The geography of women's opportunity: evidence from Indonesia*

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Abstract

This paper argues that women's birthplace strongly affects their labor force participation in adulthood. I use rich data from Indonesia and leverage variation from women moving across labor markets as children to estimate the effect on women's labor force participation of spending more time in their birthplace. My strategy compares the labor supply choices of women who currently live in the same location but who emigrated from their birthplace at different ages. I find that birthplace has strong and persistent effects on adult women's labor supply. Moreover, these effects are concentrated during the formative period between 6 and 16 years old. By the time they turn sixteen, women born in a location at the 75th of female employment will be five p.p. more likely to work than those born in a 25th percentile location. Birthplace effects are quantitatively important. Approximately 23 percent of the current spatial inequality in women's labor force participation is transmitted to the next generation of women.

Keywords: gender inequality, local labor markets, place effects

JEL Codes: J16, R19, O18

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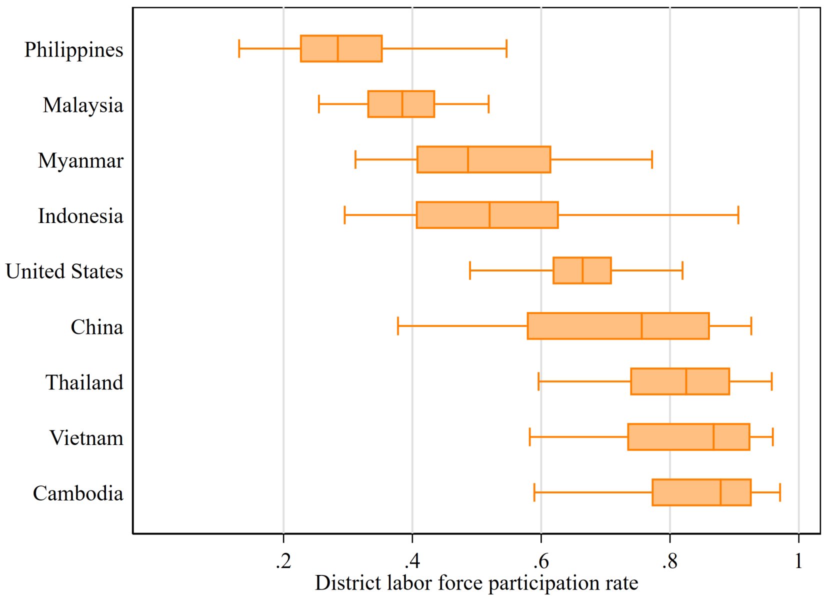
1 Introduction

There are surprisingly large and persistent differences in female labor force participation (FLFP) rates within multiple countries at different levels of development. I show this in figure 1, where I illustrate the high dispersion in subnational labor force participation within several developing countries and the United States. The FLFP rate gap between two localities within these countries can be as large as 15 percentage points (p.p.).[1] This large within-country dispersion in FLFP has generally gone unnoticed in the literature (Charles et al., 2018), and, as a consequence, we know very little about its causes and implications on women's outcomes. Particularly, there is scarce evidence of whether being born in localities with high or low participation of women in the labor market affects women's labor market participation. regarding whether being born in localities with high or low women's labor market participation influences women's own participation in the labor market. Consequently, we have limited insight into the extent to which current disparities in gender inequality across localities within countries impact the outcomes of the next generation of women.

Figure 1: Female labor force participation rates at the district level for selected countries



Note: The figure shows the distribution of female labor force participation rates for a large subset of Asian countries with geographic data available in IPUMS International. Countries are ordered by median district employment rate. I use the latest available sample from IPUMS International for each country. I aggregate data at the smallest geographical unit available which often corresponds to a district/county, except in the United States where I aggregate data for the US into Commuting Zones as in Autor and Dorn (2013). See table C.2 for data on a larger cross-section of countries.

In this paper, I show that the subnational dispersion in female labor force participation has strong effects on the labor market outcomes of women born across different areas within the same

[1] Using the interquartile range as a benchmark, the gap between the localities at the 75th and the 25th percentiles of female labor force participation rates is over 15 p.p. for 6 out of the nine countries in the figure. It is 28 p.p. for China, 22 p.p. for Indonesia, and 10 p.p. in the United States.

country. To do so, I use rich data from internal Indonesian female migrants to show that their birthplace has a strong impact on their adult labor force participation.[2] I identify the birthplace causal effect by leveraging variation coming from women living in the same labor market as adults but who left their birthplace origin at different ages as children. Therefore, I exploit variation in the time spent in the birth location to disentangle the causal effect of the birthplace from variation driven by differences in women's unobservable characteristics. My strategy boils down to comparing the labor force participation of women who emigrated in early childhood, versus those who left in their early teens. Then, if women born in places with higher female labor force participation are more likely to work the longer they stay there, I surmise that this is driven by the effect of their birth location. Moreover, by comparing women living in the same location as adults, I abstract from the effect of current labor market conditions and uncover variation that is likely driven by women's labor supply. This strategy builds on that of Chetty and Hendren (2018a), and focuses it on female outcomes in a large developing country.

My results indicate that birthplace has strong and persistent effects on adult women's labor supply. I show this in two steps. First, I show that women's birthplace is highly predictive of their labor supply choices. Conditional on living in the same local labor market, women born in localities with high female employment are much more likely to work than those born in places with low-female employment. This relationship holds true even for women who migrated at a young age when it is uncommon for women to be part of the labor force. These differences in labor supply could be the result of a birthplace effect, but they can also reflect differences in women's unobservable characteristics or omitted variable bias. Thus, next I show that this relationship reflects the causal effect of birthplace on women's employment by exploiting differences in the timing of emigration. I use a strategy similar to a Difference-in-Differences design, where I compare the labor force participation of women living in the same labor market but who emigrated from their birthplace at different times. Under the assumption that the omitted variable is constant for women emigrating at different ages, this strategy allows me to distinguish the causal effect from differences in women's characteristics.

I find that spending late childhood and early teen years in areas with high female employment makes women more likely to work as adults. Moreover, the longer they stay these locations, the likelier they are to enter the labor force. Under my preferred specification, staying in a place at the 75th percentile of female employment between the ages of 6 and 16 years old makes women five percentage points more likely to work than those born in a place at the 25th percentile. These magnitudes are quantitatively important as they imply that approximately 23% of the current spatial inequality in women's labor force participation is transmitted to the next generation of women through birthplace effects.

The causal interpretation of these birthplace effects estimates hinges on the assumption that omitted variable bias is constant across emigration ages; that is, the correlation between birthplace

[2] Migrating is a relatively common phenomenon in Indonesia, with approximately one in five Indonesians residing outside their birth locality.

female employment rate and other unobserved determinants of women's labor supply is the same no matter the age they emigrated. Note that differences between women born in different locations in factors I do not control for are not enough to violate this assumption. For example, women from high female employment locations may be more likely to work because they had parents with higher resources to invest in their education than those born in locations with low female employment. This would generate differences between women from different origins that is not driven by birthplace effects. However, this does not necessarily violate the constant bias assumption. Instead, a violation would require the resource gap to become larger or smaller for cohorts of women who emigrated at older ages. In the paper, I provide evidence demonstrating that the gap in resources and other covariates remains fairly constant across different ages of emigration, thereby supporting the assumption underlying my identification strategy.

Why would childhood exposure to the birthplace labor market have such persistent effects on women's outcomes? Previous research has suggested three main potential mechanisms: (i) higher investment in schooling, (ii) changes in parental investment, (iii) transmission of culture and/or gender norms (Molina and Usui, 2022; Fogli and Veldkamp, 2011; Blau et al., 2011). Exposure to labor markets with a higher proportion of working women could shape the career expectations of young girls, leading to greater likelihood of staying in school. However, I find limited support for this mechanism in Indonesia. Furthermore, changes in parental investments are unlikely to account for my results. My findings indicate that women who had longer childhood exposure to regencies characterized by high female employment are more likely to enter the labor market as adults. If parental investments were the primary driver behind these outcomes, it would suggest that parental investment is highly sensitive to the duration of their child's exposure. Given that parents have resided in these locations for a considerable period of time, it seems unlikely that such a high level of sensitivity exists. A more plausible explanation lies in the transmission of cultural and gender norms. I provide evidence that childhood exposure to these high-employment areas also influences decisions related to fertility and marriage. Moreover, I find that the birthplace effect is particularly pronounced during the ages when children's attitudes towards gender equality are still malleable (Jayachandran, 2021).

In the paper, I take advantage of rich Indonesian data that stores people's birthplace and current location at a detailed geographic level. My main analyses source data from all waves of the Indonesian Family Life Survey (IFLS) and the 1985, 1995, and 2005 intercensal surveys (Statistics Indonesia, 2021; Minnesota Population Center, 2020). These representative and publicly available datasets track respondents' birthplace, current location, and migration history across midsized geographies. This level of detail allows studying differences in women's labor supply and birthplace effects at a level that is not possible in other countries from traditional sources (Bryan and Morten, 2019). Throughout the paper, I identify localities as Indonesian "regencies". There are medium-sized administrative geographies akin to counties in the United States. The average regency is approximately twice the size of the US state of Rhode Island and houses eight hundred thousand people.

This paper contributes to three strands of the literature. I contribute to the growing research showing that local labor markets can permanently affect women's labor supply, fertility, and human capital investment choices (Molina and Usui, 2022; Charles et al., 2018; Boelmann et al., 2021). I make three main contributions to this literature. First, by applying techniques borrowed from the place effects literature (Chetty and Hendren, 2018a,b; Milsom, 2021), I provide causal evidence that women's birthplace has large and persistent effects on women's labor supply. This complements evidence from previous literature, which shows that exposure to current labor markets can have effects on women's expectations, labor supply, and educational investment (Molina and Usui, 2022; Boelmann et al., 2021; Milsom, 2021). Second, I also provide evidence of the ages at which birthplace is key in shaping labor supply. Although previous research has pointed out that women's childhood environment matters for their adult outcomes, this literature is mostly silent on *when* does it matter (Chetty et al., 2016). Third, my results provide new evidence that where women grow up can matter more locally. Previous research emphasizes that differences in norms, culture and other factors across large geographical areas such as states, provinces, or countries can shape women's choices (Charles et al., 2018; Boelmann et al., 2021; Alesina et al., 2013). By exploiting much more disaggregated data, my results suggest these factors can act at a more local level.

Second, this paper also contributes to the literature on place effects. Primarily using evidence from developed countries, this literature shows that where people grow up and live has important implications for intergenerational mobility (Chetty and Hendren, 2018a,b), racial inequality (Chetty et al., 2020), human capital accumulation (Molina and Usui, 2022), and criminal activity (Damm and Dustmann, 2014). I add to this literature by providing new empirical evidence linking women's birthplace to their outcomes as adults in a large developing country. In this way, my findings complement existing work showing that spatial inequality is particularly important for women's human capital investment in West Africa (Milsom, 2021) and Japan (Molina and Usui, 2022).

Finally, my paper also contributes to the literature studying the determinants of women's labor supply. This literature has primarily exploited cross-country differences in female labor supply to study its determinants and its implications (Olivetti and Petrongolo, 2008, 2014; Blau et al., 2020; Blau and Kahn, 2015). In this paper, I document the existence of large and persistent differences in female labor supply within multiple developing countries and study some of its implications. In this way, my approach is closer to the recent literature documenting that factors such as commuting and sexism can help explain the geographic differences in women's labor supply within the United States and France (Charles et al., 2018; Le Barbanchon et al., 2021; Black et al., 2014; Moreno-Maldonado, 2019).

2 Data

2.1 Data sources

My main analyses use data from the Indonesian Intercensal Survey (SUPAS) and the Indonesian Family Survey (IFLS). These two datasets record detailed data on people's birthplaces, their migration histories, and their labor supply. I supplement this data with place characteristics coming from the Indonesian Census and the National Socioeconomic Survey (SUSENAS).

My primary results come from the Intercensal Survey. This is a decennial survey containing social and demographic information for approximately 0.5% of the Indonesian population. This dataset has two advantages that make it uniquely suitable to study place effects on female labor supply. First, it records people's birthplace, previous location and location of birth in midsized geographic units. The survey tracks this information at the level of the "regency", which are administrative units similar to US counties. Research on Indonesia typically uses them to identify local labor markets (Magruder, 2013; Bazzi et al., 2022), and their size allows me to study differences in women's employment across smaller geographic units than what I could observe in alternative datasets.[3] The typical regency is home to approximately eight hundred thousand people and covers an area roughly twice size of the US state of Rhode Island. Appendix figure C.1 depicts all the 268 regencies in my dataset.

Second, rich data on historical migration patterns allows me to recover the age which individuals departed from their birthplace. Specifically, the survey records the length of time each person has lived in their current location. With this data, I can determine the age at which individuals *who have only migrated once in their lifetime* left their birthplace. These are people whose previous place of residence is the same as their birthplace. This is the key variation that I exploit in my identification strategy.

In addition to these two advantages, the Intercensal Survey also has a sizable sample size. Its main limitation, however, is that it contains limited demographic information. Therefore I supplement my main results with information coming from the Indonesian Family Life Survey (IFLS). Unlike the Intercensal Survey, the IFLS contains rich socioeconomic information, such as childhood conditions and proxy measures of parents' wealth, among others, that allow for the study of potential drivers of the birthplace effects. However, this comes at the cost of a smaller sample size. The IFLS is a panel survey that tracks the information of approximately 34,000 Indonesians across five survey years: 1993, 1997, 2000, 2007, and 2014. Overall, the IFLS is representative of 83% of the Indonesian population.[4]

I source place characteristics from the 1980-2010 Indonesian Decennial Censuses available in IPUMS International (Minnesota Population Center, 2020) and the 2012, 2013, and 2014 SUSENAS. (Statistics Indonesia, 2019, 2020). The Censuses and SUSENAS are very similar to each other but the Census has larger sample sizes. I compute all regency characteristics by restricting the sample to people aged 18 to 64 and aggregating these datasets at the regency level. Whenever possible, I compute these aggregates from the Census.

[3]Datasets available for other countries track geographic information only for states or provinces, which in most cases are either too big or too few to be interesting (Bryan and Morten, 2019)

[4]The IFLS originally sampled households from 13 of the 27 provinces that existed in 1993. These provinces account for 83% of the Indonesian population. I use retrospective work and migration history questions to construct a panel tracking the respondents' location since birth and their yearly employment history from 1988 to 2014.

2.2 Measurement

My main measure of women's labor supply is a dummy equal to one if she was employed during the year. I use this variable because it is the one I can most consistently track across years and across datasets. However, as a robustness check, I also examine alternative measures such as being a paid worker, total weekly hours worked, and being a full-time worker to confirm the robustness of my findings.

In this analysis, I link women's labor supply choices to the characteristics of their birthplace. This requires having geographic units with boundaries that remain fixed over time. Unfortunately, regency boundaries in Indonesia underwent significant changes from decade to decade between 1980 and 2010, with the creation of new regencies being a common occurrence. Appendix Table C.1 shows that between 2000 and 2010 alone, 154 new regencies were established. To address this issue, I use regency aggregates with consistent boundaries that span the period from 1970 to 2010. These regency aggregates were constructed by IPUMS International (Minnesota Population Center, 2020) and consist of 268 regencies that are only slightly larger than the "original" regencies in the data. Moving forward, I will refer to these regency aggregates as regencies.

For my main analysis, I restrict my sample to one-time internal migrants because this is the population for which I can separate the current place of residence from the birthplace. I define migration as living outside the regency of birth. Moreover, whenever I link women's employment with birthplace characteristics, such as FLFP or urbanicity, I source these from the 2010 Indonesian Census. In robustness checks, I show that my results are similar when I use information from other census years.

2.3 Summary statistics

In the this section, I provide an overview of my data and the Indonesian labor market using data from the pooled 1985, 1995, and 2005 Intercensal Surveys. I obtain a qualitatively similar picture if I use the IFLS. Table 1 provides a general description of the entire dataset, as well as statistics disaggregated by gender. This table highlights three critical features of the Indonesian labor market. Firstly, internal migration is common, with approximately one-fifth of Indonesians residing outside their birthplace. These internal migrants are the primary focus of my analysis and, as the table shows, they represent a large cross-section of the Indonesian population. Secondly, the labor market in Indonesia is predominantly informal and agrarian, with 49% of workers being self-employed and working in agriculture.[5] Additionally, there are significant gender gaps in employment, worker type, and industry. Women are 38 percentage points less likely to work than men, which while large is consistent with patterns observed in Southeast Asia. Furthermore, women are five times more likely than men to be unpaid or salary workers. Unpaid workers are people that work or help to earn an income but are not paid a wage or salary. Most unpaid workers work in agriculture

[5] This is in stark contrast to the United States, where only 10% of workers are self-employed, and 1% work in agriculture.

(82%) and the retail industry (10%) (Minnesota Population Center, 2020). Lastly, women are more likely than men to work in service and manufacturing industries.

Table 1: IFLS: summary statistics by gender and migration status

	All (1)	**Women** (2)	**Men** (3)
Age	35.54	35.36	35.72
Married	0.71	0.72	0.71
Attended at least high school	0.77	0.80	0.73
Urban	0.37	0.37	0.38
Muslim	0.81	0.81	0.81
Migrant	0.21	0.20	0.22
Share left birthplace by age 25	0.13	0.13	0.12
Employed	0.66	0.47	0.85
Type of worker			
Self-employed	0.49	0.38	0.56
Salaried	0.34	0.27	0.37
Unpaid / family worker	0.17	0.35	0.07
Industry of employment			
Agriculture	0.49	0.51	0.48
Services	0.36	0.37	0.36
Manufacturing	0.09	0.11	0.08
Construction	0.05	0.01	0.07
Observations	1,317,825	667,691	650,134

Notes: data from the 1985, 1995 and 2005 Intecensal Surveys.

Table 2: Indonesia: women's characteristics by migration status

	Non-migrants	Migrants: All	Migrants: Left young
	(1)	(2)	(3)
Age	35.50	35.43	30.35
Married	0.71	0.75	0.66
Attended at least high school	0.84	0.69	0.74
Urban	0.30	0.65	0.63
Muslim	0.81	0.83	0.85
Share left birthplace by age 25		0.66	1.00
Employed	0.48	0.42	0.40
Type of worker			
Self-employed	0.39	0.34	0.33
Salaried	0.24	0.42	0.41
Unpaid / family worker	0.37	0.24	0.26
Industry of employment			
Agriculture	0.56	0.30	0.33
Services	0.32	0.59	0.53
Manufacturing	0.11	0.11	0.13
Construction	0.01	0.01	0.01
Reason for emigrating[1]			
Work		0.14	0.10
Education		0.06	0.08
Other		0.81	0.82
Observations	518,018	134,031	47,769

Notes: data from the 1985, 1995 and 2005 Intecensal Surveys. Column (2) shows data for women living outside their birthplace, while column (3) does it for those who left before they turned 19.[1] Uses data from the 1985 Intercensal Survey. The 1995 and 2005 surveys have data on reason for migrating for only a very restricted set of migration episodes.

In table 2 I zoom in on the women migrants (emigres). They are the focus of my main analysis because they are the women for whom I can distinguish between the current place of residence and the regency of birth. I present statistics for all female migrants as well as for those who migrated before they turned 19. The table highlights significant differences between migrants and stayers. They are more educated and more likely to be employed than stayers. Moreover, they are more likely to have salaried jobs and live in urban areas. This suggests that women migrants are moving to areas with more formal labor markets and less rural surroundings. Lastly, column (3) shows that other than the marriage rates and the level of education, women who left their birthplace young are generally very similar to the typical female migrant.

In the final rows of table 2, I provide additional details on the factors driving women's migration, which are sourced from the 1985 Intercensal Survey. Women's migration is largely motivated by reasons other than work. Specifically, over 85% of female migrations are associated with either education or "other reasons". Unfortunately, the survey does not provide a breakdown for the latter category. However, data from the IFLS indicates that the majority of these moves are likely due to family-related reasons.

The fact that migrant women are more likely to work in the service sector could suggest that migration in Indonesia is predominantly rural to urban. However, table 3 shows this is not case. There are substantial rural-to-rural and urban-to-urban flows. In this table, I follow Bryan and Morten (2019) and classify regencies into urban or rural according to the share of the regency's population that lives in areas that Statistics Indonesia labels as urban in the Indonesian Census. Urban regencies are those whose urban population is above 43.3%. I chose this cutoff so that the share of people living regencies I classify as urban matches the aggregate urban share from Statistics Indonesia. I then compute migration statistics for women born in urban and rural regencies. The table shows three salient features. First, migration is not exclusive to rural regencies. Women born in urban regencies also migrate at high rates. Second, migration is not just rural-to-urban. Panel A breaks down the migration flows by origin and destination. The urban-to-rural, rural-to-rural and rural-to-rural flows are substantial. Finally, panel B shows that there is considerable heterogeneity in employment rates within each regency classification. There, I show summary statistics for the female employment rates within these categories. There is substantial dispersion in female employment *within* both of these categories. Thus, the dispersion in female employment rates I discuss in the next section is not driven by differences between urban and rural areas.

Table 3: IFLS: women's migration patterns and regency characteristics by urbanicity of regency of origin

	Birth regency		
	Rural	**Urban**	**Total**
	(1)	(2)	(3)
Number of regencies	168	100	268
Share of women born in these regencies	0.39	.61	100
Migration rate	0.18	0.23	0.20
A. Share of emigres living in:			
Rural regencies	0.44	0.31	0.38
Urban regencies	0.56	0.69	0.62
B. Characteristics of origin regency			
Women's employment rate			
Average	0.57	0.46	0.53
STD	0.14	0.11	0.14

Notes: I define migration as living outside the regency of birth. Following Bryan and Morten (2019) I classify regencies as urban if the share of population living in an urban area is above a 43.3%. I choose the cutoff to match the urban share at the national level. Data from IFLS and IPUMS International.

3 Four facts about women's labor supply

In this section, I use data from IPUMS International and the 1980-2010 Indonesian Censuses to present four empirical facts on female employment. First, I use data from several countries to show that large geographic differences in women's employment rates within countries are pervasive across the world. Next, I zoom in on Indonesia and (i) characterize the large dispersion in female employment across regencies, (ii) document that it is highly persistent over time, and (iii) show that it is not accounted for by variation in women's demographics or labor market characteristics across regencies. Taken together, these four facts suggest that structural differences could be driving the dispersion in women's labor supply within Indonesia.

3.1 Fact 1: within-country dispersion in women's labor supply is pervasive across countries

In table 4, I provide a snapshot of the within-country variation in men's and women's employment rates for a several countries, including Indonesia and the United States. These are a subset of the countries with regional employment data available below the province or state level in IPUMS

International in the appendix.[6] For all countries, I restrict the sample to people aged 18 to 64 and compute the employment rates at the smallest geographical unit available. This often corresponds to an administrative unit similar to a county or municipality. The table orders countries from highest to lowest dispersion in female employment rates, as measured by the interquartile range (IQR) in employment.

[6] Data for the full set of countries is available in table C.2 All the insights discussed in this section generalize to this larger set of countries. Further details about the cross-country data are available in section A in the appendix

Table 4: Dispersion in regional employment rates for selected countries

	Women			**Men**			**Population**	**Observations**
	IQR	**SD**	**Mean**	**IQR**	**SD**	**Mean**		
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China	0.28	0.17	0.71	0.14	0.10	0.85	266,748	2,845
Indonesia	0.22	0.14	0.53	0.05	0.04	0.87	533,867	268
Myanmar	0.21	0.13	0.51	0.07	0.05	0.86	83,531	362
Panama	0.20	0.12	0.33	0.04	0.08	0.80	56,049	35
Vietnam	0.19	0.12	0.82	0.06	0.06	0.90	79,146	674
Brazil	0.19	0.11	0.48	0.19	0.11	0.73	59,010	2,040
Mexico	0.17	0.11	0.30	0.09	0.08	0.80	27,853	2,330
Cambodia	0.16	0.11	0.84	0.08	0.05	0.90	50,186	174
Thailand	0.16	0.11	0.81	0.08	0.06	0.88	58,290	670
South Africa	0.16	0.11	0.30	0.06	0.06	0.53	138,127	224
Argentina	0.15	0.10	0.53	0.08	0.06	0.83	75,022	312
Philippines	0.13	0.10	0.30	0.08	0.06	0.82	40,423	1,274
Chile	0.12	0.08	0.51	0.05	0.04	0.79	57,826	192
Bolivia	0.12	0.06	0.58	0.05	0.03	0.86	70,323	80
Spain	0.11	0.08	0.51	0.09	0.06	0.61	105,902	286
Malaysia	0.11	0.07	0.38	0.06	0.04	0.84	91,509	133
USA	0.09	0.07	0.67	0.10	0.07	0.77	202,635	722

Notes: SD and IQR stand for Standard Deviation and Interquartile Range. The table shows statistics from a cross-section of countries in IPUMS International with data available at a small geographic level. For all countries I use census sample from 2010 or the closest available year. Rows are ordered from highest to lowest dispersion in women's labor supply. I aggregate data at the smallest geographical unit available, except for the USA where I use Commuting Zones as in Autor and Dorn (2013). Column (7) shows the total population for the average geographic unit in each country. These are unweighted cross-locality means which –might– differ from the national-level means. See table C.2 and section A in the appendix for additional details on the cross-country data.

This table highlights three insights on women's employment. First, columns 1 to 3 show that, despite the significant differences at the mean, all countries exhibit large differences in women's employment rates *within* their borders.[7] For most countries, the gap between the localities at the 75th and 25th percentiles shown in column (1) is above 15 percentage points (p.p.). A gap of 15 p.p. is fairly large even for high female employment countries such as Vietnam, Cambodia, and Thailand. Even the smaller IQR of 9 p.p. in the United States is notable, as it is equal to the change in the national US female employment rate during the last *thirty-eight years* (1984-2022).[8]

Second, the dispersion of female employment rates is a widespread phenomenon across countries at different levels of development and geographic regions of the world. Table 4 includes countries from various regions, including Asia, America, Africa, and Europe. It also includes middle income countries like Indonesia and Mexico, and high income countries like USA and Spain. These findings suggest that the factors driving the dispersion in female employment rates are not limited to specific regions or income levels.

Third, columns 3 to 6 reveal that the large within-country dispersion in employment is primarily concentrated among women. With the exception of Brazil, the United States, and Spain, the dispersion in women's employment rates is substantially larger than that of men's in all countries. In fact, in ten out of the seventeen countries, the dispersion in women's employment *more than doubles* that of men's. Therefore, while men work at high rates across all regions within these countries, women's rates vary significantly depending on the locality they live in.

3.2 Fact 2: there is large within-country dispersion in women's employment rates in Indonesia

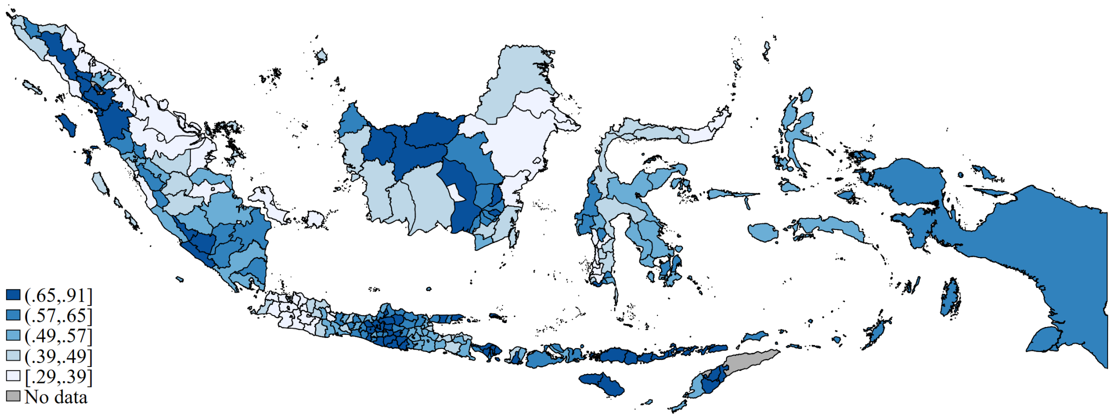
Figure 2 provides a detailed view of the variation in female employment rates within Indonesia. The map shows women's employment rates in all 268 regencies in my dataset, grouped by color into quintiles. Darker blues indicate higher employment rates. The map reveals that women work at vastly different rates across the country. For instance, the top quintile of regencies has employment rates above 65%. In contrast, the bottom quintile of regencies has rates below 29%, and this group includes significant population centers such as the Bogor regency and the city of Medan.[9] Notably, the map reveals that the dispersion in women's employment extends across the whole country and is not driven by any particular province, island, or group of regencies.

[7]Table C.3 shows that the large within-country dispersion in women's employment is not the result of regional variation in the rates of unpaid employment. For the specific case of Indonesia, 55% (IQR 12 p.p.) of the total dispersion still remains when I focus on paid employment only. This –reduced– IQR of 12 p.p. is still more than twice that of men's.

[8]This benchmark is not affected by the Covid-19 drop in women's employment. By 2022, women's employment had recovered to pre-Covid levels.

[9]Medan, the capital and largest city in the province of North Sumatra, is the third most populous city in Indonesia as of 2020 (Brinkhoff, 2022) Bogor, with over five million people, borders the Jakarta metropolitan area. Refer to their locations in figure C.1 in the appendix.

Figure 2: Indonesia: women's employment rate by regency, 2010



Note: The figure shows regency-level employment rates for women aged 18-64. It shows all the 268 regencies with consistent boundaries between 1970 and 2010. Each color groups a fifth of the regencies. The figure uses data from the 2010 Indonesian census from IPUMS international.

3.3 Fact 3: women's employment rates are highly persistent

The large dispersion in women's employment rates could be the result of (i) temporary economic shocks that depress women's employment in some parts of Indonesia, (ii) measurement error in the employment rates, or (iii) structural differences across regencies correlated with female employment. To understand the primary cause of the variation in employment rates, we can examine the persistence of these rates across years. If the dispersion arises mainly due to temporary shocks or measurement errors, we should expect very low persistence in the regencies' employment rates across years. This is because temporary shocks should dissipate after several years, and measurement error should be independent across time. In contrast, high cross-year persistence indicates that the variation in women's employment reflects structural differences across regencies.

Table 5: Indonesia: autocorrelation in regency-level women's employment rate, 1980-2010

Regressor	(1)	(2)	(3)	(4)
Female employment 10 years ago	0.80			
	(0.02)			
Female employment 20 years ago		0.72		
		(0.03)		
Female employment 30 years ago			0.70	
			(0.04)	
Same-year male employment				0.51
				(0.04)
Observations	800	534	268	1,071

Notes: The table shows the autocorrelation of regency-level employment rates across different time horizons. It also shows the simultaneous correlation between the employment of both genders. Data from 1980-2010 Indonesian Census taken from IPUMS international. Robust standard errors are in parenthesis.

In columns (1) to (3) of table 5, I show estimates of the autocorrelation of the regency-level employment rates across different time horizons. For this table, I standardize the regency employment rates by year and run regressions of the form:

$$e_{rt} = \gamma_{t-j} e_{rt-j} + \varepsilon_{rt} \tag{1}$$

where e_{rt} is the standardized employment rate in regency r at time t.

The estimates of autocorrelation suggest that the variation in women's employment rates is primarily driven by structural differences across regencies, and not by temporary shocks or measurement error. The autocorrelations are considerably high, starting at 80% for the ten-year horizon and staying as high as 70% for the thirty-year horizon. As a benchmark, I report the estimate of the simultaneous correlation with men's employment rates in column (4). Notably, women's employment rates are more correlated with themselves 30 years apart than with men's employment rates in the same year.[10]

3.4 Fact 4: dispersion in women's employment rates cannot be accounted by differences in women's demographics alone

The highly persistent variation in female employment is likely driven by structural differences across regencies. These could be, for example, differences in the family structure or the industry mix across these labor markets. Motherhood is associated with lower female attachment to the

[10]The large persistence of female employment rates is not exclusive to Indonesia. Figure C.3 shows that large 10-year auto-correlations also arise in other countries. For most countries, this auto-correlation is over 67%.

labor market (Angelov et al., 2016; Kleven et al., 2019). Moreover, differences in the industry mix account for up to 80% of the variation in women's labor supply in developed countries (Olivetti and Petrongolo, 2016). Therefore, it is possible that the observed dispersion in female employment rates reflects underlying differences in family structure and industry mix across regencies.

In table 6, I test whether permanent differences in the industry mix or women's demographics can account for most of the dispersion in female employment across regencies. This table shows the R^2 from regressions of employment rates on a series of regency-level controls. They include the share of people married, the share with small children, along with measures of the age structure, the education level by gender, and the industry mix. I run the regressions separately by gender and stack data from all the 1980-2010 censuses. Additionally, I include year fixed-effects to absorb national trends in employment. If these factors accounted for most of the variation in female employment, we should expect very high R^2 values for these regressions.

Table 6: Indonesia: share of employment rate dispersion accounted for observed regency characteristics, 1980-2010

	Women					**Men**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
R^2	0.13	0.26	0.30	0.31	0.47	0.01	0.41	0.60	0.69	0.79
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age structure		✓	✓	✓	✓		✓	✓	✓	✓
Women's education			✓	✓	✓					
Men's education								✓	✓	✓
Share married				✓	✓				✓	✓
With child under 5				✓	✓				✓	✓
Industry shares					✓					✓
N	804	804	804	804	804	804	804	804	804	804

Notes: The table reports the R^2 of a regression of regency employment rates on regency-level aggregates. Age structure controls are the shares of people aged 30-49 and 50-64. Education measures are the shares of people who attended at most middle school, high school, and college. When indicated, the regressions include 1-digit industry shares. Data from IPUMS International.

Table 6 reveals that differences in women's demographics or the industry mix account for only a moderate share of the dispersion in female employment across regencies. In column (4), controlling for women's education level and the regency's family and age structure accounts for only a third of the dispersion in employment rates. Adding a complete set of industry shares takes the R^2 to 47%. Although these factors account for a portion of the employment rate dispersion, collectively, they still leave 53% unaccounted for. In contrast, column (10) shows these same variables can account for 80% of the variation in men's employment rates. Therefore, the dispersion in female employment rates reflects variation in *other* factors that are *specific* to women. Therefore, the variation in female employment is likely driven by structural differences across regencies that are not captured by the variables included in these regressions. These could be differences in the social norms, cultural values, or institutional arrangements that shape gender roles and expectations in different contexts.

4 Empirical strategy and results

In this section, I present evidence of the large and persistent effects of birthplace on women's labor supply using data from Indonesian female migrants. I start by illustrating how I identify these effects using information from women who currently live outside their birthplace. Next, I present the empirical evidence in three steps. First, I show that, conditional on the current place of residence, birthplace is highly predictive of women's labor supply in adulthood. This persistence can reflect the causal effect of birthplace or a spurious correlation driven by women's unobserved characteristics. I then build on this result and show that birthplace also has high predictive power for women who left their birthplace before they turned 18, a sample for which parents are more likely to drive the migration decision. Finally, using a strategy similar to Chetty and Hendren (2018a), I show that the longer female early migrants stay in their birthplace, the stronger the predictive power of birthplace becomes. I interpret this as evidence that longer stay in birthplace has a causal effect on women's labor supply decisions.

4.1 Place and women's labor supply: the identification challenge

The place of residence can, directly and indirectly, affect women's labor supply. Direct effects affect the labor supply of all the current female residents. There is considerable empirical evidence documenting these effects. These might arise, for example, from factors such as the levels of childcare availability (Compton and Pollak, 2014), commuting costs (Le Barbanchon et al., 2021; Farre and Ortega, 2021), the industry makeup of employment (Olivetti and Petrongolo, 2014), or the level of sexual discrimination in the local labor market (Charles et al., 2018). Differences across localities in any of these factors will cause geographic differences in women's labor supply. However, place can also affect women indirectly by affecting their preferences and their skills. Women born and brought up in locations where many women work can internalize these norms and thus be more likely to work as adults (Charles et al., 2018; Boelmann et al., 2021). Moreover, environments with high female employment may encourage women to invest in the skills they need to participate in the labor market (Molina and Usui, 2022). These permanent indirect effects will create differences in labor supply across women born in different locations *irrespective* of where they currently reside. Evidence on these indirect effects is much more scarce in the literature (Charles et al., 2018).

The omitted variable problem

In this paper, my main interest lies in determining what women's labor supply would be if, conditional on the current place of residence, she was born in an area where more women work. This counterfactual exercise keeps the woman, her family, and her place of residence fixed and varies only her childhood experience. To answer this question, I study the labor supply of women residing outside their birthplace. Because for these women, the place of residence is different from their birthplace, I can separate the indirect effects from the direct impact of place. More formally, let us consider the following model for women's probability of employment e_{it},

$$e_{it} \quad = \quad \delta_c + \boldsymbol{\sigma} p_b + \eta_{it} \tag{2}$$

In this model, women's employment choices depend on three main factors. First, a place-of-residence fixed effect δ_c captures all the direct effects of location c on female labor supply. These might include commuting costs, childcare availability, and gender discrimination. Second, the birthplace female employment p_b is intended to capture the causal effect of growing up in a location where p_b percent of the women work. Finally, the error term η_{it} captures all other factors making some women migrants more likely to work than others.

Model (2) follows closely the tradition brought forth by the "epidemiological" approach literature (Fernández and Fogli, 2006; Fernández et al., 2004; Fernández, 2013). Women's birthplace could have multiple impacts on women's behavior as adults. Including the prevailing female employment rates as the main regressor in equation (2) relies on the idea that these rates capture the place-driven factors vital in determining women's employment choices. Moreover, focusing on the exposure in the origin location, allows to isolate variation potentially driven by environmental factors –culture, institutions–, from variation driven by purely economics factors, sub as wages, and income. This specification also facilitates testing whether alternative channels are driving the relationship with the birthplace employment rates (Fernández, 2013).

In model (2), $\boldsymbol{\sigma}$ captures the birthplace effects. It gives the counterfactual increase in women's employment if they had been born in a place with a one p.p. higher female employment rate. In the ideal, but unfeasible experiment, I would reassign women's birthplace randomly while keeping their family and the current residency fixed. Random assignment would guarantee that women's birthplace is uncorrelated with the error term. Thus an OLS regression of (2) would give a consistent estimate of $\boldsymbol{\sigma}$. In observational data, however, it is likely that the unobserved factors imbued in the error term are correlated with birthplace labor supply. Therefore, the OLS estimates of employment rate slope will conflate the causal effects of birthplace with omitted variable bias:

$$\begin{aligned}
\text{plim } \hat{\boldsymbol{\sigma}} \quad &= \quad \boldsymbol{\sigma} + \frac{\text{cov}(\tilde{p}_b, \tilde{\eta}_{it})}{\text{var}\,(\tilde{p}_b)} \\
&= \quad \boldsymbol{\sigma} + \boldsymbol{\gamma}
\end{aligned} \tag{3}$$

where tilde accents denote variables that are residualized from regency fixed effects (Angrist and Pischke, 2009). Expression (3) shows that the OLS coefficient reflects two factors: first, the causal effect of birthplace $\boldsymbol{\sigma}$, but also differences in unobservable characteristics across women from different origins $\boldsymbol{\gamma}$. The critical identification challenge is separating the selection term $\boldsymbol{\gamma}$ from the birthplace effect $\boldsymbol{\sigma}$.

The selection term $\boldsymbol{\gamma}$ highlights that even in the absence of a causal effect, birthplace could capture characteristics about a person or their family that are relevant to their work decision. Later, I will be arguing that the causal effect of place is positive ($\boldsymbol{\sigma} > 0$). That is, being born in a place where more women work, makes you more likely to work. In these circumstances, I will be more concerned with omitted variable –or selection– bias making women from high-employment birthplaces more likely to work than their low-employment counterparts. For example, previous research shows that daughters from working mothers are more likely to work (Fernández, 2007). Even in the absence of a causal effect, a positive $\hat{\boldsymbol{\sigma}}$ could simply be reflecting that, in places where more women work, girls are more likely to be raised up by a working mothers.

Using emigration age data to identify causal effects

Under additional assumptions, data on the age of emigration allows me to distinguish selection from the causal effect of place. The argument is similar to that of Chetty and Hendren (2018a). I assume that place effects are stronger the longer women stay there. Thus, the employment choice for women who emigrated at age a is determined as follows:

$$e_{it} \quad = \quad \delta_c + \lambda_a + \boldsymbol{\sigma}_a p_b + \eta_{it} \tag{4}$$

Here $\boldsymbol{\sigma}_a$ captures the cumulative effect of birthplace up to age a[11]. The age of emigration fixed-effects λ_a absorb differences in labor force participation across women who emigrated at different ages. The causal impact of staying in the birthplace at age a is then $\boldsymbol{\pi}_a = \boldsymbol{\sigma}_a - \boldsymbol{\sigma}_{a-1}$.

By an argument analogous to that in expression (3), the OLS estimates will conflate the causal effects of birthplace $\boldsymbol{\sigma}_a$ with the omitted variable bias for women migrating at age a $\boldsymbol{\gamma_a}$:[12]

$$\text{plim } \hat{\boldsymbol{\sigma}}_a \quad = \quad \boldsymbol{\sigma}_a + \boldsymbol{\gamma}_a \tag{5}$$

Assumption 1. ***Constant omitted variable bias***
Omitted variable is the same no matter the age of emigration, that is $\boldsymbol{\gamma}_a = \boldsymbol{k}$

This assumption requires that, conditional on the fixed effects of location and age of emigration, the correlation between the birthplace employment rate and the error term is consistent for women who emigrated at different ages. To make this point more concrete, let's consider work-related migration as an example. It is conceivable that women who migrated with work in mind would be more likely to be employed in their destination, and women in their 20s would be more likely to migrate because of work. At first glance, this would seem to invalidate the identification strategy. However, my strategy does not require that women migrating at different ages have the same likelihood of migrating for work. Rather, it requires a much weaker condition: that the correlation

[11] The causal effect $\boldsymbol{\sigma}$ in the previous subsection can be interpreted as a weighted average of age-specific causal effects.

[12] You can find the full derivation of this expression in appendix section B. I defined γ_a as the a-th element in the vector plim $\left[(\widetilde{P}'\widetilde{P})^{-1}\widetilde{P}'\tilde{\boldsymbol{\eta}}\right]$. Here, P is the matrix containing the interaction between the age of emigration dummies and the birthplace female employment rates. $\boldsymbol{\eta}$ is the vector of error terms. Tilde-accented variables are residualized from current location and age of emigration dummies.

between birthplace FLFP and the likelihood of work migration is the same for women migrating at different ages. Therefore, even though older teenagers are more likely to migrate for work (see Figure C.4 in the appendix), this does not violate the identification assumption.

Under the constant omitted variable bias assumption, I can isolate the birthplace causal effect from the omitted variable bias. By subtracting the OLS estimates across different emigration ages, the constant selection term $\boldsymbol{\gamma}$ goes away, leaving only the causal effects:

$$\begin{aligned} \text{plim } \hat{\boldsymbol{\sigma}}_{\boldsymbol{a}} - \hat{\boldsymbol{\sigma}}_{\boldsymbol{a-1}} &= \boldsymbol{\sigma}_a - \boldsymbol{\sigma}_{a-1} \\ &= \boldsymbol{\pi}_a \end{aligned} \tag{6}$$

this expression also shows that identification does not necessarily require constant bias across all *all* emigration ages. If, instead, bias is constant only within some age ranges, I can still identify the effects within those ranges. For example, suppose there is reason to believe that the bias for women who emigrated between 0 to 6 years old is different than for those who emigrated between the ages of 7 to 15. If constant selection holds *within* these ranges, I can still identify the place effects within the 0 to 6 and 7 to 15 ranges. In section 4.4, I present estimates from the birthplace effects along with evidence that women emigrating at different ages are similar to each other along multiple dimensions.

4.2 Birthplace is highly predictive of women's labor supply

I start by comparing the labor supply of women who *live in the same location* but were born in different regencies. I do this by regressing a dummy equal to one if the person is employed at year t (e_{it}) on year by current-regency fixed-effects (δ_{ct}), women's employment rate in her regency of birth (p_b), and a set of individual and regency-level controls X_{it}. These controls might include age, religion, education, number of books at home when growing up.

$$e_{it} = \delta_{ct} + \boldsymbol{b} p_b + X_{it}\kappa + \varepsilon_{it} \tag{7}$$

I source the regency female employment rates from the 2010 census, but I obtain similar results when using data form other census years.[13]

The parameter of interest in this regression is denoted by $\boldsymbol{b}$, which measures the relationship between women's labor supply and the prevailing female employment rate in their birthplace. I will refer to $\boldsymbol{b}$ as the birthplace persistence coefficient. Because the model includes regency of residency by year fixed-effects, $\boldsymbol{b}$ is primarily identified out of differences in labor supply of women who live in the same regency, in the same year, but who were born in different localities. This approach controls for permanent differences in the localities of residency, such as variations in average wages, industry mix, healthcare availability, and other factors, which are absorbed by the parameter δ_{ct}.

I refer to the slope of the birthplace employment rate as $\boldsymbol{b}$ to emphasize that it generally differs

[13]This is because employment rates are highly persistent.

from the causal effect discussed in Section 4.1. A positive value of $\boldsymbol{b}$ may not necessarily indicate a causal relationship between birthplace employment rates and women's labor force participation. Instead, it could capture differences in factors that are unrelated to birthplace characteristics, such as unobserved individual traits or preferences that make women from high-employment locations more likely to work than their counterparts from low-employment areas. For example, parents from women with high-employment areas could have invested more in their daughter's career.

Table 7: Indonesia: estimates of women's birthplace persistence on labor supply ($\boldsymbol{b}$)

	(1)	(2)	(3)	(4)
Women's employment rate at birthplace (p_b)	0.30***	0.30***	0.29***	0.30***
	(0.03)	(0.03)	(0.03)	(0.03)
Mean employment rate	0.41	0.41	0.41	0.41
Implied IQR gap	0.07	0.07	0.07	0.07
Regency-year FE	✓	✓	✓	✓
Age		✓	✓	✓
Religion			✓	✓
Education				✓
Observations	62,954	62,954	62,954	62,954
R^2	0.07	0.08	0.08	0.09

Notes: This table uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace. The implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone born at the 25th percentile. The IQR of female employment rates across regencies is 22 percentage points. Standard errors are clustered by regency of origin. When applicable, regressions control for a quadratic polynomial in age and fixed effects for five religious and four education categories.

Table 7 shows estimates of the birthplace persistence coefficient $\boldsymbol{b}$. Column (1) shows results from a baseline specification that includes regency by year fixed effects only. The coefficient of 0.30 indicates that birthplace is highly predictive of women's employment. To see how large this coefficient is, let us consider two women: Putri and Amanda. Putri was born in the city of Probolinggo in East Java, which has a female employment rate of 40%. In contrast, Amanda was born in the regency of Sukoharto in Central Java, with a female employment rate of 62%. These rates places these regencies at approximately the 25th and the 75th percentiles of the distribution of female employment rates. The 0.30 coefficient implies that Putri is 7 percentage points less likely to work than Amanda. This is a difference of 17% relative to the employment rate of the average woman in my data.

The additional estimates in table 7 also allow me to rule out several potential drivers of the birthplace persistence. Columns (2) and (3) show that controlling for women's age and religion barely modifies the estimate. Thus, this persistence is not explained by geographic differences in age or religion. Column (4) adds education level as a control. Recent research suggests that exposure to low-employment places can affect women's labor supply through the expectations and education channel (Molina and Usui, 2022). In areas with low female employment rates, women set low labor market expectations and thus invest less in education. However, however column (4) indicates that the birthplace persistence is not driven by differences in educational investment.

Table 8: Indonesia: estimates of men's birthplace persistence on labor supply (***b***)

	(1)	(2)	(3)	(4)
Women's employment rate at birthplace (p_b)	0.08***	0.08***	0.10***	0.09***
	(0.03)	(0.03)	(0.02)	(0.02)
Mean employment rate	0.87	0.87	0.87	0.87
Implied IQR gap	0.02	0.02	0.02	0.02
Regency-year FE	✓	✓	✓	✓
Age		✓	✓	✓
Religion			✓	✓
Education				✓
Observations	65,105	65,105	65,105	65,105
R^2	0.06	0.21	0.21	0.22

Notes: This table uses data from the Intercensal Survey and restricts the sample to men who reside outside their birthplace. The implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone born at the 25th percentile. The IQR of female employment rates across regencies is 22 percentage points. Standard errors are clustered by regency of origin. When applicable, regressions control for a quadratic polynomial in age and fixed effects for five religious and four education categories.

The strong birthplace persistence in labor supply is essentially exclusive to women. I show this in table 8, where I show estimates from regressions where I relate men's employment in adulthood to their birthplace's *female employment rate*. Note that all these estimates are below 0.10 (about 30% the estimates in women) and imply little variation in men's employment rates across regencies. For example, the estimate in column (8) implies an IQR gap of only 2 p.p.

The persistence in women's employment rates could still be driven by variation across regencies in, for example socioeconomic or demographic factors. Unfortunately, the Intercensal Survey has limited demographic and socioeconomic information. Therefore, in tables C.6 and C.7 in the appendix I take advantage of the rich data available in the IFLS to rule out additional potential drivers of the birthplace persistence.

First, in columns (1) to (4) of table C.6 I reproduce the birthplace persistence estimates for the women migrants in the IFLS using the same specifications as in table 7. Reassuringly, these results confirm the Intercensal survey estimates, with a similar implied IQR of 8 p.p. Moreover, table C.7 shows similarly small persistence estimates for men.

Moreover, Columns (5) to (8) of table C.6 rule out childhood socioeconomic status and maternal labor supply as drivers of my results. In columns (5) and (6), I study the role of childhood economic conditions. These variables come from a battery of questions where respondents reported information on their household when they were 12 years old. These include wealth and education proxies such as the number of books, the number of people per room, and whether their father was in formal employment, among others. Remarkably, adding these additional controls has little effect on the childhood persistence estimate. In addition, in columns (7) and (8), I rule out the possibility that the birthplace persistence is driven by differences in maternal labor supply. Previous literature shows that women with working mothers are more likely to work (Fernandez and Fogli, 2009). Therefore, the birthplace persistence might just be reflecting the fact that in places where more women work, there are higher shares of working mothers. Because of the panel nature of the IFLS, I can identify the maternal labor supply for a subset of women in my sample. Column (7) re-estimates the birthplace persistence for this sample. Column (8) shows the persistence estimate when I control for maternal labor supply. Although the point estimate is slightly smaller and noisier, I can rule out that maternal labor supply drives my results.

4.3 There is large persistence for those who migrated young

The birthplace persistence could be reflecting complex endogenous relationships between women's origin, their migration decision and their labor supply. Migration is a voluntary decision where the potential job opportunities at the destination are likely influence where women move to. In table 9, I focus my analysis on women who left their birthplace before they turned 19. Thirty eight percent of female migrants left their birthplace before this age. For these women, the migration decision is more plausibly driven by their parents' decisions. Reassuringly, I obtain similar persistence estimates for these sample.[14] Moreover, these estimates are robust to the choice of the migration age cutoff (see Figure C.5 in the appendix).

[14]Table C.8 shows that the men sample shows birthplace persistence estimates similar to those of women. However, as we will see in the next section, they are mostly driven by unobserved differences between men of different origins.

Table 9: Indonesia: estimates of birthplace persistence on labor supply ($\boldsymbol{b}$) for women who emigrated young

	(1)	(2)	(3)	(4)
Women's employment rate at birthplace (p_b)	0.24***	0.25***	0.24***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)
Mean employment rate	0.41	0.41	0.41	0.41
Implied IQR gap	0.05	0.05	0.05	0.06
Regency-year FE	✓	✓	✓	✓
Age		✓	✓	✓
Religion			✓	✓
Education				✓
Observations	24,178	24,178	24,178	24,178
R^2	0.08	0.08	0.08	0.09

Notes: This table uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace and who left before they turned 19. The implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone born at the 25th percentile. The IQR of female employment rates across regencies is 22 percentage points. Standard errors are clustered by regency of origin. When applicable, regressions control for a quadratic polynomial in age and fixed effects for five religious and four education categories.

4.4 The birthplace persistence is stronger the longer you stay

The strong birthplace persistence in women's employment could still reflect unobservable differences between women from different origins. Here, I address this concern by exploiting differences in the timing of migration to argue that this persistence reflects the causal effect of women's birthplace. To do so, I augment expression (7) by (i) allowing the coefficient on female employment rate to vary by the emigration age ($\boldsymbol{b_a}$), and (ii) adding age of emigration fixed-effects (λ_a).

As I discuss in section 4.1, I can decompose the OLS estimates of age specific-slopes into a cumulative causal effect $\boldsymbol{\sigma}_a$, and a selection term $\boldsymbol{\gamma}$:

$$\boldsymbol{b}_a \quad = \quad \boldsymbol{\sigma}_a + \boldsymbol{\gamma}$$

under the assumption that omitted variable bias is constant across emigration ages, I can identify the causal effect of place at any given age (π_a) by subtracting the persistence coefficients across emigration ages:

$$\boldsymbol{\pi}_a \quad = \quad \boldsymbol{b}_{a+1} - \boldsymbol{b}_a$$

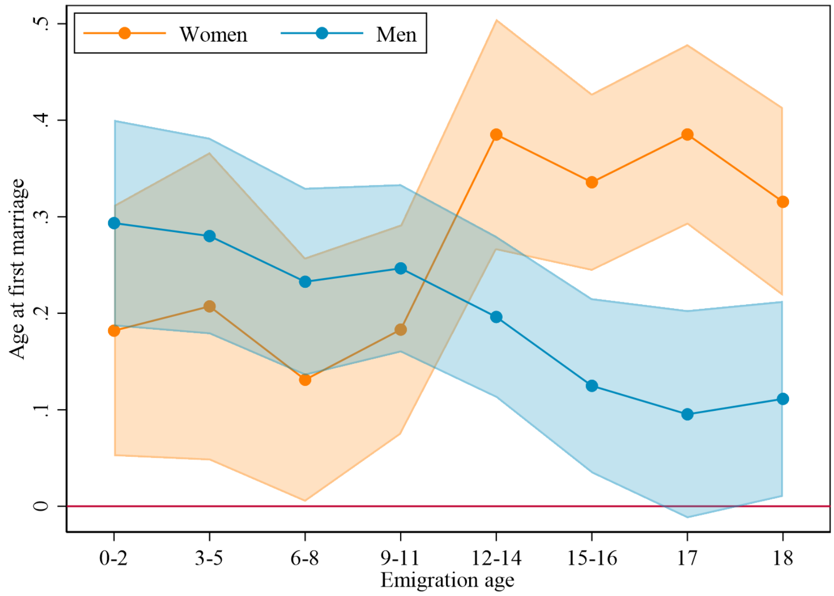
Moreover, the coefficient for least exposed cohort gives as estimate of the omitted variable bias: $\boldsymbol{\gamma} = \boldsymbol{b}_0$

To estimate this model, I leverage age of emigration data from the Intercensal survey. Because the number of migrants at any given age is relatively small relative to the number of regencies, I bin emigration age into three-year cells.

Longer stay does make you more likely to work

Figure 3 displays estimates of birthplace persistence ($\boldsymbol{b_a}$) by age of emigration for both men and women. My sample remains restricted to people who left their birthplace before they turned 19. The regressions control for a quadratic polynomial in age, as well as current regency-by-year, education, and religion fixed effects.

Figure 3: Indonesia: length of stay and marriage and fertility

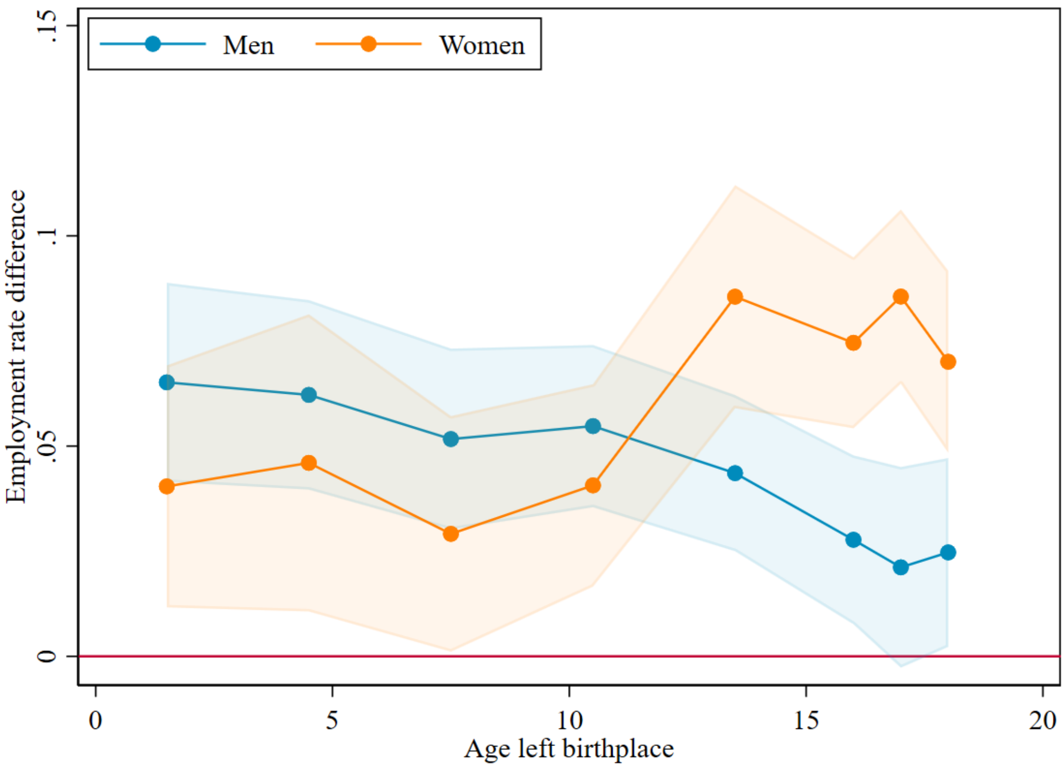


Note: The figure shows estimates of the birthplace persistence coefficients by age of emigration $\boldsymbol{b_a}$. It uses data data from 1995 and 2005 Intercensal surveys. Panel (b) uses information from the 1995 survey only, as fertility data is not available for 2005. The regression controls for current regency by year fixed-effects, a quadratic polynomial on age, and education level fixed-effects. The figure shows 90% confidence intervals.

These results show a striking pattern in the birthplace coefficients: women with longer exposure to high-employment locations are more likely to work. The birthplace persistence coefficients increase from 0.18 for women who left their birthplace between 0 to 2 years old, to 0.38 for those who left between 12 to 14 years old, and remain roughly constant thereafter. These patterns provides several insights. First, women from high-employment locations are likely to work from the outset. Women who left their birthplace before they turned three have very little exposure to their birthplace, and yet they are more likely to work than those coming from low-employment locations. Following the discussion in Section 4.2, I interpret this coefficient as reflecting unobservable differences between women from different origins (omitted variable bias). Second, longer exposure leads to higher female employment. Under the constant omitted variable bias assumption, we can attribute the increase of approximately 20 p.p. in the birthplace persistence coefficients to the effect of longer exposure to high-employment locations. Third, the birthplace effect is concentrated in late childhood and early teens, as the increase in the persistence happens between the ages of 6 to 14 years old. Staying after the age of 15 has no additional effect.

Figure 3 also shows persistence estimates for men. Like women, men form high-female-employment locations have traits that makes them more likely to work. The estimate for least-exposed men is of 29 p.p. However, the very gradual decline in the estimates suggest that longer exposure to these locations make men less likely to work. The coefficients decline by 18 percentage points, with a decline of roughly 1 p.p. per additional year of stay.

Figure 4: Indonesia: implied IQR gap in employment rate by age of emigration



Note: The figure shows estimates of $b_a\times$ regency-level IQR in female employment (22 p.p.). This is the implied gap in employment at different ages of out-migration between a person born in a regency at the 75th percentile in female employment, and another one born in a regency at the 25th percentile of female employment. Point estimates are placed at the mean point of the respective age interval. Shaded areas show 90% confidence intervals. The figure uses data from the 1985, 1995 and 2005 Interncensal Surveys.

These results suggest that place effects play a crucial role in driving geographic differences in women's labor supply. This is illustrated in Figure 4, which displays the counterfactual gaps in employment between two women, one born in a regency at 75th percentile of the employment distribution and another born at the 25th percentiles of employment, if they had left their birthplace at different ages. I call this gap the IQR gap in employment. The figure places the gap estimates at the midpoint of each of the age brackets in figure 3. If both of these women had emigrated in their first year of life, I would observe a gap of 4 p.p. in their labor supply when they are adults.

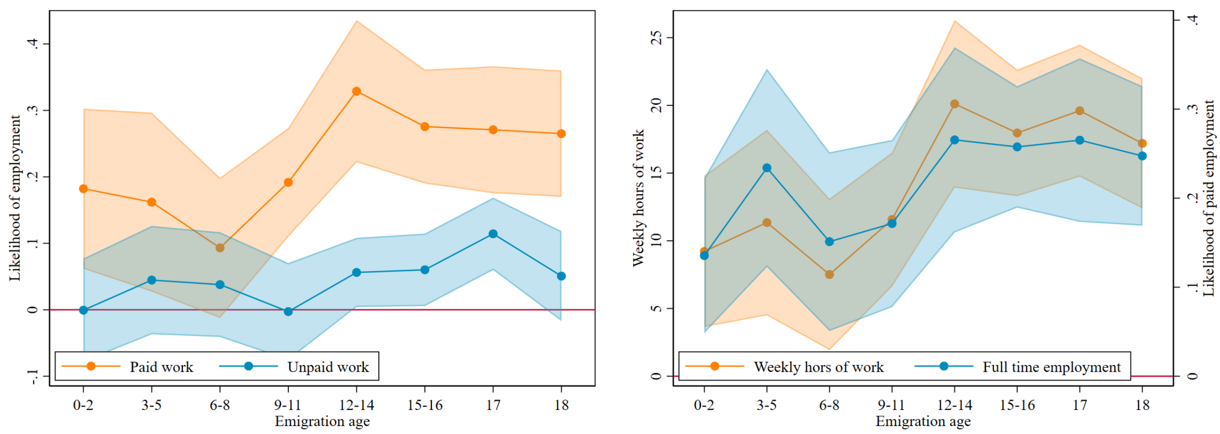
This initial gap is driven by unobservable differences between these two women. In contrast, if they stayed in their birthplace up to 13 years old, this gap would widen up to 9 p.p. The increase of 5 p.p. in the likelihood of employment is equivalent to 27% if existing gap in FLFP between these regencies and is driven by the longer exposure to their birthplace. Therefore, a significant portion of the current inequality in female labor force participation is transmitted to the next generation of women growing up in these locations through birthplace effects.

Longer stay translates into more paid employment and more hours

In figure 5 I show that longer exposure to high-employment labor markets also translates into higher paid employment and higher working hours. Panel (a) breaks down the employment into paid and unpaid work. Unpaid work accounts for about a 35% of all female employment. The increase in employment from Figures 3 and 3 is unlikely to represent more economic independence for women if it were entirely driven by unpaid work. However, panel (a) shows that increase in the birthplace persistence between 6 to 14 years old is driven by *paid employment*. The rise in the coefficients between 0 to 14 years old translates into an increase of 3.2 p.p. IQR gap in employment.This is 64% of the effect on all employment from Figure 3. This contrasts with results on unpaid work. There is little effect on the likelihood of unpaid employment up to 14 years old. Although there is an uptick in the coefficients at 17, the effect is small. In all, staying up to 17 at birthplace renders an IQR gap of 1.2 p.p.

Figure 5: Indonesia: employment type by length of stay

(a) Type of employment (b) Hours and full time employment



Note: The figure show the coefficients on the interactions between age of emigration and birthplace female labor force participation. The regressions also control for (i) age of emigration dummies, (ii) birthplace female employment rate (iii) interactions between the emigration age and birthplace female employment rate. Panel (a) uses data from the 1985, 1995 and 2005 Intercensal Surveys. Panel (b) uses data from the 1985 and 1995 surveys because hours of work data is not available in 2005. Full time employment defined as working 40 hours or more in week. The figure shows 90% confidence intervals.

Panel (b) of Figure 5 I shows additional results on the likelihood of full-time employment and weekly hours of work. Data on weekly hours of work is not available in the 2005 Intercensal

Survey, thus these results use data from the 1985 and 2005 surveys only. However, the plot shows a consistent picture: staying in high female employment places between 6 to 14 years old rises women's labor supply. The birthplace employment coefficients rise sharply at these ages and both increases are sizable. They translate into IQR gap increases of 2.5 weekly hours, and 2.86 p.p. in the likelihood of full-time employment.

So far all the evidence presents a consistent picture: longer stay in high-female employment labor markets translates into higher attachment to the labor market in adulthood. Women with more exposure to these labor markets are more likely to be paid workers, and the work longer hours. A natural question is whether they also have higher earnings. I answer this question in Figure C.6 where I show birthplace persistence coefficients in regressions with total earnings and hourly wages as dependent variables. These regressions restrict the sample to the much smaller group of migrant women with non-zero earnings. Because this is a much smaller sample, I am forced to use wider bins for the emigration age. These results are noisy, but they suggest that longer exposure to high female employment locations could lead to higher wages for women.

The data supports the constant selection assumption

The causal interpretation of the birthplace persistence coefficients hinges on the assumption that selection is independent of emigration age. More precisely, conditioning on the current location and other controls, I require that the relationship between women's unobserved characteristics and the birthplace female employment rate be the same for women who emigrated at different ages. Below, I provide results showing that selection along several observable dimensions is constant across emigration age. This suggests that the identification assumption is likely to hold in my data.

One can think of the identification assumption as an analog of the parallel trends in Difference in Differences. I expect women coming from high and low-employment regencies to be different from each other. This is not an issue. However, if there are factors correlated with female employment that change differently across emigration ages for these two groups of women, I would assign this variation to the causal effect. Thus, the lack of parallel trends could lead me to find a causal effect where there is none.

I cannot test whether the correlation between female labor force participation at birthplace and women's unobservable characteristics is constant across emigration age. However, I can test whether the correlation between the employment rate and a series of individual characteristics I do observe is the same no matter the age women migrated. To do this, I estimate the a regression where I regress a woman characteristic y_i on age of emigration fixed effects λ_a, female LFP at birthplace p_b, and interactions between age of migration and female LFP:

$$y_i = \lambda_a + \beta p_b + \sum_a \beta_a 1_a \times p_b + X_i \kappa + \varepsilon_{it} \tag{8}$$

in model 8, I chose 18 as the base category and thus the β_a can be interpreted as the difference between the slope at age a and the slope at age 18. Under constant selection across all the ages *all* *the interaction terms β_a should be jointly zero.*

In figure 6 I show estimates of the interaction terms β_a for different outcome variable. Panel (a) uses data from the Intercensal Survey while panels (b) to (d) take advantage of the richer demographic information available in the Intercensal Survey. All regressions control for a full set of education and religion dummies, and a quadratic polynomial in age. In addition, panels (a) to (c) include current-regency fixed effects.

In panel (a), I present estimates of the interactions between migration age and female employment at birthplace in regressions where I use migration motive dummies as dependent variables. Each series of coefficients in the panel represents a different regression. In Section 2.3, I showed that the reason for migration changes as women age, with older becoming more likely to migrate for work.[15] These age-related changes in the reason for migrating could pose a problem for my identification strategy if they if they differ between regencies with high and low female employment.[16] To alleviate this concern, in panel (a) I show that most of the interactions in the work-migration series are insignificant at the 5% level and, in fact, all the interactions from 3 to 17 years old are jointly insignificant. Furthermore, note the work series does not reproduce the sharp increase between 6 to 14 years from Figure 3.Panel (a) also displays analogous slopes for regressions with family and education migration dummies as outcomes. In both cases, I cannot reject that all these interactions are jointly zero. Therefore, there is no consistent evidence that changes in migration motives are the driving factor behind the birthplace persistence.

Panels (b) to (d) present similar exercises where I take advantage of the much richer demographic information available in the IFLS. These panels show a less detailed breakdown of migration ages than panel (a) because the IFLS (i) has a smaller sample size, and (ii) there is not age breakdown for migration episodes that happened before the people turned 12 years old. In panels (b) and (c) I show results from regressions that use parental wealth proxies and number of siblings as outcomes. There extensive evidence that parental investment is key determining children's outcomes (Baker and Milligan, 2016; Jayachandran and Kuziemko, 2011; Pande, 2003; Autor et al., 2019; Barcellos et al., 2014; DiPrete and Jennings, 2012). Moreover, family background and the number of siblings are important in determinants of these investments, specially in developing countries (Jayachandran and Kuziemko, 2011; Baker and Milligan, 2016; Pande, 2003). Therefore, in these two panels I test for evidence of changes in selection by parental wealth and number of siblings across migration age cohorts. All the interactions in these panels are jointly insignificant at the 5% level.

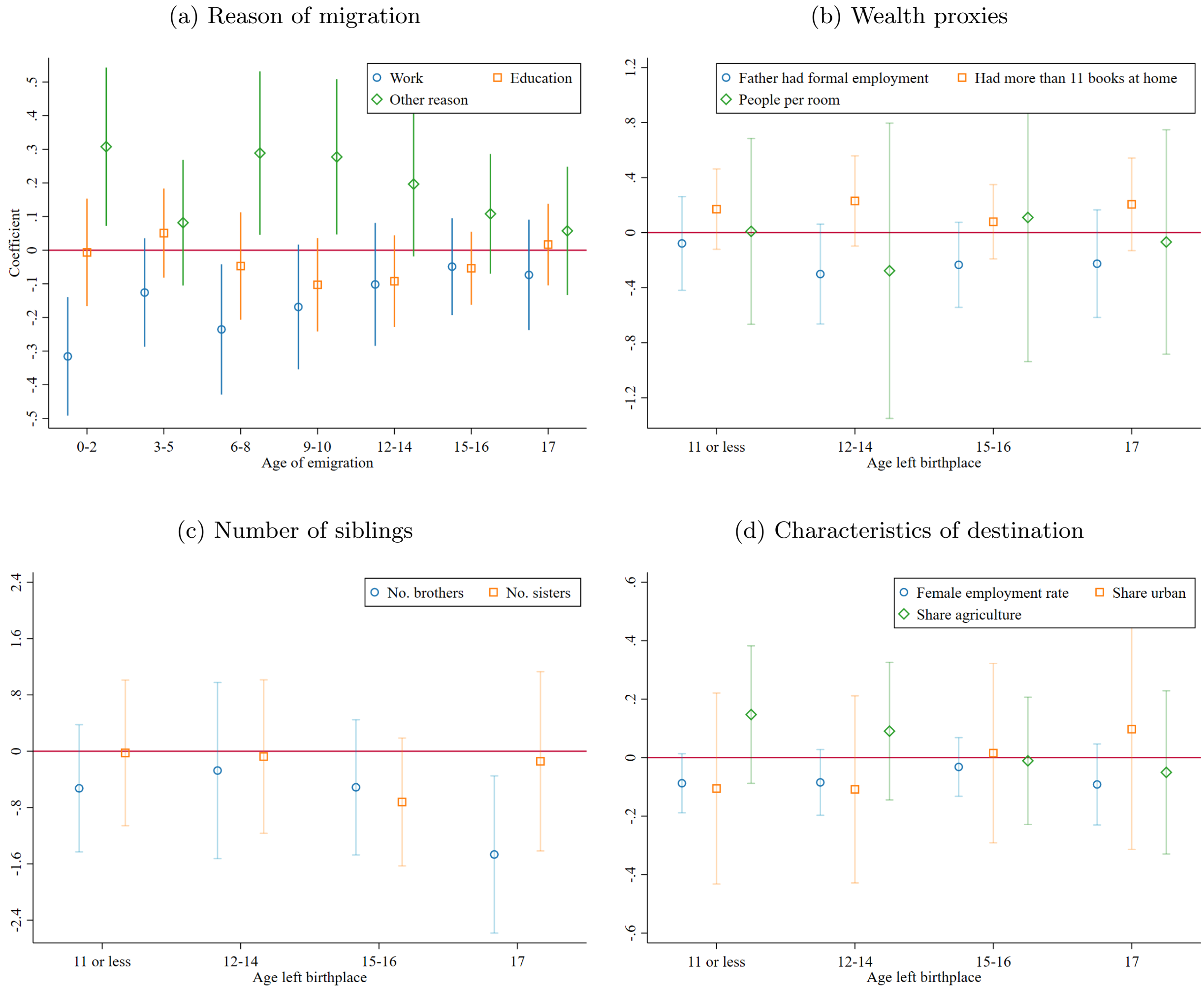
In panel (d), I present results from regressions where I use characteristics of the destination regency as dependent variable. There is evidence that skills acquired at the origin location are

[15] A limitation of the reason for migrating data in the Intercensal Survey is that it is unclear how respondents classify themselves among the possible options. For example, conceivably I can migrate because of *my* work, or my partner's *work*. However, migrating because of my partner's work could be classified as work-related migration, but it could also be interpreted as family-related migration. I note, however, that the IFLS provides a much more detailed –and less ambiguous– classification for migration motives and I obtain results similar to those in panel (a).

[16] For example, changing migration motives could account for the patterns I observe if: (i) women migrating because of work are more likely to be employed at the destination, (ii) women from high-employment regencies become even more likely to migrate because of work than those from low-employment regencies

important at determining post-migration outcomes. Thus, in this panel I explore the possibility that the birthplace persistence is the result of changes of –admittedly complicated– selection patterns across migration age cohorts. The results in this panel are similar as in the other graphs in the figure, with all the interactions being jointly insignificant. Overall, the lack of clear patterns in Figure 6 as evidence in support of the constant omitted variable bias assumption.

Figure 6: Indonesia: women and selection by age of emigration



Note: The figure show the coefficients on the interactions between age of emigration and birthplace female labor force participation. The regressions also control for (i) age of emigration dummies, (ii) birthplace female employment rate (iii) interactions between the emigration age and birthplace female employment rate. I chose 18 years old as the base category so that the interactions test whether the slopes at each age are different from that for women emigrating at 18. Data on reasons for emigrating is available only for people emigrating at 12 years old or older. Error clustered by regency of birth. The figure shows 95% confidence intervals. Data from the IFLS.

Discussion: why does birthplace matters so much?

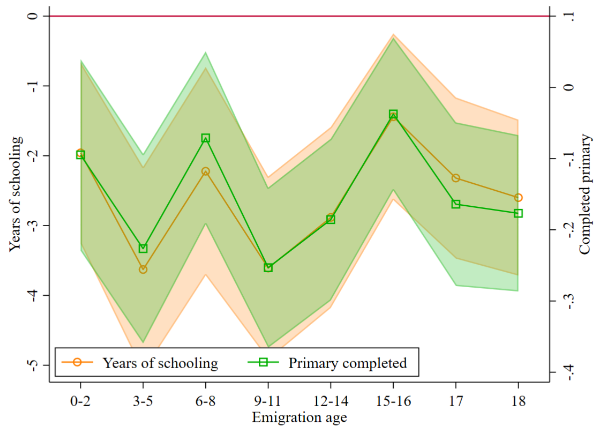
Having established that exposure childhood exposure to birthplace has a strong effect on women's choices, the natural question is then through which mechanisms do birthplace influence women's choices. Here I examine the evidence of three mechanisms: (i) human capital accumulation, (ii) schooling quality, (iii) changes in parental investments, and finally (iv) culture and/or gender norms.

Exposure to birthplace could affect women's labor supply via their career expectations and their educational investment. Being exposed to an environment where women are actively participating in the labor force could alter their career expectations and make them more likely to invest in further education. For example, Molina and Usui (2022) that in Japanese municipalities with higher female participation rates, teenagers exhibit greater educational aspirations, leading to increased investment in schooling. If higher investment in schooling accounts for my results, I should observe higher schooling in women with higher exposure to high-female employment regencies. I test this in figure 7 where I show estimates of the birthplace persistence coefficients for regressions using measures of schooling as dependent variables. The figure shows results for both the years of schooling, and a dummy equal to one if the woman completed primary.[17] The figure gives little support to education as the main channel through which the birthplace effects operate. First, the 0-2 and the 18 years old coefficients are very similar and thus there is no evidence that longer stay in high-female employment regencies leads to more overall education. Second, although there is a jump in the coefficients at 15-16 years old, the employment results showed that birthplace effects were concentrated between 6 to 14 years old. Therefore, the timing of the jump is off.

While women from areas with high female employment do not necessarily spend more time in school, the impact of birthplace can manifest through schooling if these locations offer education of higher quality. In this case, areas where women participate more actively in the labor market could have educational systems of higher quality that target women more effectively. Thus, even if women do not spend more time in schooling, women who spend more time in their birthplace would be exposed *longer* to an education system of higher quality. However, there are two pieces of evidence that point against this channel. First, note that all the coefficients in Figure 7 are *negative* and hover around -2.6. This means that women from high-employment regencies spend less time in school than their counterparts from low-employment regencies. The average coefficient of -2.6 means that women born in a regency at the 75th percentile of employment spend seven less months in school than those born at a 25th percentile regency. Second, high female employment regencies have worse overall female educational outcomes. Appendix table C.9 show that women in these regencies have worse education outcomes. In this table I split regencies at the mean of the female employment rate and compute average education outcomes for each group. On average, women in high-employment regencies stay one year less in school, and are much less likely to complete primary and secondary education. If the educational quality in high-female employment regencies

[17] Figure 3 shows the effects of birthplace are concentrated between the ages of 6 and 14. Therefore, completing primary school would be the main margin of action.

Figure 7: Indonesia: education by length of stay



Note: The figure show the coefficients on the interactions between age of emigration and birthplace female labor force participation. The regressions also control for (i) age of emigration dummies, (ii) birthplace female employment rate (iii) interactions between the emigration age and birthplace female employment rate. I chose 18 years old as the base category so that the interactions test whether the slopes at each age are different from that for women emigrating at 18. Data on reasons for emigrating is available only for people emigrating at 12 years old or older. Error clustered by regency of birth. The figure shows 90% confidence intervals. Data from the IFLS..

were higher, one would expect that women stay in the system longer and they have better overall educational outcomes. However, the evidence does not support this possibility.

Molina and Usui (2022) suggest that exposure to local labor market opportunities influences parental investment in girls' education. However, it is unlikely that this factor is responsible for the results I obtain. My findings indicate that women who were exposed longer –as children– to regencies with high female employment are more likely to join the labor market as adults. If parental investments were the driving force behind these results, it would imply that parental investment is highly responsive to the length of their child's exposure. Given that the parents have resided in this location for a considerable period of time, it seems improbable that such a high level of sensitivity exists.

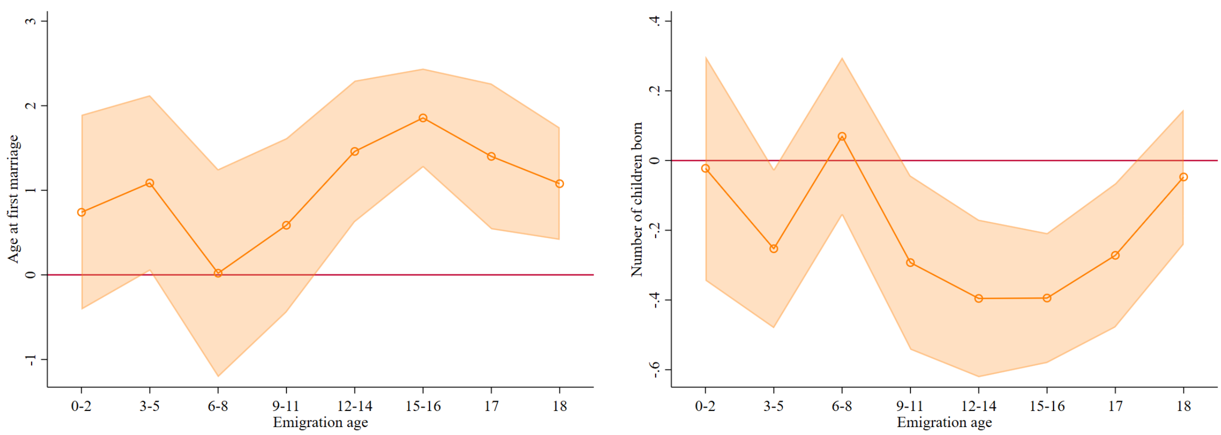
A more plausible driver of the birthplace effects is the transmission of cultural gender norms. There is a growing literature emphasizing that the transmission of culture or gender norms has permanent effects on women's labor market outcomes (Fernández et al., 2004; Alesina et al., 2013; Blau et al., 2011). Both the Intercensal Survey and the IFLS provide limited data to formally test this channel, but two pieces of evidence support it. First, I find evidence of similar birthplace effects on fertility and age of marriage, outcomes more directly linked to gender norms. In Figure 8, I present estimates of the birthplace coefficients for regressions using the age at first marriage and the number of children born as outcomes.[18] This figure reveals a pattern that closely aligns with the employment results, where longer childhood exposure is associated with delayed marriage and lower fertility rates. Moreover, these effects appear to be concentrated between the ages

[18] The Intercensal Survey only includes fertility and marriage questions for women, hence I cannot present estimates for men.

of 6 to 14 years old, although the results for the number of children are less clear due to the reversal in the coefficients after age 15. Second, the birthplace effects primarily occur during ages when gender norms are highly malleable. Late childhood and early adolescence represent a critical period when children are mature enough to form their own opinions while remaining receptive to external influences (Dhar et al., 2022). Remarkably, my findings indicate that the majority of the effects occur between the ages of 9 and 14, precisely the period when teenagers have demonstrated responsiveness to interventions targeting gender norms (Dhar et al., 2022).

Figure 8: Indonesia: length of stay and marriage and fertility

(a) Age at first marriage (b) Number of children



Note: The figure shows estimates of the birthplace persistence coefficients by age of emigration $\boldsymbol{b_a}$. Panel (a) uses data data from 1995 and 2005 Intercensal surveys, while panel (b) uses data from the 1995 survey only. This is because marriage data is available only in 1995 and 2005, and fertility data is available for 1995 only. The regression controls for current regency by year fixed-effects, a quadratic polynomial on age, and education level fixed-effects. The figure shows 90% confidence intervals.

5 Conclusions

In this paper, I document large and persistent spatial inequality in women's labor supply in Indonesia, a country with more than 118 million women. I argue that a substantial portion of this inequality is driven by the local environment women are born into. To identify the causal effect of place, I leveraged variation coming from the age women emigrated from their birthplace. I compared the labor supply choices of women who currently live in the same location, but who emigrated from their birthplace at different ages as children. If the omitted variable bias is independent of the age of emigration, this strategy allows me to distinguish the causal effect of place from variation driven by differences in women's unobserved characteristics.

I show that women's birthplace is particularly important during the formative childhood and teen years. Staying in a location at the 75th percentile of female employment between 6 and 16 years of age makes women 5 percentage points more likely to work than those born in a location at the 25th percentile. These magnitudes mean that 23 percent of the current spatial inequality in women's employment transmits to the next generation of women. Therefore, these women-specific place effects can be an important driver of the large and persistent differences in women's labor force participation within countries.

Further research should delve into the mechanisms by which childhood exposure impacts women's choices. While my findings indicate that disparities in human capital accumulation do not account for the results, I can only suggest cultural transmission as the most likely mechanism. Future studies should concentrate on elucidating the the importance of transmission of culture and norms in driving these effects and identifying the specific ways in which this transmission occurs. Additionally, it would be intriguing to ascertain whether these results can be replicated in other countries.

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A Cross-country data

I use harmonized data from IPUMS International to build figure 1 from the introduction and table 4 from section 3. They show local employment rates for men and women aged 18-64 for a cross-section of countries. For all of them, I use the latest decennial census sample available. In most cases, this corresponds to 2010 or a year close to it.

I define employment using the harmonized employment status (`empstat`). When this variable is not available, if the class of worker is available (`classwkr`), I say a person is employed if they report being self-employed, a salaried worker, or an unpaid worker in the variable. In China, employed workers are those who reported working at least 1 day in the past week. Despite these slight definition differences, table C.4 shows that the employment rates I obtain are in line with the female labor force participation rates reported by the International Labor Organization and the World Bank (International Labour Organization, 2021).[19] The differences in the age ranges I consider drive the discrepancies for the United States, Vietnam, Thailand and China.

For all countries, I compute subnational employment rates at the lowest geographic unit available. For most countries, this corresponds to a geographic area akin to a district, a county, or a municipality. The only exception is the United States, where I compute these rates by commuting zone (Autor and Dorn, 2013). Table C.5 provides further details on the unit of aggregation and samples used. I winsorize the employment rates at the 5th and 95th percentiles by country. This reduces the possibility that very small regions drive the dispersion I observe within countries.

B The Empirical Strategy

In section 4.1, when I introduced the age of emigration data, I made the assumption that women's employment decisions are determined by place of residence fixed-effects δ_c, age of emigration fixed-effects λ_a, female labor force participation at birthplace p_b, and an error term η_{it}:

$$e_{it} \quad = \quad \delta_c + \lambda_a + \boldsymbol{\sigma}_a p_b + \eta_{it} \tag{9}$$

The error term embodies factors that are potentially important in determining women's decision to work, but which I do not observe. It is likely that these factors are correlated with the woman's birthplace employment rate. For example, generally I do not observe whether a woman's mother worked. This variable is naturally correlated with the birthplace female employment rate.

[19]The only exception is the Philippines, where the data from IPUMS International implies much lower employment rates. In my data, I obtain a female employment rate of 33% for women aged 18-64. The ILOSTAT database reports a female labor force participation rate of 48% for 15+ women in 2010. The gap between these two figures cannot be accounted for by female unemployment which is of the order of 4%. That said, I am interested in within-country dispersion, these discrepancies are second order as long data collection is consistent within the country.

To simplify the discussion, I write this model in its matrix form as follows:

$$E = D\boldsymbol{\omega} + P\boldsymbol{\sigma} + \boldsymbol{\eta}$$

here D is a matrix containing place of residence and age of emigration indicators, P contains interaction between the age of emigration fixed effects and FLFP at birthplace, $\boldsymbol{\omega}$ stacks the location and age of emigration fixed-effects, $\boldsymbol{\sigma}$ is a vector containing the age of emigration effects $\boldsymbol{\sigma}_a$, and η is error term vector.

My main interest is estimating the birthplace effects vector $\boldsymbol{\sigma}$ consistently. I will express the model just in terms of the birthplace effects and the unobserved components by residualizing it from both the age and the residency fixed-effects. Let $\tilde{Z} = I - D(D'D)^{-1}D'$. Then,

$$\tilde{E} = \widetilde{P}\boldsymbol{\sigma} + \tilde{\boldsymbol{\eta}}$$

now let us consider the OLS estimate of the birthplace effects $\hat{\boldsymbol{\sigma}} = (\widetilde{P}'\widetilde{P})^{-1}\widetilde{P}'E$. From the above expression it follows that,

$$\hat{\boldsymbol{\sigma}} = \boldsymbol{\sigma} + (\widetilde{P}'\widetilde{P})^{-1}\widetilde{P}'\tilde{\boldsymbol{\eta}}$$

Therefore:

$$\begin{aligned} \text{plim } (\hat{\boldsymbol{\sigma}}) &= \boldsymbol{\sigma} + \text{plim } \left[(\widetilde{P}'\widetilde{P})^{-1}\widetilde{P}'\tilde{\boldsymbol{\mu}}\right] \\ &= \boldsymbol{\sigma} + \gamma \end{aligned} \tag{10}$$

now let us examine the meaning of expression (10) in detail. This expression implies that the OLS estimate for the birthplace persistence at age a is the sum of two terms: (i) the birthplace effect effect at that age $\boldsymbol{\sigma}_a$, and (ii) a term that captures the correlation between the residualized employment rate at the origin and the residual for people emigrating at age a $\boldsymbol{\gamma}_a$:

$$\text{plim } (\hat{\boldsymbol{\sigma}}_{\boldsymbol{a}}) = \boldsymbol{\sigma}_a + \boldsymbol{\gamma}_a \tag{11}$$

B.1 Identification

Assumption 2. *Selection on unobservables does not depend on the age of emigration, that is* $\gamma_a = \boldsymbol{k}$

Assumption 2 essentially requires that correlation between women's unobservable characteristics and women's origin is the same no matter the age at which they move. To see this, note that $\boldsymbol{\gamma}$ is driven two components:

$$\boldsymbol{\gamma} = \text{plim } \left[(\widetilde{P}'\widetilde{P})^{-1}\right] \text{plim } \left[\widetilde{P}'\tilde{\boldsymbol{\eta}}\right]$$

The term plim $\left[\widetilde{P}'\tilde{\boldsymbol{\eta}}\right]$ captures the correlation between women's birthplace and the unobserved characteristics. This is evident when examining the general term of the vector $\widetilde{P}'\tilde{\boldsymbol{\eta}}$:

$$\sum_{i=1}^{N} \widetilde{p_b^a}\tilde{\eta}_i \tag{12}$$

where $\tilde{p}_b^a$ is the residualized interaction between the birthplace female employment rates and the age of emigration dummies. By law of the large numbers, this element converges to:

$$\mathbb{E}\left(\widetilde{p_b^a}\tilde{\eta}_i\right)$$

Two sufficient but not necessary conditions for the constant selection to be satisfied are:

$$\mathbb{E}\left(\widetilde{p_b^a}\tilde{\eta}_i\right) = \boldsymbol{c} \tag{13}$$

$$plim(\widetilde{P}'\widetilde{P})^{-1} = Q \tag{14}$$

where Q non-singular matrix with: (i) diagonal elements equal to each other, and (ii) off-diagonal elements equal to each other.

The first condition requires the correlation between women's unobserved characteristics and the birthplace FLFP to be the same for women migrating at different ages as children. For instance, this condition allows for the fact that in places where more women work they were more likely to have working mothers. A violation of (14) would occur if, for example, women with working mothers stayed longer in their birthplace.

Furthermore, note that condition (13) requires constant bias *conditional on age of emigration and current place of residence* as it only contains variables that have been residualized from current location and age of emigration fixed-effects. So, for example, even though women who migrated at 12 years old are more likely to migrate because of school than those that did it at 12 years old[20], this does not necessarily violate the constant bias assumption. This would be a problem only if, after conditioning on emigration age and place of residence, women from certain origins are more likely to migrate because of school at 12 than at age 10. While I cannot fully test for this condition, in section B.1 I provide supporting evidence by correlating birthplace female employment rate with observed women's characteristics for different emigration age cohorts.

Condition (14) imposes restrictions on the correlations between birthplace female employment for women migrating at different ages as children. They will be generally satisfied if women migrating at different ages came from roughly the same origins.

[20]Secondary in Indonesia starts at 13

B.2 From OLS to causal effects

The constant selection assumption allows ne to identify the causal effects of spending more time at the birthplace. Identification follows the same intuition as in Chetty and Hendren (2018a). Because $\boldsymbol{\sigma}_a$ captures the birthplace effect accumulated up to age a, the effect of spending age a at the birthplace is just the difference across consecutive ages:

$$\boldsymbol{\pi}_a = \boldsymbol{\sigma}_a - \boldsymbol{\sigma}_{a-1}$$

Under the constant bias assimption, we can obtain estimates of the causal effect by subtracting the OLS estimates. This is because the bias term goes away in the subtraction:

$$\hat{\boldsymbol{\sigma}}_{\boldsymbol{a}} - \hat{\boldsymbol{\sigma}}_{\boldsymbol{a-1}} = \boldsymbol{\sigma}_a - \boldsymbol{\sigma}_{a-1} \tag{15}$$

With an additional normalization, the OLS estimates can also identify the size of the selection term $\boldsymbol{k}$. If we normalize the causal effect for the children with the least exposure to birthplace to zero ($\boldsymbol{\sigma}_0 = 0$), the OLS coefficient for this children is an estimate of the selection term:

$$\hat{\boldsymbol{\sigma}}_{\boldsymbol{0}} = \boldsymbol{c} \tag{16}$$

Equations (15) and (16) provide a full guide for estimating the causal effects. OLS estimates for women who migrated at the earliest ages can be used to estimate the selection terms, while differences in the OLS estimates across different ages provide an estimate of the causal effect of spending a particular age or period in the birthplace.

B.2.1 Two alternative place effect specifications

Expressions (**??**) suggests two alternative regression specifications[21]. First, a “birthplace-effect” specification that uses within-destination variation in exposure:

$$e_{it} \quad = \quad \delta_d + \lambda_a + b_{ab}p_b + b_{ad}p_d + \eta_{it} \tag{17}$$

because this specification has destination fixed-effects this regression essentially compares the labor supply of women whom I observe living in the same location as adults, but who emigrated from different locations at different ages. This specification is geared to answer the question what would

[21]In an ideal scenario by using within origin-destination variation in exposure to these locations. That is, one could estimate σ_{ab} and σ_{ad} using a regression specification that includes origin and destination fixed effects, and interactions between age of emigration FLFP at the birthplace and the destination:

$$e_{it} \quad = \quad \delta_d + \varphi_b + \lambda_a + \sigma_{ab}p_b + (\sigma_{Ad} - \sigma_{ad})p_d + \epsilon_{it}$$

however this requires substantial variation in age of emigration *within* origin-destination pair. This is not possible given the number of observations I have in IFLS and the Intercensal Survey.

have happened if these women would have stayed longer in their original locations[22].

Identification of the place effects in this specification requires that, conditional on the place of residence, birthplace and destination FLFP is uncorrelated to the error term. More formally, we can express model (17) in matrix form as:

$$E = D\boldsymbol{\delta} + P\boldsymbol{b} + \boldsymbol{\eta}$$

where $\boldsymbol{\delta}$ stacks the destination and the emigration age fixed effects, $\boldsymbol{b}$ stacks the b_{ab} and b_{ad} coefficients, D contains the appropriate set of destination and emigration age dummies, and P contains a full set of interactions between emigration age dummies and birthplace FLFP, and emigration age dummies and destination FLFP.

By an argument analogous to that of section B.1, the OLS estimate of $\boldsymbol{b}$ can be expressed as a sum of the place effects and the omitted variable bias,

$$\hat{\boldsymbol{b}} = \boldsymbol{\sigma} + (\tilde{P}'\tilde{P})^{-1}\tilde{P}'\tilde{\boldsymbol{\eta}} \tag{18}$$

where $\tilde{Z} = (I - D(D'D)^{-1}D')Z$.

Assumption 3. *Constant selection within-destination: conditional on destination and age of emigration fixed effects, omitted variable bias is constant across emigration age*

$$(\tilde{P}'\tilde{P})^{-1}\tilde{P}'\tilde{\boldsymbol{\eta}} = \boldsymbol{k} \tag{19}$$

with $\boldsymbol{k}$ *a constant vector.*

Alternatively, we can have a "destination-effect" specification that uses within-birthplace variation in exposure to the destination:

$$e_{it} = \varphi_b + \lambda_a - h_{ab}p_b + h_{ad}p_d + \nu_{it} \tag{20}$$

because this specification has birthplace fixed-effects this regression essentially compares the labor supply of women whom were born in the same origin, but who emigrated to different locations at different ages. This specification is geared to answerthe question what would have happened if these women would have arrived earlier to their destination: or in its matrix form:

$$E = B\boldsymbol{\varphi} + P\boldsymbol{h} + \boldsymbol{\nu}$$

By an analogous argument, we can express the OLS estimate in terms of the place affects and

[22] In practice, because this specification has destination fixed effects, these fixed effects will absorb most of the variation of the interactions between emigration age and FLFP at the destination. Thus, effectively, identification of $b_a d$ will be challenging.

omitted variable bias:

$$\hat{\boldsymbol{h}} = \boldsymbol{\sigma} + (\dot{P}'\dot{P})^{-1}\dot{P}'\dot{\boldsymbol{\nu}} \tag{21}$$

where $\dot{Z} = (I - B(B'B)^{-1}B')Z$.

Assumption 4. *Constant selection within-origin: conditional on birthplace and age of emigration fixed effects, omitted variable bias is constant across emigration age*

$$(\dot{P}'\dot{P})^{-1}\dot{P}'\dot{\boldsymbol{\nu}} = \boldsymbol{m} \tag{22}$$

with $\boldsymbol{m}$ *a constant vector.*

A comparison between (19) and (22) shows the differences in the identification assumptions between the two approaches. The "birthplace effect" requires constant omitted variable bias across emigration age within the same destination. In other words, this essentially requires the correlation between birthplace FLFP and the unobservable characteristics of women from different origins to be the same no matter the age they emigrated. In contrast, "destination-effect" specification requires constant omitted variable bias across emigration age within the same origin. This essentially requires the correlation between destination FLFP and the unobservable characteristics of women from different destinations to be same no matter the age they left their birthplace.

C Tables and figures

Table C.1: Indonesia: number of existing rengencies by year, 1980-2010

	1980	**1990**	**2000**	**2010**
Number of regencies	286	295	339	493

Notes: These regencies have chaning borders across decades. In my analysis, in each year, I aggregate these unis into 268 consistent-boundary regencies. Data IPUMS international.

Table C.2: Dispersion in regional employment rates within countries

	Women			Men				
Country	**IQR**	**SD**	**Mean**	**IQR**	**SD**	**Mean**	**Pop.**	**Obs.**
Benin	0.35	0.19	0.44	0.08	0.06	0.76	57,764	77
Zimbabwe	0.30	0.19	0.59	0.13	0.08	0.77	70,597	88
Guinea	0.29	0.19	0.52	0.11	0.09	0.84	22,567	209
China	0.28	0.17	0.71	0.14	0.10	0.85	266,748	2,845
Nepal	0.26	0.17	0.63	0.05	0.03	0.81	191,443	72
Ecuador	0.24	0.13	0.43	0.03	0.03	0.83	104,465	78
Zambia	0.23	0.15	0.50	0.09	0.07	0.64	108,098	55
Indonesia	0.22	0.14	0.53	0.05	0.04	0.87	533,867	268
Myanmar	0.21	0.13	0.51	0.07	0.05	0.86	83,531	362
Panama	0.20	0.12	0.33	0.04	0.08	0.80	56,049	35
Tanzania	0.20	0.12	0.69	0.09	0.05	0.82	178,632	113
Vietnam	0.19	0.12	0.82	0.06	0.06	0.90	79,146	674
Brazil	0.19	0.11	0.48	0.19	0.11	0.73	59,010	2,040
Mexico	0.17	0.11	0.30	0.09	0.08	0.80	27,853	2,330
South Africa	0.16	0.11	0.30	0.06	0.06	0.53	138,127	224
Cambodia	0.16	0.11	0.84	0.08	0.05	0.90	50,186	174
Thailand	0.16	0.11	0.81	0.08	0.06	0.88	58,290	670
Costa Rica	0.16	0.08	0.37	0.05	0.04	0.73	48,673	55
Nicaragua	0.16	0.09	0.31	0.10	0.06	0.81	38,849	68
Argentina	0.15	0.10	0.53	0.08	0.06	0.83	75,022	312
Kenya	0.15	0.10	0.68	0.06	0.06	0.79	513,569	35
Sierra Leone	0.15	0.11	0.71	0.15	0.09	0.75	27,333	126
Togo	0.14	0.10	0.72	0.08	0.05	0.80	75,345	37
Philippines	0.13	0.10	0.30	0.08	0.06	0.82	40,423	1,274
Mauritius	0.13	0.20	0.53	0.03	0.06	0.83	16,626	50
Bolivia	0.12	0.06	0.58	0.05	0.03	0.86	70,323	80
Chile	0.12	0.08	0.51	0.05	0.04	0.79	57,826	192
Spain	0.11	0.08	0.51	0.09	0.06	0.61	105,902	286
Malaysia	0.11	0.07	0.38	0.06	0.04	0.84	91,509	133
Greece	0.10	0.06	0.43	0.05	0.04	0.66	42,492	156
Uganda	0.10	0.10	0.83	0.05	0.05	0.89	111,479	136
USA	0.09	0.07	0.67	0.10	0.07	0.77	202,635	722
Ghana	0.08	0.05	0.76	0.06	0.05	0.78	122,422	102
Senegal	0.06	0.05	0.19	0.09	0.06	0.58	233,811	27
Bangladesh	0.02	0.03	0.06	0.04	0.03	0.87	1,335,491	60

Notes: SD and IQR stand for Standard Deviation and Interquartile Range. The table shows statistics for all countries in IPUMS International with geographic data below the state/province level. Rows are ordered from the highest to the lowest IQR in women's employment rates. For all countries I use census sample from 2010 or the closest available year. I aggregate data at the smallest geographical unit available, except for the USA where I use Commuting Zones as in Autor and Dorn (2013). Column (7) shows the total population for the average geographic unit in each country. I show the unweighted cross-locality means which –might– differ from the national-level means.

Table C.3: Dispersion in employment and paid employment rates for selected countries

	All employment		Paid employment		
Country	**IQR**	**Mean**	**IQR**	**Mean**	**Observations**
Benin	0.35	0.44	0.37	0.41	77
Zimbabwe	0.30	0.59	0.30	0.59	88
Guinea	0.29	0.52	0.24	0.43	209
Nepal	0.26	0.63	0.27	0.62	72
Ecuador	0.24	0.43	0.23	0.42	78
Zambia	0.23	0.50	0.06	0.27	55
Indonesia	0.22	0.53	0.12	0.34	268
Panama	0.20	0.33	0.21	0.33	35
Tanzania	0.20	0.69	0.21	0.67	113
Vietnam	0.19	0.82	0.11	0.72	674
Brazil	0.19	0.48	0.20	0.46	2,040
Mexico	0.17	0.30	0.16	0.27	2,330
Thailand	0.16	0.81	0.09	0.69	670
South Africa	0.16	0.30	0.16	0.30	224
Costa Rica	0.16	0.37	0.16	0.37	55
Nicaragua	0.16	0.31	0.16	0.31	68
Argentina	0.15	0.53	0.15	0.53	312
Kenya	0.15	0.68	0.15	0.68	35
Sierra Leone	0.15	0.71	0.16	0.66	126
Togo	0.14	0.72	0.17	0.59	37
Philippines	0.13	0.30	0.12	0.28	1,274
Mauritius	0.13	0.53	0.13	0.52	50
Bolivia	0.12	0.58	0.12	0.56	80
Chile	0.12	0.51	0.12	0.51	192
Malaysia	0.11	0.38	0.11	0.38	133
Spain	0.11	0.51	0.11	0.50	286
Greece	0.10	0.43	0.10	0.43	156
Uganda	0.10	0.83	0.12	0.76	136
Ghana	0.08	0.76	0.08	0.61	102
Senegal	0.06	0.19	0.05	0.17	27
Bangladesh	0.02	0.06	0.02	0.06	60

Notes: IQR stands for Interquartile Range. The table shows data from all countries in table C.2 with data that distinguishes unpaid and family workers from other worker types.

Table C.4: Female labor force participation rages by country: IPUMS vs ILOSTAT

Country	**IPUMS (ages 18-64)**	**ILOSTAT (ages 15+)**	**Difference**
Cambodia	0.82	0.81	0.01
China	0.74	0.64	0.10
Indonesia	0.50	0.51	-0.01
Malaysia	0.43	0.43	-0.00
Myanmar	0.50	0.53	-0.03
Philippines	0.33	0.48	-0.15
Thailand	0.77	0.64	0.13
United States	0.67	0.58	0.10
Vietnam	0.79	0.72	0.07

Notes: Uses data from IPUMS international and ILOSTAT. I restrict the sample in IPUMS to people aged between 18-64 years old.

Table C.5: Source IPUMS samples for cross-country data

Country	Geographic unit	Years of sample	
Argentina	Department	2010	2001
Bangladesh	Upazila	2011	2001
Benin	Commune	2013	2002
Brazil	Municipality	2010	2000
Cambodia	District	2013	2008
Chile	Department	2017	2002
China	Prefecture	2000	
Costa Rica	Cantón	2011	2000
Ecuador	Cantón	2010	2001
Ghana	District	2010	2000
Greece	Municipality	2011	2001
Guinea	Sub-prefecture	2014	
Indonesia	Regency	2010	2000
Kenya	District	2009	1999
Malaysia	District	2000	1991
Mauritius	Municipal ward	2011	2000
Mexico	Municipality	2010	2000
Myanmar	Township	2014	
Nepal	Municipality	2005	1995
Panama	District	2010	2000
Philippines	Municipality	2010	2000
Senegal	Department	2013	2002
Sierra Leone	Sierra Leone	2015	2004
South Africa	Municipality	2011	
Spain	Municipality	2011	2001
Tanzania	District	2012	2002
Thailand	District	2000	1990
Togo	Prefecture	2010	
Uganda	County	2014	2002
USA[1]	Commuting zone	2012	
Vietnam	District	2009	2001
Zambia	Constituency	2010	2000
Zimbabwe	District	2012	

Note: the table details the source samples from the cross-country data in IPUMS International. All cross-country comparisons are based on the most recent sample. The less recent samples are used only for cross-country comparison of employment rate persistence. [1]USA data for 2010 comes from the 5-year ACS sample for 2012.

Table C.6: Indonesia: estimates birthplace persistence on women's labor supply (***b***)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Women's employment rate at birthplace (p_o)	0.38***	0.39***	0.35***	0.37***	0.34***	0.34***	0.29***	0.24***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.08)	(0.08)
Mean employment rate	0.54	0.54	0.54	0.54	0.54	0.54	0.51	0.51
Implied IQR gap	0.08	0.09	0.08	0.08	0.08	0.08	0.06	0.05
Sample	Full	Full	Full	Full	Full	Full	Known mother	Known mother
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Regency FE	✓	✓	✓	✓	✓	✓	✓	✓
Age		✓	✓	✓	✓	✓	✓	✓
Religion			✓	✓	✓	✓	✓	✓
Education				✓	✓	✓	✓	✓
Childhood SES					✓	✓		
Siblings						✓		
Mother worked								✓
Observations	64,501	64,501	64,501	64,501	64,501	64,501	18,135	18,135
N individuals	6,115	6,115	6,115	6,115	6,115	6,115	2,640	2,640
R^2	0.10	0.12	0.13	0.14	0.14	0.14	0.14	0.14

Notes: Uses data from IFLS. Sample restricted to people residing outside their birthplace. Implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone born at the 25th percentile. The IQR of the female employment rate across regencies is of 22 percentage points. Standard errors clustered by regency of origin. When indicated, the regressions control for a quadratic polynomial in age, and fixed-effects for seven religion and for education categories. Standard errors clustered by regency of origin.

Table C.7: Indonesia: estimates birthplace persistence on men's labor supply (***b***)

	(1)	(2)	(3)	(4)
Women's employment rate at birthplace (p_o)	0.01	0.04	0.05*	0.04
	(0.03)	(0.03)	(0.03)	(0.03)
Mean employment rate	0.90	0.90	0.90	0.90
Implied IQR gap	0.00	0.01	0.01	0.01
Year FE	✓	✓	✓	✓
Regency FE	✓	✓	✓	✓
Age		✓	✓	✓
Religion			✓	✓
Education				✓
Observations	60,126	60,126	60,126	60,126
N individuals	6,293	6,293	6,293	6,293
R^2	0.05	0.17	0.17	0.18

Notes: Uses data from IFLS. Sample restricted to people residing outside their birthplace. Implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone born at the 25th percentile. The IQR of the female employment rate across regencies is of 22 percentage points. Standard errors clustered by regency of origin. When indicated, the regressions control for a quadratic polynomial in age, and fixed-effects for seven religion and for education categories. Standard errors clustered by regency of origin.

Table C.8: Indonesia: estimates of birthplace persistence on labor supply (***b***) for men who emigrated young

	(1)	(2)	(3)	(4)
Women's employment rate at birthplace (p_b)	0.19***	0.19***	0.22***	0.19***
	(0.05)	(0.04)	(0.04)	(0.03)
Mean employment rate	0.87	0.87	0.87	0.87
Implied IQR gap	0.04	0.04	0.05	0.04
Regency-year FE	✓	✓	✓	✓
Age		✓	✓	✓
Religion			✓	✓
Education				✓
Observations	19,537	19,537	19,537	19,537
R^2	0.09	0.25	0.25	0.28

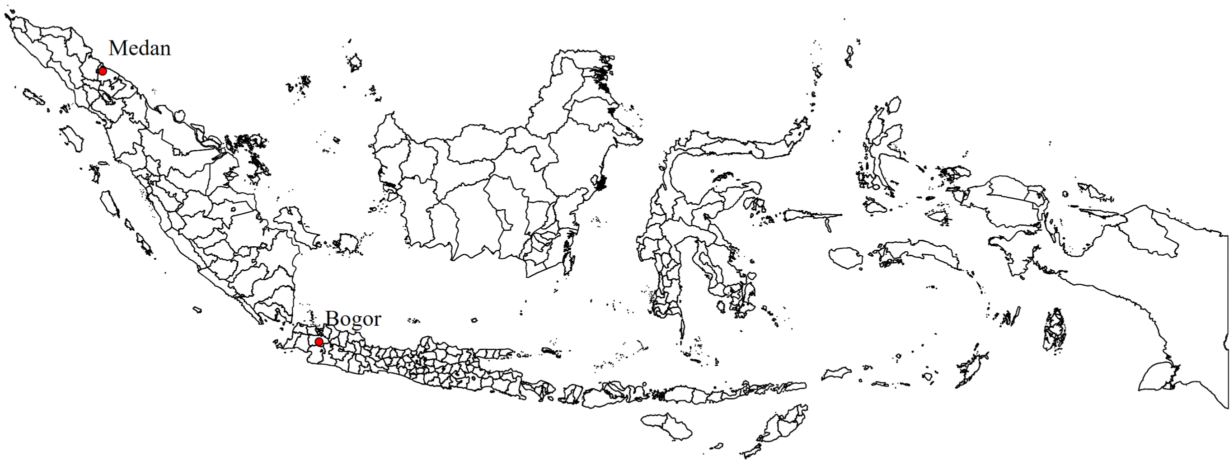
Notes: This table uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace and who left before they turned 19. The implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone born at the 25th percentile. The IQR of female employment rates across regencies is 22 percentage points. Standard errors are clustered by regency of origin. When applicable, regressions control for a quadratic polynomial in age and fixed effects for five religious and four education categories.

Table C.9: Indonesia: high female employment regencies have worse educational outcomes

	Years of schooling	**Primary completed**	**Secondary completed**
Regency group	(1)	(2)	(3)
Low female employment	7.86	0.78	0.30
	(0.13)	(0.01)	(0.01)
High female employment	6.82	0.70	0.21
	(0.13)	(0.01)	(0.01)
Observations	258	258	258

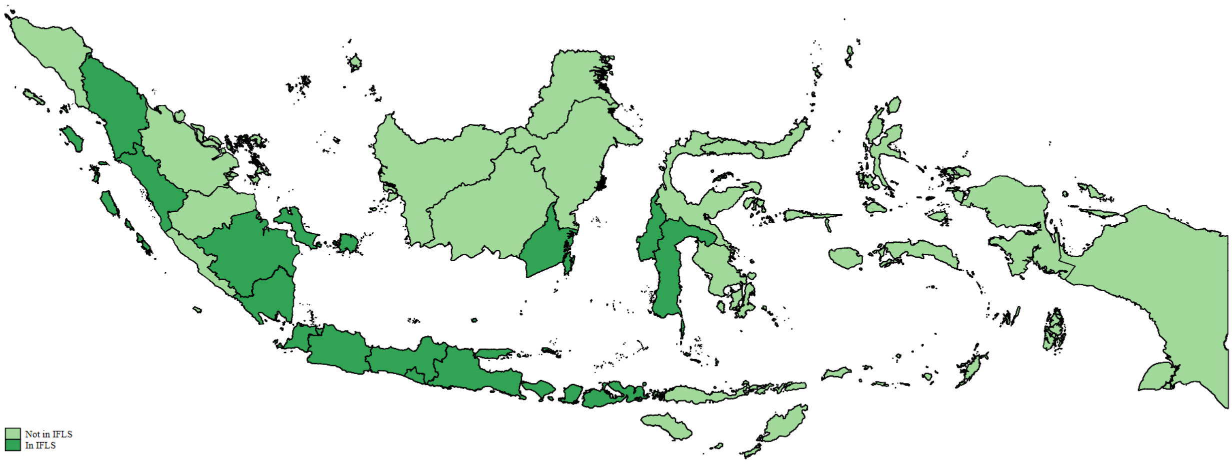
Notes: This table uses data from the 2005 Intercensal Survey. I split regencies at the median of the female employment rate.

Figure C.1: Indonesian regencies



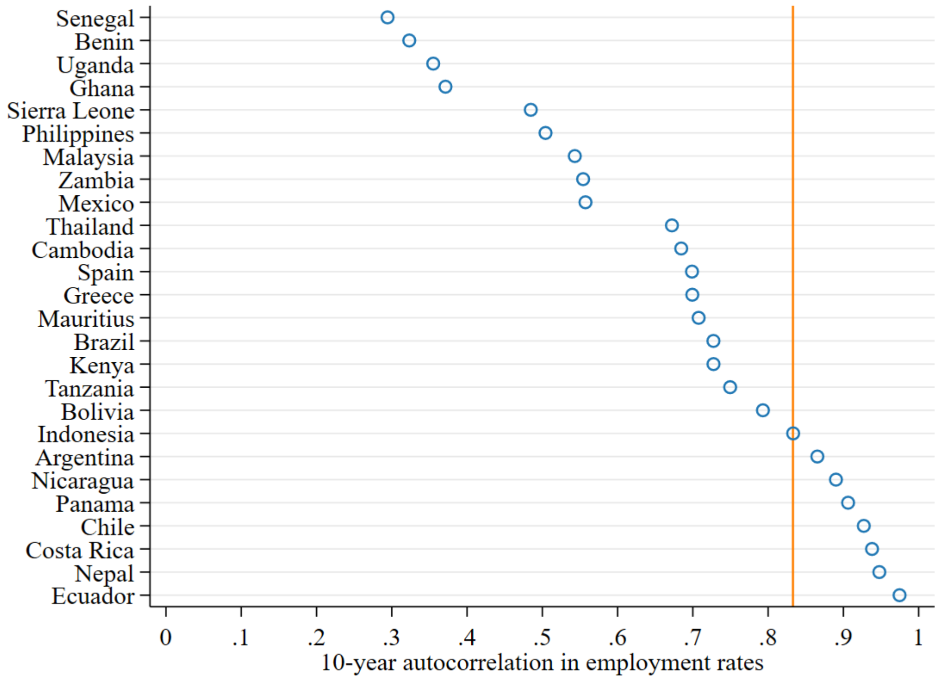
Note: The figure shows the 268 regency aggregates with consistent boundaries between 1970 and 2018. Boundaries obtained from IPUMS International. It highlights with red dots the locations of the city of Medan and Bogor regency. Medan, the capital and largest city in the province of North Sumatra, is the third most populous city in Indonesia as of 2020 (Brinkhoff, 2022). Bogor, with over five million people, borders the Jakarta metropolitan area.

Figure C.2: Provinces in the original 1993 IFLS sample



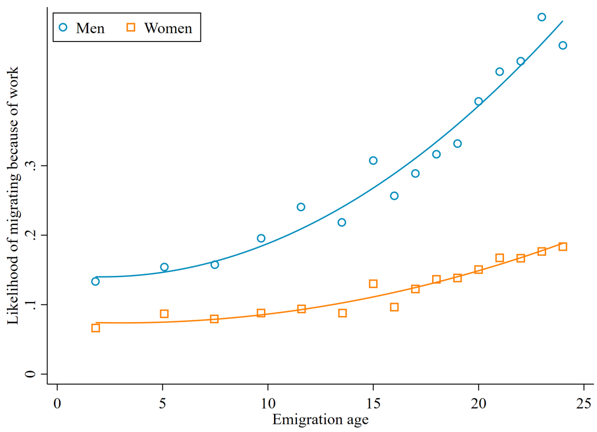
Note: The provinces from which the original 1993 IFLS sampled households. Because of migration, subsequent years can include individuals living outside these provinces. *Source:* RAND corporation.

Figure C.3: 10-year autocorrelation in female employment rates at the district level for selected countries



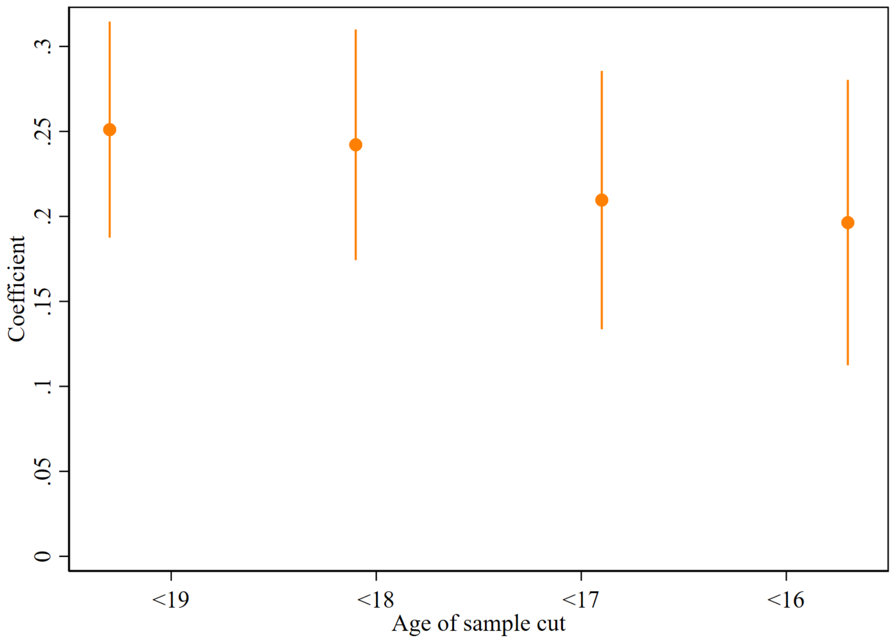
Note: The figure shows the 10-year autocorrelation in female employment rates. I aggregate data at the smallest geographical unit available which often corresponds to a district/county. Data from IPUMS international.

Figure C.4: Indonesia: likelihood of work-related migration by emigration age



Note: The survey does not distinguish whose work generated the move. Thus, the move can be related to parents' job, own job, or husband's / wife's job. Data from 1985 intercensal survey. The 1995 and 2005 surveys only list cause of migration for migration 5 years ago, and a very limited number of observations are available for people younger than 19. Figure generated on 1 Mar 2023 at 15:35:52.

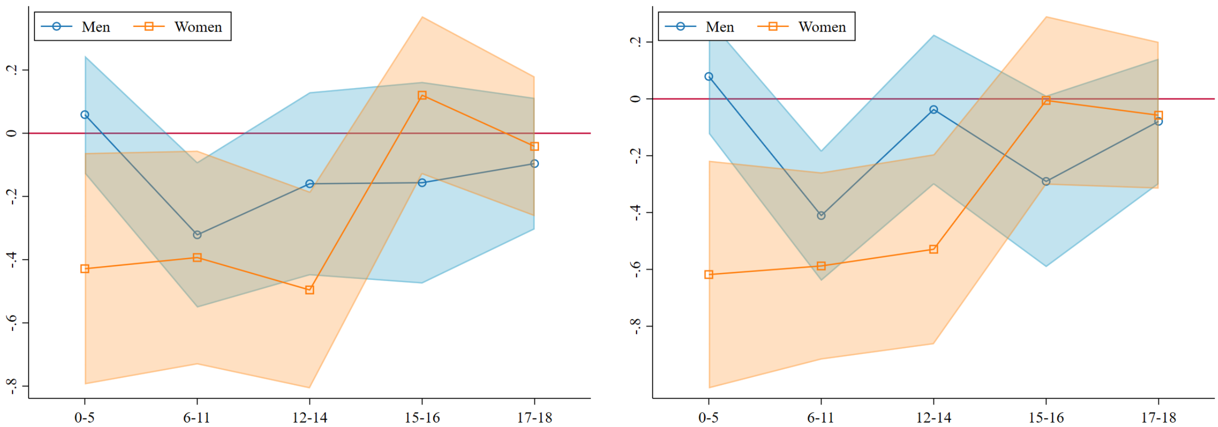
Figure C.5: Estimates of birthplace persistence for different emigration age cutoffs



Note: This figure uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace and who left before they turned 19. Standard errors are clustered by regency of origin. All regressions control for a quadratic polynomial in age and fixed effects for five religious and four education categories. The figure shows 95% confidence intervals.

Figure C.6: Indonesia: earnings and length of stay at birthplace

(a) Monthly earnings (b) Hourly wages



Note: Data from 1995 intercensal survey. The regression controls for current regency fixed-effects, a quadratic polynomial on age, and education level fixed-effects. The figure shows 90% confidence intervals.