

BOSTON UNIVERSITY  
GRADUATE SCHOOL OF ARTS AND SCIENCES

Dissertation

**ESSAYS IN GENDER, EARNINGS AND GEOGRAPHY**

by

**CÉSAR LUIS GARRO MARÍN**

B.A., Universidad de Costa Rica, 2013  
M.A., Centro de Estudios Monetarios y Financieros, 2015

Submitted in partial fulfillment of the  
requirements for the degree of  
Doctor of Philosophy

2023

© 2023 by  
CÉSAR LUIS GARRO MARÍN  
All rights reserved

Approved by

First Reader

---

Daniele Parseman, Ph.D.  
Professor of Economics

Second Reader

---

Kevin Lang, Ph.D.  
Professor of Economics

Third Reader

---

Linh Tô, Ph.D.  
Assistant Professor of Economics

## Acknowledgments

I am immensely grateful to my advisors, Daniele Paserman, Kevin Lang, and Linh Tô, for their unwavering guidance and support throughout my dissertation. Their expertise and feedback were invaluable in navigating the unfamiliar terrain of my Ph.D. journey. I am truly indebted to them for their continuous encouragement.

I would also like thank my coauthors Kevin Lang, Shulamit Khan, Costas Cavounidis, Masyhur Hilmy, and Raghav Malhotra without whom many of the projects I worked on during this journey would have been impossible to carry out. I am grateful for the opportunity to learn and grow alongside them.

I would also like to express my gratitude to the faculty of the Department of Economics and Patricia Cortes, for their insightful comments and contributions, which significantly enhanced the quality of the projects included in this thesis and those undertaken during my Ph.D.

I also extend my gratitude to my partner Lee-Ann Vidal Covas, and my friends, Nils Lehr, and Masyhur Hilmy. I greatly benefited from countless conversations and their feedback. They made this journey much easier and enjoyable.

Lastly, I would like to thank my family for their love and unwavering support. Despite the uncertainties and challenges, they have always stood by my side, offering their unwavering encouragement and assistance.

César Luis Garro Marín  
Ph.D. candidate  
Economics Department

# **ESSAYS IN GENDER, EARNINGS AND GEOGRAPHY**

**CÉSAR LUIS GARRO MARÍN**

Boston University, Graduate School of Arts and Sciences, 2023

Major Professor: Daniele Paserman, PhD  
Professor of Economics

## **ABSTRACT**

In this dissertation I study the role of local markets and firms in explaining labor market inequality across genders, and across workers. My results show that local labor markets have a relevant role in accounting for differences in labor market outcomes across genders. The dissertation is structured in three chapters, each containing a stand alone paper.

In the first chapter I show large and persistent differences exist in women's labor force participation within multiple countries. These persistent differences in employment can arise if where women grow up shapes their work choices. However, they can also arise under endogenous sorting, so that women who want to work move to places where more women work. In this chapter, I use rich data from Indonesia to argue that the place women grow up in shapes their participation in the labor market as adults. To do so, I leverage variation coming from women moving across labor markets to estimate the effect on women's labor force participation of spending more time in their birthplace. My strategy is similar to that of Chetty and Hendren (2018) and compares the labor supply choices of women who currently live in the same location, but who emigrated from their birthplace at different ages. My results indicate that birthplace has strong and persistent effects on adult women's labor supply. By the time they turn sixteen, women born in a location at the 75th of female employment

will be 5 p.p. more likely to work than those born in a 25th percentile location. Place is particularly important during the formative period between 9 and 16 years old. These results suggest that between 23 percent of the current spatial inequality in women's employment is transmitted to the next generation growing up in these locations.

The second chapter studies the relationship of big cities and gender inequality in the United States. It is well known that big U.S. cities pay higher wages, but there is growing evidence that this urban wage premium declined since the eighties (Autor, 2019). In this paper, I use data from U.S. Commuting Zones for the period between 1970 and 2020 to document that the decline in the urban wage premium affected men and women differently. While women were relatively isolated from the premium decline, men with lower education received the brunt of the impact. This caused a large relative increase in women's urban wage premium: women's premium went from being on par with men's in 1970 to being 44% larger in 2010. I go on to argue that these differential trends result from a combination of gender specialization and the evolution of urban skill premiums. Urban premiums decline the most in those skills low-education men use more intensively.

Finally, the third chapter I study the role of universities in explaining earnings inequality in U.S. academia. Previous applications from Abowd, Kramarz, and Margolis (1990) –AKM– found the best firms pay workers over and above their own productivity. These firm rents contribute to overall wage inequality. In this paper, we apply the AKM model to measure whether there are significant firm (university/college) effects on faculty earnings in academia. Specifically, we apply the model to measure the pecuniary rents associated with working as tenure-track faculty at a more prestigious university or college in the United States. To do so, we take advantage of matched employer-employee data from the Survey of Doctorate Recipients. We find

little evidence of pecuniary university premiums in the most prestigious US academic institutions. Once we control for urbanicity, the effect of university/college rankings on institutions' fixed-effects on earnings is statistically insignificant and sufficiently precisely measured that we can rule out anything larger than modest effects. We then relate our findings with those of previous literature.

# Contents

<b>1</b>	<b>The Geography of Women’s Work: Evidence from Indonesia</b>	<b>1</b>
1.1	Introduction . . . . .	1
1.2	Data . . . . .	7
1.2.1	Data sources . . . . .	7
1.2.2	Measurement . . . . .	9
1.2.3	Summary statistics . . . . .	10
1.3	Four facts about women’s labor supply . . . . .	14
1.3.1	Fact 1: within-country dispersion in women’s labor supply is pervasive across countries . . . . .	15
1.3.2	Fact 2: there is large within-country dispersion in women’s employment rates in Indonesia . . . . .	18
1.3.3	Fact 3: women’s employment rates are highly persistent . . . . .	19
1.3.4	Fact 4: dispersion in women’s employment rates cannot be accounted by differences in women’s demographics alone . . . . .	20
1.4	Empirical strategy and results . . . . .	22
1.4.1	Place and women’s labor supply: the identification challenge .	22
1.4.2	Birthplace is highly predictive of women’s labor supply . . . . .	27
1.4.3	There is large persistence for those who migrated young . . . . .	32
1.4.4	The birthplace persistence is stronger the longer you stay . . . . .	33
1.5	Conclusions . . . . .	46
<b>2</b>	<b>Gender and the Urban Wage Premium</b>	<b>47</b>

2.1	Introduction . . . . .	47
2.2	Data . . . . .	49
2.2.1	Data sources . . . . .	49
2.2.2	Descriptive patterns . . . . .	51
2.3	Empirical specification . . . . .	53
2.4	Women gradually gained an urban advantage over time . . . . .	55
2.5	Differences in worker characteristics do not account for the rise in women's advantage . . . . .	58
2.6	The rise <i>is</i> driven by workers without a college degree . . . . .	63
2.7	The rise in the advantage disappears after accounting for the urban gradient in skill content of occupations . . . . .	65
2.8	Conclusions . . . . .	67
<b>3</b>	<b>Do Elite Universities Overpay Their Faculty?</b>	<b>70</b>
3.1	Introduction . . . . .	70
3.2	AKM in the Academic Context . . . . .	72
3.3	Data . . . . .	74
3.4	Results . . . . .	80
3.4.1	How important are the institutions for determining wages? Not much! . . . . .	80
3.4.2	Time-varying individual characteristics: It's mostly rank and experience . . . . .	82
3.4.3	Institution characteristics have little impact on salaries . . . . .	83
3.4.4	Why does institutional affiliation matter so little? . . . . .	88
3.5	Discussion and conclusion: is academia different? . . . . .	93
<b>A</b>	<b>Appendix to chapter 1</b>	<b>96</b>
A.1	Tables . . . . .	96

A.2 Figures . . . . .	103
A.3 Cross-country data . . . . .	103
A.4 The Empirical Strategy . . . . .	107
A.4.1 Identification . . . . .	108
A.4.2 From OLS to causal effects . . . . .	110
<b>B Appendix to chapter 2</b>	<b>112</b>
B.0.1 Sample definitions . . . . .	112
B.1 Tables . . . . .	113
B.2 Figures . . . . .	113
<b>C Appendix to chapter 3</b>	<b>117</b>
C.1 Tables . . . . .	117
C.2 Figures . . . . .	122
C.3 A simple example . . . . .	123
C.4 Data . . . . .	125
C.4.1 Building the work history panel . . . . .	126
C.4.2 Salaries . . . . .	127
C.4.3 Building the institution characteristics dataset . . . . .	129
C.4.4 University rankings . . . . .	131
C.4.5 Imputing of the THE ranks . . . . .	132
<b>References</b>	<b>136</b>
<b>Curriculum Vitae</b>	<b>143</b>

# List of Tables

1.1	IFLS: summary statistics by gender and migration status . . . . .	11
1.2	Indonesia: women's characteristics by migration status . . . . .	12
1.3	IFLS: women's migration patterns and regency characteristics by urbanicity of regency of origin . . . . .	14
1.4	Dispersion in regional employment rates for selected countries . . . .	16
1.5	Indonesia: autocorrelation in regency-level women's employment rate, 1980-2010 . . . . .	19
1.6	Indonesia: share of employment rate dispersion accounted for observed regency characteristics, 1980-2010 . . . . .	21
1.7	Indonesia: estimates of women's birthplace persistence on labor supply ( <b>b</b> ) . . . . .	29
1.8	Indonesia: estimates of men's birthplace persistence on labor supply ( <b>b</b> )	30
1.9	Indonesia: estimates of birthplace persistence on labor supply ( <b>b</b> ) for women who emigrated young . . . . .	32
2.1	Selected summary statistics, 1970-2016 . . . . .	52
2.2	Predicted differences in average wages by gender for selected CZ . .	57
2.3	Women's conditional urban advantage . . . . .	62
2.4	Skill city size gradients account for the rise in female urban advantages	66
3.1	Summary Statistics . . . . .	79
3.2	Fixed-effect variance estimates in AKM model . . . . .	80
3.3	Do rankings increase institution fixed effects? . . . . .	87

3.4 Does endowment increase institution fixed-effects? . . . . .	88
A.1 Indonesia: number of existing regencies by year, 1980-2010 . . . . .	96
A.2 Dispersion in regional employment rates within countries . . . . .	97
A.3 Dispersion in employment and paid employment rates for selected countries . . . . .	98
A.4 Female labor force participation rates by country: IPUMS vs ILOSTAT	99
A.5 Source IPUMS samples for cross-country data . . . . .	100
A.6 Indonesia: estimates birthplace persistence on women's labor supply ( <b>b</b> )	101
A.7 Indonesia: estimates birthplace persistence on men's labor supply ( <b>b</b> )	102
A.8 Indonesia: estimates of birthplace persistence on labor supply ( <b>b</b> ) for men who emigrated young . . . . .	102
A.9 Indonesia: high female employment regencies have worse educational outcomes . . . . .	103
B.1 Farm workers, 1950 census occupational classification . . . . .	112
B.2 Selected CZ-level summary statistics, 1970-2018 . . . . .	113
B.3 Women's conditional urban advantage for non-college workers, 1970-2018	116
C.1 Effect of time-varying characteristics . . . . .	117
C.2 Salary wage changes by transition type . . . . .	118
C.3 Transition probability by ranking quintile and institution type . . . .	119
C.4 Summary statistics including wage outliers . . . . .	120
C.5 Fixed-effect variance estimates in AKM model including wage outliers	120
C.6 Do rankings increase institution fixed effects (including wage outliers)	121
C.7 Does endowment increase institution fixed effects? (including wage outliers)	122
C.8 University location classification . . . . .	134

C.9 Description of location codes . . . . .	134
C.10 Ranking imputation regressions . . . . .	135
C.11 Number of schools imputed by ranking type . . . . .	135

# List of Figures

1.1	Female labor force participation rates at the district level for selected countries . . . . .	2
1.2	Indonesia: women's employment rate by regency, 2010 . . . . .	18
1.3	Indonesia: length of stay and marriage and fertility . . . . .	34
1.4	Indonesia: implied IQR gap in employment rate by age of emigration	35
1.5	Indonesia: employment type by length of stay . . . . .	37
1.6	Indonesia: women and selection by age of emigration . . . . .	42
1.7	Indonesia: education by length of stay . . . . .	43
1.8	Indonesia: length of stay and marriage and fertility . . . . .	45
2.1	Women's urban advantage, 1970-2018 . . . . .	56
2.2	Women's urban advantage for alternative conditioning on covariates, 1970-2018 . . . . .	64
2.3	Gender gap in skill use, 1970 . . . . .	66
2.4	Skill-specific urban premium, 1970-2018 . . . . .	69
3.1	Institution pay premium and rank . . . . .	86
A.1	Indonesian regencies . . . . .	103
A.2	Provinces in the original 1993 IFLS sample . . . . .	104
A.3	10-year autocorrelation in female employment rates at the district level for selected countries . . . . .	104
A.4	Indonesia: likelihood of work-related migration by emigration age . .	105

A·5	Estimates of birthplace persistence for different emigration age cutoffs	105
A·6	Indonesia: earnings and length of stay at birthplace . . . . .	106
B·1	Women's urban advantage for alternative sample selections, 1970-2018	113
B·2	Women's urban advantage for alternative CZ size measures, 1970-2018	114
B·3	Women's urban advantage by marital status, 1970-2018 . . . . .	114
B·4	Women's urban advantage by age group, 1970-2018 . . . . .	115
B·5	Women's urban advantage for alternative conditioning on covariates, 1970-2018 . . . . .	115
C·1	Average faculty log salary and institution rankings . . . . .	122
C·2	Institution premium and institution rankings (weighted by number of movers) . . . . .	123
C·3	institution premiums and rankings weighted for grouped institutions .	123
C·4	Probability of prestige level: lowest and median quality faculty . . .	125

## List of Abbreviations

ACS	.....	American Community Survey
CZ	.....	Commuting Zone
DOT	.....	Dictionary of Occupational Titles
FLFP	.....	Female labor force participation
IFLS	.....	Indonesian Family Life Survey
IPUMS	.....	Integrated Public Use Micro Samples
p.p.	.....	Percentage points
SUPAS	.....	Intercensal Survey
SUSENAS	.....	National Socieconomic Survey

## Chapter 1

# The Geography of Women's Work: Evidence from Indonesia

### 1.1 Introduction

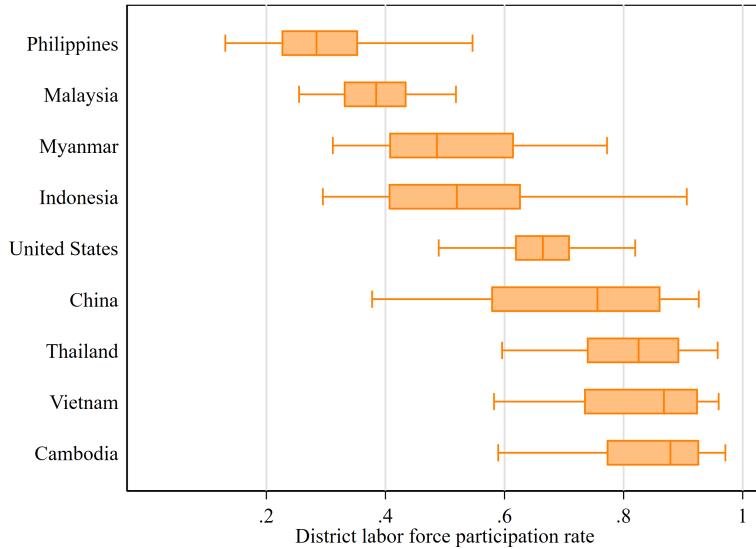
There are surprisingly large and persistent differences in female labor force participation (FLFP) rates within multiple countries at different levels of development. I show this in figure 1·1, where I illustrate the high dispersion in subnational labor force participation within several developing countries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

In this paper, I show that the subnational dispersion in female labor force partici-

---

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

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



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

pation has strong effects on the labor market outcomes of women born across different areas within the same country. To do so, I use rich data from internal Indonesian female migrants to show that their birthplace has a strong impact on their adult labor force participation.<sup>2</sup> I identify the birthplace causal effect by leveraging variation coming from women living in the same labor market as adults but who left their birthplace origin at different ages as children. Therefore, I exploit variation in the time spent in the birth location to disentangle the causal effect of the birthplace from variation driven by differences in women's unobservable characteristics. My strategy boils down to comparing the labor force participation of women who emigrated in early childhood, versus those who left in their early teens. Then, if women born

<sup>2</sup>Migrating is a relatively common phenomenon in Indonesia, with approximately one in five Indonesians residing outside their birth locality.

in places with higher female labor force participation are more likely to work the longer they stay there, I surmise that this is driven by the effect of their birth location. Moreover, by comparing women living in the same location as adults, I abstract from the effect of current labor market conditions and uncover variation that is likely driven by women's labor supply. This strategy builds on that of Chetty and Hendren (2018a), and focuses it on female outcomes in a large developing country.

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

I find that spending late childhood and early teen years in areas with high female employment makes women more likely to work as adults. Moreover, the longer they stay these locations, the likelier they are to enter the labor force. Under my preferred specification, staying in a place at the 75th percentile of female employment between

the ages of 6 and 16 years old makes women five percentage points more likely to work than those born in a place at the 25th percentile. These magnitudes are quantitatively important as they imply that approximately 23% of the current spatial inequality in women's labor force participation is transmitted to the next generation of women through birthplace effects.

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

Why would childhood exposure to the birthplace labor market have such persistent effects on women's outcomes? Previous research has suggested three main potential mechanisms: (i) higher investment in schooling, (ii) changes in parental investment, (iii) transmission of culture and/or gender norms (Molina and Usui, 2022; Fogli and Veldkamp, 2011; Blau et al., 2011). Exposure to labor markets with a higher proportion of working women could shape the career expectations of young girls, leading

to greater likelihood of staying in school. However, I find limited support for this mechanism in Indonesia. Furthermore, changes in parental investments are unlikely to account for my results. My findings indicate that women who had longer childhood exposure to regencies characterized by high female employment are more likely to enter the labor market as adults. If parental investments were the primary driver behind these outcomes, it would suggest that parental investment is highly sensitive to the duration of their child’s exposure. Given that parents have resided in these locations for a considerable period of time, it seems unlikely that such a high level of sensitivity exists. A more plausible explanation lies in the transmission of cultural and gender norms. I provide evidence that childhood exposure to these high-employment areas also influences decisions related to fertility and marriage. Moreover, I find that the birthplace effect is particularly pronounced during the ages when children’s attitudes towards gender equality are still malleable (Jayachandran, 2021).

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

This paper contributes to three strands of the literature. I contribute to the

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

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

for women’s human capital investment in West Africa (Milsom, 2021) and Japan (Molina and Usui, 2022).

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

## 1.2 Data

### 1.2.1 Data sources

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

My primary results come from the Intercensal Survey. This is a decennial survey containing social and demographic information for approximately 0.5% of the Indonesian population. This dataset has two advantages that make it uniquely suitable to study place effects on female labor supply. First, it records people’s birthplace, previous location and location of birth in midsized geographic units. The survey tracks this information at the level of the “regency”, which are administrative units similar

to US counties. Research on Indonesia typically uses them to identify local labor markets (Magruder, 2013; Bazzi et al., 2022), and their size allows me to study differences in women’s employment across smaller geographic units than what I could observe in alternative datasets.<sup>3</sup> The typical regency is home to approximately eight hundred thousand people and covers an area roughly twice size of the US state of Rhode Island. Appendix figure A.1 depicts all the 268 regencies in my dataset.

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

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

I source place characteristics from the 1980-2010 Indonesian Decennial Censuses

---

<sup>3</sup>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)

<sup>4</sup>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.

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

### 1.2.2 Measurement

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

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

For my main analysis, I restrict my sample to one-time internal migrants because this is the population for which I can separate the current place of residence from the birthplace. I define migration as living outside the regency of birth. Moreover,

whenever I link women's employment with birthplace characteristics, such as FLFP or urbanicity, I source these from the 2010 Indonesian Census. In robustness checks, I show that my results are similar when I use information from other census years.

### 1.2.3 Summary statistics

In the this section, I provide an overview of my data and the Indonesian labor market using data from the pooled 1985, 1995, and 2005 Intercensal Surveys. I obtain a qualitatively similar picture if I use the IFLS. Table 1.1 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.<sup>5</sup> Additionally, there are significant gender gaps in employment, worker type, and industry. Women are 38 percentage points less likely to work than men, which while large is consistent with patterns observed in Southeast Asia. Furthermore, women are five times more likely than men to be unpaid or salary workers. Unpaid workers are people that work or help to earn an income but are not paid a wage or salary. Most unpaid workers work in agriculture (82%) and the retail industry (10%) (Minnesota Population Center, 2020). Lastly, women are more likely than men to work in service and manufacturing industries.

---

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

**Table 1.1:** IFLS: summary statistics by gender and migration status

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

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

**Table 1.2:** Indonesia: women's characteristics by migration status

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

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

In table 1.2 I zoom in on the women migrants (emigres). They are the focus of my main analysis because they are the women for whom I can distinguish between the current place of residence and the regency of birth. I present statistics for all female migrants as well as for those who migrated before they turned 19. The table highlights significant differences between migrants and stayers. They are more educated and more likely to be employed than stayers. Moreover, they are more likely to have salaried jobs and live in urban areas. This suggests that women migrants are moving

to areas with more formal labor markets and less rural surroundings. Lastly, column (3) shows that other than the marriage rates and the level of education, women who left their birthplace young are generally very similar to the typical female migrant.

In the final rows of table 1.2, I provide additional details on the factors driving women’s migration, which are sourced from the 1985 Intercensal Survey. Women’s migration is largely motivated by reasons other than work. Specifically, over 85% of female migrations are associated with either education or “other reasons”. Unfortunately, the survey does not provide a breakdown for the latter category. However, data from the IFLS indicates that the majority of these moves are likely due to family-related reasons.

The fact that migrant women are more likely to work in the service sector could suggest that migration in Indonesia is predominantly rural to urban. However, table 1.3 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 from Statistics Indonesia. I then compute migration statistics for women born in urban and rural regencies. The table shows three salient features. First, migration is not exclusive to rural regencies. Women born in urban regencies also migrate at high rates. Second, migration is not just rural-to-urban. Panel A breaks down the migration flows by origin and destination. The urban-to-rural, rural-to-rural and rural-to-urban flows are substantial. Finally, panel B shows that there is considerable heterogeneity in employment rates within each regency classification. There, I show summary statistics for the female employment rates within these categories. There is

substantial dispersion in female employment *within* both of these categories. Thus, the dispersion in female employment rates I discuss in the next section is not driven by differences between urban and rural areas.

**Table 1.3:** IFLS: women's migration patterns and regency characteristics by urbanicity of regency of origin

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

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

### 1.3 Four facts about women's labor supply

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

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

In table 1.4, 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 are a subset of the countries with regional employment data available below the province or state level in IPUMS International in the appendix.<sup>6</sup> 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.

---

<sup>6</sup>Data for the full set of countries is available in table A.2 All the insights discussed in this section generalize to this larger set of countries. Further details about the cross-country data are available in section A.3 in the appendix

**Table 1.4:** Dispersion in regional employment rates for selected countries

Country	Women			Men			Population	Observations
	IQR (1)	SD (2)	Mean (3)	IQR (4)	SD (5)	Mean (6)		
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.2 and section A.3 in the appendix for additional details on the cross-country data.

This table highlights three insights on women's employment. First, columns 1 to 3 show that, despite the significant differences at the mean, all countries exhibit large differences in women's employment rates *within* their borders.<sup>7</sup> 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).<sup>8</sup>

Second, the dispersion of female employment rates is a widespread phenomenon across countries at different levels of development and geographic regions of the world. Table 1.4 includes countries from various regions, including Asia, America, Africa, and Europe. It also includes middle income countries like Indonesia and Mexico, and high income countries like USA and Spain. These findings suggest that the factors driving the dispersion in female employment rates are not limited to specific regions or income levels.

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

---

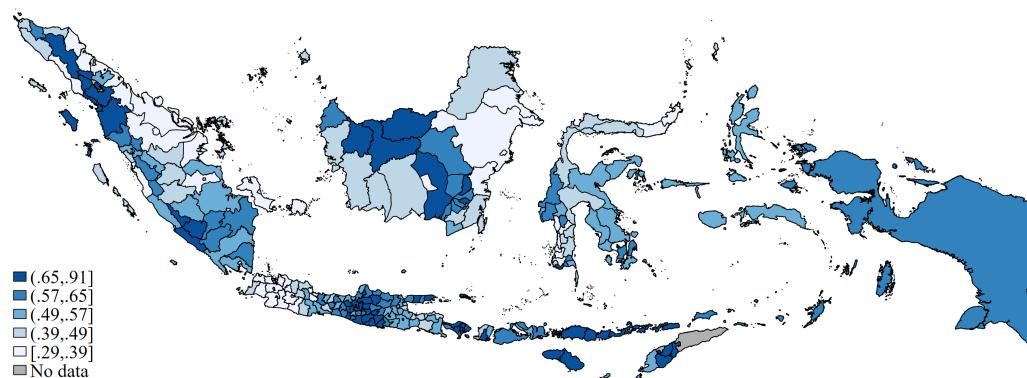
<sup>7</sup>Table A.3 shows that the large within-country dispersion in women's employment is not the result of regional variation in the rates of unpaid employment. For the specific case of Indonesia, 55% (IQR 12 p.p.) of the total dispersion still remains when I focus on paid employment only. This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

<sup>8</sup>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.

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

Figure 1·2 provides a detailed view of the variation in female employment rates within Indonesia. The map shows women's employment rates in all 268 regencies in my dataset, grouped by color into quintiles. Darker blues indicate higher employment rates. The map reveals that women work at vastly different rates across the country. For instance, the top quintile of regencies has employment rates above 65%. In contrast, the bottom quintile of regencies has rates below 29%, and this group includes significant population centers such as the Bogor regency and the city of Medan.<sup>9</sup> Notably, the map reveals that the dispersion in women's employment extends across the whole country and is not driven by any particular province, island, or group of regencies.

**Figure 1·2:** Indonesia: women's employment rate by regency, 2010



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

---

<sup>9</sup>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 A·1 in the appendix.

### 1.3.3 Fact 3: women's employment rates are highly persistent

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

**Table 1.5:** 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 1.5, I show estimates of the autocorrelation of the regency-level employment rates across different time horizons. For this table, I

standardize the regency employment rates by year and run regressions of the form:

$$e_{rt} = \gamma_{t-j} e_{rt-j} + \varepsilon_{rt} \quad (1.1)$$

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

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

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

The highly persistent variation in female employment is likely driven by structural differences across regencies. These could be, for example, differences in the family structure or the industry mix across these labor markets. Motherhood is associated with lower female attachment to the 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 1.6, I test whether permanent differences in the industry mix or women's demographics can account for most of the dispersion in female employment across

---

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

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

**Table 1.6:** 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 1.6 reveals that differences in women's demographics or the industry mix account for only a moderate share of the dispersion in female employment across regencies. In column (4), controlling for women's education level and the regency's family and age structure accounts for only a third of the dispersion in employment rates. Adding a complete set of industry shares takes the  $R^2$  to 47%. Although these factors account for a portion of the employment rate dispersion, collectively, they still leave 53% unaccounted for. In contrast, column (10) shows these same variables can account for 80% of the variation in men's employment rates. Therefore, the dispersion in female employment rates reflects variation in *other* factors that are

*specific* to women. Therefore, the variation in female employment is likely driven by structural differences across regencies that are not captured by the variables included in these regressions. These could be differences in the social norms, cultural values, or institutional arrangements that shape gender roles and expectations in different contexts.

## 1.4 Empirical strategy and results

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

### 1.4.1 Place and women’s labor supply: the identification challenge

The place of residence can, directly and indirectly, affect women’s labor supply. Direct effects affect the labor supply of all the current female residents. There is considerable empirical evidence documenting these effects. These might arise, for example, from factors such as the levels of childcare availability (Compton and Pollak,

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

### The omitted variable problem

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

$$e_{it} = \delta_c + \sigma p_b + \eta_{it} \quad (1.2)$$

In this model, women’s employment choices depend on three main factors. First,

a place-of-residence fixed effect  $\delta_c$  captures all the direct effects of location  $c$  on female labor supply. These might include commuting costs, childcare availability, and gender discrimination. Second, the birthplace female employment  $p_b$  is intended to capture the causal effect of growing up in a location where  $p_b$  percent of the women work. Finally, the error term  $\eta_{it}$  captures all other factors making some women migrants more likely to work than others.

Model (1.2) follows closely the tradition brought forth by the “epidemiological” approach literature (Fernández and Fogli, 2006; Fernández et al., 2004; Fernández, 2013). Women’s birthplace could have multiple impacts on women’s behavior as adults. Including the prevailing female employment rates as the main regressor in equation (1.2) relies on the idea that these rates capture the place-driven factors vital in determining women’s employment choices. Moreover, focusing on the exposure in the origin location, allows to isolate variation potentially driven by environmental factors –culture, institutions–, from variation driven by purely economics factors, 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 (1.2),  $\sigma$  captures the birthplace effects. It gives the counterfactual increase in women’s employment if they had been born in a place with a one p.p. higher female employment rate. In the ideal, but unfeasible experiment, I would reassign women’s birthplace randomly while keeping their family and the current residency fixed. Random assignment would guarantee that women’s birthplace is uncorrelated with the error term. Thus an OLS regression of (1.2) would give a consistent estimate of  $\sigma$ . In observational data, however, it is likely that the unobserved factors imbued in the error term are correlated with birthplace labor supply. Therefore, the OLS estimates of employment rate slope will conflate the causal effects of birthplace with

omitted variable bias:

$$\begin{aligned}\text{plim } \hat{\boldsymbol{\sigma}} &= \boldsymbol{\sigma} + \frac{\text{cov}(\tilde{p}_b, \tilde{\eta}_{it})}{\text{var}(\tilde{p}_b)} \\ &= \boldsymbol{\sigma} + \boldsymbol{\gamma}\end{aligned}\tag{1.3}$$

where tilde accents denote variables that are residualized from regency fixed effects (Angrist and Pischke, 2009). Expression (1.3) shows that the OLS coefficient reflects two factors: first, the causal effect of birthplace  $\boldsymbol{\sigma}$ , but also differences in unobservable characteristics across women from different origins  $\boldsymbol{\gamma}$ . The critical identification challenge is separating the selection term  $\boldsymbol{\gamma}$  from the birthplace effect  $\boldsymbol{\sigma}$ .

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

### Using emigration age data to identify causal effects

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

is determined as follows:

$$e_{it} = \delta_c + \lambda_a + \sigma_a p_b + \eta_{it} \quad (1.4)$$

Here  $\sigma_a$  captures the cumulative effect of birthplace up to age  $a$ <sup>11</sup>. The age of emigration fixed-effects  $\lambda_a$  absorb differences in labor force participation across women who emigrated at different ages. The causal impact of staying in the birthplace at age  $a$  is then  $\pi_a = \sigma_a - \sigma_{a-1}$ .

By an argument analogous to that in expression (1.3), the OLS estimates will conflate the causal effects of birthplace  $\sigma_a$  with the omitted variable bias for women migrating at age  $a$   $\gamma_a$ :<sup>12</sup>

$$\text{plim } \hat{\sigma}_a = \sigma_a + \gamma_a \quad (1.5)$$

**Assumption 1. Constant omitted variable bias**

*Omitted variable is the same no matter the age of emigration, that is  $\gamma_a = k$*

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

---

<sup>11</sup>The causal effect  $\sigma$  in the previous subsection can be interpreted as a weighted average of age-specific causal effects.

<sup>12</sup>You can find the full derivation of this expression in appendix section A.4. I defined  $\gamma_a$  as the  $a$ -th element in the vector  $\text{plim} \left[ (\tilde{P}' \tilde{P})^{-1} \tilde{P}' \tilde{\eta} \right]$ . Here,  $P$  is the matrix containing the interaction between the age of emigration dummies and the birthplace female employment rates.  $\eta$  is the vector of error terms. Tilde-accented variables are residualized from current location and age of emigration dummies.

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 (see Figure A.4 in the appendix), this does not violate the identification assumption.

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

$$\begin{aligned} \text{plim } \hat{\sigma}_a - \hat{\sigma}_{a-1} &= \sigma_a - \sigma_{a-1} \\ &= \pi_a \end{aligned} \tag{1.6}$$

this expression also shows that identification does not necessarily require constant bias across all *all* emigration ages. If, instead, bias is constant only within some age ranges, I can still identify the effects within those ranges. For example, suppose there is reason to believe that the bias for women who emigrated between 0 to 6 years old is different than for those who emigrated between the ages of 7 to 15. If constant selection holds *within* these ranges, I can still identify the place effects within the 0 to 6 and 7 to 15 ranges. In section 1.4.4, I present estimates from the birthplace effects along with evidence that women emigrating at different ages are similar to each other along multiple dimensions.

#### 1.4.2 Birthplace is highly predictive of women's labor supply

I start by comparing the labor supply of women who *live in the same location* but were born in different regencies. I do this by regressing a dummy equal to one if the person is employed at year  $t$  ( $e_{it}$ ) on year by current-regency fixed-effects ( $\delta_{ct}$ ),

women's employment rate in her regency of birth ( $p_b$ ), and a set of individual and regency-level controls  $X_{it}$ . These controls might include age, religion, education, number of books at home when growing up.

$$e_{it} = \delta_{ct} + \mathbf{b}p_b + X_{it}\kappa + \varepsilon_{it} \quad (1.7)$$

I source the regency female employment rates from the 2010 census, but I obtain similar results when using data from other census years.<sup>13</sup>

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

I refer to the slope of the birthplace employment rate as  $\mathbf{b}$  to emphasize that it generally differs from the causal effect discussed in Section 1.4.1. A positive value of  $\mathbf{b}$  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.

---

<sup>13</sup>This is because employment rates are highly persistent.

**Table 1.7:** Indonesia: estimates of women’s birthplace persistence on labor supply ( $b$ )

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

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

Table 1.7 shows estimates of the birthplace persistence coefficient  $b$ . Column (1) shows results from a baseline specification that includes regency by year fixed effects only. The coefficient of 0.30 indicates that birthplace is highly predictive of women’s employment. To see how large this coefficient is, let us consider two women: Putri and Amanda. Putri was born in the city of Probolinggo in East Java, which has a female employment rate of 40%. In contrast, Amanda was born in the regency of Sukoharto in Central Java, with a female employment rate of 62%. These rates places these regencies at approximately the 25th and the 75th percentiles of the distribution of female employment rates. The 0.30 coefficient implies that Putri is 7 percentage points less likely to work than Amanda. This is a difference of 17% relative to the employment rate of the average woman in my data.

The additional estimates in table 1.7 also allow me to rule out several potential drivers of the birthplace persistence. Columns (2) and (3) show that controlling for women’s age and religion barely modifies the estimate. Thus, this persistence is not explained by geographic differences in age or religion. Column (4) adds education level

as a control. Recent research suggests that exposure to low-employment places can affect women's labor supply through the expectations and education channel (Molina and Usui, 2022). In areas with low female employment rates, women set low labor market expectations and thus invest less in education. However, however column (4) indicates that the birthplace persistence is not driven by differences in educational investment.

**Table 1.8:** Indonesia: estimates of men's birthplace persistence on labor supply (*b*)

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

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

The strong birthplace persistence in labor supply is essentially exclusive to women. I show this in table 1.8, where I show estimates from regressions where I relate men's employment in adulthood to their birthplace's *female employment rate*. Note that all these estimates are below 0.10 (about 30% the estimates in women) and imply little variation in men's employment rates across regencies. For example, the estimate in column (8) implies an IQR gap of only 2 p.p.

The persistence in women's employment rates could still be driven by variation across regencies in, for example socioeconomic or demographic factors. Unfortunately, the Intercensal Survey has limited demographic and socioeconomic information. Therefore, in tables A.6 and A.7 in the appendix I take advantage of the rich

data available in the IFLS to rule out additional potential drivers of the birthplace persistence.

First, in columns (1) to (4) of table A.6 I reproduce the birthplace persistence estimates for the women migrants in the IFLS using the same specifications as in table 1.7. Reassuringly, these results confirm the Intercensal survey estimates, with a similar implied IQR of 8 p.p. Moreover, table A.7 shows similarly small persistence estimates for men.

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

### 1.4.3 There is large persistence for those who migrated young

The birthplace persistence could be reflecting complex endogenous relationships between women's origin, their migration decision and their labor supply. Migration is a voluntary decision where the potential job opportunities at the destination are likely influence where women move to. In table 1.9, I focus my analysis on women who left their birthplace before they turned 19. Thirty eight percent of female migrants left their birthplace before this age. For these women, the migration decision is more plausibly driven by their parents' decisions. Reassuringly, I obtain similar persistence estimates for these sample.<sup>14</sup> Moreover, these estimates are robust to the choice of the migration age cutoff (see Figure A.5 in the appendix).

**Table 1.9:** Indonesia: estimates of birthplace persistence on labor supply (**b**) for women who emigrated young

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

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

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

#### 1.4.4 The birthplace persistence is stronger the longer you stay

The strong birthplace persistence in women's employment could still reflect unobservable differences between women from different origins. Here, I address this concern by exploiting differences in the timing of migration to argue that this persistence reflects the causal effect of women's birthplace. To do so, I augment expression (1.7) by (i) allowing the coefficient on female employment rate to vary by the emigration age ( $\mathbf{b}_a$ ), and (ii) adding age of emigration fixed-effects ( $\lambda_a$ ).

As I discuss in section 1.4.1, I can decompose the OLS estimates of age specific-slopes into a cumulative causal effect  $\sigma_a$ , and a selection term  $\gamma$ :

$$\mathbf{b}_a = \sigma_a + \gamma$$

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

$$\pi_a = \mathbf{b}_{a+1} - \mathbf{b}_a$$

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

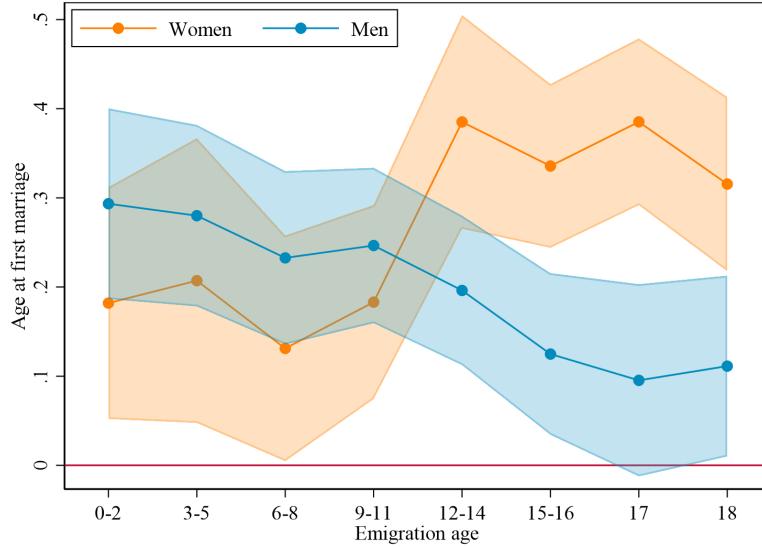
To estimate this model, I leverage age of emigration data from the Intercensal survey. Because the number of migrants at any given age is relatively small relative to the number of regencies, I bin emigration age into three-year cells.

#### Longer stay does make you more likely to work

Figure 1·3 displays estimates of birthplace persistence ( $\mathbf{b}_a$ ) by age of emigration for both men and women. My sample remains restricted to people who left their birthplace before they turned 19. The regressions control for a quadratic polynomial

in age, as well as current regency-by-year, education, and religion fixed effects.

**Figure 1·3:** Indonesia: length of stay and marriage and fertility



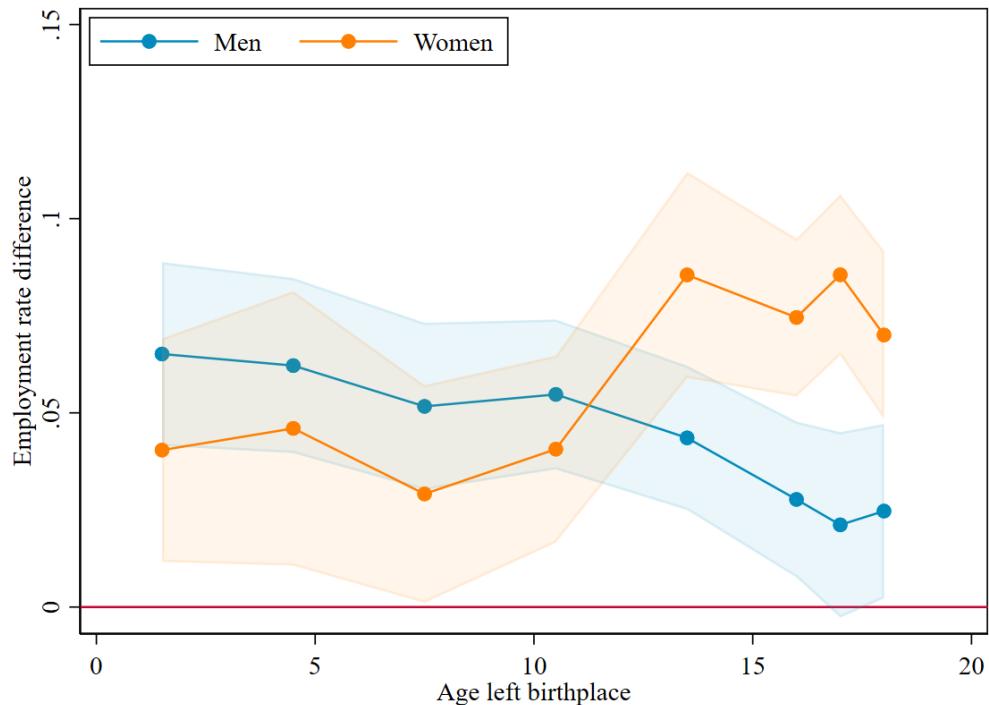
**Note:** The figure shows estimates of the birthplace persistence coefficients by age of emigration  $b_a$ . It uses data from 1995 and 2005 Intercensal surveys. Panel (b) uses information from the 1995 survey only, as fertility data is not available for 2005. The regression controls for current regency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

These results show a striking pattern in the birthplace coefficients: women with longer exposure to high-employment locations are more likely to work. The birthplace persistence coefficients increase from 0.18 for women who left their birthplace between 0 to 2 years old, to 0.38 for those who left between 12 to 14 years old, and remain roughly constant thereafter. These patterns provides several insights. First, women from high-employment locations are likely to work from the outset. Women who left their birthplace before they turned three have very little exposure to their birthplace, and yet they are more likely to work than those coming from low-employment locations. Following the discussion in Section 1.4.2, I interpret this coefficient as reflecting unobservable differences between women from different origins (omitted variable bias). Second, longer exposure leads to higher female employment. Under the constant omitted variable bias assumption, we can attribute the increase of

approximately 20 p.p. in the birthplace persistence coefficients to the effect of longer exposure to high-employment locations. Third, the birthplace effect is concentrated in late childhood and early teens, as the increase in the persistence happens between the ages of 6 to 14 years old. Staying after the age of 15 has no additional effect.

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

**Figure 1·4:** Indonesia: implied IQR gap in employment rate by age of emigration



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

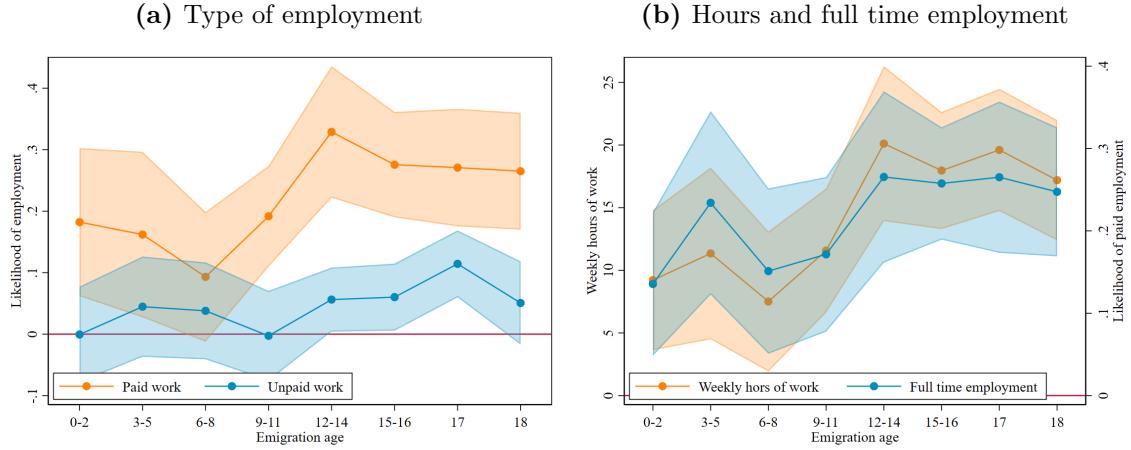
These results suggest that place effects play a crucial role in driving geographic differences in women's labor supply. This is illustrated in Figure 1·4, which displays the counterfactual gaps in employment between two women, one born in a regency at 75th percentile of the employment distribution and another born at the 25th percentiles of employment, if they had left their birthplace at different ages. I call this gap the IQR gap in employment. The figure places the gap estimates at the midpoint of each of the age brackets in figure 1·3. If both of these women had emigrated in their first year of life, I would observe a gap of 4 p.p. in their labor supply when they are adults. This initial gap is driven by unobservable differences between these two women. In contrast, if they stayed in their birthplace up to 13 years old, this gap would widen up to 9 p.p. The increase of 5 p.p. in the likelihood of employment is equivalent to 27% if existing gap in FLFP between these regencies and is driven by the longer exposure to their birthplace. Therefore, a significant portion of the current inequality in female labor force participation is transmitted to the next generation of women growing up in these locations through birthplace effects.

### **Longer stay translates into more paid employment and more hours**

In figure 1·5 I show that longer exposure to high-employment labor markets also translates into higher paid employment and higher working hours. Panel (a) breaks down the employment into paid and unpaid work. Unpaid work accounts for about a 35% of all female employment. The increase in employment from Figures 1·3 and 1·3 is unlikely to represent more economic independence for women if it were entirely driven by unpaid work. However, panel (a) shows that increase in the birthplace persistence between 6 to 14 years old is driven by *paid employment*. The rise in the coefficients between 0 to 14 years old translates into an increase of 3.2 p.p. IQR gap in employment. This is 64% of the effect on all employment from Figure 1·3. This contrasts with results on unpaid work. There is little effect on the likelihood of unpaid

employment up to 14 years old. Although there is an uptick in the coefficients at 17, the effect is small. In all, staying up to 17 at birthplace renders an IQR gap of 1.2 p.p.

**Figure 1·5:** Indonesia: employment type by length of stay



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

Panel (b) of Figure 1·5 I shows additional results on the likelihood of full-time employment and weekly hours of work. Data on weekly hours of work is not available in the 2005 Intercensal Survey, thus these results use data from the 1985 and 2005 surveys only. However, the plot shows a consistent picture: staying in high female employment places between 6 to 14 years old rises women's labor supply. The birthplace employment coefficients rise sharply at these ages and both increases are sizable. They translate into IQR gap increases of 2.5 weekly hours, and 2.86 p.p. in the likelihood of full-time employment.

So far all the evidence presents a consistent picture: longer stay in high-female employment labor markets translates into higher attachment to the labor market in

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

### **The data supports the constant selection assumption**

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

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

I cannot test whether the correlation between female labor force participation at

birthplace and women's unobservable characteristics is constant across emigration age. However, I can test whether the correlation between the employment rate and a series of individual characteristics I do observe is the same no matter the age women migrated. To do this, I estimate the a regression where I regress a woman characteristic  $y_i$  on age of emigration fixed effects  $\lambda_a$ , female LFP at birthplace  $p_b$ , and interactions between age of migration and female LFP:

$$y_i = \lambda_a + \beta p_b + \sum_a \beta_a 1_a \times p_b + X_i \kappa + \varepsilon_{it} \quad (1.8)$$

in model 1.8, I chose 18 as the base category and thus the  $\beta_a$  can be interpreted as the difference between the slope at age  $a$  and the slope at age 18. Under constant selection across all the ages *all the interaction terms  $\beta_a$  should be jointly zero.*

In figure 1·6 I show estimates of the interaction terms  $\beta_a$  for different outcome variable. Panel (a) uses data from the Intercensal Survey while panels (b) to (d) take advantage of the richer demographic information available in the Intercensal Survey. All regressions control for a full set of education and religion dummies, and a quadratic polynomial in age. In addition, panels (a) to (c) include current-regency fixed effects.

In panel (a), I present estimates of the interactions between migration age and female employment at birthplace in regressions where I use migration motive dummies as dependent variables. Each series of coefficients in the panel represents a different regression. In Section 1.2.3, I showed that the reason for migration changes as women age, with older becoming more likely to migrate for work.<sup>15</sup> These age-related changes in the reason for migrating could pose a problem for my identification strategy if

---

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

they if they differ between regencies with high and low female employment.<sup>16</sup> To alleviate this concern, in panel (a) I show that most of the interactions in the work-migration series are insignificant at the 5% level and, in fact, all the interactions from 3 to 17 years old are jointly insignificant. Furthermore, note the work series does not reproduce the sharp increase between 6 to 14 years from Figure 1·3. Panel (a) also displays analogous slopes for regressions with family and education migration dummies as outcomes. In both cases, I cannot reject that all these interactions are jointly zero. Therefore, there is no consistent evidence that changes in migration motives are the driving factor behind the birthplace persistence.

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

In panel (d), I present results from regressions where I use characteristics of the

---

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

destination regency as dependent variable. There is evidence that skills acquired at the origin location are important at determining post-migration outcomes. Thus, in this panel I explore the possibility that the birthplace persistence is the result of changes of –admittedly complicated– selection patterns across migration age cohorts. The results in this panel are similar as in the other graphs in the figure, with all the interactions being jointly insignificant. Overall, the lack of clear patterns in Figure 1·6 as evidence in support of the constant omitted variable bias assumption.

### **Discussion: why does birthplace matters so much?**

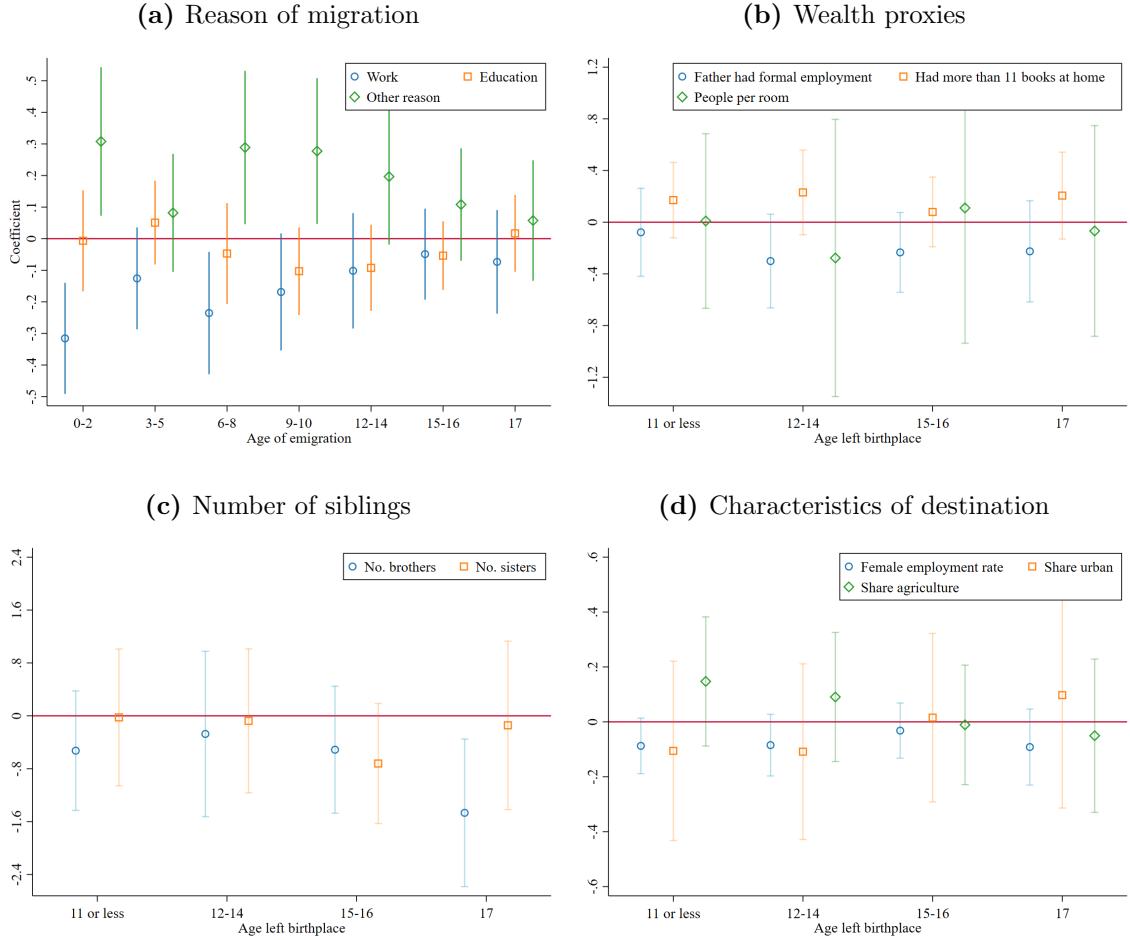
Having established that exposure childhood exposure to birthplace has a strong effect on women’s choices, the natural question is then through which mechanisms do birthplace influence women’s choices. Here I examine the evidence of three mechanisms: (i) human capital accumulation, (ii) schooling quality,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

Exposure to birthplace could affect women’s labor supply via their career expectations and their educational investment. Being exposed to an environment where women are actively participating in the labor force could alter their career expectations and make them more likely to invest in further education. For example, Molina and Usui (2022) that in Japanese municipalities with higher female participation rates, teenagers exhibit greater educational aspirations, leading to increased investment in schooling. If higher investment in schooling accounts for my results, I should observe higher schooling in women with higher exposure to high-female employment regencies. I test this in figure 1·7 where I show estimates of the birthplace persistence coefficients for regressions using measures of schooling as dependent variables. The figure shows results for both the years of schooling, and a dummy equal to one if the woman completed primary.<sup>17</sup> The figure gives little support to education as the

---

<sup>17</sup>Figure 1·3 shows the effects of birthplace are concentrated between the ages of 6 and 14. There-

**Figure 1·6:** Indonesia: women and selection by age of emigration

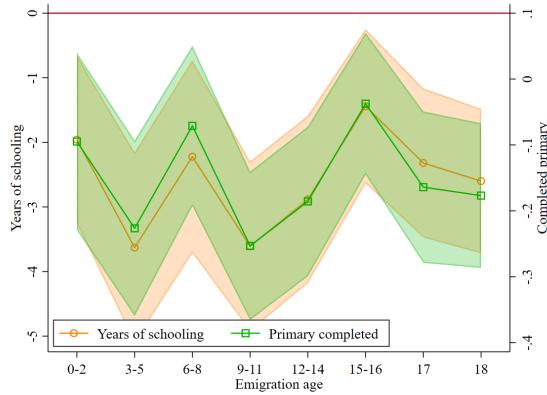


**Note:** The figure show the coefficients on the interactions between age of emigration and birthplace female labor force participation. The regressions also control for (i) age of emigration dummies, (ii) birthplace female employment rate (iii) interactions between the emigration age and birthplace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

main channel through which the birthplace effects operate. First, the 0-2 and the 18 years old coefficients are very similar and thus there is no evidence that longer stay in high-female employment regencies leads to more overall education. Second, although there is a jump in the coefficients at 15-16 years old, the employment results showed fore, completing primary school would be the main margin of action.

that birthplace effects were concentrated between 6 to 14 years old. Therefore, the timing of the jump is off.

**Figure 1·7:** Indonesia: education by length of stay



**Note:** The figure show the coefficients on the interactions between age of emigration and birthplace female labor force participation. Error clustered by regency of birth. The figure shows 90% confidence intervals. Data from the Intercensal Survey.

While women from areas with high female employment do not necessarily spend more time in school, the impact of birthplace can manifest through schooling if these locations offer education of higher quality. In this case, areas where women participate more actively in the labor market could have educational systems of higher quality that target women more effectively. Thus, even if women do not spend more time in schooling, women who spend more time in their birthplace would be exposed *longer* to an education system of higher quality. However, there are two pieces of evidence that point against this channel. First, note that all the coefficients in Figure 1·7 are *negative* and hover around -2.6. This means that women from high-employment regencies spend less time in school than their counterparts from low-employment regencies. The average coefficient of -2.6 means that women born in a regency at the 75th percentile of employment spend seven less months in school than those born at a 25th percentile regency. Second, high female employment regencies have worse overall female educational outcomes. Appendix table A.9 show that women

in these regencies have worse education outcomes. In this table I split regencies at the mean of the female employment rate and compute average education outcomes for each group. On average, women in high-employment regencies stay one year less in school, and are much less likely to complete primary and secondary education. If the educational quality in high-female employment regencies were higher, one would expect that women stay in the system longer and they have better overall educational outcomes. However, the evidence does not support this possibility.

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

A more plausible driver of the birthplace effects is the transmission of cultural gender norms. There is a growing literature emphasizing that the transmission of culture or gender norms has permanent effects on women's labor market outcomes (Fernández et al., 2004; Alesina et al., 2013; Blau et al., 2011). Both the Intercensal Survey and the IFLS provide limited data to formally test this channel, but two pieces of evidence support it. First, I find evidence of similar birthplace effects on fertility and age of marriage, outcomes more directly linked to gender norms. In Figure 1·8, I present estimates of the birthplace coefficients for regressions using the age at first marriage and the number of children born as outcomes.<sup>18</sup> This figure reveals a pattern

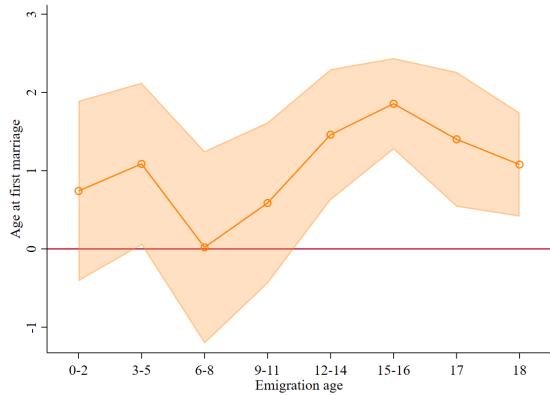
---

<sup>18</sup>The Intercensal Survey only includes fertility and marriage questions for women, hence I cannot present estimates for men.

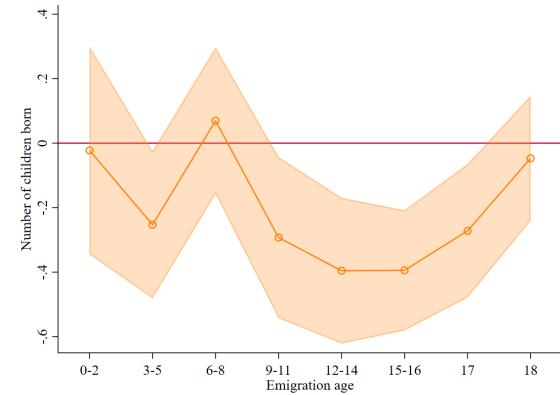
that closely aligns with the employment results, where longer childhood exposure is associated with delayed marriage and lower fertility rates. Moreover, these effects appear to be concentrated between the ages of 6 to 14 years old, although the results for the number of children are less clear due to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

**Figure 1·8:** Indonesia: length of stay and marriage and fertility

(a) Age at first marriage



(b) Number of children



**Note:** The figure shows estimates of the birthplace persistence coefficients by age of emigration  $b_a$ . Panel (a) uses 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.

## 1.5 Conclusions

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

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

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

## Chapter 2

# Gender and the Urban Wage Premium

### 2.1 Introduction

Do women benefit more than men from living in big cities? Although previous research extensively documents that big cities pay a wage premium, there is surprisingly little evidence on whether this –urban– wage premium is higher for women than for men. Most studies either focus on men only, or do not disaggregate by gender. In this paper, I document that over the last six decades women’s urban wage premium became increasingly larger than men’s in the United States. Since 1990 there is an overall decline in the urban wage premium of men and women. However, women have been less affected by this decline.

Using data for U.S. Commuting Zones (CZ), I show that there are large differences in the evolution of the urban wage premium across genders. In 1970, there was no difference between men’s and women’s urban wage premium but, over the period, a large gap opened between them. By 2016, women’s urban wage premium was 40% larger than men’s. I call this phenomenon the rise of *women’s urban advantage*. Multiple robustness checks show that these gender differences are not driven by simple changes in population composition across genders and Commuting Zones.

To provide further light on the forces behind the rise women’s urban advantage, I decompose its change into components capturing (i) differential sorting on observables across CZs by gender, (ii) the effect of CZ characteristics, and (iii) an unexplained residual. This decomposition is similar to those seen in standard Oaxaca-Blinder

literature on the gender-gap literature (Blau and Kahn, 2015). My results show that neither worker sorting nor CZ characteristics drive the rise in women’s urban advantage. Under the richest specification, I control for basic demographic characteristics, education, industry, occupation, commuting time, among others. Previous research find these factors to be important determinants of wage gaps across genders (Le Barbanchon et al., 2021; Blau and Kahn, 2015). However, in my data, they jointly only account for at most 20% of the overall increase in women’s advantage. The remaining 80% remains unexplained.

Next, I show that the rise in women’s urban advantage is driven by workers without college degrees. Previous research documents that the trends in the urban wage premium are very different for college and non-college workers (Autor, 2019). My results show that the increase in women’s urban advantage stems from non-college workers. This increase cannot be explained by worker or CZ characteristics, and it mostly stems from differential declines in the urban wage premium across genders after 1990.

I then use data from the Dictionary of Occupational Titles and show that the rise in women’s advantage for non-college workers is driven by drastic changes to the urban skill premia to certain worker skills. Over this period there was a drastic decline in the urban premia to non-routine manual and routine cognitive skills, while the premia to non-routine cognitive skills increased sharply. By virtue of their occupational distribution, men and women had different exposures to these changes and this accounts for the differential trends in their urban wage premia.

This paper is most closely related to the vast literature studying the urban wage premium (Glaeser and Maré, 2001; Glaeser and Gottlieb, 2009; Duranton et al., 2013; de la Roca and Puga, 2017; Duranton and Puga, 2020; Baum-Snow et al., 2018; Autor, 2019). Evidence for women in this literature is rare, as most studies focused either

on men or did not dis-aggregated results by gender. Notable exceptions are Bacolod (2017) and Phimister (2005). They find that women's premium is larger than men's for the US and the UK respectively. My results show this was not always the case in the US. Instead, the relative size of women's premium has continually increased relative to men's.

This paper is also related to the recent research documenting declines in the urban wage premium for non-college workers (Autor, 2019; Baum-Snow et al., 2018). The reasons behind this phenomenon are not well understood in the literature and my results highlight how it was concentrated on the jobs using certain skill intensively.

Finally, my paper is also related to the rich literature on the gender wage gap (Blau and Kahn, 2015; Gollin et al., 2021; Olivetti and Petrongolo, 2016). The bulk of this literature has focused on occupation, industry, and job flexibility as the main drivers of the gap (Goldin, 2014; Blau and Kahn, 2015). Until very recently geographical variation in the wage gap had been left unexplored. Recent contributions highlight that local amenities, such as commuting time, play an important role in determining labor market outcomes across genders (Black et al., 2014; Le Barbanchon et al., 2021; Liu and Su, 2020). My findings contribute to this literature by emphasizing that there is rich variation in the gender wage gap within the US. They also point to a rich interaction between the gender wage gap and local labor market characteristics.

## 2.2 Data

### 2.2.1 Data sources

My main analysis uses data from the US Decennial Census for the years 1970, 1980, 1990, and 2000 from IPUMS, along with the five-year samples from the American Community Survey (ACS) for the years 2011 and 2018 (Ruggles et al., 2010). The 2011 ACS contains data for the years between 2007 and 2011, while the 2018 ACS

contains data between 2014 and 2018. I label these ACS samples as 2010 and 2016 respectively.

My sample follows closely those commonly used in the gender-gap literature (Blau and Kahn, 2015). It consists of full-time year-round non-farm wage and salaried workers, aged between 18 and 64 years old, not attending school, and living outside of group-quarters.<sup>1</sup> I define full-time year-round workers as those working for at least thirty-five hours per week, for at least forty weeks in the previous calendar year.

I identify local labor markets with Commuting Zones (CZs). Commuting Zones are collections of counties with strong commuting ties with other counties within the same zone, but with weak ties with counties outside the zone. I use the 1990 CZ delineation as in Autor (2019). Throughout the paper, I use the terms city and local labor market interchangeably. Moreover, I refer to specific CZs with the name of its largest city according to 1990 population counts. Cities' names and population counts come from the delineation files provided by the Economic Research Service from the US Department of Agriculture (USDA, 2019). I follow Autor and Dorn (2013) and restrict the sample to the 722 CZs in mainland USA.

I measure city size with the log of CZ's population (Baum-Snow et al., 2018; Duranton and Puga, 2020). Whenever I include industry and occupation into the analysis, I use the occupational classification crosswalk from the 1950 census provided by IPUMS. This allows me to do a simple and consistent comparison of occupational codes across several decades.

I supplement the census data with data on skill use coming from the fourth edition of the Dictionary of Occupational Titles (DOT) and the extended version of 1971 Current Population Survey (National Academy of Sciences, 1971). I follow the task literature and construct four indexes reflecting the use of *social*, *routine-cognitive*, *Non-routine manual*, and *non-routine cognitive* skills (Autor et al., 2003; Autor and

---

<sup>1</sup>See section B.0.1 in the appendix for further details

Dorn, 2013; Deming, 2017; Cavounidis et al., 2021). These indexes are simple averages of different DOT variables, and I normalize them so that they range from 0 to 1.

### 2.2.2 Descriptive patterns

In table 2.1 I provide a general summary of my data and I preview some of the patterns I will be discussing later. The table displays national-level statistics disaggregated by gender for two samples: all people in working age (panel A), and full-time year-round workers (panel B). In addition, panel C zooms in on the spatial patterns in gender inequality.

Panels A and B of table 2.1 reflect the clear progress of women in the US labor market, as highlighted in the gender literature (Blau and Kahn, 2015; Autor and Wasserman, 2013). The gender gap in labor force participation declined by 30 percentage points (71%) between 1970 and 2016. In addition to higher participation, more women worked higher hours. The share of women among full-time workers increased by 13 p.p. (42%) over the same period. Similar patterns arise in the gender gap in wages, which declined 32 p.p. (65%), and the gap in educational attainment, where the share of women with college degrees caught up and surpassed that of men.

**Table 2.1:** Selected summary statistics, 1970-2016

	Census year					
	1970	1980	1990	2000	2010	2016
<i>A. All people aged 18-64</i>						
All people (000)	98,483	117,521	127,971	147,426	161,423	168,571
Share female	0.54	0.52	0.51	0.51	0.51	0.51
<i>Labor force participation</i>						
Men	0.92	0.90	0.89	0.85	0.86	0.85
Women	0.50	0.60	0.70	0.70	0.73	0.73
<i>B. Full time year round-workers</i>						
Study sample (000)	42,446	59,110	69,257	82,841	87,428	94,531
Share female	0.31	0.37	0.41	0.43	0.44	0.44
<i>Share college graduates</i>						
Men	0.06	0.10	0.09	0.10	0.11	0.12
Women	0.03	0.06	0.07	0.10	0.13	0.16
<i>Average log hourly wage</i>						
Men	3.21	3.19	3.17	3.17	3.16	3.15
Women	2.72	2.76	2.87	2.94	2.97	2.98
Gap (women – men)	-0.49	-0.43	-0.30	-0.23	-0.19	-0.17
<i>C. Regional tends</i>						
<i>Men's average log(wage)</i>						
Big CZ	3.22	3.20	3.18	3.18	3.17	3.16
Small CZ	2.99	3.02	2.95	2.97	2.96	2.98
Big CZ wage premium	0.23	0.18	0.23	0.21	0.21	0.18
<i>Women's average log(wage)</i>						
Big CZ	2.73	2.77	2.88	2.95	2.98	2.99
Small CZ	2.51	2.56	2.59	2.70	2.74	2.77
Big CZ wage premium	0.22	0.21	0.29	0.25	0.24	0.22
Big CZ premium gap (women – men)	-0.01	0.03	0.06	0.04	0.03	0.04

*Notes:* Sample restricted to full-time year-round workers in mainland US. Big CZ are those with population above the median. Small CZ have below median population. The table shows weighted means using the census sampling weight.

In Panel C I zoom in on the regional patterns that remain hidden in panels B and C. This panel previews some of the patterns I highlight in the next sections. In the panel I split commuting zones into “big” (above median population) and “small” (below median population) commuting zones. You can think of the typical big CZs as a city with 360 thousand people. In contrast, the typical small CZs houses approximately 22 thousand people.

Panel C previews three interesting facts that I will highlight in the next sections. First, as it is well documented, there is substantial urban wage premium (Baum-Snow and Pavan, 2012). Big CZs pay wages that are at least 18% higher than those in small CZs. Second, this premium seems to have declined over this period. For men, note the that big-city premium declined by 5 percentage points (22%) between 1990 and 2016. This decline is in line with the evidence documented in recent literature (Autor and Salomons, 2018). Third, there are important differences across genders in how the premium evolved. Women’s premium had an aggressive increase in the first two decades. Although women’s premium declined after 1990, it never fell below the level in 1970. In all, women gained an urban advantage over men. This is highlighted in the last row of the table, where I compute the difference in the big city-premium across genders. The was little difference in men’s and women’s premium in 1970, but by 2016 women’s premium was 4 percentage points (22%) higher than men’s.

In table B.2 I show selected statistics at the CZ-level. Most CZs are relatively small. Only about 25% of them have populations over 150 thousand people. Moreover, there is a great deal of variation in the gender wage gap across CZs. By 2016, the interquartile range for the gender wage gap is 6 percentage points. Note that this is a large difference, of about one third the national-level gap from table 2.1. I leverage this variation in the next section when I compute the changes in women’s urban advantage.

### **2.3 Empirical specification**

In the next section I will present several facts on the evolution of the urban wage premium by gender, and the relationship between city size and the gender wage gap over time. As it is standard in the literature, I estimate the urban wage premium by Feasible Generalized Least Squares (FGLS) (de la Roca and Puga, 2017; Ananat et al.,

2018). In a first stage, I use individual-level data to regress the log of hourly wages ( $w_{it}$ ) on Commuting Zone fixed-effects ( $\lambda_{rt}$ ), and (possibly) a series of individual level controls:

$$w_{it} = \lambda_{grt} + X_{it}\kappa_{gt} + \varepsilon_{it} \quad (2.1)$$

I estimate regression (2.1) separately by gender (thus the gender  $g$  subscript) and by decade. In a second stage, I take the gender-specific estimates of the CZ fixed effects and regress them on CZ-level controls:

$$\hat{\lambda}_{grt} = \delta_{gt} + \beta_{gt}s_{rt} + Z_{rt}\gamma_t + \eta_{rt} \quad (2.2)$$

where  $s_{rt}$  is log of the CZ population. I estimate this model separately by decade and weight observations by the inverse of the estimated variance of  $\hat{\lambda}_{grt}$ .

In regression (2.2), I am interested in the gender-specific coefficients  $\beta_{gt}$ . These can interpreted as estimates of the gender-specific urban wage premium. They indicate the observed increase in hourly wages associated with a doubling of the city size. I am interested both in magnitude of these premiums for each gender, and how these premiums evolve over time. In my results, I progressively expand the set of controls in the first ( $X_{it}$ ) and second ( $Z_{rt}$ ) stage controls to explore potential factors driving changes in the gender-specific premiums. Alternatively, by subtracting (2.2) across genders we can obtain a relationship between the city-specific gender wage gap and the city size:<sup>2</sup>

$$\hat{\lambda}_{frt} - \hat{\lambda}_{mrt} = \pi_t + \omega_t s_{rt} + Z_{rt}\rho_t + \nu_{rt} \quad (2.3)$$

in this alternative specification,  $\omega_t$  shows the slope between city size and the gender wage gap. It captures women's relative urban advantage. For example, a positive  $\omega_t$

---

<sup>2</sup>I estimate (2.3) weighting by the inverse of the estimated variance of the CZ gender wage gap.

indicates that women have an urban wage premium that is higher than men's, and thus, bigger cities feature lower gender wage gaps.

## 2.4 Women gradually gained an urban advantage over time

In panel (a) of figure 2·1 I show estimates of the urban wage premium  $\beta_{gt}$  in model 2.2 for both men and women, panel (b) zooms in on the gap between women's and men's premia using model 2.3. These estimates are based on models that do not include any additional control variables in either the first or second stages. As a result, the figure shows estimates of the *unconditional* urban wage premium and the *unconditional* female urban advantage.

Figure 2·1 shows that women have gradually gained an urban wage advantage over men. Panel (a) shows that in 1970 there was little difference in the urban wage premium across genders. At that time, a doubling of city size was associated with an increase of roughly 3.5% in both men's and women's wages. However, over time, a gap emerged and widened between these premia. By 2016, a doubling of city size was associated with an increase of 3.6% in women's wages, compared to only 2.5% for men's wages. Panel (b) zooms in on this gap and shows that the widening in the female advantage slow and steady, going from 0 to 1.1 log-points over the whole period but with –possibly– faster growth between 1970 and 1990.<sup>3</sup>

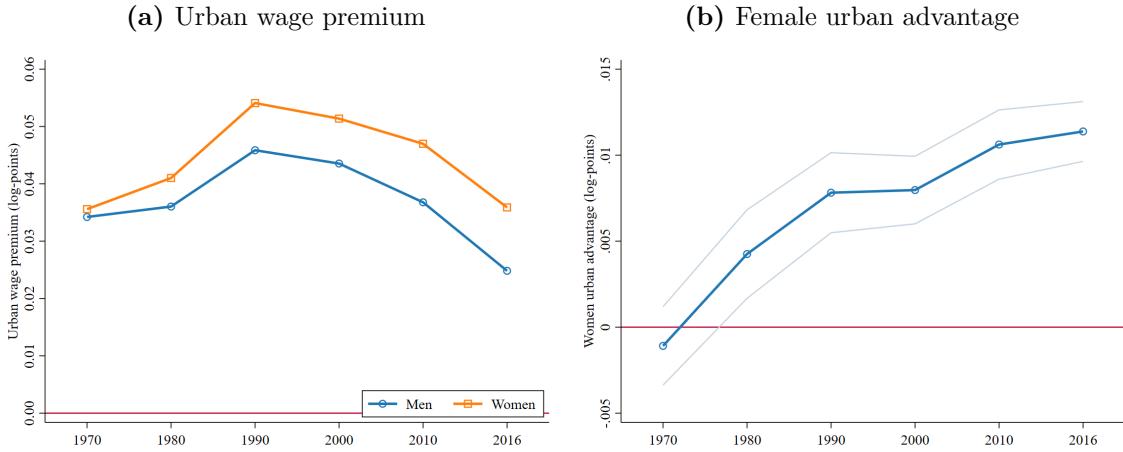
The gradual increase in the female urban advantage underlies two clear and distinct periods in the evolution of the urban wage premium. Between 1970 and 1990, the urban premia grew an accelerated pace, increasing by 1.2 log-points (34%) for men and 1.9 log-points for women (52%). Therefore, the widening of the urban advantage between 1970 and 1990 is driven by the much faster growth in women's premium.

---

<sup>3</sup>There is little change in female urban advantage between 1990 and 2000. I can reject that the increase in the advantage between 1970 and 1990 is the same as the one between 2000 and 2016 at the 5% significance level.

After 1990, there was a fast decline in the premium, but the female advantage continued to widen due to a slower decline in the female urban premium. Men's premium declined by 2.1 log-points from its 1990 peak (46%), while women's declined by 1.8 log-points (33%).

**Figure 2·1:** Women's urban advantage, 1970-2018



**Note:** The figure shows estimates of the coefficient on the log of the CZ population. In panel (a) the dependent variable is the log of hourly wages, and thus panel shows the evolution of the urban wage premium by gender. In panel (b) the dependent variable is the CZ-gender wage gap, and the panel plots the evolution of the female urban advantage. I estimate both panels by FGLS, with no additional controls in the regressions. First stage standard errors clustered at the CZ level. Panel (b) shows 90% confidence intervals..

These trends in wage premiums imply economically relevant changes in the wages across geographies and genders. Table 2.2 shows the wage differences implied by the estimates in Figure 2·1 for CZs of different sizes. Let us consider Kerrville, TX and Boston, MA as examples. Kerrville is a small Texan town that was home to just thirteen thousand people in 1970. This placed it in the 25th percentile of the CZ size distribution for that year. In contrast, Boston was –and still is– the seventh largest CZ of the US. My estimates imply that the gap in wages between Boston and Kerrville was the same for men and women in 1970. However, by 2016 women had an edge of 5 percentage points over men. Boston men's wages were 10% larger than Kerrville's, while women's were 15% larger.

**Table 2.2:** Predicted differences in average wages by gender for selected CZ

	Percentiles (1970)	Population	Men		Women	
			Wages	%Δ from p5	Wages	% Δ from p5
<i>1970</i>						
Philip, SD	5.00	2,637	2.95	0.00	2.46	0.00
Burlington, CO	10.00	5,498	2.98	0.03	2.49	0.03
Kerrville, TX	25.00	13,883	3.01	0.06	2.52	0.06
Wilmington, NC	75.00	97,798	3.08	0.12	2.59	0.13
Saginaw, MI	90.00	242,349	3.11	0.15	2.62	0.16
Youngstown, OH	95.00	446,832	3.13	0.18	2.65	0.18
Boston, MA	100.00	2,183,803	3.18	0.23	2.70	0.24
<i>2016</i>						
Philip, SD	5.00	2,793	2.94	0.00	2.71	0.00
Burlington, CO	10.00	6,295	2.96	0.02	2.74	0.03
Kerrville, TX	25.00	41,654	3.01	0.07	2.80	0.10
Wilmington, NC	75.00	259,195	3.05	0.11	2.87	0.16
Saginaw, MI	90.00	266,016	3.05	0.11	2.87	0.16
Youngstown, OH	95.00	386,753	3.06	0.12	2.88	0.18
Boston, MA	100.00	2,928,351	3.11	0.17	2.96	0.25

*Notes:* Table shows predicted differences in the average wages on a regression like (2.3). I run the regressions separately by gender. Percentiles based on 1970 population distribution.

I also note that the rise in women's advantage depicted in Figure 2·1 is robust to changes in the estimating sample, changes to my measure of CZ size, and it arises *within* multiple demographic groups. In figure B·1 in the appendix, I show that women's advantage also increases for samples that include self-employed and part-time workers. Moreover, figure B·2 shows that the patterns are similar if I use population density as regressor in the second stage.<sup>4</sup> Moreover, Figures B·3 and B·4 show that women's advantage rises within marital status and age groups. This evidence rules out the possibility that these patterns are the result of straightforward changes in demographic composition across CZ of different sizes.

<sup>4</sup>The urban literature emphasizes agglomeration economies coming from concentration of economic activity as a source of the urban wage premium (Glaeser and Gottlieb, 2009; Duranton and Puga, 2020). It is then natural to use population density as a measure of population concentration.

## 2.5 Differences in worker characteristics do not account for the rise in women's advantage

In the previous section I suggested that the differences in how men's and women's premium evolved are not driven by simple changes in worker demographic composition across CZs. Here, I make more formal argument and show that these patterns are very robust to accounting for a broad set of worker and CZ characteristics. The urban literature has extensively documented that big cities attract more educated, younger, and, in general, more productive workers. Therefore, the relative increase in women's urban wage premium might be the result of differential changes in sorting across genders, i.e. over time relatively more productive women were working in cities.

To whether differential sorting can account for the rise of urban advantage, I perform a simple composition to quantify what share of this increase can be accounted for changes in women's and men's characteristics across CZ of different sizes.

Suppose that wages are determined according to:

$$w_{it} = \lambda_{rt} + \omega_{rt} female_i + x'_{it} \beta_{gt} + z'_{rt} \kappa_{gt} + \nu_{it} \quad (2.4)$$

here  $\omega_{rt}$  is the CZ-effect on women's wages. Where  $x_{it}$  is a vector of individual-level controls, and  $z_{rt}$  is a vector of CZ-level characteristics relevant for determining wages. Note that this expression allows for gender-specific returns on individual and CZ characteristics.

If we aggregate 2.4 at the gender by CZ level, it is easy to see that the CZ gender wage gap is driven by three components:

$$w_{rtm} - w_{rmt} = \underbrace{\bar{x}'_{ft} \beta_{frt} - \bar{x}'_{mt} \beta_{mt}}_{\text{Gender gap on observables}} + \underbrace{z'_{rt} (\kappa_{ft} - \kappa_{mt})}_{\text{Gender gap from CZ characteristics}} + \underbrace{\bar{\nu}_{mrt} - \bar{\nu}_{frt}}_{\text{Unexplained component}}$$

This expression bears some resemblance to the traditional Oaxaca-Blinder decomposition from the gender gap literature (Blau and Kahn, 2015). It makes explicit that the CZ gender wage gap is a combination of three components: (i) the return adjusted gaps on observable characteristics, (ii) the return adjusted gaps on city characteristics, and (iv) an unexplained component.

The final effect of each of these components on women's urban advantage is determined by their covariance with CZ size:

$$\omega_{rt} = \underbrace{\frac{\text{cov}(\bar{x}'_{frt}\beta_{ft} - \bar{x}'_{mrt}\beta_{mt}, s_{rt})}{\text{var}(s_{rt})}}_{\text{Relative sorting on observables}} + \underbrace{\frac{\text{cov}(z'_{rt}(\kappa_{ft} - \kappa_{mt}), s_{rt})}{\text{var}(s_{rt})}}_{\text{Effect from other CZ characteristics}} + \underbrace{\frac{\text{cov}(\bar{\nu}_{mrt} - \bar{\nu}_{frt}, s_{rt})}{\text{var}(s_{rt})}}_{\text{Unexplained women's urban advantage}} \quad (2.5)$$

This expression decomposes the *levels* as a sum of three terms. The first term captures differences in the relative sorting of men and women across CZs. We can think of  $\bar{x}_{grt}\beta_{gt}$  as measures of the average observed quality of gender  $g$  in a CZ. Thus, this term says that whenever women's average quality rises faster with CZ size than men's, sorting will be an important driver of women's urban advantage. The second term captures the portion of women's advantage that is driven by CZ characteristics. These capture differential effects of CZ characteristics on the wages of each gender. Finally, we the third term is a residual. It is the portion of the advantage that I cannot account for.

I can compute each of the terms in 2.5 by simply comparing estimates of the coefficient on CZ size for specifications that condition on (i) no additional control, (ii) individual characteristics, (iii) and individual and CZ characteristics.

In table 2.3 I show the results of performing this decomposition. The table shows

estimates of women's urban advantage that condition on a progressively larger set of individual and CZ characteristics, along with estimates of the unexplained component from expression 2.5. Column (1) also presents the unconditional advantage estimates from figure 2.1. The table shows a clear and consistent message: sorting on these characteristics cannot account for the rise of women's advantage. Column (4) shows that conditioning on age, race, education, marital status and fertility variables leaves have no effect on the unexplained component. Columns (5) and (6) add a full set of occupation and industry dummies to the specification. These variables are of particular interest, because they account for about 90% of the gender wage gap at the national level (Blau and Kahn, 2015). However, column (6) shows that this factors do not make a dent in the size of the unexplained component.

In columns (7) to (9) I condition on CZ characteristics the literature found to have important gender effects. In column (7) of table 2.3 I include commuting time to work as a control in the second stage. Recent literature has emphasized that commuting is an important determinant of gender differences in labor supply (Le Barbanchon et al., 2021). Commuting time has been shown to influence women's labor force participation more heavily than men's (Black et al., 2014). Differences in commuting time preferences account for a fraction of the observed gender gap, because women accept slightly lower paid jobs in exchange for a shorter commute (Liu and Su, 2020; Le Barbanchon et al., 2021). However, column (7) shows that even after including commuting time as a control, most of the rise in women's advantage remains unexplained.

Column (8) shows the effect of including CZ labor force participation rates by gender as controls in the second stage. The literature documents substantial variation in the size and trends of the gender gaps in labor force participation across US metropolitan areas (Black et al., 2014). Under the right conditions this fact could

account for the rise in women's advantage. The key idea is that different trends in labor force participation rates imply differential trends in unobserved productivity gaps. If only the most productive individuals are in the labor force, then cities where women's labor participation is increasing a lot will feature larger increases in the gender wage gap. This is because the marginal woman entering into the labor force has increasingly low productivity, which lower the average. If selection of this sort were driving the rise in women's advantage, then we should expect that including participation rates by gender should account for a substantial portion of the increase. This is not what column (8) suggests. In fact, the unexplained change becomes *larger* than the unconditional change in column (1).

Finally, in column (9) I show estimates that include the overall CZ wage inequality as a control. I measure wage inequality as the difference between the 90th and the 10th percentile in wages in the CZ. The gender gap literature suggests that increases in wage inequality tend to increase gender wage gaps because women are usually located at the bottom of the pay distribution. Thus, they benefit less from wage increases at the top. This additional control does not modify the conclusions. This is not surprising. Wage inequality increased more in bigger cities over this period (Baum-Snow et al., 2018). This would imply faster increases of the gender gap in big cities. This is counter to the trends I document in figure 2·1.

**Table 2.3:** Women's conditional urban advantage

	Dep. var: real hourly wage								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1970	-0.001 (0.001)	0.000 (0.001)	0.005 (0.001)	0.002 (0.001)	-0.000 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.006 (0.001)	-0.006 (0.001)
2018	0.011 (0.001)	0.013 (0.001)	0.015 (0.001)	0.014 (0.001)	0.011 (0.001)	0.011 (0.001)	0.010 (0.001)	0.010 (0.001)	0.011 (0.001)
Unexplained $\Delta_{2018-1970}$	0.012 0.002	0.013 0.002	0.010 0.002	0.012 0.002	0.011 0.001	0.013 0.001	0.012 0.001	0.016 0.001	0.017 0.001
Observations	4,326	4,326	4,326	4,326	4,326	4,326	4,326	4,326	4,326
<b>Controls</b>									
<b>Individual and work characteristics</b>									
Age	✓	✓	✓	✓	✓	✓	✓	✓	✓
Race	✓	✓	✓	✓	✓	✓	✓	✓	✓
Education		✓	✓	✓	✓	✓	✓	✓	✓
Marital status			✓	✓	✓	✓	✓	✓	✓
Number of children				✓	✓	✓	✓	✓	✓
Industry					✓	✓	✓	✓	✓
Occupation						✓	✓	✓	✓
<b>Commuting time and CZ characteristics</b>									
Commuting time							✓	✓	✓
Labor force participation rates								✓	✓
CZ wage inequality									✓

Notes: Columns (1), (3), and (6) correspond to series A, B, and C in figure ???. Sample restricted to full-time year-round workers. Cells show the coefficient of an interaction between a year dummy and the log of CZ population. Each column represents a different regression. In all cases, the dependent variable is the log of the real hourly wage. . Standard errors clustered at the CZ level in parenthesis.

I also note that the results in table 2.3 are not driven by the specific years I am displaying. In Figure B·5 I display the full set of estimates of the female advantage for the specifications in columns (1) –unconditional–, (3) –basic demographics–, and (6) –full set of individual controls–. The gradual rise in the advantage arises on all the three specifications depicted.

## 2.6 The rise *is* driven by workers without a college degree

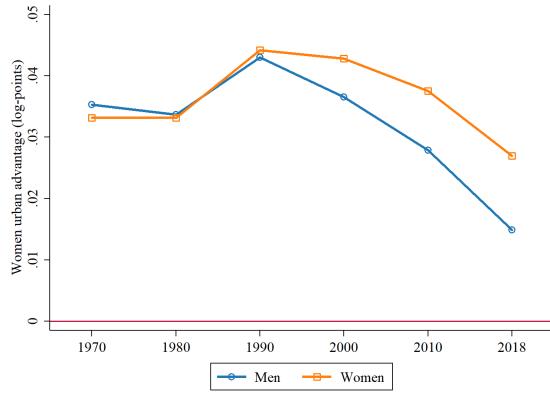
In Figure 2·2, I divided the sample based on education level into two groups: workers with and without a college degree. I then generated separate estimates for the gender-specific urban wage premia and the women’s urban advantage within each education group. Panels (a) and (b) display estimates of the urban wage premia, taking into account basic demographics as well as a full set of occupation and industry dummies. Notably, the female urban wage premium behaves differently from that of men’s only among workers without a college degree. Additionally, these differences are primarily driven by general decline in the premia after 1990: women gain an edge over men mostly because they were less affected by this overall decline. In contrast, panel (b) shows that there is little change in college graduates’ premia over the whole period. These findings echo those of Autor (2019).

Panels (c) and (d) zoom in on the premium difference across genders and also shows the gaps for specifications without any control (unconditional) and with basic demographics as controls. These panels reiterate that the rise in women’s advantage is driven by workers without a college degree. Moreover, by comparing the unconditional and full specification estimates two interesting results emerge. Panel (c) shows that the increase in the advantage between 1970 and 1990 for non-college workers disappears once I control for industry and occupation, which suggests that this rise over this period is driven by big city women accessing industries/occupations with higher

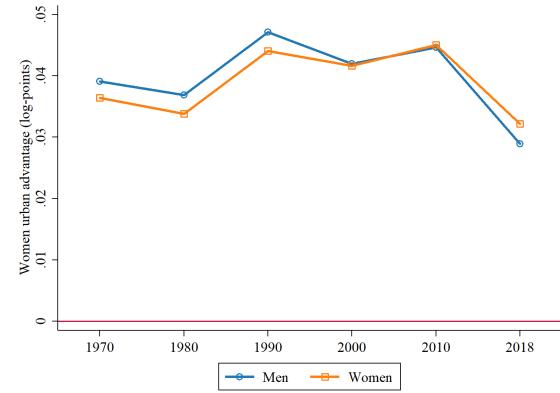
pay. Furthermore, panel (d) reveals that college women have an urban disadvantage due to differences in industrial/occupational choices between men and women.

**Figure 2·2:** Women's urban advantage for alternative conditioning on covariates, 1970-2018

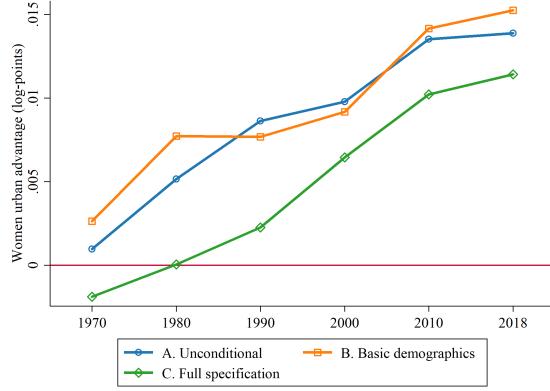
(a) Urban wage premium: workers without a college degree



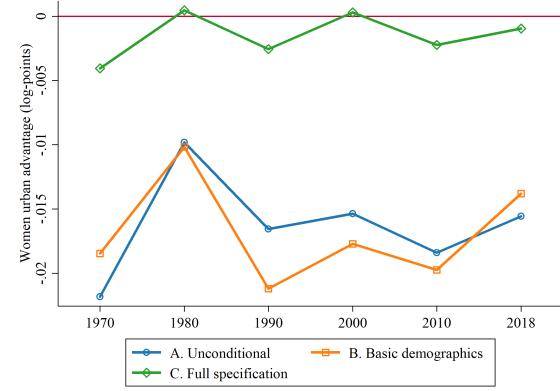
(b) Urban wage premium: college graduates



(c) Female urban advantage: workers without a college degree



(d) Female urban advantage: college graduates



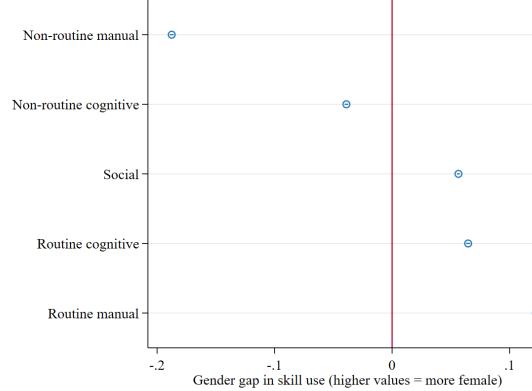
**Note:** Panels (a) and (b) correspond to the full specification in panels (c) and (d). Basic demographics control for age and race. Full specification additionally control for a full set of occupation and industry dummies. Observations are weighted by the inverse of the estimated variance of the CZ dummies. Figure shows 90% CI.

## 2.7 The rise in the advantage disappears after accounting for the urban gradient in skill content of occupations

In table 2.4 I show the result of adding interactions between DOT skill indexes and city size:

$$w_i = \lambda_{grt} + \sum_k \phi_{kt} a_k s_r + X_{it} \kappa_{gt} + \varepsilon_{it} \quad (2.6)$$

where  $a_k$  denotes the index for skill  $k$ . Autor (2019), Rossi-Hansberg et al. (2019) and Bacolod et al. (2009) show that there is a strong –employment and wage– city size gradient for occupations that certain skills, and this gradient has been changing over time. At the same time, it is well known that men and women work very different occupations and thus use skills at different intensities –see figure 2.3– (Blau and Kahn, 2017). Changes in the city size gradients could account for the differing trends in the urban wage premiums across gender by virtue of their differential exposure because of occupational segregation. Table 2.4 shows estimates of women’s urban advantage that control for the skill-city size gradients in the first state. I control for the interactions with four skill indexes: social, routine-cognitive, non-routine manual, and non-routine cognitive.

**Figure 2·3:** Gender gap in skill use, 1970

**Note:** The figure shows the coefficient on a female dummy in a regressions having the skill index as dependent variable. The sample is restricted to full-time year-round workers without a college degree. Figure shows 95% CI.

**Table 2·4:** Skill city size gradients account for the rise in female urban advantages

	Dep. var: real hourly wage		
	(1)	(2)	(3)
1970	0.002 (0.001)	0.002 (0.001)	0.006 (0.001)
2018	0.014 (0.001)	0.013 (0.001)	0.008 (0.001)
Unexplained $\Delta_{2018-1970}$	0.012 (0.002)	0.011 (0.002)	0.001 (0.002)
Observations	4,326	4,326	4,326

#### Interactions with gender

Age, race, education	✓	✓	✓
Marital status	✓	✓	✓
Number of children	✓	✓	✓

#### Interactions with log(CZ pop)

Age × gender	✓
Skill indexes	✓

*Notes:* Standard errors clustered at the CZ level in parenthesis.

Table 2·4 shows that once I control for these skill interactions I can account fully for the rise in women's urban advantage. Now, including these interactions can account for the differences across genders because either of two reasons: (i) differential

exposure to skill use across geographies, or (ii) differential exposure to changes in the urban premiums to these skills. Figure 2·4 shows that there are big differences in the evolution of the urban premia to these skills. Each panel of this figure shows estimates of the  $\phi_{kt}$  in Equation 2.6. These are estimates for the urban wage gradient for each of these skills. There is big decline in the wage gradients to non-routine manual and routine cognitive skills, while the gradient for non-routine cognitive skills had a dramatic increase over the period. The differential exposure to the changes in these premia for men and women drives the differences in trends across genders.

## 2.8 Conclusions

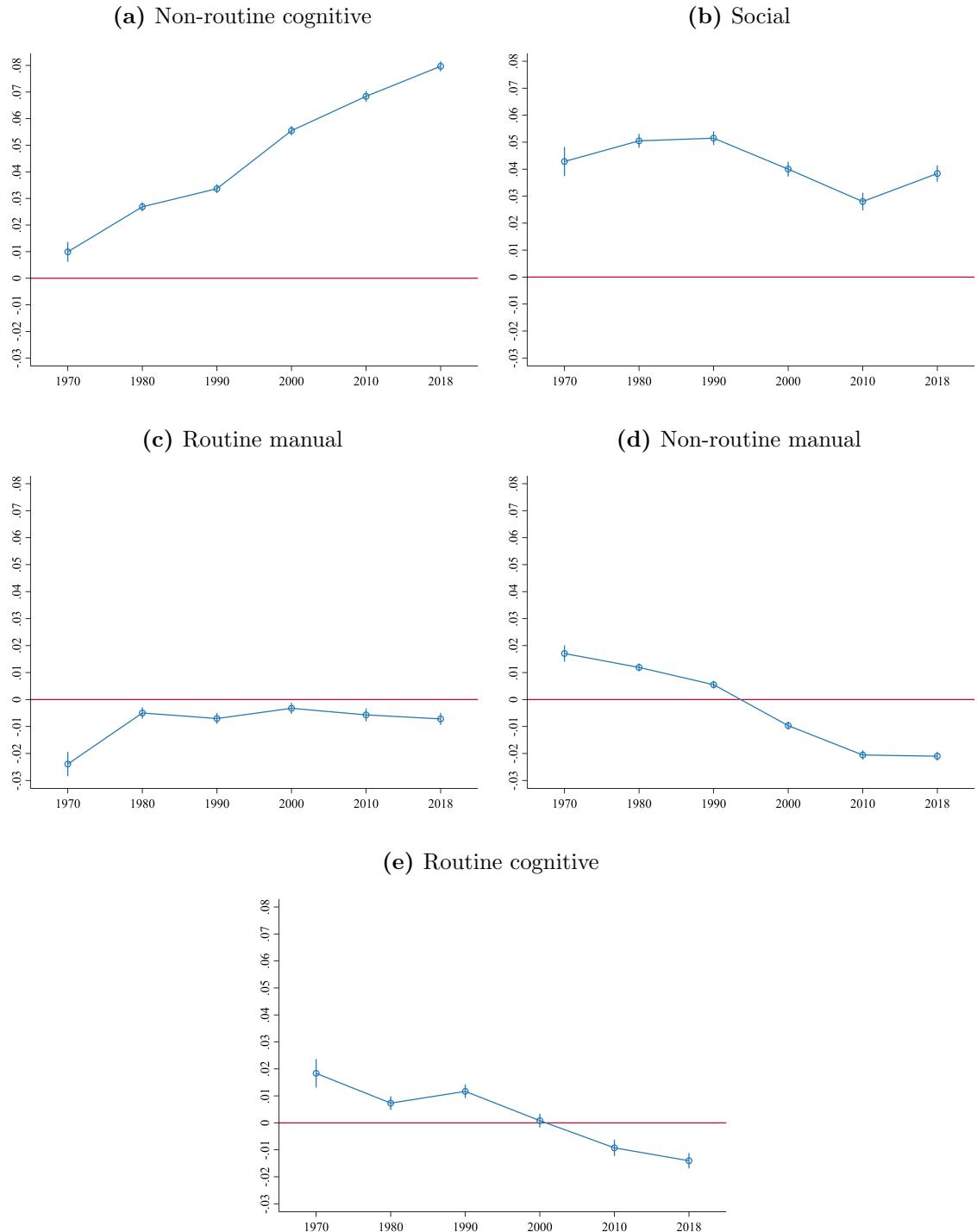
This paper shows new facts on the urban wage premium by gender. Using US data for the period between 1970 and 2018, I show that women’s urban wage premium grew relative to men’s over the whole period. This increase is robust to my sample and specification choices. Moreover, it arises *within* multiple demographic groups usually studied in the gender literature.

I then decompose the rise in women’s advantage into components driven by (i) differences in worker characteristics –sorting–, (ii) differences in CZ characteristics, (iii) and an unexplained portion. This decomposition gives clues on whether the documented pattern is driven by sorting of workers across commuting zones. Worker and CZ characteristics fail to account for the rise in women’s urban advantage. When controlling for occupation and industry, the unexplained component accounts for at most 80% of the overall increase.

Further heterogeneity analysis shows that the rise in women’s advantage is closely linked with the overall decline in the urban wage premium. The rise in women’s advantage is driven by non-college workers and happens mostly after 1990. This period coincides with the overall decline in the urban wage premium for non-college

workers.

I then use data from the Dictionary of Occupational Titles and show that the rise in women's advantage for non-college workers is driven by drastic changes to the urban skill premia to certain worker skills. Over this period there was a drastic decline in the urban premia to non-routine manual and routine cognitive skills, while the premia to non-routine cognitive skills increased sharply. By virtue of their occupational distribution, men and women had different exposures to these changes and this accounts for the differential trends in their urban wage premia.

**Figure 2·4:** Skill-specific urban premium, 1970-2018

**Note:** The figure shows the coefficients on the interaction between skill indexes and the CZ population in a regression with hourly wages as dependent variable. The sample is restricted to workers without a college degree. The figure shows 95% confidence intervals.

## Chapter 3

# Do Elite Universities Overpay Their Faculty?

César Garro-Marín<sup>1</sup>, Shulamit Kahn<sup>2</sup>, and Kevin Lang<sup>3</sup>

### 3.1 Introduction

This chapter measures the relation between faculty salaries (net of faculty quality) and university or college prestige. We find no evidence that more prestigious institutions pay premiums above the competitive salary for the quality of the faculty they hire. Indeed, using an AKM (Abowd et al., 1999) model, we find little evidence of any institution effect on salaries, although institutions in more urban areas pay higher salaries.

The absence of institution effects in the AKM model is striking because their absence implies that, aside from a random factor, faculty would receive the same salary at any university. We authors find it implausible that Oakland University would be willing to match the salaries Stanford pays its tenure-track faculty. Readers are free to draw their own conclusions.

Our evidence is based on the Survey of Doctorate Recipients (SDR), a panel survey of individuals with U.S. doctorates in fields covered by the National Science Foundation. Thus, our results apply to STEM and the social sciences but not necessarily to the humanities or faculty with professional degrees. We merge the SDR with the

---

<sup>1</sup>Boston University, email: cesarlgm@bu.edu

<sup>2</sup>Boston University, email: skahn@bu.edu

<sup>3</sup>Boston University, email: lang@bu.edu

*Times Higher Education (THE) 2017* rankings of (research) universities and the *Wall Street Journal – THE 2017* college rankings, supplemented with rankings from the *U.S. News and World Report (UNSWR)* rankings for some universities and colleges not in the other rankings and well as IPEDS institutional data.

We begin by applying a standard AKM model to the data. The variance of the institution fixed effects is as little as .006, depending on the correction we use. When we regress the estimated fixed effects on institution characteristics, the effect of university or college prestige is always small and generally insignificant. We find some evidence that institutions with larger endowments per student pay premiums, but the magnitude of the premium is modest.

We repeat the exercise but replace the two-step estimation with a single step in which we include institution characteristics rather than institution fixed effects. The results are similar, as expected, since both approaches provide consistent estimates of the same parameters.

We also examine the relation between institution prestige (as measured by rank) and faculty quality, as measured by the individual fixed effect. Consistent with our expectations (and probably the expectations of most faculty at research universities), the correlation is positive.

We briefly discuss how to reconcile the absence of a prestige premium, the positive match between prestige and faculty quality, and our sense that faculty at prestigious institutions would earn less at less prestigious institutions. In essence, we develop a toy hedonic model in which faculty transition only among similarly ranked institutions. We conclude with some thoughts about why our results differ from AKM models of the broad labor market.

### 3.2 AKM in the Academic Context

AKM uses a standard two-way fixed-effect model

$$\ln w_{ijt} = X_{it}\beta + \alpha_i + \gamma_j + \varepsilon_{ijt} \quad (3.1)$$

where  $w_{ijt}$  is annual salary,  $X_{it}$  is a vector of time-varying individual characteristics  $\varepsilon_{ijt}$  is an i.i.d. mean-zero error term.

The institution fixed effect  $\gamma_j$  captures the tendency of the institution to pay all faculty a different salary than they would receive elsewhere. It may reflect compensating differentials for institution characteristics that the econometrician does not measure or institutional rents shared with faculty.

The individual fixed effect,  $\alpha_i$ , captures whatever factors tend to raise a faculty member's wage relative to other faculty in the same (or similar) institutions. In the AKM model,  $\alpha$  is typically interpreted as a measure of worker quality or productivity, but it captures any other factor that affects pay, such as discrimination or, in our case, differentials across fields. We will largely follow tradition and treat this fixed effect as capturing worker (faculty) quality. However, we note that in an early AKM application, Eeckhout and Kircher (2011) firms pay high wages to workers they hire whether high or low skill. This induces these workers to apply despite being unlikely to receive an offer (see also Abowd et al. (2019)).

It is well known that problems arise if we treat the variance of estimated  $\gamma$  ( $\widehat{\gamma}$ ) as the variance of  $\gamma$ . We correct this bias using Andrews et al. (2008).

It is evident that (3.1) makes strong assumptions. First, AKM assumes that mobility is random. (Formally,  $\varepsilon$  and  $\gamma$  are uncorrelated.) Applied to academia, AKM assumes that faculty do not change university because the profession has changed its belief about their value or because they are particularly valuable at their new university. Instead, moves reflect changes in personal preferences, etc. Second, the

log-linear functional form is highly restrictive; the institution effect is proportional: a given university pays a constant percentage premium to all faculty it hires, except for the random error term  $\varepsilon_{ijt}$ . Similarly, an individual who earns 20 percent more than the norm at one university would also earn 20 percent more elsewhere, again, except for  $\varepsilon_{ijt}$ . These assumptions and the logarithmic form imply that better (higher  $\alpha$ ) faculty gain more in absolute terms by working at a higher-paying university (higher  $\gamma$ ).

Under these assumptions, the AKM model allows us to answer several questions:

1. How important are firms for determining salaries? (What is the variance of *gamma* in the estimated AKM model?)
2. How important are differences between individuals (variance of  $\alpha_i$ ) for determining salaries?
3. Do the best workers go to the best (highest salary) firms? (What is the covariance of  $\alpha$  and  $\gamma$  in the estimated (and corrected) AKM model?)

Unlike most applications of AKM, we can measure firm quality directly. We use published rankings and measures such as endowments, potentially correlated with a university's eliteness, to measure prestige. Thus, we address the above questions for academia and relate them to eliteness measures.

Having estimated the university fixed effects by (3.1), we can regress  $\hat{\gamma}$  on university characteristics. This reveals the characteristics associated with university salary premiums.

$$\hat{\gamma}_j = Z_j \Lambda + \eta_j + \nu_j \quad (3.2)$$

where  $Z$  is a vector of university characteristics,  $\eta$  is a random error term uncorrelated

with  $Z$  consisting of unmeasured university characteristics, and  $\nu$  is measurement error ( $\widehat{\gamma}_j = \gamma_j + \nu_j$ ).

Alternatively, we can estimate (3.1) and (3.2) in a single step by substituting for  $\gamma_j$  in the AKM equation (3.1) to get

$$\ln w_{ijt} = X_{it}\beta + Z_j\Lambda + \alpha_i + \nu_j + \varepsilon_{ijt} \quad (3.3)$$

As Amemiya (1978) shows, if the variance components of (3.2) and (3.3) are estimated in the same way, generalized least squares (GLS) estimation of the two equations is numerically identical. However, we will estimate (3.2) by feasible GLS but only correct the standard errors in (3.3), thus producing somewhat different results.

### 3.3 Data

Our primary data come from the restricted-use version of the Survey of Doctorate Recipients (SDR) from the National Center for Science and Engineering Statistics (NCSES). The SDR is a representative longitudinal panel of individuals with doctorates in natural or social sciences, engineering, or health from a U.S. academic institution. Every 2-3 years, the survey collects data on their salaries, employers, and demographic characteristics. It also identifies all U.S. academic employers using the IPEDS institution codes, enabling us to identify the work histories of the academics trained and working in the United States.

We use all SDR waves of data beginning with the 1993 major SDR restructuring through the last year currently available (1993, 1995, 1997, 1999, 2001, 2003, 2006, 2008, 2010, 2013, 2015, 2017, 2019). In most years, the SDR included most survey participants from previous waves. It added participants from newly granted PhD's (identified from the NSF's Survey of Earned Doctorates) and dropped those who aged out. However, in 2015, the SDR created a new larger panel that included only

a minority of the original sample. Therefore, most participants have data only before 2015 or from 2015 and later.

The SDR response rate among individuals in the U.S. is quite high. Typically, fewer than 5% of eligible respondents fail to respond. Including those who could not be found, are missing a key item, or live abroad, lowers the rate, but it remains high (75%-85%).

We restrict the sample to individuals employed full-time (35 hours/week for at least 40 weeks/year) in a tenure-stream (tenured or tenure-track) position at a U.S. 4-year college or university, medical school attached to a university, or university research institute. We thus exclude 2-year colleges, junior colleges, technical institutes that do not confer regular degrees, and non-educational institutions. We drop observations where respondents were in a post-doctoral position, earned less than the minimum National Institutes of Health post-doctoral stipend (\$53,760 in 2020), or worked outside the U.S. (whether in academia or not).

Unfortunately, using the SDR to study moves requires considerable data cleaning, which we describe in detail in the appendix section C.4. For example, there were 2,916 observations where the IPEDS university code changed, but the respondent reported not changing institutions. These frequently involved two institutions with similar names. Thus, a Boston University faculty member in multiple waves might be miscoded as Boston College faculty for one wave, while not reporting changing institutions. Academics know the difference; some data coders did not.

We also drop observations with large one-time salary changes within the same institution that are subsequently reversed (see appendix for details). The online appendix (Tables A1-A4) contains all tables replicated using these observations, so readers can verify that it has little effect on the results. Since these are within a person/university match, dropping them leaves the number of movers and moves

unchanged.

We supplement the SDR data with the rankings from the *Times Higher Education* 2017 World University Rankings and the *Wall Street Journal – Times Higher Education* 2017 College Rankings (Times Higher Education, 2017a,b), hereafter the rankings. We use the *USNWR* Best Colleges rankings (US News, 2021) to impute ranks for institutions without a *THE* rank (see online appendix).

As is well-known, we can only include information on institutions in the connected set in AKM estimation. Institutions may be connected directly or indirectly. If one faculty member moves from university A to university B and another from B to C, A and C are connected. We limit ourselves to the largest connected set, which consists of 679 institutions. Other connected sets were very small. One-step estimation does not require a connected set, but we use the same data to maintain consistency between the two approaches.

We matched 585 (86% of the total) of the 679 institutions to a *THE* ranking. Of the remaining 94, we imputed a rank for 59 schools ranked in *USNWR*, using the relation between *USNWR* and *THE* ranks, leaving 35 unranked schools (5% of the total). We define *research universities* as those in the *THE* university rankings or imputed from the *USNWR* National University rankings. This group is broader than R1 institutions. We define *colleges* as those included in the *THE* college rankings or imputed from any other *USNWR* ranking. Many of the *colleges* are not liberal arts colleges but simply institutions not included among the *THE* research universities or *USNWR* National Universities. Within each type of institution, we normalize the best rank to 1 and the worst to 100.<sup>4</sup>

The top-ranked research universities are Stanford, Harvard, Cal Tech, and MIT. Those at the bottom include Western Michigan University, Texas State University, Oakland University, and the University of North Carolina, Wilmington. The top-

---

<sup>4</sup>Due to ties, the lowest ranked college is at the 99<sup>th</sup> percentile.

ranked colleges are Amherst, Williams, Wellesley, and Pomona. The worst-ranked include Grambling State University, Southern University of New Orleans, Georgia Southwestern State University, and the University of Rio Grande. The unranked institutions include Texas A&M at San Antonio, Brigham Young University at Idaho, and the University of Texas at Brownsville.

Our data on institution characteristics come from the Integrated Postsecondary Education Data System (IPEDS) surveys. We obtain total enrollment, number of faculty, endowment, and dummy variables for large city, urban fringe/mid-size city/suburb, private institution, and undergraduate-only institution from 1998, 2005, 2012, and 2017. We measure endowment by the average of the beginning and ending values for nonprofit institutions and the average of the beginning and ending equity for for-profit institutions.

Panel A of Table 1.2.3 shows the frequency of moves. We have 64,537 observations on 26,614 individuals, an average of roughly 2.4 observations each. 1,868, or about 7% of individuals, changed institutions at least once. Unsurprisingly, movers are disproportionately those we observe in more waves. Movers account for roughly 13% of our observations.

Panel B shows we observe only one move for most movers. We have 2,196 transitions involving 679 institutions and 1,868 movers, or 1.2 moves per mover and 3.2 moves per institution. Transitions by institutions are highly skewed, with a minimum of 2 and a maximum of 53.

When surveyed, 45% of the faculty observations were full professors and 29% associate professors (see Panel C). A few faculty (1%) report being on the tenure track but holding a title other than assistant, associate, or full professor. About one-third of faculty are female; five-sixths are married when surveyed.

Panel D gives information on the 679 institutions in the connected set, of which 152

are ranked universities and 492 ranked “*colleges*,” with the remaining 35 unranked. They vary dramatically in size and endowment. 41% are private, and 22% serve only undergraduates.

**Table 3.1:** Summary Statistics

A: Number of movers in the sample				B: Number of transitions in the sample			
	All	Movers	Share of total		Total		Max
Total observations	64,537	8,091	0.13	Transitions	2,196		
Number of people	26,614	1,868	0.07	Number of movers	1,868		
Average obs./person	2.42	4.33		Number of institutions	679		
				Transitions/mover	1.18	1	*
				Transitions/institution	3.23	2	53

C: Summary statistics: Individuals				D: Summary statistics: University-level characteristics				
Characteristics	N	Mean	Std		Mean	Std	Min	Max
Years since Ph.D.	64,537	18.12	10.65	Research university rank	48	28	1	99
Has tenure	64,537	0.73	0.45	College rank	46	25	1	100
<i>Faculty rank</i>				Log total enrollment	8.75	1.05	5.09	10.89
Assistant Prof.	64,537	0.25	0.43	Log total endowment	18.03	2.13	10.90	24.32
				(\$2020)				
Associate Prof.	64,537	0.29	0.45	Log endowment/student	9.32	1.97	2.89	14.84
Professor	64,537	0.45	0.50	Log faculty size	5.79	0.96	0.92	8.04
Lecturer	64,537	0.00	0.03	Log faculty/student	-3.14	0.55	-5.21	-1.69
Instructor	64,537	0.00	0.04	Share in large city	0.23	0.42	0.00	1.00
Other	64,537	0.01	0.09	Share in medium city	0.34	0.47	0.00	1.00
Female	64,537	0.32	0.47	Share in small city	0.43	0.50	0.00	1.00
Married	64,537	0.83	0.38	Share private	0.41	0.49	0.00	1.00
Has child under 6	64,537	0.18	0.38	Share undergraduate	0.22	0.41	0.00	1.00
Has child aged 6-11	64,537	0.20	0.40					
Has child aged 12-18	64,537	0.20	0.40					
Has child aged 19+	64,537	0.10	0.30					

**Note:** There are 152 research universities and 492 colleges. 35 institutions are unranked and not classified as colleges or universities. \* Suppressed for confidentiality. Exceeds 4.

### 3.4 Results

#### 3.4.1 How important are the institutions for determining wages? Not much!

We first estimate the AKM model with only individual and institution fixed effects. Table 3.2 shows the overall variance of log salaries is 0.141; the variance of the individual fixed effects with no correction is .131 (93% of the overall variance). In contrast, the variance of the institution fixed effects is .029 (21% of the overall variance), in line with the 20% typically found in AKM models Card et al. (2018). Thus, their sum exceeds the total variance.

**Table 3.2:** Fixed-effect variance estimates in AKM model

	Uncorrected (1)	Corrected Andrews et al. method
<b>Individual by year level</b>		
Variance log(salary)	0.141	0.141
<i>Variance of Fixed-effects</i>		
Individual	0.131	0.105
Institution	0.029	0.012
Correlation	-0.332	-0.397
<b>Collapsed at the spell level</b>		
		Bonhomme et al. method
Variance log(salary)	0.140	0.140
<i>Variance of Fixed-effects</i>		
Individual	0.128	0.078
Institution	0.026	0.006
Correlation	-0.310	0.081

However, it is well known that we over-estimate these variances, especially in situations like ours where many institutions in the sample experience little turnover (Andrews et al 2012, Kline et al. 2020, Bonhomme et al forthcoming). While  $\hat{\gamma}$  is a consistent estimate of  $\gamma$ , the *variance* of  $\hat{\gamma}$  is not a consistent estimate of the variance of  $\gamma$ . For a simple insight into the problem, consider an extreme case where all the  $\gamma$  are 0 (so  $\sigma^2 = 0$ ) and the  $\hat{\gamma}$  are i.i.d. with variance  $\sigma_{\hat{\gamma}}^2$ . Then,  $\sigma_{\hat{\gamma}}^2$  is completely measurement error. In addition, AKM negatively biases the covariance between the

two sets of fixed effects. To see this, note that if we overestimate the institution fixed effect, we will (partially) subtract that overestimate from the individual fixed effect, leading to a negative correlation between the two sets of fixed effects.

When we use the Andrews et al. (2008) correction,<sup>5</sup> the variance of the individual fixed effects falls to .105 or 74.5% of the overall salary variance, while the variance of the institution fixed effects is only .012 or 8.5% of the overall variance (Table 2). Thus, institutions account for little of the total variance. This proportion is about half the estimate in Kline et al. (2020) for Northern Italian workers but in line with Bonhomme et al. (forthcoming) for a Swedish sample with little turnover (similar to our sample) when using the Andrews variance correction.

When we collapse the data to the spell level to reduce measurement error, as in Bonhomme et al. (forthcoming), the total variance of  $\ln(\text{salaries})$  by spell is .140, similar to the overall variance. As Table 2 shows, the uncorrected variance of the individual fixed effects is .128, but the corrected variance is .078 or 56% of the overall salary variance, somewhat smaller than with the uncollapsed spells. The uncorrected variance explained by institution fixed effects (.026) is similar to what we found without collapsing spells. After correction, this variance is negligible, .006 or only 4% of the salary variation, and somewhat lower as a proportion of variance than Bonhomme et al. (forthcoming) find for five countries, and substantially lower than Kline et al. (2020) report using their preferred correction.

We thus conclude that institution effects explain almost no variation in faculty salaries. Instead, individual faculty (worker) fixed effects explain most of the variance.

Our estimates of the correlation between faculty and institution fixed effects is sensitive to collapsing to the spell level. The uncorrected correlations are negative, as is common in AKM models due to mismeasurement bias, and equal approximately

---

<sup>5</sup>Given our data, it is not feasible to use the approaches developed by Kline et al. (2020) and Bonhomme et al. (forthcoming).

-.3 (Table 3.2). Since the individual fixed effects may partially be due to field, we also netted out field differences from the individual fixed effects before we calculated the correlations. As is clear, it makes little difference.

However, without collapsing, the corrected correlation is -.40; after collapsing, it is .08. We note that Andrews et al. find little effect of their variance correction unless they restrict the sample to movers and large firms. Since after collapsing, the correction shows institution fixed effects are negligible, it is difficult to interpret the small correlation even though it is positive.

### **3.4.2 Time-varying individual characteristics: It's mostly rank and experience**

Appendix Table C.1 shows the coefficients on the time-varying faculty characteristics in the full AKM model (3.1). Adding these variables decreases the unexplained variance from 8.5% to 4.8%. The coefficients in Table C.1 correspond to our expectations and/or past studies of academic salaries. Salaries increase with post-PhD experience, although at a declining rate. Nevertheless, the point estimate of the slope remains positive at all experience levels in the data. Academic rank, rather than tenure status, affects salaries. The small number of tenure-track lecturers and instructors earn salaries comparable to assistant professors. Associate professors earn a slight premium (5%) relative to assistant professors. In comparison, full professors earn about 10-11% more than comparable associate professors. The small “other” group lies between associate and full professors.

Family composition has little effect on male or female earnings, conditional on rank and experience. The sole exception is that men, but not women, earn about 1% more if they have teenage children. Prior research suggests that children make women less likely to take tenure-track jobs (Ginther and Kahn, 2006; Cheng, 2020; Wolfinger et al., 2008; Martinez et al., 2007). However, among women who do take tenure-

stream STEM jobs, children and marriage are positively associated with women's salary in academia (Kahn and Ginther, 2017), as are men's. Yet for both, positive association is likely due to selection which our model captures through the individual fixed effects.

We cannot meaningfully add time-varying *institution* characteristics (such as rankings) to our model because they change very slowly. When they do change, long and uncertain lags in their impact would prevent us from associating salary and institutional changes.

### **3.4.3 Institution characteristics have little impact on salaries**

Despite the near absence of firm fixed effects in the AKM model, we ask whether institution characteristics, and particularly the rank of the institution and university endowments, explain salaries. Because rank and endowment are very highly correlated, we include rank in Table 3.3 and Endowments in Table 3.4. We first regress the 679 institutional fixed effects,  $\gamma$ , from our AKM model (small as they are) on institution type and other characteristics as in equation (3.2). Results are shown in columns 1-3. Then, we instead include these characteristics directly in the ln salary equation as in equation (3.3) (columns 4-6).

Column 1 of Table 3 shows the results of the two-stage estimates, regressing firm effects on institution type and rank. This explains only 1.6% of the variation in institutional fixed effects  $\gamma$ , which itself is only 21% of log(salary) variation (see Table 3.2). Table 3.2 also showed that 60% of the variance in  $\gamma$ 's is measurement error (using Andrews et al.), so 1.6% of the (uncorrected) variance of the  $\gamma$ 's corresponds to about 4% of the non-measurement error  $\gamma$  variance.

The point estimates in Table 3.3 column 1 imply that the most prestigious university ( $\ln \text{rank} = 0$ ) pays a 15% premium and the most prestigious college pays a 10% premium relative to an unranked institution, although neither is significant

at standard levels. Comparing among ranked universities, the most prestigious pay premiums of about 10% relative to the least prestigious ( $.0212 * \ln(100)$ ), and similarly for colleges. However, the coefficient on university rank is clearly not significant and the coefficient on college rank has a p-value of .07, while jointly, their p-value is .11 ( $F=2.23$ ). Yet for all 4 variables, the joint effect of type and rank is significant ( $p=.024$ ). Column 2 includes urbanicity, that not surprisingly significantly affects salaries. However, controlling for urbanicity reduces the already small effect of the two rank variables individually and jointly ( $F=1.63$ ,  $p=.20$ ) and reduces the joint significance of the four institution type and rank variables ( $F=1.74$ ,  $p=.14$ ). Column 3 adds several additional institutional characteristics, which hardly changes the other coefficients but further decreases the significance of institution type and rank.

Columns (4)-(6) show the results using one-step estimates. The estimates are generally somewhat smaller but more precise. Consequently, we *can* reject the hypotheses that the research university dummy and university rank have no effect on earnings in column (4). Again, the most prestigious university pays about an 10% premium relative to unranked institutions and also relative to the least prestigious university (which pays roughly the same salaries unranked institutions). However, (ranked) colleges pay only a tiny premium (.009) relative to unranked institutions and there is no difference between colleges of best and worst ranks. Moreover, if we compare the R-squared of .946 in column (4) with the R-squared of .952 explained by the individual fixed effects and individual time-varying variables (Table B.1), it is clear that the 679 institution dummies add very little to the model's explanatory power.

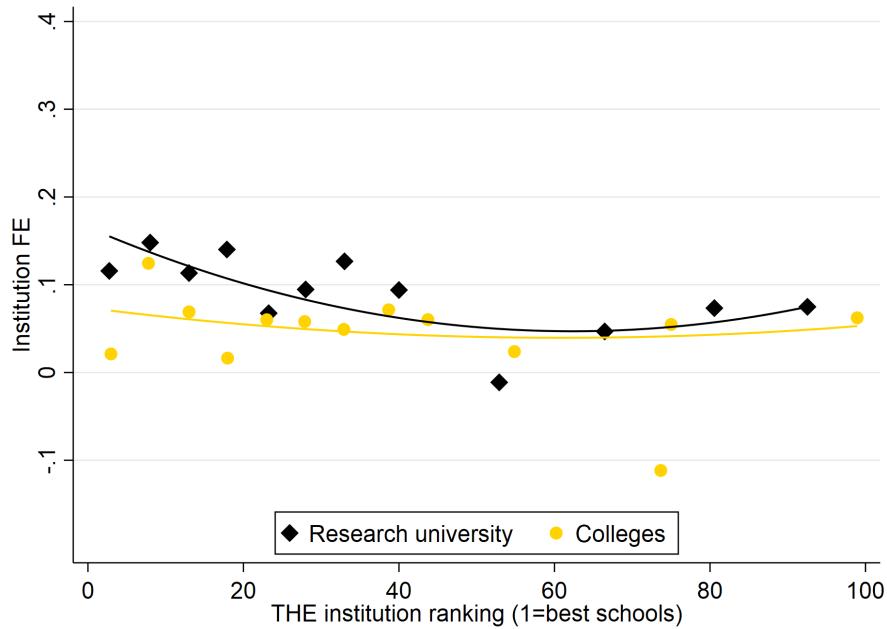
In Table 3.4, we redo the estimation of Table 3.3, replacing the rank of universities and colleges with the (log of) the endowment per student of the university, which measures the resources available to the institution and the rents it can share.

Endowment does have a statistically significant effect. Nevertheless, its impact remains small. Endowment together with university type still explains less than 2% of the variation in university effects (column 1). Moreover, the difference between the largest and smallest endowment per student predicts only a 14% difference in the institution salary effects ( $\gamma$ ) in column 1. We have estimated similar models with both endowment *and* rank variables; this lowers the size and significance of both, and R-squared remains less than 4% with all institutional factors included.

The insignificance of rank does not depend on our choice of functional form. Figure 3·1 plots binned institution fixed effects against institution rank separately for universities and colleges and fits quadratics. Both plots are somewhat U-shaped, so that better ranks are not monotonically better. For universities (shown as circles), the gap between the peak (at top ranks) and bottom institutions is noticeable but small (less than ten log points). For colleges (shown with yellow circles), even the difference between the peak and trough is negligible. This is very different from Figure C·1 in the online appendix which shows a definitive negative relationship between binned average *salary* and institution rank.

Appendix Figures C·2 and C·3 show that the institution fixed-effects figure is robust. In C·2 we choose bins to equalize the number of movers across bins. In C·3 we combine institutions with adjacent ranks until each institution or pseudo-institution has at least five movers. This primarily affects colleges because most universities are sufficiently large to have enough movers. The resulting patterns are largely unchanged.

We have also estimated simple correlations between the university logged rank and the university fixed-effects, which range from  $\rho = -.22$  to  $-.26$  in the two-step and one-step estimates, respectively (bottom Table 3). Recall that more prestigious institutions have a lower rank, so this indicates a substantial positive relationship be-

**Figure 3·1:** Institution pay premium and rank

tween institution and individual quality. The correlations between college institution effects are smaller and more dependent on which estimate is used, with  $\rho = -0.10$  and  $-.16$  for colleges in the 2-step and 1-step models, respectively.

Part of the variation in individual effects may be due to the faculty being from different fields. The most prestigious universities may be willing to pay both anthropologists and economists more than they would earn at less prestigious institutions but do not pay anthropologists and economists equal salaries. However, the correlations between university rankings and the individual fixed effects net of field is the same to 2 decimal places, the correlation between college rank and net individual effects is about .01 greater than reported in Table 3.3.

**Table 3.3:** Do rankings increase institution fixed effects?

	Two-Step Estimates			One-Step Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Institution type * log of rank</i>						
Research university	-0.021 (0.021)	-0.018 (0.021)	-0.019 (0.023)	-0.0216** (0.0098)	-0.020* (0.011)	-0.0147 (0.011)
College	-0.0218* (0.0119)	-0.0188 (0.0119)	-0.0219 (0.0141)	-0.006 (0.009)	-0.006 (0.009)	-0.0017 (0.011)
<i>Institution type (omitted=unranked)</i>						
Research university	0.148* (0.086)	0.114 (0.087)	0.107 (0.109)	0.098** (0.0446)	0.081 (0.047)	0.0357 (0.048)
College	0.096 (0.059)	0.047 (0.057)	0.079 (0.066)	0.009** (0.040)	0.000 (0.040)	-0.0281 (0.0412)
<i>Institution characteristics</i>						
Large city		0.076 (0.023)	0.068** (0.025)		0.047 (0.015)	0.043 (0.015)
Medium city		0.025 (0.021)	0.022 (0.021)		0.016 (0.012)	0.012 (0.013)
ln (total enrollment)			-0.008 (0.014)			0.010 (0.009)
Undergrad only			-0.055** (0.024)			-0.034 (0.018)
Private institution			-0.011 (0.030)			0.026 (0.019)
<i>Joint significance of 2 rank variables</i>						
F statistic	2.23	0.982	0.329	2.079	1.892	0.554
p-value	0.108	0.375	0.720	0.126	0.151	0.575
<i>Joint significance of university type and rank variables</i>						
F statistic	2.8	1.741	1.3	3.22	2.648	1.320
p-value	0.024	0.139	0.27	0.012	0.032	0.261
<i>Correlation between individual fixed-effects and ln(rankings)</i>						
Universities		-0.223		-0.264	-0.259	-0.259
Colleges		-0.095		-0.162	-0.157	-0.152
Observations	679	679	679	64,537	64,537	64,537
R squared	0.013	0.029	0.038	0.946	0.946	0.946

*Notes:* Standard errors in parenthesis. Institution rank ranges from 1 (best) to 100. Additional controls: individual fixed-effects, years since PhD, rank(lecturer, instructor, associate, full, other), tenured, female, married, children (<6, 6-11, 12-18, 19+), female\*married, female\*children. Two-step estimates are obtained by including institution fixed effects and regressing the institution coefficients on the explanatory variables. One-step estimates replace the institution fixed effects with the institution characteristics. Research universities are mainly R1 but include some R2 institutions. Colleges include all remaining post-secondary institutions granting four-year degrees. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k respectively.

In columns (5)-(9) standard errors are clustered at the institution level.

**Table 3.4:** Does endowment increase institution fixed-effects?

	Two-Step Estimates			One-Step Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
ln (endowment per student)	.0102** (0.0047)	.0096** (0.0047)	0.0108** (0.0066)	0.0083** (0.0033)	.0089** 0.0032	0.0059 (0.0041)
<i>Institution type (omitted=unranked)</i>						
Research university	0.0493 (0.0451)	0.029 (0.0454)	0.0107 (0.0509)	-0.0080 (0.0257)	-0.0223 (0.0254)	0.0392 (0.0276)
College	0.0057 (0.0413)	0.0026 (0.0412)	-0.0127 (0.0420)	-0.0288 (0.0240)	-0.0406* (0.236)	-0.0472* (0.0243)
<i>Institution characteristics</i>						
Large city		0.0713*** (0.0235)	0.0679*** (0.0253)		0.0504 (0.0147)	0.0439*** (0.0150)
Medium city		0.0317 (0.0207)	0.0286 (0.0212)		0.0165 (0.0125)	0.0133 (0.0126)
ln (total enrollment)			-0.0053 (0.0128)			0.0120 (0.0090)
Undergrad only				-0.0552** (0.0237)		-0.0323* (0.0173)
Private institution				-0.0099 (0.0296)		0.0266 (0.0193)
Observations	679	679	679	64,537	64,537	64,537
R squared	0.017	0.030	0.038	0.946	0.946	0.946

*Notes:* Standard errors in parenthesis. Institution rank ranges from 1 (best) to 100. Additional controls: individual fixed-effects, years since PhD, rank (lecturer, instructor, associate, full, other), tenured, female, married, children (<6, 6-11, 12-18, 19+), female×married, female×children. Two-step estimates are obtained by including institution fixed effects and regressing the institution coefficients on the explanatory variables. One-step estimates replace the institution fixed effects with the institution characteristics. Research universities are mainly R1 but include some R2 institutions. Colleges include all remaining post-secondary institutions granting four-year degrees. Large, medium, and small cities have populations above 250k, between 100k and 250k, and under 100k respectively. In columns (5)-(9) standard errors are clustered at the institution level.

### 3.4.4 Why does institutional affiliation matter so little?

We find the absence of institution effects counterintuitive. Consider the University of Wisconsin, Madison, and the University of Wisconsin, Oshkosh. Both schools are in our data set and have publicly available salaries. In academic year 2021, the median full professor of economics at UWM earned \$370,954 – almost three times as much as the median economics full professor at UWO, who earned \$126,193. Now, imagine the

UWM professor with the median earnings (\$370,954) moving exogenously to UWO and vice versa. What salary do you think they would receive? This exchange is hard to imagine, but our results suggest that it would not change their salaries since there are no meaningful university effects. We find it unlikely that UWM would hire anyone as a tenured Professor of Economics whom it was only willing to pay \$126,193. It is equally unlikely that UWO would be willing to hire an economics professor with tenure for almost \$100,000 more than it pays its Chancellor. Readers are, of course, free to disagree with our intuition.

### **There are no clear patterns in salary changes upon moving**

In the online appendix Table C.2, we show salary changes as people move from and to institutions, by quintile rank of universities and colleges. On average, all transitions raise salaries, which is unsurprising since we expect most people to move to better-paid jobs. However, there are few, if any, other clear patterns.

In particular, faculty do not receive larger raises when moving to a better institution (as they would if elite institutions paid more) or when moving to a worse institution (as they would if they received a compensating salary differential). If we focus on research universities, those exiting jobs in the top or second quintile see the largest gains if they end up in the second quintile; but those exiting the third quintile institution do best if they end up in the fourth quintile and worst in the third. Those starting in the fourth do slightly better ending up in the second than the fourth but noticeably better than ending in the first or third. If the AKM model is correct, the effects of moving from A to B and B to A should be equal and of opposite sign, net of any mobility premium. Instead, in our data, salary changes are independent of the direction of movement, consistent with more prestigious institutions not paying rent.

## Movement among institutions is not random

The thought experiment at the beginning of the subsection is challenging because we rarely observe movements across institutions differing so wildly in prestige. To be consistent, the AKM model requires that mobility be random; the error term must be uncorrelated with the explanatory variables, most notably the individual and faculty fixed effects. We will see that movement is not random, although not necessarily in a manner that challenges the AKM assumptions.

The tendency of faculty to move to institutions of relatively similar eliteness is clear from the transition matrix, Table C.3 in the online appendix. We suspect that the table probably overstates mobility across prestige levels since the prestige of individual departments is not always similar to overall institution prestige. Nevertheless, when tenure-stream faculty leave a university in the top quintile, almost half (45%) remain in the top university quintile, 66% within the top two quintiles, and 76% within the top two quintiles of universities *or* colleges (not shown). There is only a 0.5% chance of them moving to the lowest-quintile university and almost no chance of moving to a lowest-quintile college.

Similarly, roughly 70% of moves from a university that end in a top-tier university come from first or second-tier universities, and another 6% from top colleges. The likelihood of moving to the best university from either the lowest quintile universities, the bottom 2 quintile *colleges*, or unranked institutions is tiny. However, movements involving the most-elite university quintile are somewhat atypical in their degree of insularity. For other quintiles and for colleges, movement to proximate quintiles is more common. Movements originating in the highest quintile universities are also more common than those originating in other quintiles or in colleges. Still, regardless of an academic institution's type and rank, there is limited movement to very different institutions. 72.6% of those starting in universities move within +/- 1 university

quintile or to a more highly ranked college.

Moreover, there is relatively little movement from universities to colleges (31% of university movers, even though 44% of destination jobs are in colleges) and particularly little movement from colleges to universities (35% of college movers, even though 54% of destination jobs are in universities). Finally, of those who start and end in universities, the same percentage (21%) go to worse-ranked jobs as go to better-ranked jobs. However, of those who start and end in colleges, far more (26%) go to worse-ranked jobs than better-ranked jobs (13%).

### Hedonics may explain wages and mobility

We found a substantial positive correlation between faculty fixed effects and university and, to a lesser extent, college prestige (shown at the bottom of Table 3.3). Simultaneously, we find no evidence that more prestigious institutions pay salary premiums. Consistent with this, there is considerable mobility between institutions. However, salary changes do *not* show a pattern where moving to higher-prestige institutions increases salaries. We suggest that a hedonic model augmented with idiosyncratic tastes fits our results well.

There is a continuum of institutions with prestige,  $p$ . The salary an institution is willing to pay for a particular match,  $w_m$ , depends on the potential faculty member's quality,  $q \in Q$  and  $p$ :

$$w_m = w_m(q, p), \quad \frac{\partial w_m}{\partial p} > 0 \quad (3.4)$$

We assume that  $w_m$  is continuous in  $p$ . We further assume that for any  $p' > p''$ , there is a  $q^*$  such that

$$w_m(q^*, p') = w_m(q^*, p'') \quad (3.5)$$

and

$$w_m(q, p') > w_m(q, p'') \iff q > q^* \quad (3.6)$$

This ensures that institutions' willingness-to-pay curves cross exactly once. Under these assumptions, there will be a unique  $p$  that maximizes an individual's compensation.

To take a simple example, let

$$w_m = -p^2 + pq \quad (3.7)$$

Then salary is maximized at  $p = 0.5q$ , and salary is  $w_m = 0.25q^2$  at the maximum.

With perfect matching, the observed salary is the upper envelope of the individual institution willingness-to-pay curves. While, in the example, each institution's willingness-to-pay is linear, the equilibrium salary is convex in worker quality as in Roy (1951).

With perfect matching, we cannot distinguish between individual and worker effects. Earnings can be fully explained by either  $p$  or  $q$ . For instance, in the above example, the maximizing salary,  $w_m$  can also be expressed as  $w_m = p^2$ .

Moreover, suppose individuals deviate slightly from their optimal institutions. Then, the effect on their earnings is only second-order since the derivative of earnings with respect to prestige is 0 at the optimum. On the other hand, the difference between the imperfectly-matched faculty's  $q$  relative to other faculty at that institution is first order. Therefore, individual fixed effects and not institution fixed effects explain wages.

Consider an individual with  $p = p^*$  has and, therefore,  $q = 2p^*$  at their highest-pay institution. Consider a second institution  $p' = p^* + \varepsilon$ . The individual earns  $-(p' - \varepsilon)^2 + 2(p' - \varepsilon)(p' - \varepsilon)$  when matched to  $p^*$ , but only  $-p'^2 + 2p'(p' - \varepsilon)$  when

imperfectly matched to  $p'$ . Taking the difference gives the tiny difference  $\varepsilon^2$ . However, comparing the well-matched individual at  $p^*$  with a well-matched individual at  $p'$  who earns  $-p'^2 + 2p'(p')$ , the difference is a larger  $2p'\varepsilon$ .

Therefore, we do not observe our University of Wisconsin economists exchanging campuses because both would take significant salary cuts since they are poor matches at the other institution.

Intuitively, in the example, the mismatch between faculty and institution is not very different among proximate universities. Neither earns rents because there are similar institutions that would offer them essentially the same salary.

Online appendix C.3 develops this example. In the appendix, the variance of log salaries is .14, as in our data. If the highest and lowest quality faculty were both matched with the most prestigious institution, a highly improbable event for the latter, the ratio of their earnings would be 11. The example allows for a significant degree of mismatch. For example, the median quality faculty has a 6-7% chance of ending up in each of the top and bottom quintiles. Nevertheless, the variance of the institution effects is trivial.

### 3.5 Discussion and conclusion: is academia different?

Applying standard AKM techniques to tenure-track academic jobs, we find no evidence that prestigious institutions pay rents to their STEM faculty. Individual faculty members do differ considerably in their salaries, even when netting out field effects. Moreover, the individual effects are quite correlated with the institution's rank. However, when we use AKM methods to separate out the firm and person effects based on movements of individuals between institutions, we find that practically all of the variation is in the person effects. We present a simple model suggesting that if faculty and institution are optimally matched, AKM estimation can lead to seemingly

small institution effects.

Whether our results differ from findings for broader labor markets depends somewhat on which study we compare our results with. Nevertheless, the finding that establishment effects are small to nonexistent puts our results at the low end of the range of estimated effects. We can only speculate as to why our findings for faculty differ from the broader labor market. The most likely explanation is that the labor markets are simply different.

For instance, many dimensions along which faculty success is measured – publications in prestigious journals, appointments to prestigious societies, editorships etc. – are the same dimensions that feed into the success or prestige of the universities as well. Moreover, these dimensions are visible both inside and outside the institutions. This alone is likely to make rents unlikely in academia. In contrast, in other labor markets, individuals' contributions to productivity are often difficult for both the firm and the worker to measure, and are not visible at all outside the firm, making rents feasible.

It is also possible that the technologies are different. Faculty positions are quintessential star jobs (Baron and Dreps, 1999); successes are rare and valuable; failures are common and not very costly. In contrast, (Bose and Lang, 2017) argue that most nonacademic jobs are guardian jobs in which the gains from an especially good performance are small, but the costs of a bad performance are very large. In such settings, firms with high costs of failures would only hire workers who had demonstrated their competence and would pay those workers a premium. Mobility would primarily be upward; workers moving to high-wage firms would earn a premium. However, the premium would not be rent but a payment for their revealed high quality.

In some labor markets, higher firm salaries may be due to compensating wage differentials (Sorkin, 2018). However, in academia, non-wage aspects of the job (e.g.

light workloads, more research support, better students) are highly positively correlated with prestige, so we would not see high salaries compensating for low levels of other job characteristics.

Nothing in our results allows us to distinguish among these explanations and perhaps others that may occur to readers. However, we believe that our results, while perhaps interesting in their own right, should encourage us to reflect more on the interpretation of the AKM model.

## Appendix A

# Appendix to chapter 1

### A.1 Tables

**Table A.1:** Indonesia: number of existing regencies by year, 1980-2010

	1980	1990	2000	2010
Number of regencies	286	295	339	493

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

**Table A.2:** Dispersion in regional employment rates within countries

Country	Women			Men			Pop.	Obs.
	IQR	SD	Mean	IQR	SD	Mean		
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.3:** Dispersion in employment and paid employment rates for selected countries

Country	All employment		Paid employment		Observations
	IQR	Mean	IQR	Mean	
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.2 with data that distinguishes unpaid and family workers from other worker types.

**Table A.4:** Female labor force participation rates 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.5:** Source IPUMS samples for cross-country data

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Women's employment rate at birthplace ( $p_o$ )	0.38*** (0.04)	0.39*** (0.04)	0.35*** (0.05)	0.37*** (0.04)	0.34*** (0.04)	0.34*** (0.04)	0.29*** (0.08)	0.24*** (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

101

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

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

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

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

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

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

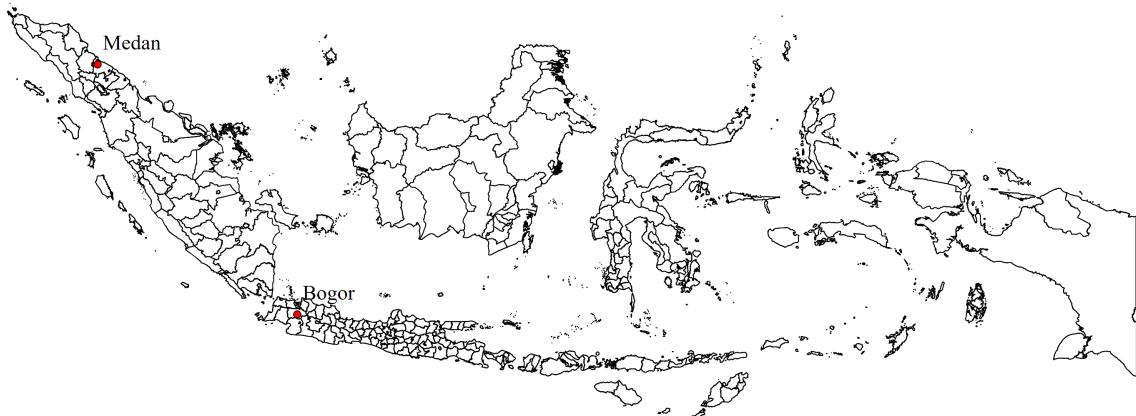
*Notes:* This table uses data from the Intercensal Survey and restricts the sample to women who reside outside their birthplace and who left before they turned 19. The implied IQR gap shows the implied employment gap between someone born at a regency at the 75th percentile of employment rate and someone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

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

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

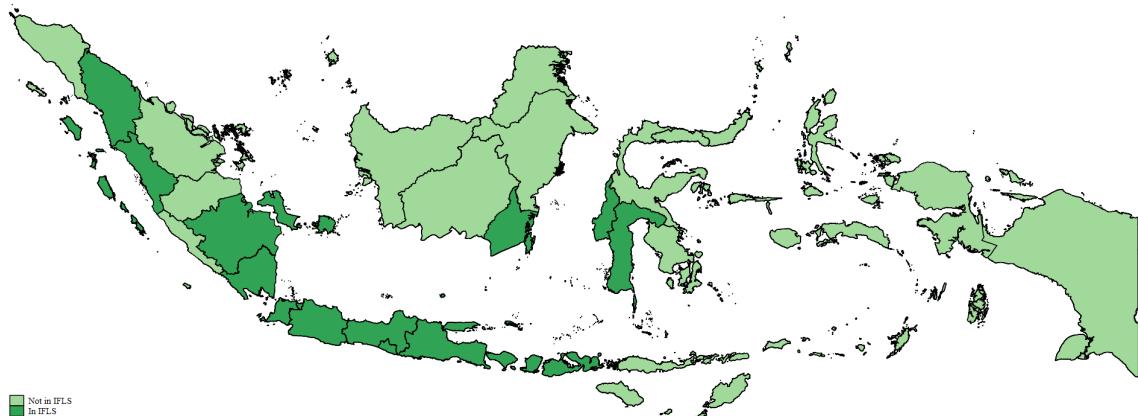
## A.2 Figures

**Figure A.1:** Indonesian regencies

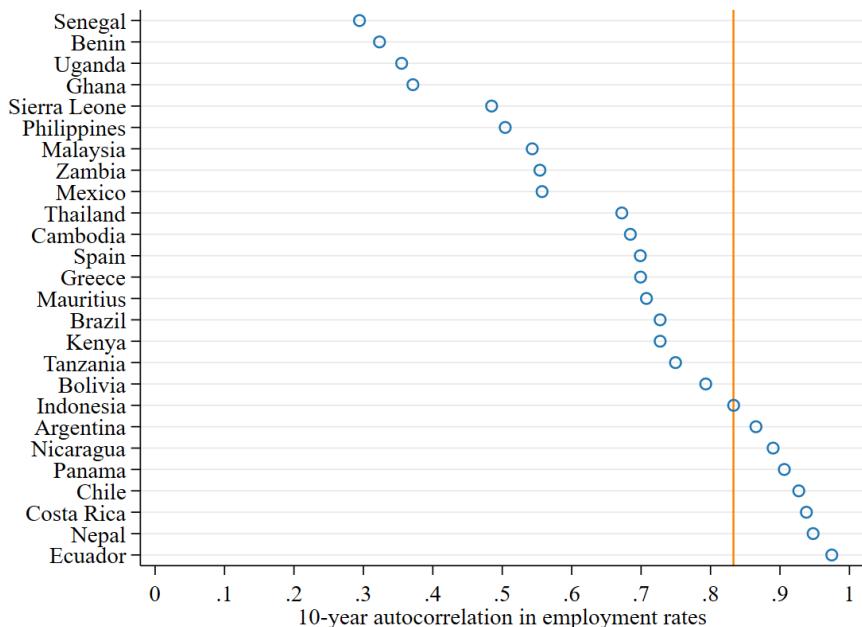
**Note:** The figure shows the 268 regency aggregates with consistent boundaries between 1970 and 2018. Boundaries obtained from IPUMS International. It highlights with red dots the locations of the city of Medan and Bogor regency. Medan, the capital and largest city in the province of North Sumatra,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

## A.3 Cross-country data

I use harmonized data from IPUMS International to build figure 1.1 from the introduction and table 1.4 from section 1.3. They show local employment rates for men and women aged 18-64 for a cross-section of countries. For all of them, I use the latest decennial census sample available. In most cases, this corresponds to 2010 or a year close to it.

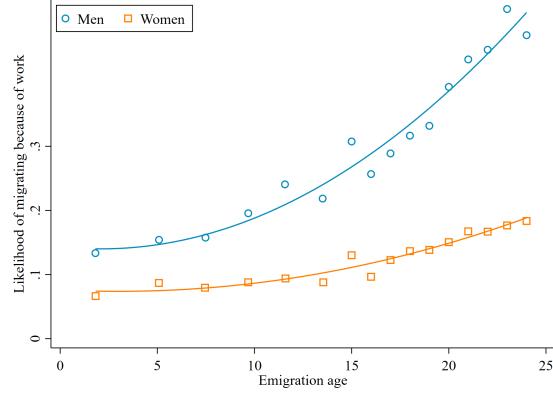
**Figure A·2:** Provinces in the original 1993 IFLS sample

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

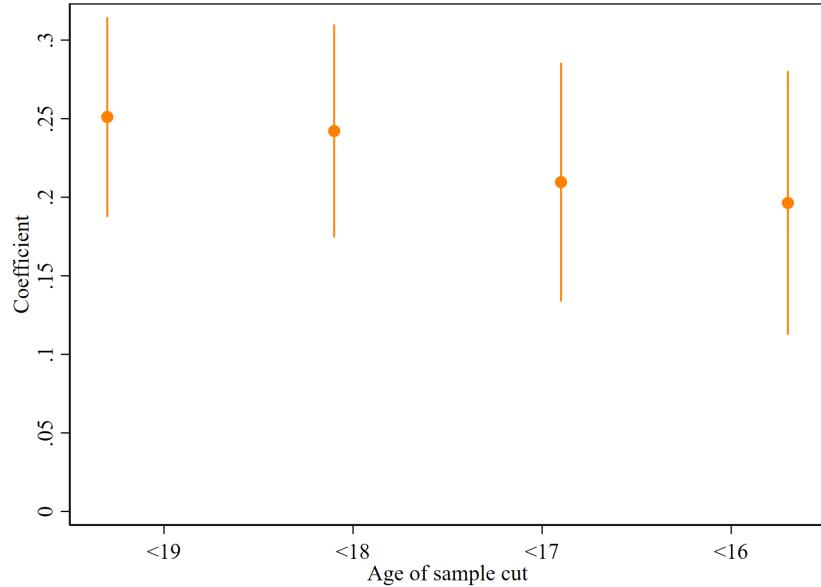
**Figure A·3:** 10-year autocorrelation in female employment rates at the district level for selected countries

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

I define employment using the harmonized employment status (`empstat`). When this variable is not available, if the class of worker is available (`classwkr`), I say a person is employed if they report being self-employed, a salaried worker, or an unpaid

**Figure A·4:** Indonesia: likelihood of work-related migration by emigration age

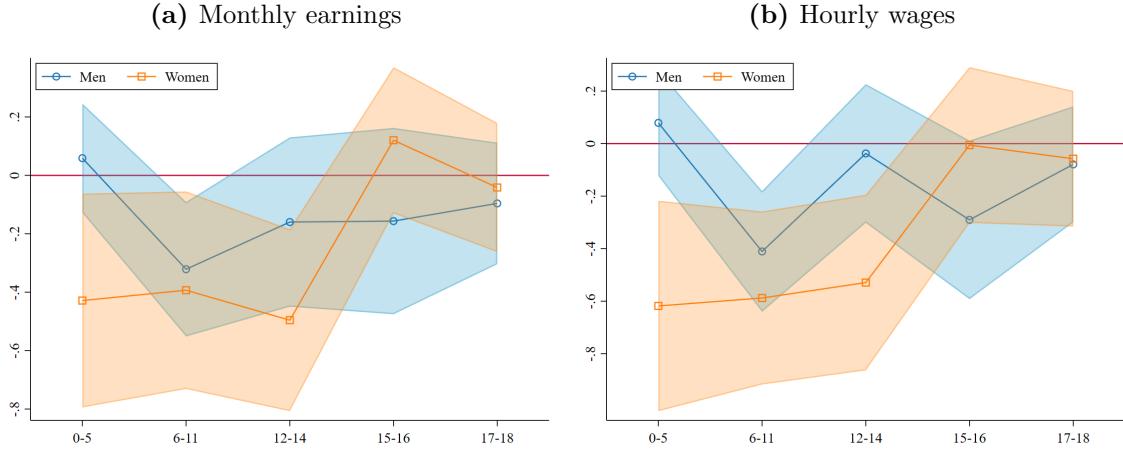
**Note:** The survey does not distinguish whose work generated the move. Thus, the move can be related to parents' job, own job, or husband's / wife's job. Data from 1985 intercensal survey. The 1995 and 2005 surveys only list cause of migration for migration 5 years ago, and a very limited number of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

**Figure A·5:** Estimates of birthplace persistence for different emigration age cutoffs

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

worker in the variable. In China, employed workers are those who reported working at least 1 day in the past week. Despite these slight definition differences, table A.4

**Figure A·6:** Indonesia: earnings and length of stay at birthplace



**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.

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).<sup>1</sup> 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.5 provides further details on the unit of aggregation and samples used. I winsorize the employment rates at the 5th and 95th percentiles by country. This reduces the possibility that very small regions drive the dispersion I observe within countries.

<sup>1</sup>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.

## A.4 The Empirical Strategy

In section 1.4.1, when I introduced the age of emigration data, I made the assumption that women's employment decisions are determined by place of residence fixed-effects  $\delta_c$ , age of emigration fixed-effects  $\lambda_a$ , female labor force participation at birthplace  $p_b$ , and an error term  $\eta_{it}$ :

$$e_{it} = \delta_c + \lambda_a + \sigma_a p_b + \eta_{it} \quad (\text{A.1})$$

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

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

$$E = D\omega + P\sigma + \eta$$

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

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

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

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

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

Therefore:

$$\begin{aligned} \text{plim } (\hat{\boldsymbol{\sigma}}) &= \boldsymbol{\sigma} + \text{plim } \left[ (\tilde{P}'\tilde{P})^{-1}\tilde{P}'\tilde{\boldsymbol{\mu}} \right] \\ &= \boldsymbol{\sigma} + \boldsymbol{\gamma} \end{aligned} \quad (\text{A.2})$$

now let us examine the meaning of expression (A.2) in detail. This expression implies that the OLS estimate for the birthplace persistence at age  $a$  is the sum of two terms: (i) the birthplace effect effect at that age  $\boldsymbol{\sigma}_a$ , and (ii) a term that captures the correlation between the residualized employment rate at the origin and the residual for people emigrating at age  $a$   $\boldsymbol{\gamma}_a$ :

$$\text{plim } (\hat{\boldsymbol{\sigma}}_a) = \boldsymbol{\sigma}_a + \boldsymbol{\gamma}_a \quad (\text{A.3})$$

#### A.4.1 Identification

**Assumption A.4.1.** *Selection on unobservables does not depend on the age of emigration, that is  $\boldsymbol{\gamma}_a = \mathbf{k}$*

Assumption A.4.1 essentially requires that correlation between women's unobservable characteristics and women's origin is the same no matter the age at which they move. To see this, note that  $\boldsymbol{\gamma}$  is driven two components:

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

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

$$\sum_{i=1}^N \tilde{p}_b^a \tilde{\eta}_i \quad (\text{A.4})$$

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

$$\mathbb{E} \left( \tilde{p}_b^a \tilde{\eta}_i \right)$$

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

$$\mathbb{E} \left( \tilde{p}_b^a \tilde{\eta}_i \right) = \mathbf{c} \quad (\text{A.5})$$

$$\text{plim}(\tilde{P}' \tilde{P})^{-1} = Q \quad (\text{A.6})$$

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

The first condition requires the correlation between women's unobserved characteristics and the birthplace FLFP to be the same for women migrating at different ages as children. For instance, this condition allows for the fact that in places where more women work they were more likely to have working mothers. A violation of (A.6) would occur if, for example, women with working mothers stayed longer in their birthplace.

Furthermore, note that condition (A.5) requires constant bias *conditional on age*

*of emigration and current place of residence* as it only contains variables that have been residualized from current location and age of emigration fixed-effects. So, for example, even though women who migrated at 12 years old are more likely to migrate because of school than those that did it at 12 years old<sup>2</sup>, this does not necessarily violate the constant bias assumption. This would be a problem only if, after conditioning on emigration age and place of residence, women from certain origins are more likely to migrate because of school at 12 than at age 10. While I cannot fully test for this condition, in section A.4.1 I provide supporting evidence by correlating birthplace female employment rate with observed women's characteristics for different emigration age cohorts.

Condition (A.6) imposes restrictions on the correlations between birthplace female employment for women migrating at different ages as children. They will be generally satisfied if women migrating at different ages came from roughly the same origins.

#### A.4.2 From OLS to causal effects

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

$$\pi_a = \sigma_a - \sigma_{a-1}$$

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

---

<sup>2</sup>Secondary in Indonesia starts at 13

subtraction:

$$\hat{\sigma}_a - \hat{\sigma}_{a-1} = \sigma_a - \sigma_{a-1} \quad (\text{A.7})$$

With an additional normalization, the OLS estimates can also identify the size of the selection term  $\mathbf{k}$ . If we normalize the causal effect for the children with the least exposure to birthplace to zero ( $\sigma_0 = 0$ ), the OLS coefficient for this children is an estimate of the selection term:

$$\hat{\sigma}_0 = c \quad (\text{A.8})$$

Equations (A.7) and (A.8) provide a full guide for estimating the causal effects. OLS estimates for women who migrated at the earliest ages can be used to estimate the selection terms, while differences in the OLS estimates across different ages provide an estimate of the causal effect of spending a particular age or period in the birthplace.

## Appendix B

# Appendix to chapter 2

### B.0.1 Sample definitions

I restrict the sample to salaried workers aged between 18 and 64 years old, not attending school and who live outside of group-quarters. My classification of non-farm workers is based on the 1950 census occupational classification. It excludes all workers working in the following occupations:

**Table B.1:** Farm workers, 1950 census occupational classification

Occupation code	Description
100	Farm owners and tenants
123	Farm managers
810	Farm foremen
820	Farm laborers, wage workers
830	Farm laborers, unpaid family workers
840	Farm service laborers, self-employed

## B.1 Tables

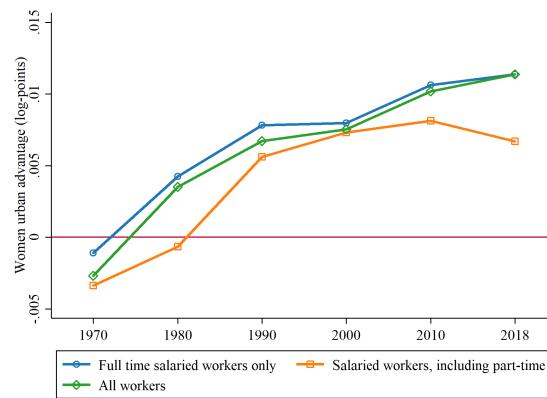
**Table B.2:** Selected CZ-level summary statistics, 1970-2018

	Census year					
	1970	1980	1990	2000	2010	2018
Observations	720	722	722	722	722	722
<i>A. CZ population (000)</i>						
p25	14.65	19.25	18.08	20.50	21.62	21.36
Mean	139.78	165.83	179.83	206.58	225.90	236.18
p75	103.11	132.47	133.32	151.91	167.36	172.92
<i>B. CZ gender wage gap (men's - women's)</i>						
sd	0.07	0.07	0.08	0.05	0.06	0.06
p25	0.44	0.39	0.31	0.23	0.18	0.16
Mean	0.48	0.44	0.35	0.27	0.22	0.20
p75	0.52	0.49	0.38	0.30	0.25	0.23

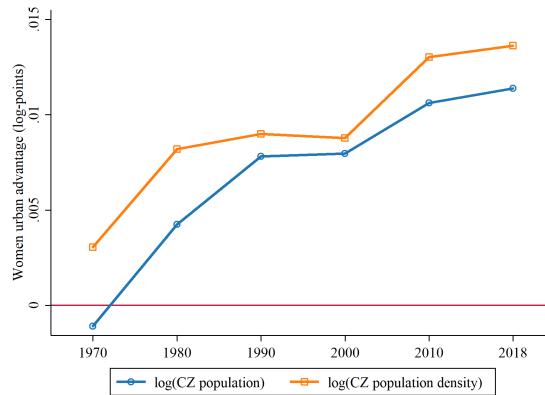
*Notes:* Sample restricted to full-time year-round workers in mainland US. The table shows means weighted by the census sampling weight.

## B.2 Figures

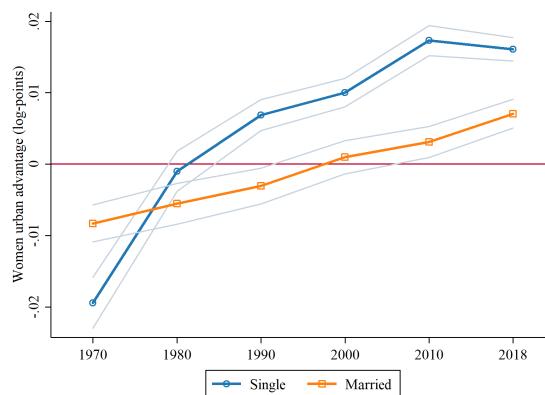
**Figure B.1:** Women's urban advantage for alternative sample selections, 1970-2018



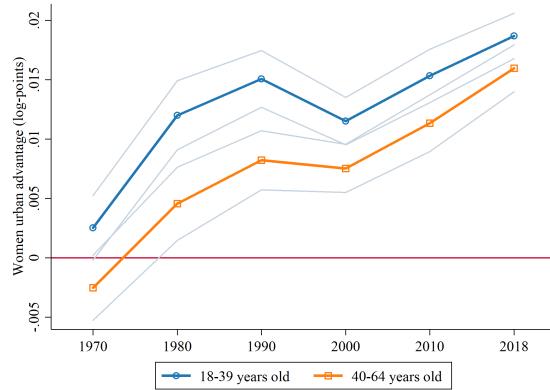
**Note:** The figure shows the unconditional urban wage advantage. All workers includes self-employed and part-time workers. Observations are weighted by the inverse of the estimated variance of the CZ-gap. Regressions are run separately each year. Figure shows 90% CI.

**Figure B·2:** Women's urban advantage for alternative CZ size measures, 1970-2018

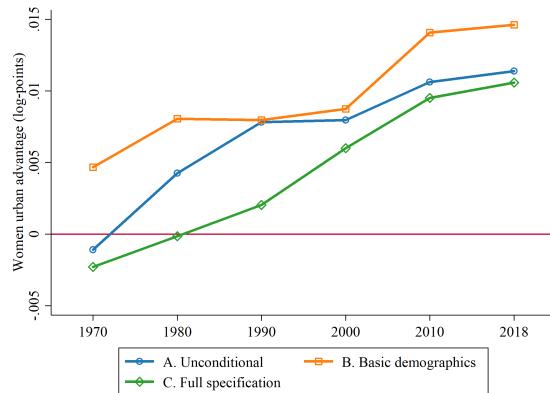
**Note:** The figure shows the unconditional urban wage advantage. All workers includes self-employed and part-time workers. Observations are weighted by the inverse of the estimated variance of the CZ-gap. Regressions are run separately each year. Figure shows 90% CI.

**Figure B·3:** Women's urban advantage by marital status, 1970-2018

**Note:** The figure shows the unconditional urban wage advantage. The estimates come from a regression of CZ-specific gender wage gaps on the log of CZ population. Observations are weighted by the inverse of the estimated variance of the CZ-gap. I don't include any controls in the first stage. . Regressions are run separately each year and marital status. Figure shows 90% CI.

**Figure B·4:** Women's urban advantage by age group, 1970-2018

**Note:** The figure shows the unconditional urban wage advantage. I do not include any controls in the first stage. The estimates come from a regression of CZ-specific gender wage gaps on the log of CZ population. Observations are weighted by the inverse of the estimated variance of the CZ-gap. . Regressions are run separately each year and age group.

**Figure B·5:** Women's urban advantage for alternative conditioning on covariates, 1970-2018

**Note:** Sample restricts to full-time year-round workers in mainland USA. First stage regressions condition on individual-level covariates. Basic demographics controls age, race and education. Full specification controls for age, race, education, and a full set of occupation and industry dummies. Observations are weighted by the inverse of the estimated variance of the CZ-gap. First stage regressions run separately each year. Basic demographics controls for age, race, and education. Full specification controls for age, race, education, and a full set of occupation and industry dummies. Observations are weighted by the FGLS weight. First stage regressions are run separately by year. Figure shows 90% CI.

**Table B.3:** Women's conditional urban advantage for non-college workers, 1970-2018

	Dep. var: real hourly wage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1970	0.001 (0.001)	0.003 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.006 (0.001)	-0.006 (0.001)
2018	0.014 (0.001)	0.015 (0.001)	0.015 (0.001)	0.013 (0.001)	0.011 (0.001)	0.011 (0.001)	0.011 (0.001)	0.011 (0.001)
Unexplained $\Delta_{2018-1970}$	0.013 0.002	0.013 0.002	0.015 0.002	0.014 0.002	0.013 0.001	0.013 0.001	0.017 0.001	0.017 0.001
Observations	4,326	4,326	4,326	4,326	4,326	4,326	4,326	4,326
<i>Controls</i>								
<b>Individual and work characteristics</b>								
Age	✓	✓	✓	✓	✓	✓	✓	✓
Race	✓	✓	✓	✓	✓	✓	✓	✓
Marital status		✓	✓	✓	✓	✓	✓	✓
Number of children			✓	✓	✓	✓	✓	✓
Industry				✓	✓	✓	✓	✓
Occupation					✓	✓	✓	✓
<b>Commuting time and CZ characteristics</b>								
Commuting time						✓	✓	✓
Labor force participation rates							✓	✓
CZ wage inequality								✓

*Notes:* Sample restricted to full-time year-round workers. Cells show the coefficient of an interaction between a year dummy and the log of CZ population. Each column represents a different regression. In all cases, the dependent variable is the log of the real hourly wage. Standard errors clustered at the CZ level in parenthesis..

## Appendix C

# Appendix to chapter 3

### C.1 Tables

Table C.1: Effect of time-varying characteristics

	(1) Full sample	(2) No outliers
Years since PhD	0.0374 (0.0071)	0.0356 (0.0068)
Years since PhD squared	-0.0003 (0.0000)	-0.0002 (0.0000)
Is tenured	0.0060 (0.0087)	0.0067 (0.0069)
Faculty rank (omitted=assistant professor)		
Lecturer	-0.0279 (0.0775)	0.0142 (0.0407)
Instructor	-0.0038 (0.0376)	-0.0069 (0.0368)
Associate professor	0.0496 (0.0100)	0.0456 (0.0079)
Professor	0.1587 (0.0124)	0.1459 (0.0098)
Other	0.0882 (0.0211)	0.0818 (0.0187)
Married	0.0081 (0.0076)	0.0052 (0.0057)
Married × female	0.0032 (0.0115)	0.0022 (0.0087)
Children below 6	-0.0010 (0.0055)	0.0018 (0.0041)
Children below 6 × female	0.0012 (0.0089)	-0.0063 (0.0075)
Children between 6 and 11	0.0021 (0.0047)	0.0039 (0.0038)
Children between 6 and 11 × female	-0.0090 (0.0073)	-0.0096 (0.0061)
Children between 12 and 18	0.0118 (0.0041)	0.0102 (0.0035)
Children between 12 and 18 × female	-0.0159 (0.0078)	-0.0181 (0.0065)
Children between 19+	0.0034 (0.0044)	0.0030 (0.0036)
Children between 19+ × female	-0.0086 (0.0097)	-0.0078 (0.0081)
Individual FE	✓	✓
Year FE	✓	✓
Observations	65893	64537
Number of movers	1868	1868
R <sup>2</sup>	0.9123	0.9516

*Notes:* Standard errors in parenthesis. Column (1) uses the full sample. Column (2) excludes extreme within-institution wage changes.

**Table C.2:** Salary wage changes by transition type

Origin	Universities					Colleges					Unranked (11)
	Best (1)	2 (2)	3 (3)	4 (4)	Worst (5)	Best (6)	2 (7)	3 (8)	4 (9)	Worst (10)	
<b>Universities</b>											
Best	0.330	0.393	0.296	0.177	N.D.	0.190	0.123	0.037	0.094	N.D.	N.D.
2	0.356	0.408	0.282	0.226	0.229	0.245	0.103	0.165	0.072	N.D.	0.253
3	0.275	0.256	0.089	0.320	N.D.	0.340	0.289	0.241	0.093	N.D.	N.D.
4	0.210	0.337	0.219	0.305	0.265	0.295	0.265	0.229	0.163	N.D.	0.183
Worst	N.D.	0.272	0.269	0.063	N.D.	N.D.	0.382	0.275	0.287	N.D.	N.D.
<b>Colleges</b>											
Best	0.356	0.218	0.297	0.347	N.D.	0.311	0.290	0.196	0.173	N.D.	N.D.
2	0.331	0.236	0.400	0.233	N.D.	0.193	0.178	0.250	0.164	N.D.	-0.015
3	0.278	0.245	0.201	0.208	0.101	0.188	0.181	0.209	0.162	N.D.	0.218
4	N.D.	0.135	0.251	0.166	N.D.	0.476	0.123	0.182	0.190	N.D.	N.D.
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.
Unranked	0.331	N.D.	N.D.	0.233	N.D.	N.D.	0.178	0.250	0.164	N.D.	N.D.

*Notes:* Data from cells with less than 5 individuals were suppressed to preserve confidentiality. We denote these cells with N.D.

**Table C.3:** Transition probability by ranking quintile and institution type

Origin	Universities					Colleges					Unranked
	Best (1)	2 (2)	3 (3)	4 (4)	Worst (5)	Best (6)	2 (7)	3 (8)	4 (9)	Worst (10)	(11)
<i>Universities</i>											
Best	0.446	0.219	0.084	0.062	N.D.	0.044	0.047	0.062	0.03	N.D.	N.D.
2	0.238	0.181	0.151	0.090	0.019	0.058	0.099	0.079	0.055	N.D.	0.025
3	0.146	0.190	0.241	0.091	N.D.	0.062	0.077	0.117	0.051	N.D.	N.D.
4	0.067	0.172	0.124	0.129	0.033	0.053	0.086	0.153	0.115	N.D.	0.057
Worst	N.D.	0.113	0.097	0.097	0.081	N.D.	0.113	0.210	0.145	N.D.	N.D.
<i>Colleges</i>											
Best	0.151	0.086	0.086	0.059	N.D.	0.092	0.217	0.184	0.079	N.D.	N.D.
2	0.084	0.154	0.044	0.062	0.022	0.141	0.163	0.167	0.132	N.D.	0.026
3	0.049	0.070	0.115	0.101	0.049	0.070	0.098	0.259	0.15	N.D.	0.035
4	N.D.	0.050	0.078	0.177	0.035	0.071	0.17	0.199	0.163	N.D.	N.D.
Worst	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	N.D.	0.333	N.D.	N.D.	N.D.
<i>Unranked</i>	N.D.	N.D.	N.D.	0.271	N.D.	N.D.	0.305	0.102	0.102	N.D.	N.D.

**Notes:** Data from cells with less than 5 individuals were suppressed to preserve confidentiality. We denote these cells with N.D.

**Table C.4:** Summary statistics including wage outliers

A: Number of movers in the sample			B: Number of transitions in the sample					
	All	Movers	Share of total		Total	Min	Max	
Total observations	65,893	8,192	0.12	Transitions	65,893	8192	0.12	
Number of people	26,873	1,868	0.07	Number of movers	26,873	1868	0.07	
Average obs./person	2.45	4.39		Number of institutions	2.45	4.39		
<b>C: Summary statistics: Individuals</b>				Transitions/mover	1.18	1	*	
Characteristics	N	Mean	Std	Transitions/institution	3.23	2	53	
Years since Ph.D.	65,893	18.18	10.66	*Suppressed, exceeds 4				
Has tenure	65,893	0.73	0.45	<b>D: Summary statistics: University-level characteristics</b>				
<i>Faculty rank</i>				Mean	Std	Min	Max	
Assistant Prof.	65,893	0.25	0.43	Research university rank	48	28	1	99
Associate Prof.	65,893	0.29	0.45	College rank	46	25	1	100
Professor	65,893	0.45	0.5	Log total enrollment	8.75	1.05	5.09	10.89
Lecturer	65,893	0	0.03	Log total endowment	18.03	2.13	10.90	24.32
				(\$2020)				
Instructor	65,893	0	0.04	Log endowment/student	9.32	1.97	2.89	14.84
Other	65,893	0.01	0.09	Log faculty size	5.79	0.96	0.92	8.04
Female	65,893	0.32	0.47	Log faculty/student	-3.14	0.55	-5.21	-1.69
Married	65,893	0.83	0.38	Share in large city	0.23	0.42	0	1
Has child under 6	65,893	0.18	0.38	Share in medium city	0.34	0.47	0	1
Has child aged 6-11	65,893	0.2	0.4	Share in small city	0.43	0.5	0	1
Has child aged 12-18	65,893	0.2	0.4	Share private	0.41	0.49	0	1
Has child aged 19+	65,893	0.1	0.3	Share undergraduate	0.22	0.41	0	1

*Note:* There are 152 research universities and 492 colleges. 35 institutions are unranked and not classified as colleges or universities.

**Table C.5:** Fixed-effect variance estimates in AKM model including wage outliers

	Uncorrected (1)	Corrected Andrews et al. method
<b>Individual by year level</b>		
Variance log(salary)	0.148	0.148
<i>Variance of Fixed-effects</i>		
Individual	0.140	0.110
Institution	0.029	0.012
Correlation	-0.325	-0.398
<b>Collapsed at the spell level</b>		
Variance log(salary)	0.140	0.140
<i>Variance of Fixed-effects</i>		
Individual	0.129	0.077
Institution	0.027	0.006
Correlation	-0.318	0.058

**Table C.6:** Do rankings increase institution fixed effects (including wage outliers)

	Two-Step Estimates			One-Step Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Institution type * log of rank (low ranks best)</i>						
Research university * ln(rank)	-0.0203 (0.0208)	-0.0174 (0.0208)	-0.0192 (0.0213)	-0.0179 (0.0100)	-0.0167 (0.0108)	-0.0104 (0.0111)
College * ln(rank)	-0.0197 (0.0122)	-0.0169 (0.0122)	-0.0220 (0.0145)	-0.0056 (0.0095)	-0.0062 (0.0095)	-0.0006 (0.0108)
<i>Institution type (omitted=unranked)</i>						
Research university	0.1502* (0.0871)	0.1190 (0.0878)	0.1113 (0.0937)	0.0873 (0.0455)	0.0724 (0.0479)	0.0233 (0.0491)
College	0.0902 (0.0605)	0.0716 (0.0607)	0.0814 (0.0676)	0.0115 (0.0413)	0.0043 (0.0401)	-0.0281 (0.0420)
<i>Institution characteristics</i>						
Large city		0.0703*** (0.0242)	0.0661** (0.0258)		0.0472*** (0.0149)	0.0403*** (0.0150)
Medium city		0.0262 (0.0215)	0.0220 (0.0218)		0.0118 (0.0124)	0.0086 (0.0124)
ln (total enrollment)			-0.0069 (0.0134)			0.0113 (0.0089)
Undergrad only			-0.0581** (0.0248)			-0.0330* (0.0181)
Private institution			-0.0089 (0.0278)			0.0378** (0.0170)
Observations	679	679	679	65,893	65,893	65,893
R squared	0.016	0.028	0.036	0.906	0.906	0.907
<i>Joint significance of 2 rank variables</i>						
F statistic	1.781	1.294	1.426	1.665	1.312	0.444
p-value	0.169	0.275	0.241	0.190	0.270	0.641
<i>Joint significance of university type and rank variables</i>						
F statistic	2.726	1.684	1.285	2.541	2.106	0.888
p-value	0.028	0.152	0.274	0.039	0.079	0.471
<i>Correlation between individual fixed-effects and ln(rankings)</i>						
Universities		-0.22		-0.261	-0.256	-0.255
Colleges		-0.093		-0.156	-0.152	-0.146

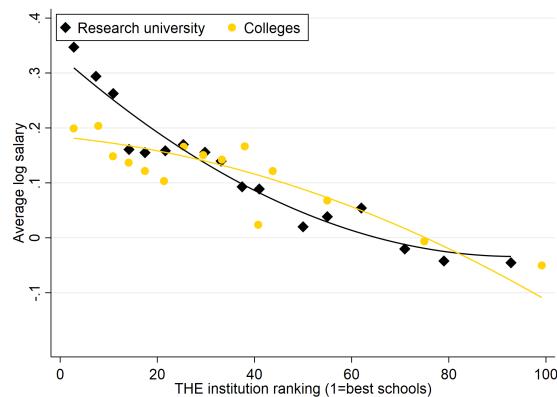
Note: See footnotes Table 3

**Table C.7:** Does endowment increase institution fixed effects? (including wage outliers)

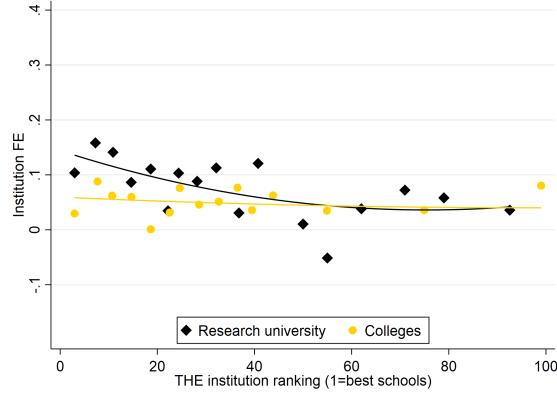
	Two-Step Estimates			One-Step Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
ln (endowment per student)	0.0094* (0.0049)	0.0089* (0.0049)	0.0118* (0.0068)	0.0076** (0.0033)	0.0084** (0.0033)	0.0046 (0.0042)
<i>Institution type (omitted=unranked)</i>						
Research university	0.0560 (0.0463)	0.0357 (0.0466)	0.0120 (0.0523)	-0.0028 (0.0258)	-0.0163 (0.0257)	-0.0310 (0.0280)
College	0.0082 (0.0424)	-0.0002 (0.0423)	-0.0118 (0.0431)	-0.0247 (0.0240)	-0.0356 (0.0237)	-0.0405* (0.0245)
<i>Institution characteristics</i>						
Large city		0.0725*** (0.0241)	0.0709*** (0.0260)		0.0499*** (0.0148)	0.0426*** (0.0151)
Medium city		0.0286 (0.0213)	0.0266 (0.0218)		0.0124 (0.0125)	0.0094 (0.0126)
ln (total enrollment)			-0.0038 (0.0132)			0.0130 (0.0092)
Undergrad only			-0.0519** (0.0244)			-0.0298* (0.0174)
Private institution			-0.0179 (0.0304)			0.0321 (0.0196)
Observations	679	679	679	65,893	65,893	65,893
R squared	0.016	0.029	0.036	0.906	0.906	0.907

*Note:* See footnotes Table 3.

## C.2 Figures

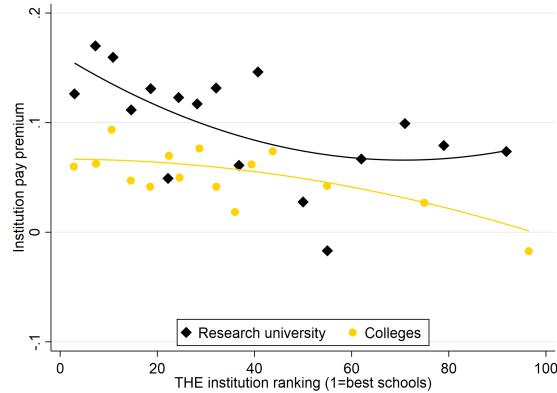
**Figure C.1:** Average faculty log salary and institution rankings

**Figure C·2:** Institution premium and institution rankings (weighted by number of movers)



**Note:** the figure weights observations so that each cell has the same number of movers.

**Figure C·3:** institution premiums and rankings weighted for grouped institutions



**Note:** the figure shows institution premium estimates for grouped institutions. We group institutions with similar rankings so that each institution “pseudo-institution” has at least five movers.

### C.3 A simple example

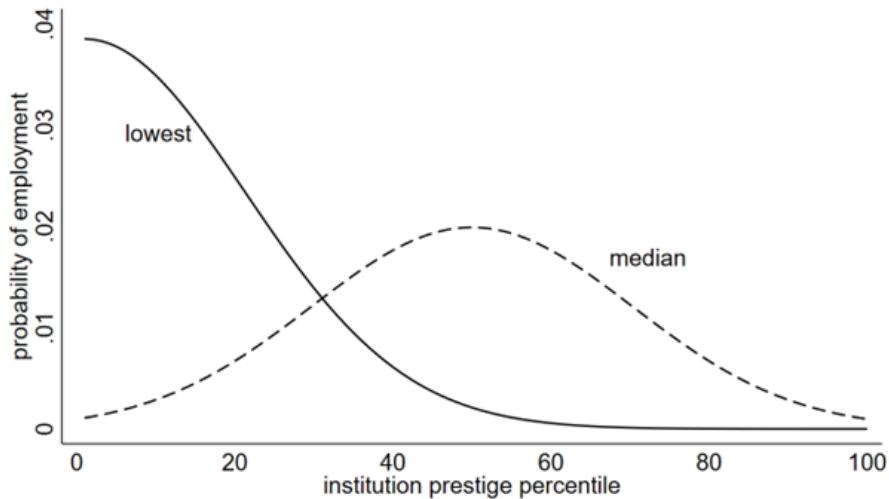
We choose functional forms to generate a realistic example but do not attempt to calibrate the example fully. We have 100 universities with prestige,  $p$ , given by  $\{.211, .222, .233, \dots, 1.30\}$ . Similarly, we have 100 faculty-quality types with quality,  $q$ , given by  $\{.422, .444, .466, \dots, 2.60\}$ . Universities pay a faculty member  $\ln w(p, q) = -p^2 + pq$ . These assumptions ensure that each faculty member maximizes their salary by choosing the university with the prestige rank equal to their quality rank.

We choose these numbers so that if both are perfectly matched, the highest type earns about five times as much as the lowest type but the highest type would earn about 17 times as much as the lowest type if they were both at the most prestigious university but would only earn about two-thirds more if they were both at the least prestigious. The utility the faculty receives from an appointment at a given university is  $u = \ln w + \eta$  where  $\eta$  is type 1 extreme value with scale parameter .1. Then the probability that a worker of quality,  $q$ , is in the job with prestige  $p'$  is given by

$$P(p', q) = \exp(10 * \ln w(p', q) / (\sum p(10 * \ln w(p, q))))$$

The AKM model fits the data well in the sense that it explains 99% of the variance. Of course, the example has no idiosyncratic errors, but the ability of the AKM model to fit the data is still striking. Although the university fixed effects are jointly significant, they are relatively unimportant with an uncorrected standard deviation of less than .01. Faculty fixed effects alone explain 83% of the variance. Appendix Figure C.4 shows the distribution of the lowest and median quality faculty. Although the lowest quality faculty is most likely matched with the lowest prestige university, they still have a nontrivial chance of ending up in the third quintile. Similarly, the median quality faculty is mostly likely to be matched with the median prestige university but has a nontrivial chance of being in either the top or bottom quintiles. The 10th percentile faculty (not shown) has a 55% chance of being in a bottom quintile university, 35% in the fourth quintile, and 9% in the fifth quintile.

**Figure C·4:** Probability of prestige level: lowest and median quality faculty



## C.4 Data

In this paper, we combine data from three sources: individual-level data from the restricted-use version of the Survey of Doctorate Recipients (SDR) from the National Center for Science and Engineering Statistics (NCSES); university and college rankings data from the *Times Higher Education* 2017 World University Rankings, the *Wall Street Journal – Times Higher Education* 2017 College Rankings, and the 2021 *US News and World Report* University and college rankings; and university characteristics from Integrated Postsecondary Education Data System (IPEDS) surveys.

Our analysis required three main steps: build a work history panel for tenure-track faculty, construct a dataset with institution characteristics, and associate each school to a unique ranking. Below we detail the main steps we used to build our final dataset.

### C.4.1 Building the work history panel

We first combine the information from all the SDR waves available between 1993 and 2017 (inclusive). We restrict the sample to people employed full-time (35 hours/week for at least 40 weeks/year) in a tenure-stream (tenured or tenure-track) position at a US 4-year college or university, medical school attached to a university, or university research institute. We also drop observations where respondents were in a post-doctoral position, earned less than the minimum National Institutes of Health post-doctoral stipend (\$53,760 in 2020), or worked outside the US (whether in academia or not). We identify employers using the IPEDS institution code reported by the SDR. We transform all salary figures into 2020 dollars using the yearly CPI for all urban consumers (U.S Bureau of Labor Statistics, 2023). This leaves us with an unbalanced panel tracking the work history of tenure-track faculty across US academic institutions.

### Determining faculty moves in the SDR

We pay special attention to ensuring that we track the moves of faculty across academic institutions correctly. The AKM model identifies the pay-premiums out of variation coming from people moving across institutions. Thus, it is crucial that we record moves correctly.

We say an academic changed employer whenever we observe a change in the IPEDS code of the current employer, except when these changes result from a leave of absence or a likely coding error. We identify leaves of absence as *temporary moves* out of a primary or home institution. These are moves satisfying three conditions:

- (i) we observe the academic in three *consecutive* SDR waves;
- (ii) the academic starts in an institution (home) and moves to a *host* institution for one period;

(iii) to then return to their home institution.

We identify 59 leaves-of-absence in our data. We exclude the host school observation for them, keeping the observations in their home school only.

We also identified and manually corrected moves that were likely the result of a coding error. There were 2,916 observations where the IPEDS university code changed, but the respondent reported not changing institutions. These frequently involved two institutions with similar names. Thus, a Boston University faculty member in multiple waves might be miscoded as Boston College faculty for one wave, while not reporting changing institutions. We manually checked these moves and corrected those we deemed likely mistakes.

Because we are interested in institution-level premiums, we merged IPEDS codes that identify units of the same university. IPEDS divides some large universities across different codes. For example, ASU-Tempe and ASU-Phoenix have different codes even though they belong to the same institution. We did not count these as moves in our dataset, since all are within ASU. Therefore, we assigned all university units to a single code in such cases. (It is possible that we missed some moves in this process but wanted to be conservative in what we considered to be moves.) Whenever we determined university campuses were independent of each other, we kept them as separate IPEDS codes. For example, we keep University of Wisconsin-Madison and University of Wisconsin Oshkosh as separate institutions.

We tried to be as conservative as possible in this process, only combining 40 institution codes into 24 codes. We can provide the list of merged codes upon request.

#### C.4.2 Salaries

In addition to excluding observations that we determined to be leaves of absence, we excluded salary observations with very large one-time salary changes that were

subsequently reversed *within the same institution*. We identify these outliers as follows:

1. First, we computed the growth in the log of salary adjusted for job experience ( $\Delta\tilde{w}_t$ ):

$$\Delta\tilde{w}_t = \Delta w_t - \Delta\hat{w}_t \quad (\text{C.1})$$

where  $\Delta w_t$  is the log change in the individual salary, and  $\Delta\hat{w}_t$  is the expected change in the log salary due to experience. This expected change comes from a regression of log salaries on years of experience, and years of experience squared:

$$w_t = \alpha_o + \alpha_1 y_t + \alpha_2 y_t^2 + \nu_t$$

where  $y_t$  denote years since Ph.D. Then we define the expected change as:

$$\Delta\hat{w}_t = \hat{\alpha}_1 \Delta y_t + \hat{\alpha}_2 \Delta y_t^2$$

The expression in C.1 measures how much actual salary growth deviates from what we should expect based on the experience profile alone.

2. We flag a *within-institution* log salary change as a *potential outlier* if, after adjusting for experience, it is larger than 0.4 in absolute value:

$$|\Delta\tilde{w}_t| = |\Delta w_t - \Delta\hat{w}_t| > 0.4$$

We note that 0.4 is a conservative threshold, in the 97<sup>th</sup> percentile of adjusted salary growth.

3. We then focus on the *potential outliers* and exclude observations as follows. We drop all observations from people with only two observations in the dataset

and who worked for only one institution. For people having at least three observations and who worked for several institutions, we apply the following procedure:

4. If  $|\Delta\tilde{w}_t| > 0.4$ , then either  $w_t$  or  $w_{t-1}$  may be the outlier. We exclude  $w_t$  if its distance from any other salary observation for that person is greater than 0.2<sup>1</sup>. That is,

$$\text{Drop } w_t \text{ if } \min_j \{d_j | d_j = |w_j - w_t|, j \neq t\} > 0.2$$

5. If  $|\Delta\tilde{w}_t| > 0.4$  but its minimum distance is less than 0.2, we apply additional sequential filters (i.e., if an observation survives filter (i) below, then we applied (ii)):
  - i. We excluded all observations where the individual's primary work activities were not teaching or research. These people are likely to be in administrative positions<sup>2</sup>.
  - ii. We excluded all salaries that were out of line with the individual's salary trend. This judgment was made on a case-by-case basis. All these modifications were codified into the do file *code/build\_database/outlier\_exclusion\_list.do*

#### C.4.3 Building the institution characteristics dataset

All university characteristics other than the rankings are extracted from IPEDS. We use the modules of institution characteristics, fall enrollment, finance, and salaries for the years 1998, 2005, 2012, and 2017. All nominal figures are converted into 2020 dollars using the CPI for all urban consumers. As we say in the paper, we cannot

---

<sup>1</sup>0.2 is the 90th percentile of the adjusted wage growth.

<sup>2</sup>In later waves, the SDR asked if the person working in an academic institution was (a) a president, provost or chancellor or (b) a dean, department head or department chair. However, this question was not asked in most SDR waves in our study so we do not use it.

meaningfully add time-varying institution characteristics to our model because they change very slowly, and when they do change, long and uncertain lags in their impact would prevent us from associating salary and institutional changes to salary shifts. Thus, we average all continuous variables across the four survey waves. For all dummy variables, we assign the maximum value across the four years. For example, we classify a university as granting a Ph.D. Degree if it ever granted a Ph.D. Degree during any of the four survey waves.

We extract the following variables from IPEDS:

- **University location:** we classify the university's location into small, medium, and large city. This variable is a recoding of IPEDS' locale variable. Table C.8 details the mapping between both variables.
- **Private university:** dummy equal to one if the university is private.
- **Undergrad-only:** dummy variable equal to one if the institution only offers undergraduate degrees.
- **Total enrollment:** sum of undergraduate and graduate enrollment, averaged over the four survey years.
- **Total faculty:** total faculty size, average of the four survey years.
- **Value of endowment:** IPEDS reports finance information separately for public institutions, private not-for-profit, and private for profit. Our endowment variable corresponds to:
  - **Public universities and private non-profits:** we average the value of endowment assets at the beginning and the end of the fiscal year.
  - **Private for-profits:** we average the value of equity at the beginning and the end of the year.

We use the average of the endowment across the four survey waves.

#### C.4.4 University rankings

Our primary sources for the institution rankings are the *Times Higher Education* 2017 World University Rankings, the *Wall Street Journal – Times Higher Education* 2017 College Rankings. The *THE* rankings consist of a list of institution names along with their position in the ranking and the state in which they are located. We linked these rankings to a unique IPEDS code using the institution name and location. In most cases, the names in *THE* and IPEDS were similar, and the linkage was straightforward. For the few cases where the linkage was not obvious, we followed the following rules:

1. Whenever names only differed in the word “college” or “university,” we use a Google search and the location information to determine if they were the same institution. For example, if the IPEDS label was “Concordia College” and the *THE* ranking name was “Concordia University”. We linked both names if and only if:
  - a. The institution state is the same in both datasets.
  - b. A search for the term “[...] college” gives “[...] university” as the first search result (or vice versa).
1. Different campuses in a university system have different IPEDS codes. Sometimes *THE* provides only one rank for a university system without reference to the campus. In this case, we associated the rank to the flagship campus. For example, the *THE* rank for “Penn State University” was associated to the IPEDS code for “Penn State University, University-Park.”

The procedure above was applied to both the *THE* World University and the *WSJ/THE* College rankings. Based on the result of the matching, we classify institutions into three mutually exclusive categories. These categories determine the value of the *institution ranking* variable we use in our regressions.

1. **Research universities:** these are institutions we matched to the *THE* World University Rankings. For these institutions, the value of *institution rank* is their position in the World University Ranking.
1. **Colleges:** there are institutions (i) not matched to the World University Ranking but (ii) matched to the College Ranking. Their *institution rank* is their position in the College Rankings. Note that many institutions in this category are not solely undergraduate institutions.
2. **Unranked universities:** these are institutions we could not match to any of the rankings. We assign a value of zero to their *institution rank*.

We matched 585 (86% of the total) of the 679 institutions to a *THE* rank. Of the remaining 94, we imputed a rank for 59 schools ranked in *USNWR*, using the relation between *USNWR* and *THE* ranks (see below), leaving 35 unranked schools (5% of the total).

#### C.4.5 Imputing of the THE ranks

The *THE* rankings are our primary source of university performance information. However, we were unable to match 94 institutions to a *THE* rank. For 59 of these institutions, we were able to impute a *THE* rank using U.S. News and World Report (*USNWR*) rankings as follows:

1. First, we merge the *THE* rankings with each of the ten available *US News* ranking lists (national, liberal arts colleges, and regionals). Merging was done

by institution (university or college) name. Names were manually checked to ensure consistency.

2. For universities ranked by both *THE* and *US News* (in any of the six lists), we run an OLS regression of their position in the *THE* list on their position in the *US News* list:

$$\text{THE\_ranking}_i = \alpha + \beta \text{US\_news\_ranking}_i + \varepsilon_i$$

We run a separate regression for each of the *US News* lists (national, liberal arts colleges, and regionals). Table C.10 shows the results of each of these auxiliary regressions.

3. We infer the position in the *THE* rankings for universities unranked by *THE* but ranked by *US News* using the predicted values of the regression in 2. That is:

$$\widehat{\text{THE}}_{\text{ranking}_i} = \alpha + \widehat{\beta} \text{US\_news\_ranking}_i$$

Note that all ten *US News* rankings are mutually exclusive. Therefore, the imputed *THE* position is unique. We treat institutions in the *national US News* ranking as *research universities*, and institutions in all other *US News* rankings (liberal arts colleges, regional universities, and regional colleges) as *colleges*. Table C.11 provides a breakdown of the imputed ranks according to the *US News* ranking list we used for the imputation.

**Table C.8:** University location classification

1998 IPEDS locale classification		Recoding used	
Codes	Labels	Codes	Labels
1	Large city	1	Large city
2	Mid-size city		
3, 4	Urban fringe of large / mid-size city	2	Mid size city / suburb
5, 6, 7	Large town, small town, rural		
9	Not assigned	3	Small city / rural town

2005-2017 IPEDS locale classification		Recoding used	
Codes	Labels	Codes	Labels
11	Large city	1	Large city
12	Mid-size city		
21, 22, 23	Suburbs	2	Mid-size city / suburbs
13	Small city		
31 - 43	Towns, rural	3	Small city / rural town

**Table C.9:** Description of location codes

Location	Description
Large city	Urban area, population above 250k
Mid-size city / suburbs	Urban area, population between 100k and 250k, or suburbs
Small city / rural town	Urban areas with population below 100k, rural areas

**Table C.10:** Ranking imputation regressions

	National rankings		Regional universities				Regional colleges			
	(1) National	(2) Liberal	(3) North	(4) South	(5) Midwest	(6) West	(7) North	(8) South	(9) Midwest	(10) West
US News ranking	1.762 (0.132)	3.115 (0.139)	3.101 (0.237)	2.671 (0.361)	2.883 (0.293)	3.872 (0.395)	3.681 (1.901)	1.715 (0.623)	7.927 (1.130)	7.938 (5.318)
Constant	82.21 (17.665)	-20.90 (15.120)	326.0 (21.710)	550.3 (24.234)	456.5 (23.468)	439.7 (25.014)	624.2 (50.416)	694.0 (23.008)	382.2 (37.954)	585.5 (68.844)
r2	0.582	0.771	0.554	0.386	0.477	0.530	0.211	0.296	0.629	0.182
F	179.3	502.0	171.4	54.61	96.79	96.04	3.748	7.571	49.24	2.228
N	131	151	140	89	108	87	16	20	31	12

*Notes:* The dependent variable in column (1) is the THE research university ranking. The dependent variables for all the columns is the THE college university ranking.

**Table C.11:** Number of schools imputed by ranking type

Ranking type	Number of schools
<i>National rankings</i>	
Universities	10
Liberal arts colleges	13
<i>Regional Universities</i>	
North	6
South	4
West	2
Midwest	8
<i>Regional colleges</i>	
North	2
South	5
West	2
Midwest	2
Total	54

## References

- Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.
- Abowd, J. M., McKinney, K. L., and Schmutte, I. M. (2019). Modeling Endogenous Mobility in Earnings Determination. *Journal of Business and Economic Statistics*, 37(3):405–418.
- Alesina, A., Giuliano, P., and Nunn, N. (2013). On the origins of gender roles: Women and the plough. *Quarterly Journal of Economics*, 128(2):469–530.
- Amemiya, T. (1978). A Note on a Random Coefficients Model. *International Economic Review*, 19(3):793.
- Ananat, E., Shihe, F., and Ross, S. L. (2018). Race-specific urban wage premia and the black-white wage gap. *Journal of Urban Economics*, 108:141–153.
- Andrews, M. J., Gill, L., Schank, T., and Upward, R. (2008). High wage workers and low wage firms: Negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society. Series A: Statistics in Society*, 171(3):673–697.
- Andrews, M. J., Gill, L., Schank, T., and Upward, R. (2012). High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. *Economics Letters*, 117(3):824–827.
- Angelov, N., Johansson, P., and Lindahl, E. (2016). Parenthood and the gender gap in pay. *Journal of Labor Economics*, 34(3):545–579.
- Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics : an empiricist's companion*. Princeton University Press.
- Autor, D., Figlio, D., Karbownik, K., Roth, J., and Wasserman, M. (2019). Family disadvantage and the gender gap in behavioral and educational outcomes. *American Economic Journal: Applied Economics*, 11(3):338–381.
- Autor, D. and Salomons, A. (2018). Is automation labor share-displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity*, 2018(Spring):1–87.

- Autor, D. H. (2019). Work of the Past, Work of the Future. *AEA Papers and Proceedings*, 109:1–32.
- Autor, D. H. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5):1553–1597.
- Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.
- Autor, D. H. and Wasserman, M. (2013). Wayward Sons: The Emerging Gender Gap in Education and Labor Markets. *Third Way Next*, pages 1–59.
- Bacolod, M. (2017). Skills, the gender wage gap, and cities. *Journal of Regional Science*, 57(2):290–318.
- Bacolod, M., Blum, B. S., and Strange, W. C. (2009). Skills in the city. *Journal of Urban Economics*, 65(2):136–153.
- Baker, M. and Milligan, K. (2016). Boy-girl differences in parental time investments: Evidence from three countries. *Journal of Human Capital*, 10(4):399–441.
- Barcellos, S. H., Carvalho, L. S., and Lleras-Muney, A. (2014). Child gender and parental investments in india: Are boys and girls treated differently? *American Economic Journal: Applied Economics*, 6(1 A):157–189.
- Baron, J. N. and Dreps, D. M. (1999). *Strategic Human Resources: Frameworks for General Managers*. New York: John Wiley & Sons, Inc.
- Baum-Snow, N., Freedman, M., and Pavan, R. (2018). Why has urban inequality increased? *American Economic Journal: Applied Economics*, 10(4):1–42.
- Baum-Snow, N. and Pavan, R. (2012). Understanding the city size wage gap. *Review of Economic Studies*, 79(1):88–127.
- Bazzi, S., Hilmy, M., and Marx, B. (2022). Religion, Education, and Development.
- Black, D. A., Kolesnikova, N., and Taylor, L. J. (2014). Why do so few women work in New York (and so many in Minneapolis)? Labor supply of married women across US cities. *Journal of Urban Economics*, 79:59–71.
- Blau, F. D. and Kahn, L. M. (2015). Immigration and the distribution of incomes. In *Handbook of the Economics of International Migration*, volume 1.
- Blau, F. D. and Kahn, L. M. (2017). The gender wage gap: Extent, trends, & explanations. *Journal of Economic Literature*, 55(3):789–865.

- Blau, F. D., Kahn, L. M., Comey, M., Eng, A., Meyerhofer, P., and Willén, A. (2020). Culture and gender allocation of tasks: source country characteristics and the division of non-market work among US immigrants. *Review of Economics of the Household*, 18(4):907–958.
- Blau, F. D., Kahn, L. M., and Papps, K. L. (2011). Gender, Source Country Characteristics, and Labor Market Assimilation among Immigrants. *The Review of Economics and Statistics*, 93(1):43–58.
- Boelmann, B., Raute, A., and Schonberg, U. (2021). Wind of Change? Cultural Determinants of Maternal Labor Supply. *SSRN Electronic Journal*.
- Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., and Setzler, B. (2020). How Much Should We Trust Estimates of Firm Effects and Worker Sorting? *Journal of Labor Economics (forthcoming)*.
- Bose, G. and Lang, K. (2017). Monitoring for Worker Quality. *Journal of Labor Economics*, 35(3):755–785.
- Brinkhoff, T. (2022). Indonesia: Administrative Division (Provinces, Regencies and Cities), retrieved from <https://www.citypopulation.de/en/indonesia/admin/>.
- Bryan, G. and Morten, M. (2019). The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy*, 127(5):2229–2268.
- Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics*, 36(S1):S13–S70.
- Cavounidis, C., Dicandia, V., Lang, K., and Malhotra, R. (2021). The Evolution of Skill Use Within and Between Jobs.
- Charles, K. K., Guryan, J., and Pan, J. (2018). The Effects of Sexism on American Women: The Role of Norms vs. Discrimination. *SSRN Electronic Journal*.
- Cheng, S. D. (2020). Careers Versus Children: How Childcare Affects the Academic Tenure-Track Gender Gap.
- Chetty, R. and Hendren, N. (2018a). The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *Quarterly Journal of Economics*, 133(3):1107–1162.
- Chetty, R. and Hendren, N. (2018b). The impacts of neighborhoods on intergenerational mobility II: County-level estimates. *Quarterly Journal of Economics*, 133(3):1163–1228.

- Chetty, R., Hendren, N., Jones, M. R., and Porter, S. R. (2020). Race and economic opportunity in the United States: An intergenerational perspective.
- Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.
- Compton, J. and Pollak, R. A. (2014). Family proximity, childcare, and women's labor force attachment. *Journal of Urban Economics*, 79:72–90.
- Damm, A. P. and Dustmann, C. (2014). Does growing up in a high crime neighborhood affect youth criminal behavior? *American Economic Review*, 104(6):1806–1832.
- de la Roca, J. and Puga, D. (2017). Learning byworking in big cities. *Review of Economic Studies*, 84(1):106–142.
- Deming, D. J. (2017). The growing importance of social skills in the labor market. *Quarterly Journal of Economics*, 132(4):1593–1640.
- Dhar, D., Jain, T., and Jayachandran, S. (2022). Reshaping Adolescents' Gender Attitudes: Evidence from a School-Based Experiment in India. *American Economic Review*, 112(3):899–927.
- DiPrete, T. A. and Jennings, J. L. (2012). Social and behavioral skills and the gender gap in early educational achievement. *Social Science Research*, 41(1):1–15.
- Donald, D., Mengus, E., and Michalski, T. (2020). Labor Market Polarization and the Great Divergence: Theory and Evidence. *NBER working paper 26955*.
- Duranton, G., Morrow, P. M., and Turner, M. A. (2013). Roads and Trade: Evidence from the US. *Review of Economic Studies*, 81(2):681–724.
- Duranton, G. and Puga, D. (2020). The economics of urban density. *Journal of Economic Perspectives*, 34(3):2–26.
- Eeckhout, J. and Kircher, P. (2011). Identifying sorting-In theory. *Review of Economic Studies*, 78(3):872–906.
- Farre, L. and Ortega, F. (2021). Family Ties, Geographic Mobility and the Gender Gap in Academic Aspirations. *SSRN Electronic Journal*.
- Fernández, R. (2007). Alfred Marshall lecture women, work, and culture. In *Journal of the European Economic Association*, volume 5, pages 305–332.
- Fernández, R. (2013). Cultural change as learning: The evolution of female labor force participation over a century. *American Economic Review*, 103(1):472–500.

- Fernández, R. and Fogli, A. (2006). Fertility: The role of culture and family experience. In *Journal of the European Economic Association*, volume 4, pages 552–561.
- Fernandez, R. and Fogli, A. (2009). Culture: An empirical investigation of beliefs, work, and fertility. *American Economic Journal: Macroeconomics*, 1(1):146–177.
- Fernández, R., Fogli, A., and Olivetti, C. (2004). Mothers and sons: Preference formation and female labor force dynamics.
- Fogli, A. and Veldkamp, L. (2011). Nature or Nurture? Learning and the Geography of Female Labor Force Participation. *Econometrica*, 79(4):1103–1138.
- Ginther, D. and Kahn, S. (2006). Does science promote women? Evidence from academia 1973-2001. In *Science and Engineering Careers in the United States: An Analysis of Markets and Employment*, pages 163–194. Cambridge, MA.
- Glaeser, E. L. and Gottlieb, J. D. (2009). The wealth of cities: Agglomeration economies and spatial equilibrium in the United States. *Journal of Economic Literature*, 47(4):983–1028.
- Glaeser, E. L. and Maré, D. C. (2001). Cities and skills. *Journal of Labor Economics*, 19(2):316–342.
- Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4):1091–1119.
- Gollin, D., Kirchberger, M., and Lagakos, D. (2021). Do urban wage premia reflect lower amenities? Evidence from Africa. *Journal of Urban Economics*, 121:103301.
- International Labour Organization (2021). ILOSTAT database: Country profiles.
- Jayachandran, S. (2021). Social Norms as a Barrier to Women’s Employment in Developing Countries. Technical report.
- Jayachandran, S. and Kuziemko, I. (2011). Why Do Mothers Breastfeed Girls Less than Boys? Evidence and Implications for Child Health in India. *Quarterly Journal of Economics*, 126(3):1485–1538.
- Kahn, S. and Ginther, D. (2017). Women and STEM.
- Kleven, H., Landais, C., and Søgaard, J. E. (2019). Children and gender inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*, 11(4):181–209.
- Kline, P., Saggio, R., and Sølvsten, M. (2020). Leave-Out Estimation of Variance Components. *Econometrica*, 88(5):1859–1898.

- Le Barbanchon, T., Rathelot, R., and Roulet, A. (2021). Gender Differences in Job Search: Trading off Commute against Wage.
- Liu, S. and Su, Y. (2020). The Geography of Jobs and the Gender Wage Gap. Technical report.
- Magruder, J. R. (2013). Can minimum wages cause a big push? Evidence from Indonesia. *Journal of Development Economics*, 100(1):48–62.
- Martinez, E. D., Botos, J., Dohoney, K. M., Geiman, T. M., Kolla, S. S., Olivera, A., Qiu, Y., Rayasam, G. V., Stavreva, D. A., and Cohen-Fix, O. (2007). Falling off the academic bandwagon. Women are more likely to quit at the postdoc to principal investigator transition.
- Milsom, L. (2021). The Changing Spatial Inequality of Opportunity in West Africa.
- Minnesota Population Center (2020). *Integrated Public Use Microdata Series, International: Version 7.3 [dataset]*. MN:IPUMS.
- Molina, T. and Usui, E. (2022). Female Labor Market Opportunities and Gender Gaps in Aspirations. *SSRN Electronic Journal*.
- Moreno-Maldonado, A. (2019). Mums and the City Female labour force participation and city size.
- National Academy of Sciences. Committee on Occupational Classification and Analysis. (1971). *Dictionary of Occupational Titles (DOT): Part I - Current Population Survey, April 1971, Augmented With DOT Characteristics and Dictionary of Occupational Titles (DOT): Part II - Fourth Edition Dictionary of DOT Scores for 1970*. Number April. Inter-university Consortium for Political and Social Research [distributor].
- Olivetti, C. and Petrongolo, B. (2008). Unequal pay or unequal employment? A cross-country analysis of gender gaps. *Journal of Labor Economics*, 26(4):621–654.
- Olivetti, C. and Petrongolo, B. (2014). Gender gaps across countries and skills: Demand, supply and the industry structure. *Review of Economic Dynamics*, 17(4):842–859.
- Olivetti, C. and Petrongolo, B. (2016). The Evolution of Gender Gaps in Industrialized Countries. *Annual Review of Economics*, 8(1):405–434.
- Pande, R. P. (2003). Selective gender differences in childhood nutrition and immunization in rural India: The role of siblings. *Demography*, 40(3):395–418.
- Phimister, E. (2005). Urban effects on participation and wages: Are there gender differences? *Journal of Urban Economics*, 58(3):513–536.

- Rossi-Hansberg, E., Sarte, P.-D., and Schwartzman, F. (2019). Cognitive Hubs and Spatial Redistribution. *Federal Reserve Bank of Richmond Working Papers*, 19(16):1–83.
- Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings.
- Ruggles, S., Alexander, J., Genadek, K., Goeken, R., Schroeder, M., and Sobek, M. (2010). *Integrated Public Use Microdata Series: Version 5.0*. Minneapolis, MN: Minnesota Population Center.
- Sorkin, I. (2018). Ranking firms using revealed preference. *Quarterly Journal of Economics*, 133(3):1331–1393.
- Statistics Indonesia (2019). *Survei Sosial Ekonomi Nasional (Susenas), 2012 Core*, <https://doi.org/10.7910/DVN/12TVW1>. Harvard Dataverse, V1.
- Statistics Indonesia (2020). *Survei Sosial Ekonomi Nasional (Susenas), 2016 Kor*, <https://doi.org/10.7910/DVN/BOXZWU>. Harvard Dataverse, V2.
- Statistics Indonesia (2021). The Indonesian Population Census.
- Times Higher Education (2017a). World University Rankings.
- Times Higher Education (2017b). WSJ/THE College Rankings 2017.
- U.S Bureau of Labor Statistics (2023). Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL]. retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/CPIAUCSL>, April 24, 2023.
- US News (2021). 2021 Best Colleges.
- USDA (2019). US Commuting Zones and Labor Market Areas.
- Wolfinger, N. H., Mason, M. A., and Goulden, M. (2008). Problems in the Pipeline: Gender, Marriage, and Fertility in the Ivory Tower. *The Journal of Higher Education*, 79(4):388–405.

# CURRICULUM VITAE

## César Luis Garro Marín

Department of Economics, Room 515  
 270 Bay State Rd  
 Boston, MA, 02215 USA  
 Personal website: [www.cesargarromarin.com](http://www.cesargarromarin.com)  
 Email: cesarlgm@bu.edu

### Education

Ph.D., Economics, Boston University, Boston MA, Aug 2023 (expected).

Dissertation Title: Essays in Gender, Earnings, and Geography

Main advisor: Daniele Paserman

Dissertation Committee: Daniele Paserman, Kevin Lang, and Linh Tô

Master in Economics and Finance, CEMFI, Madrid, Spain, 2017

Licentiate, Economics (with Honors), University of Costa Rica, Costa Rica, 2015

B. A., Economics (with Honors), University of Costa Rica, Costa Rica, 2013

### Fields of Interest

Labor Economics, Development Economics, Gender Economics

### Working Papers

“The Geography of Women’s Opportunity: Evidence from Indonesia,” April 2023. Job market paper.

“Do Elite Universities Overpay Their Faculty?” (With Shulamit Kahn and Kevin Lang), April 2023.

## **Work in Progress**

“Gender and the Urban Wage Premium”.

“Education and Skill Investment” (joint with Costas Cavouridis, Kevin Lang, Raghav Malhotra).

“Improving the Link Between Vocational Schools and Industry: Evaluation of Teacher Training in Indonesia” (joint Masyhur Hilmy)

## **Presentations**

2023 Society of the Economics of the Household Annual Meeting, Copenhagen, Denmark (scheduled).

2021 LACEA-LAMES Annual Meeting, Bogotá, Colombia.

Summer School in Urban Economics (Ph.D. Student Workshop), Virtual.

## **Fellowships and Awards**

Research Grant, Indonesian Research Fund, Spring 2021.

Research Grant, Weiss Fund for Research in Development Economics, Spring 2020.

Dean’s Student Fellowship, Boston University, 2017-2023.

Master Student Fellowship, CEMFI, 2015-2017

Honors Fellowship, University of Costa Rica, Spring 2012-Fall 2013

Honors Fellowship, University of Costa Rica, Spring 2019-Fall 2011

## **Work Experience**

### **Academic**

Research Assistant to Professor Kevin Lang, Boston University, 2019-2023.

Research Assistant to Professor Pedro Mira, CEMFI, Summer 2016.

### **Non-academic**

Junior Data Analyst, Baccredomatic, San José, Costa Rica, 2013-2014

## Referee experience

*Journal of Labor Economics, Feminist Economics*

## Teaching Experience

- Teaching Fellow, Economics of Labor Markets (Masters), Department of Economics, Boston University, Spring 2020, Spring 2021.
- Teaching Fellow, Poverty and Discrimination, Department of Economics, Boston University, Fall 2019.
- Teaching Fellow, Principles of Microeconomics, Department of Economics, Boston University, Fall 2018-Spring 2019.
- Instructor, Introduction to Economics, Department of Economics, University of Costa Rica, 2014-2015.

## Languages

Native fluency: English and Spanish

## Computer skills

R, Stata, Matlab, Git, SQL, L<sup>A</sup>T<sub>E</sub>X

## Citizenship/Visa status

Costa Rican / US F1 Visa

## References

<b>Professor Paserman</b>	<b>Daniele</b>	<b>Professor Kevin Lang</b>	<b>Professor Linh Tô</b>
Department of Economics Boston University Phone: +1 (617) 353-4449 e-mail: paserman@bu.edu		Department of Economics Boston University Phone: +1 (617) 353-5694 e-mail: lang@bu.edu	Department of Economics Boston University Phone: +1 (617) 353-4535 e-mail: linhto@bu.edu