wealth measure produced by the *DHS*. Dummy variable Firstborn indicates whether daughter is the eldest child of the mother. AME(y^m) is the estimated Average Marginal Effect of y^m. $\bar{y}$ is the average value of y in the estimating sample. AME under ignorability stands for the average marginal effect of y^m using the probit estimates under ignorability for the same variable specification.

TABLE 12 Sexual behavior: Had sex before age 16. Non-ignorable ML estimates.

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
y^m	0.652***	0.434***	0.943***	1.238***	0.735***	0.759***
	(0.155)	(0.039)	(0.050)	(0.067)	(0.192)	(0.033)
Mother 45+	0.466***	0.079**	0.275***	0.963***	0.139**	0.222***
	(0.109)	(0.032)	(0.052)	(0.054)	(0.066)	(0.037)
At most primary	-0.103	-0.122***	0.251***	0.100	0.206**	-0.143***
	(0.133)	(0.030)	(0.054)	(0.104)	(0.085)	(0.037)
Age = 16	0.370***	0.461***	0.418***	0.340***	0.410***	0.440***
	(0.089)	(0.028)	(0.044)	(0.073)	(0.059)	(0.033)
Age = 17	0.623***	0.733***	0.765***	0.592***	0.739***	0.760***
	(0.086)	(0.028)	(0.044)	(0.072)	(0.059)	(0.033)
Age = 18	0.609***	0.792***	0.764***	0.482***	0.893***	0.771***
	(0.090)	(0.029)	(0.045)	(0.074)	(0.059)	(0.033)
Rural	0.300	0.071**	0.067	-0.025	-0.171**	0.038
	(0.185)	(0.036)	(0.047)	(0.068)	(0.077)	(0.045)
Household size	0.427***	0.309***	0.541***	-0.086	0.002	0.411***
	(0.105)	(0.031)	(0.046)	(0.065)	(0.061)	(0.032)
Poor	0.443**	0.059*	0.033	0.030	-0.122	0.323***
	(0.182)	(0.034)	(0.050)	(0.070)	(0.077)	(0.047)
Firstborn	0.250**	0.077***	0.436***	0.313***	0.136*	0.257***
	(0.117)	(0.029)	(0.046)	(0.072)	(0.074)	(0.035)
N.obs	2929	19663	10548	4807	5650	20985
AME(y^m)	0.172***	0.156***	0.287***	0.279***	0.245***	0.200***
	(0.022)	(0.008)	(0.008)	(0.010)	(0.025)	(0.006)
$\overline{y}$	0.223	0.385	0.299	0.206	0.303	0.196
AME under	0.109***	0.131***	0.068***	0.062***	0.054***	0.076***
ignorability	(0.018)	(0.009)	(0.011)	(0.012)	(0.019)	(0.007)

Notes: *** p<0.01, ** p<0.05, * p<0.1. The dependent variable y is a dummy variable that takes value one if the daughter reports to have had sex before age 16 and zero otherwise. All models include survey dummies. Standard errors in parenthesis. Variable y^m takes value one if the mother reports to have had sex before age 16 and zero otherwise. Mother 45+ is a dummy variable for mother 45 and older. At most primary is a dummy variable that takes value 1 if the mother has no more than primary education. Age = 16-Age = 18 are age dummies (reference category is age 15). Rural takes value 1 when the household is located in a rural area. Household size is a dummy variable for parents households with at least seven members. Poor takes value 1 if the parents' household belongs to the two poorest quintiles of the country's population based on a continuous wealth measure produced by the *DHS*. Dummy variable Firstborn indicates whether daughter is the eldest child of the mother. AME(y^m) is the estimated Average Marginal Effect of y^m. $\overline{y}$ is the average value of y in the estimating sample. AME under ignorability stands for the average marginal effect of y^m using the probit estimates under ignorability for the same variable specification.

Despite having higher sample means for y and y^m, the results are aligned with those for TCS and produce AMEs only slightly higher in magnitude. For example, having a mother with early initiation to sex increases the probability of having had sex between 22.1 and 31.0 percentage points (see Table 11) and between 15.6 and 28.7 for sex before age 16 (see Table 12). In relative terms, these figures represent a lower effect than the model estimated in Section 4 (an average of 83.1% and 88.7% for all and the younger than 16, respectively) because early sexual behavior is more prevalent than teen childbearing in the sample. As in the case of teenage childbearing, the AMEs under ignorability (shown in the bottom of Tables 11 and 12 for comparison purposes) are much lower although still significantly positive in all countries.

6 | CONCLUSIONS

We show strong evidence of intergenerational transmission of sexual behavior, either initiation of sexual activity or its consequences in the form of teen childbearing, from mothers to daughters. Using DHS data from Bolivia, Colombia, Dominican Republic, Guatemala, Haiti, and Peru, we find that daughters of teen mothers have a significantly higher risk of teen childbearing, between 8.7 and 26.2 percentage points (or between 61 and 172%). Similarly, having a mother who had an early initiation to sex increases the probability of early sexual behavior among teens between 22.1 and 31.0 percentage points (or between 63.1 and 104.7%). Importantly, our results show that restricting the sample to matched mother-daughter pairs which, for most surveys and census data means restricting the sample to those teenagers who live with their mothers, leads to a large negative co-residential bias. The reason for such bias lies in the non-randomness of the unmatched pairs. Many teenage daughters leave their parents' home (and, consequently, become unmatched) when they are pregnant or when they become mothers, implying that missing or incomplete mother-daughter pairs are not random. We develop a Maximum Likelihood methodology to avoid the co-residential bias that enables us to use all data in the estimation, including the incomplete mother-daughter pairs, by modeling the missing process together with the teen childbearing process. This methodology is easily adaptable to other contexts where missing matches are non-random.

Our results leads us to conclude that the prevalence of high intergenerational transmission is at the core of persistent high teenage childbearing rates in Latin America and suggests alternative public policy fixes. Concretely, complementing policies targeted at teenagers with policies targeted at teens most at risk, i.e., daughters of teen mothers.

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A | APPENDIX

TABLE A.1 Terminations & live births

PANEL A: During adolescence

	% women with terminations					
	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
Only no teen-mothers	1.918	3.578	2.634	1.946	1.369	1.907
Only teen-mothers	3.694	7.879	8.707	7.246	2.795	4.935
All	2.498	4.947	5.010	3.496	1.677	2.724

	% women sexually active with terminations					
	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
Only no teen-mothers	3.074	4.728	3.898	2.927	1.869	2.988
Only teen-mothers	3.631	7.823	8.678	7.353	2.812	4.956
All	3.310	5.937	6.178	4.692	2.126	3.715

	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
Terminations rate	7.360	14.432	12.300	11.419	7.396	9.593
Chilbearing Rate	32.644	31.841	39.128	29.237	21.596	27.009

PANEL B: After adolescence

	% sexually active women with terminations					
	Bolivia	Colombia	DR	Guatemala	Haiti	Peru
All	6.151	9.836	13.525	4.047	3.828	7.186

Notes: Pooled data from all surveys post 2000. Women aged 23 during the year of interview. Terminations include abortions, misscarriages, and still births. *Childbearing rate* is the percentage of women who have had at least one live birth during adolescence. *Terminations rate* is the percentage of women with at least one termination during adolescence over all women who were pregnant during adolescence.