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

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This version: May 31, 2024

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 local 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 14 years old. By the time they turn sixteen, women born in a location at the 75th of female employment will be 5 percentage points 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

*I am indebted to my patient advisors Daniele Paserman, Kevin Lang, and Linh Tô for their constant support and helpful comments on this project. Special thanks to Bilge Erten, Dilip Mookherjee, Patricia Cortés, Martin Fiszbein, Ana Moreno-Maldonado, Johannes Schmieder, Arindrajit Dube, Silvia Prina, Nils Lehr, Masyhur Hilmy and all attendants of the Empirical Microeconomics Workshop at Boston University for helpful comments and suggestions. Special thanks to Francesco Benatti for excellent research assistance. All errors are my own.

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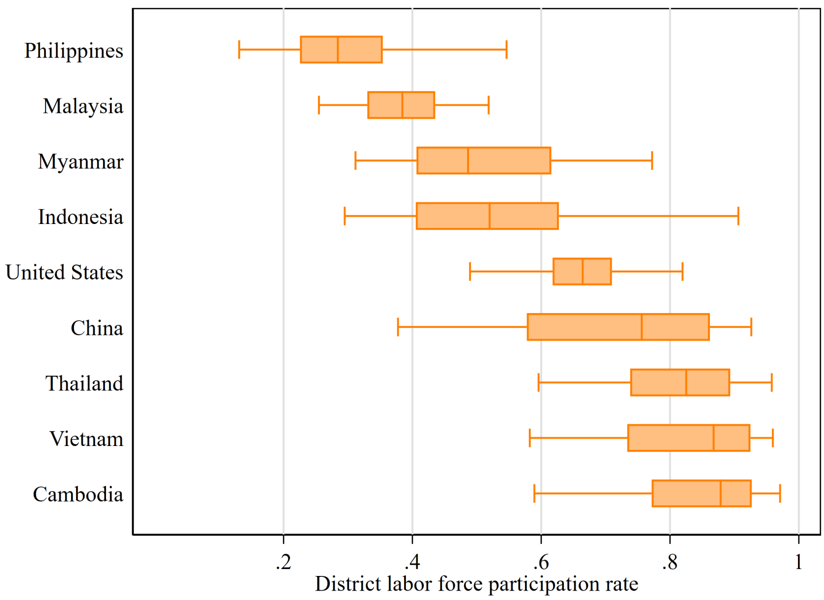
1 Introduction

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 FLFP rates within several developing countries and the United States. The FLFP rate gap between two localities within these countries is as large as 15 percentage points (p.p.) for most of them.[1] This large within-country dispersion in FLFP has generally gone unnoticed in the literature (Charles et al., 2023), and, as a consequence, we know very little about its causes and implications for 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 choices in adulthood. Consequently, we have limited insight into the extent to which current disparities are a constant feature of these localities or whether they can be transmitted across generations.

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/municipality 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, country or a municipality, except in the United States where I aggregate data for the US into Commuting Zones as in Autor and Dorn (2013). See Appendix Table A.1 for data on a larger cross-section of countries.

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

[1] Using the interquartile range as a benchmark, the gap between the localities at the 75th and the 25th percentiles of FLFP 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.

Using rich data from internal Indonesian female migrants, I demonstrate that their birthplace significantly impacts their adult labor force participation.[2] I identify the causal effect of the birthplace by leveraging variation among women who live in the same labor market as adults but who left their birthplace at different ages. This approach allows me to exploit variation in the time spent in the birthplace, disentangling the causal effect of the birthplace from differences driven by permanent characteristics of women or localities.

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. 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. 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. Unlike Chetty and Hendren (2018a), I focus on the effect of the origin rather than the destination labor market. By keeping exposure to the destination location fixed, I uncover variation that is likelier to be driven by women's labor supply choices rather than variation in the structure of labor demand across locations.

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 more likely they are to enter the labor force later in life. Under my preferred specification, residing in a place at the 75th percentile of female employment between the ages of 6 and 14 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. In contrast, I do not find similar effects for men. Depending on the specification, residing longer in high-FLFP locations has either no effect or a negative effect on men's employment in adulthood.

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) transmission of culture and/or gender norms, (ii) higher investment in schooling, and (iii) changes in parental investment (Molina and Usui, 2022; Fogli and Veldkamp, 2011; Blau et al., 2011). My results could be consistent with transmission or learning of gender norms. I find evidence evidence that women who spent more time in high-FLFP places also delay their marriage. Moreover, the birthplace effects are concentrated during the ages when children's attitudes towards gender equality are still malleable (Jayachandran, 2021). In contrast, I find little evidence indicating that these place effects are driven by changes in women's schooling decisions or parental investment. I find no evidence that women with more exposure to high-FLFP locations stay longer in school. Moreover, high-FLFP locations have worse schooling outcomes across the board, suggesting that they have lower-quality schooling. In addition, if parental investments were the primary driver behind these

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

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, such a high degree of sensitivity during such a specific age range seems unlikely.

My estimates assume that omitted variable bias is constant across emigration ages; that is, the correlation between birthplace FLFP and other unobserved determinants of women's labor supply is the same regardless of the age at which they emigrated. Note that differences in factors I do not control for between women born in different locations are not sufficient to violate this assumption. For example, women from high-FLFP locations may be more likely to work because their parents had higher resources to invest in their education compared to those born in locations with low female employment. This would create differences between women from different origins that are not driven by birthplace effects. However, this does not necessarily violate the constant bias assumption. 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 showing that the gap in resources and other covariates remains fairly constant across different ages of emigration, thereby supporting the assumption of my identification strategy.

In the paper, I use data from Indonesia, the fourth most populous country in the world and home to more than 118 million women. I take advantage of rich datasets that store people's birthplace and current location at a detailed geographic level. My main analyses source data the 1985, 1995, and 2005 intercensal surveys and all waves from the Indonesian Family Life Survey (IFLS) (Central Bureau of Statistics, 2021; Minnesota Population Center, 2023). 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." These are medium-sized administrative geographies akin to counties in the United States. The average regency in my dataset is approximately twice the size of the US state of Rhode Island and houses eight hundred thousand people.[3]

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., 2023; Boelmann et al., 2021). I make three main contributions to this literature. First, by applying techniques inspired by the place effects literature (Chetty and Hendren, 2018a,b; Milsom, 2023; Moreno-Maldonado, 2019), I provide causal evidence that a woman's birthplace has large and persistent effects on her labor supply even after exposure has ceased. This complements existing evidence showing 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, 2023). Second, I also provide evidence on the ages at which birthplace is most influential in shaping labor supply. Although previous

[3] The "regencies" in my dataset are slightly larger than the actual regencies available in the 2010 Indonesian census. I aggregate these regencies in the raw data into geographic units with consistent boundaries across time. See section 2.2 for further details.

research has pointed out that women's childhood environment matters for their adult outcomes, this literature is mostly silent on *when* it matters. Third, my results provide new evidence that where women grow up can have significant local impacts. 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., 2023; Boelmann et al., 2021; Alesina et al., 2013). By using 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), criminal activity (Damm and Dustmann, 2014), and political behavior (Brown et al., 2023). 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 and Japan (Milsom, 2023; Molina and Usui, 2022).

Finally, my paper contributes to the literature on the determinants of women's labor supply. This literature has primarily exploited cross-country differences in female labor supply to study its determinants and 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 explore some of its implications. In this way, my approach aligns more closely with recent literature documenting that factors such as commuting and sexism can explain geographic differences in women's labor supply within the United States and France (Charles et al., 2023; 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 it with place characteristics coming from the Indonesian Census and the National Socioeconomic Survey (SUSENAS).

My primary results come from the Intercensal Survey (Central Bureau of Statistics, 1985, 1995, 2005; Minnesota Population Center, 2023). 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 counties in the US. Research on Indonesia typically uses them to identify local labor markets (Magruder, 2013; Bazzi et al., 2023), and their size allows me to study differences in women's employment across smaller geographic units than what could observed in alternative datasets.[4] 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.[5]

Second, rich data on historical migration patterns allows me to recover the age at 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 of approximately two and a half million people. 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 is a panel that contains rich socioeconomic information, such as childhood conditions and proxy measures of parents' wealth, that allow for the study of potential confounders. However, this comes at the cost of a smaller sample size. The panel tracks 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.[6]

I also source place characteristics from the 1980-2010 Indonesian Decennial Censuses available in IPUMS International (Minnesota Population Center, 2023; Central Bureau of Statistics, 1980, 1990, 2000, 2010) and the 2012, 2013, and 2014 National Socieconomic Surveys (SUSENAS) (Central Bureau of Statistics, 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.

2.2 Measurement

My main measure of women's labor supply is a dummy equal to one if she was employed during the year.[7] 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.

[4]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).

[5]As Appendix Figure B.1 shows, regencies are smaller in the denser islands of Java and Sulawesi.

[6]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.

[7]This definition classifies unpaid and family workers as employed. The patterns I discuss look similar when I focus on paid workers only.

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. For example, just between 2000 and 2010, 154 new regencies were established. To address this issue, I use regency aggregates that had fixed boundaries between 1970 and 2010. These regency aggregates were constructed by IPUMS International and consist of 268 geographic units that are only slightly larger than the "original" regencies in the data (Minnesota Population Center, 2023). Additional details are found in Section C.1 of the appendix. Moving forward, I will refer to these regency aggregates as regencies.

I proxy for moving distances by calculating the distance between the centroids of the regency of residency and the regency of birth. While there is a risk of overestimating migration distances between neighboring regencies if, for example, most of the moves are happening just around the borders, this method is generally a reliable proxy for moves between regencies that are not contiguous.

For my main analysis, I restrict my sample to one-time internal migrants. This is because I can distinguish the effect of the current place of residence from the birthplace only for migrants, and I can infer the age of migration only for people who migrated only once. I define migration as living outside the regency of birth. Additionally, whenever I link women's employment to birthplace characteristics, such as FLFP or urbanicity, I source these from the 2010 Indonesian Census.

2.3 Summary statistics

In this section, I provide an overview of my data using 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. Additionally, there are significant gender gaps in employment, worker type, and industry of work. Women are 38 percentage points less likely to work than men, which, while a large gap, is consistent with patterns observed in Southeast Asia. Furthermore, women are five times more likely than men to be unpaid or family workers. Unpaid workers are people that work or help to earn an income but are not paid a wage or salary (Central Bureau of Statistics, 2018). Most unpaid workers work in agriculture (82%) and the retail industry (10%). Lastly, women are more likely than men to work in service and manufacturing industries.

Table 1: Indonesia: summary statistics by gender

	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	0.23	0.20	0.27
Urban	0.37	0.37	0.38
Muslim	0.81	0.81	0.81
Migrant	0.21	0.20	0.22
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 pooled 1985, 1995 and 2005 Intecensal Surveys. Sample restricted to people aged 18 to 64 years old. Migration is defined as residing outside of one's birthplace.

Table 2: Indonesia: women's characteristics by migration status and age of migration

		Migrants	
	Non-migrants	**All**	**Left before 18**
	(1)	(2)	(3)
Age	35.50	35.43	30.51
Married	0.71	0.75	0.66
Attended at least high school	0.16	0.31	0.25
Urban	0.30	0.65	0.61
Muslim	0.81	0.83	0.85
Children in household	0.71	0.72	0.63
Children ever born[1]	0.92	0.91	0.91
Employed	0.48	0.42	0.40
Type of worker			
Self-employed	0.39	0.34	0.33
Salaried	0.24	0.42	0.40
Unpaid / family worker	0.37	0.24	0.27
Industry of employment			
Agriculture	0.56	0.30	0.35
Services	0.32	0.59	0.52
Manufacturing	0.11	0.11	0.12
Construction	0.01	0.01	0.01
Reason for migrating[2]			
Work		0.14	0.10
Education		0.06	0.07
Other		0.81	0.83
Migration distance (km)		687	447
Observations	518,018	134,031	40,366

Notes: Data from the pooled 1985, 1995 and 2005 Intercensal Surveys. Column (2) shows data for women living outside their birthplace, while column (3) does it for those who left their birthplace before they turned 18. [1]Number of children ever born is available on the 1995 Intercensal Survey only. [2]Uses data from the 1985 Intercensal Survey only. 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. I present statistics for non-migrants, all migrants, and women who migrated before they turned 18. The table highlights some large differences between migrants and non-migrants: female migrants are more educated but less likely to be employed than non-migrants. Moreover, migrants are more likely to hold salaried jobs and live in urban areas. This suggests that they are moving to areas with more formal labor markets and less rural environments. Lastly, column (3) shows that other than the marriage rates and the level of education, women who left migrated at young ages are generally very similar to the typical female migrant.

In the final rows of table 2, I provide additional details on the characteristics of the move. 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 suggests that the great majority of these moves are due to family-related reasons. In addition, the last row summarizes migration distances in kilometers. On average, migrants undertake long-distance moves covering 687 kilometers (426 miles). To provide context, this is approximately the distance between Boston and Washington D.C which is an 8-hour drive. Even in the case of early migrants who travel shorter distances, their moves still span 438 kilometers (272 miles).

The fact that migrant women are more likely to work in the service sector could suggest that migration in Indonesia is predominantly from rural to urban areas. 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 in regencies I classify as urban matches the aggregate urban share reported by the Indonesian Cen. Next, I 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: 18% of women born in rural regencies migrate, versus the 23% of urban-born women. 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 only by differences between urban and rural areas.

Table 3: Indonesia: 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	0.61	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
SD	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 the Intercensal Survey.

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 labor supply. 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 several countries, including Indonesia and the United States. These countries are selected from a larger set with regional employment data available below the province or state level in IPUMS International.[8] 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.

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 variation in women's employment rates *within* their borders.[9] 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).[10]

Second, the dispersion of female employment rates is a widespread phenomenon across countries at different levels of development and geographic regions. Table 4 includes countries from Asia, the Americas, Africa, and Europe. It also includes middle income countries like Indonesia and Mexico, and high income countries such as 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 (4) 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 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.[11]

[8]Data for the full set of countries is available in Table A.1 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 C.2 in the appendix

[9]Table A.2 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.

[10]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.

[11]While the district employment rates are measured with error, I find unlikely that this is the primary driver of the dispersion of female employment. The variation in women's employment is much larger than that of men's across most countries. Even if measurement error were greater for women than for men, this difference would have to be substantial to account for the gender differences shown in Table 4.

Table 4: Dispersion in regional employment rates for selected countries

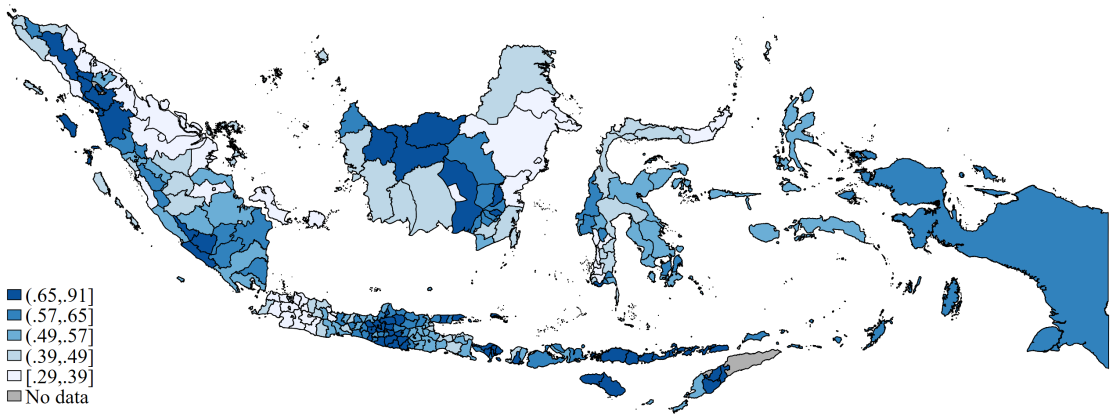
	Women			Men			Avg unit population	N. geographic units
	IQR	**SD**	**Mean**	**IQR**	**SD**	**Mean**		
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China	0.28	0.17	0.71	0.14	0.10	0.85	266,748	2,845
Indonesia	0.22	0.14	0.53	0.05	0.04	0.87	533,867	268
Myanmar	0.21	0.13	0.51	0.07	0.05	0.86	83,531	362
Panama	0.20	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 A.1 and section C.2 in the appendix for additional details on the cross-country data.

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%. This last group includes significant population centers such as the Bogor regency and the city of Medan.[12] More importantly, 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.

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



Notes: 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 that are 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 error, we should expect very low persistence in the regencies' employment rates across years. This is because temporary shocks should dissipate after several years, and I expect measurement error to be independent across decades. In contrast, high cross-year persistence indicates that the variation in women's employment likely reflects structural differences across regencies.

[12] 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 B.1 in the appendix.

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 standardized the regency employment rates separately by year and run regressions of the form:[13]

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

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

The autocorrelation estimates 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.[14]

[13]This means I extract decade-specific means in the employment rates.

[14]The large persistence of female employment rates is not exclusive to Indonesia. Figure B.2 shows that large 10-year auto-correlations also arise in other countries. For most countries, this auto-correlation is over 67%.

3.4 Fact 4: dispersion in women's employment rates cannot be accounted by differences in women's characteristics 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 of employment across these labor markets. Motherhood is associated with lower female attachment to the 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 could 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 of employment. 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 time 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. This means that 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

I start this section by showing that, conditional on the current place of residence, birthplace is highly predictive of women's labor supply in adulthood even for those that migrated before they turned 18. This persistence can reflect the causal effect of birthplace or a spurious correlation driven by women's unobserved characteristics. I then illustrate how can I use data of age at migration to separate these two sources of variation, and show evidence that the longer female migrants stay in their birthplace, the stronger the predictive power of birthplace is. I interpret this as evidence that longer stay in birthplace has a causal effect on women's labor supply decisions.

4.1 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 ($\omega_{c(i)t}$),[15] women's employment rate in her regency of birth ($p_{b(i)}$), 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.

$$e_{it} \quad = \quad \omega_{c(i)t} + \boldsymbol{b} p_{b(i)} + X_{it}\kappa + \varepsilon_{it} \tag{2}$$

I compute the employment rate $p_{b(i)}$ using the sample of all women aged 18 to 64 living in regency b in the census of 2010. I obtain similar results when using data from previous census years.[16]

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

[15] The $c(i)$ notation emphasizes that this refers to the current place of residence of individual i.
[16] This is because employment rates are highly persistent.

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 $\delta_{c(i)t}$.

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 birthplace persistence on female labor supply

	Women			**Men**		
	(1)	(2)	(3)	(4)	(5)	(6)
Female LFP rate at birthplace ($p_{b(i)}$)	0.33***	0.32***	0.33***	0.10***	0.08**	0.08***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Mean employment rate	0.423	0.423	0.423	0.862	0.862	0.862
Implied IQR gap	0.073	0.072	0.074	0.022	0.019	0.017
Regency-year FE	✓	✓	✓	✓	✓	✓
Age		✓	✓		✓	✓
Education			✓			✓
Observations	110,872	110,872	110,872	115,772	115,772	115,772
R^2	0.07	0.07	0.09	0.06	0.22	0.23

Notes: This table uses data from the pooled 1985, 1995 and 2005 Intercensal Surveys and restricts the sample to people 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 FLFP 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 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 0.33 indicates that birthplace is highly predictive of women's employment. To make the magnitude more concrete, let us consider two women: Putri and Amanda. They both live in Jakarta, but 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 Sukoharjo in Central Java, which has a female employment rate of 62%. These rates place these regencies at approximately the 25th and the 75th percentiles of the distribution of female employment rates. The 0.33 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 education barely modifies the estimate. Thus, this persistence is not explained by geographic differences in these factors. 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, column (3) indicates that the birthplace persistence is not driven by differences in educational investment.

Table 7 also shows that the strong birthplace persistence in labor supply is essentially exclusive to women. In columns (4) to (6) I display estimates from regressions where I relate men's employment in adulthood to their birthplace's *FLFP* 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 (6) implies an IQR gap of only 1.7 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 Table 8 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 (3) of Table 8 I reproduce the birthplace persistence estimates for the women migrants in the IFLS using the same specifications as in Table 8. Reassuringly, these results confirm the Intercensal survey estimates, with a similarly large implied IQR of 8 p.p.[17]

Moreover, columns (5) to (8) of Table 8 rule out childhood socioeconomic status and maternal labor supply as main 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 across regencies. 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 is the main driver of my results.

[17] Moreover, Table A.4 in the appendix shows very small persistence estimates in the male sample.

Table 8: Indonesia: estimates birthplace persistence on women's labor supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female LFP rate at birthplace ($p_{b(i)}$)	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 the IFLS. Sample restricted to people residing 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 the FLFP 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.

4.2 There is large persistence even 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 18. 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.[18] Reassuringly, I obtain similar persistence estimates for these sample.[19] Moreover, these estimates are robust to the choice of the migration age cutoff (see Figure B.3 in the appendix).

Table 9: Indonesia: estimates birthplace persistence on labor supply for women who migrated young

	(1)	(2)	(3)
Women's employment rate at birthplace (p_b)	0.33***	0.33***	0.34***
	(0.03)	(0.03)	(0.03)
Mean employment rate	0.42	0.42	0.42
Implied IQR gap	0.07	0.07	0.08
Regency-year FE	✓	✓	✓
Age		✓	✓
Education			✓
Observations	36,738	36,738	36,738
R^2	0.08	0.08	0.09

Notes: This table uses data from the pooled 1985, 1995, and 2005 Intercensal Surveys and restricts the sample to women migrated before they turned 18. 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 FLFP across regencies is 22 percentage points. Standard errors are clustered by regency of birth. When applicable, regressions control for a quadratic polynomial in age and fixed effects for four education categories.

4.3 The birthplace persistence is stronger the longer you stay

The strong birthplace persistence in women's labor supply could still reflect unobservable differences between women born at different regencies. In this section, I address this concern by exploiting differences in the timing of migration to argue that this persistence reflects the causal

[18] I cut at 17 years old because there is a large uptick in the number of people migrating at 17, which suggests at this age migrants are likely to move by their own accord.

[19] Appendix Table A.5 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.

effect of women's birthplace. I first illustrate how I use data on age of migration to identify the birthplace effects and the identification assumptions I need. Next, I show that the birthplace persistence is indeed stronger the longer women stay in their origin labor market, and that this stronger persistence is driven by access to *paid employment*. Finally, the section concludes by showing evidence that support my identification assumptions.

4.3.1 Exploiting data on length of stay

I exploit data on data on length of stay and augment expression (2) by (i) allowing the coefficient on FLFP to vary by migration age ($\boldsymbol{b_a}$), and (ii) allowing the regency fixed effects to vary by year and age of migration ($\omega_{c(i)at}$):

$$e_{it} \quad = \quad \omega_{c(i)at} + \boldsymbol{b}_a p_{b(i)} + X_{it}\kappa + \varepsilon_{it} \tag{3}$$

The age-specific persistence coefficients b_a are identified from variation within regency-year-age cells. In other words, they stem from comparing the labor supply choices of women who have been in the same destination regency for the same length of time but who were initially exposed to different FLFP rates. Therefore, differences in the b_a across ages are driven *only* by differences in the length of exposure to the origin FLFP.[20]

In specification (3), I focus on the effect of the origin labor market. This differs from Chetty and Hendren (2018a), who study the effect of the destination labor market. Two reasons support this choice. Firstly, persistent effects from the origin location even after the exposure has ceased are interesting in their own right. Secondly, by considering the origin rather than the destination, I can more effectively argue that any observed effects stem from women's labor supply choices rather than differences in labor demand structures across locations.

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

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

the selection term γ reflects omitted variable bias. This parameter captures the fact that women from the same origin are likely to share characteristics that make them more (or less) likely to work, but which are not driven by a causal effect of place. For example, parents in areas with high female employment might be richer and more likely to invest in their daughters education. Under the key assumption that this omitted variable bias is constant across migration age cohorts (i.e. γ is age-independent), I can identify the causal effect of place at any given age (π_a) by subtracting

[20] Note that the regency fixed effects also vary by survey year to allow flexibility on the effect of the current labor market. My dataset includes data from 1985 to 2005, and Indonesia experienced important structural changes during this time. For example, there was a 15% decline in the share agricultural employment, which went from 52% in 1991 to 44% in 2005 (World Bank, 2024).

the persistence coefficients across migration ages:[21]

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

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

To estimate this model, I leverage data about the age of migration from the Intercensal Survey. However, adding current-regency fixed effects that vary by survey year and by migration age imposes considerable data requirements. To identify the birthplace coefficients, the regency-year-age cells should be big enough to contain women from different birthplace regencies. However, because the number of people migrating at any given age is small relative to the number of regencies, I am forced to bin migration ages into multi-age cells: (i) 0 to 3, (ii) 4 to 8, (iii) 12 to 14 years old, and one-year cells thereafter. Table A.3 in the appendix shows that this grouping creates cells of reasonable sizes.

Adding regency-by-year-by-age fixed effects places considerable demands on the data. Therefore, when sample size becomes a concern, I also adopt a less demanding specification that uses regency-by-year ($\omega_{c(i)t}$), and year-by-migration age fixed effects (λ_{at}):

$$e_{it} \quad = \quad \omega_{c(i)t} + \lambda_a + \boldsymbol{b}_a p_{b(i)} + \boldsymbol{d}_a p_{c(i)} + X_{it}\kappa + \varepsilon_{it} \tag{4}$$

where I included the FLFP at the current regency ($p_{c(i)}$) to capture the effect of longer exposure to the current location. While this specification offers the advantage of being less demanding relative (3), it comes with the limitation of being much less flexible in terms of how the destination regency affects women's choices. Note that the model in (4) roughly identifies the age-specific persistence coefficients b_a by comparing women living in the same regency adulthood, but who migrated from regencies with different FLFP at different ages. In practice, however, the results under (3) and (4) are quite similar.

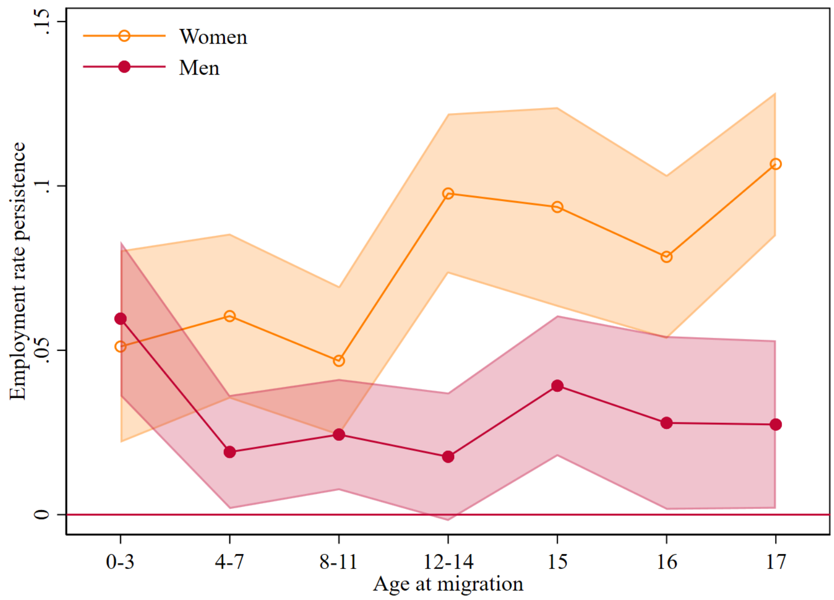
4.3.2 Longer stay does make you more likely to work

Figure 3 displays estimates of birthplace persistence ($\boldsymbol{b_a}$) by age of migration for both men and women. My sample remains restricted to people who left their birthplace before they turned 17. The regressions control for a quadratic polynomial in age, as well as current regency-year-migration age, and education-level fixed effects. The coefficients were rescaled to allow direct interpretation as the implied gap between women born in regencies at 75th percentile versus the 25th percentile of FLFP.

Figure 3 shows a striking pattern in the birthplace coefficients: women with longer exposure to high-employment locations are more likely to work. Women's slopes increase from 5.1 p.p. for

[21] Chetty and Hendren (2018a) identify the place effects by exploiting variation in the age of migration across siblings within the same family. I cannot apply this strategy with my data because neither the Intercensal Survey nor IFLS does not contain sibling information.

Figure 3: Indonesia: length of stay and likelihood of employment



Notes: The figure shows estimates of the birthplace persistence coefficients by age of migration $\boldsymbol{b_a}$. The coefficients are rescaled so that they can be interpreted as the implied gap between women from 75th and 25th percentile regencies. The regression controls for regency-by-year-by-migration age fixed-effects, a quadratic polynomial on age, and education level fixed-effects. Standard errors are clustered by regency of birth. The figure shows 90% confidence intervals. It uses data from 1985, 1995 and 2005 Intercensal surveys.

the least exposed women (those leaving at the age of four or younger), to 10.7 p.p. for the those with the most exposure. Women leaving a high-FLFP regency before the age of four have minimal exposure to their birthplace, and yet these results imply that they are more likely to work than women who left low-FLFP regencies at that same age. Following the discussion in Section 4.1, I interpret the 5.1 p.p. slope as reflecting unobservable differences that make women from high-FLFP more likely to work from the outset. In contrast, I interpret the 5.6 p.p. increase in the slopes as stemming from the effect of longer exposure to high-FLFP regencies.

These results suggest that place effects play a crucial role in driving geographic differences in women's labor supply. The 5.6 p.p. increase is fairly large when compared to multiple benchmarks: it is approximately one fourth of the gap in FLFP between the 75th and 25th regencies, and it is 14% of overall employment rate for migrant women in the sample (40%).[22]

Figure 3 also suggests that birthplace effects take effect before late adolescence. The slopes after 14 years old are roughly constant. This suggests that additional exposure during late in adolescence has little effect over women's labor supply choices later in life. Although figure 3 shows a sharp increase in the 12-14 slope, I want to emphasize that these slopes are noisy and it is possible that the birthplace effects are more gradual than what Figure 3 suggests.[23] In fact, in Figure B.5 I

[22] The employment rate for the women in the early migrant sample has changed remarkably little since 1985. It was 36% in 1985, 40% in 1995 and 42% in 2005.

[23] I can reject the hypothesis that all slopes are the same at the 1% significance level. Moreover, the 12-14 slope is

estimate the less demanding specification from equation (4) which allows me to disaggregate a bit more the age bins. Although the point estimates are very similar, the estimates at early ages are more unstable with slight increases at 3-5 and after 6 years old, which could be consistent with a more gradual effect from longer exposure to the origin labor market.

In addition, Figure 3 presents birthplace persistence estimates for men. Similar to women, men from high-FLFP locations possess traits that make them more likely to work. However, all the slopes from age 4 onwards are smaller than those for ages 0-3. Although a decline in the slopes suggests that very early exposure to these locations makes men less likely to work, the patterns for men are much less clear. Overall, there is a decline of 3.3 p.p. between the first and last slope. If were to take this decline seriously and combine it with women's results, they imply a decline of 8.9 p.p. in the gender gap in employment because of longer exposure to high-FLFP regencies.

4.3.3 Longer stay translates into similar patters for other outcomes

In Figure 4 I show that longer exposure to high-FLFP 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 Figure 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 is driven by *paid employment*. The rise in the coefficients between 0 to 17 years old translates into an increase of 3.8 p.p. in the likelihood of paid employment for women exposed longer to high-FLFP regencies. This is 68% of the effect on any employment from Figure 3. This contrasts with results on unpaid work where there is little evidence of a clear and meaningful effect.

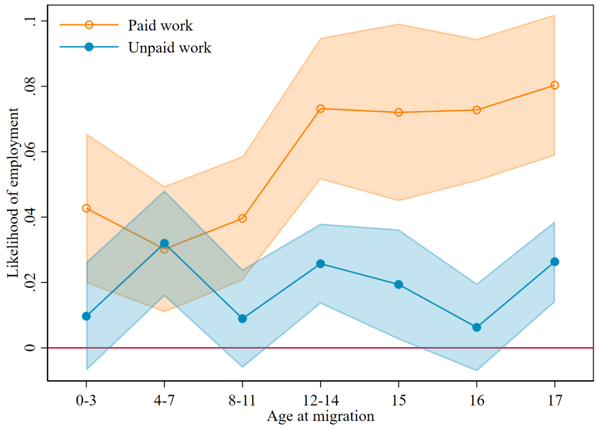
Panel (b) of Figure 4 shows additional results on weekly hours of work. Data on weekly hours of work is not available in the 2005 Intercensal Survey, thus, these results use data from the 1985 and 1995 surveys only. Although the estimates are noisier, the plot shows a picture in line with the previous results: staying in high female employment places raises women's labor supply. The overall increase in the slopes up to 17 years old translate into an increase of 3 weekly hours of work for women exposed longer to high-FLFP regencies. This an increase of 33% in work hours relative to the mean of 15 hours for the sample.

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 work longer hours. A natural question is whether they also have higher earnings. I answer this question in Figure B.6 in the appendix 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. Moreover, earnings information is only available in the 1995 survey, which further reduces the sample. Because this is a much smaller sample, I am forced to use wider bins for the emigration age. These results are noisy, but they give some

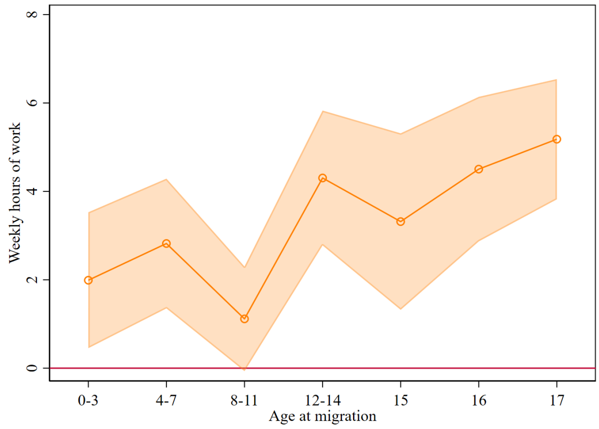
significantly greater than the 0-3 slope at the 1% level.

Figure 4: Results on alternative labor market outcomes

(a) **Type of employment**



(b) **Weekly hours and full time employment**



Notes: The figure shows estimates of the birthplace persistence coefficients by age of emigration $\boldsymbol{b_a}$. The coefficients are rescaled so that they can be interpreted as the implied gap between women from 75th and 25th percentile regencies. Uses data from the 1985, 1995 and 2005 Intercensal Surveys. The figure shows 90% confidence intervals.

suggestion that longer exposure to high female employment locations could lead to higher wages for women.

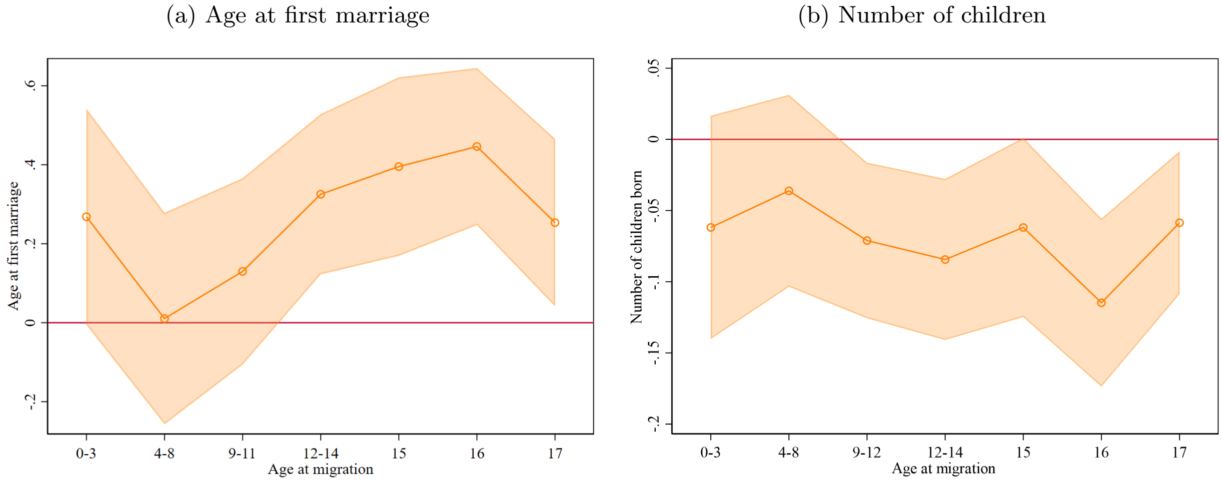
Finally, in Figure 5 I present results for age at first marriage and number of children as outcomes. Marriage and fertility decisions are often intertwined local norms and women's labor supply decisions (Fernandez and Fogli, 2009; Jayachandran, 2021). Information about age at first marriage is only available for the 1995 and 2005 surveys, while data on fertility decisions is available only in 1995. Therefore, these two figures use smaller samples. Although noisy, both panels present a pattern consistent with a slight delay in marriage. The increase in the slopes in Panel (a) between 8 and 16 years old implies a significant increase in the age at first marriage of five months. Panel (b) shows analogous results for the number of children ever born. However, the results are noisy and the pattern in the slopes is not clear.

4.3.4 The data supports the constant selection assumption

The causal interpretation of the birthplace persistence coefficients hinges on the assumption that selection is independent of the age of migration. More precisely, conditioning on the current location and other controls, I require the relationship between unobserved characteristics of women and the birthplace FLFP to be the constant across different ages of migration. Below, I present results showing that selection along various observable dimensions is fairly constant across emigration age, suggesting the likely validity of this identification assumption in my dataset.

Think of the identification assumption as analogous to parallel trends in Difference-in-Differences. While I anticipate that there are unobservable differences between women from high and low FLFP regions, this does not pose an issue for my approach. However, if factors correlated with female

Figure 5: Indonesia: length of stay and marriage and fertility



Notes: The figure shows estimates of the birthplace persistence coefficients by age of emigration $\boldsymbol{b_a}$. The coefficients are rescaled so that they can be interpreted as the implied gap between women from 75th and 25th percentile regencies. 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.

employment change differently across migration ages for these two groups, I might incorrectly attribute this variation to the causal effect. Thus, the absence of parallel trends could lead to finding a causal effect where none exists.

I cannot test the constant selection assumption. However, I can test whether the correlation between the birthplace FLFP and several observable characteristics is the same no matter the age women migrated. To do this, I use a slight modification of my main specification in (3) and regress women's characteristics y_i on current regency-year-age fixed effects (when possible), FLFP at birthplace $p_{b(i)}$, and interactions between age of migration and FLFP:[24]

$$y_i = \omega_{c(i)at} + \beta p_{b(i)} + \sum_{a=3}^{a=18} \beta_a 1_a \times p_{b(i)} + X_i \kappa + \varepsilon_{it} \tag{5}$$

as in previous sections, I normalized the FLFP rates so that the slopes can be interpreted as the IQR gap.

In model 5, I set 0 to 4 as the base category. This means that the β_a slopes represent the difference between the slope at age a relative to the slope at age 0-4. This specification facilitates visual comparison across different outcomes, as all estimates are centered around zero when the constant selection assumption holds. Under constant selection across all the ages, *all the interaction*

[24]When regency-year-age fixed effects cannot be included because, for example, the outcome is a destination regency characteristic, I add year and age of migration fixed effects.

terms β_a should be jointly zero.[25]

In Figure 6, I present estimates of the β_a interactions for three sets of outcomes: characteristics of the destination in Panels (a) and (b), reasons for migrating in panel (c), and socioeconomic characteristics in panel (d).

In Panel (a) of Figure 6, the FLFP in the destination regency is the outcome variable. If parents from high-FLFP regions were increasingly selecting locations where more women work, the correlation between FLFP at birthplace and FLFP at the destination should increase across migration cohorts. However, Panel (a) shows that this correlation remains constant regardless of migration age, with all β_a being close zero.

Panel (b) conducts a similar exercise using the share of women with at least middle school education in the destination regency as the outcome variable. This tests whether those who migrate older increasingly select locations with better education outcomes for women. Panel (b) shows no evidence of this, as all the interactions are close to zero.

In Panel (c), I test whether women from high-FLFP regencies exhibit differential changes in their migration motives if they migrated at older ages. The increase in the birthplace persistence can be consistent with a shift in the nature of the move as girls grow older. Fortunately, the 1985 Intercensal Survey includes information on the self-reported motive of migration, distinguishing between work, education, and other reasons.[26] In Panel (c), I narrow the sample to observations from the 1985 survey and use migration motives as an outcome. Due to the smaller sample size, I categorize migration ages into five-year bins for episodes before 15 years old.[27]

Panel (c) reveals little evidence of changing selection patterns in migration due to education (filled circles), as I cannot reject that all coefficients are jointly zero at the 95% confidence level. However, the figure suggests that women from regions with high FLFP seem to become more likely to move for work as they grow older (hollow circles). This is indeed a concern for my results. However, in Table A.9 in the appendix, I show that this change in migration motive is unlikely to drive the increase in birthplace persistence. If the birthplace persistence were driven by work-related migration, then the increase in the persistence should go away once I control for the work move dummy (or its interaction with age of migration dummies). Column (1) of Table A.9 shows that, at baseline, staying up to 16 is associated with an increase of 4.9 percentage points in employment. Moreover, columns (2) and (3) indicate that three-quarters of the increase in birthplace persistence still remains after controlling for a work-migration dummy and interactions between migration age and the work-migration dummy.[28]

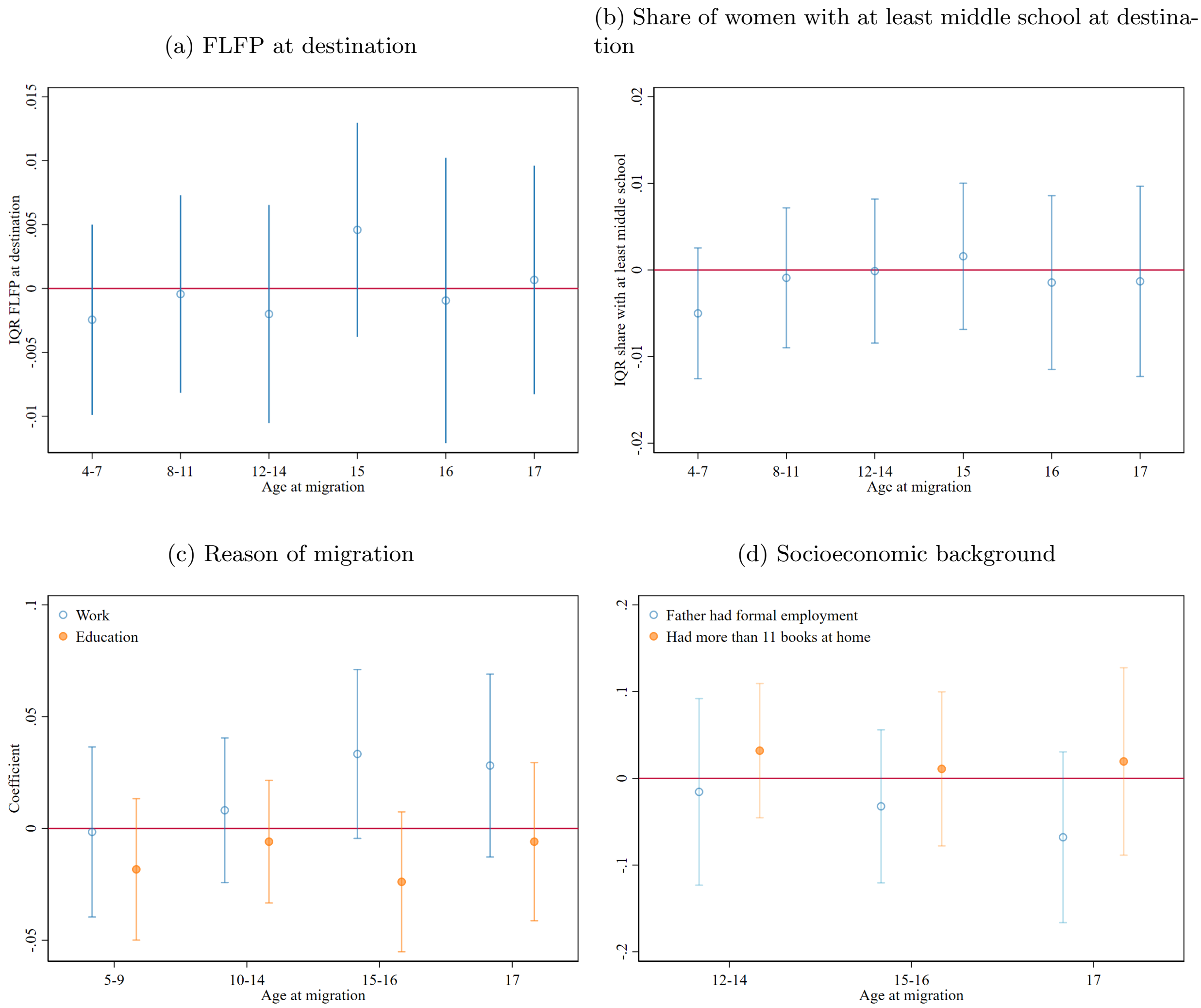
[25]Even if all the slopes are not jointly zero, identification is sill possible within the subset of ages where constant selection assumption holds. For instance, let's consider a scenario where constant selection holds during the ages from 6 to 14 but not outside of this range. In this case, I can still identify the exposure effects between 6 and 14 years old.

[26]It is worth noting that the survey does not specify whose job initiated the move. Data from IFLS suggest that the great majority of moves for other motives are driven by family-related reasons.

[27]Figure B.4 in the appendix confirms that the increase in birthplace persistence of employment also holds in this smaller sample.

[28]Although this increase is no longer statistically significant, the sample in Table A.9 is just one sixth of the sample in my baseline results.

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



Notes: The figure displays the coefficients on the interactions between the age of emigration and FLFP at birthplace (β_a) from regression (5) for various outcomes. All coefficients can be interpreted as the change in the birthplace persistence coefficients relative to the slopes for the least exposed women. Each panel controls for the primary FLFP at birthplace effect, age of migration, religion, education-level fixed effects, and a quadratic polynomial in age. In addition, panel (c) controls for current-regency fixed effects, and panel (d) controls for current-regency-by-year fixed effects. Data on migration motive is available only on the 1985 Intercensal Survey, therefore panel (c) limits the sample to people in the 1985 survey. Due to the much smaller sample, panel (c) groupes migration ages into 5 year cells for the earlier cohorts. The figure shows 95% confidence intervals. Panels (a) to (c) use data from the Intercensal Survey, while panel (d) uses data from the IFLS. The smaller sample in the IFLS requires a different age binning in panel (d). Standard errors are clustered by the regency of birth. The figure shows 95% confidence intervals.

Finally, in Panel (d), I show evidence on the economic background of early migrants using data from the IFLS. The IFLS provides richer demographic information than the Intercensal Survey, but at the cost of a smaller sample and somewhat limited information on migration episodes at early ages. The IFLS lacks information on the exact age of migration for any move before 12 years old. Therefore, all slopes in Panel (d) represent the difference in the FLFP slope relative to those migrating before turning 12. The panel shows slopes of regressions where the outcomes are dummies of whether the father had formal employment, and whether she had more than 11 books at home growing up. In developing countries, formal jobs often offer better pay and benefits, while the number of books at home is used as a proxy for parental education level. If the birthplace effects were driven by selection in parental background, then I would expect a clear upward trend in the slopes for both outcomes. This would reflect that richer and more educated parents from high-FLFP regencies became more likely to migrate as their child grew up. However, there is little evidence of this, and I cannot reject that the slopes are jointly zero at the 95% confidence level.

5 Discussion: why does birthplace matters so much?

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

5.1 Human capital

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 economic activities could alter their career expectations and make them more likely to invest in further education. For example, Molina and Usui (2022) show that in Japanese municipalities with higher female participation rates, teenagers exhibit greater educational aspirations, leading to increased investment in schooling.

However, this channel is an unlikely driver for my results because high-FLFP regencies have worse educational outcomes for women (see Appendix Table A.6). Moreover, there is little evidence that women who stay longer in these regencies invest more in education. If schooling drove the patterns observed in Figure 3, I should observe increasing persistence in regressions that use schooling measures as the outcome. However, Appendix Figure B.7 shows no evidence of this when the outcome is the likelihood of completing secondary school. Although the figure suggests an apparent increase in the likelihood of completing primary school, these slopes are imprecise, and I cannot reject the hypothesis that all of them are equal (i.e., null birthplace effects).[29]

5.2 Changes in parental investment

Molina and Usui (2022) suggests that exposure to local labor market opportunities influences parental investment in girls' education. There are two main ways through which parental investment

[29] I also cannot reject that all slopes from 8 to 17 are the same. Additionally, the *employment* persistence coefficients remain fairly unchanged when I control for interactions between birthplace FLFP, age of migration, and completed primary dummies. If higher employment were mainly due to higher completion rates of primary school, the coefficients in Figure 3 should flatten once I control for this triple interaction.

could explain my results. Although I cannot fully discard these explanations, they do not seem very plausible in my context.

The first explanation is pure selection. The increasing persistence could reflect that parents who stayed longer in high-FLFP regencies happened to invest more in their children. However, this requires a complex pattern of selection that does not seem to be supported by the data. If parents who stayed longer in high-FLFP regencies invested more in their daughters' education, one would expect that girls from these locations came from families with higher socioeconomic backgrounds. However, Panel (d) of Figure 6 shows little evidence of selection based on parental socioeconomic background. Moreover, since high-FLFP regencies have worse outcomes, it is more likely that high-investment parents would leave these locations earlier rather than later.

Another possibility is that staying longer in these locations affected parental investment. However, as I discussed earlier, there is little evidence that staying longer in these locations is associated with higher levels of education. Admittedly, investment could act through channels other than the level of schooling, but changes in investment would need to occur at a very specific time in the children's development.

5.3 Learning and norms

A more plausible driver of the birthplace effects is the transmission or learning of social norms around women's work. A growing literature emphasizes that the transmission of social norms can have permanent effects on women's decisions (Fernández et al., 2004; Alesina et al., 2013; Blau et al., 2011).

The results I document are consistent with a setting where women internalize local norms during late childhood and early adolescence. Both the IFLS and the Intercensal Survey provide limited data to formally test this channel. However, the concentration of these effects during late childhood and early adolescence aligns with psychological research, which emphasizes that children at these ages are mature enough to form their own opinions while remaining receptive to external influences (Markus and Nurius, 1986). Moreover, recent research by Dhar et al. (2022) shows that teenagers are responsive to interventions targeting gender norms.

I emphasize that to be consistent with my results, the internalization of norms must occur primarily in women, as I find no evidence that a longer stay in high-FLFP locations by the *husband* affects women's LFP decisions. In Appendix Figure B.9, I restrict the sample to households in which both husband and wife are migrants and perform an exercise similar to Fernández et al. (2004). There, I regress wives' employment on her birthplace FLFP and interactions between the husband's birthplace FLFP and the age he migrated. The figure shows that, although women's employment seems to respond to her husband's origin (all the coefficients are positive), there is little evidence that the husband's length of stay matters. This suggests that the effects of length of stay are driven by *direct* rather than indirect contact with the labor market.

6 Robustness

My results are robust to multiple variations in the estimation sample. My main estimates limit the sample to women migrating up to 17 years old and source the birthplace FLFP rate from the 2010 Indonesian Census. Section 6.1 shows that I obtain similar results if I restrict the sample to women migrating up to 16, or up to 18 years old. Moreover, Section 6.2 shows I get similar estimates when using the FLFP from the census prior to the Intercensal Survey year. In Section 6.3, I address the possibility that my results are driven by early entry to the labor market. Child labor is a significant issue in many developing countries, and in Indonesia, regency FLFP rates are correlated with the prevalence of child labor. Therefore, my employment results could be reflecting the entry of children into the labor market. However, I obtain similar results even when controlling for interactions between migration age and the child labor rate in the regency of birth.

6.1 Maximum age at migration in the sample

The sample in my main results includes all women who migrated when they were up to 17 years old. One concern regarding this sample selection is that women migrating at the ages of 17 or 18 may have been more inclined to consider their job prospects when making their location choices. As women migrating at these ages represent 27% of all women migrating before turning 19, their presence could be affecting my estimates in non-straightforward ways.

To evaluate whether this is a concern, Table 10 displays results where I limit the sample to various maximum ages of migration. The table displays estimates of the effect of longer stays for two women: one born in a regency at the 75th percentile of the FLFP distribution and another born at the 25th percentile. It shows the gap in employment attributed to the longer stay, assuming that they stayed at their regency of birth until they were 16. That is, these estimates are the difference between the gaps at 16 and 0 years old from Figure 3.

Table 10: Indonesia: birthplace effect estimates for different migration age samples

	Maximum age of migration		
	18	**17**	**16**
	(1)	(2)	(3)
Effect estimate 0-15 years old	0.039	0.040	0.041
	(0.025)	(0.025)	(0.025)
Regency'age-year FE	✓	✓	✓
Age	✓	✓	✓
Education	✓	✓	✓
Observations	42,394	35,874	30,423
R^2	0.16	0.16	0.16

Notes: This table shows the implied gap in the likelihood of employment for two women, one born in a regency at the 75th percentile of the FLFP distribution, and another born in a regency at the 25th percentile, under the assumption they stayed in their birthplace until they turn 15. Columns differ only in the maximum age of migration for the women in the sample. The estimation uses data from the pooled 1985, 1995 and 2005 Intercensal Surveys and restricts the sample to women who reside outside their birthplace. Standard errors are clustered by the regency of birth. All regressions regressions control for a quadratic polynomial in age and fixed effects for four education categories.

Varying the maximum age of migration within my sample has minimal overall effects on my birthplace effect estimates. In Table 10, my baseline estimate using the entire sample is presented in column (1). Column (3) shows that excluding all women who migrated at 17 and 18 only moves the estimate from 3.9 to 4.1 percentage points. Furthermore, the birthplace persistence coefficients (b_a) estimates across all samples exhibit similar behavior and are quite similar in magnitude, with the bulk of the increase happening between the ages of 6 to 14 years old. Overall, I interpret this as evidence that worsen selection for the oldest migrants is not driving my results.

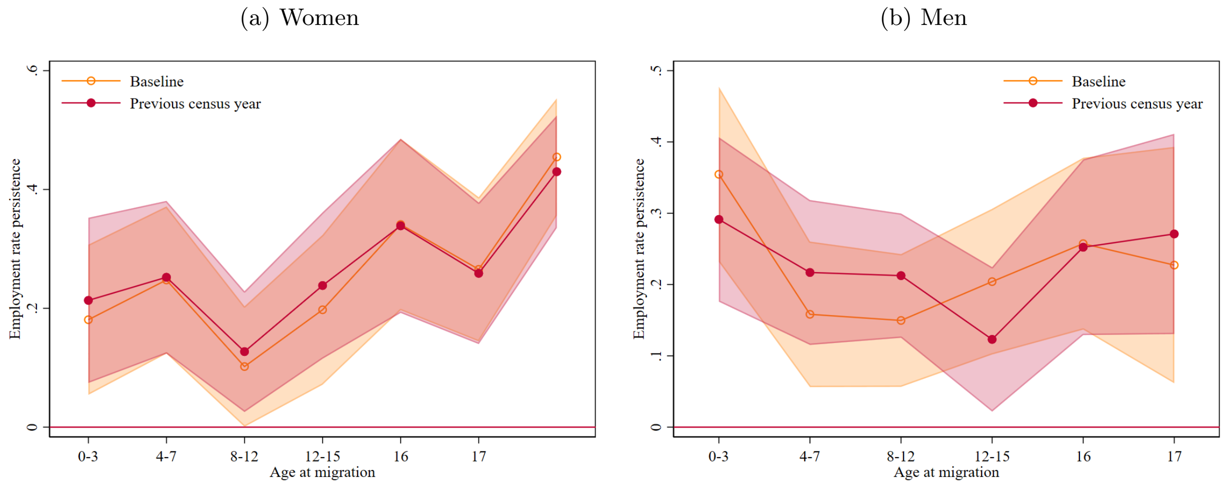
6.2 Year of reference for the birthplace FLFP

My main results source the female labor force participation rates for the regency of birth from the 2010 Indonesian Census. Although FLFP rates are very persistent (see Section 3.3), the rates in the 2010 census could be a poor proxy for the FLFP rates "experienced" by the women in the 1985 and 1995 Intercensal Surveys.

Figure 7 shows that my results are robust changes in the reference year I use for the FLFP rates. The dark red (filled) circles show coefficient estimates when I source the FLFP rates in the regency of birth from the first census prior to the Intercensal Survey year,[30] while the orange (hollow) circles use the 2010 rates from my baseline rates. The results for both women in Panel (a) and men in Panel (b) are fairly similar under both estimation strategies.

[30] That is: 1980 census for the 1985 survey, 1990 for 1995, and 2000 for the 2005 Intercensal Survey.

Figure 7: Indonesia: length of stay labor supply for different measures of birthplace FLFP



Notes: The figure shows estimates of the birthplace persistence coefficients by age of migration $\boldsymbol{b_a}$ for different measures of the birthplace FLFP rate. The baseline results source the regency FLFP rate from the 2010 Indonesian Census, while the darker estimates source it from the first census year prior to the Intercensal Survey year. Panel (a) shows estimates for women, while Panel (b) shows estimates for women. The figure uses individual-level data from the pooled 1985, 1995 and 2005 Intercensal surveys. All regressions control for current regency-migration age-year fixed effects, a quadratic polynomial on age, and education fixed effects. The figure shows 90% confidence intervals. Standard errors clustered by regency of birth.

6.3 Child labor

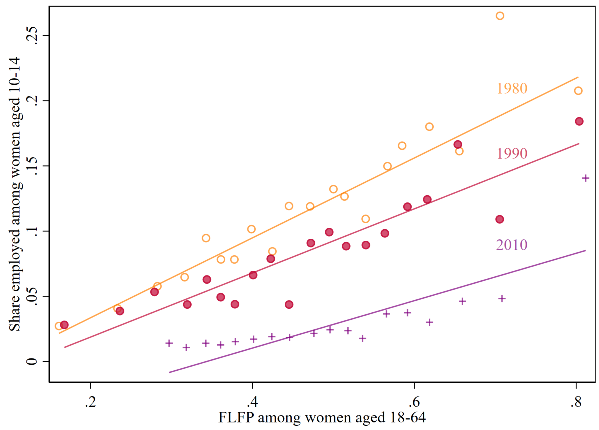
A potential concern regarding the birthplace effects is that they might be child labor. While contemporary rates of child labor in Indonesia are generally low, this was not the case in the 1980s. The rates of children aged 10-14 working declined from 11% in 1980 to approximately 3% in 2010.[31]

Moreover, the strong positive correlation between FLFP and female child labor rates (FCLR) raises the possibility that birthplace effects could be indicative of early entry into the labor market. In Figure 8 I show the rates of female child labor for 1980, 1990 and 2010 against FLFP by regency. In 1980 and 1990, regencies with high FLFP also exhibited high rates of child labor. Although this correlation is weaker in 2010, it remains positive.

However, the birthplace effects are not driven by the prevalence of female child labor in the regency. Figure 9 shows the estimates of the birthplace persistence coefficients when including the FCLR from the birthplace regency as a control. The baseline estimates in orange (hollow circles) control for regency-by-year fixed effects, a quadratic polynomial on age, and religion and education fixed effects. The estimates in red (filled circles) add as a control the FLCR from the recency of birth, while the purple estimates (plus sign markers) control for interactions between the migration age and the FLCR from the birthplace. Notably, the estimates are largely unaffected by the inclusion of the child labor rates.

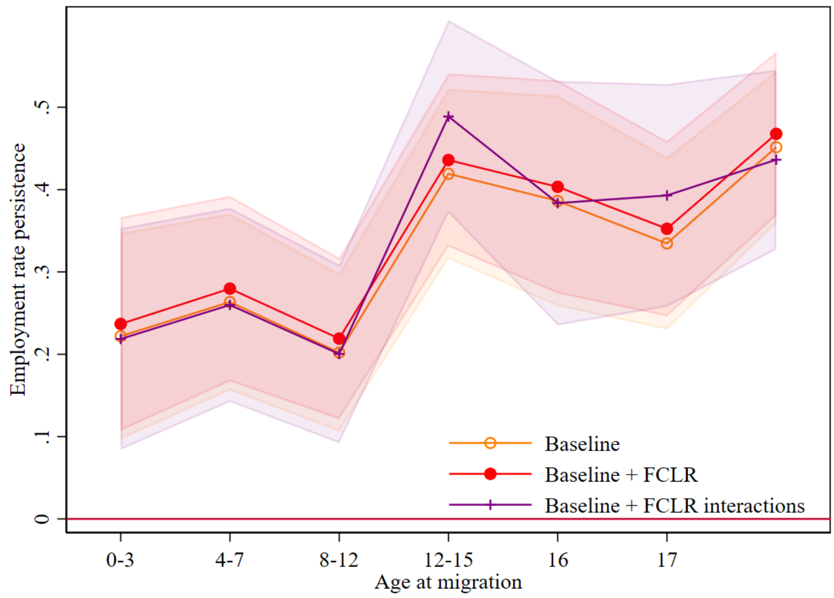
[31] Information about work is available only for people aged 10 or more

Figure 8: Indonesia: female child labor and female employment by regency



Note: The figure compares the employment rates of women between the ages of 10-14 and those aged 18 to 64. Censuses only ask work-related questions to people aged 10+. It uses data data from the 1980, 1990 and 2010 Indonesian Census.

Figure 9: Indonesia: birthplace effects controlling for female child labor rates by regency



Note: The figure shows estimates of the birthplace persistence coefficients by age of emigration $\boldsymbol{b_a}$ controlling for the female child labor rates (FCLR) at the birthplace. These FCLR values correspond to the regency's rate from the previous census year. The baseline regression controls for current regency-migration age-year fixed effects, a quadratic polynomial on age, and education level fixed-effects. Baseline + FCLR adds FCLR as a control, while Baseline + FCLR interactions adds interactions between migration age dummies and the regency's FCLR. The figure uses data data from the pooled 1985, 1995 and 2005 Intercensal surveys and sources birthplace FCLR from the 1980, 1990 and 2000 Indonesian censuses. The figure shows 90% confidence intervals.

7 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 Tables

Table A.1: 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 A.2: 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 A.1 with data that distinguishes unpaid and family workers from other worker types.

Table A.3: Indonesia: number of migrant women by survey year and migration age cells

	Survey year			
Age cell	**1985**	**1995**	**2005**	**Total**
0-3	1,071	1,635	1,539	4,245
4-8	1,495	1,606	1,988	5,089
8-12	1,818	2,123	2,386	6,327
12-14	1,884	2,547	2,624	7,055
15	1,258	1,341	1,501	4,100
16	1,145	1,602	1,628	4,375
17	1,317	2,038	2,195	5,550
18	1,544	2,417	2,655	6,616
Total	11,532	15,309	16,516	43,357

Notes: the table shows the number of migrant women by survey year and migration age cell. Data from the 1985, 1995 and 2005 Intercensal Surveys.

Table A.4: Indonesia: estimates birthplace persistence on men's labor supply using IFLS data

	(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 men 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 FLFP 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 A.5: Indonesia: estimates birthplace persistence on labor supply for men who migrated young

	(1)	(2)	(3)
Female LFP birthplace ($p_{b(i)}$)	0.20***	0.16***	0.13***
	(0.05)	(0.04)	(0.03)
Mean employment rate	0.86	0.86	0.86
Implied IQR gap	0.04	0.03	0.03
Regency-year FE	✓	✓	✓
Age		✓	✓
Education			✓
Observations	31,718	31,718	31,718
R^2	0.10	0.27	0.29

Notes: This table uses data from the pooled 1985, 1995, and 2005 Intercensal Surveys and restricts the sample to men who migrated before they turned 18. The implied IQR gap shows the implied employment gap between someone born at a regency in the regency at 75th percentile of employment rate and someone born in the regency at the 25th percentile. The IQR of FLFP rates across regencies is 22 percentage points. Standard errors are clustered by regency of birth. When applicable, regressions control for a quadratic polynomial in age and fixed effects for four education categories.

Table A.6: Indonesia: Women in high FLFP regencies have worse educational outcomes

	Years of schooling	**Primary completed**	**Secondary completed**
Regency group	(1)	(2)	(3)
Low FLFP	7.86	0.78	0.30
	(0.13)	(0.01)	(0.01)
High FLFP	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.

Table A.7: 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 A.8: 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	

Notes: 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 A.9: Indonesia: birthplace effect estimates for different migration age samples

	(1)	(2)	(3)
Effect estimate 0-16 years old	0.049*	0.037	0.037
	(0.024)	(0.024)	(0.024)
Work move		✓	✓
Work move× Migration age			✓
Migration age FE	✓	✓	✓
Regency FE	✓	✓	✓
Age	✓	✓	✓
Religion	✓	✓	✓
Education	✓	✓	✓
Observations	11,532	11,532	11,532
R^2	0.11	0.15	0.15

Notes: This table shows the implied gap in the likelihood of employment for two women, one born in a regency at the 75th percentile of the FLFP distrib ution, and another born in a regency at the 25th percentile, under the assumption they stayed in their birthplace until they turn 16. Columns differ only in the maximum age of migration of the women in the sample. The estimation uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace. Standard errors are clustered by the regency of birth. All regressions regressions control for a quadratic polynomial in age and fixed effects for five religious and four education categories.

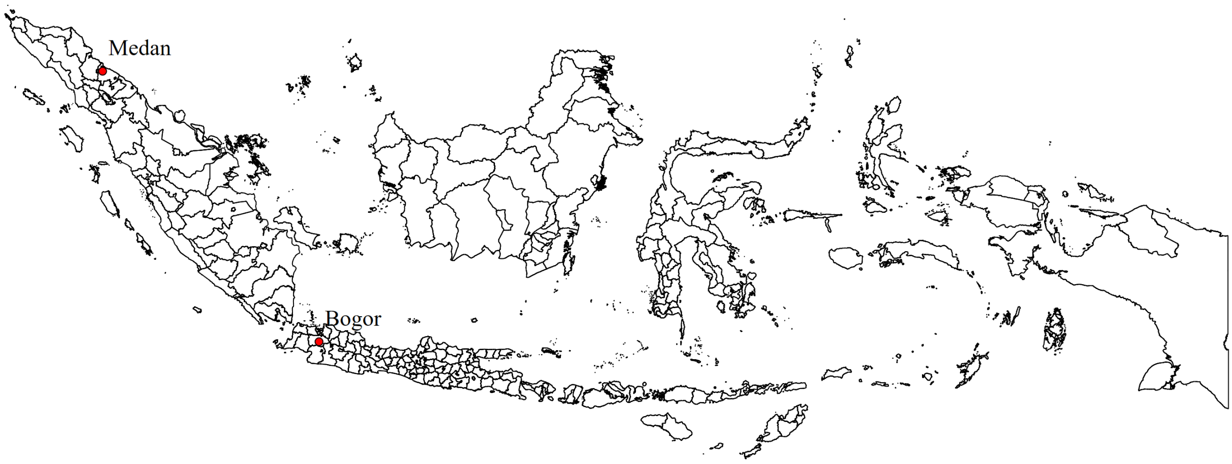
Table A.10: Indonesia: estimates of birthplace persistence for women using different regency samples

	(1)	(2)	(3)	(4)
Women's employment rate at birthplace (p_b)	0.32***	0.34***		
	(0.03)	(0.03)		
Migration age $\times p_b$				
0 to 2			0.18*	0.15
			(0.08)	(0.08)
3 to 5			0.21*	0.23*
			(0.10)	(0.10)
6 to 8			0.14	0.10
			(0.08)	(0.08)
9 to 11			0.19**	0.23**
			(0.07)	(0.07)
12 to 14			0.38***	0.41***
			(0.07)	(0.08)
15 to 16			0.35***	0.36***
			(0.06)	(0.06)
17			0.39***	0.38***
			(0.06)	(0.06)
18			0.33***	0.36***
			(0.06)	(0.06)
Sample	All regencies	Regency panel	All regencies	Regency panel
Regency-year FE	✓	✓	✓	✓
Age	✓	✓	✓	✓
Religion	✓	✓	✓	✓
Education	✓	✓	✓	✓
Age of migration FE			✓	✓
Observations	66,544	57,995	26,841	23,216
R^2	0.09	0.09	0.09	0.08

Notes: This table uses data from the Intercensal Survey and restricts the sample to women aged 18 to 64, who reside outside their birthplace. Columns (1) and (3) reproduce the results from Table **??** and Figure 3. Columns (2) and (4) restrict further restrict the sample to people residing in the 189 regencies covered by all three Intercensal surveys. 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.

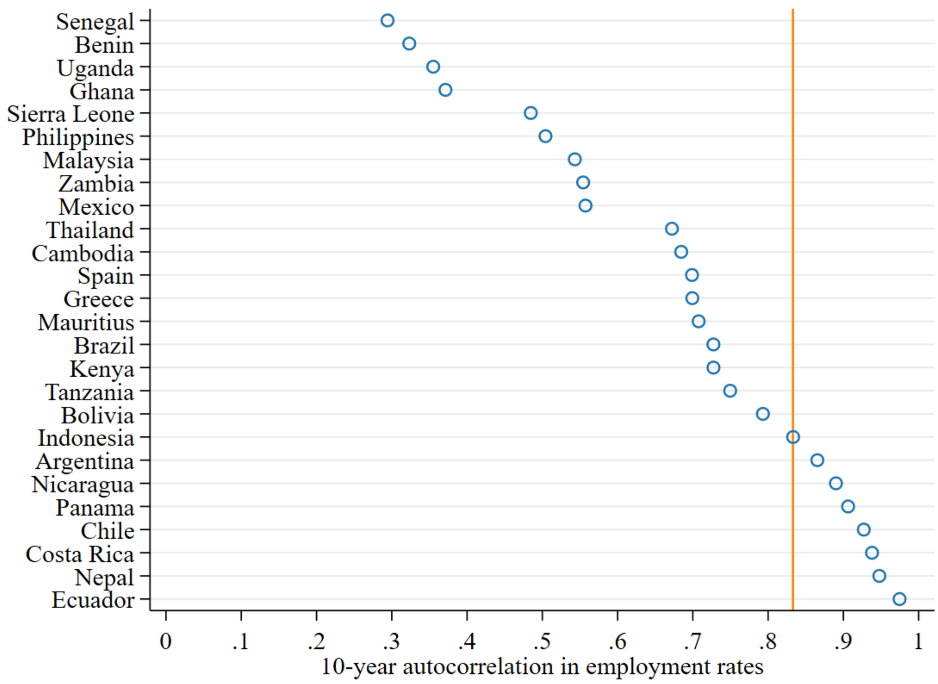
B Figures

Figure B.1: Indonesian regencies



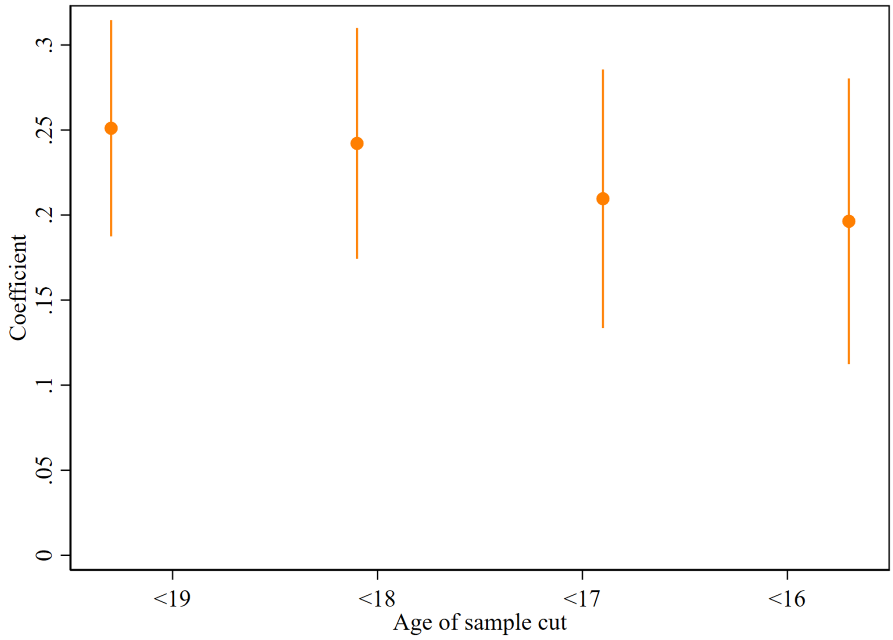
Note: The figure shows the 268 regency aggregates with consistent boundaries between 1970 and 2018. Boundaries obtained from IPUMS International. It highlights with red dots the locations of the city of Medan and Bogor regency. Medan, the capital and largest city in the province of North Sumatra, is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

Figure B.2: 10-year autocorrelation in female employment rates at the district level for selected countries



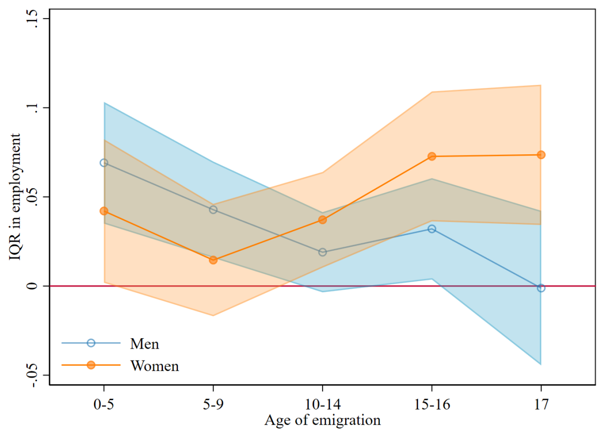
Notes: The figure shows the 10-year autocorrelation in female employment rates. I aggregate data at the smallest geographical unit available which often corresponds to a district/county. Data from IPUMS international.

Figure B.3: Estimates of birthplace persistence for different emigration age cutoffs



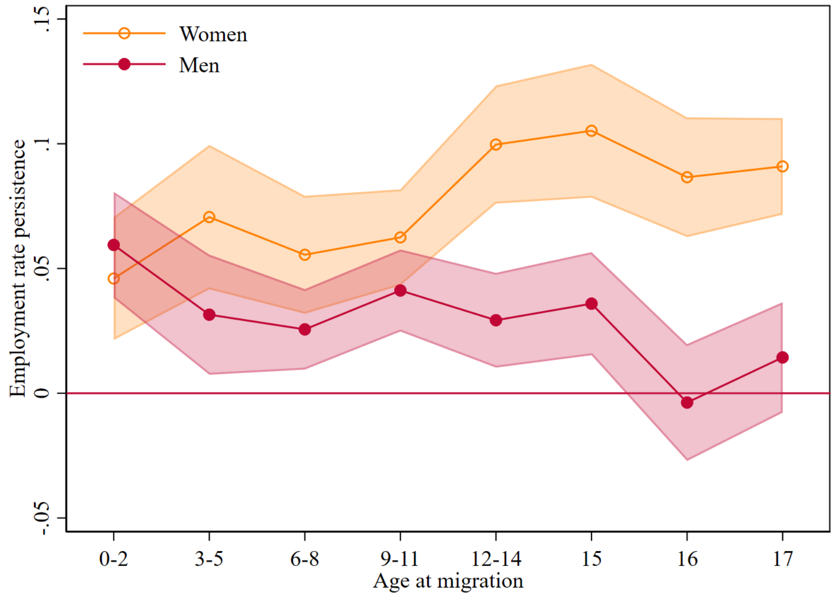
Note: This figure uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace and who left before they turned 19. Standard errors are clustered by regency of origin. All regressions control for a quadratic polynomial in age and fixed effects for five religious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

Figure B.4: Indonesia: birthplace persistence estimates in the 1985 Intercensal Survey



Notes: The figure shows estimates of the birthplace persistence coefficients by age of emigration $\boldsymbol{b_a}$ when restricting the sample to the 1985 Intercensal Survey. The regressions control for current regency-by-year fixed effects, a quadratic polynomial on age, and religion and education-level fixed-effects. The figure shows 90% confidence intervals

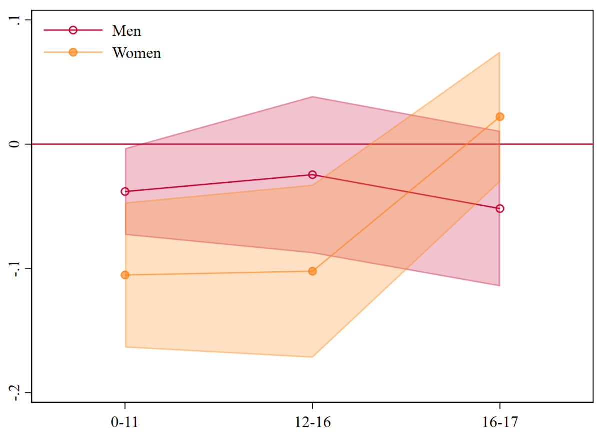
Figure B.5: Indonesia: length of stay and likelihood of employment



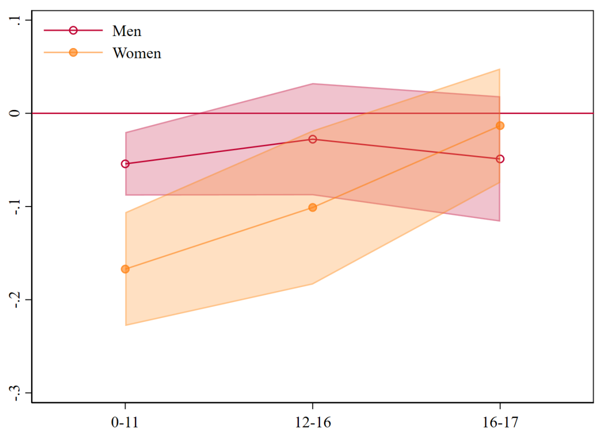
Note: The figure shows estimates of the birthplace persistence coefficients by age of migration $\boldsymbol{b_a}$. The coefficients are rescaled so that they can be interpreted as the implied gap between women from 75th and 25th percentile regencies. The regression controls for regency-by-year fixed-effects, migration age fixed effects, interactions between destination FLFP and migration age fixed effects, a quadratic polynomial on age, and education level fixed-effects. Standard errors are clustered by regency of birth. The figure shows 90% confidence intervals. It uses data from 1985, 1995 and 2005 Intercensal surveys.

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

(a) Monthly earnings

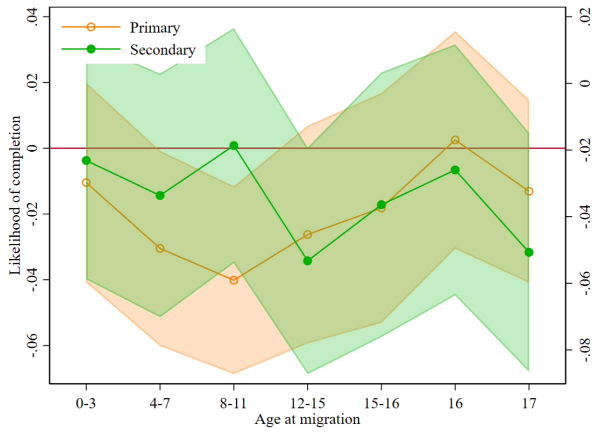


(b) Hourly wages



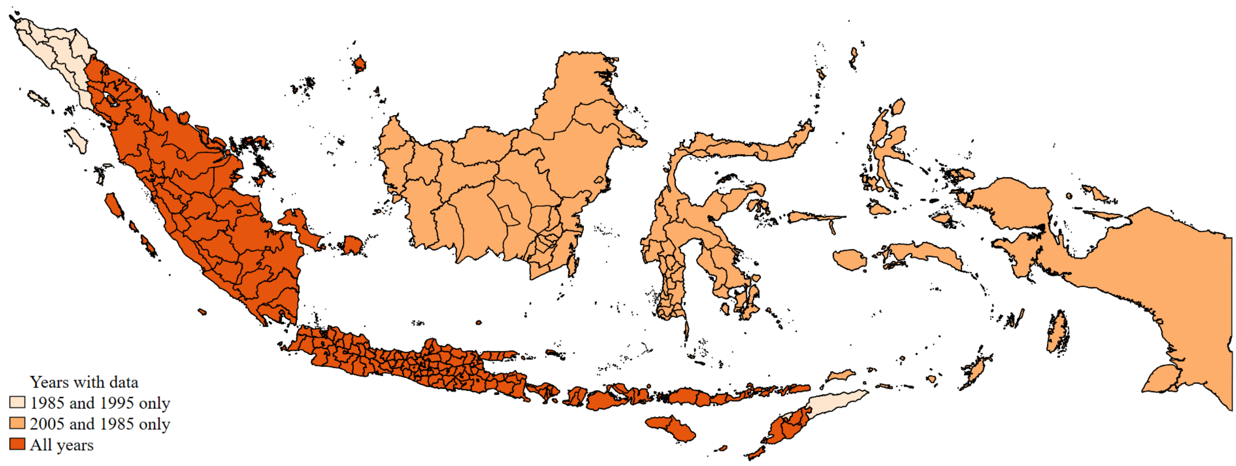
Note: Data from 1995 intercensal survey. The regression controls for current regency fixed-effects, a quadratic polynomial on age, and education level fixed-effects. The figure shows 90% confidence intervals.

Figure B.7: Indonesia: education by length of stay



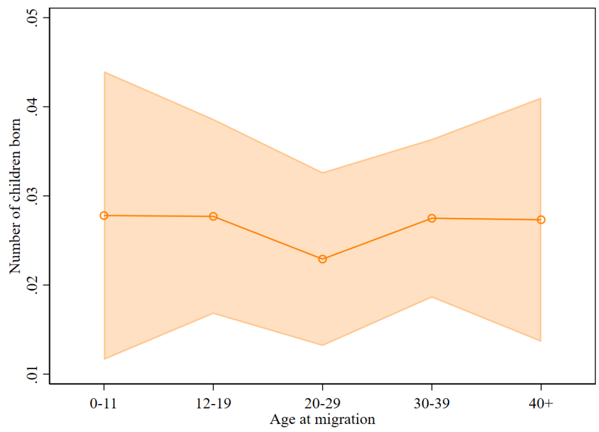
Note: The figure show the coefficients on the interactions between age of emigration and birthplace FLFP. Errors are clustered by regency of birth. The figure shows 90% confidence intervals. Data from the pooled 1985, 1995 and 2005 Intercensal Surveys.

Figure B.8: Geographic coverage of the Intercensal Survey by year



Note: The figure shows the regencies surveyed in each Intercensal Survey. The 1985 covered 100% of the Indonesian population, the 1995 survey covered 87% while the 2005 sample covered 99% of the population. In all, the regencies surveyed in all years account for 85% the Indonesian population in 2000.

Figure B.9: Indonesia: husbands' length of stay and wives' employment



Notes: The figure shows estimates of the coefficients on interactions between husbands' birthplace FLFP and his age of migration. TThe dependent variable is the a dummy equal to one if the wive was employed. The regression controls for wife's birthplace FLFP, education fixed effects, husband's age at migration fixed effects. It restricts the sample to women in households were both the wife and the husband were migrants. The figure uses data data from the 1985, 1995 and 2005 Intercensal surveys. The figure shows 90% confidence intervals.

C Data appendix

C.1 Aggregation of regencies

The total number of regencies varied considerably across years (Minnesota Population Center, 2023; Central Bureau of Statistics, 1980, 2010). In 1980 there were 286 regencies but by 2010 there were 493. To ensure a consistent definition of the local labor market across the years, I aggregated regencies into 269 geographic units with fixed boundaries between 1980 and 2010. I took the boundary definitions directly from IPUMS International (Minnesota Population Center, 2023).

For each survey, IPUMS provides a year-specific delineation for the regency of residency, the regency of birth, and a fixed-boundary definition for the regency current residence. In each survey, I use the mapping between then boundary-consistent and year-specific regencies of residency and apply it to the regency of birth to obtain the fixed-boundary regencies.

C.2 Cross-country data

I use harmonized data from IPUMS International to build Figure 1 from the introduction and Table 4. 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, I use the class of worker instead (`classwkr`). In these cases, I define a person as employed if they report being self-employed, a salaried worker, or an unpaid worker. In China, employed workers are those who reported working at least 1 day in the past week. Despite these slight definition differences, table A.7 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).[32] 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 A.8 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.

[32] 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.

D The Empirical Strategy

D.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 gender discrimination in the local labor market (Charles et al., 2023). 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., 2023; 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., 2023).

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. More formally, let us consider the following model for the probability of employment e_{it} of a female migrant,

$$e_{it} = \omega_{c(i)} + \boldsymbol{\sigma} p_{b(i)} + \eta_{it} \tag{D.1}$$

In this model, women's employment choices depend on three main factors. First, the place-of-residence fixed effect $\delta_{c(i)}$ 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 $p_{b(i)}$ is intended to capture the causal effect of growing up in a location where $p_{b(i)}$ 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 (D.1) 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 (D.1) 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, such 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 (D.1), $\boldsymbol{\sigma}$ 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 FLFP. 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 (D.1) 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 the FLFP slope will conflate the causal effects of birthplace with omitted variable bias:

$$\begin{aligned} \text{plim } \hat{\boldsymbol{\sigma}} &= \boldsymbol{\sigma} + \frac{\text{cov}(\tilde{p}_{b(i)}, \tilde{\eta}_{it})}{\text{var}\left(\tilde{p}_{b(i)}\right)} \\ &= \boldsymbol{\sigma} + \boldsymbol{\gamma} \end{aligned} \tag{D.2}$$

where tilde accents denote variables that are residualized from regency fixed effects (Angrist and Pischke, 2009). Expression (D.2) 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. In the paper, I argue 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 am be more concerned with omitted variable –or selection– bias making women from high-FLFP locations 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:

$$e_{it} = \omega_{c(i)a} + \boldsymbol{\sigma}_a p_b + \eta_{it} \tag{D.3}$$

Here $\boldsymbol{\sigma}_a$ captures the cumulative effect of birthplace up to age a[33]. 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 (D.2), the OLS estimates will conflate the causal effects of birthplace $\boldsymbol{\sigma}_a$ with the omitted variable bias for women migrating at age a $\boldsymbol{\gamma_a}$:

$$\text{plim } \hat{\boldsymbol{\sigma}}_a \quad = \quad \boldsymbol{\sigma}_a + \boldsymbol{\gamma}_a \tag{D.4}$$

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

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 us 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 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, this does not necessarily 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 of the slopes of different migration ages, the constant selection term $\boldsymbol{\gamma}$ goes away, leaving only the causal effects:

$$\begin{aligned} \text{plim } \hat{\boldsymbol{\sigma}}_{\boldsymbol{a}} - \hat{\boldsymbol{\sigma}}_{\boldsymbol{a-1}} &= \boldsymbol{\sigma}_a - \boldsymbol{\sigma}_{a-1} \\ &= \boldsymbol{\pi}_a \end{aligned} \tag{D.5}$$

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.

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